Art as a Financial Asset in Portfolio Allocation

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Abstract. With increasing interest in recent years, investors have devoted attention to the art market as a potential alternative asset class to be included in portfolios. Besides cultural and aesthetic value, investment in art could provide diversification benefits, and a hedge against market volatility and inflation. We use data on the global art auction market to analyze this asset's risk-return characteristics, and to investigate its inclusion in optimal portfolios, based on the classical Markowitz mean-variance and the mean-CVaR optimization models. The results show that art makes an interesting asset, which enters the optimal portfolios.

Keywords: Art investment · Alternative assets · Portfolio allocation · Mean-variance · Mean-CVaR

1 Introduction

In the last decades, uncertainty in financial markets has led many investors to diversify their portfolios with a mix of standard and alternative investments. Among alternative assets, art is drawing considerable attention among investors and wealth managers. Suffice it to say that ultra-high-net-worth individuals hold, on average, around 5% of their portfolios in art and collectibles [1] and 74% of asset managers in 2023 offered art wealth management services [2].

Besides finance professionals, scholars in finance have also shown interest in the art market. Starting with some isolated pioneering studies in the 1970 s and 1980 s such as the contributions of Stein [3] and Baumol [4], who estimated the rate of return on art investment, the literature on art investment has grown considerably, exploring a broad spectrum of financial themes related to the art market, as outlined in Barro et al. [5]. In particular, a number of studies over the years have investigated the role of art in portfolio allocation. Campbell [6] shows that investing a small fraction of wealth in art improves the trade-off

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between risk and return of the portfolio, while Korteweg et al. [7] argue that a better diversification is achieved by targeting specific art market segments and Tucker et al. [8] report a relevant percentage allocated to art asset. On the other hand, Worthington and Higgs [9] find that art does not provide any diversification gains, thus it is still unclear whether art should be included in a financial portfolio.

The main aim of this contribution is to investigate the role of art as an alternative asset in portfolio allocation. We consider global art auction market data on an extended and up-to-date time period; this allows us to verify whether the recent increased interest in art investments has led to an expansion of the presence of art in optimal portfolio allocations, with respect to the previous results presented in the literature, obtained with much less recent data.

Section 2 presents the data and the models employed; Sect. 3 reports the results of the portfolio allocation, and Sect. 4 concludes.

2 Data and Methodology

To carry out the analysis, we consider the perspective of an US investor who holds a well diversified portfolio of both standard and alternative investments. The data on financial markets are retrieved from Bloomberg and include: an equity market index, S&P 500 Index (SPX), a bond market index, Bloomberg Barclays U.S. Aggregate Bond Index (LBUSTRUU), the Gold to USD rate (XAUUSD), and a real estate market index, Real Estate FTSE NAREIT all equity REITS index (FNERTR).

The art price data come instead from the *All Art Index* provided by Art Market Research (AMR), a London-based firm specialized in data analysis for collectibles' market. The All Art Index (henceforth AMRAAI) monitors the most important auction houses worldwide, and all artists who sold there at least one artwork in the past 24 months are included in the computation. In detail, AMR employs a 24 months weighted moving average to determine an average price representative of each artist in its database – where smaller weights are associated to older sales – and to compute an aggregate index, all average prices are added up on a monthly basis. The AMRAAI, which is exclusive of buyer's premium, is expressed in pound sterling, and data are available with a monthly frequency, from January 1978.

We use a dataset spanning from January 1978 to December 2022. We convert the AMRAAI to a US dollar-denominated index using the monthly GBP to USD exchange rate and we adjust all the indices for US inflation, using the Consumer Price Index of the Federal Reserve Bank of St. Louis, to account for the change in the purchasing power over this extended time period.

From an analysis of the monthly returns, we find that art returns are affected by several periodic spikes, spikes that are particularly high in May and November, as confirmed by an inspection of the correlogram (not reported here for the sake of brevity). This peculiar behavior is due to the periodicity of the most important auctions, during which the most expensive works of art are auctioned.

