

Copyright is owned by the Author of the thesis. Permission is given for a copy to be downloaded by an individual for the purpose of research and private study only. The thesis may not be reproduced elsewhere without the permission of the Author.

Essays on Investment in the Chinese Art Market

A thesis presented in fulfilment of the requirements for the degree of

Doctor of Philosophy

in

Finance

at Massey University, Auckland,

New Zealand

Yue Yuan

2023

Dedication

To the ones I hold dear: my beloved parents, who have nurtured and supported me, and the enchanting world of art that has captivated and inspired my soul.

Abstract

The growing significance of investing in Chinese painting and calligraphy (hereinafter: Chinese art) has garnered widespread attention from scholars, investors, and collectors. This dissertation comprises three essays that delve into the Chinese art market. It first explores the price determinants and investment performance of Chinese art; second, the potential of art investment for portfolio diversification; and finally, the informational content of pre-sale estimates in terms of accuracy and uncertainty.

Essay 1 examines the price determinants and investment performance of Chinese art. The study utilizes 165,847 lots sold executed by 533 Chinese artists between 2000 and 2017. Using hedonic regression, this study constructs the Chinese art price index, and finds that the artwork's attributes, such as proof of authenticity, types of mounting, and large-scale auction months, have a significantly positive impact on prices. It also reveals two distinct art-market booms in 2005 and 2011, with the latter reaching a record peak. Moreover, the average holding period for Chinese art is approximately 3 years, much shorter than the 10-year average in Western art markets. This indicates that the Chinese art market exists in speculative activity. This underscores the necessity for art market participants in China need to be aware of the risk associated with art investment, as art is not necessarily for art's sake. This study comprehensively analyses hedonic attributes' impact on prices, offering valuable insights for constructing Chinese art-price indices and assessing respective returns. It is a key resource for those keen to deeply understand the Chinese art market.

Essay 2 investigates the potential diversification benefits of investing in Chinese art based on a unique dataset of 4,840 repeat transaction pairs from 2003 to 2021. Using the repeat-sale regression, it finds a semiannual art return of 6.18%, which outperforms all other investment assets and has a lower standard deviation than equities. To assess the diversification role of Chinese art, correlation analysis, the capital asset pricing model, and downside beta are employed. The study finds that Chinese art exhibits a low or negative correlation with common financial assets and a negative market

beta when the Shanghai composite stock index and Shenzhen composite stock index are used as market returns, indicating its efficacy as a diversification instrument. Additionally, Chinese art can act as a hedge against domestic stock market downturns in a diversified portfolio. Furthermore, the study adopts mean-variance portfolio optimization to assess the potential advantages of incorporating Chinese art into investment portfolios. The results show that the efficient frontier that includes Chinese art is superior to those without such an inclusion. Moreover, the inclusion of Chinese art enhances the overall utility of the portfolio across all degrees of risk aversion, as evidenced by the power utility optimization. Supplementary tests show that portfolios on the efficient frontier with Chinese art outperform the equal-weighted portfolio, and that the efficient frontier with Chinese art is superior to the efficient frontier without Chinese art during periods of underperformance in the domestic stock market. In conclusion, this study underscores the potential benefits of portfolio diversification through investing in Chinese art, thereby making a valuable contribution to the existing literature on art-related portfolio diversification strategies.

Essay 3 investigates the impact of certain variables on the informational content of pre-sale estimates in terms of accuracy and uncertainty. Using a sample of 191,102 artwork executed by 533 Chinese artists from 2000 to 2021, the study reveals that factors, such as artists' mentorship experience, the proof of authenticity, the large-scale auction months, and past-sale records, can either improve or diminish the accuracy and uncertainty of pre-sale estimates in predicting the hammer prices. This finding enriches the extant literature on the reliability of pre-sale price predictions in the art market. Moreover, it offers valuable insights for auction houses seeking to reduce prediction errors. The study further uncovers that the impact of these factors varies across price distributions, suggesting that auctioneers could utilize specific variables to enhance the accuracy of pre-sale estimates tailored to different price segments. Additionally, this study also finds that auction houses with artist-specific experience are more likely to offer precise pre-sale estimates, while they are less optimistic about reducing the uncertainty of pre-sale estimates. The study contributes to the literature

on art economics by examining the extent to which auction houses can influence the outcomes of art auctions.

Acknowledgments

I would like to thank some wonderful people who have inspired and motivated me. My heartfelt appreciation extends to each one of them.

I would like to express my deepest gratitude to my esteemed supervisors - Associate Professor Liping Zou, Professor Anne de Bruin, and Associate Professor George Wu, for their unparalleled support and priceless guidance throughout my PhD journey. Their encouragement, patience, and open-mindedness towards my research ideas have served as a driving force that has kept me motivated and on track during my academic pursuits. Their exceptional mentorship has inspired me to continually strive for excellence, with the hope of someday becoming an individual capable of providing guidance and addressing the concerns of others, just as they have generously done for me.

My heartfelt appreciation also goes to the Associate Head of School, Professor Sasha Molchanov, Professor Nick Nguyen (Auckland University of Technology), Muharram Azizova, Myrah Corrales, Mary Dawkins, Simone Hey, Mark Woods, and the entire talented team at the School of Economics and Finance for their outstanding support and the provision of indispensable resources, which have been crucial in enabling me to attain my academic goals.

I extend my heartfelt appreciation to my parents, who always give me their unconditional love. I am truly blessed.

Lastly, I would like to express my gratitude for the roses planted in my garden. To me, they are more than just plants; they have been friends accompanying me throughout these years. They never cease to remind me that the beauty of scientific research and the beauty of nature ultimately converge upon a shared path.

Table of Contents

Abstract	ii
Acknowledgments	v
List of Figures	x
List of Tables	xi
Chapter 1. Introduction	1
1.1. Background of Study	1
1.2. Essay 1	2
1.3. Essay 2	4
1.4. Essay 3	6
1.5. Research Outputs from the Thesis	7
1.6. The Sequence of the Thesis	8
Chapter 2. Art not for Art’s Sake: An Exploration of the Chinese Art Market	9
2.1. Introduction.....	9
2.2. Literature Review.....	13
2.3. Data and Methodology.....	17
2.3.1. Data Collection	17
2.3.2. Hedonic Variables.....	19
2.3.3. Heckman Two-Stage Regression Data	23
2.3.4. Repeat-Sales Data	24
2.4. Empirical Analysis.....	26
2.4.1. Baseline Hedonic Regression	26
2.4.2. Baseline Art-Price Indices and Returns	29
2.4.3. Robustness Tests.....	33
2.4.4. Heckman Two-Stage Regression.....	34

2.4.5. Masterpiece Effect	40
2.4.6. Auction-House Effect	41
2.4.7. A Comparison Between Chinese art and Common Financial Assets	45
2.5. Conclusion	47
Chapter 3. Portfolio Diversification Benefits of Chinese Art	50
3.1. Introduction.....	50
3.2. Literature Review.....	53
3.2.1. Definition and Benefits of Diversification.....	53
3.2.1.1. Evidence From the Western Art Market.....	53
3.2.1.2. Evidence From the Emerging Art Market.	54
3.2.2. Evidence From Other Alternative Investment Assets.....	56
3.3. Data and Methodology.....	57
3.3.1. Data Collection	57
3.3.1.1. Data Collection for Chinese Art.	57
3.3.1.2. Data Collection for Financial Asset Classes.....	59
3.3.2. Methodology to Calculate the Rate of Return on Chinese Art.....	59
3.3.2.1. Repeat-Sales Regression.....	59
3.3.3. Methodology to Measure the Potential Risk Diversification of Chinese Art.....	60
3.3.3.1. Single-Index Model and Time-Varying CAPM.	60
3.3.3.2. Downside Beta.	61
3.3.4. Methodology for the Assessment of the Diversification Benefits of Chinese Art in a Portfolio	62
3.3.4.1. Mean-Variance Portfolio Optimization.	62
3.3.4.2. Power Utility Optimization.....	63
3.3.4.3. Sharpe Ratio and Modified Sharpe Ratio.	63

4.4. Data and Methodology	98
4.4.1. Data Collection	98
4.4.2. Methodology to Measure the Informational Content of Pre-sale Estimates.....	98
4.4.2.1. Accuracy of Pre-sale Estimates in Predicting Hammer Prices.	99
4.4.2.2. Uncertainty of Pre-sale Estimates About the Value of the Artwork.....	102
4.5. Empirical Results	103
4.5.1. Summary Descriptive Statistics	103
4.5.2. Accuracy of Pre-sale Estimates in Predicting Hammer Prices	110
4.5.3. Uncertainty of Pre-sale Estimates About the Value of Artwork.....	122
4.5.4. Experienced Auction Houses on Accuracy and Uncertainty of Pre-sale Estimates	129
4.6. Conclusion	132
Chapter 5. Conclusion	135
5.1. Essay 1	136
5.2. Essay 2	138
5.3. Essay 3	140
References	143
Appendices.....	157
Appendix 1 Summary Description of Hedonic Variables	157
Appendix 2 Summary Descriptive of Auction Houses.....	158
Appendix 3 Baseline Art-Price Index and Return	159
Appendix 4 CAPM Model With Time-Varying Alpha and Beta	160
Appendix 5 DRC 16 Statement of Contribution.....	163

List of Figures

Figure 2.1 <i>Hedonic Price Indices</i>	31
Figure 2.2 <i>Hedonic Price Indices and Heckman price indices</i>	39
Figure 3.1 <i>Mean-Variance Efficient Frontier Analysis</i>	75
Figure 3.2 <i>Efficient Frontier for Portfolios with Chinese Art and the Equal-Weighted Portfolio. ...</i>	79
Figure 3.3 <i>Efficient Frontier for Portfolios With and Without Chinese Art During Bearish Returns in the Shanghai Composite Stock Index</i>	83
Figure 3.4 <i>Efficient Frontier for Portfolios With and Without Chinese Art During a Downturn in the Shenzhen Composite Stock Index</i>	83
Figure 3.5 <i>Portfolio With and Without Art on the Efficient Frontier During Declining Average Asset Returns</i>	84

List of Tables

Table 2.1 <i>Summary Statistics</i>	22
Table 2.2 <i>Descriptive Statistics: Heckman Two-Stage Model Sample</i>	24
Table 2.3 <i>Descriptive Statistics: Repeat-Sales Regression Sample</i>	26
Table 2.4 <i>Baseline Hedonic Regression</i>	28
Table 2.5 <i>Hedonic Art-Price Indices from 2000 to 2017</i>	29
Table 2.6 <i>Annualized Returns for Baseline Indices, Subperiod Indices, and Extensions</i>	33
Table 2.7 <i>Annualized Returns: Robustness Checks</i>	34
Table 2.8 <i>The Heckman Two-Stage Model</i>	36
Table 2.9 <i>OLS and Heckman Price Indices</i>	39
Table 2.10 <i>Masterpiece Effect</i>	41
Table 2.11 <i>Auction-House Effect</i>	45
Table 2.12 <i>Comparison of Chinese Art and Common Financial Assets</i>	47
Table 3.1 <i>Descriptive Statistics for Returns of Investment Asset Classes</i>	67
Table 3.2 <i>The Return of Correlation Between Chinese Art and Common Financial Assets</i>	69
Table 3.3 <i>The Single-Index CAPM and Time-Varying CAPM</i>	71
Table 3.4 <i>Downside Risk</i>	73
Table 3.5 <i>Mean-Variance Efficient Frontier With and Without Chinese Art</i>	74
Table 3.6 <i>Optimal Asset Allocation</i>	77
Table 3.7 <i>Robustness Test A: Efficient Frontier With Chinese Art and Equal-Weighted Portfolio</i> ..	78
Table 3.8 <i>Robustness Test B: Efficient Portfolios With and Without Chinese Art During Periods of Market Downturn</i>	81
Table 4.1 <i>Summary Descriptive Statistics</i>	105
Table 4.2 <i>Number and Frequency of Pre-sale Classifications</i>	109
Table 4.3 <i>The Effect of Factors on the Accuracy of Pre-sale Estimates</i>	114

Table 4.4 <i>Robustness Test</i>	116
Table 4.5 <i>The Effect of Factors on the Accuracy of Pre-sale Estimates Across Different Price Quantiles</i>	120
Table 4.6 <i>The Effect of Factors on the Uncertainty of Pre-sale Estimates</i>	124
Table 4.7 <i>The Effect of Factors on the Uncertainty of Pre-sale Estimates Across Different Price Quantiles</i>	127
Table 4.8 <i>The Impact of Experienced Auction Houses on the Accuracy and Uncertainty of Pre-sale Estimates</i>	132

Chapter 1. Introduction

This chapter provides an overview of three essays in this dissertation. The chapter outlines the significant contributions and motivations of each essay in presenting the body of knowledge on art investment in China. The chapter concludes by outlining the structure of the rest of the thesis.

1.1. Background of Study

The recent surge in record-breaking art auction sales indicates that art investment has gained considerable momentum as an alternative investment asset (Mandel, 2009). The growth of high-net-worth individuals (HNWIs) (Renneboog & Spaenjers, 2013) and the maturation of the art market are the two main factors behind the surge in the attractiveness of art investments. According to the Art & Finance Report 2021, 85% of wealth managers advocate the integration of art into wealth management services (Deloitte Private & ArtTactic, 2022, p. 97). As the demand for art market research and information intensifies among collectors, a notable shift in perspective is evident: in 2021, 84% of art collectors consider that wealth managers should provide art-related wealth management services, a significant increase from 65% in 2014 (Deloitte Private & ArtTactic, 2022, p. 101).

Art investment in the Western market has been relatively mature since the 1960s, shaping a market size of 65.1 billion USD in 2022. The Chinese art market, on the other hand, has developed much later than the Western market. The evolution of China's contemporary art market has been divided into four phases: the incubation period (1978-1992), the initial development period (1993-2003), the rapid growth period (2004-2011), and the mature period (2012-2018) (Wu, 2019, pp. 12-38). The incubation period witnessed the transition of the Chinese art market from a planned economic system to a market-oriented one. The subsequent phase was characterized by the establishment of multiple auction houses, which facilitated the initial development of the Chinese art market. The third stage featured explosive growth, which fundamentally restructured the international art trade landscape. The final stage was the maturation of the Chinese art market, wherein auction

strategies have evolved from a “speeding strategy” to a “quality strategy”.

In recent years, the Chinese art market has rapidly emerged as a dominant force in the global art industry, accounting for 39% of the global art-market’s turnover. This is equivalent to the US (27%) and the UK (15%) combined (Artprice, 2021, p. 11). The burgeoning art trade in Asia, particularly in mainland China and Hong Kong, underscores the escalating importance of art sales on a global scale (McAndrew, 2022b, p. 22). Despite its massive growth, the Chinese art market has been largely overlooked in previous art investment literature due to language, culture, and data limitations (Shi et al., 2018). However, as investors continue to step up their investment in Chinese art, the need for research on the Chinese art market would become more pressing.

The Chinese art market exhibits several unique characteristics in comparison to Western art markets. For instance, the primary transaction objects are Chinese painting and calligraphy, rendered with ink and water-based color on Xuan paper, which is used exclusively in China (Bian et al., 2021). Research is necessary to thoroughly comprehend the distinct attributes of traditional Chinese art. Additionally, Chinese art has yielded strong financial returns over the past decade, making them an attractive investment option. This calls for research to assess their financial performance and correlation with other asset classes. Lastly, the growing influence of the Chinese art market on the global art market necessitates a more profound understanding of Chinese art investment to capture its impact on the worldwide art market.

The rest of the chapter is divided into the following sections: Sections 1.2 to 1.4 provide an overview of Essays 1, 2, and 3 and how each essay contributes to present a body of knowledge. The research outputs are listed in section 1.5. Lastly, Section 1.6 outlines the sequence of the remainder of the thesis.

1.2. Essay 1

Art, as an asset class, is unique and heterogeneous (Demir et al., 2018), posing challenges in analyzing the factors contributing to its value. Subjective aesthetic elements are difficult to measure

accurately. Thus, they may impact the price an investor or collector is willing to pay for an artwork (McAndrew, 2010b, p. 50). Nevertheless, the value of artwork is often determined by several identifiable objective drivers of value, which can be broadly categorized into the characteristics of the artists, the artworks, and the sales (McAndrew, 2010b, p. 51).

As for artists, the characteristics of importance include their name and life status, both of which influence the perceived value of their work (Renneboog & Spaenjers, 2013; Shi et al., 2018; Taylor & Coleman, 2011). Turning to the artwork itself, it comprises the proof of authenticity, the medium used, its size, and the subject matter, all of which collectively contribute to the overall attractiveness of the work. As well, the characteristics of the sale, specifically the venue and the timing of the auction, play a significant role in determining the value of artwork (McAndrew, 2010b, pp. 56-57). For example, artworks sold at Sotheby's and Christie's command higher price premiums than at other auction houses, suggesting that these leading auction houses have high reputations (Agnello & Pierce, 1996; Higgs, 2012; Higgs & Worthington, 2005; Marinelli & Palomba, 2011; Taylor & Coleman, 2011). Additionally, Sotheby's and Christie's hold important art auctions in April, May, June, July, and November, a practice followed by many other auction houses around the world (Garay, 2021).

While the literature on art finance is extensive, most studies focus on art sales in Europe and America, with little attention given to the Chinese art market. Given the differences in influences and techniques between Chinese art and Western art, our sample that includes Chinese art presents an opportunity for new findings in the literature. Therefore, Essay 1 aims to investigate the price determinants and investment performance of Chinese art.

This study utilizes hedonic regression to calculate the price impact, taking into account the various characteristics of the artworks. The results reveal that proof of authenticity, the artwork mounted in albums and handscrolls, the size of the artwork, and the large-scale auction months all contribute to a positive price impact. The coefficients on the time-dummy variables are used to

construct the art-price index and its corresponding return, which shows that Chinese art has relatively higher returns and better return-to-volatility compared to other assets. Notably, previous research has constructed the art-price index excluding unsold artworks (Garay, 2021; Higgs & Worthington, 2005; Renneboog & Spaenjers, 2013; Shi et al., 2018; Taylor & Coleman, 2011), which may result in the problem of overestimating the price index and returns (Forster & Higgs, 2018). To address this issue, Heckman's two-stage model is used to set out a refined hedonic price index. Additionally, the study examines the existence of price anomalies, specifically the masterpiece effect and the auction-house effect in the Chinese art market.

Essay 1 adds to the existing body of literature on art market investment by drawing on a comprehensive and unique sample of Chinese art. It sheds extra light on the price impacts of artwork characteristics and considers the effect of bought-in. It also offers insight into the construction of a Chinese art-price index and respective return, as well as new findings for art market participants when considering art as an alternative investment. Importantly, it provides evidence of excessive speculative activities in the Chinese art market. Therefore, it is a timely warning to art investors of the need to understand the risk associated with art investment, as art is not necessarily for art's sake.

1.3. Essay 2

Investing in art has gained increasing attention as an analytical addition to investment portfolios in recent years (Felton, 1998). In order to position art as a valid addition to traditional investment vehicles, it is necessary to explore the potential for diversification within such portfolios (Worthington & Higgs, 2004). In case art has a low correlation with traditional financial assets, diversifying between art and traditional markets could help investors reduce portfolio risk and maintain expected returns (Worthington & Higgs, 2004).

McAndrew (2010a, p. 137) presents that art has a low and negative correlation with several other asset classes across various periods, and investing in it offers compelling diversification benefits. This finding is supported by Mei and Moses (2002), Campbell (2004), Worthington and Higgs (2004),

and Taylor and Coleman (2011). Despite existing research on the diversification benefits of art as an asset, the literature on the correlation between different art markets and the prospects for portfolio diversification-both among artworks alone and in combination with financial assets-remains limited (Worthington & Higgs, 2004), with even fewer studies that specifically focus on the Chinese art market. Therefore, essay 2 investigates the potential benefits of investing in Chinese art as a means of diversifying investment portfolios.

This study uses repeat-sale regression to calculate the rate of return on Chinese art, finding that it yields the highest semiannual return among all investment assets and has a lower standard deviation when compared to equities. Excluding bonds, the Sharpe ratio and modified Sharpe ratio of Chinese art outperform those of other assets. Moreover, by measuring the diversification gain, the result demonstrates that incorporating Chinese art into any of the considered financial assets results in incremental diversification benefits.

The study further employs correlation analysis, the capital asset pricing model (CAPM), and downside beta to assess the potential risk diversification of Chinese art, revealing that it exhibits a low or negative correlation with conventional financial assets and a negative market beta relative to the returns of the Shanghai/Shenzhen Composite Stock Indices as the market returns. These findings suggest that Chinese art may serve as a valuable tool for diversifying investment portfolios. Additionally, the finding also shows that Chinese art can act as a hedge against declines in the domestic stock market in a diversified portfolio.

The study also investigates the potential benefits derived from the incorporation of Chinese art into investment portfolios. Through the application of mean-variance portfolio optimization, it is observed that the efficient frontier with Chinese art is situated above those without it. This suggests that for a specific level of risk, portfolios containing Chinese art yield higher returns compared to those without it and exhibit lower risk for equivalent returns. Moreover, when considering the simple power utility optimization, the result demonstrates that the inclusion of Chinese art invariably

improves portfolio utility across all levels of risk aversion. The Sharpe ratio and modified Sharpe ratio are also an advantage for portfolios with Chinese art positioned on the efficient frontier, outpacing the performance of equal-weighted portfolio. Another noteworthy observation is that art-inclusive portfolios during downturn periods in the domestic stock market, wherein outperform portfolios without art, thus signifying their potential for superior performance during market adversities.

The study makes a significant contribution to the existing body of literature on the benefits of portfolio diversification associated with the arts. By employing wide-ranging and robust analytical techniques, it offers valuable insights for stakeholders with a vested interest in exploring diversification opportunities in their investment portfolios by incorporating Chinese art.

1.4. Essay 3

Pre-sale estimates represent an informed opinion from auction-house specialists regarding the potential price about an item may fetch at auction. The argument is that these estimates level the playing field between experienced wholesale participants and uninformed retail customers, consequently attracting individual investors (Mei & Moses, 2005). Auction houses bear the responsibility of acquiring and processing information on behalf of transacting parties, and their compensation depends on their effectiveness in performing this task. The accuracy of pre-sale estimates is evaluated by comparing them to ex-post-realized market prices (Bruno et al., 2018). Although providing truthful information about the item being sold is the optimal strategy (Milgrom & Weber, 1982), experts' pre-sale estimates may exhibit a downward (Bauwens & Ginsburgh, 2000; D'Souza & Prentice, 2002) or upward bias (Mei & Moses, 2005), potentially damaging the auction house's reputation and resulting in decreased bidding activity or lessened interest from investors in the artwork.

To minimize prediction errors, Bauwens and Ginsburgh (2000) suggest that auctioneers make effective use of the sales catalogue established before the auction. For example, Bruno and Nocera

(2008) show a “country effect” whereby the prediction accuracy increases and the uncertainty of the prediction decreases when Italian paintings are auctioned within Italy. Furthermore, past-sale records positively impact the reduction of the estimated bias between pre-sale estimates and hammer prices. According to Bruno et al. (2018), auction houses with artist-specific experience tend to provide precise pre-sale estimates. However, there is a dearth of research on the Chinese art market, which highlights the need for additional investigation in this field.

The final essay is inspired by this research gap, which delves into the factors that can influence the accuracy and uncertainty of pre-sale valuations in the Chinese art market. The results disclose that variables such as the artist’s mentorship experience, proof of authenticity, past-sale records, and large-scale auction months have a significant positive impact on increasing the accuracy and reducing the uncertainty of pre-sale estimates. These findings contribute to the theoretical literature aimed at improving the predictive capability of pre-sale estimates (Bauwens & Ginsburgh, 2000; Bruno et al., 2018; Bruno & Nocera, 2008). Furthermore, the study finds that the impact of the factors on the pre-sale estimates in terms of accuracy and uncertainty differs across price distributions. This underscores the importance of auction experts utilizing relevant additional public information when handling the artworks at different price levels in order to increase the accuracy and minimize the uncertainty of pre-sale estimates in predicting hammer prices. Lastly, the study extends the impact of experienced auction houses on the estimate prediction, revealing that houses with artist-specific expertise play a significant role in improving the accuracy of pre-sale estimates, but are less effective in reducing uncertainty. It enriches the literature on art economics by investigating the extent to which auction houses can influence art auction outcomes (Ashenfelter, 1989; Bauwens & Ginsburgh, 2000; McAndrew et al., 2012).

1.5. Research Outputs from the Thesis

Essay 1

The first essay has been published in *Applied Economics*:

- Zou, L., De Bruin, A., Wu, J., & Yuan, Y. (2021). Art for art's sake? An exploration of the Chinese art market. *Applied Economics*. 53(47), 5429-5447.

It has been presented at the following conference:

- Zou, L., de Bruin, A., Wu, J., & Yuan, Y. Art for art's sake? An exploration of the Chinese art market. Proceedings of the 25th New Zealand Finance Colloquium (NZFC), Waikato, New Zealand, 11 February 2021.

Essay 2

The second essay has been presented at the following conference:

- Yuan, Y. *Is art a good choice for investment?* Proceedings of the 26th New Zealand Finance Colloquium (NZFC), Christchurch, New Zealand, 17 February 2022.

1.6. The Sequence of the Thesis

The remainder of this thesis is structured as follows: Chapter 2 presents the first essay, which examines the price determinants and investment performance of Chinese art. The second essay, which investigates the portfolio diversification benefits of investing in Chinese art, is presented in Chapter 3, while the third essay, which explores the effect of certain factors on the informational content of pre-sale estimates in terms of accuracy and uncertainty, is elaborated in Chapter 4. Finally, the key findings and implications of the three essays are outlined in Chapter 5, along with the potential areas for further research.

Chapter 2. Art not for Art's Sake: An Exploration of the Chinese Art Market

2.1. Introduction

Holding art as an alternative investment has become attractive to art collectors and investors. Despite the Chinese art market's rapid growth in recent decades and its rising prominence among investors and practitioners, most academic studies concentrate on the Western art market¹. There is a limited number of academic studies investigating the Chinese art market, the world's largest emerging art market, which has experienced a remarkable economic expansion in the past few decades. Consequently, investors lack a comprehensive understanding of Chinese art. Providing effective and timely investment information for investors, collectors, galleries, and auction houses has become a pressing concern for scholars. This study aims to explore the Chinese art market using a comprehensive dataset. The study investigate price determinants and investment returns through various methods: hedonic regression, the adjacent-period hedonic approach, the Heckman two-stage model, and repeat-sales regressions. These methods highlight key attributes influencing art investment returns. These attributes arise from the unique characteristics of Chinese art market investors, such as their desire to be 'in style,' attempts to acquire exclusive items, and the phenomena of 'conspicuous consumption,' as documented in Leibenstein (1950). Additionally, the masterpiece effect and auction house effect are also examined using quantile regression and repeat-sales regression. This helps us better understanding investor behavior in the Chinese art market.

The Chinese art market has experienced remarkable growth in recent years. It accounted for only 9% of global sales in 2007, but this doubled to 18% in 2009 and reached 30% in 2011 (McAndrew, 2019, p. 33). According to the Art Market Report issued in 2016, Chinese art auction turnover totaled \$4.79 billion, capturing 38% of the global market share. This ranked China as the

¹ For example, Worthington and Higgs (2004), Higgs and Worthington (2005), Taylor and Coleman (2011), and Higgs (2012) explore the Australian art market; Hodgson and Vorkink (2004) investigate the Canadian art market; and Agnello and Pierce (1996) study the American art market.

largest art market worldwide, surpassing the U.S. art market with its \$3.5 billion (Artprice, 2017, p. 29). This was the second time China had attained the position of the largest art market after its peak in 2011. A notable example of this growth occurred on December 17th, 2017, when a collection of panels entitled ‘Twelve Landscape Screens’, created by Qi Baishi (1864-1957), a self-taught ink-brush master artist of modern China, was auctioned for \$140.8 million at the Beijing Poly auction house. This price was 140 times higher than the \$1 million that the same collection was sold in 1989. The artist took 8 years to create this masterpiece, which features a vertical frame and an elegant palette. Each screen is titled, stamped, poetized, and signed using his unique identity, including his nickname, professional name, pen name, and pseudonym, among other identifying notations. This sale broke all-time records for Chinese art, as it achieved the highest price ever achieved for Chinese artwork at any auction. Qi Baishi became the first Chinese artist to join the prestigious “\$100 million club”. Consequently, certain attributes within the artwork play a crucial role in determining the artwork’s value and, ultimately, its return on investment.

A number of factors have been identified as contributing to the expansion of the Chinese art market: 1) rapid economic development and government support in China; 2) increased interest in artworks as an alternative investment due to a ninefold increase in the number of HNWI’s over the past decade²; 3) the underdevelopment of the Chinese capital market, particularly the equity market, resulting in a scarcity of investment options; and 4) the aesthetic pleasure provided by artworks, enhancing the allure of art as an investment asset. Our unique, exclusively collected through manual efforts, comprises 165,847 Chinese art lots that were sold via different auction houses from 2000 to 2017. Firstly, a basic analysis of our data shows that while modern artists’ artworks constitute a substantial proportion (68%) of the sample size and result in the highest turnover, artworks by ancient artists command the highest prices. Furthermore, artworks executed by deceased artists are more prominent in terms of both volume and achieved prices. The examination of artwork authenticity

² Source: <https://www.reuters.com/article/us-china-economy-wealthy-idUSKBN19B059>

characteristics concludes that a work of art may fetch a higher price if it contains such indicators. Additionally, the data sample also presents 36 auction houses, of which 29 are local establishments that account for 85% of the total sales.

Secondly, hedonic regression is used to assess the price impact, effectively capturing various artworks characteristics. The results suggest that all variables relating to authenticity positively affect the price impact. Among them, the variable representing the exhibition history is found to have the most significant influence, signifying a considerable increase in value for artworks with prior exhibition records. Furthermore, artworks mounted in albums style yield the highest price impact, suggesting a preference for this particular mounting style. Similarly, the size of the artwork has a positive correlation with the price impact, although this effect diminishes beyond a certain threshold. In terms of sale timing, the most expensive artworks tend to be sold in May, followed by November, December, and June. Moreover, this study utilizes the coefficients from the time dummy variables to construct an art price index and its respective returns. The constructed index reveals two significant booms within the sample period. The first peak occurs in 2005, with a corrected price index of 309.38 (base value of 100 in 2000) and a return of 72.78%. This boom is followed by a subsequent decline over the next five years, leading to a record peak of 815.42 in 2011, marked by a return of 59.55%. Overall, the art price appreciated at an annual rate of 10.67% throughout the sample period, thereby outperforming returns reported in other countries.

Thirdly, the study performs a few robustness tests for the adjusted sample of baseline results. The adjacent-period hedonic model and repeat-sales regression are implemented to tackle potential issues inherent in the baseline hedonic regression approach. The results of the robustness tests align with the baseline results, indicating that the main results are robust. The repeat-sales data suggests considerable speculative activity in the Chinese art market, as an average holding period of approximately 3 years is observed. In comparison, Western art markets exhibit a lower turnover rate, with paintings changing ownership on average every 10 years, as documented by Mok et al. (1993).

Fourth, the Heckman two-stage regression is used to account for the effect of bought-in, which alleviates data selection bias in the hedonic regression. The results demonstrate the presence of data selection bias when unsold artworks are excluded. The study subsequently constructs a Heckit price index and compares it to the hedonic price index, concluding that the two series have almost identical patterns, thus corroborating the occurrence of two art booms in the Chinese art market during the sample period.

Fifthly, two supplementary tests are conducted to explore the masterpiece effect and the auction house effect in the Chinese art market. The findings validate the existence of both effects.

Finally, the returns on Chinese art are compared to those of other investment assets, indicating that Chinese art yields relatively higher returns and has superior return-to-volatility ratios compared to other assets. Furthermore, the correlations between Chinese art and other asset classes are extremely low, which imply that investing in Chinese art may provide diversification benefits.

This essay makes several significant contributions to the existing literature: 1) The dataset employed in this study is arguably the most comprehensive for Chinese artworks; 2) It identifies and uses a few important and unique hedonic attributes specific to Chinese art, which differentiate the current study from others; 3) the repeat-sales sample is cleaner due to the use of multiple matching criteria for selection of repeat-sales pairs; 4) the adjacent-period hedonic model is used for the full sample and various art movement subsamples; and 5) Heckman two-stage regression mitigates the sample selection bias that occurred in the hedonic regression. This essay sheds extra light on the price impacts of artwork characteristics. It also offers insights into the construction of the Chinese art price index and respective returns, as well as providing art market participants with new insights on art as an alternative investment. The results provide strong evidence that excessive speculative activities exist in the Chinese art market. Thus, art market participants in China need to be aware of the risk associated with art investment, as art is not necessarily for art's sake.

The rest of the chapter is organized as follows. Section 2 reviews the relevant literature.

Section 3 discusses data and methodology. Section 4 reports the empirical results and Section 5 concludes.

2.2. Literature Review

The pricing of the artworks differs from that of traditional financial assets, which typically employ the discounting valuation model (Baumol, 1986). The artwork is unique and heterogeneous (Demir et al., 2018), prompting researchers to use the hedonic regression (Anderson, 1974; Chanel et al., 1996; Demir et al., 2018; Garay, 2021) and the repeat-sales regression (Goetzmann, 1993; Mei & Moses, 2002; Renneboog & Spaenjers, 2013) to study the art market. Hedonic regression, a popular method, assesses artwork value based on its attributes (Marinelli & Palomba, 2011) and employs hedonic characteristics along with time-dummy variables to construct art price indices (Demir et al., 2018). This approach provides explicit estimates (Chanel et al., 1996), and much of the prior literature relies on this analysis (Agnello & Pierce, 1996; Fedderke & Li, 2019; Garay, 2021; Higgs & Worthington, 2005; Renneboog & Spaenjers, 2013; Shi et al., 2018).

Common hedonic characteristics are related to the artist's characteristics, the artwork's characteristics, and the sale's characteristics. Artwork pricing is influenced by the artist's characteristics, such as the artist's name and life status (Renneboog & Spaenjers, 2013; Shi et al., 2018; Taylor & Coleman, 2011). An artist's reputation is indicated by their name, and artwork prices tend to increase when created by well-known artists (McAndrew, 2022b, p. 53; Shi et al., 2018; Taylor & Coleman, 2011). It has long been believed that artwork prices increase after the artist's passing as the supply of their artwork becomes limited (Bernales et al., 2020; Taylor & Coleman, 2011).

The artwork's characteristics impact the value of the artwork through physical attributes such as the proof of authenticity (i.e., signature and timestamp), medium, size, and the subject matter of the painting (McAndrew, 2010b, p. 67). Artwork prices often carry a higher premium if the work is signed or dated, providing credible authentication (McAndrew, 2010b, p. 56; Renneboog & Spaenjers,

2013; Shi et al., 2018). However, some studies report insignificant coefficients for these factors (Kraeussl & Logher, 2010; Marinelli & Palomba, 2011). Prior research demonstrates that the price of the artwork increases with its size up to a certain threshold and then decreases (Higgs & Worthington, 2005; Renneboog & Spaenjers, 2013; Taylor & Coleman, 2011). Medium refers to the technique and material used to create the artwork. Common categories for Western art include works in oil, on paper, acrylic, ink, pencil, and watercolor. Works in oil often command higher prices due to their durability (Agnello & Pierce, 1996; Garay, 2021; McAndrew, 2010b, p. 54; Renneboog & Spaenjers, 2013). Subject matter classification is based on the title of the artwork and includes categories such as abstract, animal, landscape, object, portrait, religion, and self-portrait (Garay, 2021; Renneboog & Spaenjers, 2013). The evidence on the price effect of the subject matter is mixed. For example, McAndrew (2010b, p. 55) contends that male investors exhibit a greater preference for the female form in representational works, leading to higher prices compared to male forms. Conversely, Garay (2021) observes that abstract and landscape mediums are more expensive, while Fedderke and Li (2019) suggest that miniature carries a higher price premium.

The sale's characteristics refer to the venue and the date of the sale. Prior literature documents that artworks sold at Sotheby's and Christie's possess a higher price premium than those sold at other auction houses (Agnello & Pierce, 1996; Higgs, 2012; Higgs & Worthington, 2005; Marinelli & Palomba, 2011; Pesando, 1993; Taylor & Coleman, 2011), suggesting that these leading auction houses have a high reputation. Garay (2021) also documents that larger sales occur in April, May, June, July, and November, as Sotheby's and Christie's typically hold their major art auctions in these months, and many other auction houses worldwide follow this practice.

Although hedonic regression is a popular method for determining the implicit price of artworks, it solely focuses on sold artworks, excluding artworks that remain unsold after sales events. This can lead to an overestimation of the price index and returns (Forster & Higgs, 2018). To address this issue, Collins et al. (2009) and Forster and Higgs (2018) use the Heckman two-stage model to

refine the hedonic price index.

In addition to the effect of bought-in³, hedonic regression is unsuitable for calculating the price of an artwork that is sold more than once. To solve this issue, the repeat-sales regression method is introduced (Goetzmann, 1993; Mei & Moses, 2002; Park et al., 2017; Pesando, 1993). This method controls for artwork heterogeneity based on sales of the same artwork and calculates returns through matched pairs. However, the repeat-sales regression is subject to an upward selection bias⁴, as collectors may choose to sell only when the value of the artwork increases (Goetzmann, 1993; Renneboog & Spaenjers, 2013). The repeat-sales regression method suffers from small sample problems, as documented in Demir et al. (2018).

Wang (2017) also documents that the hedonic regression and the repeat-sales regression do not consider the variations in returns across different art price brackets. In practice, art investors are segmented based on their net worth. Low-net-worth investors might avoid high-valued artworks due to financial constraints, while high-net-worth investors often bypass low-value artworks because they inadequately signal their wealth and social status (Mandel, 2009). Additionally, variations in return distributions across different price brackets might cause price anomalies, with higher-priced artworks being more susceptible to speculative behaviors, as documented in Renneboog and Spaenjers (2013). In this situation, quantile regression is beneficial for addressing these issues. Unlike the OLS model, it is less affected by outliers and provides a more robust estimate (Bassett et al., 2003; Koenker & Hallock, 2001).

The debate on whether art should be considered an alternative investment has attracted much academic attention. The most important early study is by Baumol (1986) who finds a 0.55% real annual return from art which is 2% below the bond yield, implying that investing in art is inefficient

³ Bought-in refers to a situation in which there are no bids on a lot, or if bidding does not reach the reserve price, the lot is “bought in”, meaning it is left unsold and remains the property of the owner.

⁴ Although the repeat-sales regression and the hedonic regression have sample selection bias, their nature is completely different from the estimation method. The data in the repeat-sales regression suffers from an upward selection bias as collectors choose to sell only if the artwork rises in value, whereas hedonic regression only uses the artwork that was sold, thereby creating the problem of over-estimating, and biasing the art-price index.

and prices tend to float aimlessly. This conclusion is echoed by Frey and Pommerehne (1988), who describe that art is not an attractive investment asset due to its relatively low real rate of return and high financial risk. Similar findings are reported by Pesando (1993) and Pesando and Shum (1999). On the other hand, Goetzmann (1993) contends that the real rate of return on artwork exceeds both stocks and bonds after 1850. Mei and Moses (2002) demonstrate that the real annual compounded return on artworks reaches 8.2%, outperforming bonds and Treasury bills, though still underperforming stocks between 1950 and 1999. Several additional studies, including those by Mok et al. (1993), Seçkin and Atukeren (2009), Park et al. (2017), and Shi et al. (2018), conclude that the return from art consistently surpasses the stock market. Moreover, the multifaceted nature of art investment is explored by Atukeren and Seçkin (2007), who report that investing in art yields not only financial returns but also psychological returns.

Previous literature has also documented the existence of price anomalies in the art market, such as the masterpiece effect, whereby the return from the most expensive artwork outperforms the general art market. The existence of the masterpiece effect in the art market remains contested. For example, Pesando (1993) constructs a portfolio of the top 10%-20% of art pieces by price using the repeat-sales regression and finds no evidence of the masterpiece effect from 1977 to 1992. Mei and Moses (2002), utilizing repeated-sales data covering American, old master, impressionist, and modern paintings sold at Sotheby's and Christie's main sales rooms, discover a negative masterpiece effect in the American art market. Likewise, Campos and Barbosa (2008) draw a similar conclusion. Goetzmann (1996) documents that the negative masterpiece effect results from survivorship bias, while Mei and Moses (2002) attribute it to overbidding and subsequent mean reversion. On the other hand, several studies find a positive masterpiece effect in the art market. For example, Renneboog and Spaenjers (2013) conclude that the return on high-price bracket items surpasses that for items in other price brackets. This finding is supported by Park et al. (2017), Demir et al. (2018), Shi et al. (2018), and Garay (2021).

In addition to the masterpiece effect, prior research also documented the auction-house effect (Park et al., 2017). Pesando (1993) focuses on an identical art piece in different geographic locations for the period 1977-1992 and finds that the mean price of prints sold in the US is 7% and 10% higher than that of London and Europe, respectively. Mei and Moses (2002) also conclude that investors receive relatively higher returns when artworks are bought at other auction houses and subsequently sold at Sotheby's and Christie's, in line with the blue-chip reputation of these two establishments. Research on the auction-house effect in emerging markets has garnered increased attention in recent years. Park et al. (2017) find that Beijing's art exports generate a significantly higher return for short-horizon investors.

2.3. Data and Methodology

2.3.1. Data Collection

The data are collected from Artron.net, a leading art data provider for the Chinese art market and are widely used in the literature on Chinese studies (Park et al., 2017; Shi et al., 2017, 2018; Wang & Zheng, 2017). We manually collect data on Chinese art with 222,863 lots offered over the period from 2000 to 2017, consisting of 165,847 lots sold and 57,016 bought-in. Artron.net provides information on prices in RMB, USD, HKD, and EUR. The price is used in USD, and the CPI is employed by the U.S. Bureau of Labour Statistics as the inflation adjustment, in order to be consistent with prior studies. Specifically, the study identifies the names of artists who have executed Chinese art from the Art Market Monitor of Artron (AMMA)⁵. AMMA has published a semi-annual report on the Chinese Art Auction Market since 2008⁶ with the top 50 artists who have created Chinese art from each of the three categories: 1) ancient period, if the artist was born before 1840 or died before 1911; 2) the modern period, if the artist was born after 1840 or died before 2000; and 3) the contemporary period, if the artist died after 2000 or is still living. Each semi-annual report compiles

⁵ AMMA is a subsidiary of the Artron Group, monitoring the trend of the Chinese art market. AMMA has the most comprehensive and reliable database available on the Chinese art market.

⁶ AMMA was established in 2000, starting the "Report of Chinese Art Auction Market" in 2008, which contains auction transactions from 2000. Therefore, our sample starts in 2000.

the top 50 artists who have executed Chinese art from each period according to the price per square Chinese foot⁷. Therefore, 150 artists are selected for each semi-annual report, and the final dataset comprises 533 artists after removing the duplicates.

There are several reasons for the current data sample focusing exclusively on Chinese art: 1) while the booming art market has attracted significant attention to the Western art market, there is limited research for Chinese art due to cultural, language, and data constraints; 2) the turnover of Chinese art auctions has reached US \$4.79 billion, with 38% of the global market share (Artprice, 2017, p. 29). Chinese painting and calligraphy constitute a significant segment of the Chinese art market, with Artprice (2017, p. 30) reporting that it accounts for 81.59% of the Chinese art market. Furthermore, Shi et al. (2018), drawing on data from the China Antiques and Artworks Auction Market Statistical Annual Report 2014, reveal that the turnover of Chinese painting and calligraphy accounts for 95.5% of the total transaction value for Chinese paintings, while oil paintings represent only 4.5%. Owing to its exceptional quality, Chinese art has garnered considerable interest from investors. As mentioned in Artprice (2018, p. 29), investors have a high demand for Chinese art due to its relatively stable returns, making it an attractive long-term investment asset. In addition, a growing number of corporations are showing a growing enthusiasm for Chinese art, targeting the high-end segment to support and promote the development of their cultural estates (Artprice, 2017, p. 30). However, limited research on the Chinese art market has left investors and collectors with insufficient knowledge to invest effectively in Chinese art; and, finally, 3) Chinese art differs from Western art in various aspects, such as medium, mounting types, the art of black space⁸, subject matter, and inscription. Therefore, certain characteristics are uniquely applicable to Chinese art.

⁷ One Chinese foot equals 33.3 cm, and thus one square Chinese foot is approximately 1111cm², as documented in Shi et al. (2018).

⁸The prominent characteristic of Chinese painting and calligraphy is to leave white space. As documented in Fan, Zhang, and Zheng (2019), the art of leaving white space in Chinese painting is consistent with Laozi's thought that "all things in the world come into being with a form, and the form comes from the formless".

2.3.2. Hedonic Variables

Two principal methods have been used to calculate art indices: the repeat-sales index method and the hedonic price index method. The repeat-sales index method tracks changes in the value of resold paintings (Higgs & Worthington, 2005). The advantage of this method is that there is no need to measure quality; there is only a requirement that the quality of the individual assets in the sample is constant over time. However, a limitation of this method is its exclusion of data from singular sales. For assets such as works of art that are not traded very often and thus, it is challenging to pair a subsequent transaction with an initial one. As a result, the method only considers a minor fraction of all transactions. This limitation may result in sample selection bias, as infrequently traded artworks may not be representative of the large artwork population (Kräussl & Elsland, 2008).

To solve this issue, the hedonic price index method is used. Its clear advantage is its inclusivity, which utilizes all available auction data, even if datasets sometimes capture only a few attributes of each painting. In the hedonic price index method, every sale (including repeat sales) is treated as a separate transaction. Specific attributes such as the artist's name, painting dimensions, and the mounting used are catalogued. By compiling all sales data, this method enables us to estimate implicit prices for each characteristic separately from a characteristics-free price of paintings, which solely reflects the effect of time and random error (Higgs & Worthington, 2005). This methodology has been widely adopted in the previous research (Anderson, 1974; Chanel et al., 1996; Demir et al., 2018; Garay, 2021), with Chanel (1995) posited that while both the repeat-sale regression and hedonic price index method have unbiased market-wide effect, the latter shows significantly reduced variance in coefficient estimates.

The current research uses hedonic regression to capture the various characteristics of the artwork. Following Renneboog and Spaenjers (2013), we estimate the following equation:

$$\ln p_{k,t} = \alpha + \sum_{m=1}^M \beta_m X_{m,k,t} + \sum_{t=1}^T \gamma_t D_{k,t} + \epsilon_{k,t}, \quad (1)$$

where $P_{k,t}$ represents the price of art k at time t , $X_{m,k,t}$ is the characteristic m of item k at time

t , and $D_{k,t}$ is a time-dummy variable that equals 1 if item k is sold in period t (0 otherwise). The coefficient β_m reflects the attribution of a relative shadow price to each of the m characteristics.

Information on various hedonic attributes of the sample can be identified, such as the characteristics of the artist, the characteristics of the artwork, and the characteristics of the sale. Table 2.1 presents the summary statistics for hedonic variables⁹, including the number of observations, the turnover, and the mean price. Panel A presents information on the characteristics of the artists: there are 20,619 lots sold by the ancient period artists, 112,827 lots sold by the modern period artists, and 32,401 lots sold by the contemporary period artists, with an average price over the sample period of 0.167 million USD, 0.135 million USD, and 0.078 million USD, respectively. Even though the modern period artworks represent 68% of the sample with the highest total turnover, artworks by artists from the ancient period yield the highest average price. Panel A also reports information on the artist's life status (e.g., deceased) and mentoring experience, which has not been explored in previous literature. The findings reveal that the average price of the 135,878 lots sold by deceased artists is 0.142 million USD, significantly higher than the average price of 0.064 million USD for the 29,969 lots sold by living artists. Mentor artists¹⁰ outperform non-mentor artists in terms of works and average price at 120,476 and 0.141 million USD respectively.

