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NAME	Milad
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PhD in	Economics and Finance
Cycle	27
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Date__25/1/2017______

Contents

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Abstract

In the first two chapters of this dissertation, I focus on how and when art investors monetize their art collections. I study a) borrowing against the value and b) reselling of artworks as two main approaches to monetizing art collections. In the first chapter, I investigate the growing business of art-secured lending by non-bank creditors. This study documents that art collectors use art as collateral to borrow when the economy experiences a downturn and the need for liquidity is high. I also test a pecking order for borrowing by wealthy individuals, and compare art-secured borrowing to loans secured by home equity. I find that art loans are increasingly used when home equity loans are difficult to obtain. The results suggest that art-rich but potentially cash-poor individuals use art to alleviate credit frictions.

In the second chapter, I investigate the investment horizon in the global art market by studying the factors affecting the ownership duration of art. This study documents that personal valuation, home bias, and uncertainty of the market value affect the ownership duration. Moreover, I find that price tags, reputation of the artist, and some specific art characteristics are important determinants of collectors' holding period decisions, and these factors can affect the presence of artworks in resale events.

Besides the economics of art, in the third chapter, I study pricing kernel bounds, which are introduced as benchmarks to test various asset pricing models. I propose an approach to improve the pricing kernel bound studied by Almeida and Garcia (2012), which is based on divergence measures. The main contribution of my study is incorporating variations in the expectation of return in estimating the bound. Assuming two states of the economy with differing risk-free rates, I introduce a statistical framework and an optimization algorithm in order to achieve a shaper pricing kernel bound.

Chapter 1

Beautiful Collateral and Real Property

Abstract

High value art and the existence of a liquid market for it make art a potential source of collateral for loans. Recently, firms specializing in art lending have emerged to serve this market. This study explores the effect of regional variations in economic and financial conditions on art-backed lending activities. I show that demand for art loans increases when the economy experiences a downturn and the liquidity need is high. I also compare the demand for art-secured loans with home equity loans and test a pecking order theory for the borrowing of high net worth individuals. The findings suggest that art as a substitute collateral is increasingly used when home equity loans are difficult to obtain.

JEL classification: G23; Z11

Keywords: Collateral; Art-backed lending; Art market; Real estate credit market

1.1 Introduction

The art market has expanded in the last two decades and many collectors are attuned to the economic benefits of art in addition to its aesthetic value.[1] The growing population of collectors with diverse interests also consider monetizing art for their consumption or investment purposes.[2] While selling artworks may not be cost efficient, owners can use their art as collateral to borrow. In this paper, I explore the economic use of art by private collectors who borrow against their artworks from auction houses and art lending specialists.

According to Deloitte and ArtTactic reports, art collectors borrow against their art for various reasons. A wealthy entrepreneur may want to finance an interesting business idea, or a collector may find an opportunity to buy a new piece of art and need to borrow immediately using her current collection to finance the new purchase. Art owners may also borrow to fulfill sudden liquidity needs for estate planning, funding a divorce settlement, or compensating depressed earnings.

The focus of the study is to test whether collectors borrow in order to alleviate adverse circumstances or to expand their asset base. To answer this question, I characterize the cross-sectional demand for art-secured loans in the metropolitan areas of the United States and analyze the effect of regional variations in the economy on art-backed borrowing. In addition, since home equity is a widely used source of collateral, in the second set of tests, I investigate the relationship between art-secured lending, mortgages for consumption purpose, and housing return. The regional perspective is used to analyze the demand for art loans since in the time series, results can be affected by the growth of art lending business in the last decade. The findings are consistent with the hypothesis that collectors borrow from non-bank creditors in times of financial distress to fulfill their liquidity needs.

The art lending service mainly operates in the United States because of the legal environment of the Uniform Commercial Code (UCC) under which debtors can keep

[1] According to TEFAF Art Market Report (2016), the global market achieved the total sales of $64 billion in 2015 comparing to just $10 billion in 1991.

[2] Deloitte and ArtTactic Art and Finance Report, 2016.

possession of their artworks and creditors can register their security interest in collaterals. U.S. metros are home to more than 90% of the nation's GDP;[3] at the same time, they may experience various economic conditions due to the contrasting industry concentrations and this difference in metro economies sets the stage for the panel analysis in this study.

The proxy of demand for art-backed borrowing in this paper is the number of art loans originated by major auction houses and art specialized lenders for private borrowers. I use the collected UCC filings by Skate's, a business unit of ARTnews, which provides a database of all public filings used to secure pledges over artworks. To the best of my knowledge, this paper is the first study to use this dataset in an academic research. Employing panel regression methods for count data, I investigate how the demand for art loans is related to local economic conditions and the demand for loans secured by home equity.

I use the changes in regional GDP to test how art borrowing is affected when local economic performance is higher. If local entrepreneurs use their art collections as collateral to expand businesses during periods of growth, we expect art lending to increase in good times. Conversely, if art is used as collateral for emergency loans, we expect to see art owners borrow against their collection when the economy performs poorly.

The relationship between other proxies for regional economic and financial conditions and art borrowing is also investigated. These proxies are the growth of local establishments and stock performance. Creation of new businesses is an indicator of a healthy economy. I employ variations in the local establishments as a measure of economic conditions. Moreover, the poor performance of local stocks not only shows a downturn in a metro economy but also represents a negative shock to the financial wealth of local traders. This test is inspired by well-established literature on bias toward local trading, documenting the tendency of investors to hold and trade shares of local companies (Coval and Moskowitz, 1999; Ivkovic and Weisbenner, 2005; Hirshleifer and Shumway, 2003).

Art, as a new source of collateral, can be utilized by wealthy collectors as a substitute

[3] U.S. Metro Economies GMP and Employment Report: 2015-2017, The United States Conference of Mayors, June 2016.

for traditional financing practices such as the home equity line of credit. I specifically look at the co-movement of the demand for art loans with home equity mortgages. There is a broad agreement that housing wealth supports consumption (Greenspan and Kennedy, 2008; Bostic, Stuart, and Painter, 2006; and Case, Quigley, and Shiller, 2005). In addition, the importance of a collateral lending channel and the effect of housing prices on economic activities are studied by Schmalz, Sraer, and Thesmar (2015), Adelino, Schoar, and Severino (2015), and Kerr, Kerr, and Nanda (2015). Similar to art, real estate has a private value for the owner, but residential real estate as collateral is more complex to foreclose and repossess. Unlike real estate, art is highly portable and can be sold by the lender in another economy or market that is not subject to a local downturn, which makes blue-chip art a more attractive source of collateral. We would expect to see art being used more often as collateral when borrowers cannot obtain home equity loans. I test this hypothesis by investigating the rejection rates of second lien home equity loan applications and also house price appreciation in multiple areas.

This paper contributes to the literature in three respects. First, this is the first study to empirically explore the collateral usage of art as an investment asset. Art as an asset class and its return history are studied by Ashenfelter (1989), Goetzmann (1993), Pesando (1993), Chanel, Gérard-Varet, and Ginsburgh (1996), Mei and Moses (2002), Graddy, Hamilton, and Pownall (2012), Renneboog and Spaenjers (2013), and Korteweg, Kräussl, and Verwijmeren (2016) among others. This comprehensive existing literature investigates the art price formation and indices using two main methods of repeat-sales regressions and a hedonic method, and suggests estimation corrections. The resale values and capital gains to art are the main focus of the prior studies, however, this paper addresses the value provided for collectors by borrowing in times of financial need.

Second, the findings of this study help us to better understand the relation between art and other asset classes, and they link economic and financial conditions to the art market. Goetzmann, Renneboog, and Spaenjers (2011) find that equity capital growth affects art prices. They also show co-integrating relationships between top incomes and art prices, arguing that the income of the highest earners seems a key factor in art price formation. Hiraki, Ito, Spieth, and Takezawa (2009) study the effect of the late 1980s Japanese economy bubble on the art market and find that art prices and demand were affected by the Japanese asset market. These papers concentrate on the trade decisions and art price indices affected by the economic conditions and by incomes. In line with these findings, I show that decisions for monetizing the value of art by borrowing can also be affected by financial and economic conditions.

Finally, this paper empirically adds to the literature about various sources of collateral. Real estate as collateral and the relation of home equity to consumption has been studied by many scholars including Mian and Sufi (2011), Gan (2010), and Manchester and Poterba (1989). The other investigated sources of collateral include patents (Mann 2015), heavy equipment (Murfin and Pratt 2015), and airplanes (Benmelech and Bergman 2008) among others. Art as collateral and the effect of using historical prices on the value-at-risk estimation of the collateral portfolios are investigated by McAndrew and Thompson (2007). A theoretical framework for credit default swaps in the art market is also suggested by Campbell and Wiehenkamp (2008).

The remaining sections are organized as follows: The market for art-secured lending is explained in the next section, and various market participants are described. Section 3 introduces the databases used for the various tests in this paper. Section 4 briefly explains the methodology. Section 5 tests the relation of art borrowing and local economy factors. Section 6 compares the demand for art loans to the demand for home equity loans, and Section 7 concludes.

1.2 Art-secured Lending

Art is becoming a more popular investment asset and according to a recent survey by Deloitte, six percent of collectors buy art just for investment and 72% of those who buy for passion also have an investment view.[4] The majority of the collectors think about

[4] Deloitte and ArtTactic Art and Finance Report, 2016.

monetizing their art either through reselling or borrowing against the value. The same survey reveals that almost half of the collectors are interested in art borrowing services. So the question is, when and why do they monetize this passion asset? In this study, I focus on the borrowing activities, and we investigate the resale decisions in another study.

Reselling artworks in auctions to free up capital can be very costly. The owner needs to pay the seller's premium to the auctioneer, plus federal and state capital gain taxes. These costs can be substantial since the seller's premium is between 15% to 25% of the hammer price and the federal capital gain tax is usually 28%. Moreover, if the artwork remains unsold at the first auction attempt, its perceived value by the market decreases dramatically, and the owner suffers a significant loss. In contrast, borrowing against the value of art is a tax-efficient choice for monetizing allowing collectors to retain possession of their artworks when they borrow.

The art lending business is growing in the United States and it is mainly because of the legal environment of the Uniform Commercial Code (UCC) under which debtors can keep possession of their artwork and creditors can register their security interest in collaterals. When filing a lien, the creditor gives a public notice that there is a right to take possession of some personal properties of the debtor. If the debtor defaults on a secured loan in which multiple creditors have reported UCC forms against the same artwork, the first creditor who filed the form has the priority. This legal framework protects the creditors, facilitates lending, and also gives collectors immediate access to almost half of their collection's value while they still enjoy the art in their possession.

Private banks, art specialists (boutique lenders), and auctioneers are the main lenders against the value of art collections. The contract agreements and rates asked by these creditors can vary significantly. According to Deloitte and ArtTactic's art and finance report (2016), private banks ask for rates ranging between Libor plus %1 to 3% and the art specialists such as Borro or Art Finance Company ask for higher rates sometimes ranging up to Libor plus 15%. Auction houses including Sotheby's and Christie's also provide a lending service with moderately lower rates which is approximately Libor plus

5% to 7%. The market size of these lenders is predicted to be 15 (81%), 2 (11%), and 1.5 (8%) billion dollars, respectively.

Private banks provide recourse loans based on the general creditworthiness of their clients. If a borrower defaults on her art loan and selling her collection does not cover all of the costs, the lender can claim other assets of the borrower. Because of the borrower's guarantee and lower risk of lending, private banks offer lower rates. Deloitte reports that the main motivations of borrowing from private banks are (in order of importance): buying more art, investing in other business activities, and refinancing existing loans. Auction houses and art specialists, on the other hand, provide non-recourse loans and their decisions are based solely on the value of the art collections. The borrower's guarantee is not required in order to approve a non-recourse loan, and the main criterion is the art itself, not the creditworthiness of the borrower.

Loan-to-value (LTV) ratio for art loans is targeted around 50%, thus mitigating the risk of potential collateral devaluation. The value of the artwork is usually assessed by auction houses at the time of the loan application assessment. The auctioneers usually provide a price range that includes low and high estimations. Creditors use the low estimate for determining the haircut. McAndrew and Thompson (2007) examine how presale estimates can be used to assess the risk of lending against art. They suggest incorporating the bought-in rate in addition to successful historical sales to assess the downside risk of lending, and find that optimal LTV is 50% to 100% higher, ignoring the bought-ins.

Art-secured lending is an old business. In the 16th century, Lorenziola Caprotti, sister of Salai, an Italian artist and pupil of Leonardo da Vinci, secured a loan of 26 Scudi, depositing nine works of art as collateral while surprisingly the value of those works were appraised at more than 415 Scudi. This huge valuation difference might come from the fact that neither the art market, art galleries, or a mechanism for authentication was well established in those years.

Considering the fact that treasure assets such as fine art, jewelry, and antiques com-

	Total	Comment
Loans to private borrowers	429	
Lenders	8	
Metropolitan Areas	24	
States	18	
Share of auction houses	80%	Sotheby's and Christie's provide 52% and 28% of loans, respectively.
Share of art lending specialists	20%	Borro and Art Finance Partners are the main creditors in this group.

Table 1.1: Characteristics of the art-secured lending data.

prise 9.6% of the total net worth in the United States,[5] private banks including J.P. Morgan, Citi, and U.S. Trust (Bank of America), have recently shown more interest in providing art loan services to their clients and perceive this as a new revenue source rather than simply extending client relationships. Emigrant Bank, Morgan Stanley Wealth Management, and Goldman Sachs are other active banks offering this service.

Auction houses are the other creditors in this market, they provide non-recourse loans to collectors. While previously this service was a way to attract new consignments for sale events, now the lending business is an important source of revenue. Sotheby's Financial Service is the biggest art-backed creditor among auction houses whose credit line, through collaboration with GE Capital, reached almost $1 billion in 2015. The finance department of Sotheby's offers two types of loans. For some of the art-secured loans, which are called consignor advance, borrowers are committed to selling the property in the near future through the company's agency division, which is the main business of the auction house. The other loans are general purpose term loans. Sotheby's auction and private sale commission revenues accounted for 81%, 87%, and 91% of consolidated revenues in 2015, 2014, and 2013, respectively.[6] The figures are 5%, 3.5%, and 2.5% for the finance department, which is the second highest revenue-generating business in Sotheby's and increasingly contributes to the overall revenue.

[5]Barclays' Wealth Insight Report, Vol. 15.
[6]Sotheby's Annual Report, 2015.

State	Metro	State	Metro
CA	Los Angeles-Long Beach-Anaheim	MA	Boston-Cambridge-Newton
CA	Riverside-San Bernardino-Ontario	NC	Durham-Chapel Hill
CA	San Francisco-Oakland-Hayward	NC	Winston-Salem
CA	Santa Maria-Santa Barbara	NM	Santa Fe
CO	Denver-Aurora-Lakewood	NV	Las Vegas-Henderson-Paradise
CT	Bridgeport-Stamford-Norwalk	NY	New York-Newark-Jersey City
DC	Washington-Arlington-Alexandria	OH	Cleveland
FL	Miami-Fort Lauderdale-West Palm Beach	PA	Philadelphia-Camden-Wilmington
FL	Naples-Immokalee-Marco Island	RI	Providence-Warwick
FL	Tampa-St. Petersburg-Clearwater	TX	Dallas-Fort Worth-Arlington
GA	Atlanta-Sandy Springs-Roswell	VA	Charlottesville
IL	Chicago-Naperville-Elgin	WA	Seattle-Tacoma-Bellevue

Table 1.2: Metropolitan areas where borrowers reside.

1.3 Data

Skate's, a business unit of ARTnews, provides a database of all the public UCC filings used to secure pledges over artwork. These combined filings only refer to art that has been used as collateral in lending agreements by art lending specialists and auction houses in the United States since 2003. They include loans granted to both private collectors and art businesses. For each art loan, there is information about the filing and termination dates, name and location of the lenders and borrowers, and also artworks used as collateral in the loan applications. I exclude loans issued to museums, galleries, trusts, or estates of collectors. Table 1 reports information about the loans in the dataset. Almost 80% of the loans are granted by two main auction houses in the art market, Sotheby's and Christie's. Table 2 lists all the metropolitan areas where borrowers live. This list includes the major metros, namely New York, Los Angeles, Chicago, Dallas, and Washington, D.C. In addition, Table 3 presents the frequency of art loans in each year across MSAs. In the methodology section, I discuss methods to deal with excess zeros and over-dispersion in this data.