Table 1. Returns' descriptive statistics

Statistic	SPX	LBUSTRUU	XAUUSD	FNERTR	AMRAAI
Mean	0.0431	0.0160	0.0155	0.0463	0.0354
Std. dev	0.1015	0.0465	0.1233	0.1151	0.1147
Maximum	0.2523	0.1708	0.4259	0.2949	0.3741
Minimum	–0.3391	–0.1361	–0.2637	–0.4956	–0.2655
Skewness	–0.5825	0.0531	0.6183	–1.1238	0.2321
Kurtosis	4.2811	4.9091	3.8517	7.2441	3.6158
VaR (95%)	0.1326	0.0611	0.1878	0.1559	0.1613
CVaR (95%)	0.2087	0.0940	0.2382	0.2513	0.2073

Table 2. Returns' correlation matrix

	SPX	LBUSTRUU	XAUUSD	FNERTR	AMRAAI
SPX	1				
LBUSTRUU	0.223	1			
XAUUSD	0.038	–0.02	1		
FNERTR	0.667	0.17	0.114	1	
AMRAAI	0.062	–0.076	0.156	–0.002	1

In this research, we focus on investors interested in high-end works of art, which are mainly traded in May and November auctions. We thus construct semi-annual indices based on May and November values, and this allows us to overcome the issues caused by the seasonal behavior of the AMRAAI returns. The descriptive statistics for semi-annual returns are displayed in Table 1, while Table 2 reports the returns' correlation matrix. As we may see, art performs reasonably well, compared to the other asset classes, exhibiting a relatively high average return and a positive skewness, but it has a quite high standard deviation. In addition, Table 2 shows that art is practically uncorrelated with the other asset classes, as found in several previous studies (e.g. Renneboog and Spaenjers [10]), and such a low correlation persists also with a monthly frequency.

To investigate the potential benefits of including art in a multi-asset portfolio, we first resort to the classical mean-variance Markowitz model [11]. The formulation of the model is reported below:

$$\begin{aligned} \min_{\boldsymbol{w}} \quad & \boldsymbol{w}^{'}\boldsymbol{\Sigma}\boldsymbol{w} \\ \text{s.t.} \quad & \boldsymbol{w}^{'}\boldsymbol{\mu} \geq h \\ & \boldsymbol{w}^{'}\boldsymbol{e} = 1 \\ & \boldsymbol{w} \geq \boldsymbol{0} \end{aligned} \tag{1}$$

where $\boldsymbol{w}$ is the vector of the asset weights, $\boldsymbol{\Sigma}$ is the return variance-covariance matrix, $\boldsymbol{\mu}$ is the vector of the return means, h is the portfolio target return fixed by the investor, $\boldsymbol{e}$ is a vector of 1 s, and $\mathbf{0}$ is the null vector.

In addition, in order to take into account the tail risk, we apply also the mean-CVaR model that tackles risk from a different perspective, as formulated in Rockafellar and Uryasev [12]:

$$\begin{aligned}
\min_{\boldsymbol{w}, u_k, \alpha} \quad & \alpha + \frac{1}{q(1-\beta)} \sum_{k=1}^{q} u_k \\
\text{s.t.} \quad & \boldsymbol{w}^{'} \boldsymbol{r}_k + \alpha + u_k \geq 0, \quad k = 1, ..., q \\
& u_k \geq 0, \quad k = 1, ..., q \\
& \boldsymbol{w}^{'} \boldsymbol{\mu} \geq h \\
& \boldsymbol{w}^{'} \boldsymbol{e} = 1 \\
& \boldsymbol{w} \geq \mathbf{0}, \alpha \in \mathbb{R}
\end{aligned} \tag{2}$$

where $\boldsymbol{r}$ is a random vector of returns, α is the VaR of the portfolio with a confidence level β, u_k is an auxiliary variable which is equal to $(-\boldsymbol{w}^{'} \boldsymbol{r}_k - \alpha)^{+}$, and q is the number of scenarios generated.

3 Empirical Results

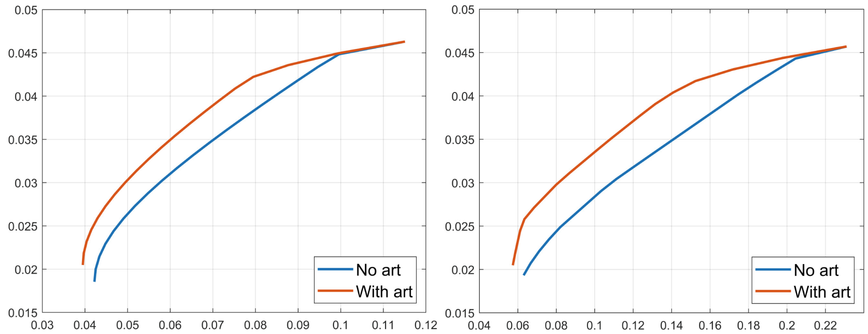
For both optimization models, the efficient frontier is obtained both in the case of portfolios consisting of all five assets considered, including art, and in the case where art is excluded from the portfolio. In the computations, h takes 20 equally spaced values between the return of the minimum variance portfolio ($h = 0.0205$) and the maximum attainable return ($h = 0.0463$).