Panel B displays the summary statistics on the characteristics of artworks, including the proof of authenticity and mounting styles. The proof of authenticity contains the variables related to the artist's signature, the artwork's timestamp, provenance, exhibition, literature, and inscription. The signature of the artist represents the ownership of the artist, and the artwork's timestamp refers to the creation of time for works of art. The provenance signifies the artwork's origin, which enhances the perceived value of the works. The exhibition is a dummy variable that takes a value of 1 if the artwork has been showcased in a gallery or museum. The literature indicates whether the artwork has been

⁹ Please see Appendix 1 for details on the hedonic variables.

¹⁰ Information on mentorship for each artist is drawn from <https://www.baidu.com/> and <https://artist.artron.net/class-0-0-0.html>

cited, demonstrating its historical significance, which provides further evidence for the authenticity of the work and tends to add value to an artwork. The inscription, a unique characteristic of Chinese art, is authored by the artwork's owner(s) and conveys their appreciation and ownership status. These elements facilitate investors in tracing the artwork's origin and deepening their understanding and admiration of the artist's work. For all authenticity variables in Panel B, the summary statistics indicate that artworks with a record of an exhibition have the highest average price of 0.656 million USD, followed by artworks with an inscription at 0.265 million USD and artworks with provenance at 0.245 million USD. Regarding the types of mounting, the artwork is categorized based on its title: albums, fans, folding screen, handscroll, heng fu, hua xin, jing kuang, jing pian, jing xin, standing scroll, and vertical scroll. The painting mounted on a folding screen yields the highest average price of 0.390 million USD, followed by handscroll and albums, with average prices of 0.357 million USD and 0.356 million USD, respectively, notably surpassing the sample average of 0.173 million USD.

Panel C addresses the characteristics of sales by categorizing auction houses into local and foreign segments¹¹. The sample comprises 29 local auction houses alongside 7 foreign sales rooms from Sotheby's and Christie's, situated in New York, Hong Kong, London, and Shanghai. The results show that the top 8 local auction houses, as well as Sotheby's and Christie's auction rooms in Hong Kong, collectively account for 86% of the total sample. Local auction houses account for 85% of total sales, with China Guardian leading in terms of both lots sold and total volume, followed by Beijing Poly. Furthermore, the foreign auction houses show superior performance in terms of the average price achieved, albeit with a lower total volume sold. Within this category, Sotheby's (HK) achieved the highest average price at 0.240 million USD, followed by Christie's (HK) at 0.193 million USD.

Panels D and E report insights on the sales characteristics regarding the year and month. Throughout the sample period, total sales peaked in 2005 with 12,509 lots sold, then declined until reaching a record high of 15,461 lots sold in 2011. The average price exhibits an overall upward

¹¹ Please see Appendix 2 for a list of all auction houses in our sample with the number of artworks, the turnover, and the average price.

pattern from 0.027 million USD in 2000 to approximately 0.261 million USD in 2011, then declines in subsequent years before rebounding to 0.241 million USD in 2017. This pattern suggests the Chinese art market's shift towards quality over time. The findings also indicate that May is the most active time of the year, followed by December, June, and November, with February being the least active due to the Chinese New Year holidays.

Table 2.1

Summary Statistics

Panel A: Artist characteristics			
Variables	N	Turnover (000,000)	Mean (000)
Art movements			
Ancient	20,619	3,440	167
Modern	112,827	15,274	135
Contemporary	32,401	2,531	78
Artist attributes			
Deceased	135,878	19,336	142
Non-deceased	29,969	1,910	64
Mentorship	120,476	17,014	141
Non-mentorship	45,371	4,232	93
Panel B: Artwork characteristics			
Authenticity variables			
Signature	146,763	19,474	133
Timestamp	85,750	12,957	151
Exhibition	6,625	4,345	656
Literature	10,771	2,321	216
Provenance	34,495	8,457	245
Inscription	10,491	2,778	265
Mounting variables			
Albums	3,482	1,241	356
Fans	9,599	293	30
Folding Screen	1,701	664	390
Handscroll	3,007	1,073	357
Heng Fu	982	113	115
Hua Xin	522	26	49
Jing Kuang	7,254	1,555	214
Jing Pian	4,662	569	122
Jing Xin	54,506	5,716	105
Standing Scroll	984	36	37
Vertical Scroll	74,775	9,168	123
Others (reference)	4,373	794	182

Panel C: Sale characteristics (auction houses)			
Auction houses variables			
Beijing Poly	20,806	4,124	198
Beijing Rongbao	12,380	861	70
China Guardian	38,486	4,688	122
Council	8,638	1,788	207
Duo Yunxuan	8,052	676	84
Han Hai	18,689	1,449	78
Sungari	8,419	765	91
Xiling Yinshe	7,583	945	125
Christie's (HK)	8,368	1,613	193
Sotheby's (HK)	5,565	1,336	240
Panel D: Sale characteristics (year)			
Year variables			
2000	1,917	51	27
2001	2,234	52	23
2002	3,759	71	19
2003	4,844	105	22
2004	11,498	406	35
2005	12,509	704	56
2006	9,868	379	38
2007	8,394	477	57
2008	7,103	438	62
2009	11,578	986	85
2010	15,250	2,682	176
2011	15,461	4,038	261
2012	10,913	1,747	160
2013	11,683	2,045	175
2014	12,682	1,899	150
2015	8,878	1,462	165
2016	8,303	1,543	186
2017	8,973	2,163	241
Panel E: Sale characteristics (month)			
Month variables			
January	5,309	172	32
February	384	12	32
March	8,680	263	30
April	10,972	938	85
May	20,904	3,767	180
June	28,376	4,443	157
July	11,771	969	82
August	3,258	71	22
September	8,099	331	41
October	9,141	1,239	136
November	25,833	3,753	145
December	33,120	5,287	160

Note: The table presents the summary statistics for the data sample, including the number of observations, turnover (USD), and mean price (USD). The hedonic dataset consists of 165,847 lots sold from 2000-2017. HK refers to the Hong Kong sales room in Sotheby's and Christie's.

2.3.3. Heckman Two-Stage Regression Data

Heckman two-stage regression is used to mitigate the effect of bought-in on artwork transactions. The data comprises 222,863 auction lots of Chinese art, consisting of 165,847 lots sold and 57,016 bought-in. Table 2.2 shows that the average rate of bough-in is 26.54% from 2000 to 2017.

The highest rate of bought-in is at 35.71% in 2006, although this drops to 19.80% in 2010. Moreover, the dataset reveals a considerable proportion of unsold artwork, averaging 26.03% across the six-year interval from 2011 to 2017.

As documented in McAndrew (2010a, p. 72), the Chinese art market exhibits distinctive characteristics, one of which is the substantial quantity of artworks remaining unsold at auction, and this phenomenon is primarily attributable to a mismatch in supply and demand dynamics between lower-end and top-tier artwork. The market is flooded with an overabundance of low-quality pieces, which consequently exacerbates the issue of counterfeit paintings permeating the market. In contrast, there is a shortage of high-quality artworks with well-established provenance, resulting in a demand that far exceeds the available supply.

Table 2.2

Descriptive Statistics: Heckman Two-Stage Model Sample

Year	Number of obs.	Sold items	Buy-ins
2000	2,735	70.09%	29.91%
2001	3,280	68.11%	31.89%
2002	5,434	69.18%	30.82%
2003	6,311	76.75%	23.25%
2004	14,368	80.03%	19.97%
2005	15,641	79.98%	20.02%
2006	15,349	64.29%	35.71%
2007	12,268	68.42%	31.58%
2008	10,266	69.19%	30.81%
2009	14,799	78.24%	21.76%
2010	19,016	80.20%	19.80%
2011	19,572	79.00%	21.00%
2012	14,936	73.07%	26.93%
2013	15,124	77.25%	22.75%
2014	17,229	73.61%	26.39%
2015	12,774	69.50%	30.50%
2016	11,588	71.65%	28.35%
2017	12,173	73.71%	26.29%

Note: Table 2.2 reports the total number of observations, lots sold, and bought-in.

2.3.4. Repeat-Sales Data

Building upon the primary dataset, the current study also collects repeat-sales data. To ensure the uniqueness of each artwork, repeat-sales records are matched based on criteria including the artist's name, the title of the artwork, the mounting type, the artist's signature, and the artwork's size.

The repeat-sales records are expressed as the buy-sell pairs, consisting of the initial buy-sell pair. If an artwork is sold more than once, every two adjacent sales thus form a pair. Employing this criterion, 4,304 pairs¹² are identified from the 165,847 lots sold between 2000 and 2017, with a minimum holding period of one semiannual.

Table 2.3 presents the summary statistics for the repeat-sale sample. There are 403 lots from the ancient period, 3,207 lots from the modern period, and 694 lots from the contemporary period. In terms of investment horizon, 1,084 repeat sales occurred within 1 year, 1,587 within 2 years, and 1,633 pieces are resold after 6 years. However, the average holding period for the entire sample is approximately 3 years, and the relatively short holding-period signals strong speculation activities in the Chinese art market. In contrast, the Western art market exhibits a comparatively lower turnover rate, with paintings changing hands, on average, every ten years. Nevertheless, the holding period of Chinese art is similar to the previous literature, for example, Park et al. (2017) document that the holding period of Chinese art is, on average, 11.25 quarters (2.8 years). Mok et al. (1993) report that the average holding period of Chinese paintings is less than 4 years, and about 20% are resold within 2 years, indicating that there is a highly speculative element in Chinese paintings. In addition, the average purchase price is approximately 0.167 million USD, with an average resale price of 0.297 million USD, which is equivalent to a 21.16 % per annum return over the 3-year holding period. Modern artists' works constitute the most active category within the repeat-sales sample. Artworks with a purchase price ranging between USD 0.05-1 million are most likely to experience repeat sales, followed by those priced between USD 0.01-0.05 million.

¹² The repeat-sales sample is much cleaner than most prior studies, as we are using very strict matching criteria to ensure the uniqueness of the artwork of each pair.

Table 2.3*Descriptive Statistics: Repeat-Sales Regression Sample*

	Full sample	Art movement			Investment horizon		
		Ancient	Modern	Contemporary	Short	Medium	Long
Number of observations	4,304	403	3,207	694	1,084	1,587	1,633
Holding period (semiannual)	6	6	7	6	2	4	12
Purchase price (1,000 USD)	167	218	183	66	110	185	188
Resales price (1,000 USD)	297	361	332	99	137	235	463
0<Purchase<=2,000	70	19	38	13	13	30	27
2,000<Purchase<=10,000	716	76	445	195	179	255	282
10,000<Purchase<=50,000	1,512	108	1,121	283	409	538	565
50,000<Purchase<=1,000,000	1,891	179	1,511	201	474	707	710
Purchase>1,000,000	115	21	92	2	9	57	49

Note: Holding period = time between two adjacent sales. Ancient period = artist died before 1911 or born after 1840; modern period = artist born after 1840 or died before 2000; contemporary period = non-deceased artists or artists who died after 2000. Short = one to two semiannual; medium = three to six semiannual; long = over six semiannual.

2.4. Empirical Analysis**2.4.1. Baseline Hedonic Regression**

Table 2.4 reports the parameter estimates derived from the baseline hedonic regression, as specified in equation (1). The dependent variable is represented by the natural logarithm of the price in USD, with the year and the artist as fixed effects. Due to a large number of observations, all coefficients of the hedonic variable coefficients are highly significant. Therefore, we focus on the attention to the economic significance by calculating the price impact of each hedonic variable by taking the exponent of the coefficient and subtracting one, as documented in Renneboog and Spaenjers (2013).

The results demonstrate that all authenticity variables have a positive impact on price, with the exhibition dummy variable making the most significant contribution, suggesting that artworks with prior exhibition records experience significant increases in value. For the type of mounting dummy variables, artworks on albums¹³ exhibit the highest impact on price, followed by handscroll¹⁴.

¹³ The paintings mounted in albums usually consist of up to 12 folded pages on a wooden or brocade-covered card cover. The paintings and calligraphy usually work together, sometimes with a poem on one page and a small painting depicting it on the facing page. The paintings may be the work of one artist or of a group of different artists, who perhaps joined together to dedicate their works to a friend for a special occasion.

¹⁴ Handscrolls are used for vertical compositions. Traditional Chinese paintings are not usually hung on a wall. They are usually mounted in handscrolls and are only taken out to be viewed in special circumstances.

This observation is attributed to the popularity, portability, and ease of storage associated with these mounting types (Ding, 2008). In addition, albums comprise multiple folded panels, each representing a unique subject, thereby enhancing their artistic merit and collection value (Ding, 2008). The results reveal that artworks mounted in the types such as fans, hua xin, jing kuang, jing pian, jing xin, and vertical scroll exhibit negative price effects, which can be attributed to the materials used. For instance, fans are usually made of stiffened silk mounted on bamboo and are prone to damage from frequent use.

It is important to note that this study does not assess hedonic variables related to the medium and subject matter, as Chinese art significantly differs from Western art in terms of technique and materials. Specifically, Western art is typically categorized into media such as oil, work on paper, acrylic, ink, pencil, and watercolor, among others, while Chinese art is executed with a brush dipped in black ink or colored pigments on Xuan paper or silk, which is the sole medium (Shi et al., 2018). On the other hand, the subject matter in Chinese art tends to be homogeneous, typically consisting of figure painting, landscape painting, and bird-and-flower painting.

Prior literature documents that the price of the artwork increases at a decreasing rate as its size increases (Garay, 2021; Higgs & Worthington, 2005). Following Agnello (2002), Higgs and Worthington (2005), Fedderke and Li (2019), and Garay (2021), this study integrates the surface area and squared surface area to evaluate their impact on price. The results suggest that the surface area has a marginally positive influence on price, which, however, diminishes and ultimately inverts to a negative effect as the size continues to increase. Most auction houses exhibit a positive impact on price, with Sotheby's (HK) having the highest impact at 162.61%, followed by the local auction house XiLing Yinshe at 44.97%. In general, domestic auction houses show relatively weaker positive price effects than foreign auction houses. The results also conclude that the most expensive artworks are sold in May, followed by November, December, and June. This trend is likely due to Chinese auction houses strategically holding major art auctions during these months, offering the most valuable pieces.

Table 2.4*Baseline Hedonic Regression*

	Coefficient	SE	T-value	Price index (%)
Year dummies	[Included]			
Artist characteristics				
Artist dummies	[Included]			
Artwork characteristics				
Authenticity dummies				
Signature	0.226	0.010	22.450	25.32
Timestamp	0.317	0.006	53.490	37.32
Exhibition	0.956	0.014	68.510	160.21
Literature	0.510	0.011	46.760	66.61
Provenance	0.324	0.007	46.350	38.30
Inscription	0.349	0.011	30.600	41.76
Mounting dummies				
Albums	0.561	0.026	21.48	75.26
Fans	-0.596	0.022	-27.69	-44.91
Folding Screen	0.088	0.032	2.7	9.15
Handscroll	0.463	0.028	16.78	58.89
Heng Fu	0.103	0.039	2.65	10.83
Hua Xin	-0.589	0.052	-11.38	-44.53
Jing Kuang	-0.093	0.022	-4.14	-8.86
Jing Pian	-0.275	0.024	-11.28	-24.07
Jing Xin	-0.124	0.019	-6.64	-11.7
Standing Scroll	0.214	0.041	5.27	23.9
Vertical Scroll	-0.113	0.019	-6.04	-10.65
Size variables				
Surface area	0.000064	4.630E-07	137.650	0.01
Squared surface area	-4.185E-11	3.721E-13	-112.470	-4.19E-09
Sale characteristics				
Auction houses dummies				
Beijing Poly	-0.428	0.011	-40.210	-34.82
Beijing Rongbao	-0.121	0.012	-9.840	-11.39
China Guardian	0.049	0.009	5.450	5.00
Council	0.151	0.014	10.720	16.32
Duo Yunxuan	0.153	0.014	10.540	16.48
Han Hai	-0.393	0.011	-36.400	-32.50
Sungari	0.195	0.014	13.990	21.53
Xiling Yinshe	0.371	0.016	23.830	44.97
Christie's (HK)	0.264	0.014	18.510	30.21
Sotheby's (HK)	0.966	0.018	53.780	162.61
Month dummies				
February	-0.462	0.057	-8.110	-37.01
March	-0.200	0.019	-10.290	-18.12
April	-0.086	0.019	-4.550	-8.25
May	0.559	0.017	32.440	74.94
June	0.481	0.017	28.780	61.69
July	0.291	0.019	15.660	33.83
August	-0.285	0.025	-11.590	-24.81
September	-0.123	0.020	-6.250	-11.56
October	0.130	0.020	6.580	13.83
November	0.504	0.017	29.810	65.56
December	0.495	0.017	29.970	64.08

Note: Dependent variable = natural log of the real price in USD. The hedonic regression yields an R^2 of 60.47%, and almost all coefficients are statistically significant. The estimated hedonic coefficients, the standard error (SE), the t-value, and the price impact are reported, of which the price impact is the exponent of the estimated coefficient and subtracting one.

2.4.2. Baseline Art-Price Indices and Returns

Based on the coefficients of the time dummies and the estimated variable of residuals in the baseline hedonic regression, the uncorrected and corrected art-price indices along with their respective returns¹⁵ are constructed, adhering to the methodology documented in Renneboog and Spaenjers (2013). These results are presented in Table 2.5, with the price level in 2000 standardized to 100. Consistent with Renneboog and Spaenjers (2013), the price index values also exhibit a relatively high level of statistical precision, with the standard deviation of the time-dummy coefficients at approximately 0.03, indicative of narrow confidence intervals for the index value. During art-boom periods, such as 2002-2005 and 2009-2011, prices rise sharply. The corrected price index reaches its first peak in 2005 at 309.38, with a return of 72.78%. It subsequently declines over the following 5 years before attaining its record peak of 815.42 in 2011, accompanied by a 59.55% return.

Table 2.5

Hedonic Art-Price Indices from 2000 to 2017

Year	Coefficient	SE	π	r	σ^2	π^*	r^*
2000			100		1.12	100	
2001	0.108	0.034	111.42	11.42%	1.12	111.47	11.47%
2002	-0.131	0.031	87.74	-21.25%	1.12	87.80	-21.23%
2003	0.277	0.030	131.88	50.30%	1.12	131.99	50.32%
2004	0.582	0.028	178.94	35.69%	1.12	179.06	35.67%
2005	1.128	0.027	309.06	72.72%	1.12	309.38	72.78%
2006	0.999	0.028	271.49	-12.16%	1.12	271.44	-12.26%
2007	0.948	0.028	258.14	-4.92%	1.12	258.09	-4.92%
2008	1.065	0.029	289.98	12.33%	1.12	290.09	12.40%
2009	1.214	0.028	336.53	16.05%	1.10	333.51	14.97%
2010	1.644	0.027	517.39	53.74%	1.10	511.06	53.24%
2011	2.101	0.027	817.76	58.06%	1.11	815.42	59.55%
2012	1.927	0.028	687.12	-15.98%	1.11	684.64	-16.04%
2013	2.060	0.028	784.46	14.17%	1.10	778.33	13.68%
2014	1.947	0.028	700.78	-10.67%	1.09	691.55	-11.15%
2015	1.605	0.028	497.80	-28.97%	1.09	490.28	-29.10%
2016	1.507	0.029	451.38	-9.33%	1.07	439.28	-10.40%
2017	1.759	0.028	580.67	28.64%	1.05	560.67	27.63%

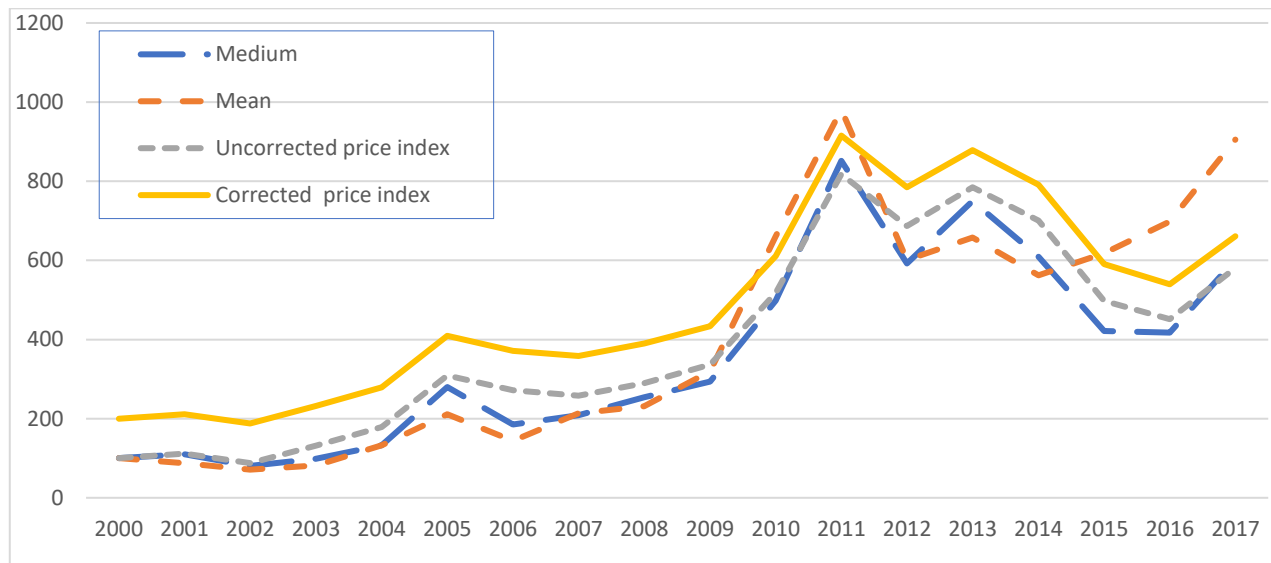
Note: This table reports the estimated time-dummy coefficients, the standard error (SE), the estimated variance of the residual (σ^2), the uncorrected price index and return, expressed as π and r, respectively, and the price index and return that are corrected for changes in price dispersion over time are represented as π^* and r^* , respectively.

¹⁵ See Appendix 3 for the development of the hedonic price index and its return.

Figure 2.1 graphically depicts the evolution of the hedonic art price indices throughout the data sample period, revealing intriguing observations about the Chinese art market booms. During the first boom period from 2002 to 2005, the Chinese art market attracted numerous new buyers, comprising entrepreneurs and HNWI's, which fueled a surge in the market's prosperity. During the second boom period, from 2009 to 2011, an expansionary monetary policy stimulated the growth of the art market (Shi et al., 2018). Furthermore, financial institutions entered the Chinese art market, launching hundreds of art funds annually. These institutions fostered extensive activities that accelerated the market's prosperity (Wu, 2019, p. 28). However, the art market boom was curtailed between 2012 and 2016 in response to the anti-corruption campaign launched by President Xi Jinping (Assaf, 2018; Masset et al., 2016). After 2016, the Chinese art market restructured its marketing strategy. For instance, the market shifted its focus to high-end auction items in an attempt to curtail speculative activities. This strategic adjustment bolstered investment confidence among market participants. Price volatility in the Chinese art market progressively stabilized post-2016 (Artprice, 2018, p. 29). Similar to Renneboog and Spaenjers (2013), Figure 2.1 also documents that an index based on average or median prices may overestimate the price volatility because it does not control for differences in quality or value over time. For example, the price spikes in 2005 and 2011 may indicate that high-value artworks disproportionately generate high sales volumes during boom periods. In addition, it did not observe a significant deviation between the corrected and the uncorrected price indices over our sample period.

Figure 2.1

Hedonic Price Indices



Note: This figure presents the baseline hedonic indices reported in Table 2.5. π is expressed as the uncorrected hedonic price indices, and π^* is the corrected price indices for changes in price dispersion over time. The figure also illustrates the average and median real prices for each year.

Table 2.6 reports the average annualized returns over the period 2000-2017. Panel A presents the geometric average returns using both the corrected and uncorrected price indices for the full sample. Using the uncorrected price index, it observes that art prices have appreciated at an annual real rate of 10.90%, while a rate of 10.67% is reported when using the corrected price index. The returns on art investments are relatively higher compared to those reported in the literature; for example, Mei and Moses (2002) report a real annual return of 8.2% for the period of 1950-1999, and Renneboog and Spaenjers (2013) demonstrate that art appreciated at an annual real rate of 3.97% between 1957 and 2007. The return is also higher than those reported for emerging markets; for example, Garay (2021) finds a real arithmetic mean annual return (in constant U.S. dollars) of 0.95% on investments in Venezuelan art for the period of 1970-2014, and Demir et al. (2018) reveal a return of 3.49% in the Turkish painting market for the period of 1990-2016. More recently, Park et al. (2017) report a quarterly return of 3.1% for Chinese paintings for the period of 1994-2012. Shi et al. (2018) document an average annual return of 8.42% in China from 2000-2015, while Huang and Li (2019) find an annual return of 8.96% in China. The superior performance of the current study is unsurprising,

as the current study encompasses the top 150 artists in each semi-annual auction report within the Chinese art market. These top-tier artists tend to have more stable and robust price indices, thus serving as a reliable basis for an accurate analysis.

Panel B reports the annualized returns for three subperiods: the Chinese art market achieved a return of 29.45% over the period 2000-2005; during the 2006-2011 subperiod, the return of the Chinese art market deteriorated due to the global financial crisis in 2008, but managed to recover to its second peak in 2011 with a return of 24.74%; however, the rate of return turned negative after 2011. This downturn may be attributed to the anti-corruption initiative proposed by the Chinese government and the decline of speculative activities in the Chinese art market. Panel C presents the returns for artworks by ancient, modern, and contemporary artists, respectively. The results show that artworks by contemporary artists exhibited the highest return of 9.75%, followed by modern artists at 9.51% and ancient artists at 3.78%. The higher returns of contemporary artworks can be attributed to their popularity among investors. As documented by McAndrew (2010a, p. 56), it is easier to trace ownership and authenticity of artwork created by contemporary artists through the artists themselves. In contrast, lower returns from ancient artists may be due to the discount given to investors as it becomes difficult, or even impossible, to identify the ownership and authenticity of the artwork. Additionally, the price of the artwork is influenced by its preservation condition. Almost all traditional Chinese paintings are created on Xuan paper or silk, which has strict storage temperature and humidity requirements. Artworks may suffer some degrees of damage and fading due to environmental changes (humidity, temperature, light, dust) and improper man-made protection. In this case, ancient paintings may be subject to a reduction in value.

Table 2.6*Annualized Returns for Baseline Indices, Subperiod Indices, and Extensions*

	Real return		
	N	Geometric mean	SD
Panel A: Baseline indices			
Art-price index π	163,345	10.90%	30.78%
Art-price index π^*	163,345	10.67%	30.95%
Panel B: Subperiod hedonic indices			
Art-price index π (2000–2005)	36,744	29.44%	35.56%
Art-price index π^* (2000–2005)	36,744	29.45%	35.54%
Art-price index π (2006–2011)	66,958	24.80%	27.70%
Art-price index π^* (2006–2011)	66,958	24.74%	28.02%
Art-price index π (2012–2017)	59,643	-4.22%	18.32%
Art-price index π^* (2012–2017)	59,643	-4.88%	18.14%
Panel C: Indices per art movement			
Ancient*	20,231	3.78%	35.08%
Modern*	111,012	9.51%	32.23%
Contemporary*	32,102	9.75%	37.37%

Note: Panel A reports the number of observations (N), geometric annualized return, and standard deviation over the period from 2000–2017 for the baseline indices. Panel B presents the number of observations (N), geometric annualized return, and standard deviation for the subperiods: 2000–2005, 2006–2011, and 2012–2017, respectively. Panel C reports the return estimates for art within the different art movements. * represents the return measured in the corrected art-price index.

2.4.3. Robustness Tests

This section performs a few robustness tests for the baseline results. Specifically, the baseline hedonic regression is repeated with the following settings: 1) exclude the types of mounting dummy variables; 2) exclude artists with fewer than 50 sales; 3) remove the artist dummy variable; 4) implement the adjacent-period hedonic model and exclude the artist and the month dummy variables; 5) apply the adjacent-period hedonic model and include the deceased and mentorship dummy variables; and 6) perform the repeat-sales regression. As documented in Renneboog and Spaenjers (2013), the coefficients from the hedonic regression are assumed to be stable across the entire sample window. To relax this assumption and address this issue, the adjacent-period hedonic model is employed, which allows the hedonic coefficients to fluctuate over time (Triplett, 2004). Furthermore, the repeat-sales regression is used as an alternative robustness test, which enhances the estimation power of the hedonic regression by capturing and uniquely identifying each artwork. This study then applies a three-stage process based on Case and Shiller (1987), also documented in Goetzmann (1993)

and Mei and Moses (2002). The results in Table 2.7 suggest that our estimates using all of the above settings do not exhibit substantial changes and align with our baseline results, indicating that our main results are robust.

Table 2.7

Annualized Returns: Robustness Checks

	Real return		
	N	Geometric mean	SD
Exclude mounting dummy variable	163,345	10.52%	30.39%
Exclude artists<50 sales	159,011	11.06%	31.00%
Exclude artist dummy variable	163,345	9.00%	32.21%
Adjacent-period hedonic model (excluding artist dummies and month)		10.54%	32.77%
Adjacent-period hedonic model (including deceased and mentorship)		10.57%	32.67%
Repeat-sales regression	4,304	14.73%	24.12%

Note: Table 2.7 presents a few robustness checks for the baseline hedonic regression. Specifically, the baseline hedonic regression is implemented as follows: 1) drop the mounting dummy variable; 2) exclude artists with fewer than 50 sales; 3) exclude the artist dummy variable; 4) perform the adjacent-period hedonic model and exclude the artist and the month dummy variables; 5) perform the adjacent-period hedonic model and include the deceased and mentorship dummy variables; and 6) perform repeat-sales regression.

2.4.4. Heckman Two-Stage Regression

The imbalance of supply and demand between low-priced and high-valued artworks leads to a high proportion of bought-in in the Chinese art market (McAndrew, 2010a, p. 72). To correct for sample selection bias in the hedonic regression, we employ the Heckman two-stage regression model (Heckit model). As documented in Forster and Higgs (2018), given the restriction $\sigma > 0$, the coefficient on λ can only be zero if $\rho = 0$. Thus, testing the null hypothesis of the zero coefficient on λ is equivalent to testing for selectivity. The result shows that the coefficient of lambda is -1.064 and is statistically significant at the 1% level, indicating that there is a selection bias when unsold art is excluded.

Table 2.8 Panel A presents the results from both the OLS model and the Heckman two-stage model. The coefficients, standard error, and t-value for these two models are shown in columns (1) to (3) and (4) to (6), respectively. Panel B presents the results from the first stage of the Heckman model. The results suggest that most of the estimated coefficients are highly consistent between the OLS model and the Heckman two-stage model. For example, in the category of artist’s characteristics,

the coefficients on the count are 0.357 and 0.356 in the two models, respectively. This variable refers to the total number of artworks offered in the auction market over the entire period, an important indicator of the artist's productivity, length of career, and the quality and desirability of their artworks. The coefficients on ancient and modern exhibit relatively higher values and are significant at the 1% level. The coefficient on mentorship is positive, indicating that the artist's learning experience from the mentor has a positive impact on the price of the artwork. However, the coefficient on the deceased is negative and insignificant in the Heckman two-stage model, which contrasts with Taylor and Coleman (2011) and Forster and Higgs (2018), but is in line with Shi et al. (2018).

Regarding physical's characteristics and sale's characteristic categories, paintings mounted in albums and handscrolls have a higher value compared to other types of mounting, which is related to the high artistic value of these two types of mounting. All the authenticity variables are positive, with exhibition having the highest value. The signs of the coefficients for the surface area and squared surface area are consistent with Czujack (1997), who finds that the price of size might be characterized as the concave function, with the surface area and squared surface area having the positive and negative relationships, respectively. Artworks auctioned by Sotheby's and Christie's fetch a higher price compared to other auction houses, and the most expensive artworks are sold in May, November, December, and June, as Chinese auction houses tend to hold important auctions around these months. The overall results from the Heckman two-stage regression are consistent with our baseline results.

Table 2.8*The Heckman Two-Stage Model*

Panel A The equation of interest						
Variable	OLS with Count			Heckman with Count		
	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficient	SE	T-value	Coefficient	SE	T-value
Year dummies	[Included]					
Artist characteristics						
Count	0.357	0.003	122.750	0.356	0.003	111.450
Artist dummies						
Ancient	0.391	0.020	19.770	0.463	0.022	20.980
Modern	0.066	0.017	3.880	0.054	0.019	2.900
Deceased	-0.092	0.017	-5.320	-0.022	0.019	-1.110
Mentorship	0.117	0.007	16.080	0.102	0.008	12.720
Work characteristics						
Authenticity dummies						
Signature	0.220	0.012	18.950	0.186	0.013	14.360
Timestamp	0.286	0.006	44.130	0.259	0.007	35.390
Exhibition	1.315	0.016	81.610	1.180	0.020	59.490
Literature	0.657	0.013	52.320	0.595	0.014	41.170
Provenance	0.461	0.008	57.250	0.429	0.009	47.220
Inscription	0.449	0.013	33.840	0.429	0.015	29.320
Mounting dummies						
Albums	0.11	0.03	3.72	0.2	0.033	6.05
Fans	-0.918	0.024	-38.08	-0.883	0.027	-32.99
Folding Screen	-0.4	0.037	-10.73	-0.295	0.041	-7.13
Handscroll	0.085	0.031	2.72	0.192	0.035	5.47
Heng Fu	-0.334	0.045	-7.42	-0.185	0.05	-3.71
Hua Xin	-0.995	0.06	-16.68	-0.972	0.068	-14.39
Jing Kuang	-0.334	0.025	-13.16	-0.267	0.028	-9.37
Jing Pian	-0.578	0.028	-20.78	-0.504	0.031	-16.21
Jing Xin	-0.412	0.021	-19.66	-0.335	0.024	-14.11
Standing Scroll	-0.066	0.047	-1.39	0.061	0.052	1.17
Vertical Scroll	-0.424	0.021	-20.46	-0.301	0.024	-12.39
Size variables						
Surface area	0.629	0.005	118.810	0.635	0.006	108.150
Squared surface area	-0.004	4.293E-05	-96.110	-0.004	4.8E-05	-86.79
Sale characteristics						
Auction houses dummies						
Beijing Poly	-0.296	0.012	-24.010	-0.253	0.014	-18.520
Beijing Rongbao	-0.096	0.014	-6.810	-0.221	0.017	-12.680
China Guardian	0.104	0.010	9.970	-0.005	0.013	-0.350
Council	0.320	0.016	19.430	0.189	0.020	9.540
Duo Yunxuan	0.071	0.017	4.250	-0.041	0.020	-2.090
Han Hai	-0.302	0.012	-24.180	-0.325	0.014	-23.780
Sungari	0.350	0.016	21.580	0.321	0.018	18.110
Xiling Yinshe	0.343	0.018	18.980	0.023	0.028	0.830
Christie's (HK)	0.512	0.016	31.220	0.351	0.021	16.960
Sotheby's (HK)	1.309	0.021	63.210	1.040	0.029	36.440

Continued Table 2.8

Panel A The equation of interest						
Variable	OLS with Count			Heckman with Count		
	(1) Coefficient	(2) SE	(3) Variable	(4) Coefficient	(5) SE	(6) Variable
Month dummies						
February	-0.441	0.067	-6.600	-0.282	0.073	-3.860
March	-0.277	0.023	-12.170	-0.324	0.025	-12.940
April	-0.087	0.022	-3.940	-0.101	0.024	-4.180
May	0.713	0.020	35.320	0.663	0.022	29.790
June	0.546	0.020	27.960	0.517	0.021	24.170
July	0.308	0.022	14.100	0.255	0.024	10.610
August	-0.298	0.029	-10.350	-0.352	0.032	-11.130
September	-0.194	0.023	-8.420	-0.203	0.025	-8.050
October	0.173	0.023	7.520	0.171	0.025	6.780
November	0.633	0.020	31.980	0.641	0.022	29.680
December	0.568	0.019	29.390	0.614	0.021	28.850
Lambda				-1.064	0.067	-15.980
Adjusted R-Square			45.37%			45.48%
Panel B The selection equation						
	(1) Coefficient	(2) SE	(3) T-value			
Year dummies						
Artist characteristics						
Count	-2.080E-04	0.003	-0.070			
Artist dummies						
Ancient	-0.137	0.019	-7.370			
Modern	0.023	0.016	1.390			
Deceased	-0.153	0.017	-9.260			
Mentorship	0.026	0.007	3.790			
Work characteristics						
Authenticity dummies						
Signature	0.077	0.011	6.880			
Timestamp	0.057	0.006	9.140			
Exhibition	0.292	0.018	16.390			
Literature	0.141	0.013	10.770			
Provenance	0.064	0.008	8.140			
Inscription	0.039	0.013	3.030			
Mounting dummies						
Albums	-0.205	0.03	-6.91			
Fans	-0.104	0.026	-4.07			
Folding Screen	-0.228	0.037	-6.24			
Handscroll	-0.248	0.031	-8.02			
Heng Fu	-0.325	0.042	-7.71			
Hux Xin	0.066	0.089	0.74			
Jing Kuang	-0.152	0.027	-5.62			
Jing Pian	-0.158	0.029	-5.38			
Jing Xin	-0.194	0.022	-8.69			
Standing Scroll	-0.309	0.044	-7.02			
Vertical Scroll	-0.295	0.022	-13.33			
Size variables						
Surface area	-0.039	0.007	-5.310			
Squared surface area	0.002	0.001	3.240			

Continued Table 2.8

Panel B The selection equation			
	(1)	(2)	(3)
	Coefficient	SE	T-value
Sale characteristics			
Auction houses dummies			
Beijing Poly	-0.084	0.011	-7.670
Beijing Rongbao	0.259	0.014	18.250
China Guardian	0.228	0.010	23.150
Council	0.267	0.016	16.770
Duo yunxuan	0.239	0.016	14.700
Han hai	0.052	0.011	4.560
Sungari	0.057	0.015	3.850
Xiling Yinshe	0.764	0.022	35.480
Christie's (HK)	0.346	0.017	20.860
Sotheby's (HK)	0.641	0.024	27.260
Month dummies			
February	-0.317	0.058	-5.430
March	0.097	0.021	4.550
April	0.028	0.020	1.400
May	0.103	0.019	5.450
June	0.048	0.018	2.660
July	0.115	0.021	5.530
August	0.118	0.027	4.430
September	0.011	0.021	0.510
October	0.006	0.021	0.270
November	-0.024	0.018	-1.320
December	-0.106	0.018	-5.960
Historical record dummy	0.940	0.031	29.980

Note: Table 2.8 presents the empirical results for the OLS and Heckman two-stage model. Panel A shows the estimated coefficients, standard errors, and t-value for these two models in Columns 1 to 3 and 4 to 6, respectively. Panel B shows the results of the selection equation.

Based on the coefficients of the time dummies in the OLS model and the Heckman two-stage regression, the art-price index from the OLS model and the Heckman two-stage model are constructed (e.g., please see Table 2.9). Following the same procedure as documented in Forster and Higgs (2018), as illustrated in Figure 2.2, these two art-price indices exhibit a highly similar pattern. Generally, the Heckit art-price index is lower than the OLS art-price index, indicating corrections for unsold artworks (Forster & Higgs, 2018). Figure 2.2 shows that the Chinese art market has undergone two boom periods: the art-price index first increased from 76.27 in 2002 to 223.56 in 2005, and then from 254.27 in 2009 to 615.19 in 2011. The prosperity of the Chinese art market and the expansionary monetary policy contributed to the boom in the Chinese art market. However, this pattern declined in 2012 due to the anti-corruption policy initiated by the Chinese government, as reported by Masset et al. (2016) and Assaf (2018).

Table 2.9

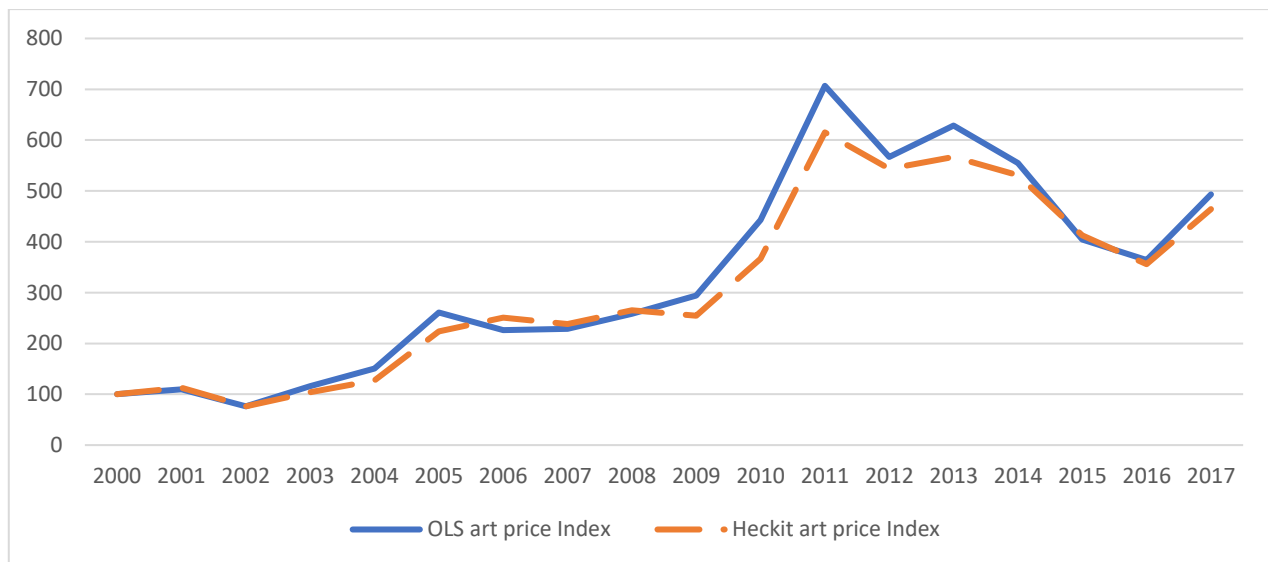
OLS and Heckman Price Indices

Year	OLS price index				Heckman price index			
	Coefficients	SE	t-Value	Index	Coefficients	SE	t-Value	Index
2000				100				100
2001	0.091	0.039	2.310	109.52	0.118	0.043	2.770	112.55
2002	-0.271	0.036	-7.540	76.28	-0.271	0.039	-6.950	76.27
2003	0.147	0.035	4.140	115.79	0.040	0.039	1.020	104.08
2004	0.411	0.032	12.680	150.77	0.240	0.037	6.510	127.10
2005	0.958	0.032	29.740	260.63	0.805	0.036	22.140	223.56
2006	0.815	0.033	24.800	225.95	0.920	0.036	25.390	250.81
2007	0.827	0.033	24.890	228.64	0.867	0.036	23.990	237.93
2008	0.948	0.034	28.170	258.08	0.975	0.037	26.660	264.99
2009	1.079	0.033	33.130	294.30	0.933	0.037	25.500	254.27
2010	1.487	0.032	46.420	442.56	1.300	0.037	35.320	366.80
2011	1.956	0.032	61.190	706.84	1.817	0.036	50.720	615.19
2012	1.735	0.033	52.980	566.67	1.693	0.036	47.470	543.50
2013	1.838	0.033	56.530	628.53	1.735	0.036	48.260	566.63
2014	1.714	0.032	52.770	555.05	1.669	0.035	47.160	530.88
2015	1.397	0.033	42.020	404.30	1.418	0.036	39.260	412.90
2016	1.292	0.034	38.440	363.87	1.270	0.037	34.760	355.98
2017	1.595	0.033	47.800	493.02	1.536	0.036	42.110	464.54

Note: Table 2.9 shows the art-price index for the OLS model and Heckman two-stage model. For each year, the estimated time-dummy coefficient, the standard error, and t-value are report.

Figure 2.2

Hedonic Price Indices and Heckman price indices



Note: This figure depicts the baseline hedonic indices reported in Table 2.9: the hedonic and Heckman price indices for changes in price dispersion over the period of 2000-2017.

2.4.5. Masterpiece Effect

It is common for investors to be advised to acquire high-quality and high-priced artworks on the assumption that masterpieces can outperform the market (Pesando, 1993). This section investigates the masterpiece effect in the Chinese art market, and the results are shown in Table 2.10. Panel A reports the results of the masterpiece effect using quantile regression. The results present that the top 5% of artworks outperform in most art movements, except those by ancient artists. This indicates the masterpiece effect in the Chinese art market, which is consistent with prior literature (Demir et al., 2018; Garay, 2021; Park et al., 2017; Renneboog & Spaenjers, 2013; Shi et al., 2018).

The adjacent-period hedonic approach offers an alternative method. It enables the quantile regression coefficients to capture variations in the valuation of hedonic attributes across price brackets, rather than across time, as documented in Renneboog and Spaenjers (2013). Panel B presents the results of the masterpiece effect using the adjacent-period hedonic regression. In line with Renneboog and Spaenjers (2013), this study executes a quantile variant of the adjacent-period hedonic regression model for each 2-year period from 2000 for the following percentiles: Q95, Q75, Q50, Q25, and Q5. The results in Panel B are similar to those in Panel A, with artworks by contemporary artists exhibiting the strongest masterpiece effect, yielding a return of 19.05% for the top 5% compared to 7.20% for the bottom 5%.

Panel C reports the results of the masterpiece effect using repeat-sales regression. Following Mei and Moses (2002), the study integrates the interaction terms of the holding horizons and the purchase price in the repeat-sales regression, with mixed results in Panel C. It shows evidence of the masterpiece effect when investors' investment horizons exceed 3 years.

Table 2.10*Masterpiece Effect*

Panel A: Quantile regression										
	Q5		Q25		Q50		Q75		Q95	
	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>
Full sample	4.76%	36.24%	7.66%	34.19%	9.85%	32.08%	11.81%	31.80%	12.66%	31.08%
Ancient	1.47%	37.86%	3.02%	37.84%	5.07%	38.03%	7.55%	36.40%	6.35%	34.24%
Modern	5.66%	35.87%	8.58%	32.85%	10.45%	32.17%	12.48%	32.64%	13.43%	33.34%
Contemporary	4.78%	41.51%	7.46%	38.65%	10.32%	36.71%	12.93%	35.42%	15.13%	39.65%
Panel B: Adjacent-period hedonic regression										
	Q5		Q25		Q50		Q75		Q95	
	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>
Full sample	6.47%	32.18%	9.41%	32.11%	11.25%	33.96%	12.95%	34.65%	15.12%	36.09%
Ancient	0.11%	33.72%	4.83%	37.77%	5.74%	37.77%	4.64%	36.79%	5.12%	35.19%
Modern	9.11%	31.39%	9.64%	32.51%	10.98%	33.73%	13.30%	36.00%	15.80%	39.79%
Contemporary	7.20%	35.22%	10.13%	34.31%	14.53%	34.52%	17.34%	34.66%	19.05%	37.20%
Panel C: Repeat-sales regression										
	Full Sample	Ancient	Modern	Contemporary	Short	Medium	Long			
γ	-0.03%	-0.26%	0.01%	-0.13%	-0.91% ^{**}	-1.02% ^{***}	0.26% ^{***}			
	(0.001)	(0.003)	(0.001)	(0.003)	(0.004)	(0.002)	(0.001)			

Note: Tale 2.10 presents the results of the masterpiece effect in the Chinese art market. The brackets report the standard error for the estimation. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

2.4.6. Auction-House Effect

The rapid development of globalization and the cross-border movement of works of art may lead to excessive speculation activities by market participants. Auction houses certainly play a critical role in determining the price achieved through the auction process. The repeat-sales sample enables us to investigate the auction-house effect in the Chinese art market in three ways: local auction houses versus foreign auction houses; state-owned auction houses versus non-state-owned auction houses; and artworks sold in Beijing versus those sold in Hong Kong.

