Art-Backed Lending: Implied Spreads and Art Risk Management

Abstract

The increasing portion of individuals' wealth in art sets the stage for art-backed lending services. Considering widely used credit default swaps, the paper applies the structure to art-backed loans and develops an extensive pricing model for the derivatives contract, explicitly taking art market characteristics into account. Using a CDS pricing methodology sheds light on current lending spreads and provides a risk management tool for art-backed lending institutions. At the same time, an introduced art credit default swap would offer an ability to transfer the lender's risk with respect to the art price. The results suggest that credit risk accounts for at most 50% of current art-backed lending spreads.

Key words: Art Market, Art-Backed Lending, CDS, Risk Management

JEL: G13, G14, Z11

1. Introduction

During the last decade, the immense availability of credit led to historically low costs of debt. Consequently, leveraged buyouts became very popular, and hedge funds gained access to cheap capital for their leveraging strategies. In the search for new investment opportunities, funds tapped ever new asset classes ranging from Chinese stocks to luxury real estate in London. Market participants also discovered the booming business of beauty and invested in the arts. Not surprisingly, prices surged. It is not only hedge funds or special art funds that caused skyrocketing prices and record sales for many artists, though. The emergence of a class of high net worth individuals (HNIs) did its part in explaining the increased demand.

Since then credit availability has fundamentally changed, and despite initial signs of the art market being decoupled, it does not seem to be sheltered from the world wide recession. Nonetheless, owning art remains to be chic. As this trend, despite the recent turmoil, is expected to continue, at least in the medium rum, an ever larger part of affluent individuals' wealth will be tied up in art. In the meantime, a number of HNIs find their art collections already now having become an important part of their assets with much of home equity wiped out.

Art as a significant part of the portfolio implies that it should also become increasingly important as collateral when individuals who possess an expensive collection are in need of cash. It is, therefore, not surprising that the crisis has actually led to an increase in art-backed lending in 2009. With its endowment down by one third, the Metropolitan Opera offering its Chagalls as collateral for a USD 35 million loan from JPMorgan Chase is just one example of the importance of art-backed lending.[1]

Current lending practices of private banks usually allow for loan to initial art value ratios of only up to 50%. McAndrew and Thompson (2007) back this conservatism by investigating the collateral value of fine art. The risk aversion of the lending institutions and the infancy of this business are further demonstrated by banks charging very high spreads to the individuals engaging in an art-backed loan. However, little is known about the art-backed lending business and the composition of current spreads, which are two issues this paper sets out to explore.

To do so, consider the development in the financial markets concerning credit derivatives which allow one to convert risks into securities and dispose of them for an appropriate price. Although the subprime crisis has reminded market participants that assuming a position in credit instruments is not a free lunch, hedge funds, but also banks, will continue to be eager to take on credit risk from others in return for a lucrative income stream; and even if this arbitrage motivated transaction volume declines, transferring risk for balance sheet management purposes will remain important. Credit default swaps (CDS), which are derivative instruments offering default insurance, have been the most widely used way to transfer credit risk and have, so far, weathered the storm to some extent; it seems that CDS have become the vehicle of choice for investing in credit as an asset.

It is the aim of this paper to combine the developments in the art and credit derivatives markets by applying the credit default swap structure to art-backed loans in line with Campbell and Wiehenkamp (2008) and obtain a

[1] "The Met Offers Chagalls as Collateral," *New York Times*, March 4, 2009.

proxy for current lending spreads. More specifically, a pricing model for the art credit default swap (ACDS) is introduced that explicitly incorporates the characteristics of art returns. The fair price for the lender transferring the risk of carrying the art object on its balance sheet, in case the borrower defaults on his loan, can, hence, be determined. With an appropriate model in place, loan spreads can be analyzed and loan portfolios stress tested using the art specific CDS. Furthermore, potential efficiency gains in art-backed lending are investigated by comparing current practice to the effects of introducing art credit default swaps.

The remainder of the paper is organized as follows: After introducing the art market and current art-backed lending services, the application of credit default swaps to art-backed loans for spread modeling purposes is discussed in section 3. The formal model for the credit spread of the ACDS contract is developed in section 4. Section 5 introduces the data set and investigates distributional properties of art returns which are crucial for implementing the formal model. In section 6, a Monte Carlo simulation for the determination of the fair credit spread is described and various sensitivity analyses are conducted. A summary of the findings and concluding remarks comprise section 7.

2. Art Market Characteristics and Art-Backed Lending

2.1. Characteristics

Before describing art-bakced loans and proceeding to the modeling of spreads, it is worthwhile to highlight some features of the art market and recent developments. In an economic environment of an increasing number of high net-worth individuals (HNIs), art has received more and more attention. The booming market of the last years has documented itself by new record sales at many auctions. In 2007, to name, but a few: Mark Rothkos' "White Center" sold for 72.8 million USD; "Green Car Crash" by Andy Warhol achieved a value at auction of 71.7 million USD. In 2008, "Triptychon" by Francis Bacon sold for a staggering USD 86.2 million. The art market has an estimated size of over 3 trillion USD and an annual turnover of about 30 billion USD (McAndrew, 2008). Figure 1 plots the performance of the market between 1984 and 2007 using the Mei-Moses repeat-sales semi-annual all art index.[2] Although the market trend is clearly upward sloping, the art market is expected to also feel the global downturn with estimated numbers ranging from a 4.5% to a 30% market decline.[3] The major players include auction houses, dealers, galleries, museums, private collectors, and art advisory.[4] Typical characteristics of the market are inefficiency, low liquidity, large transaction costs, and high barriers to entry.

Figure 1 about here

Efficient markets in the sense of Fama (1970) imply that all available information is incorporated into the price and that price movements are random; today's price is the best predictor of tomorrow's price.[5] For US stock returns predictability is by now generallly accepted (Campbell and Shiller (2001) and Cochrane (2006)), and especially long-run returns seem

[2]The authors are grateful to Michael Moses and Jianping Mei for sharing their index.

[3]Note that downturn predictions are extremely hard to quantify and even if index data was available, the issue of the index measuring the relevant market remains.

[4]Many private banks have set up art advisory services to accommodate HNIs' demands.

[5]Efficient markets are understood in terms of semi-strong form efficiency here.

to be forecastable for stocks. For art returns the opposite seems to be true. Chanel et al. (1994) suggest that, while stock returns are about fundamentals whose predictability increases with horizon, the art market is about tastes which may well be predictable for short horizons but probably not for future generations. As taste is subjective, its incorporation in the information set of the buyer seems hard, if not impossible. Therefore, prices that are governed by tastes, or preferences for characteristics in general, do not adhere to the EMH (Daniel and Titman, 2000). This might give a rationale for increased activity in the art market beyond mere purchases for aesthetic returns.

