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Documento de Trabajo Nº 107 (diciembre 2021)

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ABSTRACT

*This paper presents a new framework to evaluate the merits of an art investment which differs substantially from previous studies. First, it assumes that the investor already holds a portfolio consisting of more traditional assets and is planning to add art to it. This is far more realistic than the usual academic set up in which it is assumed that the investor is planning to deploy a given amount of cash among many assets one of which is art. Second, the approach departs from the traditional Markowitz's mean-*variance *framework in two important ways: (i) the efficient frontier is constructed based on cumulative returns (rather than average returns) and risk is assessed via potential losses and not volatility; and (ii) it relies on a semi-parametric approach to generate synthetic data based on the Gaussian copula and historic returns. The usefulness of this framework is demonstrated with an example based on art sales auction data.*

Keywords: art investments; art returns; portfolio construction; synthetic data; Gaussian copula; wealth management; risk-return profile; efficient frontier; CVaR

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Introduction

The idea that art is an attractive alternative investment that can add diversification to an existing portfolio has been pitched with increasing frequency in recent years (CAAI, 2021; Kirbaj, 2021; Mamarbachi et al., 2020; Winn, 2020). There is no doubt that this suggestion has been triggered by the combination of low interest rates and the relative shrinkage of the public versus private markets that has prevailed recently (Brown, 2020; Henderson, 2019; Stulz 2018). These two tendencies, both quite persistent in the post-subprime crisis world, have motivated private and institutional investors to search for higher yields by incorporating alternative assets to their holdings.

There are many non-financial considerations, all quite valid, to acquire a piece of part. However, this paper is only concerned with artwork acquisitions that are made with purely financial goals. This characterization might offend some purists, but artworks, in addition to being objects of aesthetic merits, are also valuable financial assets. And this begs the question: is art an attractive investment? This question obviously cannot be answered in a vacuum. It is like asking whether investing in real estate or stocks is a good idea. It all depends on the investors' risk appetite, their other holdings they might have, and the peculiarities of the art markets, a subject discussed more fully later.

Regrettably, most previous studies regarding the benefits of art investments suffer from a common shortcoming, namely, they rely on techniques at odds with the properties of art-related assets. For example, a number of authors have promoted the idea that art is lowly-correlated with more conventional assets such as stocks and bonds simply by computing correlations over a fixed time frame (Campbell, 2008). They have not paid attention to how unstable and time-dependent these correlations are, and more important, to the error associated with these correlation estimates, a topic which only a handful of authors have paid attention to (Charlin and Cifuentes, 2016; Renneboog and Spaenjers, 2013; Spaenjers, 2010). Other authors have relied on the Capital Asset Pricing Model (CAPM) to showcase the merits of art investments (Edwards, 2004; Hodgson and Vorkink, 2004; Kraeussl and Lee, 2010; Mei and Moses, 2002; Stein, 1977). Leaving aside that the empirical evidence against the validity of the CAPM with conventional assets is quite strong, the fact of the matter is that artworks violate most of the assumptions on which this model is based

(Charlin and Cifuentes, 2014; Fama and French, 2004). Finally, numerous studies have been based on the mean-variance (Markowitz) framework (e.g., Worthington and Higgs; 2004). Unfortunately, this framework assumes that investors are mean-variance minimizers (a questionable assumption in the context of art) and it is based on short-term volatility –which is not a relevant consideration given that art investors normally have long-term horizons.

Therefore, a general framework more in tune with the realities of the art market and the goals of art investors is needed. Specifically, given that usually an investor already has positions in more traditional assets like stocks, bonds, or real estate, the relevant question is: what would be the benefit of adding a work of art to such portfolio? This question is far more relevant than the more academically-driven problem of selecting the optimal weights given several potential assets one of which is art. This second formulation assumes that the investor is going to build a portfolio from scratch. The reality is that most art investors already have substantial positions in other assets, and it is in this context that an art investment should be considered.

Art Market Characteristics

The term art market in the context of this study refers to the market for paintings, and more precisely, the secondary market. The secondary market is divided between privately-arranged sales and public auctions. Both segments are roughly equivalent in size, and together they amount to approximately $50 to $70 billion in sales per year. The art market differs in many ways from more traditional markets, such and stocks and bonds, and even real estate and commodities. Some key differences are the following:

(a) The art market is unregulated and opaque. Although auction prices are public and easily accessible, information about private sales is very difficult to obtain. Conflicts of interest are common, and insiders enjoy many advantages, therefore, asymmetry of information is the norm.

(b) Art market indices are also opaque. Unlike more traditional markets where price indices are computed according to well-established statistical methods and widely disseminated rules which make them easy to replicate, art market indices, except for a few cases, are calculated based on criteria which are often subjective or not fully disclosed, or both. And often they are only available through paid websites which frequently experience operational issues. This is in stark contrast, for example, with the S&P 500 whose value can be monitored for free with any internet search engine, and whose composition is based on clearly articulated rules. Thus, interpreting the information conveyed by these indices is challenging.

(c) The art market is illiquid and transactions costs are high, sales commissions can be around 20% or more. Also, the due diligence associated with buying an artwork (e.g., verification of authenticity, rightful ownership) can take up to a few months. Not surprisingly, holding periods are typically long, on average between five to ten years.

(d) Investing in art can only be achieved by buying artworks; art investment funds have had a mixed success and they only account for a very negligible fraction of the art market. Additionally, fractional ownership, mostly via non-fungible tokens (NFTs), is still, notwithstanding its potential, a work in progress. Furthermore, a passive (index based) approach to art investment is not a feasible alternative. There are no vehicles that offer this choice to investors.

(e) Returns in the art market can only be estimated, they cannot be computed exactly (Charlin and Cifuentes, 2017). If we want to calculate the return of Alibaba between two specific dates, we can compute this figure exactly by looking at the stock price in those dates. All Alibaba stocks are fungible and thus deliver the same return. With artworks, much like in the case of real estate, we need to estimate the return based on a number of observations (prices) of similar objects (e.g., paintings) but need to control for their characteristics as they are not identical. A number of statistical techniques exist to accomplish this task; most are based on variations of the hedonic regression model (Biey and Zanola, 2005; Chanel et al., 1996; Ginsburgh et al., 2006; Renneboog and Spaenjers, 2013; Triplett, 2004). The key point is that these returns, unlike the case of stocks, are estimates, they come with an error. Thus, interpreting any further calculation based on these returns must take the error into account. More specifically, if we buy a painting by Cezanne, since we are buying a specific painting and not an average or representative painting necessarily, there is always the possibility that the return associated with that painting might deviate from the estimated return.