To investigate the auction-house effect between local and foreign auction houses, the repeat-sales sample is divided into four categories: local auction houses-local auction houses (L-L); local auction houses-foreign auction houses¹⁶ (L-F); foreign auction houses-foreign auction houses (F-F); and foreign auction houses-local auction houses (F-L). For example, “L-L” represents artworks bought at a local auction house and later sold at another local auction house. Following Mei and

¹⁶ For foreign auction houses, repeat sales records are exclusively collected data from Sotheby’s and Christie’s.

Moses (2002), the repeat-sales regression approach is to add an additional term as follows:

$$r_i = \sum_{t=b_i+1}^{s_i} \mu_t + \sum_{j=1}^3 \rho_j (s_i - b_i) \cdot H_{i,j} + \sum_{t=b_i+1}^{s_i} \varepsilon_{it} \quad (2)$$

where $H_{i,j}$ is a set of dummy variables specified as:

$H_{1,j}$ equals 1 if an artwork j is bought in a foreign auction house and sold in a local auction house, 0 otherwise.

$H_{2,j}$ equals 1 if an artwork j is bought in a local auction house and sold in a foreign auction house, 0 otherwise.

$H_{3,j}$ equals 1 if an artwork j is bought in a local auction house and sold in a local auction house, 0 otherwise.

The F-F acts as the reference to compare with L-L, L-F, and F-L, we focus on the size and direction of ρ_j , to determine whether or not there exists an auction-house effect between local and foreign auction houses. A similar approach is utilized to examine the auction-house effect between state-owned and non-state-owned Chinese auction houses¹⁷, denoted as S-N, N-S, N-N, and S-S, where S-S serves as the reference, and the effect between auction houses in Beijing (B) and Hong Kong (H).

Table 2.11, Panel A presents the results for the auction-house effect between local and foreign auction houses. It observes statistically significant positive coefficients when artworks initially purchased in a foreign auction house are subsequently sold in a local auction house, and vice versa, indicating the existence of the auction-house effect in the full sample. For the subsample, the auction-house effect does not appear to be significant for ancient artworks. The results for the modern, short-horizon, and medium-horizon subsamples are consistent with the full sample. In addition, the F-L effect holds for artworks by the long-horizon and contemporary artists, while the L-L effect is only present for contemporary artworks. The L-F effect is due to the blue-chip reputation of Sotheby's and

¹⁷ The current research categorizes the Chinese auction houses, excluding Sotheby's and Christie's, into state-owned and non-state-owned groups.

Christie's (Mei & Moses, 2002), and the F-L effect may be due to the fact that numerous Western and Asian traders regularly offer consignments of Chinese art to Sotheby's and Christie's. Artworks sold at Sotheby's and Christie's may possess certain unobserved attributes (e.g., well-estimated provenance) that confer the artwork high values (Garay, 2021).

Panel B presents the results of the auction-house effect between state-owned and non-state-owned auction houses. We find statistically significant positive coefficients for the S-N effect in the whole sample, except for ancient and contemporary artworks. The N-S effect is present for artworks from the whole sample, the modern period and the medium-horizon. The N-N effect is present for artworks from the full sample and the long-horizon. Comparing the size of the coefficients in each column of Panel B, we conclude that the S-N effect fetches the highest prices among the different ownership types of auction houses. A plausible explanation for this finding may be related to the high reputation of state-owned auction houses; these auction houses, which are affiliated with the Chinese government, leverage their prestigious standing and robust financial capacity to attract wealthy investors and acquire high-value and high-priced artworks. When these works of art are resold to non-state-owned auction houses, they can carry on this momentum and yield high returns.

Panel C presents the results for the auction-house effect between auction houses based in Beijing and Hong Kong. Our results suggest that investors attain higher prices when buying in Hong Kong and selling in Beijing for artworks from the full sample, modern artists, short-, and long-horizon. The B-H (Beijing-Hong Kong) effect exists for short and medium investment horizons, whereas the H-H effect experiences a value reduction for contemporary artworks. Comparing the size of the coefficients in each column of Panel C, the H-B effect is slightly higher than that of other locations. There are several explanations for this observation: firstly, changes in the structure of the Chinese art market have contributed to this effect. In the early 2000s, Hong Kong was one of the most active art hubs in Asia. Its low-tax-rate regime, world-class logistics, unrestricted capital inflow and outflow,

full currency convertibility, and English as the business language attracted many investors¹⁸. As reported by McAndrew (2010a, p. 73), Hong Kong has dominated the trade in Chinese art since 2005, with over 70% of sales taking place through Sotheby's and Christie's. Since 2008, this dynamic has shifted as China's domestic art market has rapidly developed and grown, challenging the US as one of the largest art markets globally. From 2004 to 2009, China's homegrown auction market expanded rapidly, with several thousand auctioneers operating throughout Hong Kong and mainland China, including 245 authorized auction houses exclusively selling art and antiques in the mainland Chinese art market and 55 in Hong Kong (McAndrew, 2010a, p. 72). In 2017, five of the world's top 10 auction houses were located in Beijing (Artprice, 2019). Beijing has gathered a greater number of auction houses, making it easier for artists and investors to transact, and providing them with the liquidity needed for this trade. In 2019, the turnover of Chinese painting and calligraphy in Beijing is 1.467 billion USD, with Hong Kong ranked second with 459 million USD.

Secondly, government support has encouraged China's homegrown auction houses to expand overseas. Foreign auction houses, on the other hand, face numerous regulations that restrict external art trade, such as the prohibition of selling cultural relics on the mainland (Cooper, 2013). In addition, the Chinese government exercises a "soft power" policy of promoting the culture industry to create jobs and build international competitiveness. In Beijing, the government has established the Beijing International Culture and Art Protection Centre to provide investors with services such as appraisal, custody, and restoration of artworks, as well as professional assistance in verifying the legality and traceability of artworks (Artprice, 2019).

Thirdly, the growth in the number of HNWI's has led to a substantial increase in the purchasing power of artworks. As one of the world's fastest-growing nations, China is rapidly expanding its population of millionaires. The burgeoning middle-class and upper-middle-class have had a significant impact on auction sales in both the local and global art markets. As for Beijing, it remains

¹⁸ Source: <https://www.yearbook.gov.hk/2000/eng/04/c04-01.htm>

one of the regions with the largest number of wealthy individuals in China¹⁹; according to China Banking News (2019), there are 101,365 HNWI²⁰ and 1,390 UHNWI²¹ in Beijing, accounting for 5% and 33% of the total, respectively. These wealthy individuals in Beijing possess immense purchasing power to invest in Chinese art.

Table 2.11

Auction-House Effect

Buy-Sale	(1)	(2)	(3)	(4)	(7)	(8)	(9)
	Full sample	Ancient	Modern	Contemporary	Short horizon	Medium horizon	Long horizon
Panel A: Local auction house – Foreign auction house							
F–L	2.61% ^{***} (0.009)	0.57% (0.041)	2.30% ^{**} (0.009)	8.80% ^{**} (0.039)	23.72% ^{***} (0.068)	4.05% [*] (0.023)	2.36% ^{**} (0.010)
L–F	2.55% ^{**} (0.012)	42.06% (0.408)	2.75% ^{**} (0.012)	4.31% (0.049)	35.78% ^{***} (0.082)	12.16% ^{***} (0.032)	0.52% (0.013)
L–L	0.68% (0.007)	-3.16% (0.034)	0.68% (0.007)	7.40% ^{***} (0.027)	5.01% (0.041)	1.41% (0.017)	0.60% (0.008)
Panel B: State-owned auction house – Non-state-owned auction house							
S–N	1.39% ^{***} (0.004)	1.84% (0.025)	1.52% ^{***} (0.005)	-1.25% (0.012)	7.73% ^{**} (0.038)	4.71% ^{***} (0.012)	0.82% [*] (0.005)
N–S	0.80% [*] (0.004)	1.77% (0.019)	0.81% [*] (0.005)	-0.36% (0.012)	2.77% (0.035)	3.84% ^{***} (0.011)	0.16% (0.005)
N–N	0.65% [*] (0.003)	1.94% (0.016)	0.29% (0.004)	1.03% (0.008)	4.48% (0.026)	0.84% (0.008)	0.63% [*] (0.004)
Panel C: Beijing auction house – Hong Kong auction house							
B–H	1.03% (0.008)	-23.23% (0.264)	1.25% (0.008)	-1.67% (0.026)	25.06% ^{***} (0.073)	5.63% ^{***} (0.022)	-0.09% (0.009)
H–B	1.96% ^{***} (0.006)	4.02% (0.030)	1.72% ^{***} (0.006)	0.81% (0.026)	17.59% ^{***} (0.062)	2.34% (0.016)	1.83% ^{***} (0.006)
H–H	-0.16% (0.007)	4.58% (0.037)	-0.19% (0.007)	-5.61% [*] (0.030)	-8.64% (0.073)	0.09% (0.019)	-0.29% (0.008)

Note: Table 2.11 reports the results of the auction-house effect in the Chinese art market. L = local auction houses; F = foreign auction houses; S = state-owned auction house; N = non-state-owned auction house; B = Beijing; H = Hong Kong; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

2.4.7. A Comparison Between Chinese art and Common Financial Assets

This section compares the return on the art-price index to those on equity, bonds, gold, commodity, and real estate. For equities, the S&P 500 Index and the SSE Composite Index are used. Bond returns are computed from the 10-year T-bonds and the 3-month T-bill. These variables are

¹⁹ Source: <https://www.bbc.com/news/business-56671638>

²⁰ High-net-worth individual (HNWI), defined as those with \$1 million-\$5 million in net worth as reported in China Banking News (2019).

²¹ Ultra-high-net-worth individual (UHNWI) refers to those with net worth in excess of \$30 million as documented in China Banking News (2019).

extracted from the Wind DataStream. Gold prices are obtained from the Wind DataStream and correspond to the gold fixing pricing at 3:00 p.m. (London time) on the London Bullion Market in U.S. dollars. The data on commodity is represented by the S&P GSCI commodity spot index, acquired from Thomson Reuters DataStream. All values, except for the Chinese T-bond and T-bill, are converted into real U.S. dollar terms using the U.S. CPI obtained from the U.S. Bureau of Labor Statistics.

Table 2.12, Panel A, presents the average annual real return, Sharpe ratios, and standard deviation over the period of 2000-2017. The average annual return on Chinese art is 14.51% (using the arithmetic mean), which is the highest return and the highest volatility among all assets. This finding is inconsistent with prior literature on the investment return of art. For example, Mei and Moses (2002), Kraeusl and Logher (2010), Higgs (2012), Renneboog and Spaenjers (2013), and Garay (2021), report that art returns are lower than those of the stock market. However, others have concluded that art outperforms the stock market, as documented by Goetzmann (1993) and Shi et al. (2018). Real estate yields an average return of 7.48% over the sample period. The reward-to-volatility ratio, as measured by the Sharpe ratio, is higher for government bonds, real estate, and gold, with art lagging behind.

Panel B presents the correlation between Chinese art and other investment assets. Art has a relatively lower correlation with other assets. For example, the correlations with the SSE Composite Index, 10-year Chinese T-bond, and 3-month T-bill are -0.300, -0.215, and -0.294, respectively, indicating possible diversification benefits from investing in art. This finding is in line with previous literature: Mei and Moses (2002), Campbell (2008), Kräusl and Elsland (2008), Worthington and Higgs (2008), and Taylor and Coleman (2011) posit that the diversification benefits derived from art investments are among its most compelling attributes. However, this finding is contrasted by Goetzmann (1993) and Demir et al. (2018), who report a positive correlation between art and the stock market, thus eroding the portfolio's diversification benefits. In addition, wine, similar to art,

shows an extremely low correlation with other assets, highlighting the notion that a portfolio involving “emotional assets” can offer diversification benefits.

Table 2.12

Comparison of Chinese Art and Common Financial Assets

Panel A: Comparison of investment performance among different assets			
	Arithmetic mean	Standard deviation	Sharpe ratio
Art	14.51%	30.95%	0.493
S&P 500	3.76%	17.60%	0.266
SSE Composite Index	11.52%	50.43%	0.249
Chinese 10-year T-Bond	1.16%	1.84%	1.408
Chinese 3-month T-Bill	0.17%	1.91%	
Gold	8.46%	15.07%	0.636
Commodities	5.23%	27.87%	0.223
Chinese real estate	7.48%	6.76%	1.293

Panel B Correlation of return								
	Art	S&P 500	SSE Composite Index	Chinese 10-year T-Bond	Chinese 3-month T-Bill	Gold	Commodities	Chinese real estate
Art	1							
S&P 500	0.169	1						
SSE Composite Index	-0.300	0.440	1					
Chinese 10-year T-Bond	-0.215	0.494	0.335	1				
Chinese 3-month T-Bill	-0.294	0.558	0.292	0.931	1			
Gold	0.196	0.001	0.416	0.191	0.001	1		
Commodities	0.229	0.342	0.279	0.509	0.358	0.647	1	
Chinese real estate	0.368	0.353	0.416	0.163	-0.021	0.415	0.693	1

Note: This table compares the return on Chinese art to those on equity, bonds, gold, commodities, and real estate. Panel A shows the average annual real return, Sharpe ratios, and the standard deviation values over the period of 2000-2017. Panel B shows the results of return of correlation between Chinese art and common financial assets.

2.5. Conclusion

The TEFAF Art Market Report reveals that auction sales in China surpassed those in the United States in 2011, making China the largest art market in the world (TEFAF, 2012, p. 13). While holding art as an alternative investment has grown increasingly attractive to art collectors and investors, research has predominantly focused on Western countries, such as Australia, European nations, and the US. Due to language, cultural, and data limitations, few studies have explored the Chinese art market. Consequently, art market participants lack a comprehensive knowledge of this market. This study addresses this gap and investigates the Chinese art market using a unique dataset covering the period from 2000 to 2017.

This study includes 222,863 Chinese art lots (including bought-in data) from 533 artists over

the sample period of 2000-2017. Firstly, a basic study of the data reveals that, even though modern artworks constitute a considerable portion of our sample (68%), ancient artworks command the highest prices. The data also indicate that the proportion and prices of artworks by deceased artists exceed those of non-deceased artists. The assessment of artwork-authenticity characteristics indicates that artworks with specific authenticity markings command higher prices. The sample includes 36 auction houses, 29 of which are local, representing 85% of total sales.

Secondly, hedonic regression is used to quantify the price impact, which captures the various characteristics of the artworks. The results suggest that all variables related to authenticity have a positive impact on price. Among them, the artworks with the record of exhibition make the most significant contribution. Moreover, paintings mounted in albums carry the highest price impact. The size of the artwork has a positive impact on price, but the impact of size on price diminishes beyond a certain size threshold. Notably, the most expensive artworks are transacted in May, followed by November, December, and June.

Utilizing the coefficients on the time-dummy variables, the art-price index and its corresponding return are constructed. The art-price index displays two booms during the sample period. At the first peak in 2005, the corrected price index reaches 309.38 (with a base value of 100 in 2000) and a return of 72.78%, then declines for the next five years before achieving a record peak of 815.42 in 2011 with a 59.55% return. Overall, the study finds that the art price has appreciated at an annual rate of 10.67% over the sample period, substantially exceeding returns reported in other countries.

Thirdly, a few robustness tests are performed to check the baseline results. The adjacent-period hedonic regression and repeat-sales regression are used to mitigate certain issues with the baseline hedonic regression approach and to enhance the estimation power. The results of the robustness tests are in line with the baseline results, indicating that the main results are robust. The repeat-sales data demonstrates that the average holding period is approximately 3 years, with the

relatively short holding period signaling strong speculative activities. In comparison, turnover in Western art markets is relatively low, with paintings changing hands on average every 10 years.

Fourthly, the Heckman two-stage method is utilized to account for the effect of bought-in and to ease the data-selection bias in the hedonic regression. The results show the presence of data-selection bias when unsold artwork is disregarded. As a result, the study further constructs the Heckit price index using the time-dummy variables and compares it to the OLS art-price index. The results show that the two series exhibit nearly identical trends, and the Heckit art-price index is lower than the OLS art-price index, aligning with the anticipated corrections for unsold works. Fifthly, two additional tests investigate the masterpiece effect and the auction-house effect. The results confirm the existence of certain masterpieces and auction-house effects in the Chinese art market.

Finally, the study compares the return on Chinese art to that of other investment assets. The results suggest that Chinese art yields the highest return and a comparatively superior return-to-volatility ratio among investment assets. Furthermore, the correlations between Chinese art and other investment assets are extremely low, implying potential diversification benefits from investing in the Chinese art.

This chapter adds to the existing body of literature on art market investment by drawing on a comprehensive and unique sample of Chinese artworks. It sheds extra light on the price impacts of artwork characteristics and considers the effect of bought-in. Moreover, it also offers insights into the construction of a Chinese art-price index and its respective return, as well as new insights for art-market participants when considering art as an alternative investment. Importantly, it provides evidence of show excessive speculative activity in the Chinese art market. Therefore, it is a timely warning to art investors of the need to understand the risk associated with art investments, as art is not necessarily for art's sake.

Chapter 3. Portfolio Diversification Benefits of Chinese Art

3.1. Introduction

The concept of portfolio diversification and its measurement have been the subject of extensive research since Markowitz (1952) introduced the mean-variance portfolio theory. Scholars have expanded their research to evaluate the potential of alternative asset classes, such as art, gemstones, and fine wines, as viable investment options for portfolio diversification. Both emerging and established investment communities are increasingly embracing alternative investments, particularly art, as a complement to conventional investment assets (Flôres et al., 1999).

There are a number of factors contributing to the inclusive of art in investor's diversified portfolios. Firstly, the global financial crisis of 2008, which led to the bankruptcy of several major financial institutions, has stimulated investors to explore alternative investment assets to mitigate portfolio risk (Lucey & Devine, 2015). Consequently, investors are not just moving away from traditional investment vehicles, which have underperformed during economic turmoil, but are instead exploring alternative investment assets that are independent of market conditions. Secondly, the growing popularity of alternative investment assets has spurred a great deal of research in this area, particularly given the unprecedented growth observed in the global art market. In 2021, global art sales were estimated to reach USD 65.1 billion, a remarkable 29% increase from 2020 (McAndrew, 2022a, p. 14). Further evidence of the importance of the international art trade comes from a survey of 2,700 HNWI's in 11 key global markets. The total value of global imports of art and antiques rose to USD 26.6 billion in 2021, an increase of 41% from the previous year (McAndrew, 2022b, p. 27). In addition, the endorsement of art as a component of wealth-management services by wealth managers increased from 53% in 2014 to 85% in 2021 (Deloitte Private & ArtTactic, 2022, p. 22). Finally, while the motivation to purchase art has traditionally been driven by emotional factors, it is worth noting that art has a low correlation with common financial assets and can thus serve as a complementary or alternative asset in the investment portfolio. In 2011, only 28% of investors

considered art as a tool for portfolio diversification. However, this attitude has seen a significant evolution; 62% of wealth managers, 70% of collectors, and 75% of art professionals now see art as a way to diversify their portfolios (Deloitte Private & ArtTactic, 2022, p. 106).

The role of art in portfolio diversification has drawn significant attention from researchers, with Goetzmann (1993), Mei and Moses (2002), Worthington and Higgs (2004), Campbell (2004), and Kräussl and Elsland (2008) investigating the diversification benefits of investing in art. Notably, this body of research has largely focused on Western art, leaving a dearth of studies on Chinese art. However, the burgeoning Chinese art market warrants attention. A key driver of this interest is the significant volume of the Chinese painting and calligraphy market, which represented 86% of all painting transactions in mainland China in 2019 (Bian et al., 2021). Furthermore, despite the Chinese art market being among the largest globally, it has not seen the same level of investment prevalence as the Western art market. More importantly, while a large body of literature advocates for the benefits of including art in an investment portfolio for diversification, the potential impact of Chinese art investment on portfolio diversification remains uncertain. Therefore, this study aims to fill this gap by providing a robust analysis that addresses the question:

What are the portfolio diversification benefits of investing in Chinese art?

To address this question, this study collects a dataset of 4,840 pairs of repeated observations from June 2003 to December 2021. Utilizing repeat-sales regression to calculate the return on Chinese art, the results show that Chinese art yields the highest semi-annual return of 6.18% among all investment assets, with a relatively lower standard deviation compared to equities. With the exception of bonds (e.g., SSE government bonds and SSE corporate bonds), Chinese art has superior performance in terms of both the Sharpe ratio and the Modified Sharpe ratio. Additionally, the diversification gain of Chinese art is measured, suggesting that the addition of Chinese art to any of the examined financial assets gains incremental diversification benefits.

This study employs correlation analysis, the capital asset pricing model (CAPM), and

downside beta to evaluate the role of Chinese art in diversifying investment risk. The results show that Chinese art has a low or negative correlation with common financial assets and exhibits a negative market beta when the returns of the Shanghai Composite Stock Index and the Shenzhen Composite Stock Index are used as market returns. These findings suggest that Chinese art is a valuable risk diversification tool in an investment portfolio. Additionally, Chinese art can act as a hedge against declines in the domestic stock market in a diversified portfolio.

The subsequent section examines the potential diversification benefits of including Chinese art in an investment portfolio. By employing the mean-variance portfolio optimization approach (MVPO), the results present that the efficient frontier is positioned higher with Chinese art than without it. Using a (simple) power utility optimization, the inclusion of Chinese art enhances the overall utility of the portfolio, irrespective of the level of risk aversion. Nevertheless, the weight of Chinese art decreases as the level of risk aversion increases, suggesting that the benefits of including Chinese art in a well-diversified portfolio may be somewhat limited.

Finally, several robustness tests are conducted, including evaluating the performance of portfolios with Chinese art on the efficient frontier relative to equally weighted portfolios, and investigating whether the inclusion of Chinese art in a portfolio can generate diversification benefits during market downturns. The results show that portfolios with Chinese art situated on the efficient frontier outperform those of the equally weighted portfolio. Moreover, during periods of underperformance in the domestic stock market, the efficient frontier with Chinese art exhibits superior performance compared to the efficient frontier without Chinese art, as evidenced by the higher Sharpe ratios and modified Sharpe ratios. Conversely, during periods of declining average asset returns, an inverse result is observed with respect to the modified Sharpe ratios.

This study contributes to the extant literature on the portfolio diversification benefits of art by specifically concentrating on Chinese art. Building upon the methods used in prior research, such as correlation analysis and the CAPM, this study extends the analytical framework by incorporating the

rolling CAPM model, downside beta, Sharpe ratio, and modified Sharpe ratio. These approaches help investors to fully understand the potential benefits of investing in Chinese art and thus, diversify their investment portfolios.

The chapter is organized as follows: Section 2 provides a literature review; Section 3 explains the data and empirical methodology; Section 4 presents the empirical results; and the final section offers concluding remarks and suggestions for further research.

3.2. Literature Review

3.2.1. Definition and Benefits of Diversification

Diversification is an important aspect of investment decisions amidst risk and uncertainty (Koumou, 2020). Often referred to as the “free lunch” for portfolio managers, it enables the reduction of total risk without sacrificing expected returns. However, achieving true diversification can be challenging, especially if its definition is not clearly understood.

The concept of diversification is formally introduced by Markowitz (1952), who proposed a widely accepted methodology for quantifying and managing diversification in investment portfolios. This approach examines the covariance between asset returns in a portfolio and combines assets with non-perfectly correlated returns to minimize portfolio risk (variance) while maintaining expected returns (Fabozzi et al., 2008).

3.2.1.1. Evidence From the Western Art Market. There have been several years of research on whether art can offer the benefits of portfolio diversification, yet a consensus has not been reached. For example, Mei and Moses (2002) find that art has an extremely low correlation with the S&P 500, at 0.04, suggesting that a diversified portfolio of artworks may play a somewhat important role in portfolio diversification. Similarly, Campbell (2004) concludes that art is a highly beneficial avenue to diversify a portfolio, demonstrating a low or even negative correlation between the Mei/Moses art index, the S&P 500, and the government from 1875 to 2002. Worthington and Higgs (2004) evaluate the correlation of art as an additional asset based on AMR art indexes from January 1976 to December

2001, showing that the correlation coefficients between art and common financial assets range from -0.3058 (small company stock) to 0.3009 (Treasury bills), indicative of the potential gains for portfolio diversification involving art investment. Taylor and Coleman (2011) collect data compiled by Australian Art Auction Records in Australia and New Zealand between 1982 and 2007 and find that the Aboriginal Art Index is negatively correlated with major traditional asset classes (equities = -0.3, real estate = -0.21, government bonds = -0.15) as well as alternative asset classes (gold = -0.1 and hedge funds = -0.39), implying that art is lack of correlation with other assets, which reduces overall portfolio risk. Conversely, Goetzmann (1993) draws a contradictory conclusion, demonstrating a high positive correlation between art and the London Stock Exchange (0.78) and Consol bond returns (0.54) from 1900 to 1986. Likewise, Renneboog and Spaenjers (2013) conclude that art exhibits a positive correlation with gold, commodities, and real estate prices, as well as lagged equity returns of 0.34 for the S&P 500 and 0.55 for global stocks.

In order to investigate whether the inclusion of art in a financial portfolio can provide diversification benefits. Several researchers present their findings, for example, Campbell (2004) finds that portfolios with art appreciate in value by 0.4% and reduce risk by almost 1% compared to portfolios that only include stocks and bonds. This finding implies that the risk-return profile may be improved by including art. Kräussl and Elsland (2008) show that investing in art does not improve the risk and return characteristics of the optimal portfolio in the absence of lending and short sales. However, when allocation restrictions of either 25% or 18.5% are imposed, 3.25% or 5.72% of the optimal portfolio is allocated to art, respectively, suggesting that a portfolio containing artwork may improve the risk-return profile of the optimal portfolio. Conversely, Worthington and Higgs (2004) construct the efficient frontier for both an exclusive art portfolio and a mixed-asset investment portfolio, concluding that the risk-return trade-off of art is inferior to that of the traditional financial market. This finding is echoed by Renneboog and Van Houtte (2002).

3.2.1.2. Evidence From the Emerging Art Market. As emerging markets continue to

expand, academic researchers are increasingly drawn to the potential advantages of portfolio diversification in the emerging art market. Seçkin and Atukeren (2009) and Demir et al. (2018) investigate the diversification potential of Turkish paintings by employing the CAPM beta estimation, with mixed results. Seçkin and Atukeren (2009) find a significant beta parameter of 0.353 between 1990 and 2005, suggesting that art investment may provide the potential benefits of portfolio diversification. However, when Seçkin and Atukeren (2009) narrow their analysis to 1995-2005 and recalculate the CAPM, the beta parameter increases to 0.436 and loses its statistical significance. Seçkin and Atukeren (2009) postulate that the length of the period could influence the significance of beta estimators. In the short term, macroeconomic developments are a common factor affecting financial asset returns, while, in the long term, the art market may play a positive role in diversifying traditional investment portfolios when market fundamentals take precedence. In addition, Demir et al. (2018) find that the beta parameters of Turkish art are equivalent to 0.11 and 0.36 when the S&P 500 and the Borsa Istanbul are used as the market returns, respectively, indicating that investing in art may offer investors a viable avenue to diversify their stock-based portfolios.

Kraeussl and Logher (2010) explore the risk-return characteristics of Russian, Chinese, and Indian art over the periods 1985-2008, 1990-2008, and 2002-2008, respectively. Their results show that Russian paintings have a high market beta of 0.65, albeit statistically insignificant, and generate positive correlations with the common financial assets, implying that Russian art is not an attractive asset for portfolio diversification. In contrast, Chinese art and Indian art have negative beta estimates, signifying that they are likely to fulfil the purpose of portfolio diversification. Furthermore, Kraeussl and Logher (2010) use the utility optimization method to construct optimal asset allocations under three levels of risk-aversion parameters, finding that with unconstrained weighting, optimal asset portfolios exclude art irrespective of risk-aversion parameters. However, upon restricting the weighting of any asset to 15%, Chinese art is a component of a well-diversified portfolio, suggesting that Chinese art can increase the utility of the portfolio. Nonetheless, the allocation to Chinese art

diminishes as the risk-aversion parameter increases. As a result, the inclusion of the emerging art market in a well-diversified portfolio remains limited.

Wang and Zheng (2017) analyze the diversification potential of Chinese oil paintings between 2000 and 2014. Their research suggests, that given the low CAPM beta and low downside beta of Chinese oil paintings, it could serve as a measure of protection against stock market declines. By developing an optimal portfolio allocation, the researchers find that the portfolio including art exhibits a higher Sharpe ratio, implying that incorporating Chinese oil paintings in a portfolio could improve the risk-return profile.

3.2.2. Evidence From Other Alternative Investment Assets

This section builds upon extant research by examining the benefits of investing in other alternative investment assets for portfolio diversification. One such alternative asset that has been examined is wine investment. Fogarty (2010) collects data from Langton's auction houses in Melbourne and Sydney between 1991 and 2000, demonstrating that wine investment is a favorable allocation, even within a well-diversified portfolio. Sanning et al. (2008) investigate wine returns using an 8-year series of monthly auction data from the Chicago Wine Company for red Bordeaux vintages from 1983 to 1998. Using the Fama-French three-factor model and the CAPM model, the findings exhibit that wine yields higher returns than those anticipated by commonly accepted factors. In a follow-up study, Aytaç et al. (2016) gather data from the Liv-ex and WineDex indices from 2007 to 2014, concluding that the wine indices from iDealwine contribute to the enhancement of the efficient frontier for French portfolios. Wine investments may prove more lucrative in times of economic turmoil, making them particularly advantageous for conservative portfolios. However, the existing literature has not yet reached a consensus on the benefits of including wine investments in financial portfolios. For instance, Fogarty and Jones (2011) and Fogarty and Sadler (2014) argue that the diversification benefits of wine investment are influenced by the return estimation method and the diversification test applied. Kourtis et al. (2012) suggest that such benefits differ by region, with

international diversification benefits existing for investors in Italian, Australian, and Portuguese fine wines, but not necessarily for those investing in French wines.

Several studies augment the existing body of literature by investigating stamps, fine violins, gemstones, and classic cars. In particular, Veld and Veld-Merkoulova (2007) find that the efficient frontier is improved by including stamps in a portfolio. This result is consistent with Cardell et al. (1995) and Dimson and Spaenjers (2011). Regarding fine violins, Graddy and Margolis (2011) examine their investment performance and find a negative correlation between the returns of fine violins and those of the S&P 500 and the FTSE. Renneboog and Spaenjers (2012) find that white and colored diamonds possess low-equity betas in investments. In a recent study, Laurs and Renneboog (2019) conclude that classic cars have a low correlation with equities and a negative correlation with bonds, bills, and gold.

3.3. Data and Methodology

3.3.1. Data Collection

3.3.1.1. Data Collection for Chinese Art. The data on Chinese art are collected from Artron.net, which is a leading art-data provider in the Chinese art market. This study manually collects 266,115 auction lots of Chinese art over the period from January 2000 to December 2021, consisting of 198,353 lots sold and 67,762 bought-in. Specifically, it identifies the names of artists who have executed Chinese art from AMMA. AMMA has published a semiannual report on the Chinese Art Auction Market since 2008 with the top 50 artists who have created Chinese art from each of the three categories. Each semiannual report compiles the top 50 artists who have executed Chinese art from each period according to the price per square Chinese foot. Finally, 150 artists are selected in each semiannual report, and our dataset comprises 533 artists after removing the duplicates. It is worth noting that Artron.net provides the price in four different currency units, RMB, USD, HKD, and EUR. For this study, the emphasis is on “price in RMB,” thus investigating the portfolio benefits of incorporating Chinese art into Chinese financial investment portfolios. More importantly, the

current research considers the transaction costs in the Chinese art market. The art market is distinct from other markets in several unique characteristics. It predominantly attracts affluent investors, and is burdened with substantial transaction costs (Penasse & Renneboog, 2022). Auction houses, for example, commonly charge commissions of around 10% for both buyers and sellers. Additionally, they might impose additional fees for insurance and shipping (Ashenfelter & Graddy, 2003; Pesando, 1993).

When a piece of work remains unsold, consignors are usually faced with “buy-back” fees, compensating the auction house for expenses like photographing, researching, and cataloging the item (Penasse & Renneboog, 2022). Moreover, sellers might not be exempt from shipping and handling costs, irrespective of whether the artwork is sold. For art ownership, the financial consideration extends beyond the point of purchase, they might take into account ongoing expenses such as preservation, storage, restoration, and insurance.

Diving deeper into the complexities of transaction costs in the Chinese art market, the seller’s commission is often a subject of negotiation, dependent on factors like the value of a particular lot, the quantity of the artworks offered, and the seller’s historical contributions to the auction houses¹. However, data on seller’s commission, insurance, shipping, administrative costs, and other transactional charges are not readily accessible to the public. Despite this, Artron.net does provide artwork prices, inclusive of the buyer’s premium. In such a case, this study has made necessary adjustments in evaluating art investment performance, specifically incorporating the buyer’s premium.

The repeat-sales data is obtained from the complete data sample, which is constructed as follows: specifically, the study matches the repeat-sales records using the artist’s name, the title of an artwork, the mounting method, signature, and size. This ensures the uniqueness of each artwork. The repeat-sales records are expressed as the buy-sell pairs, consisting of the initial buy-sell pair; if an

¹ Source from: <https://www.shengshidiancang.com/ciqi/202207/3167296.html>

artwork is sold more than once, every two adjacent sales thus form a pair. Using the criteria mentioned above, 5,029 pairs of 198,353 lots sold over the period from January 2000 to December 2021 are measured².

3.3.1.2. Data Collection for Financial Asset Classes. To construct different Chinese financial investment portfolios, this study includes stock, bond, and gold indexes³. The dataset covers the semiannual period from June 2003 to December 2021, with the start and end dates being determined by the availability of data on the SSE government bond index, the SSE corporate bond index, and the price of AU99.95 gold. For stocks, the Shanghai Composite Stock Index (SSE) and the Shenzhen Composite Stock Index (SZSE) is used. For bonds, both government bonds and corporate bonds are quoted on the SSE and are represented by the SSE Government Bond Index (govt. bonds) and SSE Corporate Bond Index (corp. bonds). The constituents of the SSE govt. bond index is fixed-rate government bonds that are traded at the SSE and represent the changes in the government bond market on the SSE. The SSE corp. bond index is composed of all eligible corporate bonds that meet certain criteria in the Chinese corporate bond market. Following Hoang et al. (2015), data on gold is related to AU 99.95 gold spot assets that are traded on the Shanghai Gold Exchange (SGE). All data are available from the Wind dataset.

3.3.2. Methodology to Calculate the Rate of Return on Chinese Art

3.3.2.1. Repeat-Sales Regression. The application of the repeat-sales regression approach has become prevalent in the art market for estimating art returns. This method is particularly beneficial in markets with illiquid and heterogeneous assets. The primary benefit of this approach is its ability to take into consideration the uniqueness of each artwork (Garay, 2021; Mei & Moses, 2002; Renneboog & Spaenjers, 2013).

² It is worth noting that the start date for the SSE government bond index, SSE corporate bond index, and AU99.95 gold on the Wind dataset is June 2003. Initially, a collection of 5,029 repeat sales pairs from January 2000 to December 2021 was gathered. To ensure homogeneity across the series, hence, only 4,840 repeat pairs from June 2003 to December 2021 have been selected in this study for the repeat sales regressions, specifically to calculate the return on Chinese art.

³ For financial indices, the semiannual returns are calculated, such as the semiannual return in the market i by the natural logarithm return of the price index at the time i such that: $R_{it} = \ln(P_{it+1}/P_{it})$

To obtain a return series, this study follows Mei and Moses (2002) by calculating pairwise returns of repeat sales.

Assuming the continuously compounded return for a certain art asset i in a period t , $r_{i,t}$, can be represented by μ_t , the continuously compounded return of a price index of art, and an error term:

$$r_{i,t} = \mu_t + \eta_{i,t} \quad (1)$$

Where μ_t may be the average return in period t of Chinese art in the portfolio. This study will use sales data about individual Chinese art to estimate the index μ over time intervals $t = 1$. The collected data includes the purchase and sales price pairs for each painting comprising the index, represented as $P_{i,b}$ and $P_{i,s}$. Additionally, the dataset provides the respective dates of purchase and sale, denoted as b_i and s_i . Therefore, the logged-price relative for a specific asset i , held between its purchase date b_i and its sales date, s_i , can be expressed as:

$$r_i = \ln\left(\frac{P_{i,s}}{P_{i,b}}\right) = \sum_{t=b_i+1}^{s_i} r_{i,t} = \sum_{t=b_i+1}^{s_i} \mu_t + \sum_{t=b_i+1}^{s_i} \eta_{i,t} \quad (2)$$

Let r is the N -dimensional vector of logged-price relatives for N repeated-sales observations. Goetzmann (1992) exhibits that a generalized least-squares regression of the form:

$$\hat{\mu} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}r \quad (3)$$

provides the maximum-likelihood estimate of μ , where X is an $N \times T$, which has a row of dummy variables for each asset in the sample and a column for each asset in the sample and a column for each holding interval. Ω is a weighing matrix.

3.3.3. Methodology to Measure the Potential Risk Diversification of Chinese Art

3.3.3.1. Single-Index Model and Time-Varying CAPM. The CAPM is tested using a two-phase regression. The equation for the initial regression phase is:

$$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it} \quad (4)$$

Where $R_{i,t}$ is the natural logarithm excess return of the asset i at time t . The intercept α_i denote the alpha, and β_i measures the systematic risk. $R_{m,t}$ is the natural logarithm excess return of the market

portfolio at time t . $\varepsilon_{i,t}$ is the model's error terms. This study considers the return of SSE, SZSE, and average return on assets as the components of the market portfolio. The risk-free asset is defined as the 6-month deposit rate in China.

In the second stage, the time-varying CAPM model is used for the estimation of the parameter's alpha and beta over a specified time span. The equation for the time-varying CAPM model is as follows:

$$r_{i\bar{t}} - r_{f,\bar{t}} = \alpha_{i,\bar{t}} + \beta_{i,\bar{t}}(r_{M,\bar{t}} - r_{f,\bar{t}}) + \varepsilon_{i,\bar{t}} \quad (5)$$

Where $r_{i\bar{t}}$ represents the natural logarithm return of the asset i at time t , and $r_{f,\bar{t}}$ is the 6-month deposit rate in China at the same time t . The intercept $\alpha_{i,\bar{t}}$ denotes the alpha at time t , while $\beta_{i,\bar{t}}$ measures the systematic risk at time t . $r_{M,\bar{t}}$ is the natural logarithm return of the market portfolio at time t . $\varepsilon_{i,t}$ refers to the model's error terms. The data are divided into 32 subperiods, each comprising a 3-year rolling regression formed by sliding windows of 36 months. It is important to note that the windows overlap between the current and previous subperiods, which allows for a comprehensive assessment of the validity of the CAPM.

3.3.3.2. Downside Beta. Ang et al. (2006) demonstrate that investors put the different weights on the possibility of investment losses versus gains. They exhibit a greater sensitivity to downside risks, consequently, require holding assets that fluctuate with the market during market declines to obtain additional compensation. This study aims to assess the extent to which art returns covary with market declines. This is accomplished by calculating a conditional measure of risk, namely the downside beta, as introduced by Ang et al. (2006). In accordance with Bawa and Lindenberg (1977) and Ang et al. (2006), the downside beta (β^-) is calculated as follows:

$$\beta^- = \frac{\text{cov}(R_i, R_m | R_m < \mu_m)}{\text{var}(R_m | R_m < \mu_m)} \quad (6)$$

Where R_i represents the natural logarithm return of a specific asset i , while R_m refers to the natural logarithm return of the market portfolio. $R_m | R_m < \mu_m$ defines the market return, given that the return is below the average market return.

3.3.4. Methodology for the Assessment of the Diversification Benefits of Chinese Art in a Portfolio

To evaluate the potential diversification benefits of adding Chinese art to an investment portfolio, this study adopts a combination of the following methods: first, mean-variance portfolio optimization is utilized to construct portfolios with and without Chinese art on the efficient frontier (see Section 3.3.4.1). Second, optimal asset allocation is employed to create diversified portfolios with and without Chinese art (Kraeussl & Lee, 2010; Kraeussl & Logher, 2010) (see Section 3.3.4.2). Third, in the robustness checks, the Sharpe ratios (Sharpe, 1964) and the modified Sharpe ratios (Favre & Galeano, 2002; Gregoriou & Gueyie, 2003) are used to assess the performance of portfolios with Chinese art compared to those without it (see Section 3.3.4.3).

3.3.4.1. Mean-Variance Portfolio Optimization. The classic Mean-Variance Portfolio Optimization (MVPO) model, initially proposed by Markowitz (1952) and subsequently refined by Bai et al. (2009) and Leung et al. (2012), can be utilized to determine asset allocation for a given amount of capital to the efficient frontier. To formally introduce the MVPO model, let's assume there are n assets and use x_i ($i = 1, \dots, n$) to represent the proportion of capital invested in asset i within portfolio P . The objective is to maximize the average return R_p , subject to a predetermined level of variance σ_p^2 . The R_i is defined as the expected return of an asset i and σ_{ij} as the covariance of returns between assets i and j , for any $i, j = 1, \dots, n$. The general MVPO model can be expressed as:

$$\text{Max} R_p = \sum_{i=1}^n R_i x_i, \text{ subject to: } \sum_{i=1}^n \sum_{j=1}^n \sigma_{ij} x_i x_j = \sigma_p^2 \text{ and } \sum_{i=1}^n x_i = 1 \quad (7)$$

This study then takes 15 efficient portfolios from the efficient frontiers and compares pairs of portfolios, with and without Chinese art. The portfolios without Chinese art consist of stocks, govt. bonds, corp. bonds, and gold, while the diversified portfolios include Chinese art in addition to these assets. The construction of these 15 portfolios is performed as follows: first, the efficient frontier is divided into 15 equal intervals along the horizontal axis; second, the 15 points (symbolizing the portfolios) and their corresponding risk-return coordinates within these intervals are pinpointed. Consequently, 15 efficient portfolios are established, exhibiting uniformly distributed returns across

the entire span of the efficient frontier.

3.3.4.2. Power Utility Optimization. The optimal asset allocation is represented as follows:

$$\max U_{avg} = (\sum_{t=0}^n E_t \left[\frac{R^{1-\gamma}}{1-\gamma} \right]) / n \quad (8)$$

Where U_{avg} is the average utility over all time periods, R is the gross return on the portfolio, γ denotes the risk-aversion parameter and n is the number of time periods.

To determine the maximum average utility, this study assesses each period as a scenario for returns on the assets under consideration. For each scenario, the corresponding utility value is calculated, and the total utility is obtained by summing up all the utilities. The average utility is derived by dividing the total utility value by the total number of time periods. The optimal allocation of assets is obtained by modifying the weighting assigned to each asset while observing two constraints: short selling is not allowed and the sum of the weights of all assets is equal to one.

In accordance with Kraeussl and Logher (2010) and Kraeussl and Lee (2010), there are three levels of risk aversion for investors: low ($\gamma=2$), average ($\gamma=5$), and high ($\gamma=10$). The optimal asset allocation is determined for two different scenarios: 1) no restrictions are imposed on the weight of assets; 2) the maximum weight that can be assigned to each asset is limited to no more than 30%.

3.3.4.3. Sharpe Ratio and Modified Sharpe Ratio. The calculation of Sharpe ratio and Modified Sharpe ratio is as follows.

Sharpe ratio:

$$Sh = \frac{R_P - R_f}{\sigma_P} \quad (9)$$

Where Sh is the Sharpe ratio. R_P is the return of portfolio; R_f is the return of the risk-free asset; and σ_P is the standard deviation of portfolio returns.

Modified Sharpe ratio:

Due to the limitations of using variance as a risk measure in cases where the return distribution is not normal distribution, this study employs an alternative risk measurement that considers the third

and fourth moments of the return distribution. The modified VaR (MVaR) proposed by Favre and Galeano (2002) is implemented as follows:

$$sh_m = \frac{R_p - R_f}{MVaR} \quad (10)$$

$$MVaR = W \left[\mu - \left\{ z_c + \frac{1}{6}(z_c^2 - 1)s + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)s^2 \right\} \sigma \right] \quad (11)$$

Where sh_m represents the modified Sharpe ratio. R_p denotes the return of the portfolio, and R_f is the return of the risk-free asset. $MVaR$ refers to the modified VaR (MVaR). W reflects the value of the portfolio, which is exposed to risk (following Aytac et al., 2016, this factor is 1 in current calculations). μ signifies the average return. Z_c represents the statistical value of the normal distribution law at 5%, where $Z_c = -1.96$. S is the skewness, K is the excess kurtosis compared to 3, and σ is the standard deviation of returns.

3.4. Empirical Result

3.4.1. Summary Descriptive Statistics of Investment Asset Classes

Table 3.1 presents the principal descriptive statistics (in logarithm terms of the return) for the investment asset classes. Chinese art has the highest average semiannual return among all investment asset classes, at 6.18%, followed by the SZSE and gold at 4.94% and 3.80%, respectively. In comparison, the return on govt. bonds is lower, at 1.72%. The standard deviation of asset returns used to measure risk, ranges from 2.29% for govt. bonds to 26.29% for the SZSE. Equities, such as SSE and SZSE, are the most volatile, closely followed by Chinese art, while govt. bonds and corp. bonds are the least volatile. These findings are consistent with Wang and Zheng (2017) and Shi et al. (2018). For example, Wang and Zheng (2017) report that Chinese oil paintings exhibit the highest semi-annual return of 7.89% and are less risky than the Shanghai Composite Stock Index. Similarly, Shi et al. (2018) find that traditional Chinese art has the highest average semiannual return of 5.63%, with a standard deviation that follows the Shanghai composite stock index at 24.47%. However, these findings contrast with those of Garay (2021), who concludes that Venezuelan art is an inferior investment asset with a real arithmetic-average annual return of 0.95% (the nominal arithmetic

average annual return of 5.18%), significantly lower than that of all investment assets except Treasury bills, and with a relatively high standard deviation, ranking behind the Caracas Stock Exchange and the Exchange rate (Bs./\$). Li et al. (2021) also investigate the investment performance of the global art market from 1957 to 2016 and reveal that art underperforms financial investment assets.

While the evidence suggests that there are advantages to investing in Chinese art, investors should be cautious and consider transaction costs when comparing the risk-return characteristics of art and common financial assets. Li et al. (2021) document that auction houses charge a “premium” to the buyer and a “commission” to the seller, resulting in a round-trip fee of approximately 25% of the hammer price for an average auction transaction. Additionally, the purchase of artwork is associated with high insurance and storage fees (Frey & Eichenberger, 1995; Renneboog & Spaenjers, 2013; Wang & Zheng, 2017). Therefore, investors should carefully consider these transaction costs when investing in art. While transaction costs may be affordable for investors who hold art for a long period of time, for investors with a shorter investment horizon, the returns on art may be unfavorable relative to some liquid financial assets (Li et al., 2021).

To evaluate the shape of the distributions, skewness, kurtosis, and Jarque-Bera statistics are measured. Skewness measures the asymmetry of a distribution, and the results reveal that Chinese art, SZSE, govt. bonds, and corp. bonds are positively skewed, while SSE and gold are negatively skewed. Kurtosis, a statistical indicator that measures the heaviness of the tails in the distribution, shows that Chinese art has a platykurtic distribution with a kurtosis of less than 3, while other financial assets exhibit leptokurtic distributions with a kurtosis greater than 3. The Jarque-Bera statistic and p-value are used to test the normality assumption of the return distribution. The results demonstrate that the return distributions of Chinese art, SSE, and SZSE follow a normal distribution, while the return distributions of govt. bonds, corp. bonds, and gold do not hold.