Art investment is not new, though. Whereas Goldthwaite (1993) discusses the importance of a market for the proliferation of art in 1300-1600 Italy, today return considerations matter. The establishment of *The Fine Art Fund*, for example, shows the emergence of art as an alternative investment class. Horowitz (2007) provides a qualitative overview of art market investments and art funds in particular. Campbell (2005) and Mei and Moses (2002), among others, find that art investments have a low correlation with other asset classes and are attractive from a portfolio selection point of view. This view is not unanimously shared, though. Goetzmann (1993), for instance, finds a strong correlation between the demand for art and aggregate wealth.

2.2. Art-Backed Lending

No matter what drives the demand for art, be it investment opportunities or non-financial motivations, with art constituting a significant part of the portfolio, more attention will be given to art as collateral.[6] Apart from

[6] McAndrew and Thompson (2007) investigate the revived interest in using art as collateral for loan contracts.

the previously mentioned high profile art-backed lending transaction of the Metropolitan Opera, lending institutions report an overall increased interest in collateralizing art with originations being up by 40% for some in 2009.[7]

Taking a closer look at active lenders in the market, one can identify three different types. It is first traditional lenders that have set up art advisory and art finance services, usually within their private banks. Despite allowing art to be used as collateral, they usually require the borrower to be an existing client of the bank and possibly even to pledge other assets. Spreads are, hence, a function of the art piece as well as general creditworthiness of the borrower. The asset based lenders mark the second group of active players. They are mostly (financial) boutiques specialized in art lending. Unlike the traditional banks, the art work typically constitutes the most important component of the lending agreement. As a result, rates are usually much higher, too. Also note that the piece of art is often stored with the lender throughout the duration of the contract. Lastly, also auction houses engage in lending. For them, however, this is rather an auxiliary service offered to clients who consign the art work to be auctioned. Table 1 provides an overview of current art-backed lending services.

The differences in lenders can be attributed to them focusing on client demands ranging from short-term liquidity provisions and auction advances to long-term loans for either strategic investment purposes or in conjunction with further collecting activities. Despite these subtle differences, all institutions require the art to be internationally recognized, and some even explicitly require an existing previously recorded sale by the same artist.

[7] "That Old Master? It's at the Pawnshop," *New York Times*, February 24, 2009.

Table 1 about here

3. Art Credit Default Swaps

Having described the basics of art related lending transactions, consider a CDS applied to art-backed loans as introduced by Campbell and Wiehenkamp (2008) in order to understand the spreads being charged in the market. A standard CDS setup (see e.g. Duffie (1999) for details), refers to a contract between parties A and B terminating at the earlier of maturity and credit event. Commonly, the latter is referred to as default of the reference entity C.[8] For the case at hand, default is equal to C being unable to meet its obligations on the loan. Now, upon default, the protection seller B pays A an amount that is the difference between face value and the recovery value[9] of the reference asset plus accrued interest. In return for receiving default insurance, the protection buyer A pays a periodic fee, the CDS spread, to B until the credit event or the termination of the contract, which ever occurs earlier.[10] The basic structure of a CDS contract is depicted in figure 2.

[8]The International Swap and Derivatives Association (ISDA) provides six formal definitions of a credit event. The categories are (1) Bankruptcy, (2) Obligation acceleration, (3) Obligation Default, (4) Failure to pay, (5) Moratorium, and (6) Restructuring. The formal definitions can be downloaded from www.isda.org.

[9]The recovery value is equal to the market value of the reference asset after default and is endogenous in the model presented in section 4.

[10]The default payment by B can differ based on the contractual specification. Possibilities include physical delivery against repayment of par or cash settlement, with the latter being of increasing importance (Barrett and Ewan, 2006). Other information typically provided in the contract are: (1) reference obligor and asset, which in the example are entity C and the corresponding loan; (2) the notional of the CDS; (3) start day of protection and maturity of the contract; and (4) the frequency of the spread payments. The spread is usually quoted in basis points and, multiplied with the notional, gives the required fee payment by the protection buyer.

Figure 2 about here

In the current setup, having granted an art-backed loan to the reference entity C, the lender seeks protection to avoid running the risk of carrying the art on its balance sheet. Consequently, the structure would allow the transfer of risks, that are associated with the underlying collateral, to market participants with more risk appetite. These could be art funds, but also museums may be interested in receiving the fee payments of a CDS. Additionally, the latter are offered a chance to acquire art in case of default that would otherwise remain in the hands of private owners or that would be auctioned at possibly much higher prices than those agreed in the contract. Especially in case of museums which are often publicly owned, counterparty risk of the CDS is likely to be negligible. In other cases, the risk is comparable to standard CDS contracts and marks no special feature of the ACDS contract. For that matter, counterparty risk will subsequently not be in the focus of attention.

While a traded ACDS would clearly enhance efficiency of art-backed lending, modeling lending spreads using the insights from credit derivatives pricing can help understanding the spreads currently being charged in the market, even without traded ACDS contracts.

4. Modeling the Credit Spread

In an attempt to put a price tag on default risk, Hull and White (2000) point out that the present value of the cost of default equals the price of a risk free bond minus the value of a defaultable bond, if one is willing to assume that the possibility of default is the only reason for the two to differ.[11] The arbitrage argument is usually applied to the bond market, and not quite applicable to the proposed structure. Nonetheless, the paper briefly highlights this reasoning to offer a bit of background on the pricing of most traded credit default swaps. The reader, familiar with the setup, may safely skip the next two paragraphs.

A long position in a CDS and a defaultable bond of equal maturity should trade close to the risk-free bond. By considering two portfolios, the possible arbitrage that would arise if this was not true is reviewed in the following.[12] Portfolio I consists of a defaultable bond $\overline{C}$ with interest payments $\overline{c}$ and maturity T_N and a CDS on that bond with spread $\overline{s}$. Portfolio II consists of a default-free coupon bond C with the same face value and payment dates, and coupon $\overline{c} - \overline{s}$. Both portfolios have equal cash flows in case of survival, namely $\overline{c} - \overline{s}$. If the reference entity defaults on its obligations, the CDS contract ensures that the bank receives the face value of the bond, assuming no default risk on the side of the protection seller; an assumption that is maintained throughout the paper. Unwinding portfolio II at the time of default, one obtains two portfolios that should cost the same. Otherwise an investor could short one portfolio and take a long position in the other leading to an arbitrage profit.[13] Consequently the yield to maturity of $\overline{C}$ should exceed that of C by exactly $\overline{s}$, the price of the CDS.