To measure the economic performance of metropolitan areas, I utilize the data for the variations in regional GDP provided by the Bureau of Economic Analysis (BEA). GDP by metropolitan area is the sub-state counterpart of the gross domestic product in the

Art Loans	Freq.	Percent	Cum.
0	337	78.55	78.55
1	56	13.05	91.61
2	15	3.50	95.10
3	6	1.40	96.50
4-10	4	0.93	97.44
10-20	3	0.70	98.14
>20	8	1.85	100
Total	429	100	

Table 1.3: Frequency of observed loans at the MSA-by-year level.

country. This data, which is based on changes in the real GDP in chained dollars, includes activities of all of the industries in metropolitan areas. Local business establishments data, which is used as another proxy for economic conditions, is from the Census Bureau's Statistics of U.S. Businesses. The other economic performance measure in this study is based on the performance of the local stocks. To compute the local stock market indices, I use the Compustat database which provides the location information for the headquarters of listed firms and I also employ the price, return, and trading volume data from the CRSP database.

For the mortgage information, I use the Home Mortgage Disclosure Act data (HMDA), which requires most mortgage lending institutions such as main private banks, savings associations, credit unions, mortgage and consumer finance companies in the United States to disclose information about their home loans. This federal law ensures that financial institutions serve the housing credit needs of the local communities with no discriminations. The HMDA database is representative of most home lending activities and includes information about the lien status (first or second lien) and purpose of each loan (home purchase, home improvement, or refinancing). For further analysis, I use the housing return data from the Freddie Mac house price index. Table 4 reports the summary statistics of the variables used in each test.

I use several explanatory variables in the study and it is important to know how they are correlated. Table 5 shows that within the metropolitan areas where borrowers reside, there are positive correlations between changes in real GDP, creation of establishments,

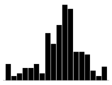
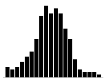
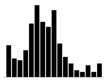
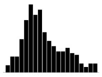
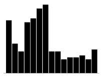
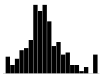
	Mean	Std. Dev.	Min	Max	Distribution
ΔReal GDP (%)	1.62	3.01	-6.10	8.10	
Δ Establishments (%)	0.59	1.99	-4.73	6.57	
Local Stock Return (%)	21.09	34.83	-43.76	124.20	
Housing Return, 5 yrs (%)	21.11	43.13	-61.70	139.10	
ΔMortgage Demand (%)	8.01	57.71	-80.61	140.87	
ΔMortgage Rejection Rate (%)	2.07	20.67	-40.58	60.13	

Table 1.4: This table presents summary statistics of the independent variables used in the analyses. All variables are winsorized at both tails and calculated at MSA-by-year level.

and the return on housing. The correlation of demand for and rejection rate of mortgages with other variables is not significant.

1.4 Methodology

I count the number of annual secured loans in each metropolitan area and use this number to measure the demand for art-backed borrowing by wealthy individuals in an area. The

	ΔGDP	ΔEstabl	Stock Return	House Return	ΔMortg Demand	Mortg Reject
ΔGDP	1.00					
ΔEstabl	**0.64**	1.00				
Stock Return	0.06	-0.11	1.00			
House Return	**0.51**	**0.61**	**0.23**	1.00		
ΔMortg Demand	**0.48**	**0.54**	0.09	**0.65**	1.00	
ΔMortg Reject	0.04	0.13	-0.15	-0.05	-0.09	1.00

Table 1.5: This table presents the correlations of the main explanatory variables. All variables are calculated at MSA-by-year level. Coefficients in bold are significant at 1% level.Δ*Establ* measures the changes in establishments. *House Return* is the annual return on house prices .Δ*Mortg* is the change in the total demand for second lien mortgages. Δ*Mortg Reject* represents the change in the rejection percentage of mortgage applications.

dependent variable in this paper is treated as count data, which takes non-negative integer values. Due to specific characteristics of the data, the dependent variable is assumed to follow the zero-inflated Poisson or negative binomial processes. The difference between these two distributions is in the variance assumption. In the Poisson model, the variance and mean are assumed to be equal, which is usually not the case if there is an excess number of zero counts or over-dispersion. Nevertheless, the Poisson distribution is the simplest but the most appropriate way of modeling count data. The zero-inflated model does not have the assumption of equality of mean and variance and is suitable for fitting to the over-dispersed data we have in this study. In the negative binomial model, the variance is a linear or quadratic function of the mean. Coefficients produced by this generalization of the Poisson distribution are more efficient, and the standard errors and test statistics are more accurate.

In the analyses, there are repeated measures of individuals (MSA level loans) over time which leads us to consider panel models for count data and also to incorporate fixed effects in order to control for time-invariant predictors. The fixed effects help to control for all of the between-location variability of the loan count. Over-dispersion is produced only by the omitted variables that vary over time within locations. Although the zero-inflated Poisson model with fixed effects is not always easy to estimate and interpret, I report and discuss the results. The negative binomial model itself can be used to fit count data with a large number of zero counts according to Allison (2009). For the negative binomial model with the fixed effects we use unconditional maximum likelihood estimation by including dummy variables for all locations as also suggested and discussed by Allison (2009). Model specifications are in Appendix A.

1.5 Art Lending and the Local Economy

The art market and art-secured lending business has expanded over recent decades. Figure 1 exhibits the art market index from the study by Korteweg, Kräussl, and Verwijmeren

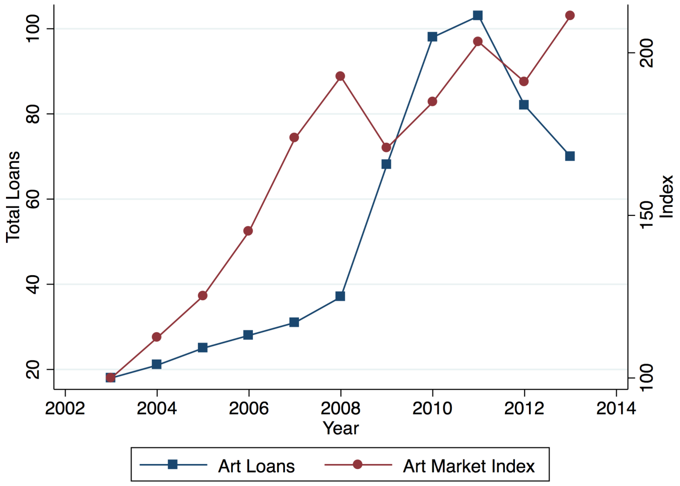


Figure 1.1: This figure shows the art market index together with the total number of art-backed loans granted since 2003. The market index is from the study by Korteweg, Arthur, Roman Kräussl, and Patrick Verwijmeren. "Does it pay to invest in art? A selection-corrected returns perspective." Review of Financial Studies, 2016.

(2016) together with the total number of art loans granted since 2003. Figure 2 plots quarterly loans. Since the recent financial crisis, the total demand for art loans has increased substantially. This observation is in line with the hypothesis that demand for art loans increases at the time of financial difficulties. Since there is almost a positive correlation between the volume of loan and the art market index, one might think of appraised art values or growth in the supply side of art-backed credits as the main factors affecting the art lending business.

To control for the tendency of collectors to borrow in the case of appraised values, we need to know artist-level return indices. These indices are not accessible for this study, but the appraised prices should not be the leading factor of art loan demand because of the following reasons: First, the valuation of art is not straightforward, mainly due to illiquidity. Even appraised prices for some traded works of a certain artist do not necessarily mean that her other artwork is appreciated in the same way. Second, creditors usually lend on artworks of very well known artists and an extensive price increase is unlikely in only a decade of data in this study. Finally, creditors lend based on lower estimates which are usually conservative, and loan haircuts are substantial. These factors can decrease the sensitivity of art borrowers with respect to increased prices.

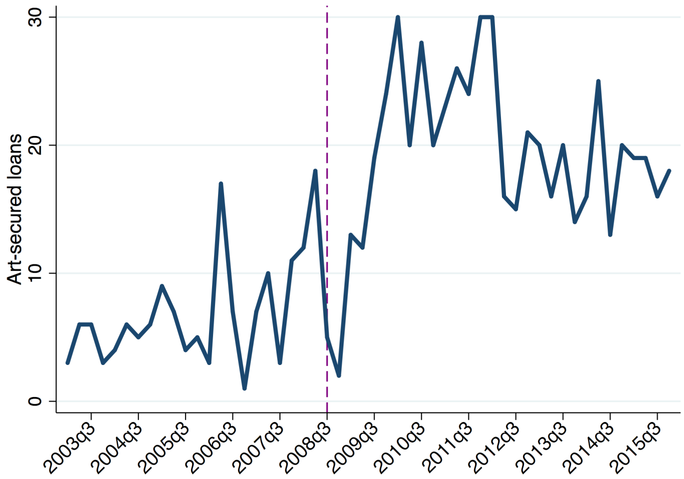


Figure 1.2: Quarterly plot of art-backed loans granted since 2003.

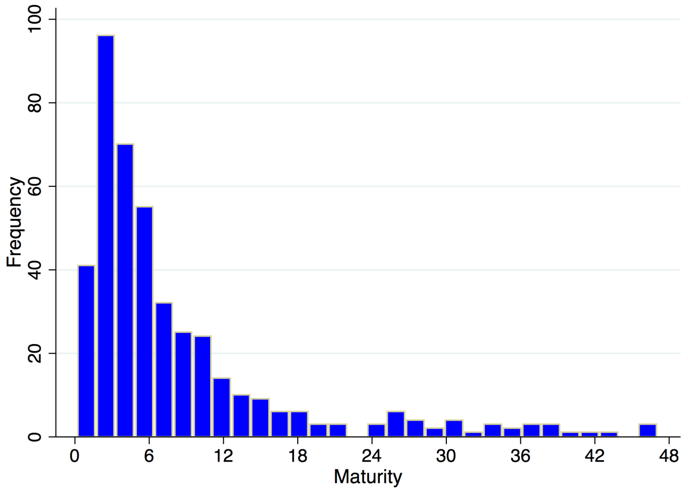


Figure 1.3: This figure shows the histogram of loan maturities. The difference between the UCC filing and termination dates of a same loan is considered as the duration.

For each art loan, the UCC forms provide filing and termination dates which can be used to calculate the maturity. Most of the loans have a maturity of less than a year. Figure 3 shows the frequency of the observed maturity of loans. These loans are mainly short term because of high interest rates or the high possibility of bridge loans (consignor advance) to sell in the near future by the auctioneer. Figure 4 is a map showing the location of borrowers, which includes all private and art businesses who have borrowed. States with darker colors have more borrowers. New York, California, Florida, and Connecticut are the states with the highest number of borrowers.

First, I consider the regional variation in the economic performance. In Table 6, I

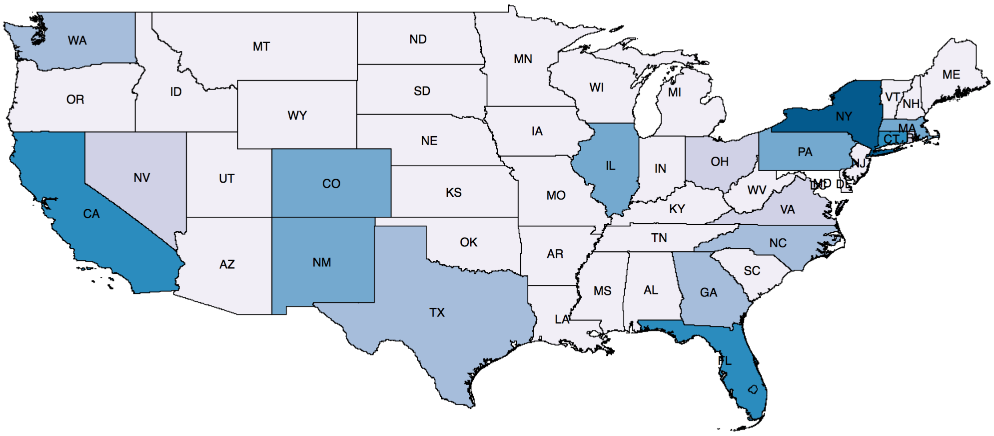


Figure 1.4: This map shows the relative frequency of art-secured loans granted across the United States. All of the private collectors, who borrowed using art since 2003, are considered in this map. In states with darker colors, more art loans are granted. New York, California, Florida, and Connecticut are the states with the highest number of loans.

use changes in the real GDP as the independent variable to explain the variations in art lending. The regional GDP, which is reported at the metropolitan area level, measures economic activities in a specific area of the country. Metropolitan areas play a critical role in the economy and a negative shock to their GDP is a sign of an overall poor performance of the local businesses which can sometimes be transferred to the entire economy.

The zero-inflated and negative binomial models are used to control for the excess zero counts in the number of art loans and also for over-dispersion in the distribution. In the zero-inflated model, the excess zero count is explained by the number of art loans in the preceding year and a dummy variable which identifies the years after the financial crisis (this dummy is equal to one for each year after 2008). In both regressions, year and location fixed effects are estimated following Allison (2009) for panel count data. The significant and negative correlations show that there is higher art borrowing activity when the economy does not perform well.

The next test uses the data on MSA-level "births and deaths" of establishments in order to track local economic conditions. I compute the explanatory variables in Table 7 by dividing the net increase in the initial number of establishments at the beginning of each year. While the first variable employs all the data available for establishments with any size, the second explanatory variable in this table uses only information on small

	Zero-Inflated Poisson		Negative Binomial	
Count (Art Loans)				
ΔReal GDP	-0.0887**	(0.0424)	-0.129***	(0.0374)
Year FE	YES		YES	
Location FE	YES		YES	
Logit				
Lag Art Loans	1.087	(0.932)		
After Crisis	17.60***	(0.656)		
Observations	275		300	
χ^2	1686.6		1885.2	
Pseudo R^2			0.417	

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: This table presents the effect of the regional variation in real GDP on art-secured borrowing. The regional GDP is defined based on the metropolitan areas in the United States. The time horizon is from 2003 until 2014. The excess zero count is explained by the number of art loans in the preceding year (*Lag Art Loans*) and the dummy variable (*After Crisis*) which is equal to one for each year after 2008.

establishments, which are those with less than 20 employees. As the results suggest, a decrease in the number of establishments is associated with an increase in art lending activities. This finding is similar to the previous result and supports our hypothesis about distress borrowing. However, coefficients in the zero-inflated model are not statistically significant.

Another measure of local financial conditions is the return on local stocks which can be an indicator of the local economy's performance and also the financial wealth of locals. There is a well established literature on bias toward local trading which discusses the tendency of investors to hold and trade shares of local companies. The reason for nearby trading could be information asymmetry (Coval and Moskowitz, 1999) as local investors sometimes have easier access to information by communicating with managers, employees, and suppliers of local firms. Another reason for this friction associated with distance could be that investors may be more comfortable investing in firms that they hear about frequently in the local media or through personal connections. Also local brokers may encourage local investing because of their connections.

Pirinsky and Wang (2006) document a strong degree of co-movement for the stock

	Zero-Inflated Poisson		Negative Binomial	
Count (Art Loans)				
ΔEstablishment	-0.130		-0.256**	
	(0.116)		(0.109)	
ΔSmall Establishment		-0.0818		-0.174*
		(0.108)		(0.0911)
Year FE	YES		YES	
Location FE	YES		YES	
Logit				
Lag Art Loans	0.617**	0.609**		
	(0.310)	(0.295)		
After Crisis	16.56***	18.41***		
	(0.708)	(0.697)		
Observations	207	207	230	230
χ^2	1637.8	1647.1	1455.6	1451.9
Pseudo R^2			0.404	0.401

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: This table presents the relationship between the variation in local establishments and art-secured borrowing. “Births and deaths” of total or just small establishments in each metro area are used to calculate the explanatory variables. In this analysis, the small establishments have less than 20 employees. The time horizon is from 2004 until 2013. The excess zero count is explained by the number of art loans in the preceding year (*Lag Art Loans*) and the dummy variable (*After Crisis*) which is equal to one for each year after 2008.