In terms of the relationship between risk and return, the value of the coefficient of variation (the standard deviation divided by the mean return) serves as an indicator of risk relative to return. A

high coefficient of variation indicates a greater dispersion around the mean, leading to a less favorable risk-return trade-off. Among the investment assets, govt. bonds (1.335) and corp. bonds (1.488) have the lowest coefficients of variation, while equities (e.g., SSE and SZSE) have the highest coefficients of variation, with 9.990 and 5.326, respectively. The Sharpe ratio assesses risk-adjusted returns and, with the exception of bonds (e.g., govt. bonds and corp. bonds), Chinese art has the highest Sharpe ratio (0.291) among all investment assets, indicating that it provides better risk-adjusted performance than equities and gold. However, the Sharpe ratio presumes that asset returns follow a normal distribution, which may not be applicable to all assets. To address non-normality, a modified Sharpe ratio is utilized, which replaces the standard deviation with the absolute value of the MVAR. After adjusting for anomalies, Chinese art remains the most valuable investment asset compared to equities and gold, with the exception of govt. bonds and corp. bonds.

Additionally, the ADF analysis of asset returns at their respective levels demonstrates that all investment assets are stationary. The diversification-gains calculation, based on Blume (1984) and Elton et al. (1987), reveals that adding Chinese art to any of the five broad asset classes considered provides incremental diversification benefits.

Table 3.1*Descriptive Statistics for Returns of Investment Asset Classes*

	Mean	Std. Dev.	Skewness	Excess Kurtosis	Jarque-Bera	Jarque-Bera P-Value	ADF tests (Level series)	Coefficient of variance	Sharpe ratio	Modified Sharpe ratio	Diversification gains
Chinese art	6.18%	17.67%	0.416	-0.418	1.338	0.512	-5.689***	2.860	0.291	0.246	
SSE	2.42%	24.19%	-0.193	0.850	1.342	0.511	-5.740***	9.990	0.057	0.036	Yes
SZSE	4.94%	26.29%	0.229	0.582	0.847	0.655	-5.457***	5.326	0.148	0.108	Yes
Govt. bonds	1.72%	2.29%	0.478	5.638	50.416***	0.000	-3.288*	1.335	0.296	0.461	Yes
Corp. bonds	2.45%	3.65%	0.860	3.144	19.809***	0.000	-6.892***	1.488	0.388	0.596	Yes
Gold	3.80%	10.32%	-0.836	2.733	15.816***	0.000	-6.281***	2.719	0.267	0.185	Yes

Note: Table 3.1 shows the descriptive statistics (calculated on log returns) for the financial asset classes for the period 2003-2021. The return on investment is calculated as the natural logarithm of the return on a semi-annual basis. To evaluate the shapes of the distributions, skewness, kurtosis, and Jarque-Bera statistics are measured. To assess relationships between risk and return, the value of the coefficient of variation (standard deviation divided by the mean return) is used. To measure risk-adjusted returns, the Sharpe ratio is calculated. The Sharpe ratio is the semiannual mean rate of return minus the risk-free rate, divided by its standard deviation. The risk-free rate is the six-month deposit rate in China. However, the Sharpe ratio assumes that asset returns are normally distributed, which may not be the case for all assets. To address non-normality, Favre and Galeano (2002) developed a modified Sharpe ratio that is utilized by replacing the standard deviation with the absolute value of the MVaR. Additionally, ADF unit root tests and diversification gains are implemented. For Augmented Dickey-Fuller (ADF) tests, hypotheses are H_0 : unit root, H_1 : no unit root (stationary). The lag orders in the ADF equations are determined by the significance of the coefficients for the lag terms. Intercepts and trends are included in the level series. The diversification gains are computed using the method described by Blume/Elton et al. Specifically, the incremental diversification benefit of adding Chinese art to an existing asset is measured if the Sharpe ratio for Chinese art exceeds the Sharpe ratio of the existing asset multiplied by the correlation coefficient between Chinese art and the existing financial assets. *, **, and *** significance at the 10%, 5%, and 1% confidence levels, respectively.

3.4.2. The Potential Risk Diversification of Chinese Art

3.4.2.1. Return of Correlation Between Chinese Art and Common Financial Assets.

Table 3.2 shows the correlation matrix for the investment asset classes, where the Pearson method is used below the diagonal and the Spearman method is employed above the diagonal. The results indicate that the correlation coefficients between Chinese art and financial asset classes vary from -0.248 for govt. bonds to 0.036 for gold, using the Pearson method, and from -0.288 for govt. bonds to 0.121 for gold, using the Spearman method. These results indicate that Chinese art can potentially offer investors diversification benefits by reducing the overall risk of their investment portfolios. These findings are similar to those of Mei and Moses (2002), Campbell (2008), and Li et al. (2021). Specifically, Mei and Moses (2002) observe that art has an extremely low correlation with the S&P 500 Index (0.04) and Dow Industrial (0.03). They also report a negative correlation with govt. bonds (-0.15), corp. bonds (-0.10), and Treasury bills (-0.03). Similarly, Campbell (2008) shows a correlation of 0.0419 between art with the S&P 500 and a negative correlation of -0.04 with government bonds. Li et al. (2021) demonstrate that art has a significant correlation with global commodities (0.40) and gold (0.32) but holds negative correlations with Dow Jones Corp. bonds (-0.23), S&P 500 stocks (-0.11), and global government bonds (-0.10). These researchers conclude that art can provide diversification benefits when included in investment portfolios. In contrast, Goetzmann (1993) reports a high positive correlation between art and the return of the London Stock Exchange (0.78) and Consol bond returns (0.54) from 1900 to 1986, suggesting that art is a poor investment tool for portfolio diversification. Likewise, Renneboog and Spaenjers (2013) find that art is positively correlated with gold, commodities, and real estate prices. In their additional analysis, they also observe correlations between art and lagged equity returns of 0.34 (S&P 500) and 0.55 (global stocks).

Table 3.2*The Return of Correlation Between Chinese Art and Common Financial Assets*

	Chinese art	SSE	SZSE	Govt. bonds	Corp. bonds	Gold
Chinese art	1	-0.088	-0.112	-0.288	-0.196	0.121
SSE	-0.060	1	0.912***	-0.487***	-0.445***	0.111
SZSE	-0.081	0.908***	1	-0.381	-0.344**	0.118
Govt. bonds	-0.248	-0.334**	-0.339**	1	0.845***	-0.142
Corp. bonds	-0.173	-0.400**	-0.365**	0.898***	1	-0.253
Gold	0.036	0.120	0.096	-0.113	-0.275*	1

Note: This table shows the results of the return of correlation between Chinese art and common financial assets, where the Pearson method is used below the diagonal and the Spearman method above the diagonal. *, **, and *** significance at the 10%, 5%, and 1% confidence levels, respectively.

3.4.2.2. Single-Index Model and Time-Varying CAPM. The CAPM regression measures the systematic risk of art as an asset class, with the results presented in Table 3.3. Panel A displays the estimates for investment assets within the single-index model, as exemplified by Equation (4). Using the returns of the SSE and SZSE as proxies for systematic market factors, the beta coefficients for Chinese art are -0.0451 and -0.0550, respectively, albeit insignificant. This result is consistent with our expectation that the Chinese art market is largely uncorrelated with the stock markets. Such a result echoes the findings of Kraeussl and Logher (2010), who report an insignificant negative market beta of -0.22 for Chinese art when using the return of the S&P 500 as the market return, suggesting that Chinese art could effectively hedge against the stock market declines. In contrast, Wang and Zheng (2017) demonstrate that the beta parameters for Chinese oil paintings are 0.0095 and 0.3490 when using the returns of the domestic stock index and the MSCI World Equity Index as the market return, respectively, but these parameters are also found to be insignificant. This observation suggests that Chinese oil paintings exhibit a similar directional movement to the stock market, and the increase in oil painting prices might be attributable to the stock market's wealth effect. Additionally, Kräussl (2015) finds a statistically significant beta of 1.103 for paintings from the Middle East and Northern Africa (MENA), indicating that MENA paintings not only move in same direction as the stock market but are also subject to greater systemic risk than the MSCI World Equity Index.

When the average return on assets is used as the systematic market factor, the beta coefficient for Chinese art rises to 0.527, suggesting that it may not effectively facilitate portfolio diversification. In contrast, regardless of the market return employed, bonds (e.g., govt. bonds and corp. bonds) consistently exhibit significantly negative beta coefficients. This indicates that their movements are inversely related to the market, rendering them potential diversifying components within a well-balanced portfolio. Furthermore, gold has relatively low market beta coefficients, implying that it could also serve as a valuable diversification instrument.

It is also noteworthy that Chinese art generates a significant positive alpha at the 10% level. Depending on the SSE and SZSE, Chinese art yields semi-annual returns of 0.052 or 0.054 above those anticipated by the CAPM, suggesting that Chinese art offers diversification opportunities and that investing in this asset could enhance the performance of Chinese investors.

In addition to the single-index model, a rolling regression model is implemented to examine time-varying estimates of alpha and beta across a specific time horizon. Panel B presents the mean values of alpha and beta for the CAPM using rolling regression. In line with Panel A, when using SSE and SZSE returns as market returns, the average market beta for Chinese art is relatively low at 0.033 and -0.016, respectively, indicating that Chinese art can be used as a diversified asset class in a traditional portfolio. However, when the return on average assets is used as the market return, the average market beta for Chinese art increases to 0.119. In addition, in either case, Chinese art exhibits positive average alphas.

Table 3.3*The Single-Index CAPM and Time-Varying CAPM*

Panel A: Single-index model						
The return of Shanghai composite stock index as market return						
	Chinese art	SZSE	Gold	Govt. bonds	Corp. bonds	
Alpha	0.052*	0.025	0.027	0.007*	0.015**	
	(1.773)	(1.375)	(1.568)	(1.950)	(2.631)	
Beta	-0.045	0.987***	0.052	-0.031*	-0.059**	
	(-0.367)	(12.808)	(0.730)	(-1.982)	(-2.487)	
R Squared	0.38%	82.42%	1.50%	10.09%	15.02%	
The return of Shenzhen composite stock index as market return						
	Chinese art	SSE	Gold	Govt. bonds	Corp. bonds	
Alpha	0.054*	-0.019	0.026	0.008**	0.016***	
	(1.810)	(-1.094)	(1.504)	(2.121)	(2.759)	
Beta	-0.055	0.835***	0.038	-0.0286*	-0.050**	
	(-0.488)	(12.808)	(0.581)	(-2.016)	(-2.230)	
R Squared	0.68%	82.42%	0.96%	10.40%	12.44%	
Average asset returns as the market return						
	Chinese art	SSE	SZSE	Gold	Govt. bonds	Corp. bonds
Alpha	0.038	-0.052***	-0.032	0.018	0.009**	0.018***
	(1.281)	(-2.875)	(-1.582)	(1.067)	(2.339)	(3.050)
Beta	0.527	2.577***	2.783***	0.363*	-0.088*	-0.161**
	(1.554)	(12.533)	12.103	(1.849)	(-1.993)	(-2.354)
R Squared	6.45%	81.78%	80.71%	8.90%	10.19%	13.67%
Panel B: CAPM with time-varying alpha and beta						
The return of Shanghai composite stock index as market return						
	Chinese art	SZSE	Gold	Govt. bonds	Corp. bonds	
Alpha (av. value)	0.050	0.033	0.028	0.009	0.019	
Beta (av. value)	0.033	0.997	0.044	-0.038	-0.049	
The return of Shenzhen composite stock index as market return						
	Chinese art	SSE	Gold	Govt. bonds	Corp. bonds	
Alpha (av. value)	0.048	-0.019	0.021	0.009	0.019	
Beta (av. value)	-0.016	0.817	0.012	-0.031	-0.037	
Average asset returns as the market return						
	Chinese art	SSE	SZSE	Gold	Govt. bonds	Corp. bonds
Alpha (av. value)	0.058	-0.064	-0.049	0.018	0.012	0.024
Beta (av. value)	0.119	2.758	3.039	0.331	-0.105	-0.141

Note: Table 3.3 evaluates the systematic risk of art as an asset class. Panel A displays the estimates for various investment assets based on the single index model. Panel B presents the average values of alpha and beta for the CAPM model using rolling regression.

3.4.2.3. Downside Beta. While beta estimated using the CAPM model provides an unconditional measure of risk, investors typically place more emphasis on downside risk and demand additional compensation for holding assets that covary with the market during downside movements (Ang et al., 2006).

Table 3.4 presents the results of the downside risk analysis. When the return of the SSE and SZSE is below their average market return, the downside beta of Chinese art exhibits relatively low at 0.148 and 0.166, respectively, albeit insignificant. This finding suggests that Chinese art experiences less volatility than the equity market. Furthermore, when combined with its return characteristics, investing in art produces higher average downside log returns of 6.91% and 7.86%, respectively. These findings are consistent with Wang and Zheng (2017), who report an insignificant downside risk beta of 0.1644 and a log excess return of 7.17% for Chinese oil paintings, suggesting that Chinese oil paintings can serve as a hedge against stock market declines in a diversified portfolio.

However, when the average return on assets underperforms, the downside risk beta for Chinese art rises to 0.962, implying that there is limited room for art to offer protection against downward trends in the market. Such an observation contrasts with the results of Kräussl and Elsland (2008) and Campbell (2008). For example, Kräussl and Elsland (2008) provide evidence that the German Art All Index has a negative downside risk beta of -0.0924 and a low log excess return of 0.004, suggesting that the inclusion of art in a portfolio of asset classes reduces the conditional downside risk of the total risk. Campbell (2008) finds that art investments offer protection against downside movements in the market portfolio, as most extreme events in the stock market occur when there is little movement in the art market.

Table 3.4*Downside Risk*

The period of bearish returns in the Shanghai composite stock index				
	Downside return	Downside beta	T-value	R squared
Chinese Art	6.91%	0.148	0.557	1.70%
SZSE	-12.70%	0.923***	8.679	80.71%
Gold	2.34%	0.092	0.577	1.82%
Govt. bonds	1.27%	-0.052	-1.382	9.59%
Corp. bonds	2.36%	-0.101*	-1.872	16.30%
The sustained downturn in the return of the Shenzhen composite stock index				
	Downside return	Downside beta	T-value	R squared
Chinese Art	7.86%	0.166	0.628	2.14%
SSE	-14.00%	1.023***	9.478	83.31%
Gold	0.97%	-0.107	-0.635	2.19%
Govt. bonds	1.03%	-0.066	-1.589	12.31%
Corp. bonds	2.08%	-0.102	-1.696	13.78%
The period of declining average asset return				
	Downside return	Downside beta	T-value	R squared
Chinese Art	2.35%	0.962	1.492	10.01%
SSE	-12.36%	2.582***	7.132	71.78%
SZSE	-10.36%	2.538***	6.314	66.59%
Gold	0.07%	0.208	0.505	1.26%
Govt. bonds	1.20%	-0.116	-1.158	6.28%
Corp. bonds	2.41%	-0.175	-1.232	7.05%

Note: Table 3.4 shows the results of the downside risk measures. All downside betas are calculated using the excess log return relative to the 6-month deposit interest rate. The SSE composite stock index, the SZSE composite stock index, and the average asset return are proxies for market returns, respectively. The calculation is given by $\beta^- = \frac{cov(r_i, r_m / r_m < \mu_m)}{var(r_m / r_m < \mu_m)}$. All returns are excess log returns given in percentages. *, **, and *** significance at the 10%, 5%, and 1% confidence levels, respectively.

3.4.3. Diversification Benefits of Adding Chinese Art to Portfolio

3.4.3.1. Mean-Variance Portfolio Optimization. Table 3.5 presents a comparative analysis of the risk-return characteristics of the portfolios with and without Chinese art on the efficient frontier. The results show that the semi-annual log returns and standard deviations of the portfolios with Chinese art range from 2.07% to 6.18% and 1.83% to 17.43%, respectively. In contrast, most of the portfolios without Chinese art exhibit lower returns and higher standard deviations. The risk-adjusted analysis further shows that portfolios with Chinese art have consistently outperformed their counterparts, as evidenced by the higher Sharpe ratios. Similarly, portfolios with art also improve the risk-return profile after accounting for the non-normality of the data, as indicated by the larger modified Sharpe ratio, especially after PF6.

Table 3.5*Mean-Variance Efficient Frontier With and Without Chinese Art*

Portfolios with art	Mean	Std. Dev.	Sharp ratio	Modified Sharp ratio
Portfolios without art				
PF1	2.07%	1.83%	0.566	0.254
	1.89%	1.98%	0.433	0.255
PF2	2.36%	1.97%	0.673	0.258
	2.11%	2.09%	0.514	0.262
PF3	2.66%	2.22%	0.730	0.266
	2.33%	2.27%	0.570	0.270
PF4	2.95%	2.51%	0.762	0.271
	2.54%	2.48%	0.608	0.276
PF5	3.24%	2.91%	0.758	0.258
	2.76%	2.72%	0.635	0.280
PF6	3.54%	3.70%	0.675	0.238
	2.98%	3.22%	0.604	0.239
PF7	3.83%	4.72%	0.592	0.225
	3.20%	4.33%	0.499	0.206
PF8	4.12%	5.85%	0.527	0.215
	3.41%	5.71%	0.416	0.185
PF9	4.42%	7.04%	0.480	0.207
	3.63%	7.21%	0.360	0.171
PF10	4.71%	8.26%	0.445	0.201
	3.85%	8.77%	0.321	0.160
PF11	5.00%	9.50%	0.417	0.197
	4.07%	10.36%	0.292	0.151
PF12	5.30%	10.81%	0.394	0.196
	4.28%	13.02%	0.249	0.135
PF13	5.59%	12.39%	0.368	0.199
	4.50%	16.87%	0.205	0.123
PF14	5.88%	14.18%	0.342	0.201
	4.72%	21.26%	0.173	0.114
PF15	6.18%	17.43%	0.295	0.246
	4.94%	25.93%	0.150	0.108

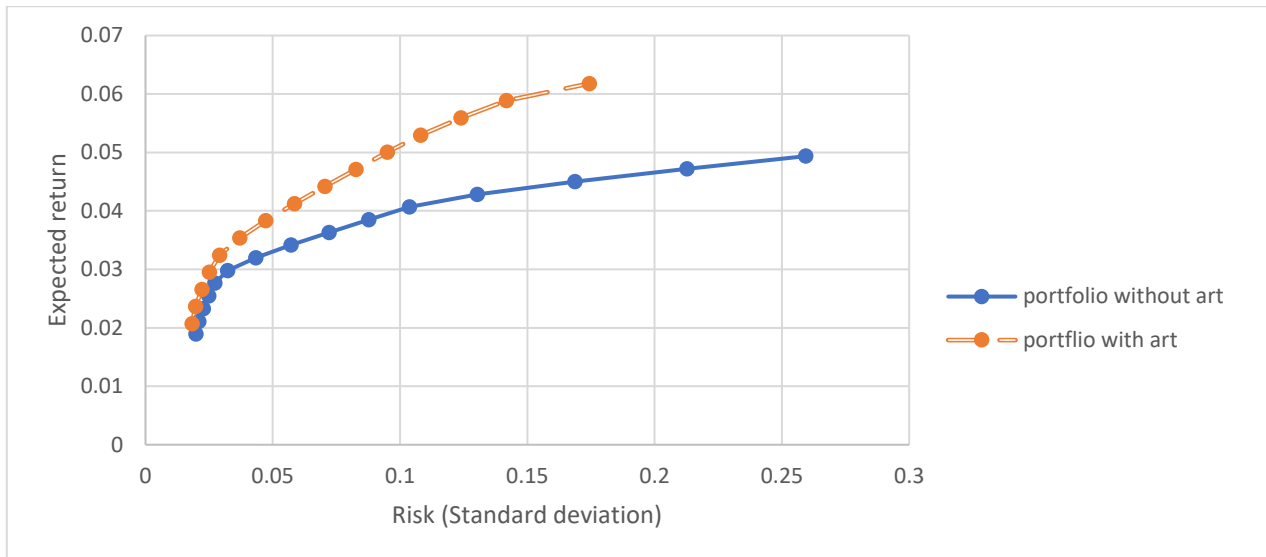
Note: Table 3.5 presents the results of a comparison of the return-risk characteristics of portfolios with and without Chinese art on the efficient frontier. The upper (lower) value in each cell represents the with-Chinese art (without-Chinese art) portfolios.

Figure 3.1 illustrates the mean-variance efficient frontier analysis by partitioning each efficient frontier into 15 portfolios, with PF1 being the minimum-variance portfolio and PF15 representing the maximum-return portfolio. The figure demonstrates that efficient frontiers with Chinese art surpass those without in all cases. This means that by including Chinese art in the reference portfolio, investors can obtain higher returns for the same level of risk or lower risks for the same rate of return. As a result, including Chinese art in a diversified portfolio can offer significant diversification benefits, and investors should consider it a valuable asset for diversification purposes. This finding contradicts previous studies which suggest that art investments have an inferior risk-

return profile compared to the traditional financial asset market, leading to limited diversification benefits within multi-financial asset portfolios (Renneboog & Van Houtte, 2002; Worthington & Higgs, 2004).

Figure 3.1

Mean-Variance Efficient Frontier Analysis



3.4.3.2 Optimal Asset Allocation. Table 3.6 presents the results of an optimal asset allocation analysis. Panel A reports the results of the optimal asset allocation under unconstrained weights. At a risk-aversion level of 2, Chinese art is included in the optimal portfolio, with allocations of 56.80% in Chinese art, 15.17% in SZSE, and 28.03% in gold. At an average level of risk aversion ($\gamma=5$), the analysis still suggests investing in Chinese art. However, the proportion of investment in Chinese art decreases relative to the previous case, resulting in an optimal allocation of 27.91% in Chinese art, 9.37% in SZSE, 23.09% in gold, and 39.63% in corp. bonds. As the risk-aversion level increases to 10, the optimal asset allocation encompasses 16.97% in Chinese art, 6.85% in SZSE, 16.74% in gold, and 59.44% in corp. bonds.

Panel B shows the results of the optimal asset allocation under a constraint where the maximum asset weight is set at 30%. The optimal allocation for a low level of risk aversion ($\gamma=2$) consists of 30% in Chinese art, 18.87% in SZSE, 30% in gold, and 21.13% in Corp. bonds. For the

average level of risk aversion ($\gamma=5$), the optimal allocation is 30% in Chinese art, 10.03% in the SZSE, 29.97% in gold, and 30% in Corp. bonds. At high levels of risk aversion ($\gamma=10$), the optimal allocation shows slight variations in the weightings of the asset classes, including to a lesser extent Chinese art, with an optimal allocation of 18.96% in Chinese art, 7.02% in the SZSE, 20.08% in gold, 23.94% in Govt. bonds, and 30% in Corp. bonds.

In either case, Chinese art is included in the optimal allocation to improve the overall utility irrespective of risk aversion levels. However, as the level of risk aversion increases, the weight of Chinese art in the optimal portfolio decreases. As a result, the benefits of including Chinese art in a well-diversified portfolio may be limited to some extent. This finding is similar to that of Kraeusl and Lee (2010), who find that artwork is included in the optimal asset allocation in all cases. Although the proportion of artworks executed by Global 500 artists in the optimal portfolio decreases as risk aversion increases, their works still make a significant contribution to a diversified portfolio. Moreover, there are slight similarities with Kraeusl and Logher (2010), who observe that neither Russian art nor Chinese art is comprised in the optimal portfolio when the weights are unconstrained. However, when the weight of each asset is constrained to 15%, the optimal allocation includes Chinese art instead of Russian art at any level of the risk-aversion parameter, suggesting that the inclusion of Chinese art leads to higher utility and thus, achieves the goal of optimal portfolio diversification. Nonetheless, as level of the risk-aversion increases, Chinese art becomes underweighted in the optimal portfolio. As a result, the benefits of including emerging art markets in a well-diversified portfolio are rather limited.

Table 3.6*Optimal Asset Allocation*

Panel A: Optimal asset allocation under unconstrained weights						
Weights unconstrained	Exclusion of art			Inclusion of art		
	$\gamma=2$	$\gamma=5$	$\gamma=10$	$\gamma=2$	$\gamma=5$	$\gamma=10$
Chinese art				56.80%	27.91%	16.97%
SSE	0	0	0	0	0	0
SZSE	17.71%	9.96%	7.23%	15.17%	9.37%	6.85%
Gold	53.45%	29.23%	20.69%	28.03%	23.09%	16.74%
Govt. bonds	0	0	0	0	0	0
Corp. bonds	28.85%	60.81%	72.08%	0	39.63%	59.44%
Utility	-0.970	-0.224	-0.089	-0.960	-0.219	-0.086
Std. deviation	7.16%	3.80%	3.02%	11.08%	5.58%	3.59%
Panel B: Optimal asset allocation under constraint weights						
Weights 30%	Exclusion of art			Inclusion of art		
	$\gamma=2$	$\gamma=5$	$\gamma=10$	$\gamma=2$	$\gamma=5$	$\gamma=10$
Chinese art				30.00%	30.00%	18.96%
SSE	0	0	0	0	0	0
SZSE	25.50%	11.48%	10.00%	18.87%	10.03%	7.02%
Gold	30.00%	30.00%	30.00%	30.00%	29.97%	20.08%
Govt. bonds	14.50%	28.52%	30.00%	0	0	23.94%
Corp. bonds	30.00%	30.00%	30.00%	21.13%	30.00%	30.00%
Utility	-0.972	-0.226	-0.092	-0.962	-0.220	-0.087
Std. deviation	7.17%	4.16%	3.92%	7.57%	6.35%	3.99%

Note: Table 3.6 presents the results of an optimal asset allocation analysis. Panel A reports the results of the optimal asset allocation under unconstrained weights. Panel B shows the results of the constrained optimal asset allocation, where the maximum asset weight is set at 30%.

3.4.4. Robustness Tests

3.4.4.1. Efficient Portfolios Versus Equal-Weighted Portfolio. In this section, a number of robustness checks are performed, which firstly analyze whether an efficient frontier portfolio containing Chinese art outperforms an equal-weighted portfolio, and secondly, assess the potential benefits of including Chinese art in a portfolio during a market downturn.

The impetus for the first robustness check lies in determining the effectiveness of Markowitz (1952) and the findings drawn by DeMiguel et al. (2009) in the context of portfolios diversified with Chinese art. Markowitz (1952) proposes that efficient frontier portfolios are expected to outperform all other portfolios within the frontier, including the equal-weighted portfolio. Conversely, DeMiguel et al. (2009) argue that the naive equal-weighted portfolio would outperform the efficient portfolios. To evaluate the applicability of these arguments to the inclusion of Chinese art in investment

portfolios, this study compares the performance of the portfolio with Chinese art on the efficient frontier (PF1-PF15) with that of the equal-weighted portfolio, using the Sharpe ratio and the modified Sharpe ratio.

Table 3.7 presents the performance outcomes of portfolios with Chinese art on the efficient frontier (PF1-PF15) and the equal-weighted portfolio. The results show that the average log returns of efficient portfolios ranging from PF1 to PF6 are inferior to those of the equal-weighted portfolio; nevertheless, this pattern changes after PF7. Moreover, the standard deviation of the majority of efficient portfolios, which includes PF1-PF10, is considerably lower compared to the equal-weighted portfolios. The efficient portfolios possess a superior risk-return profile, as evidenced by their higher Sharpe ratios and modified Sharpe ratios.

Table 3.7

Robustness Test A: Efficient Frontier With Chinese Art and Equal-Weighted Portfolio

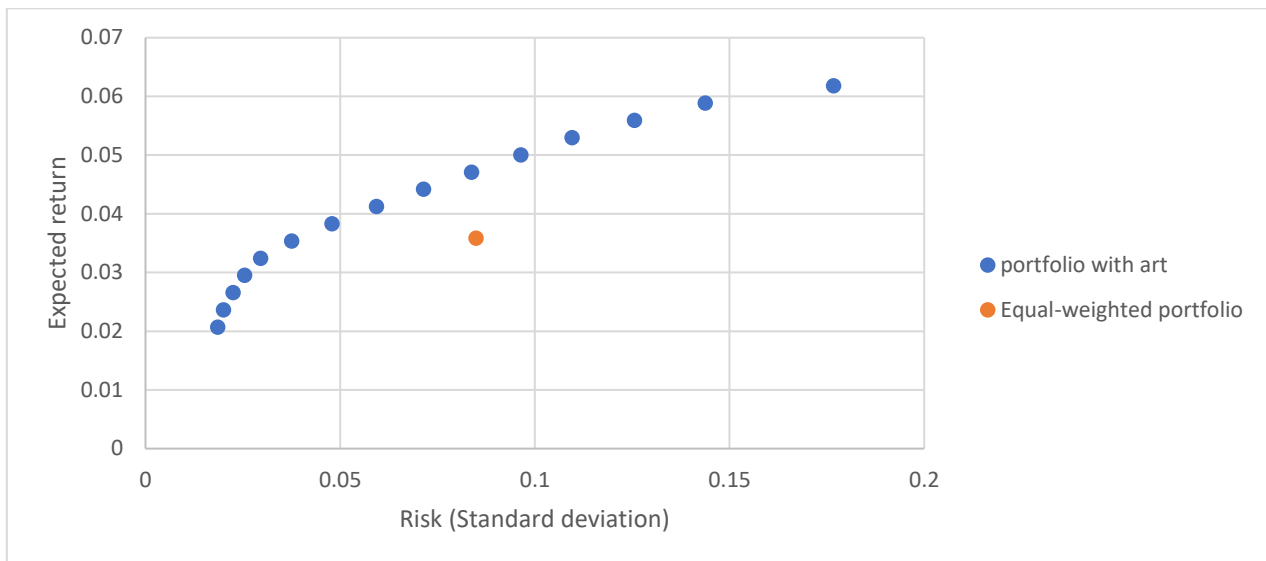
	Mean	Std. Dev.	Sharp ratio	Modified Sharp ratio
PF1	2.07%	1.85%	0.558	0.254
PF2	2.36%	2.00%	0.664	0.258
PF3	2.66%	2.25%	0.721	0.266
PF4	2.95%	2.55%	0.752	0.271
PF5	3.24%	2.95%	0.747	0.258
PF6	3.54%	3.75%	0.666	0.238
PF7	3.83%	4.79%	0.584	0.225
PF8	4.12%	5.93%	0.520	0.215
PF9	4.42%	7.14%	0.474	0.207
PF10	4.71%	8.37%	0.439	0.201
PF11	5.00%	9.63%	0.412	0.197
PF12	5.30%	10.95%	0.389	0.196
PF13	5.59%	12.56%	0.363	0.199
PF14	5.88%	14.38%	0.337	0.201
PF15	6.18%	17.67%	0.291	0.246
Equal-weighted portfolio	3.58%	8.49%	0.300	0.134

Note: Table 3.7 reports the performance results for portfolios with Chinese art on the efficient frontier (PF1 to PF15) and the equal-weighted portfolio.

Figure 3.2 depicts the efficient frontier for portfolios with art (PF1-PF15) and the equal-weighted portfolio, it is observed that the equal-weighted portfolio is situated within the efficient frontiers, suggesting that the efficient portfolios deliver the higher expected rate of return for each given level of risk.

Figure 3.2

Efficient Frontier for Portfolios with Chinese Art and the Equal-Weighted Portfolio.



In conclusion, these results are consistent with Markowitz (1952) and contradict DeMiguel et al. (2009), who contend that the naive equal-weighted portfolio would perform better than the efficient portfolios. The finding suggests that the inclusion of Chinese art in a portfolio would lead to more efficient diversification.

3.4.4.2. Inclusion of Chinese Art in a Portfolio When Stock Markets are in a Downturn.

Table 3.8 shows the results of the risk-return characteristics of portfolios with and without Chinese art on the effective frontier during market downturns. More specifically, Panel A compares the performance of portfolios with and without Chinese art on the efficient frontier during a period of bearish returns in the SSE. The results show that, on average, portfolios with Chinese art (PF1-PF10) yield significantly higher log returns compared to portfolios without art. Despite this, the standard deviation of portfolios with Chinese art exceeds that of portfolios without art after PF3. The Sharpe ratio and the modified Sharpe ratio are employed to quantitatively measure the degree of return per unit of additional risk for each pair of portfolios. The results present that the portfolios with art outperform the portfolios without art in terms of return per unit of risk (Sharpe ratio) from PF1-PF9. The ranking of portfolios based on the modified Sharpe ratio (MVaR) is similar to that of the Sharpe

ratio. It should be noted that the magnitude of the Sharpe ratio is relatively higher than that of the modified Sharpe ratio. This is because the former may underestimate tail risk. Figure 3.3 shows the efficient frontier for portfolios both with and without Chinese art in relation to the underperformance of the stock market (SSE). It illustrates that in most cases, the efficient frontier with Chinese art is superior to that without Chinese art, suggesting greater efficiency for art-inclusive portfolios.

Panel B reports the results of the risk-return analysis for portfolios with and without Chinese art on the effective frontier during a sustained downturn in the return of SZSE. The results in Panel B are consistent with those of Panel A, demonstrating that the average log return and standard deviation of portfolios with Chinese art are higher than those of portfolios without Chinese art. Moreover, the inclusion of Chinese art in investment portfolios enhances the risk-return profile of the portfolios, which is evident from the higher values of the Sharpe ratios and modified Sharpe ratios. As shown in Figure 3.4, the efficient frontier for portfolios with and without Chinese art during a prolonged downturn in SZSE returns holds similar results as depicted in Figure 3.3.

Panel C examines the risk-return characteristics of portfolios with and without Chinese art during the period of declining average asset return. The results of Panel C differ from those of Panel A and B, showing that portfolios with and without Chinese art have little significant difference in the average log return and standard deviation. With regard to the Sharpe ratio, portfolios with Chinese art display slightly higher values than those without Chinese art. However, after adjusting for the non-normality of portfolio returns, the modified Sharpe ratio produces a different ranking in comparison to the traditional Sharpe ratio measured. Portfolios with Chinese art fail to have superior performance under non-normal conditions. This observation aligns with the conclusion of Alexander and Baptista (2003) that performance rankings based on the reward-to-VaR ratio differ from those based on the Sharpe ratio when normality is not assumed. Figure 3.5 illustrates the portfolio with and without Chinese art on the efficient frontier during a trough in average asset returns. The analysis indicates

that the portfolio with Chinese art only marginally outperforms the one without, and both portfolios converge towards the end. The gap between these two portfolios is minimal.

Table 3.8

Robustness Test B: Efficient Portfolios With and Without Chinese Art During Periods of Market

Downturn

Panel A: Efficient portfolios with and without art during a period of bearish returns in the SSE				
Portfolios with art	Mean	Std. Dev.	Sharpe ratio	Modified Sharpe ratio
Portfolios without art				
PF1	1.95%	2.13%	0.415	0.134
	1.32%	2.39%	0.109	0.043
PF2	2.37%	2.19%	0.598	0.222
	1.47%	2.40%	0.168	0.067
PF3	2.79%	2.34%	0.739	0.319
	1.61%	2.41%	0.226	0.090
PF4	3.21%	2.66%	0.808	0.344
	1.75%	2.43%	0.282	0.114
PF5	3.64%	3.03%	0.848	0.365
	1.89%	2.46%	0.336	0.137
PF6	4.06%	3.58%	0.835	0.361
	2.03%	2.50%	0.387	0.161
PF7	4.48%	4.77%	0.716	0.345
	2.18%	2.55%	0.435	0.184
PF8	4.90%	6.29%	0.610	0.333
	2.32%	2.61%	0.479	0.208
PF9	5.32%	7.96%	0.535	0.324
	2.46%	2.72%	0.513	0.231
PF10	5.74%	9.70%	0.483	0.318
	2.60%	2.84%	0.542	0.255
PF11	6.17%	11.47%	0.445	0.312
	2.74%	2.96%	0.567	0.278
PF12	6.59%	13.27%	0.416	0.308
	2.88%	3.09%	0.590	0.302
PF13	7.01%	15.08%	0.394	0.304
	3.03%	3.22%	0.609	0.325
PF14	7.43%	16.91%	0.377	0.301
	3.17%	3.36%	0.626	0.349
PF15	7.85%	18.75%	0.362	0.311
	3.31%	4.15%	0.541	0.372

Panel B: Efficient portfolios with and without art during a sustained downturn in the return of SZSE				
Portfolios with art	Mean	Std. Dev.	Sharpe ratio	Modified Sharpe ratio
Portfolios without art				
PF1	1.15%	2.11%	0.060	0.017
	0.65%	2.25%	-0.164	-0.050
PF2	1.69%	2.16%	0.311	0.106
	0.82%	2.26%	-0.088	-0.029
PF3	2.24%	2.32%	0.526	0.230
	0.99%	2.28%	-0.013	-0.005
PF4	2.79%	2.61%	0.677	0.344
	1.16%	2.31%	0.061	0.023
PF5	3.34%	3.09%	0.749	0.388
	1.33%	2.36%	0.131	0.056
PF6	3.88%	3.65%	0.784	0.432
	1.50%	2.42%	0.198	0.094

Continued Table 3.8

Portfolios with art		Mean	Std. Dev.	Sharpe ratio	Modified Sharpe ratio
Portfolios without art					
PF7		4.43%	4.61%	0.740	0.496
		1.67%	2.50%	0.260	0.139
PF8		4.98%	5.85%	0.676	0.535
		1.84%	2.58%	0.318	0.195
PF9		5.52%	7.29%	0.617	0.518
		2.01%	2.68%	0.368	0.254
PF10		6.07%	8.86%	0.570	0.506
		2.18%	2.84%	0.408	0.279
PF11		6.62%	10.48%	0.534	0.497
		2.35%	3.00%	0.442	0.301
PF12		7.16%	12.15%	0.506	0.489
		2.52%	3.18%	0.471	0.321
PF13		7.71%	13.84%	0.483	0.483
		2.69%	3.37%	0.496	0.339
PF14		8.26%	15.55%	0.466	0.478
		2.86%	3.56%	0.516	0.355
PF15		8.81%	17.27%	0.451	0.474
		3.03%	4.19%	0.479	0.718

Panel C: Efficient portfolios with and without art during the decreasing periods of declining average return					
Portfolios with art		Mean	Std. Dev.	Sharpe ratio	Modified Sharpe ratio
Portfolios without art					
PF1		1.32%	2.02%	0.155	0.048
		1.23%	2.22%	0.102	0.042
PF2		1.47%	2.03%	0.226	0.076
		1.39%	2.23%	0.169	0.077
PF3		1.61%	2.05%	0.294	0.108
		1.54%	2.26%	0.234	0.120
PF4		1.76%	2.10%	0.356	0.148
		1.69%	2.30%	0.296	0.175
PF5		1.90%	2.17%	0.412	0.198
		1.84%	2.36%	0.352	0.251
PF6		2.05%	2.26%	0.460	0.262
		1.99%	2.45%	0.402	0.362
PF7		2.19%	2.37%	0.500	0.336
		2.14%	2.55%	0.445	0.474
PF8		2.34%	2.49%	0.534	0.378
		2.29%	2.66%	0.484	0.562
PF9		2.48%	2.62%	0.564	0.421
		2.44%	2.78%	0.518	0.629
PF10		2.63%	2.75%	0.589	0.464
		2.60%	2.90%	0.547	0.696
PF11		2.77%	2.89%	0.611	0.507
		2.75%	3.04%	0.573	0.764
PF12		2.92%	3.03%	0.630	0.551
		2.90%	3.17%	0.596	0.831
PF13		3.06%	3.18%	0.646	0.595
		3.05%	3.32%	0.615	0.899
PF14		3.21%	3.33%	0.660	0.675
		3.20%	3.47%	0.633	0.967
PF15		3.35%	3.69%	0.636	2.026
		3.35%	3.69%	0.636	2.026

Note. Table 3.8 analyzes the risk-return characteristics of portfolios with and without Chinese artwork on the effective frontier during periods of the market downturn. Panel A compares the performance of portfolios with and without Chinese art on the efficient frontier during the return of SSE in a bear market period. Panel B reports the results of the risk-return analysis of portfolios with and without Chinese artwork on the effective frontier during a bear market period in the return of SZSE. Panel C examines the risk-return characteristics of portfolios with and without Chinese art during a declining average asset return.

Figure 3.3

Efficient Frontier for Portfolios With and Without Chinese Art During Bearish Returns in the Shanghai Composite Stock Index

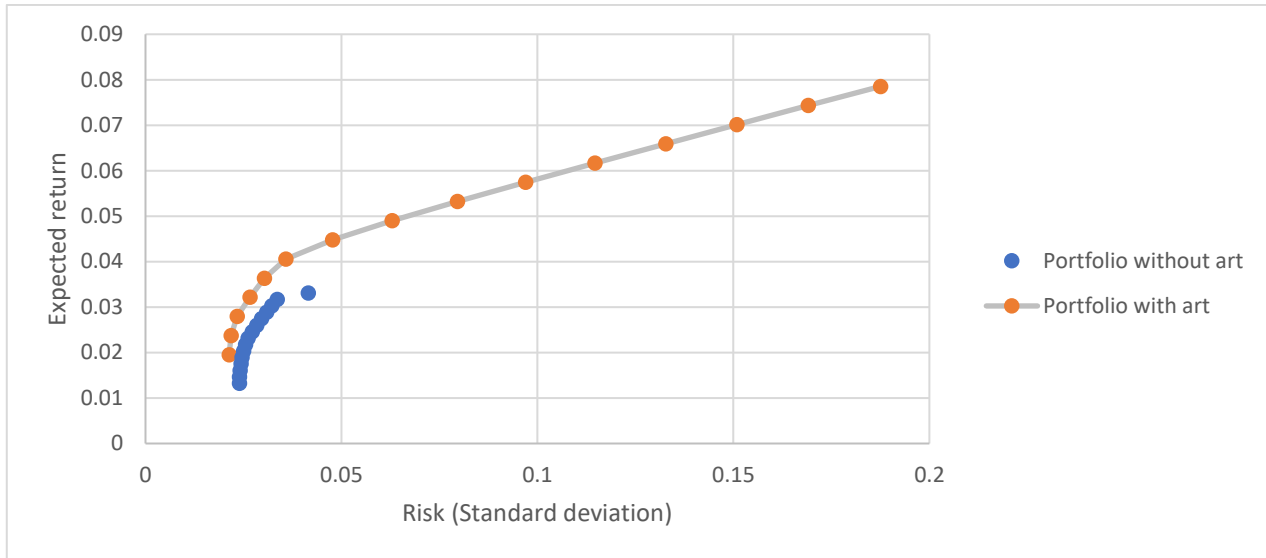


Figure 3.4

Efficient Frontier for Portfolios With and Without Chinese Art During a Downturn in the Shenzhen Composite Stock Index

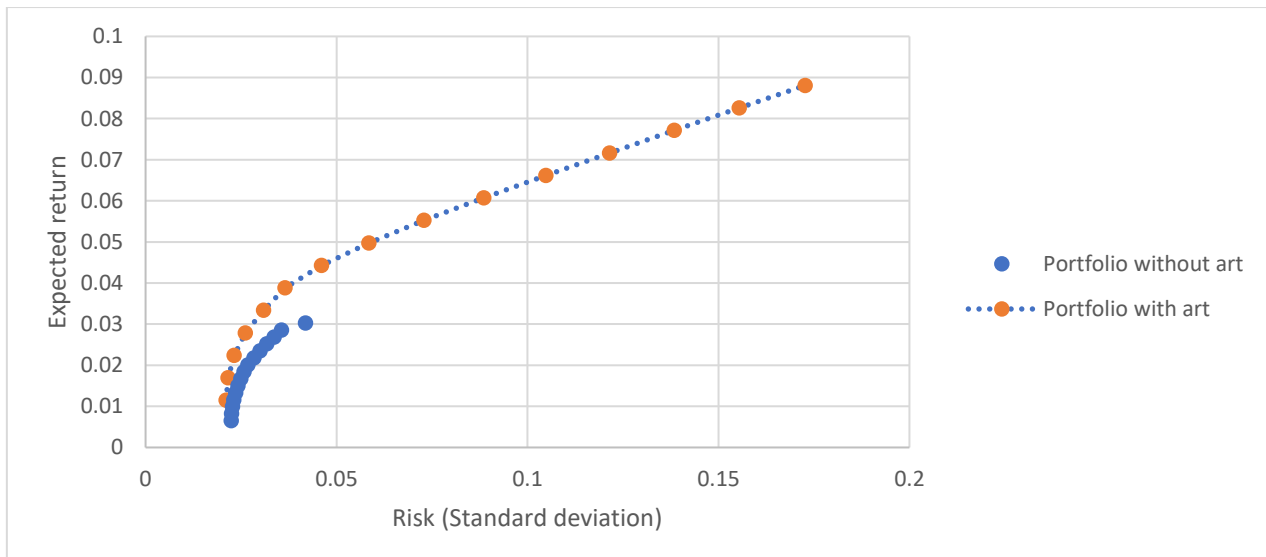
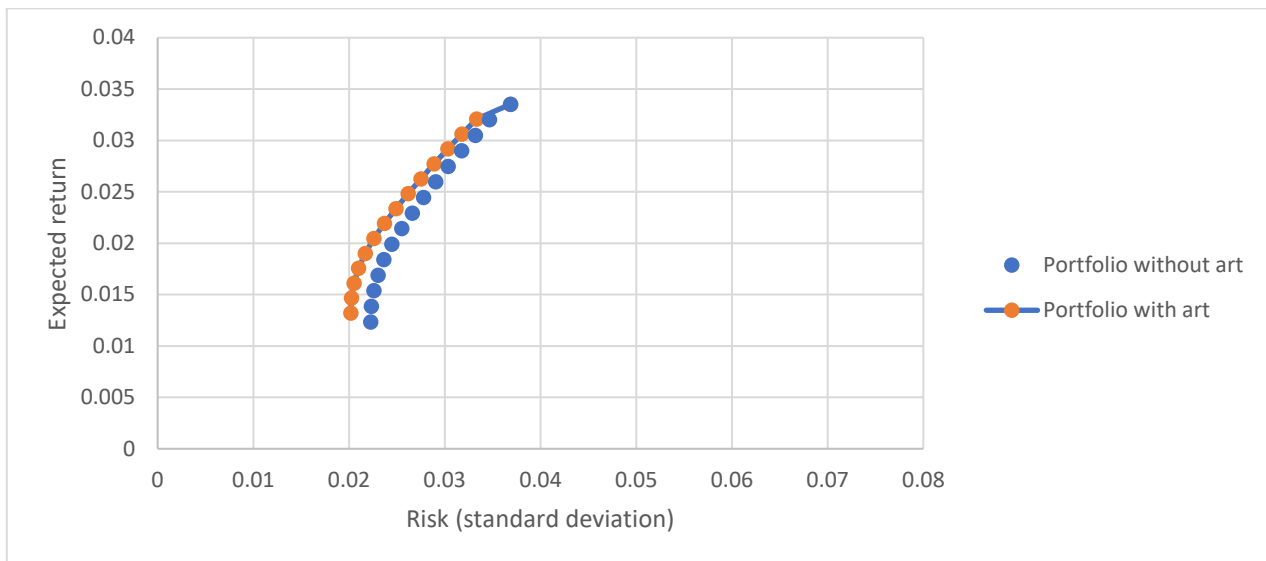


Figure 3.5

Portfolio With and Without Art on the Efficient Frontier During Declining Average Asset Returns



3.5. Conclusion

Diversification becomes less effective during economic downturns as correlations between financial asset classes generally rise (Masset & Weisskopf, 2018). As a result, investors attempt to diversify their portfolios by including non-traditional assets, such as art, which is less correlated with traditional financial assets.