Unfortunately, as the default free security needs to be sold before maturity in order to compare the two portfolios, the just described arbitrage strategy

[11]Few parts of this section are adapted from Campbell and Wiehenkamp (2008).
[12]The notation is adopted from Schönbucher (2003).
[13]A short position in a bond can be implemented by a repo transaction.

will not work exactly. This is due to an interest rate risk that affects the price for which the bond is traded and results in its value almost certainly differing from par. Additional caveats include the difficulty of implementing short positions in a bond, the fact that payment dates may not coincide, and specifications in the CDS contract that may lead to payoffs at later days than the point of default. Of additional importance is the availability of risk-free financing. Although government securities are considered to be risk-free, they are inappropriate for the valuation of credit derivatives, because of liquidity risks. These risks are not found in swaps as they are synthetic (Houweling and Vorst, 2001). Furthermore, using swaps has the advantage that these rates are closer to the refinancing rates of financial institutions. Although there is the disadvantage of swaps including a risk premium, Duffie and Huang (1996) find this to be very small and Duffie et al. (2003) use the swap curve in their empirical analysis of the spread curve.

The fact that the proposed ACDS structure is based on a loan complicates the applicability of the arbitrage argument for pricing purposes even further. Given these drawbacks and the fact that it is much more difficult to assess the default risk of an art collector, the charged interest rate on the loan might not appropriately reflect the credit risk. This introduces a bias when comparing the risk-free rate and the interest rate on the loan for ACDS pricing purposes. Hence, instead of modeling the loan, art prices and exogenous default shocks are introduced in the well-known framework of Hull and White (2000), Schönbucher (2003), Duffie (1999) and others. In order to correctly price the ACDS, one needs to determine the credit spread such that the present value of the total fee payments made by the bank equals the expected credit loss in today's terms. As is common in the literature, default probabilities and interest rates are assumed to be independent.

Following Hull and White (2000), the expected loss is a function of the default probability at time t and the amount by which the face value of the loan exceeds the value of the collateral at a particular instant in time, calculated in present terms. Consider a loan whose face value is set to x% of the value of the art piece or art collection at $t = 0$. At present, lending institutions use a maximum of 50% of the current market price of the artwork to back the loan; see table 1. The idea of this financing structure using the ACSD is to transfer the risk of the art price falling below the loan value. The relation between loan value and art price is shown in equation (1),

$$P_{t=0}^{Loan} = x\% P_{t=0}^{Art}, \tag{1}$$

where $P_{t=0}^{Loan}$ and $P_{t=0}^{Art}$ are the prices of the loan and art work at $t = 0$, respectively.

Default is modeled as an exogeneous shock in the well-known hazard rate framework (see e.g. Duffie (1999)).[14] The probability density function of default at time t, required for the expected loss determination, is the probability given by

$$q(t) = h(t) \exp\left(\int_0^t h(\tau) d\tau \right), \tag{2}$$

where $h(t)$ is the hazard rate, which is modeled to be constant, but contingent

[14]This extends Campbell and Wiehenkamp (2008) where default is depending on the non-observable event of the art price falling below the face value of the loan.

on whether the borrower engages in an asset based transaction or takes out a loan from a traditional lender. In the former case, the borrower accepts very high spreads (see table 1) implying that he is more liquidity constraint and, hence, riskier as captured by a higher hazard rate. In case of default, the protection seller will be required to pay the difference between the face value of the loan and current market value of the collateral plus any accrued interest to the bank. Assuming (2) to represent a risk-neutral probability density function, this can be discounted at the risk-free rate. Unlike in the modeling of credit events for defaultable bonds, the recovery rate is an endogenous variable in (3). It is determined by the market price of art immediately after default which will be modeled based on the distributional properties of the data in section 5. Accounting for the fact that the lender recovers the full loan value at maximum and letting

$$v(t) = \begin{cases} e^{-r_f t} P_{t=0}^{Loan} \left(1 - \min\left(\frac{P_t^{Art}}{P_{t=0}^{Loan}}, 1\right) + y\delta_t\right) & \text{in case of default} \\ 0 & \text{otherwise} \end{cases}, \quad (3)$$

where δ_t is the fraction of the year since the last interest payment and y is the interest rate charged on the loan to the art collector, the expected loss can be expressed by equation (4);

$$ECL = \int_0^T q(t)v(t)dt. \quad (4)$$

As noted above, the expected credit loss (ECL) should equal the present value of the fee payments. With payments being made until default or maturity of the ACDS, whichever occurs earlier, the costs of default can be expressed as a weighted average of the two. For a maturity of T years and ω payments per year, it is straightforward to see that, in the case of no default, the present value of these payments is

$$su(K) = \sum_{k=1}^{K} s\omega^{-1}(x\%P_{t=0}^{Art})e^{-r_f T_k}, \tag{5}$$

where s is the credit spread quoted on an annual basis, and $T_1, ..., T_K$ are the fee payment dates. The probability weight corresponding to no credit event is

$$\pi = 1 - \int_0^T q(t)dt. \tag{6}$$

If default occurs before maturity at time τ, the present value of the payments is the sum of the fees paid at payment dates before default and the accrued value since the last payment date T_n and the time of default:

$$sg(\tau) = \sum_{k=1}^{n(\tau)} s\omega^{-1}(x\%P_{t=0}^{Art})e^{-r_f T_k} + s\delta_t^{'}(x\%P_{t=0}^{Art})e^{-r_f \tau}, \tag{7}$$

with $\delta_t^{'}$ being the year fraction since T_n and $n(\tau)$ being the number of payment dates prior to default. Putting the equations together, one obtains the value of the fee payments:

$$s\left(\int_0^T q(t)g(t)dt + \pi u(K)\right) \tag{8}$$

which gives, after equating fee payments in (8) and expected credit loss in

(4), the credit spread of the ACDS, s

$$s = \frac{\int_0^T q(t)v(t)dt}{\int_0^T q(t)g(t)dt + \pi u(K)}. \tag{9}$$

Charged spreads are likely to materially depend on the recovery value which, in turn, should also incorporate liquidity in the art market. The remainder of this section, hence, tries to explicitly capture liquidity effects that arise from forced sales following default and are note typically represented in the data.