	Zero-Inflated Poisson		Negative Binomial	
Count (Art Loans)				
Local Stock Return	-0.00606*	(0.00346)	-0.00733**	(0.00363)
Year FE	YES		YES	
Location FE	YES		YES	
Logit				
Lag Art Loans	0.870***	(0.321)		
After Crisis	1.994***	(0.724)		
Observations	240		260	
χ^2	1081.9		1433.0	
Pseudo R^2			0.356	

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: This table presents the relationship between lagged local stock performance and art-secured borrowing. The local stocks (Nasdaq-listed companies) are identified based on the location of the head-quarter. The stock return index is computed using the weighted average return of stocks with a price of more than $3 at MSA-by-year level. The time horizon is from 2003 until 2015. The excess zero count is explained by the number of art loans in the preceding year (*Lag Art Loans*) and the dummy variable (*After Crisis*) which is equal to one for each year after 2008.

returns of firms with headquarters in the same geographic area because of the trading pattern of local residents. Ivkovic and Weisbenner (2005) address the availability of asymmetric information in financial markets and show that households can exploit local knowledge by investing locally. According to their study, an average household generates an additional return from its local holdings relative to its non-local holdings. These studies find evidence suggesting that traders buy local stocks and earn benefit from their local holdings. Based on the previous studies it is assumed that variations in local stocks affect local investors more than non-local investors. Poor performance of local stocks not only shows a downturn in the economy, but also represents a negative shock to the financial wealth of the local traders.

Inspecting the local stocks also helps to test the effect of variations in financial wealth on art borrowing behavior. The geographical holdings are more significant for small capitalization stocks (Coval and Moskowitz, 1999) and those that are not in the S&P 500 index, which leads us to focus on Nasdaq-listed companies following Ivkovic and Weisbenner (2005). Focusing on intra-day trading and time zone differences, Loughran and Schultz (2004) present some evidences to show that a disproportionate amount of trading is observable in the cities where the Nasdaq-listed companies are placed.

After identifying the location of Nasdaq-listed firms using Compustat data, I build a value-weighted return index for each MSA, based on the set of companies headquartered in that area. The impact of low price stocks is diminished by excluding stocks in every year that has a price of less than $3 at the beginning of the year. Metro areas with less than three companies are also excluded in this test. Table 8 shows the effect of the local stock market performance on the subsequent art-backed borrowings.[7] The main explanatory variable is the local stock market return in the preceding year. Goetzmann, Renneboog, and Spaenjers (2011) find that lagged stock price growth has a significant impact on art prices. The negative coefficients in this test also suggest that lagged stock

[7]The analysis with winsorized dependent variable gives a regression coefficient of -0.00774 with the standard deviation of 0.00389 and significant at 5%.

performance has an effect on art borrowing, which increases when stocks perform poorly.[8]

1.6 Art Loans vs. Home Equity Loans

Real estate is one of the main sources of collateral used for borrowing. There is a broad agreement in the literature that housing wealth supports consumption. Greenspan and Kennedy (2008) use survey results and find that a considerable part of the equity from refinancing or home equity loans is used to repay non-mortgage debt such as credit card loans. Moreover, the marginal propensity to consumption is argued to be larger for housing wealth compared to financial wealth according to Bostic, Stuart, and Painter (2006), and Case, Quigley, and Shiller (2005).

The collateral lending channel and the effect of housing prices on businesses and individuals is also widely investigated. Adelino, Schoar, and Severino (2015) show that increased collateral values facilitate lending for small establishments during the housing price boom of 2002–2007. Schmalz, Sraer, and Thesmar (2015) study the effect of housing price appreciation on homeowners and renters in France and find that homeowners are more likely to become an entrepreneur with an increase in collateral value. However, Kerr, Kerr, and Nanda (2015) argue that the link of home prices to the rate of entrepreneurship through home equity channels is modest in economic magnitude.

This study links art-secured borrowing to economic condition and consumption needs. Since there are documented findings about the relationship between housing wealth, consumption, and economic activities, it is also interesting to test the connection between the art-secured lending market and the real estate credit market. I specifically compare the demand for art-backed loans with the demand for home equity loans and also housing prices to test a pecking order theory for high net worth individuals.

Investigating the relationship between the demand for art-secured loans and second lien

[8] I also use local financial income share following Mian, Rao, and Sufi (2013) as another indicator of the financial situation. This measure considers the market value of stock and bond holdings in a specific area with the assumption that a typical household owns the market index of securities. There is no significant relationship between this measure and art lending.

	Zero-Inflated Poisson	Negative Binomial
Count (Art Loans)		
ΔMortg Demand	-0.00367	-0.00349
	(0.00470)	(0.00451)
ΔMortg Rejection Rate	0.0115**	0.0134***
	(0.00501)	(0.00486)
Year FE	Yes	Yes
Location FE	Yes	Yes
Logit		
Lag Art Loans	0.796**	
	(0.345)	
After Crisis	2.168***	
	(0.721)	
Observations	247	247
χ^2	1976.6	3904.1
Pseudo R^2		0.357

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: This table presents the relationship between the rejection rate of second lien mortgages and art-secured borrowing. This test considers the second lien mortgages with a value of more than $50k which are not used for the purpose of home purchase, and borrowed by individuals with the income of more than $250k. The change of demand and rejection rate are computed in each MSA area based on the number of the applications and granted loans. The time horizon is from 2004 until 2015. The excess zero count is explained by the number of art loans in the preceding year (*Lag Art Loans*) and the dummy variable (*After Crisis*) which is equal to one for each year after 2008.

home equity loans is the next exercise. A second lien mortgage is a loan which borrowers can take out using their homes as collateral while they have another more senior loan secured by the same home. These loans are mainly home equity lines of credit, which are revolving credit lines similar to credit cards. Some of these second lien mortgages are closed-end term loans. Such mortgages facilitate debt-financed consumption and also home purchase as a piggyback loan, helping borrowers to buy homes with small down payments. Manchester and Poterba (1989) report that there is a negative correlation between the stock of second mortgage debt by a household and its net worth which means the rise in second mortgage borrowing is based on financing personal consumption. This type of financing increased after 2005 and some economists regard it as a contributor to the recent financial crisis.

For the mortgage test in Table 9, the HMDA database is used from 2004 until 2015. I consider only the second lien mortgages which are not used for purchasing the house. This

	Zero-Inflated Poisson		Negative Binomial	
Count (Art Loans)				
House Return	-0.0107**	(0.00501)	-0.00867***	(0.00417)
Year FE	YES		YES	
Location FE	YES		YES	
Logit				
Lag Art Loans	1.349	(1.556)		
After Crisis	16.92***	(0.770)		
Observations	312		336	
χ^2	1705.1		1840.8	
Pseudo R^2			0.407	

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: This table shows the correlation between the housing market return and demand for art-secured loans. The *House Return* variable at each year measures the cumulative return in the preceding five years using MSA-level Freddie Mac House Pricing Index. The time horizon is from 2003 until 2015. The excess zero count is explained by the number of art loans in the preceding year (*Lag Art Loans*) and the dummy variable (*After Crisis*) which is equal to one for each year after 2008.

helps us to focus on loans used for a consumption purposes, although buying a house is not entirely an investment activity. For each MSA available in the art loan data, I count the number of second lien loan applications with a value of more than \$50k borrowed by applicants with an income of more than \$250k. Since we can observe whether the loans are actually granted after the applicant's request, it is possible to compute the rejection rate of mortgages based on the number of applications.

The main explanatory variables in Table 9 are the changes in demand and rejection rate of mortgages. These variables are expressed in percentages and based on the number of loan applications at the MSA-by-year level. On average there are 517 loan applications each year in a metro area and the rejection rate is around 49% in our sample. As the top panel of the table suggests, higher rejection rates of second lien loans are correlated with higher art-backed financing. One standard deviation change in the rejection rate can increase the number of art loans by 27.8%. As the results suggest, art as collateral is increasingly used when home equity loans are difficult to obtain.

As discussed before, art can be a substitute for real estate when the value of housing decreases. One would think about a negative correlation between the housing return and

	(1)	(2)	(3)	(2)
	Jackknife Std Err	Winsorized Dep Var	Jackknife Std Err	Winsorized Dep Var
Count (Art Loans)				
ΔReal GDP	-0.129***	-0.103***		
	(0.0210)	(0.0381)		
ΔMortg Demand			-0.00349	-0.00424
			(0.00223)	(0.00458)
ΔMortg Rejection Rate			0.0134***	0.0138***
			(0.00400)	(0.00486)
Year FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Observations	300	300	247	247
Pseudo R^2	0.328	0.360	0.357	0.338

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11: This table presents the robustness tests for the main results obtained by the negative binomial panel regression. In columns 1 and 3, the jackknife standard errors are reported. In each trial of the jackknife bootstrapping, one subset of the observations for a metro area is left out. In columns 2 and 4, the dependent variable is winsorized to limit the effect of the extreme values.

art lending. This also happens if the housing market moves in the same direction as the economy. In the final test, I analyze how art lending behavior changes with housing prices. I use Freddie Mac's Housing Price Index. Since the dataset has a monthly housing price index, I average the prices in each year. Table 10 shows the result of the panel regression with the return on housing as the covariate. As expected, there is a negative and significant correlation between housing prices and art lending behavior. This evidence also supports the hypothesis that art as a cash producing technology is used in times of financial needs.

Table 11 shows the results of some robustness tests. Since the dependent variable (number of art loans) is over-dispersed and our data sample is small, one might think that the results could be affected by the outliers. I limit the extreme values by winsorizing the dependent variable and repeating the main tests using the changes in GDP and rejection rate of mortgage applications as covariates in separate regressions in columns 2 and 4. I also use the jackknife bootstrap method to compute the standard errors for the regressions in columns 1 and 3. In each trial of the jackknife bootstrapping, one subset of the observations for a metro area is left out. This helps to ensure that the coefficients are not hugely affected by some observations from one single metro area. In this table and any other test, the independent variables are winsorized to protect the results from the effect of outliers. As shown in the table, we obtain the same significant results.

1.7 Conclusion

The art lending business is growing in the United States mainly because of the legal environment of the Uniform Commercial Code under which debtors can keep possession of their artworks, and creditors can register their security interest in collateral. Selling artworks may not be cost and tax efficient. Therefore, following the boom in the art market during the last two decades, a growing population of collectors is using art lending specialists to secure loans against the value of their collections. These collectors are borrowing to finance their businesses, buy new art, or fulfill sudden liquidity needs.

This study investigates private collectors borrowing from auction houses and art lending specialists. I analyze the effect of regional variations in the local economy on the art-backed lending activities in the metropolitan areas in the United States to reveal how the demand for such loans is related to the regional financial and economic conditions. Using various measures of regional economic performance including the GDP, establishments growth, and local stocks returns, I show that collectors borrow when the economy does not perform well.

I investigate the potential of art as collateral used a substitute for real estate. Specifically, I look at home equity as another main source of collateral and also the effect of housing prices. I find that art-backed borrowing increases when the rejection rate of home equity loans is higher or when housing prices decline. A natural interpretation of these results is that both new and traditional creditors in the art market accept art as collateral for liquidity borrowing by wealthy individuals when the economy performs poorly, and particularly in situations when home equity loans are difficult to obtain.

Investigating the collateral usage of art is particularly relevant after the boom in art collecting. High net worth individuals, who allocate a considerable portion of their wealth to art and possess artworks of high market value and demand, can now use this new approach to financing in addition to traditional practices. Furthermore, art as a new source of collateral needs more investigation since it is portable and marketable around the world, which makes it a specific asset class, distinct from other sources of collateral with private value, such as real properties. If borrowers default, creditors can liquidate art in non-local markets and realize their value by reaching out to broader demand in a more stable economy. As this lending service is becoming more prevalent in some countries, we may also expect to see it becoming a component of art price due to its potential value for borrowing as an alternative to fire sales. This mechanism could affect the prices of "blue-chip" artworks with high common market value, which is the topic of another study.

Appendix A : Count data regression models

If y_{it}, the loan count of area i at time t, follows a negative binomial distribution, then:

$$Pr(y_{it} = k) = \frac{\Gamma(\theta+k)}{\Gamma(\theta)\Gamma(k+1)}(\frac{\lambda_{it}}{\lambda_{it}+\theta})^k(\frac{\theta}{\lambda_{it}+\theta})^k,\ k = 0, 1, 2, ...$$

where θ is the over-dispersion parameter, $\Gamma(.)$ is the gamma function, and λ_{it} is the expected value of y_{it} which is estimated by:

$$log(\lambda_{it}) = \mu_t + \beta x_{it} + \alpha_i$$

Allison (2009) suggests using unconditional maximum likelihood estimation by including dummy variables for all individuals. Allison and Waterman (2002) document that this method does not show any substantial bias due to incidental parameter problem. In this paper, x_{it} is any explanatory variable used including the GDP, stock return, and mortgage demand or rejection rate.

In zero-inflated Poisson model, y_{it} is generated by two separate processes. One process generates only zero counts and is chosen by probability φ_{it}, wheres the other process generates counts from a Poisson model and is chosen by probability $1 - \varphi_{it}$. This can be represented as:

$$y_{it} \sim \begin{cases} 0 & \varphi_{it} \\ f(y_{it}|x_{it}) & 1 - \varphi_{it} \end{cases}$$

where $f(.)$ is the distribution function for a Poisson process. If the probability φ_{it} depends on z_{it} vector of characteristics, which are called zero-inflated covariates, then:

$$Pr(y_{it} = k|x_{it}, z_{it}) = \begin{cases} (1 - \varphi(\gamma z_{it}))f(0|x_{it}) + \varphi(\gamma z_{it}) & k = 0 \\ (1 - \varphi(\gamma z_{it}))f(k|x_{it}) & k > 0 \end{cases},\ k = 0, 1, 2, ...$$

and γ can be specified by a logit or probit model. Unlike the Poisson process, the zero inflated Poisson model demonstrates over-dispersion and does not have the equality of mean and variance as an assumption. In this paper, z_{it} is a vector including the dummy indicator for years after the recent financial crisis and art-backed loans originated in $t-1$.

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Chapter 2

Art and Investment Horizon

Abstract

Over the past two decades, the perception of purchasing art as an asset class has attracted many collectors with investment goals to the art market. In this paper, I examine how collectors invest in the art market by focusing on their investment horizons. Controlling for quality and market conditions, I show that collectors' personal taste and home biases positively affect ownership duration, while uncertainty in the valuation may have negative influences. I also find that the price tag, reputation of the artist, and some specific art characteristics are determinants of art owners' investment horizons, and that these factors could potentially affect the presence of art in the market for resale events. The natural conclusion of these findings is that artworks with high common market value are traded more frequently, while higher personal valuation can lead to longer ownership duration.

JEL classification: Z11

Keywords: Art market; Investment horizon; Private valuation

2.1 Introduction

The booming art market has attracted many wealthy individuals over the last few decades. These collectors trade artwork through auctions in a mysterious but visible market. In this paper, I study holding periods of artworks auctioned in the main salesrooms all around the world, in order to understand the factors that influence collectors' decisions to resell art in their possession. Investigating these factors sheds light on trade incentives, and also illuminates the effects of different players in the art market (e.g. creators, intermediaries, and consumers) on the secondary market supply.

While collectors enjoy possessing art for its aesthetic pleasure and social status, some may also consider its pecuniary gains from resale revenues, which add up to its ownership value. As suggested by Mandel (2009), art can be considered both a consumption good and an investment asset, and one can view art as an asset with non-tradable emotional dividends, for which the improved risk-adjusted return can be the motive for investing.

Similar to other financial assets, investors' decisions to buy art for a subsequent resale can be influenced by their appraisal of expected profit related to the capital gain from resale. Therefore, if an investor considers purchasing artwork for its pecuniary benefits, she also needs to consider the investment horizon. Art with a shorter investment horizon will have a higher probability of being resold in a specified time horizon. We use a dataset comprised of artworks auctioned in leading auction houses around the world from 1990 through 2008 in order to evaluate the factors affecting this probability, and at the same time the holding period intervals.

Since this study explores the holding periods, we specifically focus on resale decisions. Art collectors' decisions to resell is affected by the market and their own private valuations. Our results are consistent with the hypothesis that art with higher common or market value has shorter investment horizons. Based on our findings, we believe that higher common value can be attributed to higher-priced modern art paintings created by famous artists. On the other hand, the collectors' personal taste can be observed by higher bids, and buying national art leads to longer holdings.