This study looks into the portfolio diversification benefits of art investment in China. Using a unique dataset comprising 4,840 repeat pairs, the repeat-sales regression is used to calculate the return on Chinese art. It generates the highest semiannual return of 6.18% among all investment assets, coupled with a lower standard deviation than equities. In addition, Chinese art offers superior risk-adjusted returns, outperforming all but bonds in terms of Sharpe and modified Sharpe ratios. A measurement of diversification gains, integrating such art into any of the considered financial assets yields incremental diversification advantages.

To assess the role of Chinese art in risk diversification, correlation analysis, CAPM methods, and downside beta are utilized. The results show that Chinese art has an extremely low or even negative correlation with common financial assets, suggesting that it may serve as an effective

diversification instrument. Furthermore, when the returns of the SSE composite index and the SZSE composite index are used as proxies for systematic market factors, the beta coefficient of Chinese art is negative, albeit insignificant. Further implementation of time-varying estimates of alpha and beta within specific timeframes, the results are consistent with the single-index model. Regarding downside beta values, the outcomes demonstrate that, within a well-diversified portfolio, Chinese art can act as a hedge against domestic stock market declines.

The next section investigates whether including Chinese art in a financial portfolio provide diversification benefits. Adhering to the mean-variance portfolio optimization, the results demonstrate that the efficient frontier for portfolios containing Chinese art is better than those without Chinese art. Thus, for a given level of risk, portfolios with Chinese art have a higher rate of return compared to those without it, or a lower risk for a given level of return. In accordance with a (simple) power utility optimization, the results exhibit that the inclusion of Chinese art in the optimal portfolio enhances the utility, thereby achieving the goal of optimal portfolio diversification. Nevertheless, as risk aversion increases, the weighting of Chinese art in the optimal portfolio decreases. Therefore, the advantages of including Chinese art in a well-diversified portfolio may be somewhat limited.

The two additional robustness tests further validate the advantages of portfolios that include Chinese art. Specifically, portfolios with Chinese art on the efficient frontier outperforms the equal-weighted portfolio. Furthermore, during times of underperformance in the domestic stock market, the efficient frontier with Chinese art exhibits greater performance in comparison to the efficient frontier without Chinese art. However, it is noteworthy that when average asset returns are declining, the modified Sharpe ratios seems to show an opposite trend.

This study highlights the importance of Chinese art as an alternative investment asset for portfolio diversification. Nonetheless, it is essential to acknowledge that art poses unique risks that differentiate it from financial assets. These potential physical risks, such as damage, theft, and deterioration over time, as well as the possibility of reattribution to a different artist and authentication

issues. Given these intricacies, it is imperative that those considering this avenue exercise caution and remain acutely aware of these risks when investing in art.

There are many interesting possibilities for building upon this research by employing other financial analytic instruments in the art market. Following Chanel (1995), Ginsburgh and Jeanfils (1995), and Czujack et al. (1996), one may study the short- and long-term relationships between the arts and financial markets. Previous research shows that the wealth effect of the stock market can influence the art market, leading to a thriving art market. However, the exact strength and longevity of this causal relationship in the Chinese art market remain unclear. Additionally, as stated by Worthington and Higgs (2004), the momentum-investing literature might provide valuable insights into the study of the art market.

Chapter 4. Investing in Chinese Painting and Calligraphy: Informational Content of Presale Estimates

4.1. Introduction

At China Guardian's Autumn Auction on 12 December 2022, a pinnacle work titled *Gao Shan Yang Zhi*, executed by Fu Baoshi in 1962, sold for RMB 58,000,000 (including a buyer's premium of RMB 66,700,000), rendering it the top-grossing lot in the auction. Prior to the sale, the auctioneer provided a range of pre-sale estimates from RMB 58,000,000 to RMB 68,000,000. The accuracy of such price predictions (e.g., if the hammer price fall within the range of the pre-sale estimates) is in line with Milgrom and Weber (1982), who contend that the optimal strategy for the auction houses is to provide truthful information about the item being sold.

Sotheby's Institute of Art (n.d.) proposes a definition of pre-sale estimates within the art market: *each lot is given a low and high estimate, representing the opinion of auction experts about the range in which the lot might sell at auction. Published in the online and printed catalogue, an estimate provides prospective buyers with an important preliminary guide to value and is generally the basis for establishing the reserve price.* Pre-sale estimates hold significant importance in the art-valuation process and are likely to considerably impact art buyers' investment decisions, particularly for novice investors who are more susceptible to behavioral biases. It is therefore essential for these individuals to recognize the predictive potential of pre-sale estimates (Bruno & Nocera, 2008).

Academic research on pre-sale estimates has been an active area of inquiry for several decades, with scholars approaching this topic from three perspectives. The first strand focuses on the informational efficiency of pre-sale estimates, while the second concerns the impact of the range of pre-sale estimates on the uncertainty of the hammer price and the relationship between the uncertainty of pre-sale estimates and the likelihood of sales. The third one investigates the anchoring effect in the art market, wherein past-sales price records can serve as reference points for future sales. While extensive research has explored the art market with respect to pre-sale estimates, only a few studies

have examined the extent to which specific factors affect the informational content of pre-sale estimates in terms of accuracy and uncertainty in predicting the hammer price.

Auction houses aim to estimate the price that an item will fetch when offered for sale (Ashenfelter, 1989). However, in some cases, experts' pre-sale estimates may be biased downward (Bauwens & Ginsburgh, 2000; D'Souza & Prentice, 2002) or upward (Mei & Moses, 2005). Therefore, it is essential to investigate the impact of certain factors on the accuracy and uncertainty of pre-sale estimation. The effectiveness of pre-sale estimates can refine the process of price estimations and facilitate the provision of more precise estimates to potential bidders, thereby better assisting them in pricing decisions and building buyers' confidence in auction houses (Beggs & Graddy, 2009). Furthermore, examining the factors that influence the accuracy and uncertainty of pre-sale estimates can help auction houses manage risk effectively and reduce the likelihood of overestimating or underestimating the value of a lot.

This study utilizes a comprehensive database centered on Chinese art. The Chinese art market performed remarkably well, as reported by Artprice (2021, p. 11), in 2020, its turnover accounted for 39% of the global art market, almost equivalent to the combined turnovers of the US (27%), and the UK (15%). Despite its relatively short history of fewer than 45 years, the Chinese art market has emerged as one of the largest and most influential art markets globally (Bian et al., 2021). Nevertheless, the existing literature on the Chinese art market, especially regarding pre-sale estimates, is sparse. Additionally, the Chinese art market contrasts with the established Western art market in several significant ways, which raises the possibility that particular factors may have distinctive impacts on Chinese artwork. To the best of our knowledge, hardly any studies have investigated the extent to which specific factors affect the informational content of pre-sale estimates in terms of accuracy and uncertainty for the Chinese art market. To bridge this knowledge gap, this study examines a heterogeneous set of variables that may impact the accuracy and uncertainty of pre-sale estimates offered by a wide range of auction houses, aiming to address two primary questions: 1.

Which factors influence the accuracy of pre-sale estimates in predicting the hammer price at auction?

2. Which factors affect the uncertainty of pre-sale estimates about the value of artwork?

To address the above research questions, this study collects data on 191,102 lots sold Chinese art executed by 533 artists, covering the period from 2000 to 2021. Factors such as the characteristics of the artist, the artworks, the sales, and other attributes are analyzed. It is found that the artworks created by deceased artists either lower the accuracy or increase the uncertainty of price prediction relative to the living artist. On the other hand, the artist's mentorship experience, the proof of authenticity, large-scale auction months, and past-sale records can significantly enhance the accuracy and certainty of presale estimates. Furthermore, the impact of certain factors on auction houses' estimation varies depending on the price distribution, suggesting that auctioneers can improve the accuracy of masterpieces by incorporating additional public information, such as mentorship, exhibition, literature, and past-sale records. It is noteworthy that auction houses with artist-specific experience are more likely to provide precise pre-estimates, benefiting the demand-side market participants. However, they are less optimistic about reducing the uncertainty of pre-sale estimates with regard to the value of the artwork.

The current research investigates the impact of various factors on the informational content of pre-sale estimates in the Chinese art market. Numerous variables are identified as having a significantly positive influence on improving the accuracy and reducing the uncertainty of the pre-sale estimates, implying that auctioneers can mitigate prediction bias by considering this valuable information generated from this study. The investigation adds to the theoretical literature focused on improving the predictive power of pre-sale estimates (Bruno & Nocera, 2008). Furthermore, this study highlights that the impact of certain factors on auction house estimates varies across price distributions. This shows that auctioneers can use public information more effectively to set precise pre-sale estimates for masterpieces. Lastly, the study conducted in the Chinese art market provides empirical evidence that experienced auction houses can affect the accuracy and uncertainty of pre-

sale estimates when predicting hammer prices. This enriches the literature on art economics by exploring whether auction houses can affect the results of art auctions (Ashenfelter, 1989; Bauwens & Ginsburgh, 2000; McAndrew et al., 2012).

The chapter is organized as follows. Section 4.2 reviews the relevant literature. Section 4.3 discusses the data sources and methodology. Section 4.4 presents the empirical analysis, and Section 4.5 concludes the chapter.

4.2. Literature Review

Qualified auctioneers provide the pre-sale estimates of potential artwork prices, which they release in auction catalogs prior to the sales taking place (Beggs & Graddy, 2009). Pre-sale estimates were first introduced in the mid-1790s, which attract individual investors and level the playing field between experienced wholesale participants and uninformed retail customers (Mei & Moses, 2005). The pre-sale estimates are a reflection of the “expert opinion” of auction house specialists regarding the likely sale price of a work at auction (Beggs & Graddy, 2009). Pricing artwork is challenging because of its heterogeneity, leading to pre-sale estimates being presented in a range that includes both low and high estimates (Aubry et al., 2023). Accurately setting pre-sale estimates requires considerable expertise in the knowledge of artistic factors and market trends, much of which is acquired through frequent interactions between art brokers and their clients (Bruno et al., 2018).

Academic research on pre-sale estimates has been ongoing for several decades and can be classified into three main categories. The first category examines the informational efficiency of pre-sale estimates, with findings from previous studies varying considerably. Some studies, such as those by Milgrom and Weber (1982), support the notion that pre-sale estimates are unbiased for most auction-house models. In subsequent research, Ashenfelter (1989) collects data about the prices fetched by impressionist paintings sold at London and New York auctions held by Sotheby’s and Christie’s between 1980 and 1982, generally finding that auction houses are truthful, with the average of auctioneers’ high and low estimates highly correlated with the actual price fetched. The conclusion

drawn by Ashenfelter (1989) is that auction experts provide genuine and unbiased estimates, and honesty is the most important rule for an auctioneer. Louargand and McDaniel (1991) reach similar conclusions and demonstrate the validity of auctioneers' pre-sale estimates published for 1,835 works of art sold at Sotheby's New York in 1989-1990.

Nevertheless, some studies find evidence of downward and, in some cases, upward bias in pre-sale estimates. For instance, Bauwens and Ginsburgh (2000) report deviations in pre-sale estimates between auction houses for 1,621 English silver coffee and teapots that were sold at Christie's and Sotheby's in London between 1976 and 1990, with Christie's consistently underestimating realized prices and Sotheby's tending to overestimate inexpensive works and to underestimate expensive ones. However, this finding contradicts the results reported by Ashenfelter (1989) and Milgrom and Weber (1982). According to Bauwens and Ginsburgh (2000), to minimize prediction errors, auctioneers should take full account of the information available in the sales catalogues and include it in the hedonic function to provide accurate auction estimates. Furthermore, Teti et al. (2014) further document that the pre-sale estimates of 287 artworks executed by five artists (e.g., Giacomo Balla, Umberto Boccioni, Carlo Carra, Luigi Russolo, and Gino Severini) between 2000 and 2010 underestimate the hammer price at auction. Likewise, D'Souza and Prentice (2002) collect 160 paintings from an auction held by a renowned auctioneer and valuer in Australia and show that auction-house experts tend to provide downward estimates of the prices, as this encourages more bidders. In contrast, Mei and Moses (2005) reveal an upward bias in expensive art prices for the American market, particularly in New York, over a period of up to 30 years.

However, McAndrew and Thompson (2003) argue that hammer prices are underestimated by previous studies due to the omission of unsold works. To address this issue, they develop a four-step statistical procedure that solves the left-censoring issues caused by unsold pieces. This result shows that pre-sale estimates tend to be unbiased across the complete price distribution. They further replicate the procedure used in prior research, utilizing a censored version of their sample, showing

that the bias is artificially caused by the exclusion of unsold data. This finding is supported by Czujack and Martins (2004), who examine whether art specialists provide a good predictor of realized prices based on 675 Picasso paintings from 1975 to 1994. Using a sample-selection model, they prove that Sotheby's and Christie's behave in exactly the same way and accurately predict the prices of sold works. In contrast, Ekelund et al. (2013) collect 500 works executed by early 20th-century American artists from 1987 and use Heckman regression to correct the selection bias, finding that pre-sale estimates tend to underestimate the prices of paintings.

The second category of research is interested in whether the width of the range of the pre-sale estimates affects the uncertainty about the value of the artwork. Ashenfelter and Graddy (2003) explore the motivations behind auctioneers' determination of the spread between high and low estimates in the pre-sale catalog. The auctioneers' evaluation of price uncertainty or variability can be a plausible explanation for this spread. A wider range of estimates indicates higher price variability or greater uncertainty (Ashenfelter & Graddy, 2003; Bruno et al., 2018; Bruno & Nocera, 2008; Mei & Moses, 2005; Nozari, 2022). According to Nozari (2022), uncertainty surrounding artwork valuation may come from either an emerging artist's unfamiliarity with the market or auctioneer's lack of experience in evaluating the price estimations (Bruno et al., 2018). On the other hand, the range of pre-sale estimates is closely linked to the likelihood of sales. Sellers conventionally set their reserve price below the low estimate. As documented in Ekelund et al. (1998), a narrow range of presale estimates implies a relatively high reserve price, which can drive low estimates towards the highest estimates, making it challenging to sell the artwork and leading to more "no sales." Conversely, a wide range of pre-sale estimates indicates a lower reserve price and increases the chance of sale (Ashenfelter et al., 2003; Bruno et al., 2018). Despite this, the results of Nozari (2022) contradict the previous studies. He utilizes a dataset that comprises 659,874 works of art created by 49,751 artists and auctioned at leading auction houses worldwide from 1990 to 2008. However, he only takes into account the works of art that have been sold at least once. Within the sample time

frame, 15,429 artworks are resold at least once following their initial sale. Nozari (2022) observes that as the range between high and low estimates widens, they are less likely to be resold within a given interval, suggesting that the narrower estimate ranges towards a shorter retention period for works of art.

The third category investigates the anchoring effect in the art market. Anchoring is a cognitive bias that describes the tendency of individuals to excessively rely on initially received information (known as the “anchor”) when making subsequent numerical estimates (Bian et al., 2021). While the anchoring heuristic was initially examined in laboratory experiments conducted by Tversky and Kahneman (1974), it has also been observed in nonexperimental studies. The investigation of the anchoring effect in the art market has been demonstrated by Beggs and Graddy (2009), who find that auctioneers use past auction prices to anchor their estimates of the pre-sale price. In the follow-up study, Bian et al. (2021) extend the research on the anchoring effect by examining bidders and auctioneers in the Chinese art market using a dataset of 180,177 transaction records from 35 major auction houses between 2000 and 2019. The study finds that both bidders and auctioneers rely on previous auction prices as a point of reference and this anchoring effect is more pronounced when the time interval between two auctions of the same painting is relatively short. Moreover, when a painting is re-offered by the same auction house, the auctioneer’s pre-sale valuations are influenced by both the past auction price and the previous pre-sale estimates.

4.3. Hypotheses

Pre-sale estimates have a significant impact on the dynamics of the art market by proposing anticipated sale prices for the artwork, thus assisting both sellers and buyers in their auction preparations (Beggs & Graddy, 2009). As emphasized by Milgrom and Weber (1982), auctioneers are entrusted with the responsibility to present accurate and transparent information about the auction lots. Such disclosure not only mitigates bidder’s uncertainty but also enhances their confidence, potentially resulting in higher selling prices. However, there can be bias in pre-sale price estimates,

either downward (Bauwens & Ginsburgh, 2000; D'Souza & Prentice, 2002) or upward (Mei & Moses, 2005). These biases, stemming from information gaps, can encourage sellers to recalibrate estimation methods or necessitate management interventions. More efficient use of information from pre-sale sales categories can potentially minimize prediction errors (Bauwens & Ginsburgh, 2000). Understanding the factors that influence the accuracy and uncertainty of pre-sale estimates is therefore essential. By segmenting the artwork attributes into the characteristics of the artists, the artworks, and the sales, this study seeks to identify the impact of certain factors on the informational content of pre-sale estimates in predicting the hammer price.

Based on previous evidence on the market for Chinese art, this research derives several hypotheses in order to analyze the informational content of pre-sales estimates in terms of accuracy and uncertainty in the Chinese art market.

4.3.1. Hypotheses on the Accuracy of Pre-sale Estimates

In relation to the accuracy of art auction pre-sale estimates, several hypotheses warrant exploration. Hypotheses on first, artist characteristics, second, artwork characteristics, and third, sale characteristics, impact on the accuracy of pre-sale estimation, are set out.

Hypothesis 1 (H1): The characteristics of artists impact accuracy of pre-sale estimates.

The artists' characteristics are operationalized as their reputation, which has been previously acknowledged as a crucial determinant of pre-sale estimates (Sproule & Valsan, 2006). The study focuses on two specific artists' characteristics: the artist's vital status (specifically, deceased artist) and their experience of mentorship.

Deceased artist status negatively affects the accuracy of pre-sale price estimates, as observed by Barnes et al. (2023), The limited supply of works from deceased artists (Ursprung & Wiermann, 2011), equipped with uncertainties surrounding their legacy and future demand, are posited as contributing factors to this reduced precision. Accordingly, the study hypothesizes that deceased artists decrease the accuracy of pre-sale estimates.

Mentorship is a unique attribute related to Chinese artists that has not been previously identified in the literature. It is posited that artist with mentorship has increased visibility and richer information about their work when working with established artists. Such a relationship may provide the auctioneers with extensive knowledge of the artist's work and market demand, thereby influencing the accuracy of pre-sale valuations. The study, therefore, hypothesizes that artists with mentorship experience contribute to increased accuracy in pre-sale estimates.

The second overarching hypothesis put forward relates to the implications of artwork characteristics:

Hypothesis 2 (H2): The characteristics of artworks impact the accuracy of pre-sale estimates.

In the realm of traditional Chinese paintings, proof of authenticity is substantiated through various forms of documentation, including signatures, timestamps, celebrity inscriptions, the records of exhibition, literature, and provenance (Cahill & Silbergeld, 2001). This proof of authenticity not only confirms the artwork's legitimacy but may also furnish additional information that enhances the public's understanding of its value. Consequently, the study hypothesizes that proof of authenticity increases the accuracy of pre-sale estimates.

Furthermore, the research also classifies artwork into one of the following mounting categories based on its title: albums, fans, folding screen, handscroll, heng fu, hua xin, jing kuang, jing pian, jing xin, standing scroll, vertical scroll, and other types. Given that the form of mounting can be a variable that informs market perception and thus valuation, the study hypothesizes that the accuracy of pre-sale estimates varies with the type of mounting of the artwork.

This study aims to validate Hypothesis 2 (H2), positing that both proof of authenticity and the type of mounting are crucial determinants that collectively contribute to shaping the accuracy of pre-sale estimates in the art market.

Thirdly, it is proposed that sale characteristics influence the accuracy of pre-sale estimates:

Hypothesis 3 (H3): The characteristics of sales impact the accuracy of pre-sale estimates.

Sales characteristics are measured by the auction venue and the date of the auction. Works of art are categorized by the auction house where they were sold, distinguishing between those sold at the top ten auction houses (ranked by turnover) and those sold at other auction houses. The top-tier auction houses employ experienced auctioneers with specialized knowledge of traditional Chinese paintings and a deep understanding of art market dynamics. In addition, these auction houses also have extensive networks, allowing them better insights into market demand and enabling them to refine pre-sale estimates accordingly. Given these advantages, this study hypothesizes that artworks auctioned at the top 10 auction houses are more likely to have pre-sale estimates that are statistically significantly more accurate. Moreover, Sotheby's and Christie's hold major art auctions during May, June, November, and December, respectively. These large-scale months are characterized by a surge in market activity, attracting a large number of sellers and bidders. This heightened interest and competition contributes to a more accurate representation of an artwork's true market value. Accordingly, the study hypothesizes that artworks sold during the large-scale auction months are more likely to have accurate pre-sale estimates.

Both the auction houses and the timing of the auction are postulated to have a joint influence on the accuracy of pre-sale estimates, thereby providing empirical support for Hypothesis 3 (H3).

4.3.2. Hypotheses on the Uncertainty of Pre-sale Estimates

Expanding upon the analytical framework used to explore the accuracy of pre-sale estimates, this study introduces additional hypotheses specifically aimed at examining the uncertainty of pre-sale estimates. These new hypotheses are developed using similar foundational considerations that guided the examination of estimate accuracy.

Hypothesis 4 (H4): The characteristics of artists impact the uncertainty of pre-sale estimates.

Hypothesis 5 (H5): The characteristics of artworks impact the uncertainty of pre-sale estimates.

Hypothesis 6 (H6): The characteristics of sales impact the uncertainty of pre-sale estimates.

4.3.3. Hypotheses on the Anchoring Effect of Past Sales Records in Pre-sale Estimates

The art market's valuation is substantially influenced by the anchoring effect. This cognitive bias leads auctioneers and bidders to rely heavily on past sales data when setting pre-sale estimates, as highlighted by Beggs and Graddy (2009). In the subsequent research, Bruno et al. (2018) find that artwork with recent auction records provides a clearer benchmark for valuation in subsequent auctions. Consequently, past sales records serve not only as archival data but also as a guide to future auction expectations.

Hypothesis 7 (H7): Artwork with past sales records increases the accuracy of pre-sale estimates.

Hypothesis 8 (H8): Artwork with past sales records reduces uncertainty of pre-sale estimates.

4.3.4. Hypotheses on the Auction Houses with Artist-Specific Experience in Pre-sale Estimates

There are at least three mechanisms, which are not mutually exclusive, that would provide explanations for the superior auction results of experienced auction houses, as highlighted in previous studies (Ashenfelter, 1989; Lacetera, Larsen, Pope, & Sydnor, 2016; Milgrom & Weber, 1982; Vincent, 1995). Firstly, experienced auction houses possess an extensive network of relationships that can be used to minimize search frictions and match artworks with the most suitable buyers. Secondly, they can employ strategic tactics during the auction, such as setting the starting bid price, modulating the pace of price adjustments, or placing strategic 'off the wall' bids, which can have a significant impact on the realized prices (Bruno et al., 2018). Finally, their profound market insight allows them to align sellers' expectations with realistic market values, increasing both the likelihood of sales and the accuracy of pre-sale valuations (Bruno et al., 2018).

Building on these insights, several studies have investigated the proficiency of experienced auction houses as informants and intermediaries. In particular, Bruno et al. (2018)'s finding underscores that houses with artist-specific experience tend to provide more accurate pre-sale estimates. This observation prompts an investigation into whether experienced auction houses in the Chinese art market exhibit similar expertise in pre-sale estimation. Consequently, this study posits the following hypotheses:

Hypothesis 9 (H9): Accuracy of pre-sale estimates increases with the experience of auction houses in the Chinese art market.

Hypothesis 10 (H10): Uncertainty of pre-sale estimates decreases with the experience of auction houses in the Chinese art market.

4.4. Data and Methodology

4.4.1. Data Collection

The auction price data on Chinese art is collected from Artron.net, a leading art-data provider in the Chinese art market. This study manually collects 266,115 auction lots of Chinese art over the period from January 2000 to December 2021, consisting of 198,353 lots sold and 67,762 bought-in. Specifically, the study identifies the names of artists who have executed Chinese art at AMMA. AMMA has published a semi-annual report on the Chinese Art Auction Market since 2008 with the top 50 artists who have created Chinese art in each of the three categories. Each semi-annual report compiles the top 50 artists who have executed Chinese art from each period according to the price per square Chinese foot. Finally, 150 artists are selected from each semiannual report, and the dataset comprises 533 artists after removing the duplicates. The current research includes only those lots that have reached the reserve price set by the seller; unsold lots are not considered. Excluding 7,099 artworks for which the data provider did not publish information on pre-sale estimates and 152 outliers due to human error on the part of the data provider, this research finally obtains 191,102 pieces of Chinese art created by 533 artists between January 2000 and December 2021.

4.4.2. Methodology to Measure the Informational Content of Pre-sale Estimates

Bruno and Nocera (2008) define the informational content of pre-sale estimates in terms of accuracy and uncertainty. Bruno et al. (2018) propose a method to measure the accuracy of pre-sale estimates. They calculate the absolute value of the difference between the midpoint of the estimation range and the hammer price divided by the hammer price. On the other hand, the uncertainty of pre-sale estimates depends on certain determining factors. It is gauged by the ratio of the difference

between the high and low estimates to the mean of these estimates. A wider range of pre-sale estimates indicating greater uncertainty about the value of the artwork (Ashenfelter & Graddy, 2003; Bruno et al., 2018; Bruno & Nocera, 2008; Mei & Moses, 2005; Nozari, 2022).

4.4.2.1. Accuracy of Pre-sale Estimates in Predicting Hammer Prices. This study investigates the impact of specific factors on the accuracy of pre-sale estimates. Following Bruno et al. (2018), the precision of the pre-sale estimates is measured by the absolute value of the difference between the midpoint of the pre-sale estimates and the hammer price, divided by the hammer price. The specified reference regression model is as follows:

$$Accuracy_{it} = f(artist_{it}, artwork_{it}, sale_{it}, past - sale records_{it}, controls) + \epsilon_{it}, \quad (1)$$

Where $Accuracy_{it}$ represents the accuracy of the pre-sales occurring at the time t corresponding to a painting i . A value of zero indicates perfect prediction of the hammer price; $artist_{it}$ signifies the characteristics of the artist for the item i at the time t ; $artwork_{it}$ is the characteristics of the artwork for item i at the time t ; $sale_{it}$ defines the characteristics of the sale for item i at the time t ; $past - sale records_{it}$ describes whether artwork i has a prior sales record at the time t . Additionally, the current research contains observable control variables that affect auction outcomes and could be correlated with accuracy, such as window ($window_{it}$), overestimation ($overestimation_{it}$), underestimation ($underestimation_{it}$), and the year ($year_{it}$). The current research uses Eq. (1) to verify Hypothesis 1 (H1)-Hypothesis 3 (H3) and Hypothesis 7 (H7).

There are several recognizable and objective drivers of value in the art market, centered on the characteristics of the artist, the artwork, and the sale. The characteristics of the artist are associated with the reputation of the artist. An artist's reputation is the strongest and most obvious measurable determinant of pre-sale estimates (Sproule & Valsan, 2006). Reputation is shaped by artist's vital status (specifically, if they are deceased) and mentorship. Following Taylor and Coleman (2011), this study assigns a dummy variable equal to 1 if an artist is deceased at the time of the auction and 0 otherwise. Chinese artists who study under famous mentors learn their craft and imitate earlier

masters (Li & Fischer, 2007). After gaining a good grounding, the artists developed their own painting styles, reflecting their personalities and characteristics. In current research, mentorship is assigned 1 if the artist follows a famous mentor and 0 otherwise.

The characteristics of the artwork are related to the information on the proof of authenticity and the type of mounting. When setting pre-sale estimates, auctioneers must take the authenticity of the artwork into account, as the price discrepancy between an original and a fake painting is significant. However, the identification of Chinese art is rather complex, as Chinese artists have historically acquired painting techniques and craftsmanship by imitating and copying masters, making it difficult to distinguish copies from originals, especially for paintings that are very old. Consequently, the appraisal of traditional Chinese paintings relies heavily on documentary evidence, including signatures, time stamps, celebrity inscriptions, the records of exhibition, literature, and provenance (Cahill & Silbergeld, 2001). Therefore, the current research identifies these dummy variables to quantify the authenticity of works.

In terms of the type of mounting of paintings, Chinese art is classified into one of the following mounting categories depending on its title: it assigns a set of dummy variables equal to 1 if the painting belongs to albums, fans, folding screen, handscroll, heng fu, hua xin, jing kuang, jing pian, jing xin, standing scroll, vertical scroll, and other types¹, respectively, and 0 otherwise.

The characteristics of the sale are related to the auction venue and the auction date. Ranking the auction houses based on their turnover, a set of dummy variables is assigned equal to 1 if the artwork was sold at the top 10 auction houses (e.g., China Guardian, Beijing Poly, Council, Christie's (HK), Han Hai, Sotheby's (HK), Beijing Rombon, Xiling Yinshe, Holly, and Sungari), and 0 otherwise. In addition, the month dummy variables have a value of 1 if the observation refers to the corresponding month, and 0 otherwise.

Furthermore, this study also puts emphasis on the effect of past-sale records on the estimation

¹ The category "other types" refers to paintings that do not fall under any of the aforementioned classifications based on their titles. This dummy variable is used as the reference category to avoid collinearity in the data.

prediction in terms of accuracy. As suggested by Beggs and Graddy (2009), past-sale records can serve as an anchor for the value of bids in subsequent auctions. It is expected that artwork with past sale history can improve the accuracy of pre-sale estimates, as the past auction records may provide additional public information to experts. In this regard, the past-sale records are considered and are assigned a dummy variable equal to 1 if artwork has at least one prior sale record and 0 otherwise. Furthermore, to explore the extent to which the anchoring effect is stronger for artworks with multiple past-sale records, a series of dummy variables are measured: *past-sale_2nd* - a dummy variable that is equal to 1 if the artwork has one past-sale record and 0 otherwise; *past-sale_3rd* - a dummy variable that is equal to 1 if the artwork has two past-sale records and 0 otherwise; *past-sale_4th* - a dummy variable that is equal to 1 if the artwork has three past-sale records and 0 otherwise; *past-sale_5th* - a dummy variable that is equal to 1 if the artwork has four past-sale records and 0 otherwise.

In addition to the variables capturing the artwork's attributes and past-sales records, the current research considers certain control variables. First, the year dummy variables control for time-specific effects. Each dummy variable has a value of 1 if the observation refers to the corresponding year, and 0 otherwise. Second, following Ekelund et al. (1998), the estimation range captures the uncertainty of pre-sale estimates about the value of an artwork. It is postulated that if an auction house sets a wider range of estimates, the distance from the midpoint of pre-sale estimates to the hammer price will be large. In such a case, the study controls the variable of the window, which exhibits the uncertainty of an auction taking place at the time t corresponding to painting i . By controlling for this variable, the study can ensure that the influences of other variables in the analysis are not confounded by the uncertainty of the auction timing. Third, overestimation indicates whether the hammer price of work i is overestimated by low estimates at the time t , and it is represented by a dummy variable equal to 1 if the hammer price is below the low estimate and 0 otherwise. If the hammer price of an artwork is overestimated, it tends to impact the accuracy of estimation predictions. In addition, systematic overestimations might reflect a common misapprehension of the appraiser or

the market about certain attributes of artworks. By including this factor as a control variable, it might more accurately measure how other attributes influence the precision of price estimations without the interference of overestimation. A similar explanation can be applied to underestimation, the study measures the underestimation variable as being equal to 1 if the hammer price is above the high estimate and 0 otherwise. Controlling for this variable allows us to gain a clearer insight into the genuine impact of other attributes on the accuracy of pre-sale estimates.

4.4.2.2. Uncertainty of Pre-sale Estimates About the Value of the Artwork.

Ekelund et al. (1998) conclude that auction specialists provide a range of low and high estimates for each work of art. These estimates capture supply and demand factors and forecast an “equilibrium” price range. The dollar amount of this range varies for each piece, as does the percentage of this range in relation to the average of the low and high estimates. Ashenfelter and Graddy (2003) find that the spread between the low and high estimates is related to the degree of uncertainty or disagreement about the value of an artwork. In line with Ekelund et al. (1998), Ashenfelter and Graddy (2003), Mei and Moses (2005), and Nozari (2022), this study measures the uncertainty about the value of works and defines the spread between the low and high estimates as a window:

$$\text{Window} = (\text{High estimate} - \text{Low estimate}) / \text{Mean of pre-sale estimate} \quad (2)$$

More importantly, the model regarding the effect of certain factors on the uncertainty of presale ranges about the value of the artwork is as follows:

$$\text{Window}_{it} = f(\text{artist}_{it}, \text{artwork}_{it}, \text{sale}_{it}, \text{past} - \text{sale records}_{it}, \text{year}_{it}) + \epsilon_{it}, \quad (3)$$

Where Window_{it} represents the uncertainty of an auction occurring at the time t corresponding to painting i , measured as the distance between the low and high estimates, divided by the midpoint of the pre-sale estimates. This ratio indicates the risk avoidance on the part of auctioneers arising from a lack of certainty about the market value of the piece (Ekelund et al., 1998). A wider range (window) indicates a higher degree of uncertainty surrounding the value of the painting; artist_{it} represents the characteristic of the artist for item i at the time t ; artwork_{it} is the characteristic of the artwork for

item i at the time t ; $sale_{it}$ defines the characteristics of the sale for item i at the time t ; $past - sale records_{it}$ describes whether artwork i has a prior sales record at the time t ; the year represents the year when i sold at the time t . ϵ_{it} is the error term. Please refer to Section 4.4.2.1., where the definitions of these variables are provided. It is important to note that the impact of undervaluation and overvaluation on the spread of pre-sale estimates is not analyzed. It is because pre-sale estimates are generated and made public before the auction takes place, and hence they do not affect the *window*, whether it will be under or over-valued. The Eq. (3) is applied to validate Hypothesis 4 (H4)-Hypothesis 6 (H6) and Hypothesis 8 (H8).

4.5. Empirical Results

4.5.1. Summary Descriptive Statistics

Table 4.1 shows descriptive statistics for a sample of the hammer price and pre-sale estimates, including the mean values of hammer price, pre-sale estimates, estimation distance, and window.

Regarding artist characteristics, the results suggest that pre-sale estimates for deceased and mentorship have been underestimated by 0.19 and 0.19, respectively, as they are lower than their respective hammer prices. Additionally, the window values for deceased and mentorship are relatively low, at 0.36 and 0.35, respectively.

In terms of artwork characteristics, the results exhibit that the exhibition has the highest hammer price of 3,005,309, followed by literature² (1,918,780) and inscription (1,396,039), while signature and timestamp are of comparatively lower value. Moreover, the pre-sale estimates for all variables are much lower than their corresponding hammer prices, with provenance being particularly undervalued by 21%. The window values range from 0.34 for literature to 0.37 for provenance, indicating that auctioneers can predict the value of these works with relatively less uncertainty.

With regard to the mounting types, the results show that the paintings mounted in albums and handscrolls fetch higher prices, while those mounted in fans, standing scrolls, and hua xin sell for

² Artron.net has made additions to the data related to the literature for some paintings, and our data has been updated synchronously.

less. This may be attributed to an unwritten “collection code”³ in the Chinese art market, whereby handscrolls and albums are deemed to have the greatest collector’s value, while fans are considered to be the least valuable. Additionally, the pre-sale estimates for all the variables, except for the standing scroll, are below its corresponding hammer price, with hua xin (-0.31) and fans (-0.25) exhibiting a significant estimation gap. Likewise, hua xin has the highest window value, indicating the auctioneers have the highest level of uncertainty in predicting the hammer price for this type of mounted work.

Looking at sale characteristics, the results reveal that auction houses such as Sotheby’s (HK), China Guardian, and Christie’s (HK) significantly undervalue artworks, as the pre-sale estimates are lower than the hammer prices. It is plausible that this underestimation strategy attracts more bidders to the art pieces. Once engaged in bidding, the competition for acquiring the artwork usually results in higher prices being attained. Furthermore, as observed in Ekelund et al. (2013), an undervaluation of the hammer price may increase the likelihood of a sale. Regarding the timing of auctions, the results show that artworks sold during large-scale auction months (May, June, October, November, and December) tend to achieve higher hammer prices, lower estimated distances, and lower window values compared to those sold during other auction months.

For the year category, the results demonstrate that hammer prices peak in 2011 and 2020. The Chinese art market experienced a significant boom in 2011 due to expansionary monetary policy and extensive financial activity (Shi et al., 2018; Zou et al., 2021). Several factors contributed to the prosperity of the Chinese art market in 2020, such as the strong purchasing power of high-net-worth individuals (HNWIs) who were largely unaffected by the pandemic; the tendency of some collectors to sell their works in response to financial pressures, which increased the supply of masterpieces at auction houses; and the fact that, given the money-printing policies of many countries in that year, art enthusiasts among HNWIs were keen to convert their cash assets into cultural goods and artworks

³ Source: <http://art.people.com.cn/n/2013/0605/c226026-21740933.html>

(Artprice, 2021, p. 11).

Notably, the pre-sale estimates for all years are lower than their hammer prices, with an overall mean of -18.78% for estimate_distance across the data sample. This observation suggests that the Chinese art market consistently underestimates the actual hammer prices, which is in agreement with the previous studies conducted by Bauwens and Ginsburgh (2000), Teti et al. (2014), and D’Souza and Prentice (2002). Auction houses can benefit from conservative forecasting strategy that systematically undervalue paintings at auction (Ekelund et al., 2013). This strategy enables auction houses to manage the owner’s and bidder’s expectations while maximizing their profits. If the actual sale price exceeds the low estimate, the owner may be satisfied and subsequently entrust the auction house with future paintings (Agnello & Pierce, 1996; Ekelund et al., 2013). Additionally, undervalued prices may lower the reserve price, increasing the chance of a sale (Ekelund et al., 2013). On the demand side, undervaluing the value of paintings may lure in more bidders, ultimately driving up the final selling price. However, this result contrasts with Ashenfelter (1989), who argue that “auctioneers do seem to provide genuine expertise in predicting prices” and is inconsistent with Milgrom and Weber’s (1982) theoretical statement that “honesty is the best policy”.

Table 4.1

Summary Descriptive Statistics

	Hammer	Pre-sale estimates	Estimation distance	Window
Artist Characteristics				
Deceased	783,598	574,578	-0.19	0.36
Mentorship	784,442	574,487	-0.19	0.35
Artwork Characteristics				
Authenticity dummies				
Signature	732,282	538,976	-0.19	0.36
Timestamp	823,492	596,669	-0.20	0.35
Exhibition	3,005,309	2,205,572	-0.20	0.35
Literature	1,918,780	1,427,637	-0.20	0.34
Provenance	1,246,020	910,070	-0.21	0.37
Inscription	1,396,039	1,035,408	-0.18	0.35
Mounting dummies				
Albums	1,783,334	1,327,608	-0.17	0.35
Fans	179,338	108,785	-0.25	0.38
Folding Screen	1,358,493	985,389	-0.17	0.34
Handscroll	1,716,513	1,200,271	-0.19	0.35
Heng Fu	684,627	535,490	-0.16	0.35
Hua Xin	407,055	222,186	-0.31	0.48

Continued Table 4.1

	Hammer	Pre-sale estimates	Estimation distance	Window
Artwork Characteristics				
Authenticity dummies				
Jing Kuang	1,285,173	913,331	-0.19	0.34
Jing Pian	638,356	482,055	-0.18	0.38
Jing Xin	589,450	438,030	-0.21	0.36
Standing Scroll	203,178	179,670	0.03	0.32
Vertical Scroll	707,644	521,755	-0.17	0.35
Other mounting types	860,855	640,775	-0.17	0.30
Sale characteristics				
Auction houses dummies				
Beijing Poly	1,083,379	883,998	-0.11	0.41
Beijing Rongbao	489,709	359,276	-0.19	0.37
China Guardian	675,341	458,245	-0.30	0.42
Council	1,205,200	913,885	-0.17	0.24
Han Hai	385,309	298,009	-0.11	0.27
Holly	835,598	762,506	-0.05	0.32
Sungari	482,209	466,798	0.01	0.39
Xiling Yinshe	681,820	524,743	-0.19	0.35
Christie's (HK)	1,143,386	699,453	-0.22	0.32
Sotheby's (HK)	1,454,189	797,025	-0.30	0.34
Other auction houses	516,961	380,255	-0.19	0.34
Month dummies				
January	255,371	206,266	-0.13	0.34
February	217,346	233,716	-0.09	0.41
March	161,014	98,244	-0.27	0.39
April	615,151	401,511	-0.17	0.35
May	938,603	640,344	-0.22	0.34
June	836,843	629,516	-0.18	0.36
July	507,637	389,256	-0.18	0.36
August	455,963	322,302	-0.21	0.37
September	224,124	145,200	-0.26	0.38
October	917,680	631,050	-0.22	0.39
November	782,927	563,759	-0.19	0.34
December	810,557	643,620	-0.15	0.36
Year dummies				
2000	115,816	101,007	0.00	0.30
2001	126,223	105,824	-0.05	0.30
2002	92,287	80,650	-0.05	0.30
2003	119,763	82,969	-0.20	0.29
2004	190,520	126,081	-0.21	0.35
2005	313,656	238,790	-0.20	0.38
2006	223,078	196,811	-0.08	0.31
2007	309,461	236,839	-0.14	0.31
2008	323,820	272,697	-0.13	0.32
2009	419,119	286,176	-0.21	0.34
2010	871,978	516,919	-0.30	0.35
2011	1,286,760	885,716	-0.24	0.35
2012	847,679	650,871	-0.17	0.38
2013	1,007,016	699,503	-0.22	0.37
2014	860,232	665,507	-0.17	0.35
2015	929,944	711,695	-0.16	0.35
2016	1,075,793	844,329	-0.18	0.38
2017	1,131,950	874,164	-0.19	0.39
2018	937,811	742,758	-0.18	0.39
2019	838,349	646,156	-0.16	0.41
2020	1,173,754	852,230	-0.25	0.40
2021	875,912	685,342	-0.19	0.39

Note: Table 4.1 shows descriptive statistics of the sample of the hammer prices and pre-sale estimates

Table 4.2 reports the number and frequency of pre-sale estimates for the entire sample (Panel A) and the subsample (Panel B) of the attributes for artists, artworks, and sales across the different pre-sale classifications (specifically, overestimation-if the hammer price is below the minimum estimate; underestimation-if the hammer price is above the maximum estimate; correction estimation-if the hammer price falls into the range of the pre-sale estimates)

The results of Panel A show that the pre-sale overestimates, correct pre-sale predictions, and pre-sale underestimates account for 4.80%, 45.17%, and 50.03%, respectively. It is important to note that the current data sample only includes sold items that reached the reserve price set by the seller, which may explain the low percentage of pre-sale overestimates. This finding is consistent with Bauwens and Ginsburgh (2000), who report a variation in the proportion of hammer prices that fall within the range of pre-sale estimates ranging between 49% (in 1982 and 1989) and 37% (in 1988 and 1990), with a relatively low rate of pre-sale overestimation, as it only includes lots that exceeded the reserve price. However, this result varies slightly from that of Bruno and Nocera (2008), who report that the proportion of hammer prices within the pre-sale estimate range is 37%. Over- and under-estimations account for 43% and 20%, respectively.

Panel B reports the results on the number and frequency of pre-sales estimates in relation to the artwork's attributes. Focusing on the characteristics of the artist, the results exhibit that for deceased artists, the range of pre-sale overestimation, the correction of pre-sale prediction, and pre-sale underestimation is 4.94%, 45.33%, and 49.73%, respectively. In the case of mentorship, these ranges fall between 4.82%, 44.92%, and 50.27%, respectively, indicating that pre-sale underestimation is predominant in both cases.

The characteristics of artwork are related to the proof of authenticity and the way in which works are mounted. The results show that pre-sale underestimation accounts for the majority of the categories related to authenticity. Regarding the type of mounting, the results are mixed. Albums, heng fu, fans, handscrolls, hua xin, jing kuang, jing xin, and vertical scroll are the most undervalued,

with hua xin generating the highest value at 63.73%, followed by fans at 57.7%. Hua xin refers to a painting completed by the artist on rice paper without any framing, and the fans are almost circular and are mounted on bamboo with stiffened silk. These paintings require special care and are expensive to maintain, with little collector's value. In such cases, the auctioneer may set relatively low pre-sale estimates for them due to their low demand. In contrast, the auctioneer provides relatively accurate estimates for jing pian and folding screens, with correction of pre-sale predictions being 51.80% and 48.72%, respectively.

In terms of sale characteristics, the results show a variation in the pre-sale estimates across different auction houses. The Chinese mainland auction houses such as Beijing Poly, Han Hai, Holly, Sungari, and Xiling Yinshe, exhibit a higher proportion of correct pre-sale predictions. This could be due to their increased expertise and access to information on artworks and market conditions (e.g., the behavior of bidders) (Bruno & Nocera, 2008). Conversely, China Guardian, Christie's (HK), and Sotheby's (HK) demonstrate higher rates of pre-sale undervaluation, with 63.38%, 67.87%, and 57.00%, respectively. This finding is consistent with Bauwens and Ginsburgh (2000), who observe that Sotheby's and Christie's generate a higher proportion of pre-sale underestimation as compared to other auction houses.

Table 4.2*Number and Frequency of Pre-sale Classifications*

Panel A Summary statistic for entire data sample			
	Overestimation ($P_{hammer} < \hat{p}_{min}$)	Correction estimation ($\hat{p}_{min} \leq P_{hammer} \leq \hat{p}_{max}$)	Underestimation ($P_{hammer} > \hat{p}_{max}$)
	9,171 (4.80)	86,315 (45.17)	95,616 (50.03)
Panel B Summary statistic for subsample related to artist-, work-, sale-characteristics category			
	Overestimation ($P_{hammer} < \hat{p}_{min}$)	Correction estimation ($\hat{p}_{min} \leq P_{hammer} \leq \hat{p}_{max}$)	Underestimation ($P_{hammer} > \hat{p}_{max}$)
Artist Characteristics			
Deceased	7,828 (4.94)	71,799 (45.33)	78,759 (49.73)
Mentorship	6,703 (4.82)	62,520 (44.92)	69,966 (50.27)
Artwork Characteristics			
Authenticity dummies			
Signature	8,382 (5.00)	75,016 (44.72)	84,353 (50.28)
Timestamp	5,013 (5.11)	42,249 (43.07)	50,839 (51.82)
Exhibition	215 (2.63)	3,548 (43.38)	4,415 (53.99)
Literature	1,073 (3.68)	12,880 (44.18)	15,198 (52.14)
Provenance	1,712 (4.15)	17,523 (42.51)	21,982 (53.33)
Inscription	607 (5.00)	5,613 (46.22)	5,924 (48.78)
Mounting dummies			
Albums	264 (6.77)	1783 (45.74)	1851 (47.49)
Fans	379 (3.57)	4116 (38.73)	6132 (57.70)
Folding Screen	184 (3.25)	2759 (48.72)	2720 (48.03)
Handscroll	244 (7.70)	1345 (42.44)	1580 (49.86)
Heng Fu	98 (8.85)	499 (45.08)	510 (46.07)
Hua Xin	59 (7.11)	242 (29.16)	529 (63.73)
Jing Kuang	467 (4.94)	4232 (44.77)	4753 (50.29)
Jing Pian	70 (0.90)	4049 (51.80)	3697 (47.30)
Jing Xin	2597 (4.34)	26025 (43.47)	31247 (52.19)
Standing Scroll	290 (28.35)	399 (39.00)	334 (32.65)
Vertical Scroll	116 (5.80)	895 (44.73)	990 (49.48)
Other types of mounting	4,403 (5.14)	39,971 (46.67)	41,273 (48.19)

Continued Table 4.2

Panel B Summary statistic for subsample related to artist-, work-, sale-characteristics category			
	Overestimation ($P_{hammer} < \hat{p}_{min}$)	Correction estimation ($\hat{p}_{min} \leq P_{hammer} \leq \hat{p}_{max}$)	Underestimation ($P_{hammer} > \hat{p}_{max}$)
Sale characteristics			
Auction houses dummies			
Beijing Poly	535 (2.57)	11,770 (56.56)	8,503 (40.86)
Beijing Rongbao	804 (5.47)	6,696 (45.59)	7,189 (48.94)
China Guardian	632 (1.47)	15,112 (35.15)	27,251 (63.38)
Council	399 (4.47)	4,168 (46.71)	4,357 (48.82)
Han Hai	2,206 (11.40)	8,997 (46.48)	8,154 (42.12)
Holly	276 (4.07)	4,398 (64.90)	2,103 (31.03)
Sungari	1,660 (17.50)	5,442 (57.36)	2,385 (25.14)
Xiling Yinshe	10 (0.10)	5,272 (53.80)	4,517 (46.10)
Christie's (HK)	205 (3.10)	1,917 (29.03)	4,482 (67.87)
Sotheby's (HK)	1,157 (12.05)	2,970 (30.94)	5,471 (57.00)
Other auction houses	1,287 (3.06)	19,573 (46.53)	21,204 (50.41)

Note. Table 4.2 reports the number and frequency of pre-sale estimates for the entire sample (Panel A) and the subsample of the artwork's attributes across the different pre-sale classification (Panel B).