Before doing so, note that liquidity may also matter in derivatives markets. Longstaff et al. (2005) present a theoretical model for both credit and liquidity premia in bond spreads by using information from the CDS market. While the authors assume perfect liquidity in the CDS market, Bühler and Trapp (2007) extend the analysis to modeling liquidity in the CDS market as well. Looking at the bid-ask spreads[15], they find that the liquid credit spread differs from the mid credit spread in the CDS market. Although bid-ask spreads are not considered here, the authors' conclusion of CDS transactions being protection demand driven is applicable for ACDS contracts too, as the structure is described by banks trying to avoid the risk of carrying the art on their balance sheets. As pointed out by Duffie et al. (2005) in their approach to modeling illiquidity in OTC markets, the bank's bargaining position depends on the availability of counterparties. Search costs for finding a counterparty are, thus, a property of the OTC market that should

[15]Transaction costs are a typical measure for liquidity in financial markets; see e.g. Lybek and Sarr (2003) for a discussion.

generally be kept in mind. As the paper tries to highlight peculiarities of art derivative transactions, though, the bank's search costs are not explicitly modeled here.

In contrast, expenditures for finding a counterparty in an art transaction are much more important than for liquid asset markets, and, hence, deserve some attention. Amihud et al. (2005) highlight that if an asset needs to be sold quickly, not all natural buyers may be available. Search frictions such as price concessions arise when the art piece needs to be sold conditional on default of the underlying loan. Therefore the model of the previous section is extended to incorporate this illiquidity.[16]

The modeled spread in (9) uses the art price from regular sales. The just presented discussion, however, highlights the importance of introducing liquidity explicitly; especially when default forces agents to sell. While Amihud et al. (2005) model liquidity costs as the present value of all future transaction costs, the approach taken here is adopted from Ericsson and Renault (2006). In case of default, the art object has to be brought to the market, and the illiquid price is seen as fraction, $\widetilde{\kappa}_t$ of the previously considered price in that case. The model fraction should have the property that it approaches one as the number of participants increases. Following Ericsson and Renault (2006), denote by $f^n(\kappa)$ the probability density function that κ is the best price fraction among the n offers, the expectation with respect to

[16]If the ACDS contract was traded, the importance of liquidity considerations in the art market would depend on the counterparty of the CDS. A museum would likely opt for physical delivery in case of default. For counterparties providing protection for financial reasons, liquidation could, however, be expected to be a non-negligible issue.

n is expressed by

$$E[\kappa] = \int_0^1 \kappa f^n(\kappa) d\kappa. \tag{10}$$

Assuming a uniform distribution for κ and n independent offers, the cumulative distribution of no offer exceeding x is

$$(F(x))^n = x^n. \tag{11}$$

Consequently,

$$f^n(x) = \frac{\partial (F(x))^n}{\partial x} = n x^{n-1}, \tag{12}$$

which, after substituting and evaluating the integral in (10), yields

$$\widetilde{\kappa} = E[\kappa] = \frac{n}{n+1}. \tag{13}$$

Let n follow a Poisson distribution with mean number of art buyers λ. Now the illiquid recovery is a function of $\widetilde{\kappa}$ and the liquid recovery value. Adjusting (3), define

$$v^*(t) = \begin{cases} e^{-r_f t} P_{t=0}^{Loan} \left(1 - \widetilde{\kappa}_t \min\left(\frac{P_t^{Art}}{P_{t=0}^{Loan}}, 1\right) + y\delta_t\right) & \text{in case of default} \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

to obtain the credit spread of the ACDS that explicitly incorporates liquidity

$$s^* = \frac{\int_0^T q(t) v^*(t) dt}{\int_0^T q(t) g(t) dt + \pi u(K)}. \tag{15}$$

5. Analyzing the Distribution of Art Returns

To estimate the recovery value at default, possible art price paths need to be modeled. This is done by considering the distribution of art returns and repeated sampling from this distribution to construct art price realizations over the duration of the ACDS contract. This, in turn, allows inference with respect to the probability of default.[17]

For most financial assets it is intuitively clear what is meant by return. It is the gain or loss of a security in a particular period. Stocks or bonds are frequently traded, and there exist numerous homogeneous securities issued by one firm. Consequently, one can easily speak of yearly, monthly or even daily returns. With art this is quite different. Any one piece of art is nearly unique,[18] and often many years pass by before an item is sold again, if there exists a second recorded sale at all. The above discussion of efficiency also highlights that price movements are seldom the result of news, but that, possibly time varying, tastes matter. Ashenfelter and Graddy (2003) note that characteristics of a painting determine part of its price. They model the price of painting i at time t. In a formal framework, the model reads

$$p_{i,t} = p_i + p_t + \epsilon_{i,t}, \tag{16}$$

where p_i is time invariant and specific to a painting, p_t captures time varia-

[17]Alternatively, one could have followed the strategy of implementing a continuous time model for art prices. For example, heavy tails could be incorporated with a jump-diffusion. However, art data does not contain enough time series observations to estimate the model parameters. Furthermore, using a continuous time specification for assets that are almost never traded at all seems counterintuitive.

[18]Prints may be an exception here.

tion, and $\epsilon_{i,t}$ is an idiosyncratic error term.

From here returns can be investigated by means of hedonic regressions or repeat sales. The former technique models

$$p_i = \beta' x_i + \epsilon_i \tag{17}$$

where x_i are hedonic characteristics. Proponents of this approach point out (see e.g. Higgs and Worthington (2005)) that hedonic regressions strip the measurable characteristics of the art work from the total value and assign a price to perceived attributes. Additionally, the setup does not restrict the sample to repeat sales which implies that all data can be used.

The major drawback for the purpose of this analysis, though, lies in the fact that hedonic regressions are only useful for the construction of art price indices, but do not allow for an investigation of the distribution of art returns. It is, however, exactly the latter that is needed to simulate sample paths of P_t^{Art} in order to determine the spread of the credit default swap in (9) or (15).

Looking at repeat sales, this drawback can be overcome. By comparing prices of the same object at two distinct points in time, returns can be computed as for any other asset. Appropriately standardizing the holding period returns, yearly, monthly or daily return distributions can be constructed. Although allowing for the investigation of the distribution of returns, it is worth noting that repeat sale methods also suffer from drawbacks. The most troubling one is the fact that repeat sales analysis suffers from substantial selection bias (Gatzlaff and Haurin, 1997). In terms of the ACDS contract this upward bias could imply that defaults occur more often than suggested by the data, highlighting the importance of a conservative distributional choice for simulations.

5.1. The Data Set

The value of the most important pieces of art is determined by public auctions (Ashenfelter and Graddy, 2003). The word "auction" has Latin roots; "auctio" can be translated with "to increase". Sotheby's, Christie's and others adhere to "ascending price" auctions where the bidding stops at the highest value.

For this study, auction data from Sotheby's, London is used in a similar manner to Mei and Moses (2002) and Mei and Moses (2005). The data set, obtained from Sotheby's sales catalogs, consists of over 4,500 art pieces for which there are at least two known sales. Some items are reported to have sold already nine times through the course of the centuries while for the majority of objects there exists only one repeat sale. Most of the included pieces are Impressionists paintings, Victorian pictures, Old Masters, 16th century British paintings, and Modern Art.