To fully understand the private valuation of art, we distinguish buyers based on their taste, while comparing their bids to the appraisals provided by experts. Auction houses are the main sources of information about the quality of art. Their reputation and certainty in providing price estimates are also important factors affecting the market and trade decisions. Moreover, it is clear that collectors consider different characteristics of art and artists when they trade, and we thus control for all of those aspects. Finally, in our analyses, the macroeconomic conditions, such as time or country of trade, are considered.

If pre-sale estimates reflect the real value of art as suggested by Milgrom and Weber (1982) and also Mei and Moses (2005), those who pay higher than the estimates should have a stronger taste comparing to the general audience. We consider hammer price over pre-sale estimate ratio as a proxy for taste and find that those with a stronger taste, which we call them collectors, keep for a longer period. Moreover, our results suggest that the uncertainty of experts in art appraisal leads to longer possession intervals. We need to mention that before any auction event, art experts evaluate the artworks and provide price estimates for potential buyers. This estimation is a price range which has a low- and high-price estimate. We regard a bigger gap between these estimates as a higher uncertainty of the auction house about the real market value of the art.

Also, for each artwork, we inspect the collecting categories, size, price tag, and medium. Since the artist defines the quality of her artwork, it is also crucial to explore her influence on the resale decisions. We link the fame and importance of an artist to her origin and number of works she presented in auction sales. We document that higher priced artworks and modern art are more probable to reappear in auctions. Moreover, we find that if the artist is from some leading European countries in art or the US, and also she presented a higher number of works in auction sales, her artworks are traded more frequently.

Finally, the transaction costs are high in this market (15% on average) and could be important for those who pay attention to financial gains. However, we find that the holding period of buyers with any taste is not affected by the transaction cost. It could be the case that investors keep art long enough to justify the resale by an appropriate financial return and amortize the transaction cost over the possession interval.

This paper adds to the literature of art as an investment asset which is previously studied by Ashenfelter (1989), Goetzmann (1993), Pesando (1993), Chanel, Gérard-Varet, and Ginsburgh (1996), Mei and Moses (2002), Graddy, Hamilton, and Pownall (2012), Renneboog and Spaenjers (2013), and Korteweg, Kräussl, and Verwijmeren (2016) among others. This extensive existing literature investigates the art price formation and indices using two primary methods of repeat-sales regressions and hedonic method and suggests estimation corrections. The resale values and capital gains to art are the primary focus of the prior studies. However, this paper provides new insights into factors affecting the resale events researchers observe in a particular time horizon of their study.

The study closest in spirit to our work is by Lovo and Spaenjers (2014). In a theoretical framework, they model the trade of unique, durable assets, where agents exchange and enjoy art. In their model, agents buy and sell, according to their private value of assets, in addition to the expected resale gains. They show that strong taste of collectors leads to aggressive bidding, and they sell only in the case of a liquidity shock. These liquidity shocks, which usually force owners to sell at a low price, are known as 3 Ds: debt, divorce, and death. On the other hand, speculators who have little pleasure from ownership resell quickly. They empirically find that financial returns and holding periods are negatively correlated, since the speculators, who care about financial return, sell quickly.

Finally, the holding period of investments in some assets has been previously studied. For stocks, Amihud and Mendelson (1986) propose that investors would hold assets with a high bid-ask spread with a longer holding period. Atkins and Dyl (1997) find that transaction costs and firm size have a positive effect on the holding period of stocks while price volatility has an adverse effect. The impact of property type, return, and time on holding periods of real estate is studied by Collett, Lizieri, and Ward (2003). They show that holding periods varied over the period of their study and the greater the return, the higher the propensity to sell.

The remaining sections are organized as follows. The art market's mechanism is explained in the next section and a reader familiar with the art market may safely skip this part. Section 3 introduces the database used for different tests in this paper. Section 4 analyzes the effect of various factors, which are discussed in this introduction, on the holding periods and finally, we conclude in section 5.

2.2 The Art Market's Mechanism

The art market has been growing in the last decades. According to Arts Economics, global sales reached almost $66 billion in 2007, while it was less than $10 billion in 1991.[1] After the financial crisis in 2007, sales declined, but it bounced back to the same level in 2014. Art sales take place in auction houses all around the world, such as Christie's or Sotheby's. Almost all art is sold in the ascending price auction. The bidding starts at a low price, and the auctioneer calls out for higher bids. The final price is called "hammer price." The seller has a reserve price and does not sell to bids below this price. The unsold item is called "bought in." The highest bid wins the auction only if it is more than the reserve price, and the winner pays his bid plus a commission (buyer's premium) to the auction house. The seller also receives a fraction of the highest bid and has to pay the seller's commission. If the highest bid does not meet the reserve price, the seller has to pay a fee to the auction house for organizing the event, which gives the motivation to set a lower reserve price.

Before the auction event, the auction house evaluates the artwork and provides the price estimates for potential buyers. The estimate is a price range that has a low- and high-price estimate. Auction houses publish catalogs a few months in advance with a complete description of artworks and price estimates. According to Milgrom and Weber (1982), honesty in providing information is the best policy for the seller in the first price auction. Although Mei and Moses (2005) show that price estimates for expensive paintings have an upward bias, they document that these estimates, on average, are not biased. Bruno, Garcia-Appendini, and Nocera (2014) document that the experience of auction houses in

[1] TEFAF, Art Market Report 2014.

trading works of an artist can lead to better price estimations for her other artworks.

The low-price estimate is an indicator of the reserve price, and by regulation, it should be higher than the reserve price. Ashenfelter and Graddy (2011) estimate that the reserve prices for contemporary art auctions are about 70 percent of the low-price estimates provided by the auction houses. On the other hand, the upper bound of the estimate or the high-price estimate shows the evaluation of the auction house from the market condition and potential bidders. It is also argued by Bauwens and Ginsburg (2000) that higher price estimates discourage buyers from showing up at the sale event.

2.3 Data

Our dataset consists of paintings and works on paper auctioned in main auction rooms all around the world from 1990 until 2008.[2] The paintings (works on canvas) are 76% of the total data, while works on paper are just 24%. In these observations, 659,874 unique artworks from 49,751 artists are put up for 714,031 auctions. These items belong to one of the main three collecting categories of old-masters, 19th century, and modern art. The dataset tracks 36 auction houses in 39 different cities.

The dataset represents information about auctioned items such as the title of the work, artist's name and origin, size, and year of creation. It also includes data for the date of each auction event, location and name of the auction house. The low and high-price estimates, hammer price (if there is any), the currency, and finally equal values of estimated and hammer price in USD, EUR, and GBP are also provided. Figure 1 represents the total number of auctioned artworks in each year. Our data excludes artworks with a price of less than 1000 USD.

Successful auctions, which led to a transaction, are 62% of the total observations. 26% of all observations are old-masters, 32% are from the 19th century, and finally 42% are modern art. 33% of items are auctioned in Christie's, 30% in Sotheby's, and just less than

[2] The Art Market Database is provided by Brunella Bruno and Giacomo Nocera and based on ARTINDEX-Munus raw data.

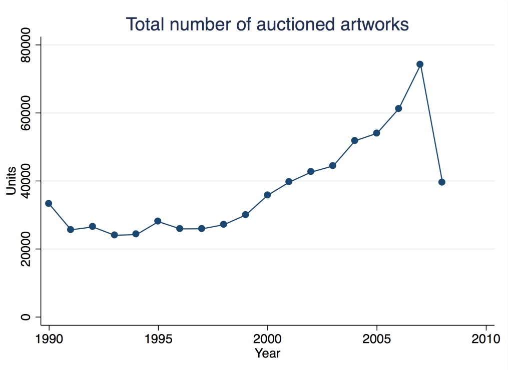


Figure 2.1: Total number of artworks auctioned per year in the global art market.

Country	Volume Share
UK	36%
US	23%
Italy	11%
France	7%
Austria	7%
Germany	6%
Netherlands	6%
Other	4%

Table 2.1: The volume share of different countries in the global art market.

7% are brought to Dorotheum. Table 1 shows the distribution of the sample in countries where auctions took place.

Since studying the possession intervals is the primary goal, we consider artworks which were sold at least once. These artworks provide us with 417,125 observations. 15,429 unique artworks are put up for another auction at least once more after their initial purchase in the available time horizon, and 73% of these items were successfully sold again. For the items that we tracked for 230 months, the average holding time is almost 219 months (restricted mean survival time). Clearly, we can only track artworks if they are sold in the salerooms which we cover in our study. However, our dataset is moderately comprehensive and can represent 60-70% of the total market. For example, while the art market report provided by Artprice (2010) suggests $2.5 billion turnovers for fine art auctions in 2002, our data shows $1.8 billion of sales.

2.4 Survival Analysis of the Art Ownership

Think of a time interval which begins when a collector purchases an artwork and ends whenever she tries to resell the art in another auction. We would like to know which factors can affect this time interval and make collectors resell their artworks more quickly. For this reason, it is beneficial to take advantage of information for unsold items, and hence the stopping point of our interval is an attempt to sell, which can be successful or not. With including the unsuccessful auctions, we can track the collector's motive better than just looking at repeat sale data, where the focus is just on successful resales.

In the time horizon of our study, some artworks remained unsold after the initial purchase, and this makes the data censored. The survival analysis has been widely used to examine the timing of different events of such data, e.g. investigation of the unemployment duration (Kiefer, 1988). Implementing this analysis provides insights into the investment horizon in the art market, and more importantly, keeps our statistical approach robust.

We use Cox proportional hazard model or the relative risk model, which is one of the most implemented duration models. This semi-parametric model has no assumption of the shape of hazard functions, and just the underlying hazard rate is a function of independent variables. Here, the hazard function is the probability of trying to resell in the next time interval, given that the artwork has been kept until this period by the owner. This model assumes proportional hazards and linearity within each group of covariates.

Before discussing the results, we need to know which factors should be considered in our model. First, we need a proxy for taste to answer this question whether art lovers keep artworks for a longer period of time or not. We use the hammer price over the pre-sale estimate ratio as the measure of personal valuation and love. Buyers who pay more than expert estimates are considered to have higher passion or stronger taste for an special work of art. The average of low and high-price estimates is used as the overall pre-sale estimate in this study.

Second, we employ several art characteristics which potentially can affect the hazard function and holding intervals. We use the artwork's characteristics such as the price paid

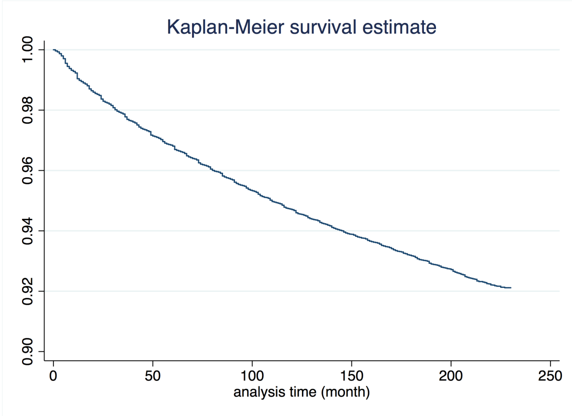


Figure 2.2: The Kaplan-Meier survival estimate for the entire population of observations.

at the time of purchase, in addition to the collecting category, medium, and even size. We also include some measures of the artist's fame by considering her origin (country of birth) and number of unique artworks she presented around the world through auctions. In brief, these covariates consider quality and fad factors to some extent.

In addition, the uncertainty or disagreement about the value of artworks is used and proxied by $\frac{High\,Estimate - Low\,Estimate}{Average\,Price\,Estimate}$, which is the gap between the low and high-price estimates. Our hypothesis is that works with certain valuation should have evident demand in the market. Finally, the effect of transaction cost on holding period is also considered. Specifically, the commission paid on the purchase is included as another covariate. One might think that if art is more like an investment asset, then we would expect to see a negative impact of transaction costs on the holding period.

Figure 2 shows the Kaplan-Meier survival curve for the entire art market. In the art market the possession time is very long and almost 92% of items that we observed remained unsold after their initial purchase. For the items that we tracked for 230 months, the average holding time is almost 219 months.

2.4.1 Univariate Tests and Selecting the Predictors

Before building the survival model including all potential predictors, we need to have some univariate analysis to select the covariates. The Kaplan-Meier curve for the categorical

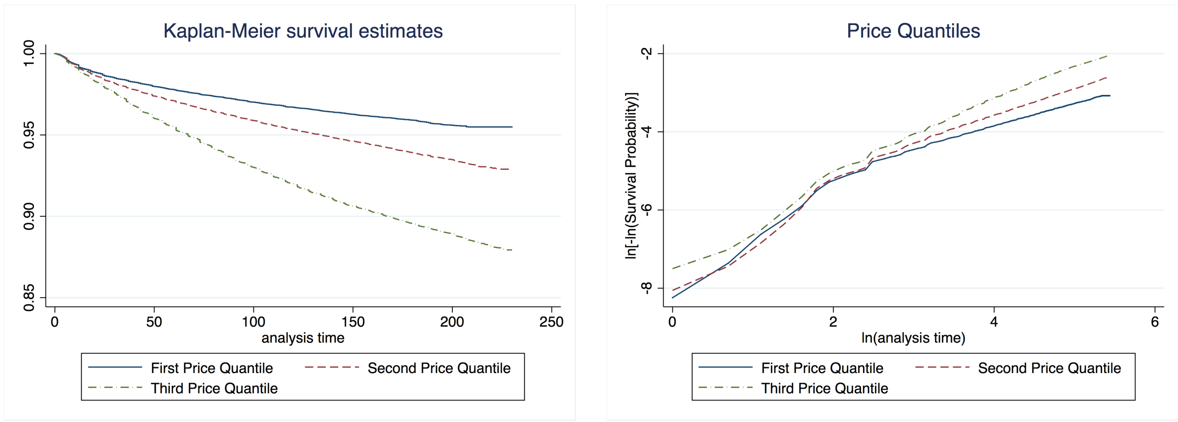
	(1)	(2)	(3)	(4)	(5)	(6)
log(Price)	0.232***					
	(50.99)					
log(Total Works)		0.377***				
		(67.32)				
Price/Estimate			-0.0734***			
			(-6.45)			
Estimation Gap				-0.709***		
				(-11.49)		
Buyer's Premium					-0.125	
					(-0.70)	
log(Size)						-0.0219*
						(-1.72)
Observation	417,125	417,125	417,125	417,125	417,125	414,935

z statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.2: The univariate Cox regression tests for the continuous covariates.

predictors provides some insight into the shape of the survival function for each group and their proportionality. The log-rank test of equality across these strata also helps us to identify proper categorical predictors in the final model. Similarly, for continuous variables, we examine some univariate Cox proportional hazard regressions. For the continuous covariates, we also group observations by a specific predictor and visually inspect the survival functions.

Table 2 represents the results of the univariate tests for continuous predictors we employ in building the final model. The hammer price, buyer's premium, size of artworks, the total number of unique artworks by the artist, price over pre-sale estimate ratio, and pre-sale estimation gap are the considered continuous predictors. Positive coefficients suggest that increase in the value of the predictor intensifies the probability of reselling in a given time interval. The size of artworks has a little effect on the hazard function and it is excluded from the final model. The buyer's premium does not produce a statistically significant result, but since previous research on stocks and real estate show the connection of the transaction cost and holding period, we still keep this predictor in the analysis. It does worth to mention that unlike the seller's commission, the buyer's premium is not



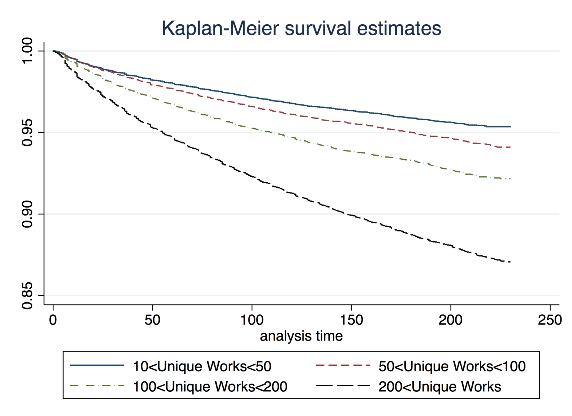
(a) (b)

Figure 2.3: a) Kaplan-Meier b) log minus log survival curves for price quantiles.