(f) Since art trades infrequently, the art market suffers from scarcity of data. Unlike stocks, currencies, and commodities, which enjoy the benefit of daily prices and thus returns can be computed for any time-interval, art returns can only be computed for much longer time windows. For highly traded artists such as, for instance, Picasso, Warhol or Renoir, return calculations for semesters can be done. But for the majority of artists, annual returns are the norm.

(g) Although the returns of financial assets in general do not conform to normality, it is possible when dealing with short time-windows to assume normality in certain cases. However, in the art market, given the long length of the holding periods, the normality-of-returns assumption is grossly inadequate.

It might seem, at first sight, that the above-mentioned characteristics amount to an indictment on art market investments, but that is not the case. These observations simply suggest that investing in art is a high-risk high-return proposition, pretty much like participating in private equity, venture capital, or angel investments.

The shortcomings of the traditional mean-value (Markowitz) framework—which is based on linear correlations, standard deviation of returns, and implicitly assumes extensive availability of data—are clearly inadequate to deal with the art market. There is no evidence that art investors are variance-minimizers, if anything, they seem to be less risk averse than most conventional investors. Furthermore, computations based on short-term volatility for an asset that is normally held for five to ten years has little practical relevance. Cumulative returns, and loss-related metrics based on the relevant time-window are much more informative. Therefore, the need to have a different theoretical framework to deal with art investments seems warranted. This paper aims to make a contribution in that direction.

Portfolio Construction: a Review of Recent Advances

Markowitz's seminal paper framed the portfolio selection problem as a formal optimization problem and in doing so he gave birth to a new subdiscipline within finance: modern portfolio theory (Markowitz, 1952). The basic ideas behind his formulation, the so-called mean-variance (MV) portfolios, are rooted on the benefits of diversification and the necessary tradeoff between risk and return. These concepts have resisted well the test of time.

However, the practical implementation of these ideas has been problematic. Calculating the correlation-of-returns matrix—an essential element of the MV formulation—is challenging. DeMiguel et al. (2009) estimated that for a portfolio of 25 assets, at least 3,000 months of monthly returns would be required to estimate such matrix with any degree of confidence. Not surprisingly, solving for the MV portfolios often results in unstable solutions, as discussed in Ban et al. (2018). Additionally, DeMiguel et al. (2009) concluded that none of the many MV-portfolios they considered could consistently beat the trivially determined equally-weighted portfolio (also known as 1/N) based on out-of-sample performance.

Staring in the 1980s most efforts in the portfolio optimization arena were dominated by attempts to address these two challenges. These attempts relied on robust optimization (see Xidonas et al., 2020 for a survey), regularization techniques (see Ban et al., 2018 and Pagnoncelli et al., 2021a for examples), the introduction of Bayesian techniques such as the work of Black and Litterman (1992), the addition of risk-parity criteria to the optimization (Bai et al., 2016), and a number of numerical techniques (e.g., denoising, detoning as described by Lopez de Prado, 2020) whose specific objective was to mitigate the error propagation that results from ill-conditioned correlation matrices. It is fair to say that no approach emerged as a clear winner in this contest.

However, the 21st century brought some fresh air to the portfolio selection problem. In this regard, we recognize three shifts in thinking.

(a) The Conditional-Value-at-Risk (CVaR), introduced in a formal manner by Rockafellar and Uryasev (2002), has firmly established itself as the preferred risk metric in the financial engineering space. (Note: the CVaR is considered a better alternative than the Value-at-Risk (VaR) since the VaR does not satisfy the subadditivity condition.) The standard deviation of returns—strictly speaking, a measure of uncertainty, not risk—has been consistently losing ground as a risk metric. An important advantage of the CVaR is that by focusing on losses is more in tune with the way investors think about risk. Advances in behavioral economics have shown that most investors are actually loss averse rather than risk averse (Friedman et al., 2004; Kahneman, 2003). Thus, it is easier to articulate investors preferences in terms of the CVaR rather than the standard deviation of returns. For instance, suppose that an investor who has a $100 million portfolio claims that: "I want to make sure that with a high degree of certainty, say 90%, my losses, in an adverse situation, will not exceed $20 million." And adds that: "If one of those negative scenarios were to occur, I would like my losses, on average, not to exceed $30 million." It is not possible to articulate those sentiments in terms of the standard deviation of returns. On the contrary, VaR = $20 million and CVaR = $30 million (estimated both with a 90% confidence) capture well the investor's wishes.

(b) The correlation matrix is useful when dealing with linear relationships, and ideally, with normally distributed random variables. But art returns depart significantly from normality. Copulas, a modeling tool introduced by Sklar in the late 1950s, have been steadily gaining acceptance among financial engineering practitioners to handle interdependence among different assets returns (Sklar, 1959). A copula is a mathematical procedure that builds a multivariate distribution based on the marginal distributions of a group of individual random variables while incorporating their interdependence. This approach has proven to be superior to the linear correlation-based scheme characteristic of the Markowitz formulation. An important property of the copulas is that they do not impose constraints on the marginal distributions; in fact, the marginal distributions do not need to be normal. The Gaussian copula (there are many others) is the most widely used in finance (Gutierrez et al., 2019; Jackel, 2002; Jouanin et al., 2004).