Prices of the last sale are reported in GBP. To make these prices comparable to previous sales, items then not sold in GBP were converted using the sales day's exchange rate which was obtained from `http://www.oanda.com`. Observations for which the GBP price was not obtainable were dropped from the data set. Descriptive statistics are reported in table 2.

Table 2 about here

Possibly contrary to popular perception, an item is not necessarily sold in an auction. Only if the highest bid exceeds the reserve price of the seller, the painting is sold. Otherwise, the piece is "bought-in" in the sense that it is sold at a later date, on rare occasions bought by the auction house, or taken off the market (see Ashenfelter (1989) or Ashenfelter and Graddy (2003) for more details). For French Impressionists, both Ashenfelter (1989) and McAndrew and Thompson (2007) find buy-in rates of about 30% of the pieces put to auction.[19] Whenever a piece is reported to having been bought in, and there is, thus, no sales price available, the sale had to be deleted from the data set.

For other database entries where the price is given including the buyer's premium only, the hammer price was estimated by assuming the premium to be 20% on the first 120,000 GBP and then 12% on any value above this point.[20] In order to determine the holding period return, the mid point of the stated sales date range was chosen whenever the exact selling date is unavailable.

After all adjustments and incorporation of data availability constraints, the data set allows the construction of 398 nominal holding period returns. Nominal returns are considered because it is also the nominal value of the loan that matters. It is only for art related investment decisions that real returns should be analyzed.

As already mentioned at the end of the previous section, the repeat sales sample is subject to selection bias (Goetzmann, 1993). Art work that drastically falls in value or no longer attracts enough interest to be put to auction

[19]Ashenfelter (1989) investigates data from the early 1980s; McAndrew and Thompson (2007) consider a data set from 1985 to 2001.

[20]These estimate are in line with current research practice.

is not represented by the data at hand.[21] This is a problem comparable to the survivorship bias in mutual fund performance (see e.g. Elton et al. (1996)), but, unlike a dead fund, currently unpopular artists may well regain recognition, such that the issue is not deemed to materially alter conclusions.

5.2. Empirical Distribution.

From the 398 holding period returns, annualized returns can be computed.[22] The following analysis of the distribution of art returns rests on the assumption of a time invariant return distribution. Given the long holding periods of paintings, it is difficult to subdivide the data set into subsamples containing both, enough observations plus sale and repeat sale in the same subsample.

Additionally, no distinction is made between returns from voluntary and forced sales. In general people sell art because of changing tastes, new opportunities, to cash in, or due to the necessity to sell (Art, 2007). The motivation likely affects the patience of the seller and subsequently the terms at which art pieces exchange hands. The existence of loss aversion, which is typically found for securities (see e.g. Odean (1998)), consequently hints at different distributional shapes for forced and voluntary sales, with the former being more appropriate for the art sales in connection to defaults. The available data does not allow for such a distinction, though, and possible differences

[21] Also on the high end, the sample is likely to be truncated; master pieces may end up being donated to museums, making a repeat sale observation impossible.

[22] The standardization is based on

$$(1 + r_{annual})^T = 1 + r_T \quad \Leftrightarrow \quad r_{annual} = (1 + r_T)^{-T} - 1,$$

where r_T is the holding period return.

in the return distributions are ignored. This assumption is less troubling as there is no strong evidence of loss aversion in the art market (Beggs and Graddy, 2005).

Annualized returns have a mean of about 4.8%. Also notice the large dispersion which is due to art returns taking on extreme values, ranging from -80%, which almost represents a complete loss, to more than 430% on an annualized basis. This standard deviation of 25% also motivates the loan to value ratio of 50%, currently being employed for art-backed lending, as a two standard deviation move may already put severe pressure on the collateral value. From figure 3 and the skewness value in table 2 it is obvious that the annualized art returns are distributed with a heavy tail to the right. This primarily stems from the one positive extreme observation in the data set. Furthermore, the kurtosis value indicates that the distribution is leptokurtic; i.e. more probability mass around the peak and fatter tails than the normal distribution. The reported values for skewness and kurtosis give a first indication of the characteristics of the art return distribution, although they are empirical values, and the true ones are unlikely to match their sample counterparts.[23]

Figure 3 about here

The Jarque-Bera statistic plus the skewness and kurtosis values suggest a significant departure from the normal distribution for art returns. The logistic distribution is an example of a leptokurtic distribution that might better

[23] Owen (2001) discusses the estimation of confidence intervals for kurtosis and skewness values using empirical likelihood estimation.

fit the data. Also Student's t-distribution has the ability to capture fat tails. Those two distributions, plus the normal one, are fitted to the data. The densities are shown in figure 3 alongside the histogram. The parameters of the distributions are found by maximum likelihood estimation; table 3 shows the parameter estimates. Figure 3 illustrates that assuming returns to be normal, does not fit the data at all. Comparisons of the logistic and t-distributions vis-à-vis the data seem to favor the latter one.

Table 3 about here

In order to formalize the analysis of the art return distribution, consider known distribution functions, like the one of the t-distribution, that are compared to the empirical distribution.

Definition 1. *Let $X_1, X_2, ..., X_n$ be independent random variables each having the same distribution function $U(x) = Prob(X_i < x)$ and let $I(x)$ be the indicator function*

$$I(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0. \end{cases} \tag{18}$$

The function

$$F_n(x) = \frac{1}{n} \sum_{j=1}^{n} I(x - X_j) \tag{19}$$

is called the empirical distribution function.[24]

$F_n(x)$ gives the proportion of random numbers that are smaller than x. It is a step function that is computed from the data. $F_n(x)$ is a consistent

[24]The notation is adopted from Darling (1957).

estimator of $U(x)$ as $n \to \infty$; i.e. the strong law of large number applies and $F_n(x) \to U(x)$ with probability 1 for each x (Stephens, 1986).

A class of statistics for measuring the discrepancy between $F_n(x)$ and $U(x)$ is the one of quadratic statistics, also called Cramer-von Mises family given by

$$Q_n^2 = n \int_{-\infty}^{\infty} (F_n(x) - U(x))^2 \psi(x) dU(x). \tag{20}$$

For $\psi(x) = 1$ the Cramer-von Mises statistic, W_n^2 is obtained. The Anderson-Darling statistic, A_n^2, follows for $1/\psi(x) = U(x)(1 - U(x))$.

With the test statistics introduced, it is now the aim to test

$$H_0 : U(x, \theta) = F(x, \theta), \tag{21}$$

where $F(\cdot)$ is the hypothesized continuous distribution function and $\theta \in \Theta$ is a vector of parameters. The null hypothesis states that the art returns' unknown distribution $U(\cdot)$ is equal to a given distribution $F(\cdot)$ which could be the normal or any other.