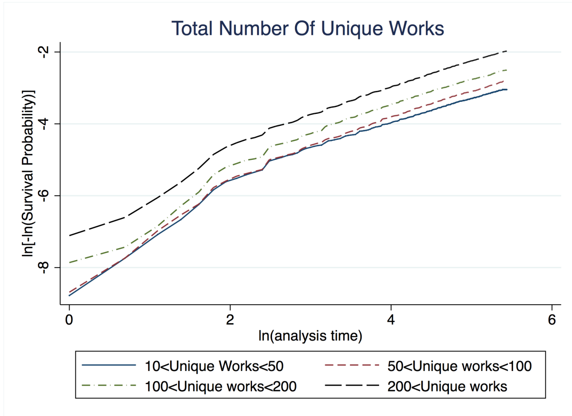
negotiable with the house because it gives an advantage to one buyer competing with others.

One way to observe the variations of the survival function due to changes in a continuous predictor is to make a categorical variable from the predictor. Just for a visual reason, we split the observations into three quantiles based on their log of the hammer price (Figure 3). We also group observations into four, by the total number of unique artworks that their artists have (Figure 4). Figure 3 and 4 show that an artwork with a higher price and for an artist with lots of work presented in the market are kept for a shorter time. In Figure 5, we also split art owners into three, based on the purchased price over pre-sale estimate ratio. In this figure, underpayers are those who pay less comparing to pre-sale estimates, and overpayers bid aggressively. Figure 5 shows that underpayers, who pay less compared to estimates, sell quicker that those who overpay.

For the categorical variables, we look at log minus log plots for the survival probability. If the curves associated with strata have approximately constant differences over time, then it is possible to include the covariate in the final model, and be confident about the linear modeling of risk factors in the hazard rate (for more information about relative risk regression models look at [Kalbfleisch and Prentice, 2002]). Figure 6 represents the estimated survival functions when different types of artworks or collecting categories form the strata. Tis figure exhibits a constant separation between subsets of observation. We

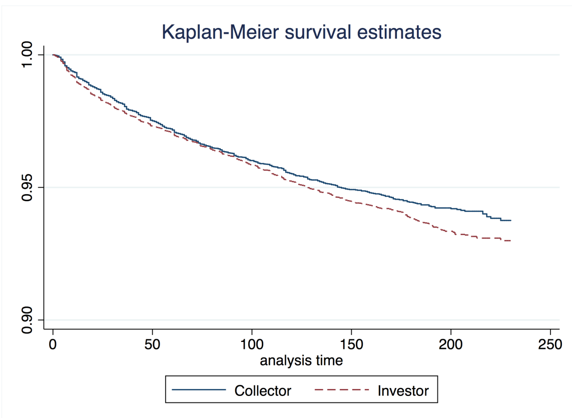


(a)

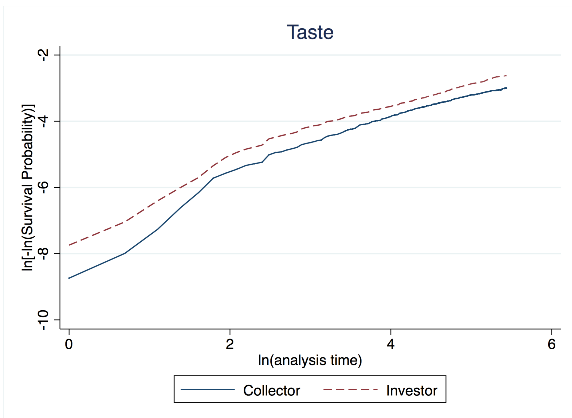


(b)

Figure 2.4: a) Kaplan-Meier b) log minus log survival curves based on artist's total number of unique works.

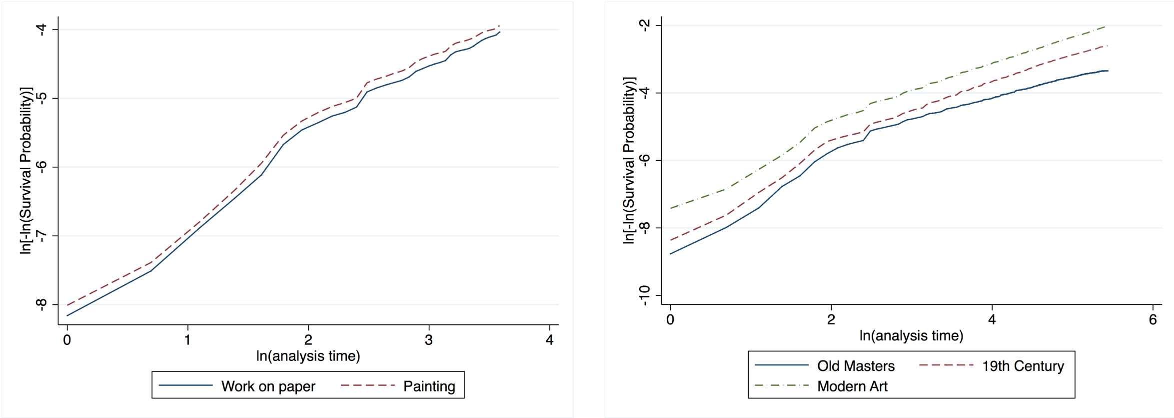


(a)



(b)

Figure 2.5: a) Kaplan-Meier b) log minus log survival curves based on art owner's taste.



(a) (b)

Figure 2.6: The log minus log survival curves based on a) type b) collecting category of art.

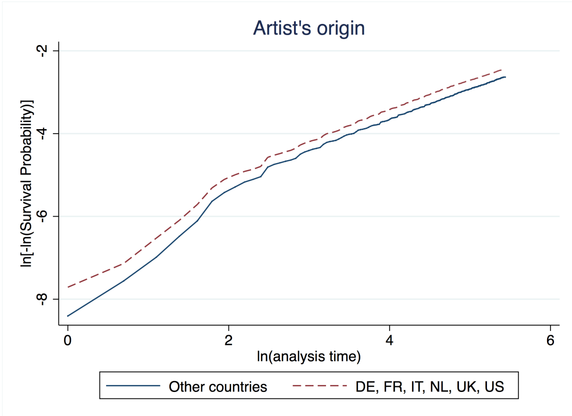
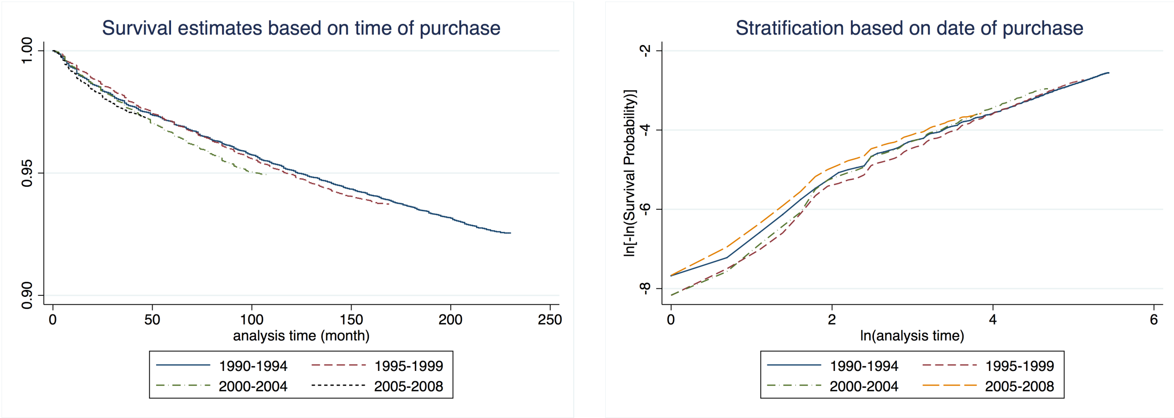


Figure 2.7: The log minus log plot based on the origin of artists.

split the observations into two categories based on the origin of artist. 68% of artworks belong to artists with an origin in France, Italy, Germany, Netherlands, UK, or the US, while the remaining 32% belong to artists with a different origin. Figure 7 suggests that the proportional hazard specification for the origin of artists is reasonable.

To adjust for the variations in the macroeconomic conditions, it is helpful to control for the time and location of purchase. We group artworks based on the date of purchase, and divide the time horizon into four almost equal windows, which controls for trends in sales or taste. Figure 8 shows Kaplan-Meier and log minus log survival curves for groups of artworks separated by their purchase date. We can observe that those who purchased after 2000 are more likely to resell in an identical time interval. Figure 9 shows the survival curves based on the location of purchase. Since there are departures from



(a) (b)

Figure 2.8: a) Kaplan-Meier b) log minus log survival curves based on date of purchase.

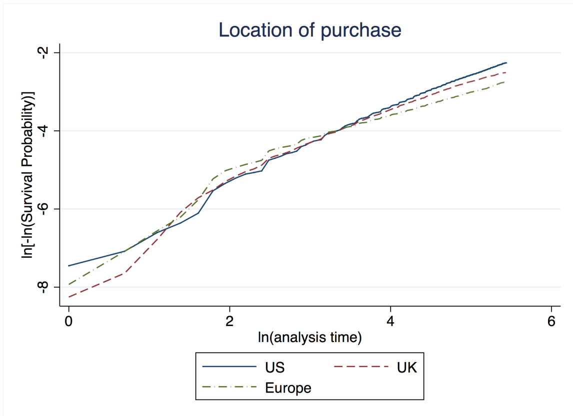


Figure 2.9: The log minus log plot based on the location of purchase.

constant separation, we can use the location and time of purchase to define the strata for baseline hazards.

2.4.2 The Relative Risk Model for the Art Ownership

Table 3 gives the estimates of the regression parameters and hazard ratios for the relative risk model of ownership time. In this analysis baseline hazards for each country and year is assumed to be heterogeneous. To have a closer look to different art markets in the world, we repeat the analysis for Europe, US, and UK separately in Table 4. Replicated regressions for each time window defined before are also presented in Table 5.

Covariates with a positive coefficient increase the probability of resale in a given time

	Coefficient	Hazard Ratio
Modern Art	0.526***	1.69
	(29.84)	
Painting	0.0566***	1.06
	(3.06)	
Compatriot	-0.0512***	0.95
	(-2.61)	
Auction House	-0.0895***	0.91
	(-3.35)	
Artist's Origin	0.242***	1.27
	(12.32)	
log(Price)	0.130***	1.14
	(21.69)	
log(Total Works)	0.258***	1.29
	(40.50)	
Price/Estimate	-0.118***	0.89
	(-9.38)	
Estimation Gap	-0.594***	0.55
	(-6.70)	
Buyer's Premium	0.150	1.16
	(0.44)	
Observation	417,125	

z statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3: The Cox regression model with the heterogeneous baseline hazard for each country and year of purchase.

	US	UK	Europe
Modern Art	0.349***	0.591***	0.638***
	(10.81)	(20.84)	(19.41)
Painting	0.0599*	0.0230	0.136***
	(1.85)	(0.77)	(3.86)
Compatriot	-0.174***	-0.0599*	0.151***
	(-4.54)	(-1.77)	(4.33)
Auction House	-0.0634	0.0654	-0.279***
	(-0.99)	(1.39)	(-6.37)
Artist's Origin	0.211***	0.293***	0.141***
	(6.10)	(9.51)	(3.51)
log(Price)	0.144***	0.144***	0.102***
	(13.80)	(14.11)	(7.87)
log(Total Works)	0.268***	0.237***	0.275***
	(23.92)	(22.67)	(22.95)
Price/Estimate	-0.126***	-0.101***	-0.135***
	(-5.63)	(-5.30)	(-5.17)
Estimation Gap	-0.559***	-0.487***	-0.401***
	(-3.30)	(-3.16)	(-2.66)
Buyer's Premium	2.110***	-0.318	-0.426
	(2.96)	(-0.47)	(-0.81)
Observation	106,327	152,573	154,052

z statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: The Cox regression model based on the location of purchase with the heterogeneous baseline hazard associated to the year of purchase.

interval. Estimated parameters do not change significantly after adding interactions one by one (not reported here). Although some of the interactions have statistically significant coefficients, their impact on the holding period is very small, and they cannot add more power to the model represented in Table 3. One can also repeat the test with altering the final point of intervals from the reappearances to successful resales, but it is not clear how to interpret the results since there are many other factors influencing a successful sale and the demand side.

The results suggest that the modern art has a shorter holding period comparing to other artworks and old masters have a longer one. Indeed, keeping all other variables constant, the rate of reselling increases by 70% for modern art. Our results are not surprising, and a former head of 19th-century pictures at Christie's, Wendy Goldsmith

	1990-1994	1995-1999	2000-2004	2005-2008
Modern Art	0.496***	0.400***	0.573***	0.707***
	(15.28)	(11.63)	(17.89)	(13.94)
Painting	-0.0499	0.000552	0.116***	0.307***
	(-1.51)	(0.01)	(3.46)	(6.21)
Compatriot	-0.0396	-0.00827	-0.0559	-0.161***
	(-1.05)	(-0.21)	(-1.64)	(-3.08)
Auction House	0.0166	-0.0424	-0.0559	-0.237***
	(0.30)	(-0.72)	(-1.24)	(-3.72)
Artist's Origin	0.163***	0.246***	0.291***	0.358***
	(4.90)	(6.56)	(7.57)	(6.17)
log(Price)	0.196***	0.183***	0.0781***	0.00501
	(19.16)	(12.62)	(6.60)	(0.32)
log(Total Works)	0.192***	0.244***	0.296***	0.396***
	(17.25)	(19.69)	(24.54)	(21.74)
Price/Estimate	-0.198***	-0.157***	-0.0491**	-0.0488
	(-7.76)	(-6.05)	(-2.32)	(-1.59)
Estimation Gap	-0.641***	-0.657***	-0.449***	-0.407*
	(-4.04)	(-3.72)	(-2.73)	(-1.74)
Buyer's Premium	-1.251	1.943*	0.265	-0.643
	(-1.12)	(1.65)	(0.45)	(-1.25)
Observation	80,542	83,421	123,123	130,039

z statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: The Cox regression model split based on the date of purchase with the heterogeneous baseline hazard for each country of purchase.

told the New York Times: "*Old Masters just aren't sexy. There's so little on the market and it's difficult to learn about. There are no young dealers coming through the ranks, and there just isn't the same financial upside that you get with contemporary art.*" As Goldsmith indicates, if unlike prior to 1980s, the market does not appreciate old masters and the demand force is not as powerful as the one for modern art, then there is less motivation to put up old masters for sales.

Comparing the paintings to works on paper, art analysts also believe that the demand is in favor of paintings. In our test also paintings are more probable (by 6% to 30%) to be resold in a given time interval compared to works on paper. The origin of the artist and presence of her works in the market are also important factors defining the probability of resale. The results also suggest that it is more probable to see works of artists from the US and some European countries repeatedly, and works of artists with more presence in the market are more likely to be resold in a given time. Furthermore, if an American artist's work is purchased in the US, then it is more probable (by 17%) to be kept, while European works which are bought in their own country are more probable to get resold (by 15%) in a given time interval. In addition, those who buy from Sotheby's or Christie's in Europe are less likely to sell their artworks (by 28%).

The positive coefficient for the price over estimate ratio suggests that those collectors who overpay compared to pre-sale estimates hold for a longer period. These buyers with a stronger taste do not sell their art collection unless they have to. Moreover, we find that more expensive artworks are more probable to be put up for another auction. An increase in the log of price by one unit increases the resell rate by 14%. Higher price tags could mean higher quality, and quality works have more demand and more reappearance.

The positive coefficient of price can also be attributed to the effect of private value. If we think about the hedonic regression, the unexplained part of price by covariates can be associated to private valuation of the art and in the cox regression, we also have some factors that can explain the price to some extent in a linear model, so the positive coefficient for the price unexplained by other covariates can be attributed to private valuation. Finally, we can think of a situation that people get richer as they get older and those who buy expensive artworks die in a short time which leads to quick reappearance of their works in the market.