4.5.2. Accuracy of Pre-sale Estimates in Predicting Hammer Prices

Table 4.3 shows the results of the impact of certain factors on the accuracy of pre-sale estimates in predicting hammer prices. Columns 1-2 offer a comprehensive view of the results based on the entire sample. For additional insights, the sample is divided into different pre-sale classifications, such as pre-sale overestimation (Columns 3-4), correct pre-sale prediction (Columns 5-6), and pre-sale underestimation (Columns 7-8). The majority of coefficients are statistically significant and thus, the analysis concentrates on their economic significance.

Focusing on the results presented in the full sample (Columns 1-2), starting with the artist characteristics, the results indicate that paintings created by deceased artists at the time of the auction increase the estimated bias between the pre-sale estimates and hammer prices by 1%, compared to living artists. This finding is consistent with Barnes et al. (2023), who assert that an artist's death tends to diminish the accuracy of pre-sale price estimates, suggesting that the art market struggles

with challenges in pricing the paintings of deceased artists. Accordingly, these results lend empirical support to the hypothesis, affirming that the accuracy of pre-sale estimates is adversely affected in the case of deceased artists.

On the other hand, artists with mentoring experience reduce the estimated bias by 0.40% compared to those without such experience. This finding corroborates the hypothesis that mentorship has a significantly positive effect on the accuracy of pre-sale estimates. Several underlying factors contribute to the mentoring experience improving the accuracy of pre-sale estimates. For instance, artists with mentorship experience benefit from increased visibility. They gain access to comprehensive information about their work when they collaborate closely with established artists. This collaboration positively impacts the accuracy of pre-sale estimates, as auctioneers with a broader range of information and insights about the artist's artwork and market demand. Furthermore, auctioneers can refer to the artworks created in a similar style by the artist's mentor when establishing pre-sale estimates.

The contrasting impacts of deceased artists and mentorship on estimation accuracy collectively support the overarching Hypothesis 1 (H1) that the characteristics of artists significantly affect the accuracy of pre-sale estimates.

With respect to the characteristics of artworks, the proof of authenticity is quantified by signature, timestamp, exhibition, literature, provenance, and inscription. The results demonstrate that, all proof of authenticity, with the exception of signature and provenance, positively affect the accuracy of price prediction. This supports hypothesis that authenticated information can act as a valuable resource for enhancing the accuracy of price predictions, offering a significant advantage to auctioneers.

Concerning the type of mounting, the results are mixed. More specifically, paintings mounted on fans, handscrolls, hua xin, and standing scrolls decrease the precision of pre-sale price prediction, with hua xin having the highest bias of 10.3%. In contrast, other types of mounting narrow the

estimated gap between pre-sale estimates and hammer prices, thus partially validating the hypothesis that the accuracy of pre-sale estimates varies based on the style of mounting.

These results collectively validate Hypothesis 2 (H2) by highlighting that both proof of authenticity and type of mounting are crucial factors that contribute to the accuracy of pre-sale estimates. This supports the overarching H2 that the characteristics of artworks significantly influence the accuracy of pre-sales estimates.

Concerning the characteristics of sales, including both the auction house and the auction month, the findings offer mixed support for Hypothesis 3 (H3). The hypothesis that artworks auctioned at top-tier auction houses are more likely to have accurate pre-sale estimates, is not empirically substantiated. Local auction houses in mainland China, such as Beijing Poly, Beijing Rombon, Council, Holly, Sungari, and Xiling Yinshe, positively influence the accuracy of pre-sale estimates. These auction houses specialize in the Chinese art market. They have auctioneers with substantial expertise in Chinese art history and the traditional painting scene. With their extensive market dataset and solid industry connections, they can provide more reliable pre-sale estimates. However, China Guardian, Han Hai, Sotheby's (HK), and Christie's (HK) have the opposite result. A possible explanation for this divergence may be attributed to investors being more credulous about the estimates given by the larger auction houses, in the spirit of Mei and Moses (2005). This perspective suggests that art buyers are susceptible to being influenced by price estimates and may be inclined to pay more for paintings with higher estimates. Consequently, this could result in higher hammer prices and thus, causing a significant gap between the pre-sale estimates and hammer prices (Bruno et al., 2018).

Turning to the timing of auctions, the results are consistent with the hypothesis that artworks sold during peak auction months would yield more accurate pre-sale estimates. This phenomenon is likely driven by several interconnected factors: firstly, peak auction months are characterized by heightened market activity, with robust engagement on the part of sellers and bidders. This dynamic

marketplace provides a more accurate reflection of an artwork's true market value, subsequently narrowing the gap between pre-sale estimates and hammer prices; secondly, the concentration of auctions within these months provides a wealth of information on market trends, preferences, and buyer behavior. This aggregated information equips auctioneers with the necessary insights to adjust their estimates, thereby improving their accuracy and more reliably predicting hammer prices; finally, the enhanced marketing by auction houses during peak months attracts a wider investor, thus creating a more competitive bidding environment and further aligning hammer prices with pre-sale estimates.

Consideration of the role of past-sale records in enhancing the accuracy of pre-sale estimates. It is observed that artworks with a history of previous auctions are more accurately estimated, and this improvement in valuation becomes more pronounced as the number of previous auctions increases. This suggests that past auction records serve as an anchor, providing additional public information that can improve auction-house estimates. In light of these observations, Hypothesis 7 (H7), which posited the beneficial impact of past sale records on estimation accuracy, is empirically supported.

This study further delves deeper into the influence of specific factors on the pre-sale classification. The results for pre-sale overestimation (Columns 3 and 4) deviate from the main findings. Specifically, there is no evidence to suggest differences in the impact of artist characteristics, the proof of authenticity (excluding signature and timestamp), and the anchoring effect on the accuracy of price prediction. However, the artwork, regardless of the form in which it is mounted, has a positive effect on the accuracy of price prediction. It is noteworthy that almost all auction houses tend to provide pre-sale estimations that are closely matched the hammer price.

Moving on to the correction of price prediction (Columns 5 and 6), the results exhibit slight deviations from the main findings. For instance, there is no evidence indicating differences in prediction accuracy among mounting categories (excluding handscrolls). Certain auction houses, such as Beijing Poly and Holly exhibit a negative effect on the accuracy of auction estimates.

Regarding pre-sale underestimation, the results show that almost all variables are consistent with the main findings, except for the mounting category.

Table 4.3

The Effect of Factors on the Accuracy of Pre-sale Estimates

	Full sample		Overestimation ($P_{hammer} < \hat{\rho}_{min}$)		Correction estimation ($\hat{\rho}_{min} \leq P_{hammer} \leq \hat{\rho}_{max}$)		Underestimation ($P_{hammer} > \hat{\rho}_{max}$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Artist characteristics								
Deceased	0.010*** (7.50)	0.010*** (7.50)	-0.004 (-0.39)	-0.004 (-0.39)	0.007*** (7.44)	0.007*** (7.44)	0.013*** (6.98)	0.013*** (6.97)
Mentorship	-0.004*** (-3.91)	-0.004*** (-3.90)	0.001 (0.08)	0.001 (0.09)	-0.003*** (-4.38)	-0.003*** (-4.38)	-0.006*** (-4.37)	-0.006*** (-4.37)
Artwork characteristics								
Authenticity dummies								
Signature	0.001 (0.73)	0.001 (0.72)	-0.062*** (-4.21)	-0.062*** (-4.21)	-0.002** (-2.29)	-0.002** (-2.30)	0.004* (1.92)	0.004* (1.92)
Timestamp	-4.609E-04 (-0.46)	-4.590E-04 (-0.46)	-0.013* (-1.75)	-0.013* (-1.74)	-0.002*** (-3.64)	-0.002*** (-3.62)	-1.772E-05 (-0.01)	-1.181E-05 (-0.01)
Exhibition	-0.008*** (-3.19)	-0.008*** (-3.18)	0.022 (0.87)	0.022 (0.87)	-0.007*** (-3.88)	-0.007*** (-3.86)	-0.014*** (-4.21)	-0.014*** (-4.20)
Literature	-0.021*** (-14.78)	-0.021*** (-14.78)	-0.010 (-0.89)	-0.010 (-0.89)	-0.013*** (-13.72)	-0.013*** (-13.72)	-0.026*** (-13.55)	-0.026*** (-13.56)
Provenance	0.005*** (3.82)	0.005*** (3.83)	0.002 (0.18)	0.002 (0.18)	-0.005*** (-5.90)	-0.005*** (-5.89)	0.005*** (3.39)	0.005*** (3.39)
Inscription	-0.003 (-1.34)	-0.003 (-1.35)	-0.003 (-0.21)	-0.003 (-0.21)	-0.001 (-0.97)	-0.001 (-0.97)	0.001 (0.54)	0.001 (0.54)
Mounting dummies								
Albums	-0.001 (-0.26)	-0.001 (-0.26)	-0.125*** (-3.74)	-0.125*** (-3.74)	0.002 (0.77)	0.002 (0.77)	0.024*** (4.04)	0.024*** (4.04)
Fans	0.022*** (6.28)	0.022*** (6.28)	-0.123*** (-3.88)	-0.123*** (-3.88)	0.003 (1.16)	0.003 (1.16)	0.044*** (9.38)	0.044*** (9.38)
Folding Screen	-0.006 (-1.01)	-0.006 (-1.01)	-0.096** (-2.35)	-0.096** (-2.35)	0.002 (0.69)	0.002 (0.68)	0.003 (0.40)	0.003 (0.40)
Handscroll	0.014*** (-2.93)	0.014*** (-2.93)	-0.091*** (-2.66)	-0.091*** (-2.66)	0.006* (1.95)	0.006* (1.95)	0.038*** (5.91)	0.038*** (5.91)
Heng Fu	-0.007 (-1.06)	-0.007 (-1.06)	-0.076* (-1.75)	-0.076* (-1.75)	0.002 (0.49)	0.002 (0.49)	0.020** (2.16)	0.020** (2.16)
Hua Xin	0.103*** (12.97)	0.103*** (12.97)	-0.345*** (-5.74)	-0.345*** (-5.74)	-0.007 (-1.05)	-0.007 (-1.05)	0.097*** (10.00)	0.097*** (10.00)
Jing Kuang	-0.021*** (-5.79)	-0.021*** (-5.79)	-0.101*** (-3.30)	-0.101*** (-3.30)	-0.001 (-0.37)	-0.001 (-0.37)	-0.009* (-1.75)	-0.009* (-1.75)
Jing Pian	-0.011*** (-2.94)	-0.011*** (-2.94)	-0.123** (-2.54)	-0.123** (-2.54)	0.003 (1.35)	0.003 (1.35)	0.004 (0.87)	0.004 (0.87)
Jing Xin	-0.006* (-1.94)	-0.006* (-1.94)	-0.121*** (-4.46)	-0.121*** (-4.46)	-0.002 (-1.08)	-0.002 (-1.08)	0.013*** (3.17)	0.013*** (3.17)
Standing Scroll	0.01 (1.33)	0.01 (1.33)	-0.130*** (-3.80)	-0.130*** (-3.80)	0.008 (1.54)	0.008 (1.54)	-0.016 (-1.38)	-0.016 (-1.38)
Vertical Scroll	-0.012*** (-3.91)	-0.012*** (-3.91)	-0.107*** (-3.99)	-0.107*** (-3.99)	0.003 (1.56)	0.003 (1.56)	0.003 (0.86)	0.003 (0.86)

	Full sample		Overestimation ($P_{hammer} < \hat{\rho}_{min}$)		Correction estimation ($\hat{\rho}_{min} \leq P_{hammer} \leq \hat{\rho}_{max}$)		Underestimation ($P_{hammer} > \hat{\rho}_{max}$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sale characteristics								
Auction houses' dummies								
Beijing Poly	-0.010*** (-5.02)	-0.010*** (-5.01)	0.003 (0.13)	0.003 (0.13)	0.019*** (16.07)	0.019*** (16.08)	-0.021*** (-7.70)	-0.021*** (-7.69)
Beijing Rongbao	-0.047*** (-22.43)	-0.047*** (-22.42)	-0.072*** (-4.03)	-0.072*** (-4.03)	-0.037*** (-26.29)	-0.037*** (-26.30)	-0.042*** (-14.81)	-0.042*** (-14.81)
China Guardian	0.045*** (28.64)	0.045*** (28.63)	-0.041** (-2.28)	-0.041** (-2.27)	0.005*** (4.61)	0.005*** (4.61)	0.044*** (22.37)	0.044*** (22.36)
Council	-0.026*** (-10.01)	-0.026*** (-10.02)	-0.046** (-2.18)	-0.046** (-2.18)	-0.006*** (-3.38)	-0.006*** (-3.37)	-0.035*** (-10.13)	-0.035*** (-10.15)
Han Hai	0.032*** (16.64)	0.032*** (16.63)	-0.078*** (-5.73)	-0.078*** (-5.73)	0.004*** (3.28)	0.004*** (3.28)	0.004 (1.47)	0.004 (1.47)
Holly	-0.052*** (-18.43)	-0.052*** (-18.43)	-0.096*** (-3.85)	-0.096*** (-3.85)	0.005*** (3.30)	0.005*** (3.30)	-0.066*** (-14.37)	-0.066*** (-14.38)
Sungari	-0.043*** (-17.71)	-0.043*** (-17.72)	-0.086*** (-5.68)	-0.086*** (-5.68)	-0.010*** (-6.97)	-0.010*** (-6.97)	-0.078*** (-18.15)	-0.078*** (-18.15)
Xiling Yinshe	-0.060*** (-23.83)	-0.060*** (-23.84)	0.076 (0.70)	0.076 (0.70)	-0.024*** (-15.68)	-0.024*** (-15.69)	-0.049*** (-14.03)	-0.049*** (-14.03)
Christie's (HK)	0.061*** (23.77)	0.061*** (23.77)	-0.037** (-2.33)	-0.037** (-2.33)	-0.003 (-1.37)	-0.003 (-1.37)	0.046*** (14.14)	0.046*** (14.13)
Sotheby's (HK)	0.053*** (16.87)	0.053*** (16.87)	-0.037 (-1.33)	-0.037 (-1.33)	0.005* (1.91)	0.005* (1.91)	0.035*** (9.03)	0.035*** (9.03)
Month dummies								
February	-0.002 (-0.16)	-0.002 (-0.16)	6.237*** (18.41)	6.237*** (18.41)	0.013* (1.89)	0.014* (1.90)	-0.010 (-0.54)	-0.010 (-0.54)
March	0.038*** (10.47)	0.038*** (10.47)	-0.088*** (-2.83)	-0.088*** (-2.83)	0.005** (2.25)	0.005** (2.25)	0.043*** (8.76)	0.043*** (8.76)
April	0.015*** (4.26)	0.015*** (4.25)	-0.039* (-1.65)	-0.039* (-1.65)	0.006** (2.50)	0.006** (2.50)	0.020*** (4.03)	0.020*** (4.03)
May	0.007** (2.34)	0.007** (2.34)	-0.015 (-0.62)	-0.015 (-0.62)	0.002 (1.10)	0.002 (1.11)	0.017*** (3.86)	0.017*** (3.86)
June	0.009** (2.95)	0.009** (2.95)	-0.043* (-1.91)	-0.043* (-1.91)	0.003* (1.70)	0.003* (1.70)	0.023*** (5.50)	0.023*** (5.50)
July	0.006* (1.83)	0.006* (1.83)	0.027 (1.05)	0.027 (1.04)	0.001 (0.67)	0.001 (0.68)	0.018*** (3.96)	0.018*** (3.96)
August	0.038*** (8.71)	0.038*** (8.71)	0.021 (0.62)	0.021 (0.62)	-0.004 (-1.24)	-0.004 (-1.23)	0.052*** (8.78)	0.052*** (8.77)
September	0.028*** (7.87)	0.028*** (7.88)	-0.016 (-0.56)	-0.016 (-0.56)	0.005** (1.99)	0.005** (1.99)	0.032*** (6.62)	0.032*** (6.61)
October	0.009*** (2.66)	0.009*** (2.66)	-0.060** (-2.30)	-0.059** (-2.30)	-0.002 (-1.01)	-0.002 (-1.01)	0.021*** (4.37)	0.021*** (4.37)
November	0.008*** (2.71)	0.008*** (2.71)	0.016 (0.72)	0.016 (0.72)	0.006*** (3.10)	0.006*** (3.10)	0.015*** (3.45)	0.015*** (3.45)
December	0.001 (0.35)	0.001 (0.35)	-0.019 (-0.90)	-0.019 (-0.90)	0.007*** (3.72)	0.007*** (3.72)	0.012*** (2.96)	0.012*** (2.96)
Past-sale records dummies								
Past-sale record	-0.036*** (-11.77)		0.001 (0.05)		-0.008*** (-4.22)		-0.049*** (-11.32)	
Past-sale_2 nd		-0.035*** (-11.23)		0.002 (0.09)		-0.008*** (-3.87)		-0.049*** (-11.03)
Past-sale_3 rd		-0.050*** (-3.74)		-0.015 (-0.15)		-0.016** (-2.06)		-0.053*** (-2.71)
Past-sale_4 th		-0.009 (-0.29)		-0.040 (-0.12)		-0.012 (-0.60)		-0.009 (-0.23)
Past-sale_5 th		-0.168* (-1.81)				0.043 (0.93)		-0.319 (-1.64)
Observations	191,102	191,102	9,171	9,171	86,315	86,315	95,616	95,616
R squared	31.09%	31.09%	14.90%	14.90%	38.46%	38.46%	15.28%	15.29%

Note: Table 4.3 shows the results of the impact of certain factors on the accuracy of pre-sale estimates. The coefficients and t-statistics are reported in parentheses. Years, window, overestimation, and underestimation as control variables are included in the regression analysis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The current investigation conducts several robustness tests on the baseline results, which are presented in Table 4.4. The selection of low estimates and high estimates as evaluative metrics is due to their importance in the realm of art auctions. The low estimates have a close relationship with the secret reserve prices, typically constituting approximately 70%-80% of an auctioneer's low estimates (McAndrew & Thompson, 2003). An overestimation of low estimates could result in an increased bought-in rate, as potential bidders may abstain from participating. As such, this study examines how certain variables affect the accuracy of low estimates in predicting hammer prices (Columns 1-2). The results reveal that the majority of variables are consistent with the primary baseline results shown in Table 4.3.

On the other hand, high estimates represent the maximum anticipated selling price for the artwork. They signal the perceived value of an artwork and the likelihood of a high selling price to buyers. Such an impression can attract more buyers to the auction, leading to greater bidding activity. Thus, it is necessary to investigate the impact of certain factors on the precision of high estimates in estimating hammer prices. The results of almost all variables are qualitatively similar to the baseline results reported in Table 4.3. Nevertheless, it is noted that Beijing Poly has a negative effect on the precision of high estimates in price prediction.

Table 4.4

Robustness Test

	Low estimates		High estimates	
	(1)	(2)	(3)	(4)
Artist Characteristics				
Deceased	2.025E-04 (0.15)	2.013E-04 (0.15)	0.018*** (11.86)	0.018*** (11.85)
Mentorship	-0.002* (-1.73)	-0.002* (-1.73)	-0.008*** (-6.11)	-0.008*** (-6.11)
Artwork Characteristics				
Authenticity dummies				
Signature	-0.004** (-2.51)	-0.004** (-2.51)	-0.001 (-0.75)	-0.001 (-0.75)
Timestamp	0.002* (1.71)	0.002* (1.71)	-0.004*** (-3.90)	-0.004*** (-3.90)
Exhibition	-0.007*** (-2.80)	-0.007*** (-2.79)	-0.014*** (-4.90)	-0.014*** (-4.88)
Literature	-0.015*** (-10.64)	-0.015*** (-10.64)	-0.029*** (-17.94)	-0.029*** (-17.94)

Continued Table 4.4

	Low estimates		High estimates	
	(1)	(2)	(3)	(4)
Artwork Characteristics				
Authenticity dummies				
Provenance	0.009*** (7.72)	0.009*** (7.73)	-0.002 (-1.36)	-0.002 (-1.36)
Inscription	-0.003* (-1.66)	-0.003* (-1.66)	-0.003 (-1.47)	-0.003 (-1.47)
Mounting dummies				
Albums	-0.003 (-0.70)	-0.003 (-0.70)	-0.003 (-0.61)	-0.003 (-0.61)
Fans	0.035*** (9.77)	0.035*** (9.77)	0.010** (2.55)	0.010** (2.55)
Folding Screen	0.001 (0.21)	0.001 (0.21)	-0.012* (-1.87)	-0.012* (-1.87)
Handscroll	0.013*** (2.69)	0.013*** (2.69)	0.015*** (2.85)	0.015*** (2.85)
Heng Fu	0.002 (0.31)	0.002 (0.31)	-0.011 (-1.45)	-0.011 (-1.45)
Hua Xin	0.079*** (9.95)	0.079*** (9.95)	0.095*** (10.62)	0.095*** (10.63)
Jing Kuang	-0.017*** (-4.66)	-0.017*** (-4.66)	-0.022*** (-5.22)	-0.022*** (-5.22)
Jing Pian	-2.41E-04 (-0.06)	-2.42E-04 (-0.06)	-0.017*** (-3.87)	-0.017*** (-3.87)
Jing Xin	0.003 (1.08)	0.003 (1.08)	-0.014*** (-4.17)	-0.014*** (-4.17)
Standing Scroll	-0.024*** (-3.15)	-0.024*** (-3.15)	0.032*** (3.78)	0.032*** (3.78)
Vertical Scroll	-0.007** (-2.50)	-0.007** (-2.50)	-0.013*** (-3.95)	-0.013*** (-3.94)
Sale Characteristics				
Auction houses dummies				
Beijing Poly	-0.025*** (-13.10)	-0.025*** (-13.10)	0.014*** (6.33)	0.014*** (6.33)
Beijing Rongbao	-0.047*** (-22.40)	-0.047*** (-22.40)	-0.055*** (-23.07)	-0.055*** (-23.07)
China Guardian	0.055*** (35.25)	0.055*** (35.24)	0.025*** (13.90)	0.025*** (13.89)
Council	-0.027*** (-10.64)	-0.027*** (-10.65)	-0.027*** (-9.26)	-0.027*** (-9.26)
Han Hai	0.005** (2.37)	0.005** (2.36)	0.056*** (25.61)	0.056*** (25.61)
Holly	-0.055*** (-19.71)	-0.055*** (-19.72)	-0.036*** (-11.37)	-0.036*** (-11.37)
Sungari	-0.095*** (-38.66)	-0.095*** (-38.66)	-0.001 (-0.40)	-0.001 (-0.40)
Xiling Yinshe	-0.041*** (-16.47)	-0.041*** (-16.48)	-0.073*** (-25.78)	-0.073*** (-25.79)
Christie's (HK)	0.049*** (19.34)	0.049*** (19.34)	0.055*** (18.90)	0.055*** (18.90)
Sotheby's (HK)	0.062*** (19.50)	0.062*** (19.50)	0.028*** (7.94)	0.028*** (7.94)
Month dummies				
February	-0.026** (-2.11)	-0.026** (-2.11)	0.015 (1.08)	0.015 (1.09)
March	0.043*** (12.08)	0.043*** (12.08)	0.028*** (6.99)	0.028*** (6.98)

Continued Table 4.4

	Low estimates		High estimates	
	(1)	(2)	(3)	(4)
Sale Characteristics				
Month dummies				
April	0.006* (1.78)	0.006* (1.78)	0.011*** (2.74)	0.011*** (2.74)
May	0.011*** (3.63)	0.011*** (3.63)	-0.001 (-0.19)	-0.001 (-0.19)
June	0.017*** (5.79)	0.017*** (5.80)	-0.002 (-0.51)	-0.002 (-0.52)
July	0.013*** (3.95)	0.013*** (3.95)	-0.004 (-1.16)	-0.004 (-1.16)
August	0.030*** (6.94)	0.030*** (6.94)	0.030*** (6.08)	0.030*** (6.08)
September	0.031*** (8.88)	0.031*** (8.89)	0.020*** (4.89)	0.020*** (4.88)
October	9.189E-05 (0.03)	9.185E-05 (0.03)	0.001 (0.27)	0.001 (0.27)
November	0.010*** (3.40)	0.010*** (3.40)	0.003 (0.79)	0.003 (0.79)
December	0.003 (0.88)	0.003 (0.88)	-0.001 (-0.29)	-0.001 (-0.29)
Past-sale records dummies				
Past-sale record	-0.038*** (-12.49)		-0.034*** (-9.90)	
Past-sale_2 nd		-0.038*** (-12.02)		-0.033*** (-9.37)
Past-sale_3 rd		-0.045*** (-3.43)		-0.054*** (-3.61)
Past-sale_4 th		-0.021 (-0.68)		-0.007 (-0.21)
Past-sale_5 th		-0.132 (-1.43)		-0.061 (-0.58)
Observations	191,102	191,102	191,102	191,102
R squared	49.57%	49.57%	23.83%	23.83%

Note: Table 4.4 shows the results of robustness tests. The coefficients and t-statistics are reported in parentheses. Years, window, overestimation, and underestimation as control variables are included in the regression analysis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

As Malpezzi (2003) and Wang (2017) point out, the evaluation of the hedonic characteristics in the art-price distribution differs depending on high- or low-value item qualities. This observation offers insight into how the impact of factors on pre-sale auction estimation may vary across different price distributions. Studying these factors can shed light on market trends and the artwork's perceived value. With such knowledge, not only can accurate art pricing, but collectors can also better understand the factors that influence the value of their collections.

To investigate this, the current data sample is divided into quartiles (Q1-Q4) based on the hammer price for each time period: Q1 represents the bottom 25% of prices (Columns 1-2), while Q2

covers the 25%-50% range for the low-middle prices (Columns 3-4). Q3 includes the next 25% of prices in the high-middle range (Columns 5-6), and the top 25% of prices are classified as masterpieces (Columns 7-8).

Table 4.5 shows the results of how certain factors influence the accuracy of the pre-sale estimates across different price quantiles. Starting with low-priced artwork (Columns 1-2), the results present no significant impact of mentorship on the accuracy price prediction. Although evidence suggests that the proof of authenticity has a positive effect on reducing the discrepancy between pre-sale estimates and hammer prices, most coefficient parameters are not significant. Nevertheless, the precision of pre-sale estimates tends to improve irrespective of the mounting type, with the exception of hua xin. Furthermore, the sale of artworks sold at Beijing Poly, China Guardian, Han Hai, and Christie's (HK) has a negative impact on the accuracy of pre-sale evaluations. This observation may be attributed to investors' heightened confidence in estimates provided by larger auction houses, as proposed by Mei and Moses (2005). In contrast, other local auction houses significantly improve the precision of price predictions. Moreover, there are no significant differences in the influence of past sales records on the accuracy of predictions.

As prices increase towards masterpieces, mentorship, exhibition, literature, and past-sale records become statistically significant and positively influence the accuracy of auction houses' predictions. It is postulated that high-value artworks may have been exhibited in prestigious galleries or museums. An artwork's exhibition history can provide valuable context regarding its value, which aids in making pre-sale estimates to predict the hammer price. Furthermore, high-valued artworks are more likely to have extensive coverage in literature and art publications. This documentation provides insights into their significance and value. Auctioneers can leverage this information to develop their understanding of the artwork's position in the art market and thus, make a well-informed decision on pre-sale estimates. Regarding other variables, China Guardian, Christie's (HK), and Sotheby's (HK) continue to have a negative effect on enhancing the accuracy of pre-sale auction predictions, while

other local auction houses show the opposite result. Artworks sold during large-scale auction months shorten the distance between the pre-sale estimation and hammer price.

Table 4.5

The Effect of Factors on the Accuracy of Pre-sale Estimates Across Different Price Quantiles

	Low-price		Low-middle price		High-middle price		Masterpieces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Artist Characteristics								
Deceased	0.010*** (3.99)	0.010*** (3.98)	0.003 (1.03)	0.003 (1.03)	0.012*** (4.09)	0.012*** (4.09)	0.003 (0.79)	0.003 (0.79)
Mentorship	0.002 (0.75)	0.002 (0.75)	-0.001 (-0.41)	-0.001 (-0.41)	-0.010*** (-4.52)	-0.010*** (-4.53)	-0.013*** (-5.66)	-0.013*** (-5.65)
Artwork Characteristics								
Authenticity dummies								
Signature	-0.030*** (-9.98)	-0.030*** (-9.98)	-0.005 (-1.55)	-0.005 (-1.56)	0.012*** (3.34)	0.012*** (3.33)	0.011*** (3.15)	0.011*** (3.15)
Timestamp	-0.002 (-0.76)	-0.002 (-0.75)	0.002 (1.05)	0.002 (1.05)	-0.006*** (-2.87)	-0.006*** (-2.87)	0.003 (1.64)	0.003 (1.63)
Exhibition	-0.015 (-1.11)	-0.015 (-1.12)	0.013* (1.87)	0.013* (1.86)	-0.005 (-0.83)	-0.005 (-0.83)	-0.007** (-2.10)	-0.007** (-2.09)
Literature	-0.005 (-0.95)	-0.005 (-0.95)	-0.018*** (-5.55)	-0.018*** (-5.54)	-0.028*** (-10.19)	-0.028*** (-10.18)	-0.025*** (-11.32)	-0.025*** (-11.34)
Provenance	0.004 (1.31)	0.004 (1.31)	0.005** (1.98)	0.005** (1.98)	0.005** (2.15)	0.005** (2.15)	0.002 (0.97)	0.002 (0.97)
Inscription	-0.001 (-0.27)	-0.001 (-0.27)	-0.005 (-1.14)	-0.005 (-1.14)	-0.003 (-0.63)	-0.003 (-0.63)	0.004 (1.31)	0.004 (1.30)
Mounting dummies								
Albums	-0.041*** (-3.80)	-0.041*** (-3.80)	-0.008 (-0.87)	-0.008 (-0.87)	0.016* (1.76)	0.016* (1.76)	0.023*** (3.23)	0.023*** (3.24)
Fans	-0.027*** (-3.82)	-0.027*** (-3.82)	0.039*** (5.57)	0.039*** (5.57)	0.060*** (7.96)	0.060*** (7.96)	0.097*** (11.66)	0.097*** (11.66)
Folding Screen	-0.030** (-2.21)	-0.030** (-2.21)	-0.012 (-1.04)	-0.012 (-1.04)	0.021* (1.84)	0.021* (1.84)	0.006 (0.72)	0.006 (0.72)
Handscroll	-0.030*** (-2.71)	-0.030*** (-2.71)	0.014 (1.38)	0.014 (1.38)	0.036*** (3.60)	0.036*** (3.59)	0.033*** (4.29)	0.033*** (4.29)
Heng Fu	-0.042*** (-2.99)	-0.042*** (-2.99)	-0.011 (-0.84)	-0.011 (-0.84)	0.01 (0.68)	0.01 (0.68)	0.028** (2.12)	0.028** (2.12)
Hua Xin	0.054*** (3.05)	0.054*** (3.05)	0.065*** (4.74)	0.065*** (4.74)	0.145*** (9.33)	0.145*** (9.33)	0.153*** (8.78)	0.153*** (8.79)
Jing Kuang	-0.046*** (-4.71)	-0.046*** (-4.71)	-0.022*** (-2.87)	-0.022*** (-2.87)	-0.004 (-0.53)	-0.004 (-0.53)	-0.006 (-0.93)	-0.006 (-0.93)
Jing Pian	-0.043*** (-5.22)	-0.043*** (-5.22)	-0.016** (-2.23)	-0.016** (-2.23)	0.012 (1.60)	0.012 (1.60)	0.004 (0.60)	0.004 (0.60)
Jing Xin	-0.042*** (-6.50)	-0.042*** (-6.50)	-0.006 (-0.97)	-0.006 (-0.98)	0.018*** (2.90)	0.018*** (2.90)	0.015*** (2.73)	0.015*** (2.73)
Standing Scroll	-0.023* (-1.81)	-0.023* (-1.81)	0.006 (0.44)	0.006 (0.44)	0.061*** (3.58)	0.061*** (3.58)	0.025 (1.01)	0.024 (1.01)
Vertical Scroll	-0.046*** (-7.28)	-0.046*** (-7.28)	-0.011* (-1.75)	-0.011* (-1.75)	0.008 (1.31)	0.008 (1.31)	0.011** (2.05)	0.011** (2.06)
Sale Characteristics								
Auction houses dummies								
Beijing Poly	0.027*** (6.57)	0.027*** (6.57)	-0.019*** (-4.99)	-0.019*** (-4.99)	-0.026*** (-6.48)	-0.026*** (-6.48)	-0.013*** (-3.66)	-0.013*** (-3.66)
Beijing Rongbao	-0.009** (-2.11)	-0.009** (-2.11)	-0.070*** (-18.23)	-0.070*** (-18.23)	-0.069*** (-16.68)	-0.069*** (-16.67)	-0.039*** (-8.81)	-0.039*** (-8.80)

Continued Table 4.5

	Low-price		Low-middle price		High-middle price		Masterpieces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sale Characteristics								
Auction houses dummies								
China Guardian	0.018*** (5.91)	0.018*** (5.91)	0.037*** (12.81)	0.037*** (12.81)	0.063*** (19.27)	0.063*** (19.27)	0.065*** (19.09)	0.065*** (19.09)
Council	-0.028*** (-3.52)	-0.028*** (-3.52)	-0.030*** (-5.84)	-0.030*** (-5.84)	-0.030*** (-6.14)	-0.030*** (-6.14)	-0.025*** (-5.60)	-0.025*** (-5.62)
Han Hai	0.051*** (14.75)	0.051*** (14.75)	0.014*** (3.75)	0.014*** (3.75)	0.015*** (3.45)	0.015*** (3.45)	0.015*** (3.32)	0.015*** (3.32)
Holly	-0.037*** (-6.72)	-0.037*** (-6.72)	-0.041*** (-7.30)	-0.041*** (-7.30)	-0.045*** (-7.60)	-0.045*** (-7.60)	-0.059*** (-10.86)	-0.059*** (-10.87)
Sungari	-0.032*** (-6.25)	-0.032*** (-6.25)	-0.048*** (-10.78)	-0.048*** (-10.77)	-0.061*** (-12.72)	-0.061*** (-12.72)	-0.040*** (-7.93)	-0.040*** (-7.93)
Xiling Yinshe	-0.063*** (-9.46)	-0.063*** (-9.46)	-0.057*** (-12.30)	-0.057*** (-12.29)	-0.063*** (-13.30)	-0.063*** (-13.30)	-0.063*** (-13.67)	-0.063*** (-13.68)
Christie's (HK)	0.021** (2.37)	0.021** (2.36)	0.017*** (3.52)	0.017*** (3.52)	0.054*** (11.26)	0.054*** (11.26)	0.109*** (24.19)	0.109*** (24.19)
Sotheby's (HK)	-0.040*** (-2.96)	-0.040*** (-2.96)	-0.023*** (-3.35)	-0.023*** (-3.34)	0.028*** (4.64)	0.028*** (4.64)	0.106*** (19.22)	0.106*** (19.21)
Month dummies								
February	0.031* (1.86)	0.031* (1.89)	0.003 (0.11)	0.003 (0.11)	-0.057 (-1.43)	-0.057 (-1.44)	-0.019 (-0.56)	-0.019 (-0.57)
March	0.024*** (4.41)	0.024*** (4.41)	0.041*** (6.40)	0.041*** (6.40)	0.076*** (8.56)	0.076*** (8.56)	0.093*** (7.72)	0.093*** (7.71)
April	0.008 (1.32)	0.008 (1.32)	0.004 (0.57)	0.004 (0.57)	0.011 (1.39)	0.011 (1.39)	0.042*** (4.43)	0.042*** (4.43)
May	0.003 (0.59)	0.003 (0.59)	-0.008 (-1.41)	-0.008 (-1.42)	-0.001 (-0.14)	-0.001 (-0.14)	0.020** (2.39)	0.020** (2.38)
June	-0.003 (-0.66)	-0.003 (-0.66)	0.014*** (2.69)	0.014*** (2.69)	0.015** (2.08)	0.015** (2.08)	0.029*** (3.47)	0.029*** (3.48)
July	0.001 (0.16)	0.001 (0.16)	0.008 (1.37)	0.008 (1.37)	0.004 (0.48)	0.004 (0.48)	0.016* (1.80)	0.016* (1.79)
August	0.028*** (4.06)	0.028*** (4.06)	0.029*** (3.58)	0.029*** (3.58)	0.044*** (4.26)	0.044*** (4.26)	0.067*** (5.58)	0.067*** (5.57)
September	0.031*** (5.58)	0.031*** (5.58)	0.027*** (4.23)	0.027*** (4.22)	0.032*** (3.83)	0.032*** (3.83)	0.033*** (3.23)	0.034*** (3.24)
October	0.036*** (5.56)	0.036*** (5.56)	-3.510E-06 (0.00)	-1.1E-05 (0.00)	-0.011 (-1.38)	-0.011 (-1.38)	0.016* (1.80)	0.016* (1.80)
November	0.015*** (2.95)	0.015*** (2.95)	-0.001 (-0.15)	-0.001 (-0.15)	-0.007 (-0.98)	-0.007 (-0.98)	0.012 (1.45)	0.012 (1.45)
December	-0.004 (-0.71)	-0.004 (-0.71)	0.005 (0.93)	0.005 (0.93)	0.007 (1.00)	0.007 (0.99)	0.014* (1.65)	0.014 (1.64)
Past-sale records dummies								
Past-sale record	-0.015 (-1.45)		-0.018*** (-2.85)		-0.041*** (-6.71)		-0.039*** (-8.84)	
Past-sale_2 nd		-0.014 (-1.32)		-0.019*** (-2.89)		-0.040*** (-6.52)		-0.039*** (-8.44)
Past-sale_3 rd		-0.116 (-1.43)		0.000 (-0.01)		-0.045* (-1.65)		-0.050*** (-2.91)
Past-sale_4 th		0.021 (0.20)		-0.075 (-0.54)		-0.010 (-0.17)		0.003 (0.07)
Past-sale_5 th		0.022 (0.10)				-0.202 (-0.97)		-0.228** (-1.97)
Observations	47,734	47,734	47,816	47,816	47,194	47,194	48,358	48,358
R squared	27.04%	27.04%	35.97%	35.97%	34.25%	34.25%	33.99%	34.00%

Note: Table 4.5 reports the results of how different factors influence the accuracy of the pre-sale estimates across different price quantiles. The coefficients and t-statistics are reported in parentheses. Years, window, overestimation, and underestimation as control variables are included in the regression analysis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.5.3. Uncertainty of Pre-sale Estimates About the Value of Artwork

Table 4.6 presents the results of how certain factors affect the uncertainty of pre-sale estimates for the value of works. In accordance with Table 4.3, Columns 1-2 provide a comprehensive perspective on the results for the entire sample. For additional insights, the sample is divided into different pre-sale classifications, including pre-sale overestimation (Columns 3-4), correct pre-sale prediction (Columns 5-6), and pre-sale underestimation (Columns 7-8).

Focusing on artist characteristics within the full data sample (Columns 1-2), the results reveal that artworks created by deceased artists at the time of auction increase the uncertainty in value by 0.80% compared to artworks created by living artists. This finding is in line with Barnes et al. (2023), who ascertain that deceased artists contribute to increased uncertainty in auction house estimates. Conversely, artists with mentorship experience significantly reduce the distance between high and low estimates by 1.1% in comparison to artists without such experience. This outcome may be ascribed to mentorship acting as an endorsement from an established artist, elevating the artwork's perceived value, and imbuing auctioneers with greater confidence in its potential value, resulting in a narrower estimate range.

The observed opposing impacts-whereby deceased artists negatively affect the reduction of uncertainty of pre-sale estimates and mentorship positively influences the certainty of price estimation - jointly corroborate Hypothesis 4 (H4), which posits that artist characteristics significantly influence on the uncertainty of pre-sale estimations.

Turning to artwork characteristics, variables related to the proof of authenticity (excluding signatures) positively affect the reduction of the uncertainty of pre-sale estimates. This implies that accessible evidence of authenticity provides additional public information, which reduces the uncertainty of pre-sale estimates. In contrast, the styles of mounting adversely affect the certainty of the pre-sale estimates. Among these, hua xin is associated with the most significant spread between low and high estimates, accounting for a 15.3% variance. This discrepancy indicates that the types of

mounting can substantially influence an artwork's valuation, thereby increasing the pre-sale estimate uncertainties. Taken together, these findings lend comprehensive support to Hypothesis 5 (H5), which posits that the uncertainty of pre-sale estimates is significantly affected by the characteristics of the artwork.

Regarding sale characteristics, this study initially focuses on the effect of auction houses on the uncertainty of pre-sale estimation. It is observed that auction houses like Council, Han Hai, Holly, and Xiling Yinshe demonstrate a narrower range of pre-sale estimates, implying that they have more expertise and access to comprehensive information about the artworks and/or market factors (e.g., bidder behavior). Conversely, Beijing Poly, Beijing Rombon, China Guardian, and Sungari do not conform to these expectations despite their having attained a high reputation. These divergent findings do not support the hypothesis that artworks auctioned at the top 10 auction houses are more likely to have pre-sale estimates that are statistically significantly more certain. To interpret these mixed results, it is important to consider a few factors. The range of pre-sale estimates not only gives insight into the auctioneer's certainty regarding an artwork's value, but also is associated with the probability of sale, as indicated by Ekelund et al. (1998), Ashenfelter et al. (2003), and Bruno et al. (2018). This suggests that a wider pre-sale range can be a marketing strategy, making the artwork more accessible and appealing to a broader range of bidders. In addition, in the world's leading auction houses⁴, success is gauged by meeting or exceeding pre-sale estimates and having a low bought-in rate compared to competitors. Auction houses that consistently achieve these standards are generally considered reliable and dominant in the industry.

Concerning the timing of the auction, the results align with the hypothesis that artworks auctioned during peak auction months, specifically May and November, are subject to reduced uncertainty in pre-sale estimates. The artworks sold in peak months are characterized by increased market activity and comprehensive information availability, which likely narrows the pre-sale

⁴ Source: <https://www.artsy.net/article/artsy-editorial-auction-house-estimates>

estimate gaps.

Furthermore, past auction records can serve as value bid anchors and thus, increase the certainty of pre-sale estimation in predicting the hammer price. This lends to support Hypothesis 8 (H8).

This study further investigates the impact of certain factors on the uncertainty of pre-sale estimates across different pre-sale classifications. The results for the pre-sale overestimation category (Columns 3-4) contradict the main findings. For instance, limited authentication variables provide auctioneers with additional information to minimize the uncertainty of pre-sale estimates. There is no proof of dissimilarities between auction houses (e.g., Beijing Poly, Beijing Rongbon, China Guardian, Xiling Yinshe, and Sotheby's (HK)) and past sale records. In contrast, artwork mounted in albums, jing kuang, jing xin, folding screens, and vertical scroll significantly reduces the uncertainty of pre-sale estimates. The outcome for correct pre-sale prediction (Columns 5-6) and pre-sale underestimation (Columns 7-8) are in line with the baseline results.