For the practical implementation of the Cramer-von Mises test, note that $W_n^2 = n \int_{-\infty}^{\infty} (F_n(x) - U(x))^2 dU(x)$ can be evaluated to give

$$W_n^2 = \sum_{i=1}^{n} \left(z_i - \frac{2i-1}{2n} \right)^2 + \frac{1}{12n} \tag{22}$$

which is used to compute the test statistic (see e.g. Csörgö and Faraway (1996) or Stephens (1986)).[25]

[25] The test statistics in table 4 were computed using Matlab; the code is available upon request.

Table 4 about here

Table 4 confirms what has already been concluded from the visual inspection and is in line with intuition – art returns are not normal. The test statistic of almost 12 allows to clearly reject the null hypothesis at all conventional levels of significance.

Care must, however, be taken when interpreting the test statistics for the t- and logistic distributions. As the parameters are estimated, the test statistics' distributions are not free of nuisance parameters, as has been discussed above. Consequently the standard critical values offer only an indication of whether or not to reject the null hypothesis.

As it is the aim of the empirical distribution analysis to find a parametric distribution that best fits the data, which then can be used for modeling art price realizations, the hypothesis tests themselves are of less importance. Instead, one tries to find the pdf that is *closer* to the data than others. The Cramer-von Mises statistics reported in table 4 allow to draw such conclusions. Recalling that $W_n^2 = n \int_{-\infty}^{\infty} (F_n(x) - U(x))^2 dU(x)$, the Cramer-von Mises statistic actually is a distance measure that compares the vertical distance between the empirical distribution function and the hypothesized cdf. The larger W_n^2, the greater the discrepancy between the two. Therefore, the distribution that results in the smallest W_n^2 is the best approximation of the true art return distribution. As can be seen from table 4, this is the case for the t-distribution with the parameters specified in table 3.

One caveat is in order, though; the fact that the parameters are subject to estimation error introduces some uncertainty with respect to the exact distance measure. This is, however, not deemed to alter the result of the

t-distribution best describing the nature of art returns.

6. Monte Carlo Study & Sensitivity Analyses

In order to find the credit spread of the ACDS in (15) and understand lending spreads, Monte Carlo methods have been adopted. All simulations were conducted in GAUSS based on $10,000$ realizations.[26] The crucial ingredient for determining the credit spread is the recovery value. This determines the expected credit loss and the total fee payments. For that matter, art price realizations are constructed based on the initial art price, which is subsequently adjusted for price movements. Those are sampled from the t-distribution that has been found above to best capture return behavior.[27] As noted above, default is modeled as an exogenous event with constant hazard rate depending on the type of lending arrangement. For art-back loans from traditional lenders, the Poisson process determining default is chosen to haven an intensity of 200bps; for the more risky asset-based lending transactions, the intensity is chosen to be 400bps.[28] The parameter choices for the two typical loan types, as motivated by table 1, are summarized in table A1.

Expected credit loss and the value of the fee payments are computed by averaging over the credit losses and fee payments for all realization, respectively. Dividing the former by the latter gives the ACDS spread.

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[26]The code is available from the authors.
To generate realizations from the t-distribution the code from Urzúa (2007) was adapted.

[27]Note that the sampled annualized returns are transformed to daily returns for simulation purposes, although art objects are hardly traded at all. This is a necessary assumption as there is a trade off between the long horizon of art returns and the theoretical possibility of default occurring at any point in time. Daily returns are deemed to be the appropriate compromise.

[28]These choices correspond to hazard rate estimates in the literature.

Consider the spread of a typical 5 year loan of a traditional lender. Assuming a fairly liquid art market (soon to be relaxed) with a mean number of available buyers equal to 100, the model implied credit spread lies at 1.2%, or at about half of the currently charged spreads (compare table 1). This suggests that the bank is compensated for more than the credit risk of the borrower, with recovery and liquidity risks being natrual candidates.

As asset-based loans are typically of shorter maturity, the one year contract serves as the benchmark case here. According to intuition, a riskier borrower implies a higher credit spread. Modeled spreads are, however, nowhere close to current market spreads. Apart from the same reasons brought forward for traditional lenders, an additional explanation may come from a information perspective. Since private banks have an established relationship with the borrower, they can be expected to know more about borrower quality than the outside lender. Furthermore, the client's portfolio extends well beyond the art-backed loan contract, comforting the risk manager. Lastly, another important difference between market spreads are the funding costs of the lenders, with the latter being much lower for big banks.

If one further considers the possibility of a traded ACDS contract, the results suggests that lenders can dispose of the risk of having the art piece on their balance sheet, while still keeping the non-default component of lending spreads. This hints at the ability of the proposed structure to improve efficiency in art-backed lending.

In the following the robustness of the result with respect to the chosen parameters is analyzed. To highlight the impact of the distributional choice, results are also compared to the convenient, but oversimplifying assumption of art returns being Gaussian.

Liquidity. Campbell and Wiehenkamp (2008) note that in order to reconcile the modeled credit spread with current market spreads, the liquidity premium must be substantial. While they do not model liquidity, it is incorporated here according to the adjustments discussed in section 4. Upon default the number of potential art buyers, n, is assumed to follow a Poisson distribution with probability mass function $P(X = n \,|\, \lambda) = \frac{e^{-\lambda}\lambda^n}{n!}$, where λ is the mean number of art buyers; i.e. $E[X] = \lambda$. This determines the fraction of illiquid to liquid price, $\widetilde{\kappa}$, in (13) and subsequently the recovery value and the spread.

The effect of adjusting for a finite number of art buyers upon default is highlighted in tables 5 and 6 which show the credit spreads as function of λ. Expectedly, as λ increases, $\widetilde{\kappa}$ approaches one and the spread approaches its liquid counterpart.

Tables 5 and 6 about here

This, together with the results of tables 5 and 6, implies that liquidity premia are indeed substantial when the number of art buyers is small. The higher the value of the art piece initially, the more likely it is that the number of art buyers in case of default will be small. As art pieces that reach record sales prices of a couple of million USD are mostly auctioned among a very limited number of buyers, liquidity can explain part of today's art-backed lending practice.

Loan as Percentage of initial Art Price. If one were to introduce the ACDS contract, it has been hinted at that one could allow for a higher fraction of the art value serving as collateral than present practice. To investigate the credit spread's sensitivity to the value of the loan vis-à-vis the initial art price, consider a loan to value ratio of 75% in a traditional lending agreement, cetris paribus. The fact that, conditional on default, the risk of the art piece being worth less than the loan value outstanding increases the credit spread by about 23bps to 147bps. As is to be expected, the spread is positively related to $x\%$. With the relationship between spread and loan to value ration established, there is no need to limit the fraction of loan to initial art value to 50%. The ACDS structure would allow for the disposal of the risk independent of $x\%$.