The buyer's premium or transaction cost does not seem to affect the propensity to resell, but higher uncertainty of experts in assessing artworks leads to a longer possession time. The coefficient of the estimation gap is negative meaning that the higher is the gap between high and low price estimates, the lower is the probability of resale in a given time interval. Uncertainty about the value can be due to the lack of acquaintance to the artist's works either because the artist is new in the market or auction house did not have experience dealing with the artist as suggested by Bruno, Garcia-Appendini, and Nocera (2014). In both cases, this could possibly translate in to the fact that buyers are not

	(1)	(2)	(3)	(4)
Modern Art	0.468***	0.600***	0.500***	0.535***
	(14.53)	(15.36)	(14.75)	(14.09)
Painting	0.0454	0.0728*	0.0824**	0.0266
	(1.31)	(1.79)	(2.35)	(0.68)
Compatriot	-0.0320	0.0104	-0.0749**	-0.0831*
	(-0.90)	(0.24)	(-1.97)	(-1.95)
Auction House	-0.0189	-0.148**	0.00914	-0.208***
	(-0.37)	(-2.53)	(0.18)	(-3.72)
Artist's Origin	0.276***	0.234***	0.253***	0.191***
	(7.67)	(5.43)	(6.68)	(4.55)
log(Price)	0.166***	0.117***	0.119***	0.110***
	(15.34)	(8.54)	(10.34)	(8.14)
log(Total Works)	0.234***	0.261***	0.287***	0.258***
	(20.85)	(18.02)	(22.55)	(19.11)
Price / Estimate	-0.614***	-0.0540	-0.323**	-0.0917***
	(-4.26)	(-0.13)	(-2.47)	(-4.69)
Estimation Gap	-0.957***	-0.514**	-0.229	-0.664***
	(-5.60)	(-2.47)	(-1.39)	(-3.46)
Buyer's Premium	0.405	0.409	-0.538	0.287
	(0.59)	(0.53)	(-0.83)	(0.40)
Observation	129,015	79,615	104,476	104,019

z statistics in parentheses
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 2.6: The Cox regression model based on quantiles of price over estimate ratio with the heterogeneous baseline hazard.

familiar with the artist and therefore less demand is probable to be anticipated.

2.4.3 Overpayers vs. Underpayers

It is possible to think of art market traders as a spectrum where on one side, participants value artworks per se and enjoy collecting (collectors), and on the other side, people mainly buy art to resell and enjoy the capital gain (speculators). Collectors would be expected to bid aggressively in auctions to acquire artwork, and do not sell unless they want to sell to change their collection or pay their debts. We would expect that side costs, such as commissions, should not influence their decisions. Some of these collectors would keep their artworks until the end of their life, and their collections are brought for resale by their inheritors. Naturally, we can think these buyers should hold art for an extended period. On the other hand, speculators should bid less and keep for a shorter period until the time they find a proper opportunity to resell their artworks. They should rationally sell when there is a capital gain on the resale. Assuming auction houses are aware of the market condition, potential buyers, and artwork's quality, we can think of collectors as those who pay more, on average, compared to the pre-sale price estimates provided.

If we categorize buyers by their price over pre-sale estimate ratio, in the top deciles there are overpayers (collectors) who paid much more than the estimates (the ratio is around 2), while in the bottom deciles, underpayers (investors) could win with lower prices than expected (ratio around 0.7). We repeat the Cox regression analysis in Table 6 by grouping buyers based on price over estimate quantiles. We observe that possession intervals of buyers are not affected by transaction costs (buyer's premium), suggesting that unlike other assets, art owners do not wait to justify costs. There is not much of a difference in the estimation across quantiles, possibly a hint that reselling due to illiquidity shocks for buyer's with a strong taste is not a serious phenomenon in the art market.

However, there are some concerns with the definition of collectors and investors based on the price over estimate ratio. First, if the estimation is not accurate (defining *accurate* is also controversial), a higher ratio does not perfectly mean that the buyer has a stronger taste. Although we think that this should not be vey serious, since the auction houses are the major reference in the market and have the expertise to evaluate the common value of artworks as good as any market participant. Moreover, according to Mei and Moses (2005), the overall estimates are not biased, and the bias is upward just for the expensive works, and this makes the relation between the price over estimate ratio and the taste (private value) even stronger.

Second, what if the estimation is accurate, but a low hammer price realizes due to a sudden decision of the owner to fire sale? In this situation, the owner sets a very low reserve price just to sell, and since the market does not anticipate the presence of the artwork, there could be less competition, and the hammer price could be much lower than expectations. We think that this also should not have a huge effect because the

	Sold Artworks	Bought-In Artworks
Modern Art	0.526***	0.178***
	(29.84)	(14.29)
Painting	0.0566***	0.331***
	(3.06)	(22.94)
Compatriot	-0.0512***	0.0928***
	(-2.61)	(7.11)
Auction House	-0.0895***	-0.0145
	(-3.35)	(-0.85)
Artist's Origin	0.242***	0.0964***
	(12.32)	(7.13)
log(Price)	0.130***	
	(21.69)	
log(Total Works)	0.258***	0.119***
	(40.50)	(33.01)
Price/Estimate	-0.118***	
	(-9.38)	
Estimation Gap	-0.594***	-0.345***
	(-6.70)	(-5.56)
Buyer's Premium	0.150	
	(0.44)	
Observation	417,125	249,652

z statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: The Cox Regression model with the heterogeneous baseline hazard for country and year of purchase for successfully sold and initially bought-in artworks.

auction events are scheduled in advance and the information spreads few months before any auction event.

2.4.4 Sold vs. Bought-in Artworks

In all the previous sections, the holding period starts from an initial purchase and this means that the owner of the artwork is changed at the initial point. In this section, we focus on artworks that were unsuccessfully tried to be resold (bought-in), and then we define the period from the first to the second try for reselling. The owner is usually the same person after the first unsuccessful trial, and should be more decisive to sell compared to other owners we focused on previously (unless the auction house itself buys the artwork according to an agreement). Indeed, Kaplan-Meier survival curve shows this

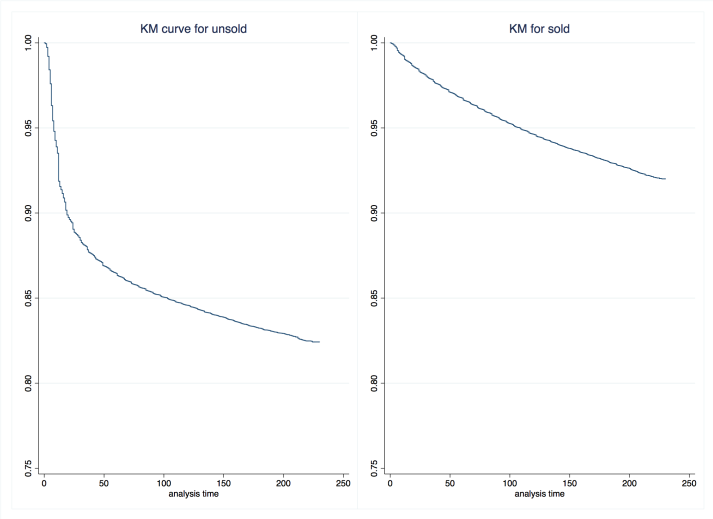


Figure 2.10: The Kaplan-Meier survival curves for initially bought-in and successfully sold artworks.

strong intention in Figure 10.

The art owners retry to sell their art pieces very quick. This is just the tip of the iceberg, since many of bought-in works should be sold somewhere outside of the main auction houses because of the reputation risk. The bought in artworks lose a lot of value, and this can be observed in Figure 11, where we compare the second estimates to the initial ones. For unsold artworks, or bought-in, the histogram of second to first pre-sale estimate ratio is mainly accumulated below 1, while for successfully purchased artworks the density of this ratio is more spread out. Table 7 shows the result of Cox regression for initially bought-in artworks. There is no initial price, but the previous results on quality measures still hold.

2.4.5 Proportionality and Goodness of Fit

To test for the proportionality of continuous covariates, in addition to categorizing, we also estimate Schoenfeld residuals. These residuals, that are computed per observation per covariate at observed event time, measure the difference between the value of each covariate for each individual and weighted mean of that covariate values for those in the risk set. Figure 12, shows the scaled residuals for our continuos covariates. Grambsch and Therneau (1994) show that $E(s_t) + \hat{\beta} \approx \beta_t$, where s_t, $\hat{\beta}$, and β_t are respectively scaled

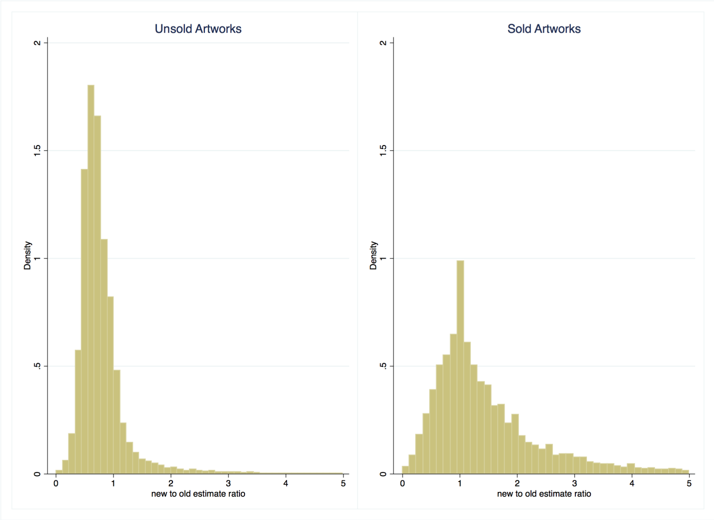


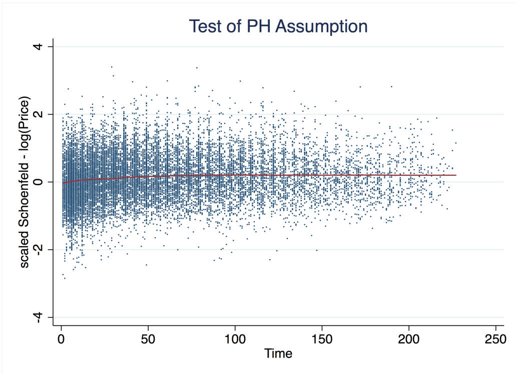
Figure 2.11: The new to old pre-sale price estimate ratio for initially bought-in and successfully sold artworks.

Schoenfled residual, estimated coefficient form Cox model, and time-variant coefficient of the regressor. By the proportional hazard assumption, there should be no time variation in the coefficients, and this implies a near zero Loess curves, which are the red lines in Figure 12. The same test is done for some dummy covariates we use in our model and the results are reported in Figure 13.

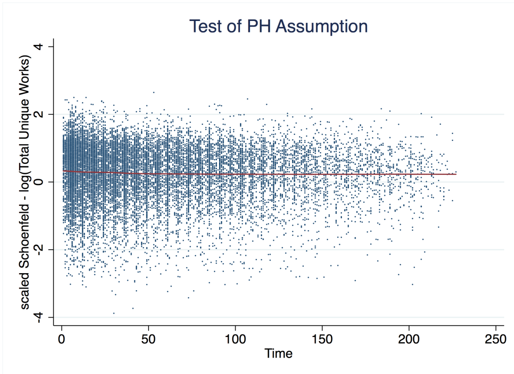
The model's goodness of fit is evaluated by using the Cox-Snell residuals. If the cumulative hazard function conditional on the covariates has an exponential distribution with a hazard rate of one, then the proposed model has a good fit for data. The hazard function in Figure 14 follows the 45-degree line except for large values of time, which is common in such data. According to these tests, the proportionality assumption is justified and the model properly fits to the data.

2.5 Conclusion

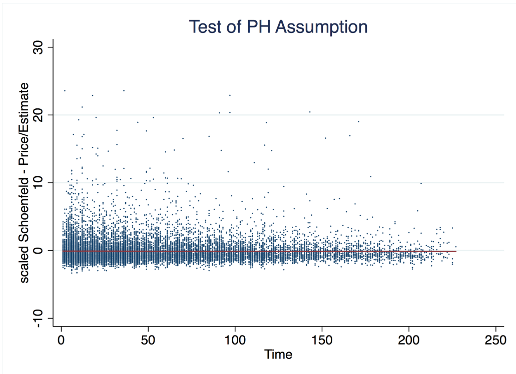
We investigate the factors that could potentially influence ownership duration and cause artwork to be more likely to reappear in auctions. Art collectors' decisions to resell are affected by the market and their own private valuations. We document that those with a stronger taste, who overpay (compared to the experts appraisal), keep their collection



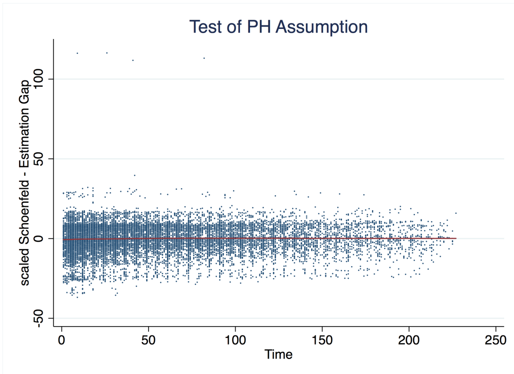
(a)



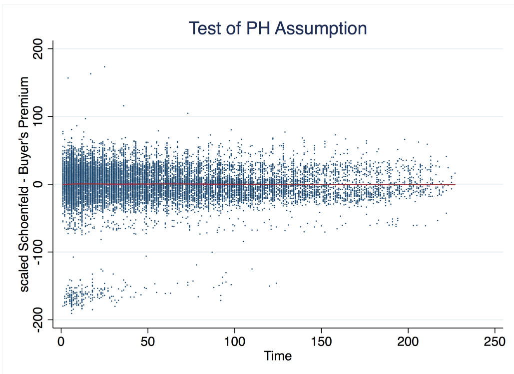
(b)



(c)

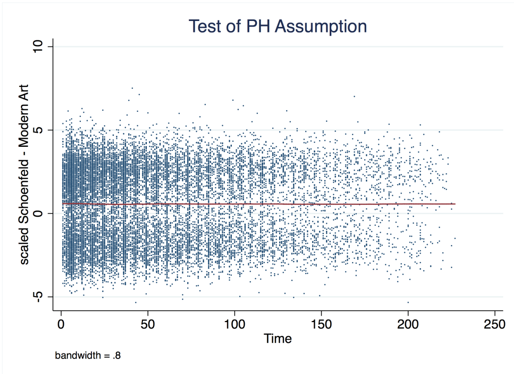


(d)

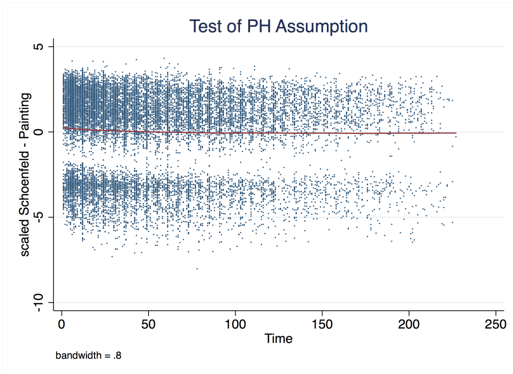


(e)

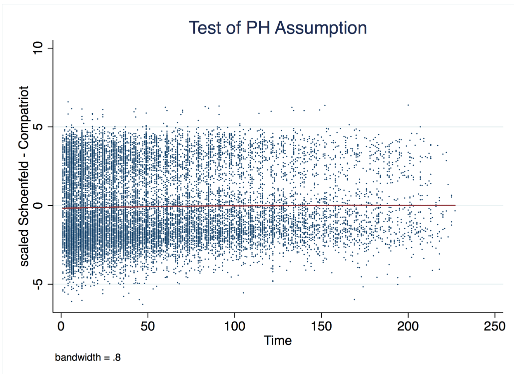
Figure 2.12: The Schoenfeld residuals for a) log(price) b) log(total unique works) c) price over estimate ratio d) estimation gap e)buyer's premium



(a)



(b)



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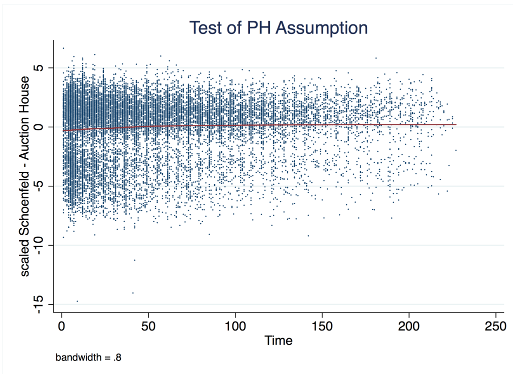
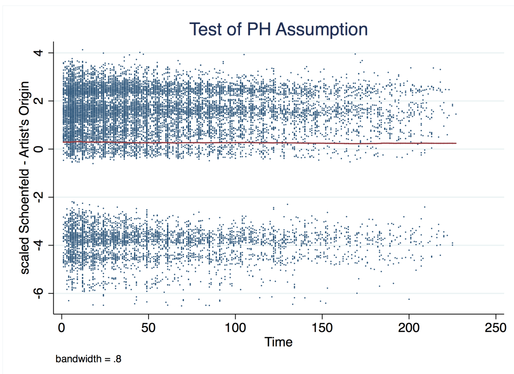


(d)



(e)

Figure 2.13: The Schoenfeld residuals for the dummy variables: a) modern art b) painting c) compatriot d) auction house e) artist's origin

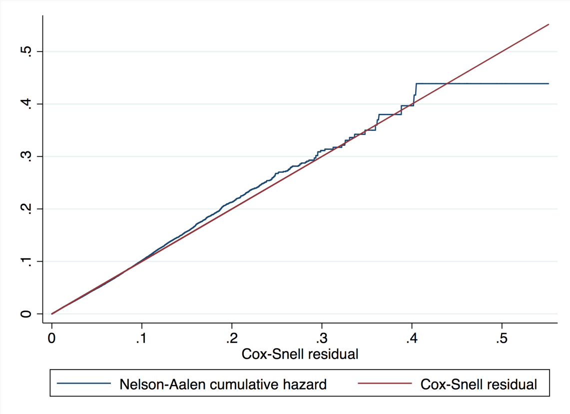


Figure 2.14: The goodness of fit is measured by using the Cox-Snell residuals.

for a longer period of time. Our results suggest that more expensive artwork is more foreseeable to be put up for other auctions, and higher uncertainty surrounding the value of art leads to a longer time of possession. We also find that in a given time interval, modern art is more likely to reappear for resale compared to old masters, and paintings have a shorter holding period versus works on paper. Finally, the origin of the artist and presence of her art in the market are relevant factors that impact the probability of resale, while transaction costs seem to not play a significant role.