Table 4.6

The Effect of Factors on the Uncertainty of Pre-sale Estimates

	Full sample		Overestimation ($P_{hammer} < \hat{p}_{min}$)		Correction estimation ($\hat{p}_{min} \leq P_{hammer} \leq \hat{p}_{max}$)		Underestimation ($P_{hammer} > \hat{p}_{max}$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Artist Characteristics								
Deceased	0.008*** (7.75)	0.008*** (7.76)	0.018*** (4.69)	0.018*** (4.67)	0.007*** (4.87)	0.007*** (4.88)	0.007*** (5.33)	0.007*** (5.34)
Mentorship	-0.011*** (-13.73)	-0.011*** (-13.73)	-0.009*** (-3.10)	-0.009*** (-3.06)	-0.011*** (-9.56)	-0.011*** (-9.56)	-0.011*** (-9.86)	-0.011*** (-9.85)
Artwork characteristics								
Authenticity dummies								
Signature	0.023*** (19.89)	0.023*** (19.88)	0.086*** (16.30)	0.086*** (16.30)	0.019*** (11.74)	0.019*** (11.73)	0.018*** (10.66)	0.018*** (10.66)
Timestamp	-0.008*** (-12.03)	-0.008*** (-12.02)	-0.009*** (-3.41)	-0.009*** (-3.41)	-0.007*** (-6.63)	-0.007*** (-6.61)	-0.009*** (-8.97)	-0.009*** (-8.96)
Exhibition	-0.017*** (-9.32)	-0.017*** (-9.32)	0.004 (0.47)	0.004 (0.46)	-0.018*** (-6.52)	-0.018*** (-6.49)	-0.017*** (-6.80)	-0.017*** (-6.82)
Literature	-0.018*** (-17.43)	-0.018*** (-17.42)	-0.011** (-2.50)	-0.011** (-2.48)	-0.019*** (-12.86)	-0.019*** (-12.86)	-0.017*** (-11.94)	-0.017*** (-11.93)
Provenance	-0.001* (-1.67)	-0.001* (-1.66)	-0.011*** (-3.16)	-0.011*** (-3.15)	-0.001 (-1.00)	-0.001 (-0.99)	-0.001 (-1.11)	-0.001 (-1.12)
Inscription	-0.006*** (-3.97)	-0.006*** (-3.97)	-0.001 (-0.19)	-0.001 (-0.18)	-0.007*** (-3.36)	-0.007*** (-3.36)	-0.004* (-1.93)	-0.004* (-1.93)

Continued Table 4.6

	Full sample		Overestimation ($P_{hammer} < \hat{\rho}_{min}$)		Correction estimation ($\hat{\rho}_{min} \leq P_{hammer} \leq \hat{\rho}_{max}$)		Underestimation ($P_{hammer} > \hat{\rho}_{max}$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Artwork characteristics								
Mounting dummies								
Albums	0.025*** (8.08)	0.025*** (8.08)	-0.031** (-2.53)	-0.031** (-2.53)	0.035*** (7.70)	0.035*** (7.70)	0.021*** (4.59)	0.021*** (4.59)
Fans	0.064*** (25.79)	0.064*** (25.79)	-0.005 (-0.44)	-0.005 (-0.43)	0.078*** (21.16)	0.078*** (21.16)	0.056*** (15.79)	0.056*** (15.79)
Folding Screen	0.014*** (3.62)	0.014*** (3.62)	-0.030** (-1.98)	-0.030** (-1.98)	0.025*** (4.42)	0.025*** (4.42)	0.006 (1.06)	0.006 (1.06)
Handscroll	0.033*** (9.88)	0.033*** (9.88)	-0.007 (-0.52)	-0.007 (-0.52)	0.047*** (9.60)	0.047*** (9.60)	0.022*** (4.44)	0.022*** (4.43)
Heng Fu	0.052*** (10.66)	0.052*** (10.66)	-0.014 (-0.89)	-0.014 (-0.88)	0.058*** (8.15)	0.058*** (8.15)	0.047*** (6.46)	0.047*** (6.46)
Hua Xin	0.153*** (27.32)	0.153*** (27.31)	0.259*** (11.85)	0.259*** (11.84)	0.103*** (10.47)	0.103*** (10.47)	0.138*** (18.71)	0.138*** (18.70)
Jing Kuang	0.024*** (9.17)	0.024*** (9.17)	-0.028** (-2.53)	-0.028** (-2.53)	0.044*** (11.58)	0.044*** (11.58)	0.007* (1.88)	0.007* (1.88)
Jing Pian	0.048*** (17.95)	0.048*** (17.95)	0.006 (0.32)	0.006 (0.32)	0.056*** (14.96)	0.056*** (14.96)	0.042*** (10.84)	0.042*** (10.83)
Jing Xin	0.031*** (14.36)	0.031*** (14.36)	-0.032*** (-3.18)	-0.031*** (-3.17)	0.038*** (12.41)	0.038*** (12.41)	0.026*** (8.49)	0.026*** (8.49)
Standing Scroll	0.017*** (3.21)	0.017*** (3.21)	0.005 (0.43)	0.005 (0.43)	0.032*** (3.92)	0.032*** (3.93)	-0.022** (-2.39)	-0.022** (-2.39)
Vertical Scroll	0.030*** (14.11)	0.030*** (14.11)	-0.028*** (-2.81)	-0.028*** (-2.81)	0.042*** (14.19)	0.042*** (14.20)	0.019*** (6.31)	0.019*** (6.31)
Sales Characteristics								
Auction houses dummies								
Beijing Poly	0.067*** (50.07)	0.067*** (50.08)	-0.005 (-0.71)	-0.005 (-0.69)	0.073*** (39.86)	0.073*** (39.86)	0.061*** (29.85)	0.061*** (29.86)
Beijing Rongbao	0.035*** (23.64)	0.035*** (23.66)	-0.006 (-0.93)	-0.006 (-0.94)	0.039*** (18.01)	0.039*** (18.01)	0.039*** (18.35)	0.039*** (18.35)
China Guardian	0.084*** (77.31)	0.084*** (77.30)	-0.003 (-0.53)	-0.003 (-0.52)	0.074*** (43.98)	0.074*** (43.96)	0.092*** (61.99)	0.092*** (61.99)
Council	-0.106*** (-59.08)	-0.106*** (-59.07)	-0.066*** (-8.47)	-0.066*** (-8.46)	-0.115*** (-44.35)	-0.115*** (-44.35)	-0.103*** (-39.31)	-0.103*** (-39.28)
Han Hai	-0.054*** (-40.32)	-0.054*** (-40.32)	0.042*** (8.60)	0.042*** (8.61)	-0.064*** (-32.69)	-0.064*** (-32.69)	-0.064*** (-31.45)	-0.064*** (-31.46)
Holly	-0.021*** (-10.44)	-0.021*** (-10.43)	-0.023** (-2.56)	-0.023** (-2.56)	-0.030*** (-11.98)	-0.030*** (-11.98)	-0.007** (-2.14)	-0.007** (-2.14)
Sungari	0.048*** (27.88)	0.048*** (27.87)	0.078*** (14.28)	0.078*** (14.28)	0.050*** (21.76)	0.050*** (21.76)	0.045*** (13.75)	0.045*** (13.75)
Xiling Yinshe	-0.007*** (-3.92)	-0.007*** (-3.92)	-0.054 (-1.37)	-0.054 (-1.37)	-0.019*** (-7.92)	-0.019*** (-7.93)	0.009*** (3.44)	0.009*** (3.45)
Christie's (HK)	-0.002 (-1.15)	-0.002 (-1.15)	-0.015*** (-2.58)	-0.015*** (-2.58)	0.011*** (3.52)	0.011*** (3.52)	-0.002 (-0.94)	-0.002 (-0.94)
Sotheby's (HK)	0.002 (0.85)	0.002 (0.85)	0.010 (1.00)	0.010 (0.99)	0.008** (2.14)	0.008** (2.14)	-1.726E-04 (-0.06)	-1.552E-04 (-0.05)
Month dummies								
February	0.031*** (3.54)	0.031*** (3.54)	-0.131 (-1.06)	-0.131 (-1.06)	0.022** (2.01)	0.022** (2.01)	0.034** (2.39)	0.034** (2.39)
March	4.302E-04 (0.17)	4.318E-04 (0.17)	-0.020* (-1.74)	-0.020* (-1.74)	-0.007* (-1.89)	-0.007* (-1.89)	0.010*** (2.60)	0.010*** (2.61)
April	-0.001 (-0.33)	-0.001 (-0.33)	-0.040*** (-4.57)	-0.040*** (-4.57)	-9.153E-05 (-0.03)	-9.798E-05 (-0.03)	0.006 (1.50)	0.006 (1.50)
May	-0.020*** (-9.13)	-0.020*** (-9.13)	-0.027*** (-3.09)	-0.027*** (-3.08)	-0.016*** (-5.28)	-0.016*** (-5.27)	-0.019*** (-5.79)	-0.019*** (-5.78)

Continued Table 4.6

	Full sample		Overestimation ($P_{hammer} < \hat{p}_{min}$)		Correction estimation ($\hat{p}_{min} \leq P_{hammer} \leq \hat{p}_{max}$)		Underestimation ($P_{hammer} > \hat{p}_{max}$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales Characteristics								
Month dummies								
June	0.003 (1.29)	0.003 (1.29)	-0.053*** (-6.56)	-0.053*** (-6.57)	0.001 (0.36)	0.001 (0.36)	0.013*** (4.06)	0.013*** (4.07)
July	0.005** (2.00)	0.005** (2.00)	-0.040*** (-4.23)	-0.040*** (-4.22)	-0.003 (-0.84)	-0.003 (-0.84)	0.016*** (4.68)	0.016*** (4.69)
August	0.009*** (2.77)	0.009*** (2.76)	-0.002 (-0.15)	-0.002 (-0.15)	0.005 (1.08)	0.005 (1.07)	0.016*** (3.48)	0.016*** (3.49)
September	-0.003 (-1.01)	-0.003 (-1.00)	-0.111*** (-10.98)	-0.111*** (-10.98)	-0.001 (-0.18)	-0.001 (-0.17)	0.006* (1.68)	0.006* (1.69)
October	0.022*** (8.71)	0.022*** (8.71)	-0.014 (-1.45)	-0.014 (-1.45)	0.021*** (6.03)	0.021*** (6.03)	0.030*** (8.14)	0.030*** (8.14)
November	-0.024*** (-11.11)	-0.024*** (-11.12)	-0.029*** (-3.67)	-0.029*** (-3.66)	-0.027*** (-8.79)	-0.027*** (-8.79)	-0.017*** (-5.09)	-0.017*** (-5.08)
December	0.011*** (5.11)	0.011*** (5.11)	-0.019** (-2.44)	-0.019** (-2.44)	0.009*** (2.97)	0.009*** (2.97)	0.016*** (5.16)	0.017*** (5.17)
Past-sale records dummies								
Past-sale record	-0.014*** (-6.60)		-0.011 (-1.24)		-0.015*** (-4.93)		-0.014*** (-4.32)	
Past-sale_2 nd		-0.013*** (-6.02)		-0.010 (-1.13)		-0.013*** (-4.35)		-0.014*** (-4.16)
Past-sale_3 rd		-0.021** (-2.20)		-0.034 (-0.95)		-0.029** (-2.34)		-0.003 (-0.23)
Past-sale_4 th		-0.061*** (-2.83)		0.129 (1.04)		-0.066** (-2.15)		-0.067** (-2.16)
Past-sale_5 th		-0.063 (-0.97)				-0.029 (-0.40)		-0.197 (-1.33)
Observation	191,102	191,102	9,171	9,171	86,315	86,315	95,616	95,616
R squared	15.82%	16.22%	21.38%	16.09%	16.10%	16.46%	17.32%	17.32%

Note: Table 4.6 presents the results of how certain factors affect the uncertainty of pre-sale estimates. The coefficients and t-statistics are reported in parentheses. Years as control variables are included in the regression analysis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4.7 presents the results of how different factors affect the uncertainty of pre-sale estimates across different price distributions. Employing the same classification as in Table 4.5, the results exhibit that, although the majority of variables are consistent with the main results, several noteworthy results are highlighted. Specifically, auctioneers depend on authenticity factors, such as timestamp and literature, to minimize the discrepancy between low and high estimates of low-priced artwork. However, as the value of art reaches the level of masterpieces, only the timestamp remains with a significantly negative coefficient. Conversely, factors such as signatures and literature slightly widen the range of pre-sale valuations. Exhibitions, provenance, and inscriptions, on the other hand, do not have a significant impact. These observations suggest that auction specialists rely on a limited number of authenticity factors to reduce the uncertainty of price predictions. This phenomenon is

attributable to the artwork's rarity and the seller's strategic pricing. Masterpieces are usually unique and exceptional, making them rare in the marketplace. Due to their scarcity, finding comparable sales data is challenging. This makes setting an accurate price range complicated. Additionally, auction houses can broaden the range of pre-sale estimates as an enticement to attract more potential buyers. In addition, past-sale records have a significant positive impact on reducing the uncertainty of pre-sale estimates for medium-low works and masterpieces.

Table 4.7

The Effect of Factors on the Uncertainty of Pre-sale Estimates Across Different Price Quantiles

	Low-price		Low-Middle price		High-Middle price		Masterpieces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Artist Characteristics								
Deceased	-7.871E-05 (-0.04)	-8.681E-05 (-0.04)	0.013*** (7.36)	0.013*** (7.36)	0.029*** (16.22)	0.029*** (16.23)	0.036*** (18.62)	0.036*** (18.62)
Mentorship	-0.010*** (-5.67)	-0.010*** (-5.67)	-0.005*** (-3.69)	-0.005*** (-3.69)	-0.006*** (-4.67)	-0.006*** (-4.67)	-0.005*** (-3.99)	-0.005*** (-3.99)
Artwork Characteristics								
Authenticity dummies								
Signature	0.026*** (11.05)	0.026*** (11.06)	0.012*** (5.44)	0.012*** (5.44)	0.016*** (7.08)	0.016*** (7.08)	0.005*** (2.64)	0.005*** (2.65)
Timestamp	-0.003* (-1.87)	-0.003* (-1.88)	-0.003* (-1.89)	-0.003* (-1.89)	-0.004*** (-3.12)	-0.004*** (-3.11)	-0.005*** (-4.23)	-0.005*** (-4.24)
Exhibition	0.035*** (3.34)	0.035*** (3.30)	-0.009* (-1.79)	-0.009* (-1.79)	0.003 (0.91)	0.003 (0.90)	-0.001 (-0.72)	-0.001 (-0.73)
Literature	-0.014*** (-3.17)	-0.014*** (-3.15)	-0.001 (-0.28)	-0.001 (-0.28)	-0.002 (-0.99)	-0.002 (-1.00)	0.004*** (2.69)	0.004*** (2.68)
Provenance	0.010*** (4.34)	0.010*** (4.35)	0.005*** (2.78)	0.005*** (2.78)	0.001 (0.83)	0.001 (0.83)	0.001 (1.12)	0.001 (1.12)
Inscription	0.005 (1.14)	0.005 (1.15)	0.004 (1.21)	0.004 (1.21)	-0.003 (-1.16)	-0.003 (-1.17)	-0.001 (-0.60)	-0.001 (-0.60)
Mounting dummies								
Albums	0.072*** (8.44)	0.072*** (8.44)	0.018*** (2.76)	0.018*** (2.76)	0.008 (1.40)	0.008 (1.41)	0.001 (0.14)	0.001 (0.14)
Fans	0.095*** (17.40)	0.095*** (17.40)	0.039*** (7.88)	0.039*** (7.88)	0.028*** (5.97)	0.028*** (5.97)	0.021*** (4.14)	0.021*** (4.14)
Folding Screen	0.043*** (4.01)	0.043*** (4.01)	0.016** (2.00)	0.016** (2.00)	0.01 (0.88)	0.01 (0.88)	-0.009* (-1.80)	-0.009* (-1.80)
Handscroll	0.065*** (7.43)	0.065*** (7.44)	0.016** (2.21)	0.016** (2.21)	0.026*** (4.18)	0.026*** (4.18)	0.003 (0.74)	0.003 (0.74)
Heng Fu	0.094*** (8.43)	0.094*** (8.43)	0.036*** (3.88)	0.036*** (3.88)	0.024*** (2.79)	0.024*** (2.79)	3.74E-05 (0.00)	3.79E-05 (0.00)
Hua Xin	0.284*** (20.44)	0.284*** (20.44)	0.082*** (8.50)	0.082*** (8.50)	0.077*** (7.94)	0.077*** (7.94)	0.115*** (11.08)	0.115*** (11.07)
Jing Kuang	0.079*** (10.38)	0.079*** (10.39)	0.008 (1.52)	0.008 (1.52)	4.82E-04 (0.10)	4.79E-04 (0.10)	-0.012*** (-3.22)	-0.012*** (-3.22)
Jing Pian	0.092*** (13.99)	0.092*** (13.99)	0.032*** (6.17)	0.032*** (6.17)	0.025*** (5.14)	0.025*** (5.14)	0.009** (2.19)	0.009** (2.19)
Jing Xin	0.077*** (15.28)	0.077*** (15.28)	0.021*** (4.84)	0.021*** (4.84)	0.01 (1.31)	0.01 (1.31)	-0.012*** (-3.74)	-0.012*** (-3.73)
Standing Scroll	0.037*** (3.79)	0.037*** (3.79)	-4.31E-04 (-0.04)	-4.23E-04 (-0.04)	0.036*** (3.37)	0.036*** (3.38)	0.093*** (6.39)	0.093*** (6.39)
Vertical Scroll	0.077*** (15.37)	0.077*** (15.36)	0.017*** (3.92)	0.017*** (3.92)	0.00 (1.12)	0.00 (1.12)	-0.008** (-2.42)	-0.008** (-2.42)

Continued Table 4.7

	Low-price		Low-Middle price		High-Middle price		Masterpieces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales Characteristics								
Auction houses dummies								
Beijing Poly	0.112*** (34.94)	0.112*** (34.94)	0.085*** (32.86)	0.085*** (32.85)	0.074*** (30.16)	0.074*** (30.17)	0.040*** (18.42)	0.040*** (18.42)
Beijing Rongbao	0.042*** (11.92)	0.042*** (11.92)	0.050*** (18.61)	0.050*** (18.60)	0.047*** (18.22)	0.047*** (18.26)	0.027*** (10.31)	0.027*** (10.31)
China Guardian	0.114*** (47.50)	0.114*** (47.51)	0.086*** (42.93)	0.086*** (42.92)	0.080*** (39.83)	0.080*** (39.84)	0.063*** (31.00)	0.063*** (31.00)
Council	-0.066*** (-10.67)	-0.066*** (-10.67)	-0.078*** (-21.57)	-0.078*** (-21.58)	-0.100*** (-33.34)	-0.100*** (-33.34)	-0.098*** (-38.01)	-0.098*** (-38.00)
Han Hai	-0.131*** (-50.02)	-0.131*** (-50.01)	-0.002 (-0.60)	-0.002 (-0.61)	0.018*** (6.72)	0.018*** (6.73)	0.011*** (3.94)	0.011*** (3.94)
Holly	-0.025*** (-5.65)	-0.025*** (-5.65)	-0.027*** (-6.96)	-0.027*** (-6.97)	-0.019*** (-5.01)	-0.019*** (-5.01)	0.004 (1.23)	0.004 (1.24)
Sungari	0.095*** (23.32)	0.095*** (23.32)	0.057*** (18.26)	0.057*** (18.26)	0.045*** (15.32)	0.045*** (15.33)	0.037*** (12.41)	0.037*** (12.40)
Xiling Yinshe	0.034*** (6.50)	0.034*** (6.51)	-0.006* (-1.95)	-0.006* (-1.96)	-0.008*** (-2.64)	-0.008*** (-2.64)	-0.004 (-1.56)	-0.004 (-1.55)
Christie's (HK)	-0.008 (-1.17)	-0.008 (-1.19)	0.005 (1.43)	0.005 (1.43)	0.009*** (3.18)	0.009*** (3.18)	0.011*** (3.95)	0.011*** (3.94)
Sotheby's (HK)	0.043*** (4.06)	0.043*** (4.06)	0.031*** (6.41)	0.031*** (6.41)	0.012*** (3.37)	0.013*** (3.38)	0.010*** (2.89)	0.010*** (2.90)
Month dummies								
February	0.012 (0.90)	0.012 (0.88)	-1.434E-04 (-0.01)	-1.542E-04 (-0.01)	0.060** (2.43)	0.060** (2.42)	0.052*** (2.62)	0.052*** (2.62)
March	-0.026*** (-5.98)	-0.026*** (-5.98)	0.005 (1.11)	0.005 (1.11)	-0.002 (-0.32)	-0.002 (-0.32)	0.007 (0.91)	0.007 (0.92)
April	-0.033*** (-7.10)	-0.033*** (-7.10)	0.007 (1.62)	0.007 (1.62)	0.014*** (2.70)	0.014*** (2.70)	-0.006 (-0.97)	-0.006 (-0.97)
May	-0.019*** (-4.30)	-0.019*** (-4.31)	-0.007* (-1.86)	-0.007* (-1.86)	-0.011** (-2.51)	-0.011** (-2.51)	-0.020*** (-3.91)	-0.020*** (-3.91)
June	0.025*** (6.13)	0.025*** (6.13)	0.012*** (3.28)	0.012*** (3.28)	-0.004 (-0.79)	-0.003 (-0.79)	-0.018*** (-3.53)	-0.018*** (-3.53)
July	0.014*** (3.16)	0.014*** (3.16)	0.016*** (3.82)	0.016*** (3.82)	0.008* (1.65)	0.008* (1.65)	-0.006 (-1.21)	-0.006 (-1.21)
August	-0.007 (-1.35)	-0.007 (-1.35)	0.007 (1.27)	0.007 (1.27)	0.011* (1.68)	0.011* (1.68)	-0.008 (-1.05)	-0.008 (-1.06)
September	-0.033*** (-7.52)	-0.033*** (-7.53)	0.009* (1.90)	0.009* (1.90)	0.001 (0.20)	0.001 (0.19)	0.002 (0.37)	0.002 (0.40)
October	0.030*** (5.68)	0.030*** (5.69)	0.029*** (6.31)	0.029*** (6.31)	0.019*** (3.89)	0.019*** (3.89)	0.003 (0.56)	0.003 (0.56)
November	-0.032*** (-7.82)	-0.032*** (-7.83)	-0.013*** (-3.24)	-0.013*** (-3.24)	-0.010** (-2.30)	-0.010** (-2.30)	-0.023*** (-4.46)	-0.023*** (-4.46)
December	0.036*** (9.05)	0.036*** (9.05)	0.026*** (7.10)	0.026*** (7.11)	0.005 (1.23)	0.005 (1.24)	-0.014*** (-2.91)	-0.014*** (-2.91)
Past-sale records dummies								
Past-sale record	-0.004 (-0.46)		-0.012*** (-2.70)		0.006 (1.48)		-0.009*** (-3.33)	
Past-sale_2 nd		-0.006 (-0.68)		-0.011*** (-2.50)		0.006* (1.65)		-0.008*** (-3.08)
Past-sale_3 rd		0.037 (0.57)		-0.022 (-1.04)		0.007 (0.43)		-0.005 (-0.50)
Past-sale_4 th		0.091 (1.07)		-0.112 (-1.15)		-0.081** (-2.17)		-0.043* (-1.89)
Past-sale_5 th		0.121 (0.72)				0.001 (0.01)		-0.108 (-1.56)
Observations	47,734	47,734	47,816	47,816	47,194	47,194	48,358	48,358
R squared	31.08%	31.08%	16.40%	16.40%	15.64%	15.65%	12.21%	12.22%

Note: Table 4.7 presents the impact of various factors on the uncertainty of pre-sale estimates across different price distributions. The coefficients and t-statistics are reported in parentheses. Years as control variables are included in the regression analysis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.5.4. Experienced Auction Houses on Accuracy and Uncertainty of Pre-sale Estimates

Bruno et al. (2018) find that auction houses with artist-specific experience are more likely to provide more precise pre-sale estimates. The concept of experienced auction houses refers to those that have gained extensive exposure to deals conducted in a specific market, which allows them to develop superior skills in interpreting the subtle signals related to these deals. Expanding upon this finding raises an inquiry as to whether experienced auction houses in the Chinese art market are also capable of offering precise price estimates.

Following Bruno et al. (2018), this study quantifies the expertise of auction houses by calculating the number of paintings of an artist was auctioned at that particular auction house and town during the T years preceding the current auction, divided by the total number of times that the artist has been auctioned at any auction house in the same period. The model is presented below:

$$Experience_t^{I,J} = \frac{\sum_{\tau \in [t-T, t]} x_{i \in I} x_{i \in J} (1 - \frac{t-\tau}{T})}{\sum_{\tau \in [t-T, t]} x_{i \in I} (1 - \frac{t-\tau}{T})} \quad (4)$$

Where T is the length of the time horizon along which the experience is measured, τ is any date, with $t - T \leq \tau \leq t$, in which an auction occurred. Following Bruno et al. (2018), the length of the time horizon is setting as 5 years; $x_{i \in I}$ is an indicator function taking a value one if the painting on auction is by artist I , and 0 otherwise, and $x_{i \in J}$ is an indicator function taking a value one if the auction occurs in auction house-town J , and 0 otherwise.

The primary research objective, which is aligned with the testing of Hypothesis 9 (H9) and Hypothesis 10 (H10), is to explore the influence of auction house experience on the accuracy and uncertainty of pre-sale estimates. The models are as follows:

$$y_{ijt} = \beta_o + \beta_1 Experience_{ijt} + \beta_2' X_{ijt} + \gamma_c + \delta_h + \lambda_l + \eta_t + \mu_{ijt} \quad (5)$$

Where y_{ijt} denotes the primary outcome variable (e.g., accuracy) or the second outcome variable (uncertainty) of the auction that takes place at time t for a painting of artist i in the auction house-town j . X_{ijt} is a vector comprising observable control variables that affect the auction outcome

and may be correlated with *Experience*, such as the artist-visibility, multiple, market share, and the past-sales record. Notably, the artist-visibility variable determines how frequently an artist's works are presented in auctions. It is calculated as the number of times an artist's works were auctioned in all auction houses within a specified time horizon T . In this case, T equals 5 years. This variable accounts for any potential trends related to a specific artist, and recognizes that artists with a more extensive auction presence may have more information available about them. *Multiple*⁵ is a ratio of the high estimates to low estimates, while market share is calculated as the proportion of total sales within a specific auction house, town, or year relative to the total sales across all auction houses during the same year. The fixed effect γ_c , δ_h , λ_l , and η_t are assigned to the artist's category, the auction house, the auction location, and the year, respectively. The error term is represented by μ_{it} .

To rigorously test Hypothesis 9 (H9) and Hypothesis 10 (H10), this study estimates three specifications using Eq. (5): Specification I conducts a regression analysis that includes all control variables, which consist of fixed effects for auction houses, town, category, and year. However, Specification I poses a fundamental identification challenge. Many unobserved factors are accessible to auction houses, bidders, or sellers, but remain hidden from the econometrician. These omitted factors could potentially explain the observed relationship between the experience and the various outcomes. To solve this, following Khwaja and Mian (2008), Specification II implements the fixed effect for the combination of the auction house, town, year, and category to control for the differences in the composition of investors (demand) across different auction houses, towns, and years, and within the category of artworks. Specification III controls for each artist's fixed effect with the year of auction. Throughout time, artists' popularity and styles can fluctuate, leading to potential "stylistic risks". For instance, particular artworks and artists may lose their value after their initial auction sales, as noted by Goetzmann (1993). Consequently, the prior specification may unintentionally compare artists in their peak periods. During peak periods, auction houses are more eager to sell, and investors'

⁵ It is worth noting that the variable of multiple is not included in the regression when we consider the effect of experienced auction houses on the uncertainty of pre-sale estimates.

estimations match more precisely. In contrast, artists might face higher bought-in rates and more challenging price estimations in less favorable periods. To control this trend, this study implements this specification.

Table 4.8 presents the results of the impact of experienced auction houses on the accuracy and uncertainty of pre-sale estimates in predicting hammer prices. Three Specifications, I to III, are employed to address potential confounding factors and ensure the robustness of the findings.

Consistent with the expectations set forth in Hypothesis 9 (H9), the experienced auction houses significantly contribute to the accuracy of price estimates. Specifically, the coefficients for experience in Columns 1-3 of Table 4.8 are negative, suggesting that more experienced auction houses provide more accurate estimates. However, it is worth noting that the coefficients in Column 2 are not statistically significant, which may be attributed to reduced cross-section variation within the selected subset of auctions, towns, and years. This observation resonates with findings from Bruno et al. (2018), who conclude that auction houses with greater experience can effectively minimize search frictions, thereby matching artworks with the most appropriate buyers. The strategic decisions made by these auction houses, such as initial bid pricing, adjusting the rate of price increments, or placing strategic “off-the-wall” bids, further support this interpretation.

On the other hand, the results pose a challenge to Hypothesis 10 (H10). Specifically, the experience variable has a generally positive coefficient when it comes to the uncertainty of pre-sale estimates, as evidenced in all columns. This indicates that experienced auction houses fail to reduce the gap between high and low estimates. Drawing on Bruno et al. (2018), one plausible explanation is that experienced auction houses have deep market knowledge. They might negotiate with optimistic sellers, adjusting reservation prices to match lower expected market prices. While this could increase demand for the artworks, it also has the potential side effect of widening the gap between high and low estimates.

Table 4.8*The Impact of Experienced Auction Houses on the Accuracy and Uncertainty of Pre-sale Estimates*

	Dependent variable =Accuracy			Dependent variable =Uncertainty		
	(1)	(2)	(3)	(4)	(5)	(6)
Experience	-0.026*** (-4.33)	-0.008 (-1.35)	-0.024*** (-2.83)	0.018*** (4.71)	0.004 (1.00)	0.030*** (5.63)
Observations	147,117	147,117	147,117	147,117	147,117	147,117
R-squared	16.30%	18.40%	23.30%	19.60%	25.00%	27.60%
Control	Yes	YES	YES	Yes	YES	YES
Auction House F.E.	Yes	NO	YES	Yes	NO	YES
Town F.E.	Yes	NO	YES	Yes	NO	YES
Year F.E.	Yes	NO	NO	Yes	NO	NO
Category F.E.	Yes	YES	NO	Yes	YES	NO
House-Town-Year F.E.	No	YES	NO	No	YES	NO
Artist-Year F.E.	No	NO	YES	No	NO	YES

Note: This table shows the results of experienced auction houses on the accuracy and uncertainty of pre-sale estimates. The coefficients and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.6. Conclusion

Auction estimates hold an essential role in the art market as they provide a prediction of the sale price of an artwork, benefiting both buyers and sellers in their auction preparation (Beggs & Graddy, 2009). Milgrom and Weber's (1982) argument emphasizes that auctioneers have an ethical obligation to provide truthful information about the items being auctioned. Disclosing complete information reduces uncertainty and encourages the confidence of bidders, benefiting the auctioneer by increasing the likelihood of the item being sold for a higher price. Nevertheless, experts' pre-sale price estimates exhibit a downward (Bauwens & Ginsburgh, 2000; D'Souza & Prentice, 2002) or upward bias (Mei & Moses, 2005). Erroneous estimates that arise from incomplete knowledge may lead sellers to seek alternative auction houses, or management may take action to improve the estimation process (Louargand & McDaniel, 1991). As reported by Bauwens and Ginsburgh (2000), prediction error could be minimized if the auctioneer effectively utilized the information contained in the pre-sales catalogues. Consequently, investigating the impact of certain factors on the informational content of pre-sale estimates in terms of accuracy and uncertainty could provide valuable insights.

This study analyzes the influence of certain factors on the accuracy and uncertainty of pre-

sale estimates in predicting hammer prices. It utilizes a comprehensive database of Chinese art, which consists of 191,102 pieces of Chinese art created by 533 artists spanning the period from 2000 to 2021. The descriptive statistics analysis reveals that Chinese art is undervalued, which is in line with previous studies by Bauwens and Ginsburgh (2000), Teti et al. (2014), and D'Souza and Prentice (2002). Auction houses may benefit from undervaluing art systematically during auctions by using conservative forecasting strategy. This approach allows them to manage the expectations of both the owner and the bidders while maximizing profits. Undervaluing paintings from the demand side can attract more bidders, increasing the likelihood of a sale and ultimately driving up the final selling price. However, this contrasts with Ashenfelter's (1989) argument that "auctioneers do seem to provide genuine expertise in predicting prices" and is inconsistent with Milgrom and Weber's (1982) theoretical statement that "honesty is the best policy."

The study further presents that mentorship, proof of authenticity, past-sale records, and large-scale auction months either improve the accuracy or reduce the uncertainty of presale estimates. These findings help auctioneers mitigate prediction bias using the valuable information derived from this research. This investigation contributes to the theoretical literature on improving the predictive power of pre-sale estimates (Bruno & Nocera, 2008). Moreover, the impact of certain factors on pre-sale estimates varies across the different price distribution. Auctioneers would leverage public information, such as the artist's mentorship experience, exhibition history, literature, and past-sale records to refine their price predictions. This emphasizes the importance of auction experts in using relevant information to sharpen predictions for artworks at various price levels. Lastly, this study suggests that auction houses with artist-specific expertise significantly improve the accuracy of pre-sale estimates. However, they might not effectively reduce the uncertainty of pre-sale estimates. This could be because experienced auction houses use their market expertise to negotiate with overly optimistic sellers. They set reserve prices lower to align with market expectations, driving demand. This strategy often leads to a broader spread between low and high estimates. The study enriches the

literature on art economics by investigating the extent to which auction houses can influence the outcomes of art auctions (Ashenfelter, 1989; Bauwens & Ginsburgh, 2000; McAndrew et al., 2012).

Chapter 5. Conclusion

This thesis contributes to the existing body of literature on Chinese art investment by presenting three original empirical studies, each reported in three independent essays. In the subsequent sections, this chapter emphasizes the findings, insights, and implications of each essay. Additionally, the chapter delineates the limitations of the current research based on specific articles and offers suggestions for potential future research endeavours.

5.1. Essay 1

Using a comprehensive dataset of 165,847 Chinese artworks sold by 533 artists, Essay One investigates the price determinants and investment performance of Chinese artworks, spanning a 17-year period from January 2000 to December 2017. This dataset is arguably the most extensive in the realm of the Chinese art market.

Hedonic regression and repeat-sale regression are the predominant methods for constructing art price indices. Hedonic regression is distinguished by its use of all available auction data. As noted by Chanel (1995), while both methods have unbiased market-wide effects, hedonic regression yields a significantly reduced variance in coefficient estimates. Essay One delves into the price determinants of Chinese art, the hedonic regression is particularly beneficial. It allows for the estimation of implicit prices for each characteristic separately from a characteristic-free price of paintings, which is mainly influenced by the effect of time and random error (Higgs & Worthington, 2005).

In Essay One, the emphasis is on evaluating the pricing impact by taking into account the artwork's attributes and capturing the characteristics of the various artworks. The findings demonstrate that all proof of authenticity variables have a positive effect on price, with the exhibition dummy variable having the highest effect. This suggests a significant increase in value for artworks with previous exhibition records. The positive effect on the price of artworks mounted in albums and the size of the artwork is also evident, though the effect of the latter diminishes beyond a certain threshold. Almost all auction houses exhibit positive price effects, with Sotheby's having the greatest effect, followed by Xiling Yinshe. Furthermore, the most expensive artworks are sold in May, November, December, and June, as Chinese auction houses organize their premier art auctions in these months, offering the most valuable works.

The yearly art-price index and its corresponding return are constructed using the coefficients of time-dummy variables. The art-price index depicts two boom periods within the sample period, with the first peak occurring in 2005, when the corrected price index reached 309.38 (using a base

value of 100 in 2000) and a return of 72.78%. This is followed by a decline over the next five years before reaching a record peak of 815.42 in 2011, with a return of 59.55%. These boom periods could be attributed to the emergence of new buyers, including entrepreneurs and HNWIIs, as well as expansionary monetary policies.

Robustness tests are conducted to check the basic results using the adjacent-period hedonic regression and the repeat-sales regression. The outcomes confirm that the main results remain unchanged. Additionally, the repeat-sale data reveals that the average holding period for Chinese art is approximately 3 years, which is significantly shorter than the average 10-year turnover in the Western art markets, indicating the presence of speculative activity in the Chinese art market.

To address the issue of overestimation of price indices and returns due to data selection bias, the Heckman two-stage model is employed to refine the hedonic price index, finding that data selection bias exists if unsold artworks are excluded. When comparing the Heckit price index to the OLS art-price index, it is found that the two series exhibit nearly identical trends. However, the Heckit art-price index is slightly lower than the OLS art-price index. This is consistent with anticipated adjustments for unsold works. Moreover, two supplementary tests are conducted to investigate the masterpiece effect and the auction-house effect, implying the existence of such phenomena in the Chinese art market.

Comparing the return of Chinese art with that of other investment assets, it is found that Chinese art provides the highest return and a relatively superior return-to-volatility ratio among investment asset classes. With a low correlation to other investment assets, the findings suggest potential diversification benefits arising from investing in Chinese art.

This study contributes to the existing body of literature on art market investment by utilizing a comprehensive and unique sample of Chinese art. It extends our understanding of the price effects associated with artwork characteristics and addresses the effect of bough-in. Additionally, this study offers valuable insights into the construction of the Chinese art-price index and its corresponding

returns, providing novel insights for art-market participants contemplating art as an alternative investment. Furthermore, it presents evidence of excessive speculative activity within the Chinese art market. Thus, this study is a timely reminder for art investors to carefully assess the risks associated with art investments. It emphasizes that the pursuing art is not solely for the sake of art itself.

The potential avenue to expand on this study is that art prices should reflect investors' expectations of the future development of the economy and be influenced by economic conditions. By developing art price indices for China, it may be possible to determine whether art returns can help predict the future evolution of macroeconomic variables. If this is the case, the extent to which art prices are derived from auctions could serve as a leading economic indicator for central banks and policy-makers⁶.

5.2. Essay 2

During economic downturns, traditional diversification strategies may not offer adequate protection for investors due to the increasing correlation between conventional financial assets (Masset & Weisskopf, 2018). Investing in art has emerged as a viable diversification option because of the low correlation between art and traditional financial assets. With the rapid expansion of the Chinese art market and the escalating global demand for Chinese art, investing in Chinese art has become an attractive choice for investors seeking to diversify their portfolios.

The second essay delves into the benefits of investing in Chinese art for portfolio diversification. Utilizing a unique dataset of 4,840 repeat pairs of Chinese art from June 2003 to December 2021, the study uses repeat-sale regression to calculate a semi-annual return of 6.18% for Chinese art, outperforming all common investment asset classes while exhibiting a lower standard deviation than equities. In terms of Sharpe ratios and Modified Sharpe ratios, Chinese art produces the highest risk-adjusted returns, ranking behind SSE government bonds and SSE corporate bonds. Furthermore, the inclusion of Chinese art in any of the financial assets considered would have resulted

⁶ Renneboog and Spaenjers (2013) obtain the art return data to construct a preliminary investor sentiment index.

in incremental diversification benefits.

Correlation analysis and the Capital Asset Pricing Model are used to determine the risk diversification potential of Chinese art. The correlation between Chinese art and common financial assets is extremely low, suggesting its effectiveness as a diversification tool. Moreover, when using the returns of the Shanghai / Shenzhen Composite Stock Indices as market returns, the beta coefficient for Chinese art is negative, albeit insignificant. This is in line with our expectation that Chinese art is largely uncorrelated with the stock markets. In addition, the downside beta assesses the extent to which art returns are correlated with the downside of the market and finds that Chinese art can act as a hedge against declines in the domestic stock market when included in a diversified portfolio.

To investigate the diversification benefits of including Chinese art in a portfolio, mean-variance portfolio optimization (MVPO) and simple power utility optimization are used. The findings show that the efficient frontier with Chinese art outperforms the efficient frontier without Chinese art, suggesting that the inclusion of Chinese art leads to higher returns for a given level of risk or lower risk for a given level of return. In addition, the inclusion of Chinese art improves the overall utility of the portfolio regardless of the level of risk aversion. However, as the level of risk aversion increases, the weight of Chinese art decreases, suggesting that the benefits of including Chinese art in a well-diversified portfolio may be somewhat limited.

Furthermore, the superiority of portfolios containing Chinese art is corroborated by the two supplementary tests. Specifically, portfolios with Chinese art that are situated on the efficient frontier consistently outperform their equal-weighted counterparts, as evidenced by higher Sharpe ratios and modified Sharpe ratios; during times when the domestic stock market lags, the portfolios on the efficient frontier that includes Chinese art demonstrate a more effective return-risk profile compared to those that do not, as indicated by superior Sharpe ratios and modified Sharpe ratios. However, it is worth noting that during periods characterized by a decline in average asset returns, the modified Sharpe ratios appear to have a contrasting trend.

This study provides investors with valuable perspective on the advantages of adding Chinese art to their portfolios for portfolio diversification. Investing in Chinese art can lead to higher risk-adjusted returns, thereby improving their overall investment performance. Building on the findings, there is a ripe opportunity for financial institutions to develop their product offering. One effective route is the development of specialized art-investment financial products or wealth management services. However, it is imperative for investors to acknowledge the unique set of challenges and costs that come with investing in art. While art provides substantial benefits, it is essential that investors remain fully aware of any additional costs that may be incurred.

There are many interesting opportunities to build upon this essay by applying well-established financial analysis tools to the art market. One potential avenue is to follow Ginsburg and Jeanfils (1995), Chanel (1995), and Czujack et al. (1996) in investigating the short-term and long-term relationships between art and financial markets. While a few studies have investigated the wealth effect link between stock and art markets, suggesting that surges in the stock market led to booms in art markets (see, for example, Goetzmann, 1993; Chanel, 1995), the exact strength and persistence of this causal relationship remains less well understood. Another avenue for this essay is to examine the arbitrage opportunities that exist between different geographic markets. By exploring these opportunities, investors can gain greater empirical certainty about the global efficiency of art markets. Understanding the dynamics of arbitrage between different art markets can help identify inefficiencies and investment opportunities for market participants, leading to better-informed decisions and improved market outcomes.

5.3. Essay 3

In the realm of the art market, the provision of accurate pre-sale price estimates is crucial, as they offer a forecast of the sale price of an artwork. Auctioneers bear an ethical responsibility to provide truthful information about the items on auction, which can mitigate uncertainty about the price estimations, encourage lower bidders to be more assertive, and subsequently exert upward

pressure on other bidders' bids, aligning with the auctioneer's interests (Ashenfelter, 1989). However, experts' pre-sale estimates may be biased either downwards or upwards. It is therefore essential to examine the impact of specific factors on the informational content of pre-sale estimates in terms of accuracy and uncertainty to refine the valuation process within the art market.

The third essay seeks to investigate the influence of specific factors on the informational content of pre-sale estimates in terms of accuracy and uncertainty in predicting hammer prices in the Chinese art market. This investigation uses an extensive and comprehensive dataset of 191,102 sold lots of Chinese art created by 533 artists over a 21-year period, ranging from January 2000 to December 2021. Descriptive statistical analysis reveals that the Chinese art market undervalues art. This finding is supported by Bauwens and Ginsburgh (2000), Teti et al. (2014), and D'Souza and Prentice (2002). Auction houses may benefit from a conservative forecasting strategy to balance the expectations of both owner and bidder, thereby increasing the chances of a successful sale. However, this finding contradicts Ashenfelter's (1989) claim about an auctioneer's "genuine expertise in price prediction" and contradicts Milgrom and Weber's (1982) assertion that "honesty is the best policy".

To examine the impact of specific factors on the accuracy and uncertainty of pre-sale estimates, the findings reveal that the artist's mentorship experience, the proof of authenticity, the large-scale auction months, and past-sale records can either improve or reduce the accuracy and uncertainty of pre-sale estimates in predicting the hammer prices. Moreover, the impact of these factors varies across the different price distributions. The findings show that auctioneers could leverage additional public information (e.g., mentorship, exhibition, literature, and past-sale records) to improve the accuracy of pre-sale estimates for masterpieces; however, these factors lose efficiency in reducing the uncertainty of pre-sale estimates for masterpieces due to their rarity and strategic pricing. Furthermore, the auction houses with artist-specific experience are more likely to offer precise pre-sale estimates. This observation is consistent with Bruno et al. (2018), who conclude that experienced auction houses attain superior auction outcomes by employing various auction strategies,

such as adjusting starting bid prices, controlling the pace of price adjustments, or placing deceptive ‘off-the-wall’ bids that may influence final realized prices and provide accurate pre-sale estimates. However, experienced auction houses may not be optimistic about reducing the uncertainty of pre-sale estimates, as they use their market expertise to negotiate with overly optimistic sellers and lower reserve prices to align with market expectations. This strategy increases demand but results in a wider gap between low and high estimates.

Drawing upon the findings of this study, the implications are manifold, affecting auction houses, art collectors, and academics. The findings suggest that by enhancing the accuracy and certainty of pre-sale estimates, the efficiency and transparency of the art market can be improved, thereby fostering greater trust between auction houses and investors. By recognizing the factors that influence the accuracy and uncertainty of pre-sale estimates into their valuation methodologies and incorporating them into their valuation methodologies, auction houses can refine their pricing strategies, ultimately leading to a more robust and dynamic art market that benefits all participants. Furthermore, emphasizing the importance of artist-specific experience underscores the value of specialized knowledge and expertise within the auction industry that can inform the development of optimal practices for both established and emerging art markets.

References

- Agnello, R. J. (2002). Investment returns and risk for art: Evidence from auctions of American paintings. *Eastern Economic Journal*, 28(4), 443-463.
- Agnello, R. J., & Pierce, R. K. (1996). Financial returns, price determinants, and genre effects in American art investment. *Journal of Cultural Economics*, 20(4), 359-383.
- Alexander, G. J., & Baptista, A. M. (2003). Portfolio performance evaluation using value at risk. *The Journal of Portfolio Management*, 29(4), 93-102.
- Anderson, R. C. (1974). Paintings as an investment. *Economic Inquiry*, 12(1), 13-26.
<https://doi.org/10.1111/j.1465-7295.1974.tb00223.x>
- Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *Review of Financial Studies*, 19(4), 1191-1239.
- Artprice. (2017). *Artprice's annual report on the global art market in 2016*.
<https://www.artprice.com/artprice-reports/the-art-market-in-2016>
- Artprice. (2018). *Artprice's annual report on the global art market in 2017*.
<https://www.artprice.com/artprice-reports/the-art-market-in-2017/the-art-market-in-2017>
- Artprice. (2019). *Beijing: market transformation and art Beijing's strategy*.
<https://www.artprice.com/artmarketinsight/beijing-market-transformation-and-art-beijings-strategy>
- Artprice. (2021). *Artprice 2020 art market report*. <https://www.artprice.com/artprice-reports/the-art-market-in-2020>
- Ashenfelter, O. (1989). How auctions work for wine and art. *Journal of Economic Perspectives*, 3(3), 23-36.
- Ashenfelter, O., & Graddy, K. (2003). Auctions and the price of art. *Journal of Economic Literature*, 41(3), 763-787.

- Ashenfelter, O., Graddy, K., & Stevens, M. (2003). *A study of sale rates and prices in impressionist and contemporary art auctions*. Unpublished manuscript. Economic Department. University of Oxford.
- Assaf, A. (2018). Testing for bubbles in the art markets: An empirical investigation. *Economic Modelling*, 68, 340-355.
- Atukeren, E., & Seçkin, A. (2007). On the valuation of psychic returns to art market investments. *Economics Bulletin*, 26(5), 1-12.
- Aubry, M., Kraeussl, R., Manso, G., & Spaenjers, C. (2023). Biased auctioneers. *The Journal of Finance*, 78(2), 795-833. <https://doi.org/https://doi.org/10.1111/jofi.13203>
- Aytaç, B., Hoang, T.-H.-V., & Mandou, C. (2016). Wine: To drink or invest in? A study of wine as an investment asset in French portfolios. *Research in International Business and Finance*, 36, 591-614. <https://doi.org/10.1016/j.ribaf.2015.03.001>
- Bai, Z., Liu, H., & Wong, W. K. (2009). Enhancement of the applicability of Markowitz's portfolio optimization by utilizing random matrix theory. *Mathematical Finance: An International Journal of Mathematics, Statistics and Financial Economics*, 19(4), 639-667
- Barnes, S., Mendez, B., & Schrowang, A. (2023). Analysts' accuracy following information shocks: Evidence from the art market. (Working paper). <http://dx.doi.org/10.2139/ssrn.4337085>
- Bassett, G. W., Tam, M. Y., & Knight, K. (2002). Quantile models and estimators for data analysis. *Metrika: International Journal for Theoretical and Applied Statistics*, 55(1-2), 17. <https://doi.org/10.1007/s001840200183>
- Baumol, W. J. (1986). Unnatural value: Or art investment as floating crap game. *The American Economic Review*, 76(2), 10-14.
- Bauwens, L., & Ginsburgh, V. (2000). Art experts and auctions are pre-sale estimates unbiased and fully informative? *Recherches Économiques de Louvain/ Louvain Economic Review*, 66(2), 131-144.

- Bawa, V. S., & Lindenberg, E. B. (1977). Capital market equilibrium in a mean-lower partial moment framework. *Journal of Financial Economics*, 5(2), 189-200.
- Beggs, A., & Graddy, K. (2009). Anchoring effects: Evidence from art auctions. *The American Economic Review*, 99(3), 1027-1039.
- Bernales, A., Reus, L., & Valdenegro, V. (2020). Speculative bubbles under supply constraints, background risk and investment fraud in the art market. *Journal of Corporate Finance*. <https://doi.org/10.1016/j.jcorpfin.2020.101746>
- Bian, T. Y., Huang, J., Zhe, S., & Zhang, M. (2021). Anchoring effects in the Chinese art market. *Finance Research Letters*, 43, 102050. <https://doi.org/10.1016/j.frl.2021.102050>
- Blume, M. E. (1984). The use of “alphas” to improve performance. *The Journal of Portfolio Management*, 11(1), 86-92.
- Bruno, B., Garcia-Appendini, E., & Nocera, G. (2018). Experience and brokerage in asset markets: Evidence from art auctions. *Financial Management*, 47(4), 833-864. <https://doi.org/10.1111/fima.12207>
- Bruno, B., & Nocera, G. (2008). Investing in art: The informational content of Italian painting pre-sale estimates. (SSRN, 1179183). <https://dx.doi.org/10.2139/ssrn.1179183>
- Buelens, N., & Ginsburgh, V. (1993). Revisiting Baumol’s “Art as Floating Crap Game.” *European Economic Review*, 37(7), 1351–1371. [https://doi.org/10.1016/0014-2921\(93\)90060-N](https://doi.org/10.1016/0014-2921(93)90060-N)
- Cahill, J., & Silbergeld, J. (2001). Chinese art and authenticity. *Bulletin of the American Academy of Arts and Sciences*, 55(1), 17-36. <https://doi.org/10.2307/3824253>
- Campbell, R. (2004). *The art of portfolio diversification*. (Limburg Institute of Financial Economics Working Paper 04-009). Maastricht University.
- Campbell, R. (2008). Art as a financial investment. *The Journal of Alternative Investments*, 10(4), 64-81.