(c) Monte Carlo simulations, in which one explores the performance of a given portfolio by looking at many possible (feasible) scenarios, have become the preferred method to evaluate risk-and-return tradeoffs. These simulations are based on the ability to create many realistic return scenarios. One approach to create such return scenarios is to rely on parametric models such as VAR and GARCH models to generate many representative returns. Once calibrated, these models can generate an arbitrary high number of return samples with little computational cost. However, strong assumptions such as normality are often required, and estimating the key parameters of such models is challenging from a numerical stability viewpoint. Another alternative is to avoid parametric characterizations and return distribution assumptions, and work directly with the historic data. This approach offers a great deal of flexibility and the advantage of capturing better the key features of the past (observed) data. Unfortunately, the scarcity of data problem—discussed in detail by Israel et al. (2020) in reference to traditional assets—becomes more acute when dealing with art returns given that only annual returns estimates are available, and in general for periods of at most twenty to thirty years. And even if data for longer periods were available it is doubtful whether it would capture the features of the art market today; in other words, it would be like sampling from a different universe. A successful approach to deal with this situation consists of creating synthetic returns data compatible with the existing data. Combining historic (observed) returns with the Gaussian copula has proven to be a successful choice to generate such synthetic data. Additionally, this approach has demonstrated that is fairly stable and that can generate extreme scenarios, that is, adverse returns scenarios compatible with the existing data even if those scenarios have not been observed (Pagnoncelli et al., 2021b).

Problem Statement

The problem at hand can be stated more formally as follows: suppose an investor has N holdings spread over non-art-related assets (e.g., stocks, bonds, commodities) and is considering adding art to this portfolio by investing in a specific artist. The question is: how would the risk-return profile of this portfolio change if we were to add a specific artist in various degrees of exposure.

The formulation we are advocating assumes that the investor has already achieved a certain level of financial comfort, has exposure to more conventional assets, and wishes to explore the merits of including art as a small fraction of the portfolio to benefit from more diversification. This situation does not involve solving any optimization problem. It simply reduces to examining how the risk in the portfolio would change if art were to be added in different proportions. To be clear, we are not planning to make out-of-sample return predictions involving art. Our goal is humbler and a bit more realistic: we seek to explore how we can alter the risk-return profile of a given portfolio by incorporating art.

Proposed Approach

Suppose the investor's portfolio (which does not include art) is defined by N weights, $\omega_1, \ldots, \omega_N$, such that they add to one. The investor is considering adding to this portfolio a λ exposure to a specific artist. We assume that we have data regarding past annual returns for all these assets for M years. We designate the new portfolio weights as $\alpha_1, \ldots, \alpha_N, \alpha_{N+1}$ where, $\alpha_{N+1} = \lambda$. This approach requires that we have also defined a rule to calculate the new weights (α_i's) based on the original weights (ω_i's) for i =1, …, N; no specific restriction is imposed on this rule other than the resulting weights must, again, add to one. We further assume that the investor is planning to hold the art-asset for K years.

The first observation is that we will focus on K-years cumulative returns rather than average returns over K-year periods. This observation might seem innocuous. However, in general, evaluating the performance of a portfolio based on the average return, that is, $(x_1 + \ldots + x_K) / K$, versus the cumulative return (that is, $(1+ x_1)\ x \ldots x\ (1+ x_K) -1$) does not always yield the same rank order. Since the investor is considering keeping the art position for K years, we pose that the cumulative return over a K-year period is a more adequate figure of merit to describe performance. It follows from this observation that the Sharpe ratio, since it relies on volatility (i.e., year-to-year return variations) is not adequate to capture the relevant risk. Instead, we use the CVaR of cumulative returns over a K-year period to assess risk. Consequently, we gauge the risk-adjusted return by computing a return-risk ratio (termed RRR) defined as follows:

$$RRR = \frac{E(cumR)}{CVaR} \tag{1}$$

where both, the expected cumulative return, *E(cumR)*, and the CVaR are based on the K-year return. These two estimates are computed numerically via a Monte Carlo simulation.

In short, we proceed as follows:

[1] We compute for each of the N + 1 assets, based on the annual returns, all the possible K-year cumulative returns (M – K + 1 in total). That is, we consider all the possible K-year periods permitted by the data, considering overlapping, that is, the first period is (1, …, K) and the last is (M - K +1, …, M). This is very much in line with the approach suggested

by Gutierrez et al. (2019) and Pagnoncelli et al. (2021b). In short, we have created M – K + 1 return vectors, each of dimension N + 1.

[2] Invoking the Gaussian copula procedure, in combination with the M – K + 1 (historic) return vectors, we generate many, say P, return scenarios (Monte Carlo simulation), each one defined by an N + 1 vector. Together, these scenarios constitute what is called a synthetic data set. Several open-source software options are available to accomplish this task. Additionally, a number of commercial statistical packages, such as SAS or MATLAB, for example, include procedures to this effect.

[3] For each of the relevant λ's (i.e., 0%, 1%, 2%, etc.) we determine the corresponding α's, and then, for each of the P scenarios, we calculate the portfolio return for that scenario using the α's as weighting factors. The *E(cumR)* is the average cumulative return computed over the P scenarios.

[4] For each λ, we now estimate the CVaR. The CVaR is estimated discretely based on the P scenario returns, considering a pre-established confidence level, say β. To this end, the P returns (say, $Z_1, \ldots, Z_P$) are ordered from the lowest to the highest. Let Q be the observation such that Q is the maximum integer such that $Q / P < 1 - \beta$. The CVaR is simply the average of the losses experienced by the first Q scenarios. (Note: this also means that the VaR, is given by Z_Q.) Then, for each λ we calculate the corresponding RRR (see Eq.[1]).

With these elements, as we will demonstrate in the next example, we have all the ingredients to assess the merits of adding art to the portfolio.

Example of Application

Consider an investor who holds positions in stocks, investment grade (IG) bonds, gold and real estate, represented by the following indices, respectively, S&P 500, Vanguard VFICX, Gold Fixing price and the S&P/ Case-Shiller U.S. National Home price index. The proportions (ω's) are: 45%, 20%, 15% and 20%. We refer to this as the basic or reference portfolio. Let us also assume that the investor is looking at the possibility of adding a small investment in art (λ) at the expense of reducing in equal amounts the exposure to stocks, bonds and gold while keeping the real estate position unaltered. In short, for various values of λ we seek to evaluate the risk-return properties of a portfolio defined by: α_1 = 45% – λ/3; α_2 = 20% – λ/3; α_3 = 15% – λ/3; α_4 = 20% and α_5 = λ.