Our results are consistent with the hypothesis that artwork with higher common or market value has a shorter investment horizon. We believe that higher common value can be attributed to higher-priced modern art paintings created by famous artists. However, the collectors' personal taste, which can be observed by higher bids and buying national art, lead to longer holdings.

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Chapter 3

The Information Content of the Risk-free Rate for the Pricing Kernel Bound

Abstract

The pricing kernel bound is a function of the risk-free rate. I unconditionally incorporate the fluctuation in the risk-free rate to tighten the restrictions on the admissible pricing kernel space. This semi-parametric framework improves the minimum discrepancy information bound introduced by Almeida and Garcia (2012), and can be used to test various asset pricing models. In this study, variations in the risk-free rate are attributed to two possible states of the economy. The proposed approach identifies these states; in which we observe clear shifts in the risk-free rate.

JEL classification: C1; C5; G1

Keywords: Pricing Kernel; Divergence Measure; Information-Theoretic Bound

3.1 Pricing Kernel Bounds

We can represent most of the asset pricing models in the form of the following fundamental valuation equation:

$$E(m_t R_t \Big| Z_{t-1}) = \mathbf{1} \tag{3.1}$$

where the random variable m_t is the pricing kernel (PK) and maps the vector of returns R_t to the prices. Here, Z_{t-1} is the vector of instruments at time $t-1$, and the pricing is conditional on this public information. The stochastic discount factor (SDF) is almost the similar concept as the pricing kernel, but the later is mainly a mathematical notion. While Equation (1) is in the historical world, we can also formulate the valuation equation in the risk-neutral (RN) world.

The academic research suggests that the feasible values of any pricing kernel are subject to some restrictions. Originally, Hansen and Jagannathan (1990) propose a lower bound (HJ bound) for the variance of any SDF which satisfies the fundamental valuation equation. The HJ bound identifies the feasible region on the mean-standard deviation plane of pricing kernel, where the lower variance bound of the pricing kernel is a function of its mean (or equally the expected risk-free return).

The PK bounds are used to test various asset pricing models. In other words, if a candidate stochastic discount factor (SDF) obtained from a proposed asset pricing model cannot satisfy the HJ bound, it fails to satisfy the fundamental valuation equation in the first place. Moreover, the PK bounds are useful to evaluate the contribution of return data for pricing assets, and also to measure the performance of investment vehicles such as hedge funds. In addition, they can assist in predictability studies, variance spanning, and market integration tests.

Finding more restrictions on the admissible PK space provides us with more powerful tests to evaluate the asset pricing models. Many scholars have proposed improvements for PK bounds. Gallant, Hansen, and Tauchen (1990) and Bekaert and Liu (2004) use the conditional information to improve the PK bound. In addition, Snow (1991) and Chabi-Yo (2008) focus on higher moments of the assets return and propose better restrictions on the moments of the SDFs.

Gallant et.al. (1990) develop a strategy to utilize conditioning information efficiently. They construct a new payoff space with combining the primitive set of asset payoffs and the conditioning information. Their suggested bound (GHT bound hereafter) is derived by computing the variance of the unconditional projection of the pricing kernel onto this new space. They use the semi-nonparametric methodology introduced by Gallant and Tauchen (1989) to estimate the conditional distributions of asset payoffs, and also to infer conditional moments.

The GHT procedure has not been used very much in practice. Instead, in many studies returns are scaled with predictive variables in the information set in order to augment the space of the available payoffs, and then the standard HJ bound for the augmented space is computed.[1] Bekaert and Liu (2004) use the conditioning information to effectively increase the dimension of the available asset payoffs. Their optimally scaled bound is efficient and leads to sharper bounds. Unlike GHT bound, their proposed bound is robust to the misspecification of the conditional mean and variance. They argue that the scaling only improves the HJ bound if the weight Z_t has information about the future return.

There is another strand of literature which proposes a new variation in computing the PK bound by employing information criteria. This strand emphasizes the link between the historical and risk-neutral probability measures. For example, based on the minimization of Kullback-Leibler Information Criterion (KLIC), Stutzer (1995) introduces the information bound, and shows the equivalence of the bound problem to the portfolio optimization problem under CARA utility function. In contrast to the HJ bound, the information bound incorporates the positivity of state price densities (SPD). The benchmark (optimal) SPD is selected by minimizing the KLIC distance between the set of RN and historical probability measures. When the RN probability measure diverges from the

[1] The scaled returns are asset payoffs equal to $Z_t' r_{t+1}$ and prices $Z_t' \mathbf{1_n}$. Look at the studies by Cochrane and Hansen (1992), Bekaert and Hodrick (1992) for some examples.

historical probability measure, the information bound is larger.

Similar to the variance bound, the information bound has a minimum distance interpretation. In order to construct the variance bound, we find SDFs as a particular affine combination of returns which is closest, in the mean square distance, to any admissible SDF.[2] Equivalently, to derive the information bound, we find the KLIC-closest SPD to any feasible SPD. To generalize the information bound, Almeida and Garcia (2008, 2012) employ another information criterion to measure the distance between the risk-neutral and true probability measure.

Almeida and Garcia (2008, 2012) improve the information bound using the minimum contrast measure of Cressie and Read (CR) (1984) and show the duality of their solution with the portfolio optimization problem under a general HARA utility function. This method considers higher moments of the return distribution. Unlike the PK bound suggested by Snow (1991), their measure puts implicit weights on a potentially infinite number of the higher order moments. The associated dual portfolio problem also corresponds to the Generalized Empirical Likelihood estimator, and some of its specific solutions correspond to the Empirical Likelihood or Exponential Tilting estimator, which are alternatives to the celebrated GMM.

The alternative interpretation for the information bound comes from the Bayesian perspective. For building an information bound, we choose the RN measure with incorporating the prior knowledge of the actual probability measure and the moment conditions. Stutzer (1995) describes that it is reasonable to consider a measure which does not embody irrelevant information other than the moment conditions. Hence, minimizing the information gained by the change of measure while satisfying the moment condition is the final technical objective of this strand of literature.

[2] An admissible SDF satisfies the fundamental valuation equation.

3.2 Risk-free Rate and PK Bound

Documented facts suggest regime switching (RS) behavior in assets return (e.g. Ang and Bekaert (2002); Ang and Timmermann (2011) among others). RS models can match abrupt changes in financial markets, which persist for several periods. Some behaviors of financial series such as fat tails, heteroskedasticity, time-varying correlations, and skewness can be captured by these models. To illustrate the effect of this feature of data on the SDF bounds, Bekaert and Liu (2004) formulate a regime-switching version of the unconstrained VAR model with the consumption growth, stock and bond returns as the variables of the VAR process. They define regimes based on the consumption growth and use RS models with constant and time-varying transition probabilities to calculate the conditional moments. They propose a new bound by optimally choosing the scaling vector which depends on the conditional moments of the return. The scaling vector augments the payoff space and delivers the best (largest) HJ bound. They find that the bounds generated by RS models are indeed sharper than the simply scaled bound. Indeed, the sharpest bound is generated by the most nonlinear model with time-varying transition probabilities.

The idea of incorporating the fluctuation in the risk-free rate in this study is inspired by this vast literature of the regime switching models and also empirical findings of Bekaert and Liu (2004). Moreover, our suggested approach is closely related to deciding about the status of the short rate in the framework of Bertholon, Monfort, and Pegoraro (2008). In the same spirit as their framework, this paper focuses on the status and importance of the risk-free rate for defining the relationship between historical and risk-neutral (RN) dynamics.

Bertholon et. al (2008) introduce the RN constrained framework as a part of their econometric asset pricing modeling (EAPM) approach. Their approach has three main ingredients, namely historical dynamics (which depends on the information in the economy), stochastic discount factor (which they consider to be an affine function of the information), and finally, the RN dynamics (which is a function of the other two). In their framework, the short rate can be exogenous or can be a function of the information in the economy and its status should be clearly decided before moving to the next steps. The next step is to constrain the historical and RN dynamics to belong to a given family and after that, the affine estimation of the discount factor and its relation to the information in the economy can be obtained. The short rate in their model can belong to a parametric family, but due to the nonparametric nature of our study, we assume that the risk-free rate in any time belongs to one of two possible states in the economy with a fixed expected rate in each state.

Our methodology is mainly based on the minimum discrepancy (MD) bound of Almeida and Garcia (2008, 2012), which focuses on the historical and RN probability measures to construct the PK bound. Employing their methodology provides us with a setup to unconditionally implement the fluctuations in the risk-free rate and also solve the numerical optimization problem with extending their proposed dual of the solution. The challenge of the study is in preserving the unconditional structure of the bound. We use a simple specification of the historical dynamics and constrain the RN dynamics by minimizing the discrepancy between the historical and RN probability measures.

Our findings are as follows. First, we obtain more restriction on the admissible pricing kernel space by considering a potential shift in the risk-free rate. In other words, with adding a possibility for the value of the risk-free rate to fluctuate over time, a sharper PK bound can be obtained. Second, there is a clear difference between the average risk-free rates in the states of the economy we identify. Finally, we observe that the state of the economy with a lower risk-free rate contributes more to the restriction of the admissible pricing kernel space.

The proposed improvement for the minimum discrepancy bound is also noteworthy because of many nice properties of the original bound. First, the original formulation of the problem considers higher moments in the distribution of returns and is suitable to analyze nonlinearities in asset pricing models and trading strategies. For example, hedge funds have dynamic trading strategies and their return exhibits nonlinear patterns, and the MD bound can capture nonlinearities and measure the alpha performance of hedge funds. Second, the solution of MD bound corresponds to an optimal portfolio problem under the HARA utility function which has a convenient economic interpretation. The special cases of HARA utility function include CARA, CRRA, and quadratic utility functions. The HARA utility function has a decreasing absolute risk aversion and decreasing absolute prudence, and this feature makes it a better choice comparing to the quadratic utility function, which is embedded in the dual problem for the HJ bound.

Unlike Bekaert and Liu (2004) or Chabi-Yo (2008) who include the regimes to compute the conditional moments in a parametric way, we use the potential information included in the fluctuation of the risk-free rate in a nonparametric setup. However, the only estimated parameter in each step is the Lagrange multiplier of the optimization problem, which indeed makes this approach semi-parametric.

3.3 Naive MD Information Bound

Almeida and Garcia (2008, 2012) find a nonparametric estimate of the SDF bound which considers higher moments in the distribution of return. Their bound employs the minimum discrepancy (MD) measure of Cressie and Read (1984), hereafter CR to restrict the risk-neutral (RN) probabilities. Formally, for an admissible pricing kernel (m), we have

$$E(mR_i) = 1, \qquad i = 1, .., N \tag{3.2}$$

the Euler equation, for all N basis gross assets returns, R_i. This unconditional moment is obtained by applying the law of iterated expectations to Equation (1). Divide the above equation by the PK mean, $E(m) = a$:

$$E\left[R_i \frac{m}{E(m)}\right] = \sum_{j=1}^{T} p_j R_i \frac{m_j}{E(m)} = \frac{1}{a} \tag{3.3}$$

where p_j is the historical probability measure. In order to have an adjustment for risk, it is possible to compactly write:

$$E_q\left[R_i\right] = \sum_{j=1}^{T} q_j R_i = \frac{1}{a} \tag{3.4}$$

where q is the risk-neutral or implied probability measure. In other words, the risk-adjusted expectation of the assets rerun is equal to the risk-free rate. In Equation (4), the risk-free rate corresponds to $1/a$, which is the reciprocal of the PK mean. Therefore, we implicitly have the following change of the probability measure:

$$q_j = \frac{m_j}{E(m)} p_j \tag{3.5}$$

In the Bayesian paradigm, there is an intention of choosing a RN measure, while using the prior knowledge of the actual probability measure and the moment condition (4), which defines the risk neutrality. As described by Stutzer (1995), it is reasonable to consider a measure which does not embody irrelevant information other than the moment conditions. Therefore, minimizing the information gained by the change of the probability measure while satisfying the moment condition leads us to this objective. While Stutzer (1995) uses KLIC to measure the information gain, Almeida and Garcia (2008, 2012) use the minimum contrast measure of Cressie and Read.

Cressie and Read (1984) introduce a multinomial goodness-of-fit test, which includes power divergence test statistics to evaluate the fit of observed frequencies to expected frequencies. As a special case, their test corresponds to Pearson's chi-squared test. This test statistic can also be used to test the goodness-of-fit of two probability distributions. Almeida and Garcia (2008, 2012) use CR family of discrepancies to measure the information gain due to the change from true (historical) to implied (risk-neutral) probability measure. Their measure as a special case includes the KLIC used by Stutzer (1995). In discrete form, the CR discrepancy measure between two probability measures p and q is:

$$I(q,p) = \frac{1}{\gamma(\gamma+1)} \sum_{j=1}^{T} q_j \left(\left(\frac{q_j}{p_j} \right)^{\gamma} - 1 \right) \tag{3.6}$$

The MD pricing kernel bound can be obtained by solving the minimization problem (7) subject to the moment constraint (4).

$$q^{MD} = argmin_q \, I(q,p) \tag{3.7}$$

The solution of this minimization problem is obtained by identifying the risk-neutral measure q. The objective function in Equation (7) is a function of the pricing kernel, and hence we can formulate everything as a function of the pricing kernel. Our constraints are the sample form Euler equation and the strict positivity of pricing kernels, which the later is needed by construction and because of the non-negativity of state price densities $(\frac{q_j}{p_j} = \frac{m}{E(m)})$. When the true probability measure is uniformly distributed, or in other words, for a flat prior equal to $1/T$ (T is the data set size), Almeida and Garcia (2008, 2011) solve:

$$\hat{m}_{MD} = \underset{m_1,\ldots,m_T}{argmin} \frac{1}{T} \sum_{j=1}^{T} \phi(m_j) \tag{3.8}$$

where ϕ is the general discrepancy function, and is obtained from substituting Equation (5) in Equation (6). The Problem (8) belongs to a space with the dimension equal to T, and is impractical to solve. The practical solution with z much smaller dimension N can be realized from the following dual problem:

$$\hat{\lambda}_\gamma = \underset{\lambda \in \Lambda_{CR}}{arg\ sup} \frac{1}{T} \sum_{j=1}^{T} \left(\frac{a^{\gamma+1}}{\gamma+1} - \frac{1}{\gamma+1}(a^\gamma + \gamma\lambda'(\mathbf{R}_j - \frac{1}{a}\mathbf{1}_{\mathrm{N}}))^{\frac{\gamma+1}{\gamma}}\right) \tag{3.9}$$

$$\Lambda_{\mathrm{CR}} = \left\{ \lambda \in \mathbb{R}^{\mathrm{N}},\ \text{s.t for j} = 1, ..., \mathrm{T}:\ 1 + \gamma\lambda'(\mathbf{R}_{\mathrm{j}} - \frac{1}{a}\mathbf{1}_{\mathrm{N}}) > 0 \right\}$$

The solution of the optimization problem corresponds to an optimal portfolio selection with the HARA utility function. For some fixed values of γ or as a limit to zero or one, important one-step alternatives to GMM can be obtained such as Empirical Likelihood or Exponential Tilting estimators. Generally, solutions of the mentioned optimal portfolio problem correspond to the Generalized Empirical Likelihood estimator of Smith (1997).