In the CVaR portfolio optimization, $q = 10,000$ scenarios are generated for the asset returns based on the historical simulation, assuming that the distributions of the returns do not vary over time. The application of the Augmented Dickey-Fuller test, where the order of the model is selected using the Akaike Information Criterion, shows that all the time series of returns of the assets in our portfolio are indeed stationary at the 5% significance level (results are not reported but can be submitted upon request). The confidence level is $\beta = 0.95$.

The results show that investing in art enables the investor to obtain a better portfolio in terms of standard deviation and rate of return (Fig. 1a). Moreover, the results are confirmed for the CVaR model (Fig. 1b), and indeed the better performance seems substantial, more notably with the CVaR model.

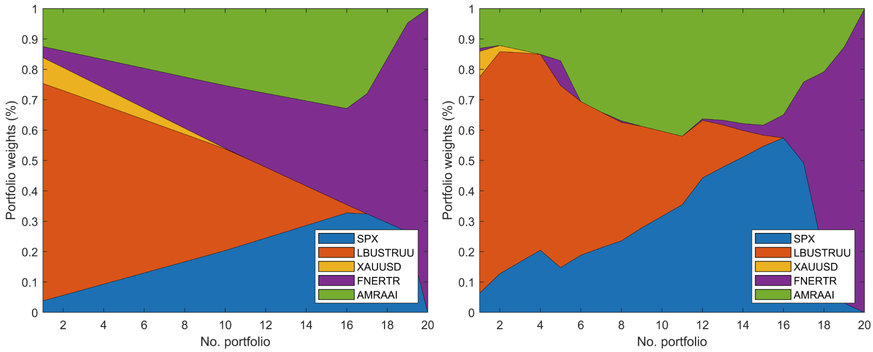
Figure 2 illustrates the composition of the optimal mean-variance and CVaR portfolios that include art. In both cases, the allocation in art is relevant, especially for more aggressive portfolios. For example, in optimal CVaR portfolio no. 10, over 30% of total wealth is allocated to art (see the left panel in Fig. 2).

However, it is unlikely that an institutional investor would allocate such a large proportion to an alternative investment asset. Therefore, we have extended



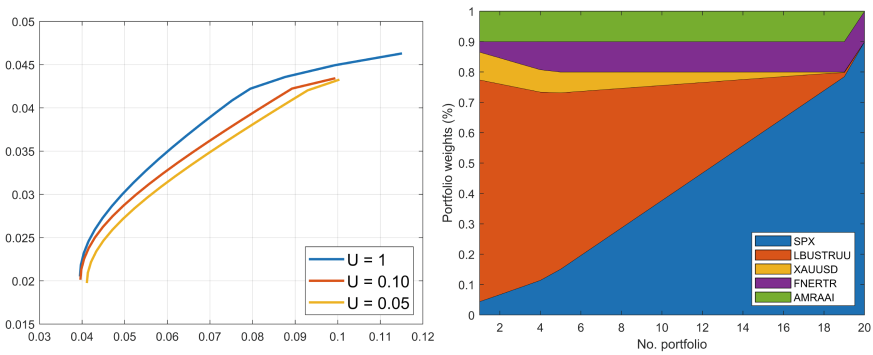
(a) Mean-variance, $h \in [0.0205, 0.0463]$ (b) Mean-CVaR, $h \in [0.0205, 0.0457]$

Fig. 1. Efficient frontiers of portfolios with art and with no art; expected return of the portfolio on the y-axis, risk measure (std. dev. and CVaR) on the x-axis



(a) Mean-variance (b) Mean-CVaR

Fig. 2. Efficient portfolio weights



(a) Efficient frontier as U varies (b) Efficient portfolio weights, $U = 0.10$

Fig. 3. Mean-variance constrained portfolios

our analysis introducing weight restrictions on the alternative asset positions; more precisely, we introduce an upper bound U on the weight of each alternative asset (XAUUSD, FNERTR, AMRAAI). For the sake of brevity, we present only the results for the mean-variance model. Figure 3a shows the behavior of the efficient frontier as the upper bound U varies; Fig. 3b displays the optimal allocation as the target return h varies, for $U = 0.10$. We may notice that the upper bound on the weight for art is always reached, with the exception of the most aggressive portfolio, which is composed only of equity and real estate.

4 Conclusions

The results obtained show that, even including the most recent data for the global art auction market, the optimal portfolios allocate a relevant share to art, in accordance with the results of several previous contributions in the literature, thus confirming that art makes an interesting asset for portfolio diversification purposes. On the other hand, some peculiarities of the art market, such as the low liquidity and the high transaction costs, could be explored more in depth, together with their effects on the portfolio allocation. Further research could also investigate the effects of the inclusion of additional alternative assets, e.g., commodities and cryptocurrencies.

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