Distribution. Using the normal distribution for modeling art price changes would facilitate the analysis, but extreme price movements would possibly be too infrequent. In the normality case, the credit spread for traditional lenders is 82bps, ceteris paribus, which would clearly understate the recovery risk and, hence, the credit risk component as implied by the CDS. This highlights the importance of the appropriate distributional assumption and the necessity to incorporate fat tails when using art returns.

However, also for the t-distribution, the parameters, that are used for modeling art price realizations, are estimated from the data, and , therefore, subject to uncertainty. Especially, the independence assumption of art returns is likely to be violated, implying that parameters are possibly misspecified. To investigate the impact of this uncertainty on the spread, table 7 reports the impact of deviating one standard error from the maximum likelihood estimates based on the numbers in table 3.

Table 7 about here

The credit spread is relatively robust with respect to estimation error of the location parameter, μ. A positive or negative deviation of one standard error from the maximum likelihood estimate causes the fair price of the protection to change by less than 1bp. The scale parameter, on the other hand, has a much bigger influence on the ACDS spread. One standard error added to the maximum likelihood estimate increases the spread by about 7bps. The effect of parameter uncertainty, however, does not affect the spread in anywhere close to a magnitude induced by liquidity constraints considered above.

Other. Other sensitivity analyses that have been conducted include the impact of the time to maturity and the interest charged on the loan. For asset-based lenders there is an approximately 12bps difference for one versus five year maturity loans, with the latter demanding the higher credit risk compensation. On the contrary, the charged interest rate on the loan has virtually no effect on the CDS spread.

7. Summary and Conclusion

The increasing importance of art in rich people's portfolios gives a motivation for art-backed lending services. Recent evidence further shows that art as collateral has gained acceptance during the aftermaths of the financial crisis with two main lender types emerging. Traditional lenders engage in art-backed lending services for existing clients as one product in their service mix. On the contrary, asset-based lenders purely rely on the collateral value of the art piece in the lending transaction.

Using a credit risk pricing methodology, the paper shows that the CDS structure can be applied to art-backed loans and develops a pricing model for the proposed ACDS in order to better understand current lending spreads. This allows an assessment of credit risk that can be decoupled from loan pricing. The results suggest that lenders currently charge much more than what can be explained by credit risk alone. More concretely, credit risk of art-backed loans accounts for only about 50% of the spreads charged for private banks and even only 10% for aseet-based lenders .

Apart from having identified funding costs and informational advantages of the traditional lenders as drivers for the lower spreads compared to asset-based institutions, the paper also shows that liquidity in the art market can significantly affect the pricing of the credit risk component via the recovery value. The latter, in turn, is modeled by explicitly taking art market characteristics into account.

For risk management purposes, understanding and quantifying the components of charged spreads highlights the different risks that the lending institutions take, which is a prerequisite for managing them. Especially the sensitivity analyses allow an investigation of pricing as a function of recovery risk and other loan inputs. Hence, the ACDS structure offers an opportunity to stress test art-backed loan portfolios. Furthermore, the ACDS structure could even be traded, further enhancing risk management by allowing to transfer the risk with respect to the art piece.

A word of caution is in order, if one were to actually introduce the ACDS contract, though. Credit derivatives which have been introduced to allocate risks among market participants according to their risk appetite, have surged during a world wide booming economic period. Duffie and Singleton (2003) and Jobst (2002) point to potential problems of moral hazard when a bank no longer watches the credit quality of a borrower given that it can transfer the credit risk to a third party. With the subprime squeeze, this is exactly what seems to have happened. Risk premiums have surged, indicating that original pricing did not capture the true underlying risks, and the ability of credit derivatives to mitigate a financial crisis, instead of fueling it, has become a questioned issue. Although presented spreads are at best suggestive, the risk management potential of the ACDS will crucially depend on an appropriate pricing model such as the one developed here.

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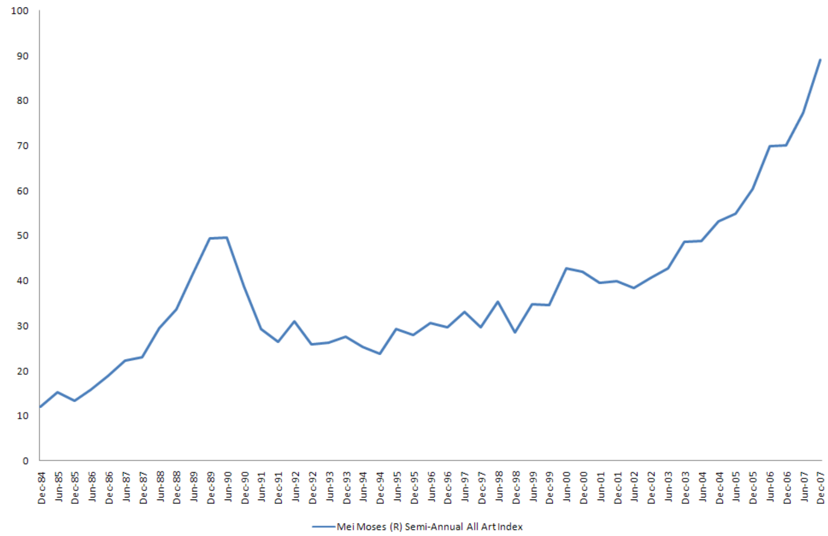