Solving for λ in (9), we can also have the minimum discrepancy pricing kernels:

$$\hat{m}^j_{MD} = a\frac{(a^\gamma + \gamma\hat{\lambda}_\gamma(\mathbf{R}_j - \frac{1}{a}\mathbf{1}_\mathrm{N}))^{\frac{1}{\gamma}}}{\frac{1}{T}\sum_{j=1}^{T}(a^\gamma + \gamma\hat{\lambda}_\gamma(\mathbf{R}_j - \frac{1}{a}\mathbf{1}_\mathrm{N}))^{\frac{1}{\gamma}}}, \qquad j = 1, 2, ..., T \tag{3.10}$$

Since there is no knowledge of agent's risk-adjusted expectation of return, or in other words, no knowledge of the risk-free rate, we need a grid of the PK mean. For a meaningful grid of the PK mean, $A = \{a_1, ..., a_K\}$, the minimum discrepancy pricing kernel frontier is given by the following expression:

$$I_{MD}(a_k, \gamma) = \frac{1}{T}\sum_{j=1}^{T}\frac{(\hat{m^j}_{MD,a_k})^{\gamma+1} - a_k^{\gamma+1}}{\gamma(\gamma+1)a_k^{\gamma+1}}, \qquad k = 1, 2, ..., K \tag{3.11}$$

3.4 Improved MD Information Bound

The idea of incorporating the fluctuation in the risk-free rate in this study is inspired by the vast literature of regime switching models and also empirical findings of Bekaert and Liu (2004). In addition, our proposed approach to incorporate the unconditional fluctuations of the risk-free rate is closely related to the concept of deciding about the status of the short rate in the EAPM framework of Bertholon et al. (2008). In the same spirit as their study, our approach focuses on the status of the risk-free rate and its connection to the available information in the economy to define the relationship between historical and risk-neutral (RN) dynamics.

For our setup, we constrain the RN dynamics by using the Cressie and Read (CR) minimum discrepancy measure to minimize the difference between the historical and RN probability measures. Here, the historical dynamics is a flat prior equal to $1/T$ (T is the data set size). Intuitively, we assume that there are two states of the economy with different risk-free rates.

Assume the situation when the mean of the pricing kernel on the entire data set is $a_k \in A$, which hereafter we call this overall mean the *base pricing kernel mean.* We assume that there exist two subsets of data (D_1 and D_2) with the respective pricing kernel mean equal to $a_{k,1}$ and $a_{k,2}$ satisfying the following conditions simultaneously:

$$E(m_i|i \in D_1 \cup D_2) = a_k$$

$$E(m_i|i \in D_s) = a_{k,s} \;\; s \in \{1,2\}, i \in \{1,...,T\}$$

Clearly, there is no knowledge of the risk-free rate, however, whatever this overall rate is, there are two possibilities for the value of the risk-free rate over the entire data set. This assumption helps us to extract more relevant information in the data associated with the potential variations in the risk-free rate.

The probability of being in each state of the economy depends on the share of that state from the entire time horizon. For R_s, T_s, p_s, and q_s ($s \in \{1,2\}$) respectively denoting the return matrix, data set size (length), true and RN probability measure in each subset of data, we can write:

$$E_q(R) = \sum_{s=1}^{2} \frac{T_s}{T_1 + T_2} E_{q_s}(R_s) \tag{3.12}$$

$$E_q(R) := \frac{1}{a_k} = \sum_{s=1}^{2} \frac{T_s}{T_1 + T_2} \frac{1}{a_{k,s}} \tag{3.13}$$

As formalized in the Equation (12) and (13), the overall risk-adjusted return is the weighted average of the risk-adjusted return in each state of the economy and the weight is the relative data set size (length). While $a_{k,1}$ and $a_{k,2}$ can be different, condition (13) binds them together.

The CR discrepancy measure between the overall historical probability measure p and the new RN probability measure q' is:

$$I(q',p) = \sum_{s \in \{1,2\}} \frac{1}{\gamma(\gamma+1)} \sum_{j \in D_s} \frac{T_s}{T_1 + T_2} q_{j,s} \left(\left(\frac{\frac{T_s}{T_1+T_2} q_{j,s}}{p} \right)^{\gamma} - 1 \right) \tag{3.14}$$

where for the overall data set, the new RN probability measure q' is equal to $\frac{T_s}{T_1+T_2} q_{j,s}$ and p is the flat prior of $1/(T_1 + T_2)$. Here, the RN measure also depends on the states of the economy. Now, it is possible to obtain the CR discrepancy measure over the total data set by dividing the entire time horizon into two subsets and separately compute the CR measures in each subset. In the next section, we discuss how we split the data into two parts to form the subsets. It is possible to show that the overall discrepancy measure can be obtained by using the weighted average of the discrepancy measures in each subset:

$$I(q', p) = \sum_{s \in \{1,2\}} \frac{T_s}{T_1 + T_2} \frac{1}{\gamma(\gamma+1)} \sum_{j \in D_s} q_{j,s} \left(\left(\frac{q_{j,s}}{p_s} \right)^{\gamma} - 1 \right) \tag{3.15}$$

Therefore, the optimization problem can be split into two disjoint parts. For minimizing the overall discrepancy measure in Equation (15) we just need to minimize the discrepancy measures in each state of the economy (subset of the data) separately and then add up the measures together. Same as before, we need to solve for the dual of the optimization to reduce the dimension of the problem from estimating T pricing kernels to just N Lagrange multipliers, where N is the number of assets in the return space.

3.5 Estimating the Improved MD Bound

The next step in our setup is assigning the data points to the states of the economy. Consecutive observations are more probable to belong to the same state, as we usually see clustering of the same feature in any return data. For this reason and for simplifying the numerical calculation, we divide the time horizon into n parts (partitions) and each partition could potentially belong to any of the two possible states of the economy. These partitions are pairwise disjoint and their union forms the total observations. Practically, we divide the entire time horizon (data set) into n equal length partitions.

Since each partition can belong to two states, the entire data can be split between these states with $2^n - 2$ possible combinations. We call each of these combinations a *partitioning order*. As n increases, borders between the states of the economy can be identified more accurately. On the other hand, large n means small partitions and this raises questions concerning the small sample size. In addition, the numerical optimization with a large n can last forever. Nevertheless, our objective is not identifying the states of the economy with the high precision but is incorporating more relevant information to improve the MD pricing kernel bound. The exact identification of the states of the economy might provide us with the best improvement of the bound, however, we find that even a very simple identification of these states can improve the PK bound significantly.

In another step in our setup, we let $a_{k,s}$ vary in a neighborhood around a_k and then for each possible partitioning order and arbitrary a_k we identify which $a_{k,s}$ gives the highest information gain. Finally, within the meaningful grid of the PK mean, $A = \{a_1, ..., a_K\}$, we identify a partitioning order which mostly improves the MD bound better than any other. Therefore, for any possible partitioning order (allocating data subsets to the states of the economy), we track how likely is that the naive bound is improved. The partitioning order with the tightest restriction provides us with the best-improved bound.

The byproduct of this process is the identification of the states of the economy (subset of data). There is no unique partitioning order that can outperform in all the possible base mean of pricing kernel. However, it is always possible to identify some partitioning orders which improve the MD bound in all the possible base mean of pricing kernel and then select the one which provides a better restriction on average.

The numerical optimization can be tricky and time-consuming in this approach and hence, we add few selected assets to build the return space. Consequently, to estimate the bound, we just use the portfolio of large firms following Almeida and Garcia (2008). We consider three largest size portfolios in the ten deciles size portfolios constructed by Fama and French as large firms. As it is shown by Almeida and Garcia (2008), the information content of large firms is a good proxy for both small and large firms. In other words, the small firms do not add much information to restrict the admissible pricing kernel region. The return data in our test is value weighted and monthly from July 1926 to December 2012.

Figure 1 shows the minimum discrepancy information bound obtained by the naive method of Almeida and Garcia (2012, 2008) and by incorporating the information content

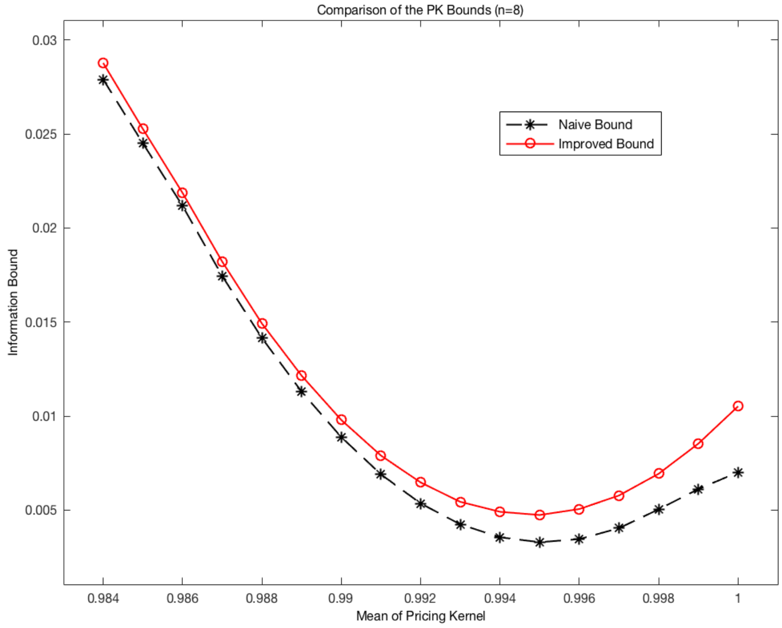

Figure 3.1: Comparison of the minimum discrepancy pricing kernel bounds (n=8).

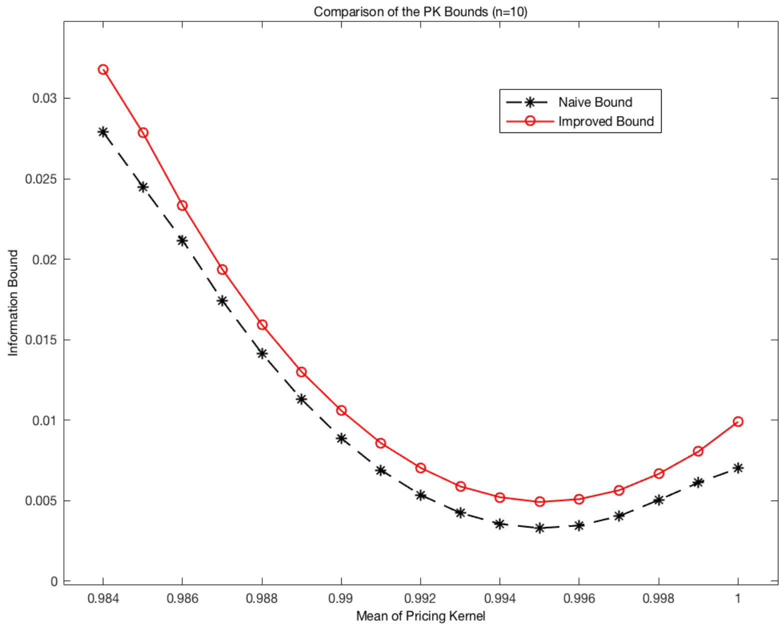

Figure 3.2: Comparison of the minimum discrepancy pricing kernel bounds (n=10).

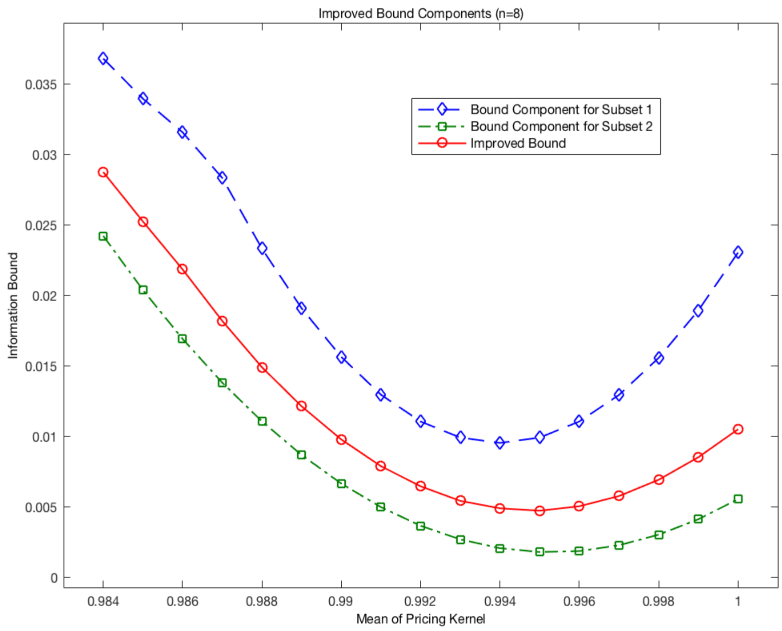

Figure 3.3: Components of the improved bound (n=8).

of the risk-free rate. In this test, we partition the data into eight equally sized subsets ($n = 8$) and then compute the possible improvements for any combination of subsets and also risk-free rate shifts around the baseline. The dashed line is the naive MD pricing kernel bound and the solid line is our improved MD bound which restricts the admissible region more than the naive one. In Figure 2, construct the same bound and compare it to the benchmark for $n = 10$. Not all possible partitioning orders put more restriction on the admissible region, and this is due to the irrelevant information content of assigning data points to an inappropriate state of the economy.

The restriction, that each state of the economy (subset of data) provides, is illustrated in Figure 3. The characteristics of these states are in Table 1, where we see a clear difference between the risk-free rate in the identified subsets. In Figure 3, the solid line is the improved MD bound and the information content (restriction) of different subsets of data is shown by the dashed lines. The line with the diamond markers provides more restriction and belongs to a subset of data with a lower risk-free rate. Including this subset of data causes the main restriction on the admissible pricing kernel region.

	Total data set	**Subset 1**	**Subset 2**
Size	1038	393	645
Time horizon	1926:07-2012:12	1947:12-1969:05 2001:08-2012:12	1926:07-1947:11 1969:06-2001:07
Real risk-free rate	0.0343%	-0.0025%	0.0568%

Table 3.1: The observed monthly risk-free rate for the identified states of the economy (n=8).

Table 1 shows the identified states of the economy where the timing of these states is obtained from our method. We observe in the real data that the risk-free rates are different in these two subsets (states of the economy). We believe, the same results for larger values of n can be achieved, however, the numerical optimization may be very time-consuming.

3.6 Conclusion

In order to introduce more powerful tests for evaluating arbitrage-free asset pricing models, several academic studies have suggested various approaches to tighten the restrictions on the admissible pricing kernel space. While some use the original Hansen and Jagannathan bound, and try to scale the return space or incorporate higher moments, another strand of literature concentrates on historical and risk-neutral probabilities in order to build new bounds with better economic intuition. In the later strand, different measures of discrepancies between probability measures lead to various pricing kernel bounds, with different properties and dual representations that contain distinct economic meanings.

The status of the risk-free rates is important in defining the link between historical and risk-neutral probability measures. We unconditionally incorporate the informational content of the risk-free rates in order to tighten the pricing kernel bound. Our method identifies the variation in the risk-free rate in different subsets of data, which enables us to introduce better restrictions on the pricing kernel space. This method is based on the Cressie and Read divergence measure (1984) and improves the minimum discrepancy bound introduced by Almeida and Garcia (2012).

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