The investor is considering six artists as potential candidates for the art position: Jean-Michel Basquiat, Pierre Bonnard, Joan Mitchell, Claude Monet, Pablo Picasso, and Zao Wou-Ki. We further assume that the investor is looking at a 5-year horizon and that we have annual return data for the years 1996-2020, that is, 25 years, which, in turn, results in 21 overlapping 5-year windows. That is, from the data we can estimate 21 5-year cumulative returns. The annual returns for the six artists considered were estimated using the hedonic regression technique normally used to estimate art returns (see, for example, Ginsburgh et al., 2006) based on public auction sale prices, which were downloaded from the artnet.com website. Table 1 summarizes the key return statistics for all the assets. In what follows all returns are real returns (i.e., adjusted for inflation using the U.S. CPI).

A few observations are in order: (i) the higher stocks return (23.52%) compared to IG bonds (9.07%) is somewhat expected and in line with broader historic experience based on long-time periods; (ii) the much higher return of gold (39.54%) compared to the three more traditional assets (stocks, bonds and real estate) is mainly due to the gold rally after the subprime crisis, triggered possibly by inflation fears; recall that gold remained essentially flat during the 20-year period preceding the subprime crisis (2007/2008); and (iii) more noticeable are the wide dispersions in returns observed for the artists. This hints that the question of investing in art can only be answered in reference to a specific artist and not in reference to art in general.

Table 2 shows the return correlations for all the assets. Note that of the 45 correlation coefficients only 16 are significant at the higher-than-90% level. And the correlations that are significant are mostly between two artists and not between an artist and a financial asset. In fact, the correlations between the artists and the S&P 500 are not significant (we cannot state that they are different from zero). And in the case of IG bonds and artists, only one correlation is significant (Monet's). This suggests that deriving conclusions about the merits of adding art to a traditional stocks-and-bonds portfolio based only on computing correlations is hopelessly naïve.

Figure 1(a) shows the histogram of returns for the basic (reference) portfolio (i.e., art is not included). Two things are clear. First, the returns distribution departs from normality. And second, the granularity of the dataset—only 21 points—is insufficient to estimate discreetly any loss-based risk metric such as the CVaR (or VaR). Hence, the necessity to enhance the size of the dataset, in this case with synthetic data created via the Gaussian copula, is warranted. The resulting histogram is depicted in Figure 1(b). This histogram, generated with the COPULA procedure in SAS, consists of 10,000 observations generated from the 21 return vectors (SAS, 2021). Notice that the copula procedure has generated several extreme-losses scenarios which permit estimating the CVaR with better accuracy.

Figure 2 shows the position of the basic portfolio as well as all the other assets in a two-dimensional risk-return diagram based on the 5-year cumulative return and the CVaR. This diagram is far more informative than the traditional diagram based on average returns and their standard deviations. This figure suggests some interesting features, namely, that some artists (Mitchell and Zao Wou-Ki) offer extraordinary returns with little risk, while others (most notably Picasso and Monet) offer very unattractive returns for the risk they entail. Picasso's return, in particular, is comparable to that of IG bonds with roughly ten times more risk.

Table 3 shows for different λ's, and for each of the six artists, how they would alter the risk profile of the basic portfolio. Limiting λ to 15% is reasonable since the investor is planning to add some art to the basic portfolio, but not taking a major art position. These risk- and return- estimates are also based on 10,000 synthetic scenarios generated via a Monte Carlo-Gaussian copula simulation. By applying the corresponding weighting factors (α's) to each of these 10,000 vectors we can calculate for any portfolio (with or without art) both, the expected cumulative return and the CVaR. The expected portfolio cumulative return is simply the average over all the scenarios. For the CVaR computation we employ a 90% level of accuracy. A higher level of accuracy seems unreasonable considering the uncertainty implicit in art returns. Thus, the CVaR is simply the average of the losses corresponding the worst 1,000 scenarios. Table 3 is self-explanatory: Basquiat, Mitchell and Zao Wou-Ki clearly emerge as the best choices to improve the profile of the basic portfolio, which is not surprising considering their positions on the diagram shown in Figure 2. These three artists contribute to important improvements in all three figures of merit, which increase monotonically with λ in the range explored; in brief, adding them in any amount will only improve the risk profile of the basic portfolio. Monet, Picasso and Bonnard tell a very different story. They can only marginally alter the return (in the case of Picasso and Monet always for the worst) at the expense of less noticeable variations in risk. A perceptive reader might also notice that for $\lambda = 0$, Table 3 shows slightly different values for the three key entries; in theory, they should be identical for the six artists. These discrepancies, more noticeable in the RRR estimate since it is more sensitive to variations in the denominator, are common in numerical simulations where analytical solutions are not possible.

Finally, Figures 3 and 4 show the corresponding efficient frontiers based on the expected cumulative return and the CVaR. For reasons of scale the top 3 and bottom 3 artists, based on their average returns according to Table 1, are shown in different diagrams. Although adding 50% of any artist (Figure 3), which, incidentally requires shorting gold, is not reasonable in the context of this situation, it is necessary to describe more fully the entire risk-return curve. It is interesting to observe that the efficient frontiers in Figure 3, and that of Bonnard as well (Figure 4), are all defined by values of λ higher than certain threshold. Quite the contrary, Picasso's and Monet's efficient frontiers are defined by values of λ lower than some threshold. Figures 3 and 4 show more graphically what Table 3 has already indicated: Basquiat, Mitchell and Zao Wou-Ki are by far the most attractive choices to improve the risk-return features of the basic portfolio.

Given the fact that art investors normally hold art positions for several years, we argue that this version of the efficient frontier—based on the cumulative return over the relevant holding period and a risk metric based on potential losses (CVaR) over that period and not return fluctuations over the holding period (volatility)—addresses better the needs of such investors. It follows from this observation that the RRR gauges better the risk-adjusted return than the Sharpe ratio (which is based on volatility).

Conclusion

The most important conclusion of the previous analysis—perhaps not surprisingly—is that the question of whether it is convenient to add art to an existing portfolio is not something that can be answered in general for the answer depends on the specific artist considered. The example showcases vividly how the answer can differ depending on the artist selected, and the amount added. Also, the example shows clearly that making an assessment of the diversification benefits of adding art to a portfolio based only on computing correlations can be misleading.