Figure 1: Mei Moses (R) Semi-Annual All Art Index

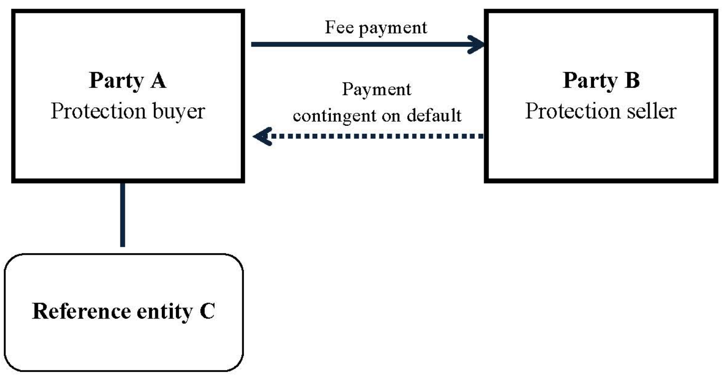

Figure 2: Structure of a CDS

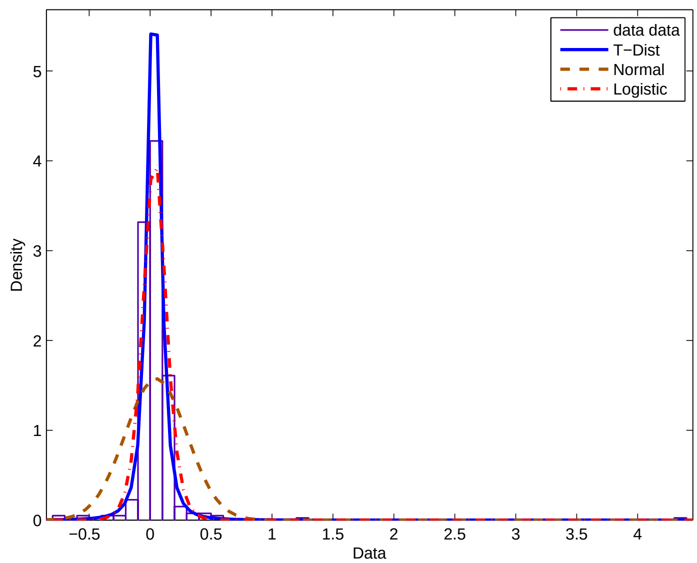

Figure 3: Histogram and fitted distributions for annualized art returns

Table 2: Descriptive statistics of annualized art returns

	Annualized returns
Mean (in %)	4.80
Median (in %)	3.28
Maximum (in %)	432.71
Minimum (in %)	-79.86
Std. Dev. (in %)	25.35
Skewness	12.20
Kurtosis	207.20
Jarque-Bera	701379.26
Probability	0.000

Table 3: Maximum likelihood estimates of distributional parameters of annualized art returns

Distribution	Log likelihood	Parameter Estimates			Std. Err.		
		μ	σ	df	μ	σ	df
Normal	-17.9506	0.0480	0.2535	N/A	0.0127	0.0090	N/A
Logistic	265.193	0.0366	0.0618	N/A	0.0050	0.0027	N/A
t	378.457	0.0319	0.0561	2.1157	0.0038	0.0034	0.2420

Table 4: Cramer-von Mises test statistics

Hypothesized distribution	Cramer-von Mises statistic		Critical Values	
	W_n^2	Adj. Statistic $\widetilde{W}_n^2$	95%	99%
H_0: $U(x, \widehat{\theta}) = N(\widehat{\theta})$	11.8866	11.90153	0.461	0.743
H_0: $U(x, \widehat{\theta}) = t\text{-distribution}(\widehat{\theta})$	0.5479	N/A	0.461	0.743
H_0: $U(x, \widehat{\theta}) = \text{Logistic}(\widehat{\theta})$	1.5423	N/A	0.461	0.743

NOTE. Critical values are taken from Anderson and Darling (1952). For the t- and logistic distributions critical values are only indicative as the distribution of the test statistic is non-standard when the parameters are estimated.

Table 5: Traditional art credit spread and art market liquidity

λ	5	7	10	12	15	20	50	100	500	1000
Credit spread (bp) Trad. Lender	1,278	870	666	579	486	388	192	124	68	61

NOTE. Price realizations for recovery estimation are based on t-distribution; Loan-to-value ratio: 50%; n in (13) is drawn from a Poisson distribution with varying parameter λ; loan interest is 6%, maturity is five years and hazard rate equals 200bps; parameter choices are summarized in table A1

Table 6: Asset-based art credit spread and art market liquidity

λ	5	7	10	12	15	20	50	100	500	1000
Credit spread (bp) Asset-based	2,490	1,670	1,260	1,085	899	702	310	173	60	46

NOTE. Price realizations for recovery estimation are based on t-distribution; Loan-to-value ratio: 50%; n in (13) is drawn from a Poisson distribution with varying parameter λ; loan interest is 15%, maturity is one year and hazard rate equals 400bps; parameter choices are summarized in table A1

Table 7: Credit spread and the impact of varying maximum likelihood estimates

	- 1 SE	MLE	+ 1 SE
μ	0.0281	0.0319	0.0357
Credit spread (bp)	124	124	125
σ	0.0527	0.0561	0.0595
Credit spread (bp)	119	124	131

NOTE. Price realizations for recovery estimation are based on t-distribution; Loan-to-value ratio: 50%; n in (13) is drawn from a Poisson distribution with $\lambda = 100$; loan interest is 6%, maturity is five years and hazard rate equals 200bps; parameter choices are summarized in table A1

Table 1: Art-backed lending practices

	Traditional Lenders		
	Citigroup Art Advisory Service	**Emigrant Bank Fine Art Finance**	**Bank of Amerika Private Bank**
Rates	≈ LIBOR + 225bps; depending on client	*competitive rates*	≈ LIBOR + 150-300bps; depending on client
LTV	50%	50%	50%
Loan value	\$5 - \$100 million	\$1 - \$100 million	
Duration		Loans up to 20 years Credit lines for 1 - 5 years	
Other	Borrower must be bank client Marketable art (no regional markets) Annual Revaluations min \$200,000 per piece Requires other collateral too		Borrower must be bank client

	Asset Based Lenders		
	Art Capital Group	**Art Finance Partners**	**Art Loan**
Rates	6% - 16%	min spread 16% - 19%	15% - 35%
LTV	50%	40% - 50%	35% - 55%
Loan value		min \$500,000	
Duration	3 months to 3 years	Short & long term	4 months
Other	Art work stored in facility Reliable auction estimate Certified ownership	Previous auction price (of artist) Flexible structures	Art work stored in facility Renewal possible

	Auction Houses		
	Sotheby's	**Christie's**	
Rates	≈ Prime + 300bps		
LTV	40%	50%	
Loan value	min \$1 million		
Duration			
Other	Property needs to be consigned to auction Borrower and art characteristics matter	Property needs to be consigned to auction Borrower and art characteristics matter	

NOTE. When no information was attainable, cell is left blank. The table does not claim to capture all active art-backed lending institutions, but intends to give a representative overview of the players.

Appendix

Table A1: Parameters of the base case

Parameter	Value	
	Traditional lender	Asset-based lender
Loan as fraction of $P^{Art}_{t=0}$, $x\%$	50%	50%
Time to Maturity, T_K	5 years	1 year
Risk-free rate, r_f	3%	3%
Interest on loan, y	6% paid annually	15% paid annually
Fee payment dates, T_k	annually in arrears	annually in arrears
Default intensity	200 bps	400 bps
Mean number of art buyers, λ	100	100
μ	0.0319	0.0319
σ	0.0561	0.0561
df	2.1157	2.1157