- Campos, N. F., & Barbosa, R. L. (2008). Paintings and numbers: an econometric investigation of sales rates, prices, and returns in Latin American art auctions. *Oxford Economic Papers*, 61(1), 28-51.
- Candela, G., & Scorcu, A. E. (1997). A price index for art market auctions. *Journal of Cultural Economics*, 21(3), 175-196.
- Cardell, N. S., Kling, J. L., & Petry, G. (1995). Stamp returns and economic factors. *Southern Economic Journal*, 62(2), 411-427.
- Case, K. E., & Shiller, R. J. (1987). Prices of single family homes since 1970: New indexes for four cities. *New England Economic Review* Sept/Oct, 45-56.
- Chanel, O. (1995). Is art market behaviour predictable? *European Economic Review*, 39(3-4), 519-527.
- Chanel, O., Gérard-Varet, L.-A., & Ginsburgh, V. (1996). The relevance of hedonic price indices. *Journal of Cultural Economics*, 20(1), 1-24.
- China Banking News. (2019). China now home to world's second largest number of wealthy individuals at 2.3 million in total. <https://www.chinabankingnews.com/2019/11/03/china-now-home-to-worlds-second-largest-number-of-wealthy-individuals/>
- Collins, A., Scorcu, A., & Zanola, R. (2009). Reconsidering hedonic art price indexes. *Economics Letters*, 104(2), 57-60. <https://doi.org/10.1016/j.econlet.2009.03.025>
- Cooper, R. (2013, April 9). Christie's gets go-ahead to sell art in China. *The Telegraph*. <https://www.telegraph.co.uk/finance/newsbysector/retailandconsumer/9981568/Christies-gets-go-ahead-to-sell-art-in-China.html>
- Czujack, C. (1997). Picasso paintings at auction, 1963–1994. *Journal of Cultural Economics*, 21(3), 229-247.

- Czujack, C., Flôres, R., & Ginsburgh, V. (1996). On long-run price comovements between paintings and prints. In V. A. Ginsburgh & P. M. Menger (Eds.), *Economics of the arts: Selected essays* (pp. 85–112). Elsevier.
- Czujack, C., & Martins, M. F. O. (2004). Do art specialists form unbiased pre-sale estimates? An application for Picasso paintings. *Applied Economics Letters*, 11(4), 245-249. <https://doi.org/10.1080/13504850410001674894>
- Deloitte Private and ArtTactic. (2022). *Art & finance report 2021*. <https://www2.deloitte.com/lu/en/pages/art-finance/articles/art-finance-report.html>
- DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, 22(5), 1915-1953.
- Demir, E., Gozgor, G., & Sari, E. (2018). Dynamics of the Turkish paintings market: A comprehensive empirical study. *Emerging Markets Review*, 36, 180-194.
- Dimson, E., & Spaenjers, C. (2011). Ex post: The investment performance of collectible stamps. *Journal of Financial Economics*, 100(2), 443-458.
- Ding, J. (2008). Painting and calligraphy album: “blue chip stock” with value investment. *Board of Directors* (04), 114–115.
- D’Souza, C., & Prentice, D. (2002). Auctioneer strategy and pricing: evidence from an art auction. *Marketing Intelligence & Planning*, 20(7), 417-427.
- Ekelund, R. B., Jackson, J. D., & Tollison, R. D. (2013). Are art auction estimates biased? *Southern Economic Journal*, 80(2), 454-465. <https://doi.org/10.4284/0038-4038-2012.087>
- Ekelund, R. B., Ressler, R. W., & Watson, J. K. (1998). Estimates, bias and “no sales” in Latin-American art auctions, 1977–1996. *Journal of Cultural Economics*, 22(1), 33-42. <https://doi.org/10.1023/A:1007471016277>
- Elton, E. J., Gruber, M. J., & Rentzler, J. C. (1987). Professionally managed, publicly traded commodity funds. *Journal of Business*, 175-199.

- Fabozzi, F. J., Markowitz, H. M., & Gupta, F. (2008). Portfolio selection. In F. J. Fabozzi (Ed.), *Handbook of finance* (vol II, pp. 3–13). Wiley.
<https://doi.org/10.1002/9780470404324.hof002001>
- Fan, Z., Zhang, K., & Zheng, X. S. (2019). Evaluation and analysis of white space in Wu Guanzhong's Chinese paintings. *Leonardo*, 52(2), 111-117.
- Favre, L., & Galeano, J.-A. (2002). Mean-modified value-at-risk optimization with hedge funds. *The Journal of Alternative Investments*, 5(2), 21-25.
- Fedderke, J. W., & Li, K. (2019). Art in Africa: Hedonic price analysis of the South African fine art auction market, 2009–2014. *Economic Modelling*.
- Felton, M. (1998). Review of: economics of the arts: selected essays. *Journal of Economic Literature*, 36(1), 286-287.
- Flôres, R. G., Ginsburgh, V., & Jeanfils, P. (1999). Long-and short-term portfolio choices of paintings. *Journal of Cultural Economics*, 23(3), 191-208. <https://doi.org/10.1023/A:1007515710962>
- Fogarty, J. J. (2010). Wine investment and portfolio diversification gains. *Journal of Wine Economics*, 5(1), 119–131. <https://doi.org/10.1017/S1931436100001401>
- Fogarty, J. J., & Jones, C. (2011). Return to wine: A comparison of the hedonic, repeat sales and hybrid approaches. *Australian Economic Papers*, 50(4), 147-156.
<https://doi.org/10.1111/j.1467-8454.2011.00416.x>
- Fogarty, J. J., & Sadler, R. (2014). To save or savor: A review of approaches for measuring wine as an investment. *Journal of Wine Economics*, 9(3), 225–248.
<https://doi.org/10.1017/jwe.2014.27>
- Forster, J., & Higgs, H. (2018). Artwork characteristics and prices in the New Zealand secondary art market, 1988–2011. *New Zealand Economic Papers*, 52(2), 150-169.

- Frey, B. S., & Eichenberger, R. (1995). On the rate of return in the art market: Survey and evaluation. *European Economic Review*, 39(3/4), 528–537. [https://doi.org/10.1016/0014-2921\(94\)00059-9](https://doi.org/10.1016/0014-2921(94)00059-9)
- Frey, B. S., & Pommerehne, W. W. (1988). Is art such a good investment? *Public Interest*, 91, 79.
- 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>
- Ginsburgh, V., & Jeanfils, P. (1995). Long-term comovements in international markets for paintings. *European Economic Review*, 39(3-4), 538-548.
- Goetzmann, W. N. (1992). The accuracy of real estate indices: Repeat sale estimators. *The Journal of Real Estate Finance and Economics*, 5(1), 5–53.
- Goetzmann, W. N. (1993). Accounting for taste: Art and the financial markets over three centuries. *The American Economic Review*, 83(5), 1370–1376.
- Goetzmann, W. N. (1996). How costly is the fall from fashion? Survivorship bias in the painting market. *Contributions to Economic Analysis*, 237, 71–84.
- Graddy, K., & Margolis, P. E. (2011). Fiddling with value: violins as an investment? *Economic Inquiry*, 49(4), 1083–1097.
- Gregoriou, G. N., & Gueyie, J.-P. (2003). Risk-adjusted performance of funds of hedge funds using a modified Sharpe ratio. *The Journal of Wealth Management*, 6(3), 77-83.
- Higgs, H. (2012). Australian art market prices during the global financial crisis and two earlier decades. *Australian Economic Papers*, 51(4), 189-209. <https://doi.org/10.1111/1467-8454.12001>
- Higgs, H., & Worthington, A. (2005). Financial returns and price determinants in the Australian art market, 1973-2003. *Economic record*, 81(253), 113-123.

- Hoang, T.-H.-V., Wong, W.-K., & Zhu, Z. (2015). Is gold different for risk-averse and risk-seeking investors? An empirical analysis of the Shanghai Gold Exchange. *Economic Modelling*, 50, 200-211. <https://doi.org/10.1016/j.econmod.2015.06.021>
- Hodgson, D. J., & Vorkink, K. P. (2004). Asset pricing theory and the valuation of Canadian paintings. *Canadian Journal of Economics*, 37(3), 629–655.
- Huang, J., & Li, Y. (2019). Chinese art as an investment: Characteristics and interactions in offshore and onshore markets. *Journal of Financial Research*, 468((6): 188-206.
- Khwaja, A. I., & Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4), 1413-1442.
- Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives*, 15(4), 143-156.
- Koumou, G. B. (2020). Diversification and portfolio theory: a review. *Financial Markets and Portfolio Management*, 34(3), 267-312.
- Kourtis, A., Markellos, R. N., & Psychoyios, D. (2012). Wine price risk management: International diversification and derivative instruments. *International Review of Financial Analysis*, 22, 30-37.
- Kraeussl, R., & Lee, J. (2010). *Art as an investment: The top 500 artists*. (Working paper). Department of Finance. VU University Amsterdam.
- Kraeussl, R., & Logher, R. (2010). Emerging art markets. *Emerging Markets Review*, 11(4), 301-318.
- Kräussl, R. (2015). Art as an alternative asset class: Risk and return characteristics of the Middle Eastern and Northern African art markets. In O. Velthuis & S. Baia Curioni (Eds.), *Cosmopolitan canvases: The globalization of markets for contemporary art* (pp. 147–169). Oxford Academic.

- Kräussl, R., & van Elsland, N. (2008). *Constructing the true art market index: A novel 2-step hedonic approach and its application to the German art market*. (CFS Working Paper No. 2008/11). Center for Financial Studies Frankfurt University.
- Lacetera, N., Larsen, B. J., Pope, D. G., & Sydnor, J. R. (2016). Bid takers or market makers? The effect of auctioneers on auction outcome. *American Economic Journal: Microeconomics*, 8(4), 195-229.
- Laur, D., & Renneboog, L. (2019). My kingdom for a horse (or a classic car). *Journal of International Financial Markets, Institutions and Money*, 58, 184-207. <https://doi.org/10.1016/j.intfin.2018.10.002>
- Leibenstein, H. (1950). Bandwagon, snob, and veblen effects in the theory of consumers' demand. *The quarterly journal of economics*, 64(2), 183-207.
- Leung, P.-L., Ng, H.-Y., & Wong, W.-K. (2012). An improved estimation to make Markowitz's portfolio optimization theory users friendly and estimation accurate with application on the US stock market investment. *European Journal of Operational Research*, 222(1), 85-95.
- Li, J., & Fischer, K. W. (2007). Respect as a positive self-conscious emotion in European Americans and Chinese. In J. L. Tracy, R. W. Robins, & J. Price Tangney (Eds.), *The self-conscious emotions: Theory and research* (pp. 224–242). Guilford Press.
- Li, Y., Ma, M. X., & Renneboog, L. (2021). Pricing art and the art of pricing: On returns and risk in art auction markets. *European Financial Management*.
- Louargand, M. A., & McDaniel, J. R. (1991). Price efficiency in the art auction market. *Journal of Cultural Economics*, 15(2), 53-65.
- Lucey, B. M., & Devine, L. (2015). Was wine a premier cru investment? *Research in International Business and Finance*, 34, 33-51. <https://doi.org/10.1016/j.ribaf.2014.09.003>
- Malpezzi, S. (2003). Hedonic pricing models: a selective and applied review. *Housing economics and public policy*, 1, 67-89.

- Mandel, B. R. (2009). Art as an investment and conspicuous consumption good. *American Economic Review*, 99(4), 1653-1663.
- Marinelli, N., & Palomba, G. (2011). A model for pricing Italian contemporary art paintings at auction. *The Quarterly Review of Economics and Finance*, 51(2), 212-224.
<https://doi.org/10.1016/j.qref.2011.02.001>
- Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77-91.
<https://doi.org/10.1111/j.1540-6261.1952.tb01525.x>
- Masset, P., & Weisskopf, J.-P. (2018). Raise your glass: Wine investment and the financial crisis. In *World scientific reference on handbook of the economics of wine: Volume 1: Prices, finance, and expert opinion* (pp. 271–295). World Scientific.
- Masset, P., Weisskopf, J.-P., Faye, B., & Le Fur, E. (2016). Red obsession: The ascent of fine wine in China. *Emerging Markets Review*, 29, 200-225.
- McAndrew, C. (2010a). *The International Art Market 2007 - 2009 : Trends in the Art trade during Global Recession*. Helvoirt: The European Fine Art Foundation.
- McAndrew, C. (2019). *The Art Basel and UBS global art market report 2018*.
https://d2u3kfwd92fzu7.cloudfront.net/Art%20Basel%20and%20UBS_The%20Art%20Market_2018-1.pdf
- McAndrew, C. (2022a). *The Art Basel and UBS global art market report 2022*. Retrieved from
<https://d2u3kfwd92fzu7.cloudfront.net/Art%20Market%202022.pdf>
- McAndrew, C. (2022b). *A survey of global collecting in 2022*. Retrieved from
https://d2u3kfwd92fzu7.cloudfront.net/A_Survey_of_Global_Collecting_in_2022.pdf
- McAndrew, C. (Ed.) (2010b). *Fine art and high finance: Expert advice on the economics of ownership*. New York: Bloomberg Press.
- McAndrew, C., Smith, J. L., & Thompson, R. (2012). The impact of reserve prices on the perceived bias of expert appraisals of fine art. *Journal of Applied Econometrics*, 27(2), 235-252.
<https://doi.org/10.1002/jae.1188>

- McAndrew, C., & Thompson, R. (2003). *Pre-sale estimates, risk analysis, and the investment quality of fine art*. (Working paper).
- Mei, J., & Moses, M. (2002). Art as an investment and the underperformance of masterpieces. *American Economic Review*, 92(5), 1656-1668.
- Mei, J., & Moses, M. (2005). Vested interest and biased price estimates: Evidence from an auction market. *The Journal of Finance*, 60(5), 2409–2435.
- Milgrom, P. R., & Weber, R. J. (1982). A theory of auctions and competitive bidding. *Econometrica*, 50(5), 1089-1122.
- Mok, H. M. K., Ko, V. W. K., Woo, S. S. M., & Kwok, K. Y. S. (1993). Modern Chinese paintings: An investment alternative? *Southern Economic Journal*, 59(4), 808-816.
- Nozari, M. (2022). Investment horizon for private-value assets: Evidence from the art market. *Journal of Financial Research*, 45(2), 229-246. <https://doi.org/10.1111/jfir.12273>
- Park, H., Ju, L., Liang, T., & Tu, Z. (2017). Horizon analysis of art investments: Evidence from the Chinese market. *Pacific-Basin Finance Journal*, 41, 17-25. <https://doi.org/10.1016/j.pacfin.2016.11.001>
- Penasse, J., & Renneboog, L. (2022). Speculative trading and bubbles: Evidence from the art market. *Management Science*, 68(7), 4939-4963.
- Pesando, J. E. (1993). Art as an investment: The market for modern prints. *The American Economic Review*, 83(5), 1075-1089.
- Pesando, J. E., & Shum, P. M. (1999). The returns to Picasso's prints and to traditional financial assets, 1977 to 1996. *Journal of Cultural Economics*, 23(3), 181-190.
- Renneboog, L., & Spaenjers, C. (2012). Hard assets: The returns on rare diamonds and gems. *Finance Research Letters*, 9(4), 220-230.
- Renneboog, L., & Spaenjers, C. (2013). Buying beauty: On prices and returns in the art market. *Management Science*, 59(1), 36-53.

- Renneboog, L., & Van Houtte, T. (2002). The monetary appreciation of paintings: From realism to Magritte. *Cambridge Journal of Economics*, 26(3), 331-358.
- Sanning, L. W., Shaffer, S., & Sharratt, J. M. (2008). Bordeaux wine as a financial investment. *Journal of Wine Economics*, 3(1), 51–71. <https://doi.org/10.1017/S1931436100000559>
- Seçkin, A., & Atukeren, E. (2009). Investment characteristics of the market for paintings in Turkey: 1990-2005. *Investment Management and Financial Innovations*, 6(2), 7-14.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425-442.
- Shi, Y., Conroy, P., Wang, M., & Dang, C. (2018). The investment performance of art in mainland China. *Emerging Markets Finance and Trade*, 54(6), 1358–1374. <https://doi.org/10.1080/1540496X.2017.1281800>
- Shi, Y., Wang, M., Conroy, P., & Xu, H. (2017). Home bias in domestic art markets: Evidence from China. *Economics Letters*, 159, 201–203. <https://doi.org/10.1016/j.econlet.2017.08.015>
- Sotheby's Institute of Art. (n.d.). Auction terminology: A glossary. <https://www.sothebysinstitute.com/news-and-events/news/auction-terminology>
- Sproule, R., & Valsan, C. (2006). Hedonic models and pre-auction estimates: Abstract art revisited. *Economics Bulletin*, 26(5), 1-10.
- Taylor, D., & Coleman, L. (2011). Price determinants of Aboriginal art, and its role as an alternative asset class. *Journal of Banking & Finance*, 35(6), 1519-1529. <https://doi.org/10.1016/j.jbankfin.2010.10.027>
- Teti, E., Galli, T. C., & Sacco, P. L. (2014). Ephemeral estimation of the value of art. *Empirical Studies of the Arts*, 32(1), 75-92.
- The European Fine Art Foundation (TEFAF). (2012). *The international art market in 2011: Observations on the art trade over 25 years*. <https://tbamf.org.uk/portfolio/tefaf-art-market->

[report-2012-the-international-art-market-in-2011-observations-on-the-art-trade-over-25-years/](#)

- Triplett, J. (2004). Handbook on Hedonic indexes and quality adjustments in price indexes: Special application to information technology products. (STI Working Paper 2004/9), Directorate for Science, Technology and Industry, Organization for Economic Co-operation and Development, Paris.
- Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, 185(4157), 1124-1131.
- Ursprung, H. W., & Wiermann, C. (2011). Reputation, price, and death: An empirical analysis of art price formation. *Economic Inquiry*, 49(3), 697-715.
- Veld, C., & Veld-Merkoulova, Y. V. (2007). Portfolio diversification benefits of investing in stamps. *The Journal of Alternative Investments*, 10(1), 56-61.
- Vincent, D. R. (1995). Bidding off the wall: Why reserve prices may be kept secret. *Journal of Economic theory*, 65(2), 575-584.
- Wang, F. (2017). Which part of the Chinese art market is more worth investing in? Applying the quantile regression to analyze Chinese oil paintings 2000–2014. *Emerging Markets Finance and Trade*, 53(1), 44-53.
- Wang, F., & Zheng, X. (2017). Performance analysis of investing in Chinese oil paintings based on a hedonic regression model of price index. *China Finance Review International*, 7(3), 323-342. <https://doi.org/10.1108/CFRI-03-2016-0009>
- Worthington, A. C., & Higgs, H. (2004). Art as an investment: risk, return and portfolio diversification in major painting markets. *Accounting & Finance*, 44(2), 257-271. <https://doi.org/10.1111/j.1467-629X.2004.00108.x>
- Wu, K. (2019). *Chinese art market report 2019*. <https://2019.amr.tefaf.com/>

Zou, L., De Bruin, A., Wu, J., & Yuan, Y. (2021). Art for art's sake? An exploration of the Chinese art market. *Applied Economics*, 53(47), 5429-5447.

Appendices

Appendix 1 Summary Description of Hedonic Variables

Variables	Description
Art Movement	
Ancient	Ancient period is described as the artist who died before 1911 or was born before 1840
Modern	Modern period is defined as the artist who was born after 1840 or died before 2000
Contemporary	Contemporary period is expressed as the non-deceased artists or the artists who died after 2000
Artist characteristics	
Deceased	A dummy variable is equal to 1 if an artist is deceased at the time of the auction, 0 otherwise
Mentorship	A dummy variable is equal to 1 if an artist has learned from the mentor, 0 otherwise
Work characteristics	
Authenticity dummies	
Signature	A dummy variable is equal to 1 if the artwork has the signature of the artist, 0 otherwise
Timestamp	A dummy variable is equal to 1 if the artwork has a record of the creation time, 0 otherwise
Exhibition	A dummy variable is equal to 1 if the artwork has a record of being exhibited, 0 otherwise
Literature	A dummy variable is equal to 1 if the artwork has a citation in literature, 0 otherwise
Provenance	A dummy variable is equal to 1 if the artwork has a record of provenance, 0 otherwise
Inscription	A dummy variable is equal to 1 if the artwork has the inscription from the celebrity, 0 otherwise
Mounting dummies	
Albums	A dummy variable is equal to 1 if the artwork is mounted in the type of albums, 0 otherwise
Fans	A dummy variable is equal to 1 if the artwork is mounted in the type of fan-shape, 0 otherwise
Folding screen	A dummy variable is equal to 1 if the artwork is mounted in the type of folding screen, 0 otherwise
Handscroll	A dummy variable is equal to 1 if the artwork is mounted in the type of handscroll, 0 otherwise
Heng fu	A dummy variable is equal to 1 if the artwork is mounted in the type of heng fu, 0 otherwise
Hua xin	A dummy variable is equal to 1 if the artwork is mounted in the type of hua xin, 0 otherwise
Jing kuang	A dummy variable is equal to 1 if the artwork is mounted in the type of jing kuang, 0 otherwise
Jing pian	A dummy variable is equal to 1 if the artwork is mounted in the type of jing pian, 0 otherwise
Jing xin	A dummy variable is equal to 1 if the artwork is mounted in the type of jing xin, 0 otherwise
Standing scroll	A dummy variable is equal to 1 if the artwork is mounted in the type of standing scroll, 0 otherwise
Vertical scroll	A dummy variable is equal to 1 if the artwork is mounted in the type of vertical scroll, 0 otherwise

Appendix 2 Summary Descriptive of Auction Houses

Appendix 2 presents the ranking results by sorting auction houses based on turnover, including the number of observations, the turnover of auction houses, and the mean price. The top 10 auction houses in terms of turnover are selected for the hedonic regression, and other auction houses served as the reference.

N	Auction Houses	Number of observations	Turnover (000,000)	Mean (000)
1	China Guardian	38,486	4,688	122
2	Beijing Poly	20,806	4,124	198
3	Council	8,638	1,788	207
4	Christie's (HK)	8,368	1,613	193
5	Han hai Auction	18,689	1,449	78
6	Sotheby's (HK)	5,565	1,336	240
7	Xiling Yinshe Auction	7,583	945	125
8	Beijing Rongbao	12,380	861	70
9	Sungari International Auction	8,419	765	91
10	Duo yun xuan	8,052	676	84
11	Holly's International Auction	5,330	538	101
12	SH Tianheng	1,929	459	238
13	Tranthy's	1,576	403	256
14	Chengxuan	4,225	390	92
15	Huachen Auctions	4,706	266	57
16	Beijing Chieftown Auction	1,455	199	137
17	Sotheby's (NY)	825	142	172
18	Hong Kong Poly	98	75	763
19	Forever international auction	1,274	71	56
20	Nanjing Classic Auction	891	69	78
21	Shanghai Jiahe Auction	353	61	173
22	Jinghua Auction	1,455	57	39
23	Shanghai Chong yuan Arts Auction	1,950	54	28
24	Beijing Googut Auction	564	44	77
25	Duton's	384	38	99
26	Henan Jindi Auction	442	37	84
27	Canton Treasure Auction	209	23	109
28	Dowmin Auctions	191	21	111
29	ShangHai Johhan Auction	421	13	32
30	Sotheby's (London)	108	12	113
31	Christie's (NK)	153	10	66
32	Rong bao zhai (SH) Auction	72	8	109
33	Zhong yuan Auction	111	5	43
34	Christie's (London)	78	5	59
35	Tongfang Auction	60	3	46
36	Christie's (SH)	1	0.4	432

Appendix 3 Baseline Art-Price Index and Return

Following Renneboog and Spaenjers (2013), the antilog of the estimates of γ_t from Equation (1) is used to construct an art-price index that controls for time variation in the quality of the art sold. The value of the hedonic index in year t is as the following with the time-dummy coefficient set equal to 0 for the initial period:

$$\Pi_t = \exp(\hat{\gamma}_t) \times 100 \quad (1)$$

This gives an estimated return in year t as the following:

$$r_t = \frac{\Pi_t}{\Pi_{t-1}} - 1 \quad (2)$$

This study also uses the following corrected index estimation if there is time variation in the distribution of prices, as suggested by Silver and Heravi (2007) and Triplett (2004):

$$\Pi_{t^*} = \exp\left[\hat{\gamma}_t + \frac{1}{2}(\hat{\sigma}_t^2 - \hat{\sigma}_0^2)\right] \times 100 \quad (3)$$

where $\hat{\sigma}_t^2$ and $\hat{\sigma}_0^2$ are the estimated variances of the residuals of observations in periods 0 and t, respectively.

The corrected return estimate on year t can be defined as:

$$r_t^* = \frac{\Pi_{t^*}}{\Pi_{t-1}^*} - 1 \quad (4)$$

Appendix 4 CAPM Model With Time-Varying Alpha and Beta

Appendix 4 shows the results of the CAPM model with time-varying alpha and beta, reporting the coefficient parameters of alpha and beta as well as R square. The data are divided into 32 sub-periods. The three-year rolling regression is formed by moving windows every 36 months. The data overlaps from the current sub-periods to previous sub-periods. The top of Appendix A shows the results of CAPM model when the return of the Shanghai Composite Stock Index (SSE) is used as a market return. The middle section of Appendix A exhibits the results of the CAPM model when the return of the Shenzhen composite stock index (SZSE) is taken as the market return. The bottom of the appendix displays the results of the CAPM model when the average return on each asset is considered a market return. The 6-month deposit rate in China represents the risk-free rate. *, **, and *** significance at the 10%, 5%, and 1% confidence levels, respectively.

		SSE is used as a market return														
		Chinese art			SZSE			Gold			Govt. Bonds			Corp. Bonds		
		Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²
31/12/2003	30/06/2006	0.212**	-1.029**	74.75%	-0.011	1.198***	97.56%	0.073	0.279	26.13%	0.003	-0.061	4.97%	0.012	-0.105	7.04%
30/06/2004	31/12/2006	0.208**	-0.897**	81.16%	-0.021	0.842***	84.45%	0.040	0.112	10.78%	0.012	-0.038	4.20%	0.027	-0.085	11.00%
31/12/2004	30/06/2007	0.165**	-0.706***	86.72%	0.009	1.057**	71.46%	0.060	-0.007	0.06%	0.030	-0.104	48.71%	0.050	-0.159	47.80%
30/06/2005	31/12/2007	0.219**	-0.713**	66.54%	0.012	1.019*	64.17%	0.050	0.091	5.60%	0.047**	-0.153**	78.15%	0.075**	-0.264**	77.46%
31/12/2005	30/06/2008	0.012	-0.063	2.72%	0.037	0.955**	83.90%	0.077	0.028	2.24%	0.000	-0.013	10.04%	0.004	-0.048	22.58%
30/06/2006	31/12/2008	-0.045	0.008	0.06%	0.042	0.959***	87.36%	0.040	0.090	19.50%	0.006	-0.035	33.21%	0.010	-0.082	47.74%
31/12/2006	30/06/2009	0.010	0.115	13.95%	0.041	0.962***	88.22%	0.030	0.074	16.73%	0.006	-0.035	34.79%	0.013	-0.074	42.50%
30/06/2007	31/12/2009	0.066	0.213*	54.47%	0.095	1.072***	95.12%	0.058	0.099	19.41%	0.003	-0.041	41.77%	0.006	-0.084	45.73%
31/12/2007	30/06/2010	0.135*	0.196	31.03%	0.055*	0.987***	98.89%	0.089*	0.134	38.13%	0.007	-0.033	35.22%	0.009	-0.085	44.83%
30/06/2008	31/12/2010	0.140*	0.202	29.78%	0.092***	1.052***	99.36%	0.073*	0.104	28.26%	0.006	-0.034	33.22%	0.020	-0.063	37.22%
31/12/2008	30/06/2011	0.174*	0.173	12.20%	0.062	1.054***	94.45%	0.061	0.143	30.55%	0.009	-0.065**	71.00%	0.023	-0.111*	64.04%
30/06/2009	31/12/2011	0.186**	0.041	0.82%	0.041	1.131***	92.75%	0.073**	0.068	11.46%	0.002	-0.03**	83.51%	0.007	-0.042	31.96%
31/12/2009	30/06/2012	0.163*	0.033	0.18%	0.055	1.246***	87.50%	0.069*	0.136	14.13%	0.001	-0.041***	85.86%	0.007	-0.076	36.19%
30/06/2010	31/12/2012	0.126	-0.055	0.34%	0.020	1.135**	81.42%	0.037	0.013	0.31%	0.000	-0.042***	85.53%	0.011	-0.058	25.56%
31/12/2010	30/06/2013	0.118	0.442	17.32%	0.034	1.260**	72.75%	-0.006	0.576	26.43%	0.000	-0.029**	73.99%	0.011	-0.007	0.49%
30/06/2011	31/12/2013	0.059	0.037	0.09%	0.020	1.101*	60.64%	-0.028	0.422	11.65%	0.000	-0.022*	63.96%	0.009	-0.013	0.83%
31/12/2011	30/06/2014	-0.001	-0.112	4.46%	0.052	1.174**	70.87%	-0.017	0.425	10.42%	0.001	-0.022*	59.80%	0.013	-0.005	0.12%
30/06/2012	31/12/2014	0.014	-0.234*	57.01%	0.045	0.453**	68.23%	-0.066	0.093	1.70%	0.002	0.018	49.69%	0.018*	0.019	5.87%
31/12/2012	30/06/2015	0.005	-0.266*	62.74%	0.081	0.726	51.31%	-0.078	0.124	3.55%	0.003	0.026	52.15%	0.016*	0.030	16.36%
30/06/2013	31/12/2015	0.008	-0.258**	70.16%	0.105	0.709*	61.64%	-0.084	0.099	3.18%	0.010	0.003	0.46%	0.023**	0.005	0.60%
31/12/2013	30/06/2016	-0.033	-0.114	25.19%	0.079	0.803**	66.39%	0.030	-0.288	40.73%	0.012*	-0.004	1.12%	0.024**	0.004	0.29%
30/06/2014	31/12/2016	-0.029	-0.114	25.03%	0.050	0.804*	64.44%	0.024	-0.287	38.18%	0.014**	-0.004	2.00%	0.028**	0.003	1.55%
31/12/2014	30/06/2017	-0.008	-0.121	11.21%	0.029	0.823*	62.97%	0.017	-0.273	36.26%	0.013**	-0.006	2.18%	0.024**	0.006	1.02%
30/06/2015	31/12/2017	-0.017	-0.126	5.68%	0.046	1.255**	75.36%	0.014	-0.290	23.35%	0.010	-0.016	5.99%	0.020**	-0.019	5.03%
31/12/2015	30/06/2018	0.008	0.174	6.27%	-0.040	0.512**	68.38%	-0.011	-0.345	15.45%	0.004	-0.088**	73.86%	0.012*	-0.083	51.88%
30/06/2016	31/12/2018	-0.005	0.466	29.13%	-0.053*	0.823**	81.80%	-0.006	-0.597	42.56%	0.004	-0.083**	68.73%	0.012*	-0.064	43.29%
31/12/2016	30/06/2019	-0.034	0.132	2.99%	-0.041*	1.210**	93.79%	0.012	0.135	8.10%	0.009	-0.045	25.84%	0.015**	-0.011	1.70%
30/06/2017	31/12/2019	-0.010	0.180	3.77%	-0.017	1.275***	88.70%	0.039	0.230	32.79%	0.010*	-0.042	21.03%	0.016**	-0.012	2.21%
31/12/2017	30/06/2020	-0.082	0.141	1.63%	0.023	1.278**	76.58%	0.060	0.224*	17.40%	0.014**	-0.037	21.29%	0.020***	-0.005	0.82%
30/06/2018	31/12/2020	-0.015	0.766	22.11%	0.025	1.221**	80.50%	0.054	0.072	2.15%	0.016***	-0.044*	58.68%	0.019**	-0.020	15.05%
31/12/2018	30/06/2021	-0.066	1.062	27.55%	0.026	1.199**	73.20%	0.050	-0.126	3.15%	0.015***	-0.047	49.36%	0.021***	-0.038	38.09%
30/06/2019	31/12/2021	-0.102	1.496	28.99%	0.074*	0.610	52.48%	0.048	-0.149	2.20%	0.017***	-0.063	48.11%	0.018***	-0.019	5.55%

SZSE is taken as a market return

		Chinese art			SSE			Gold			Govt. Bonds			Corp. Bonds		
		Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²
31/12/2003	30/06/2006	0.202**	-0.851**	0.751	0.009	0.815***	0.976	0.076	0.183	0.166	0.003	-0.045	0.040	0.011	-0.073	0.051
30/06/2004	31/12/2006	0.180**	-0.948**	0.762	0.034	1.003***	0.845	0.040	0.181	0.236	0.011	-0.055	0.074	0.025	-0.105	0.141
31/12/2004	30/06/2007	0.132	-0.440	0.527	0.039	0.676**	0.715	0.062	-0.019	0.007	0.031*	-0.094*	0.626	0.048	-0.131	0.509
30/06/2005	31/12/2007	0.163	-0.431	0.394	0.073	0.630*	0.642	0.063	0.030	0.010	0.043***	-0.128***	0.883	0.062*	-0.194**	0.674
31/12/2005	30/06/2008	0.010	-0.038	0.011	-0.010	0.878**	0.839	0.080	0.006	0.001	0.002	-0.023	0.322	0.006	-0.051	0.269
30/06/2006	31/12/2008	-0.047	0.028	0.009	-0.030	0.911***	0.874	0.038	0.071	0.127	0.008	-0.040	0.466	0.013	-0.080	0.475
31/12/2006	30/06/2009	0.003	0.139	0.213	-0.028	0.917***	0.882	0.029	0.055	0.096	0.008	-0.040	0.478	0.015	-0.072	0.420
30/06/2007	31/12/2009	0.051	0.164	0.390	-0.083	0.887***	0.951	0.053	0.066	0.103	0.007	-0.040	0.489	0.013	-0.073	0.421
31/12/2007	30/06/2010	0.124	0.200	0.319	-0.056	1.001*	0.989**	0.081*	0.135	0.381	0.009	-0.033	0.354	0.014	-0.082	0.413
30/06/2008	31/12/2010	0.122	0.198	0.319	-0.087	0.945***	0.994***	0.065	0.106	0.321	0.009	-0.033	0.358	0.026	-0.063	0.407
31/12/2008	30/06/2011	0.166*	0.121	0.070	-0.056	0.896***	0.945	0.052	0.149	0.392	0.013	-0.058**	0.670	0.029*	-0.097*	0.581
30/06/2009	31/12/2011	0.185**	0.041	0.012	-0.032	0.820***	0.927	0.069**	0.091	0.277	0.003	-0.025**	0.768	0.008	-0.030	0.229
31/12/2009	30/06/2012	0.162*	0.036	0.004	-0.046	0.702***	0.875	0.064*	0.152	0.311	0.002	-0.027**	0.683	0.011	-0.041	0.189
30/06/2010	31/12/2012	0.134	0.053	0.005	-0.028	0.717**	0.814	0.040*	0.065	0.121	0.002	-0.029**	0.665	0.014	-0.023	0.064
31/12/2010	30/06/2013	0.104	0.249	0.120	-0.032	0.577**	0.727	-0.031	0.093	0.015	0.001	-0.020**	0.818	0.012	0.010	0.023
30/06/2011	31/12/2013	0.050	-0.130	0.021	-0.036	0.551*	0.606	-0.064	-0.198	0.051	0.001	-0.016**	0.724	0.011	0.011	0.012
31/12/2011	30/06/2014	0.008	0.078	0.043	-0.050	0.604**	0.709	-0.047	-0.090	0.009	0.002	-0.016*	0.594	0.014	0.009	0.008
30/06/2012	31/12/2014	0.025	-0.327	0.337	-0.052	1.505**	0.682	-0.060	-0.033	0.001	0.002	0.020	0.172	0.019*	-0.001	0.000
31/12/2012	30/06/2015	0.016	-0.239	0.520	-0.011	0.707	0.513	-0.075	0.061	0.009	0.002	0.028	0.607	0.016	0.023	0.100
30/06/2013	31/12/2015	0.036	-0.297**	0.757	-0.067	0.870*	0.616	-0.096	0.118	0.037	0.009	0.006	0.017	0.024*	0.000	0.000
31/12/2013	30/06/2016	-0.025	-0.120	0.270	-0.047	0.827**	0.664	0.047	-0.271	0.351	0.012*	-0.001	0.001	0.024*	-0.002	0.001
30/06/2014	31/12/2016	-0.024	-0.120	0.277	-0.021	0.801*	0.644	0.030	-0.227	0.240	0.013**	0.004	0.014	0.028***	0.006	0.043
31/12/2014	30/06/2017	-0.002	-0.169	0.235	0.002	0.765*	0.630	0.017	-0.212	0.235	0.012*	0.008	0.043	0.023**	0.015	0.081
30/06/2015	31/12/2017	-0.010	-0.146	0.160	-0.029	0.601**	0.754	0.022	-0.168	0.163	0.009	0.010	0.051	0.020**	0.013	0.052
31/12/2015	30/06/2018	0.022	0.348	0.096	0.029	1.335**	0.684	-0.042	-0.739	0.273	0.002	-0.108	0.422	0.014	-0.058	0.097
30/06/2016	31/12/2018	0.021	0.525	0.306	0.041	0.994**	0.818	-0.017	-0.470	0.218	-0.001	-0.096	0.774	0.009	-0.070	0.427
31/12/2016	30/06/2019	-0.031	0.072	0.014	0.032	0.775***	0.938	0.017	0.114	0.090	0.008	-0.027	0.150	0.015**	-0.006	0.009
30/06/2017	31/12/2019	-0.006	0.192	0.079	0.011	0.696***	0.887	0.042*	0.173	0.341	0.010	-0.018	0.069	0.016**	-0.002	0.001
31/12/2017	30/06/2020	-0.084	-0.027	0.001	-0.018	0.599**	0.766	0.056*	0.238	0.418	0.015**	-0.010	0.032	0.020***	0.001	0.000
30/06/2018	31/12/2020	-0.022	0.306	0.065	-0.016	0.659**	0.805	0.050	0.141	0.150	0.016***	-0.023	0.282	0.020***	-0.011	0.082
31/12/2018	30/06/2021	-0.057	0.394	0.074	-0.007	0.611**	0.732	0.043	0.053	0.011	0.015**	-0.019	0.165	0.021***	-0.021	0.217
30/06/2019	31/12/2021	-0.085	0.622	0.036	-0.037	0.861	0.525	-0.019	0.540	0.205	0.017*	-0.031	0.081	0.013*	0.031	0.097

Average return on each asset is considered as a market return

		Chinese art			SSE			SZSE			Gold			Govt. Bonds			Corp. Bonds		
		Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²	Alpha	Beta	R ²
31/12/2003	30/06/2006	0.419**	-4.313**	66.96%	-0.201**	4.188***	89.48%	-0.248**	4.940***	84.70%	0.013	1.257	27.06%	0.004	-0.021	0.03%	0.013	-0.050	0.08%
30/06/2004	31/12/2006	0.410**	-4.831**	71.92%	-0.208*	5.098**	79.41%	-0.233**	4.929***	88.37%	-0.008	0.996	26.00%	0.011	-0.044	0.17%	0.029	-0.149	1.04%
31/12/2004	30/06/2007	0.251	-2.429	46.68%	-0.163	3.963**	71.38%	-0.284**	5.681***	93.88%	0.069	-0.124	0.86%	0.053*	-0.478	46.69%	0.074	-0.612	32.27%
30/06/2005	31/12/2007	0.229	-1.637	15.85%	-0.151	3.620*	59.17%	-0.323*	5.427**	82.12%	-0.002	0.702	15.06%	0.093***	-0.778***	91.52%	0.154***	-1.335***	89.14%
31/12/2005	30/06/2008	-0.004	0.113	0.94%	-0.049	2.905***	89.99%	-0.026	3.014***	89.09%	0.071	0.158	7.56%	0.001	-0.043	11.41%	0.007	-0.145	21.82%
30/06/2006	31/12/2008	-0.050	0.194	4.47%	-0.022	2.910***	94.04%	0.015	2.983***	93.96%	0.036	0.310	25.88%	0.007	-0.120	44.34%	0.012	-0.277*	60.43%
31/12/2006	30/06/2009	-0.002	0.497	31.98%	-0.041	2.759***	93.92%	-0.006	2.834***	94.40%	0.025	0.250	23.86%	0.008	-0.112	44.44%	0.017	-0.229	49.98%
30/06/2007	31/12/2009	0.043	0.595*	60.94%	-0.100***	2.630***	99.07%	-0.012	2.818***	94.10%	0.047	0.302	25.70%	0.007	-0.113	45.77%	0.015	-0.233	50.78%
31/12/2007	30/06/2010	0.107	0.645	46.52%	-0.132**	2.646***	96.99%	-0.076*	2.635***	97.52%	0.070*	0.404	48.14%	0.011	-0.096	40.77%	0.021	-0.235	47.19%
30/06/2008	31/12/2010	0.109	0.657	46.13%	-0.145**	2.569***	96.82%	-0.062	2.723***	97.68%	0.058	0.327	40.68%	0.011	-0.097	39.94%	0.030	-0.179	43.62%
31/12/2008	30/06/2011	0.139	0.659	24.91%	-0.142**	2.582***	94.46%	-0.091	2.785***	93.32%	0.035	0.485	49.99%	0.019**	-0.190***	86.15%	0.040**	-0.321**	75.78%
30/06/2009	31/12/2011	0.165*	0.380	10.36%	-0.126*	2.485***	89.78%	-0.113*	3.000***	94.84%	0.058*	0.280	27.98%	0.005	-0.070*	64.69%	0.011	-0.074	14.58%
31/12/2009	30/06/2012	0.142*	0.729	16.50%	-0.113*	2.040**	78.17%	-0.094*	2.869***	87.14%	0.046	0.546	42.41%	0.005	-0.071	49.81%	0.014	-0.113	15.09%
30/06/2010	31/12/2012	0.122	1.079	21.92%	-0.090	1.962*	65.18%	-0.086	2.776**	82.47%	0.034*	0.305	28.88%	0.004	-0.072	42.94%	0.016	-0.050	3.21%
31/12/2010	30/06/2013	0.097	1.134	36.40%	-0.048*	1.696***	91.66%	-0.027	2.181**	69.40%	-0.034	1.077	29.48%	0.001	-0.052**	78.17%	0.012	-0.037	4.53%
30/06/2011	31/12/2013	0.073	1.031	13.63%	-0.030	2.016***	84.87%	-0.017	1.942	39.40%	-0.037	1.072	15.71%	0.001	-0.037	38.99%	0.010	-0.023	0.60%
31/12/2011	30/06/2014	0.005	-0.098	0.66%	-0.025	2.141***	87.82%	0.026	2.683**	70.91%	-0.021	1.264	17.66%	0.001	-0.038	35.17%	0.014	0.048	2.24%
30/06/2012	31/12/2014	0.016	-0.969*	58.93%	0.000	3.751***	84.42%	0.043	1.810*	65.28%	-0.079	1.279	19.25%	0.002	0.063	34.64%	0.018*	0.066	4.26%
31/12/2012	30/06/2015	0.009	-0.957**	75.05%	0.004	2.965**	81.04%	0.060	2.935**	77.27%	-0.093	0.873	16.25%	0.003	0.094*	62.31%	0.016	0.091	14.23%
30/06/2013	31/12/2015	0.019	-1.022***	88.12%	-0.023	3.237**	84.03%	0.073	2.872**	81.22%	-0.101	0.862	19.37%	0.009	0.028	3.38%	0.023*	0.022	0.84%
31/12/2013	30/06/2016	-0.024	-0.506	30.85%	-0.062	3.744***	87.37%	0.007	3.718***	88.77%	0.045	-0.972	28.98%	0.012*	-0.007	0.21%	0.023*	0.024	0.76%
30/06/2014	31/12/2016	-0.022	-0.511	32.59%	-0.043	3.577**	83.60%	-0.008	3.748***	91.41%	0.031	-0.827	20.70%	0.014**	-0.005	0.21%	0.028***	0.017	2.55%
31/12/2014	30/06/2017	-0.001	-0.524	14.03%	-0.034	3.550***	84.53%	-0.023	3.759***	88.15%	0.022	-0.799	20.88%	0.013*	-0.006	0.19%	0.024**	0.021	0.98%
30/06/2015	31/12/2017	-0.012	-0.382	5.72%	-0.034	2.747**	82.59%	-0.005	4.168***	91.00%	0.021	-0.538	8.80%	0.010	0.007	0.14%	0.021**	-0.002	0.01%
31/12/2015	30/06/2018	0.025	1.576	30.32%	-0.012	3.306*	64.51%	-0.041	1.927*	57.14%	0.012	-0.154	0.18%	0.003	-0.359**	72.31%	0.012	-0.297	39.35%
30/06/2016	31/12/2018	0.016	2.072*	60.52%	-0.004	2.454*	63.20%	-0.045	2.475**	77.70%	0.020	-0.496	3.09%	0.002	-0.282**	83.74%	0.011*	-0.224*	55.74%
31/12/2016	30/06/2019	-0.029	0.609	11.33%	0.014	2.273***	91.76%	-0.023	2.826***	90.79%	0.015	0.442	15.39%	0.008	-0.100	22.61%	0.015**	-0.051	6.96%
30/06/2017	31/12/2019	-0.014	0.955	24.75%	-0.014	1.893**	82.95%	-0.035	2.692***	91.64%	0.035	0.542	42.08%	0.011*	-0.059	9.40%	0.016**	-0.024	1.84%
31/12/2017	30/06/2020	-0.083	0.735	10.09%	-0.014	1.905**	82.57%	0.005	2.813***	84.47%	0.057*	0.585	26.95%	0.015**	-0.040	5.45%	0.020***	0.002	0.02%
30/06/2018	31/12/2020	-0.048	1.986	41.15%	-0.030	1.803***	90.00%	-0.013	2.311**	79.82%	0.053	0.044	0.22%	0.017***	-0.091**	67.46%	0.020***	-0.052	29.17%
31/12/2018	30/06/2021	-0.095	2.611*	54.87%	-0.005	1.542**	78.38%	0.017	2.002**	67.28%	0.046	-0.008	0.01%	0.016***	-0.076	42.68%	0.021***	-0.070	41.37%
30/06/2019	31/12/2021	-0.152	3.722**	66.38%	0.010	1.295*	62.04%	0.074*	0.965	48.61%	0.034	0.146	0.79%	0.017***	-0.093	38.36%	0.018***	-0.036	6.95%

Appendix 5 DRC 16 Statement of Contribution

DRC 16



STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Yue Yuan	
Name/title of Primary Supervisor:	Associate Professor Liping Zou	
Name of Research Output and full reference:		
Zou, L., De Bruin, A., Wu, J., & Yuan, Y. (2021). Art for art's sake? An exploration of the Chinese art market. <i>Applied Economics</i> . 53(47), 5429-5447.		
In which Chapter is the Manuscript /Published work:	Chapter 2	
Please indicate:		
<ul style="list-style-type: none"> The percentage of the manuscript/Published Work that was contributed by the candidate: 		
and		
<ul style="list-style-type: none"> Describe the contribution that the candidate has made to the Manuscript/Published Work: 	Chapter 2 of Yue Yuan's thesis draws significantly on this article and while the supervisors have made a contribution, which is reflected by co-authorship, the article is essentially the work of Yue.	
For manuscripts intended for publication please indicate target journal:		
Candidate's Signature:	Yue Yuan	Digitally signed by Yue Yuan Date: 2023.03.14 13:34:29 +13'00'
Date:	2023.03.14	
Primary Supervisor's Signature:	Liping Zou	Digitally signed by Liping Zou DN: cn=Liping Zou, o=Massey University, ou=School of Economic and Finance, email=L.Zou@massey.ac.nz Date: 2023.03.16 19:37:48 +13'00'
Date:	2023.03.16	

(This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis)

GRS Version 4– January 2019