Second, we argue that the approach presented herein is more suited to assess the merits of adding an art investment to an existing portfolio compared to the more conventional approach based on Markowitz's efficient frontier, which is based on the standard deviation of returns estimated via correlation matrices. The key reasons are:

(i) art investors tend to hold their positions for several years and thus, the expected cumulative return over the relevant holding period—and not the average return computed based on sub-divisions of such holding period—is more useful to represent performance; and

(ii) the CVaR, a metric based on potential losses, is more amenable to capture better the investor's risk preferences as investors are in general loss averse rather than risk averse.

And third, the idea of augmenting the available (historic) dataset by creating synthetic data via a combination of Monte Carlo simulation-Gaussian copula is an effective way to deal with the scarcity of data problem frequently present in art investment situations. More specifically, this approach permits a more granular description of the risk-return tradeoffs.

At present, the idea of adding specific amounts of art exposure to a portfolio might seem problematic from an execution viewpoint. After all, exposure to art can only be achieved by buying paintings, an exercise which is discrete in nature. It is hoped, however, that future progress in fractional ownership might facilitate gaining exposure at more granular levels.

Finally, it should be clear that the framework introduced herein can be easily applied to more general situations. For example, a case in which an investor wishes to explore how the risk-return profile of an existing portfolio can be altered by incorporating a new position, not necessarily in art. And for investors with a long-term view and not concerned with liquidity constraints—but with potential losses—the RRR metric is a more informative figure of merit than the more conventional Sharpe ratio.

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Table 1 **Key metrics for different assets based on 5-year cumulative returns: 1996-2020 period**

Asset	Average 5–Year Cumulative Return	Standard Deviation	Minimum	Maximum
Jean-Michel Basquiat	89.51%	93.81%	−10.1%	392.5%
Pierre Bonnard	40.31%	67.89%	−34.3%	223.7%
Joan Mitchell	132.35%	119.51%	−0.7%	498.3%
Claude Monet	19.05%	44.08%	−59.3%	107.7%
Pablo Picasso	9.38%	41.76%	−52.7%	122.2%
Zao Wou-Ki	86.48%	72.40%	−2.0%	281.2%
Case-Shiller Index	12.63%	23.57%	−33.5%	46.2%
Gold	39.54%	57.91%	−37.2%	145.4%
Investment Grade (IG) Bonds	9.07%	7.68%	−5.6%	22.4%
S&P 500 Index	23.52%	42.57%	−30.6%	89.7%

Table 2 Correlation Coefficients among all artists and portfolio assets (N = 21)

	Jean-Michel Basquiat	Pierre Bonnard	Joan Mitchell	Claude Monet	Pablo Picasso	Zao Wou-ki	Case-Shiller Index	Gold	IG Bonds	S&P 500 Index
Basquiat	1.000	**0.686*** **	**0.741*** **	0.163	**0.881*** **	**0.683*** **	0.235	0.274	0.048	−0.111
Bonnard	**0.686*** **	1.000	**0.518***	−0.101	**0.599** **	**0.553** **	**0.453***	0.264	−0.050	−0.050
Mitchell	**0.741*** **	**0.518***	1.000	−0.094	**0.699*** **	**0.512***	0.140	**0.384†**	−0.143	−0.304
Monet	0.163	−0.101	−0.094	1.000	0.244	0.122	−0.007	**−0.505***	**−0.395†**	0.320
Picasso	**0.881*** **	**0.599** **	**0.699** **	0.244	1.000	**0.710*** **	0.135	0.214	−0.044	−0.149
Zao Wou-Ki	**0.683*** **	**0.553** **	**0.512***	0.122	**0.710*** **	1.000	−0.179	0.283	0.058	0.235
Case-Shiller	0.235	**0.453***	0.140	−0.007	0.135	−0.179	1.000	**−0.505***	0.080	0.171
Gold	0.274	0.264	**0.384†**	**−0.505***	0.214	0.283	**−0.505***	1.000	−0.068	**−0.577** **
IG Bonds	0.048	−0.050	−0.143	**−0.395†**	−0.044	0.058	0.080	−0.068	1.000	−0.092
S&P 500	−0.111	−0.050	−0.304	0.320	−0.149	0.235	0.171	**−0.577** **	−0.092	1.000

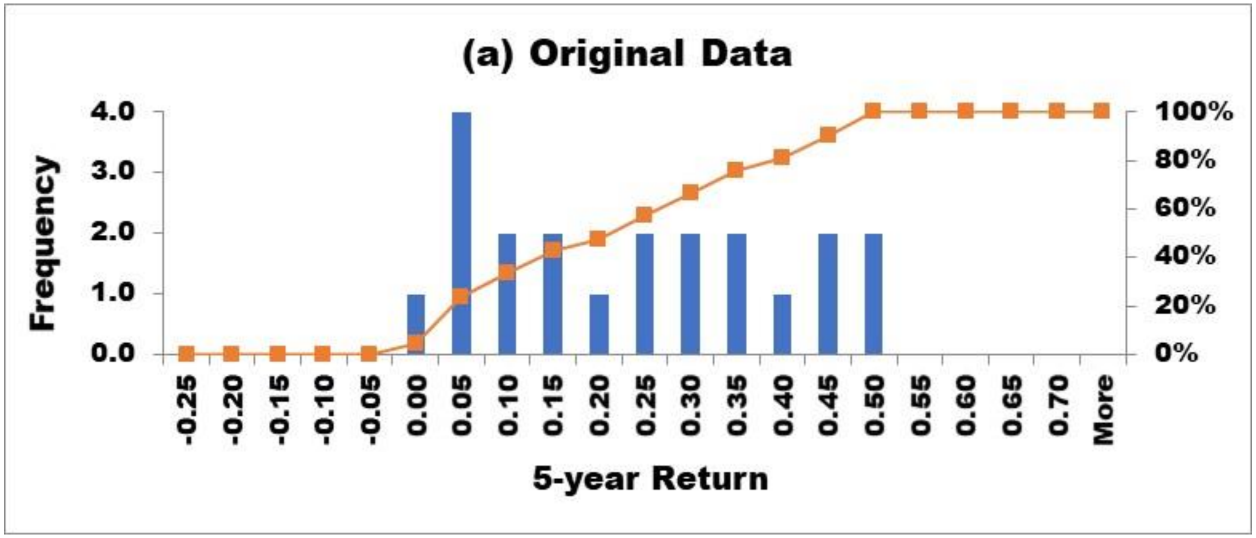
† p<0.10; * p<0.05; ** p<.01; *** p<0.001 N is the number of observations (5-year returns)

Table 3 Effect of adding different percentages (λ) of each artist to the basic portfolio

λ (%) Added	**Basquiat**			**Bonnard**			**Mitchell**			**Monet**			**Picasso**			**Zao Wou-Ki**		
	Return	**CVaR**	***RRR***[*]	**Return**	**CVaR**	***RRR***[*]	**Return**	**CVaR**	***RRR***[*]	**Return**	**CVaR**	***RRR***[*]	**Return**	**CVaR**	***RRR***[*]	**Return**	**CVaR**	***RRR***[*]
0	21.10%	4.52%	4.67	21.01%	4.96%	4.24	21.23%	4.45%	4.77	21.02%	4.94%	4.25	20.85%	4.89%	4.26	20.99%	4.89%	4.30
1	21.81%	3.71%	5.88	21.19%	4.85%	4.37	22.35%	3.17%	7.06	20.97%	4.44%	4.72	20.71%	4.67%	4.43	21.64%	4.37%	4.95
2	22.51%	3.16%	7.12	21.37%	4.79%	4.46	23.47%	2.38%	9.84	20.92%	3.98%	5.25	20.56%	4.50%	4.57	22.29%	3.92%	5.68
3	23.22%	2.77%	8.39	21.54%	4.77%	4.52	24.58%	1.86%	13.19	20.87%	3.56%	5.86	20.41%	4.37%	4.67	22.93%	3.56%	6.44
4	23.92%	2.48%	9.66	21.72%	4.78%	4.54	25.70%	1.52%	16.91	20.82%	3.18%	6.54	20.27%	4.28%	4.74	23.58%	3.25%	7.26
5	24.63%	2.26%	10.91	21.90%	4.83%	4.53	26.82%	1.26%	21.24	20.77%	2.86%	7.26	20.12%	4.23%	4.75	24.23%	2.98%	8.13
6	25.34%	2.08%	12.19	22.07%	4.91%	4.50	27.94%	1.06%	26.23	20.72%	2.60%	7.97	19.98%	4.24%	4.72	24.87%	2.76%	9.01
7	26.04%	1.94%	13.40	22.25%	5.01%	4.44	29.05%	0.92%	31.72	20.67%	2.41%	8.58	19.83%	4.28%	4.63	25.52%	2.57%	9.94
8	26.75%	1.83%	14.59	22.43%	5.14%	4.36	30.17%	0.79%	37.96	20.62%	2.29%	9.01	19.69%	4.36%	4.51	26.17%	2.41%	10.88
9	27.45%	1.75%	15.73	22.60%	5.29%	4.27	31.29%	0.70%	44.55	20.57%	2.23%	9.21	19.54%	4.48%	4.37	26.81%	2.27%	11.82
10	28.16%	1.68%	16.81	22.78%	5.46%	4.18	32.41%	0.63%	51.50	20.52%	2.24%	9.17	19.40%	4.62%	4.20	27.46%	2.15%	12.80
11	28.86%	1.62%	17.77	22.96%	5.65%	4.06	33.52%	0.57%	59.12	20.47%	2.30%	8.90	19.25%	4.79%	4.02	28.11%	2.04%	13.80
12	29.57%	1.59%	18.64	23.13%	5.86%	3.95	34.64%	0.51%	67.46	20.42%	2.43%	8.39	19.10%	4.99%	3.83	28.75%	1.94%	14.83
13	30.28%	1.56%	19.44	23.31%	6.09%	3.83	35.76%	0.47%	76.50	20.38%	2.63%	7.74	18.96%	5.21%	3.64	29.40%	1.85%	15.86
14	30.98%	1.54%	20.09	23.49%	6.33%	3.71	36.88%	0.43%	85.84	20.33%	2.88%	7.06	18.81%	5.46%	3.44	30.05%	1.78%	16.88
15	31.69%	1.53%	20.65	23.66%	6.59%	3.59	37.99%	0.40%	94.87	20.28%	3.18%	6.38	18.67%	5.73%	3.26	30.69%	1.72%	17.88

[*]RRR = Return−Risk Ratio

Figure 1 Histograms of basic portfolio returns based on: (a) Original data (N=21) and (b) Simulation with Gaussian copula (synthetic) data (N=10,000)



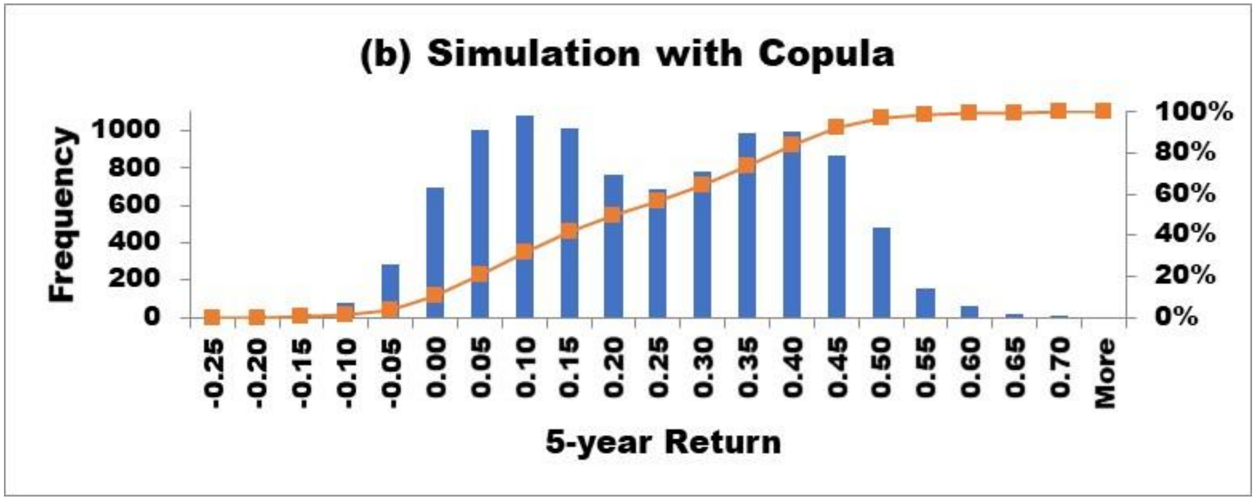


Figure 2 Average cumulative 5-Year returns versus CVaR

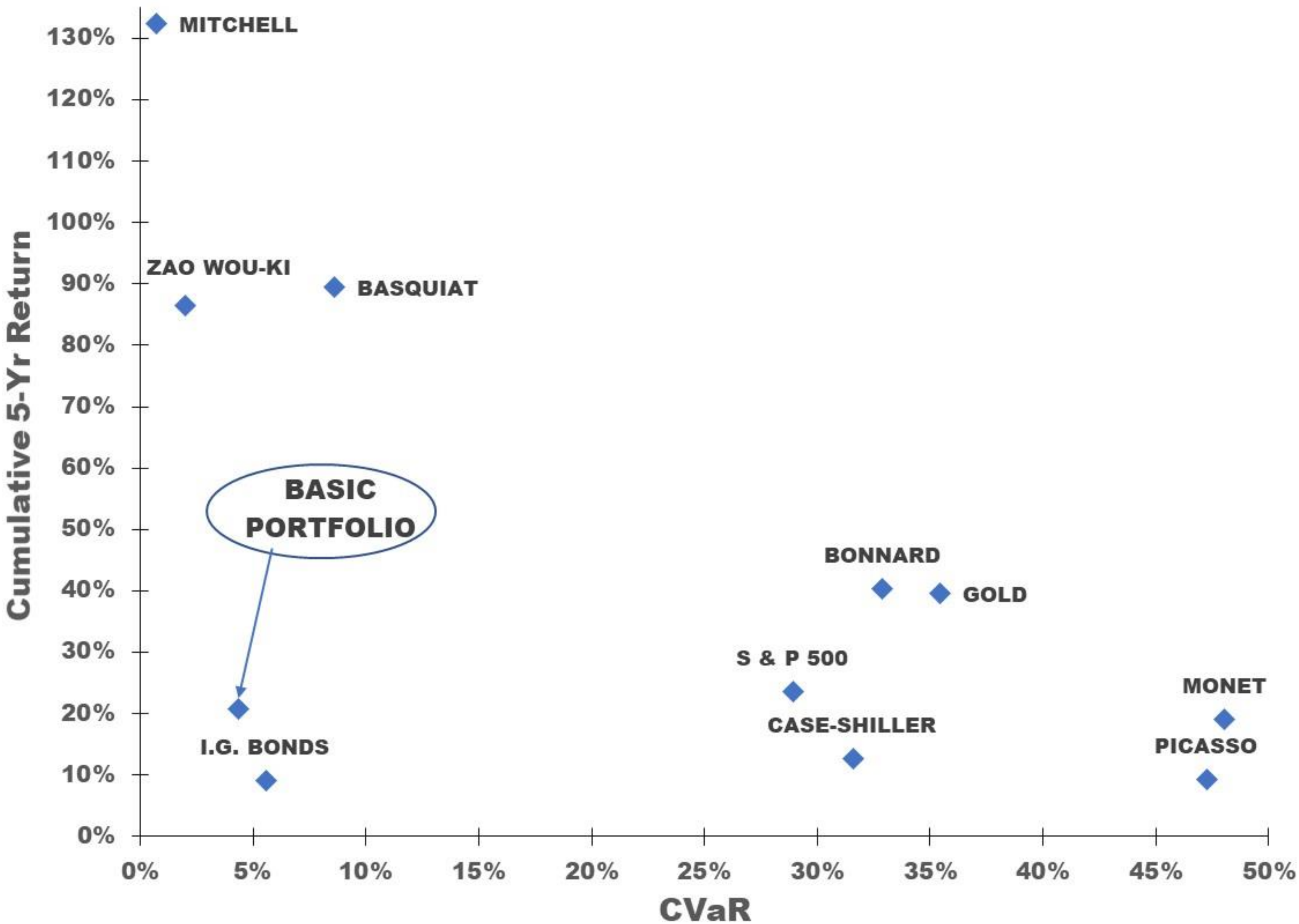


Figure 3 Efficient Frontier for the top 3 artists considered: Cumulative 5-Year returns versus CVaR

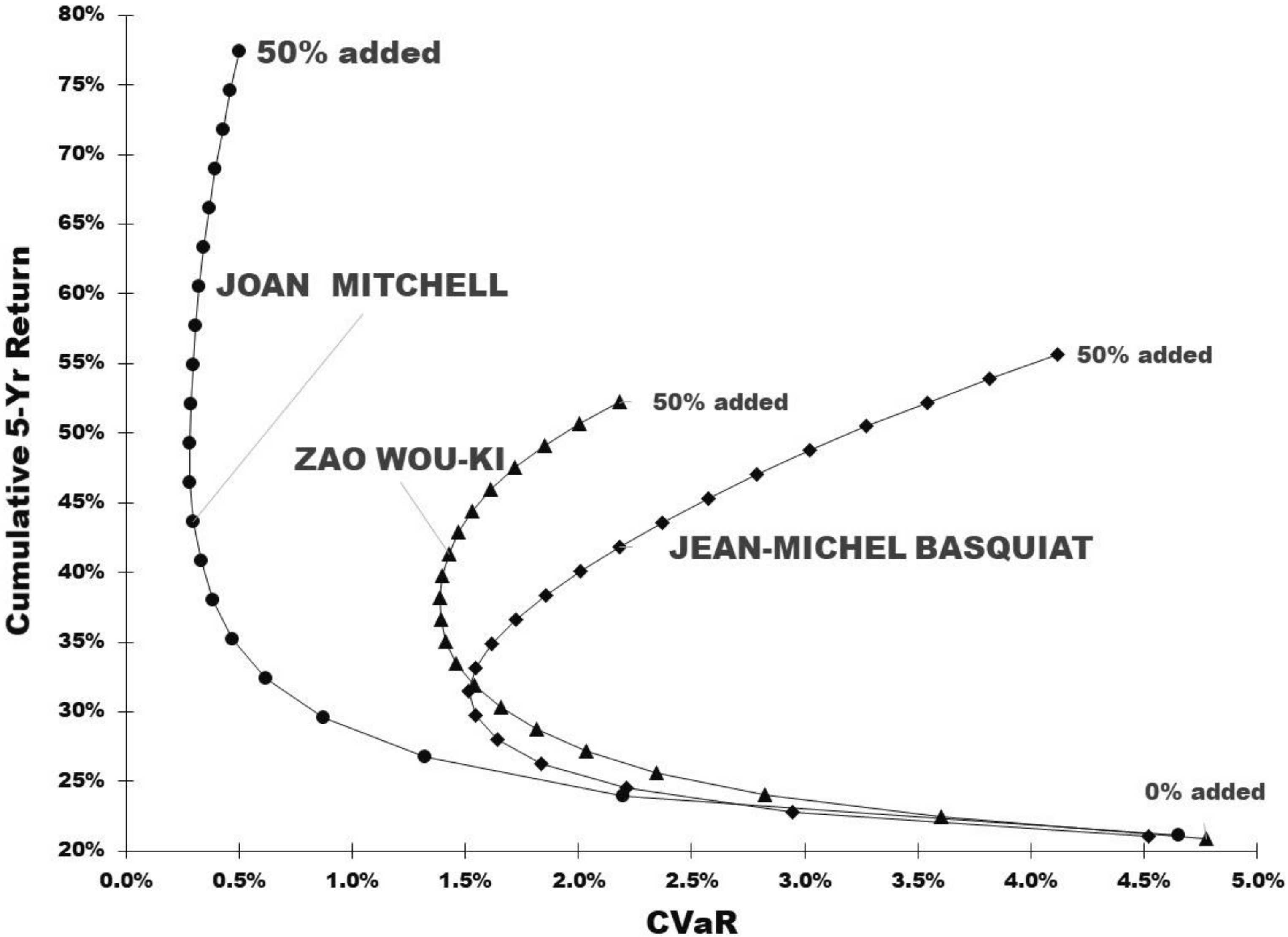
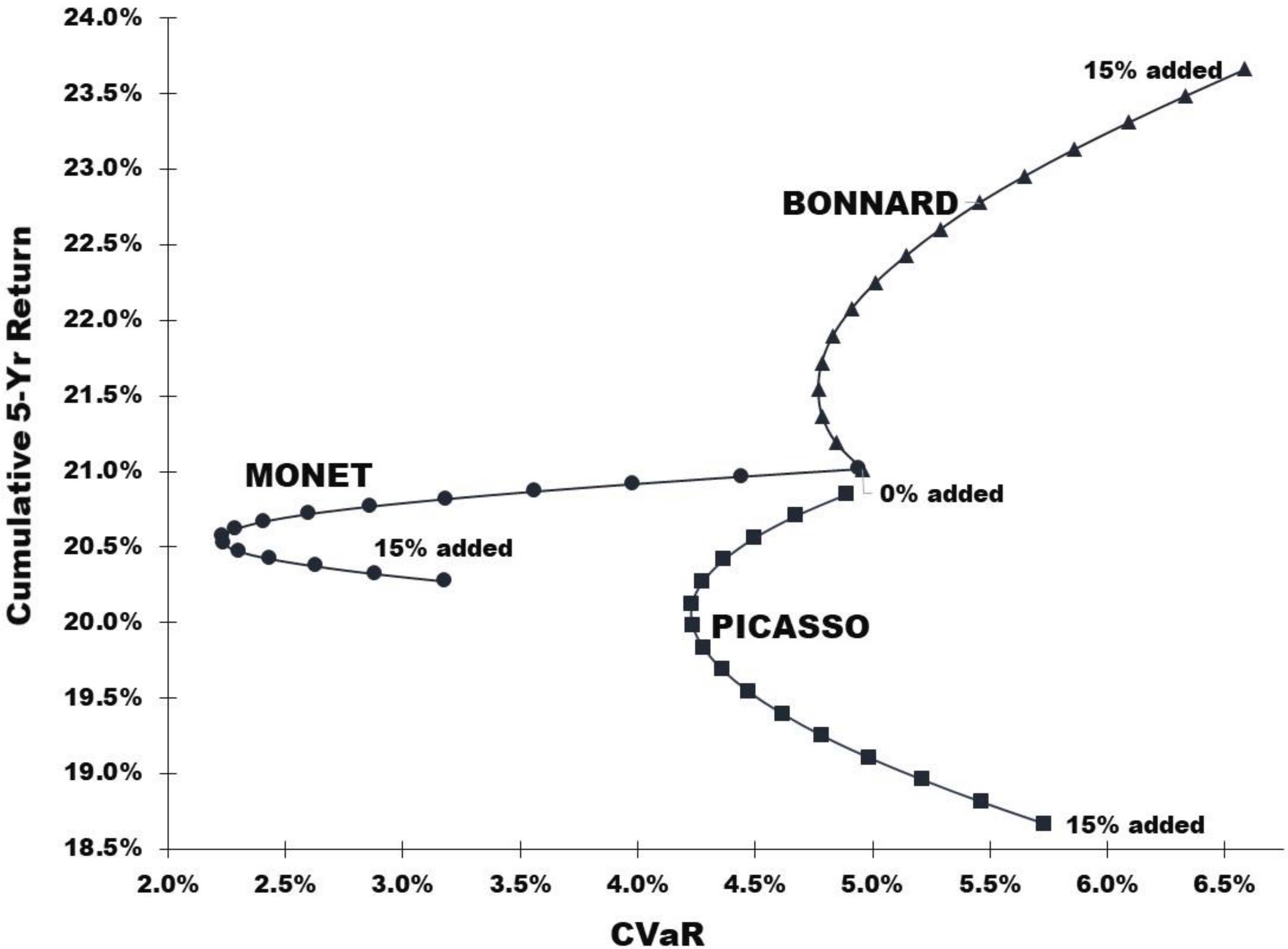


Figure 4 Efficient Frontier for the bottom 3 Artists: Cumulative 5-Year returns versus CVaR



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