Asset Management and Alternative Risk Premia: Are Fees Justified?

Francesc Naya, Jahja Rrustemi and Nils S. Tuchschmid*
Haute Ecole de Gestion de Fribourg
HES-SO // University of Applied Sciences and Arts Western Switzerland
Chemin du Muse 4 CH-1700
Fribourg,Switzerland
*corresponding author: +41 26 429 63 50; nils.tuchschmid@hefr.ch
This version : May, 2022
First version : November 2021

Abstract

This study aims at analyzing the ability of managers of Alternative Risk Premia (ARP) portfolios to outperform benchmarks and to deliver alphas. Using a sample of more than 200 ARP indices, we first distinguish performance between allocation strategy and picking ability. Our first results show that the capacity of optimized portfolios to beat a naïve, diversified strategy strongly depend on the set investment constraints that have been initially selected. In a second part, we simulate managers' picking ability. For that, we rank the ARP indices for the coming quarter according to their performance and divide them into two quantiles. We then assume that the portfolio manager is able to choose a pre-defined number of indices in the top quantile. We modulate this ability and bootstrap each possible scenario a thousand times. Our results show, for example, that a manager possessing an ability to choose correctly 10% of his portfolio, can expect to deliver an average 1.6% alpha. In a third part, we concentrate our analysis on strategy picking ability, that is, we study whether any additional alpha stems from the right choice of individual indices or from an implicit exposure to strategies. Results indicate that it is clearly difficult to separate the two. Yet, there is less variability at choosing strategies than at picking ARP indices. This stresses once more that the choice of the provider matters. Two indices offering exposure to the same strategy do not deliver the same performance. In a final part, we analyze the performance of the ARP funds of funds industry. If some funds of funds are distinguishable, we cannot find on average, any alpha. The average annualized alpha is close to zero and even negative. These last results stress once more how difficult it is practically to generate extra returns. Stated otherwise, net of costs, picking ability broadly defined, does not show up in the results.

Acknowledgments

This research was supported by «Réseaux de compétences : RCSO Economie & Management » (RCSO ; N° SAGEX : 105679 ; Primes de Risque Alternatives et crises financières : quels bénéfices pour les investisseurs institutionnels ?). We would like to thank Mr. Zannoni, Mr. Alessandrini and the Alternative Investments team from Banque Cantonale Vaudoise and Mr. Fatemi from Investcorp-Tages, for their numerous and valuable suggestions and for providing us with a set of data that are used in this study. We are also grateful to Mr. Berset from EFG Bank for his useful comments. All remaining errors are ours.

Conflicts of Interest Statement

The authors declare that they have no conflicts of interest. Nils S. Tuchschmid received a research grant from "Réseaux de compétences : RCSO Economie & Management »

Introduction

The relevance of active investing in the asset management industry has been a long-debated issue. The relationship between the managers' performance and the fees that must be paid will always be topical. A good example is the famous "two and twenty" rule that had been synonymous with hedge funds for a long-time. According to HFR (2020), the management fee has now declined to an average of 1.4%, whereas the performance fee amounts to 16.4%. Different factors can explain the pressure on fees. First, the underperformance of active management compared to passive products could be one of them. It is well illustrated by the development of ETFs and their huge popularity nowadays as ETFs are being perceived as a cheaper alternative to active investing for a lot of actors in the financial industry (Rompotis, 2009). Second, the recent advent of fintech and robo-advisors could be another factor. Hence, an argument could be made that the market is valuing less and less the additional performance that active management is supposed to bring.

When it comes to comparing active with passive investing, most studies focus on equities. In this study, our attention is on Alternative Risk Premia (ARP). ARP contrast with traditional risk premia that stem from exposures to financial markets and securities as equity and fixed income. Traditional investment somehow means beta exposure and being "long". Contrarily, ARP are seen as uncorrelated or weakly correlated products. They tend to be structured in the form of a long/short investment. ARP can also be seen as the version 2.0 of hedge fund clones. The latter were presented as cheap and efficient solutions to a direct allocation to hedge funds. Developing the solution further, the industry unbundled the clones and naturally could propose individual strategies. Investors can thus allocate capital to a US equity momentum strategy, to a long/short European quality product, to a commodity trend-following strategy, or to a tail-risk solution as it suits them. To summarize, ARP seek to offer hedge fund return profiles by applying certain long/short investment strategies while arguing that they are cheap, liquid and transparent. Yet, rare are the investors that select ARP themselves. They let professionals, that is asset managers, pick and allocate on their behalf and they get access to ARP through certificates or funds. Managers' performance thus stems either from their allocation strategy or from their picking ability.

The rapid development of the ARP offering available to institutional investors over the last decade has caught the attention of practitioners and academics who have explored in more detail these investment products and some specific issues associated to them. Gorman and Fabozzi (2022b) discuss extensively the many difficulties when dealing with ARP data provided by investment banks (IB), such as differences in classification or embedded costs, among others, which lead to challenges for building useful benchmarks for performance evaluation. Kuenzi (2020) presents qualitatively eight potential sources of return dispersion among seemingly equivalent ARP products: firm history and philosophy, amount of systematic risk, instrument choice and inclusion, model parametrization, weighting mechanisms, crowding, data choices and execution timing. This heterogeneity is analyzed at IB's ARP index level by Naya and Tuchschmid (2019), who also evaluate the impact of *backtesting bias* among ARP indices, by calculating the indices' return and risk-adjusted return differential of *live* versus *backtested* data. Suhonen, Lennkh and Perez (2017) also quantify *backtesting bias*. Both studies find very similar results, suggesting Sharpe ratio *haircuts* of up to 75%. Monarcha (2019, 2020), Gorman and Fabozzi (2022a, 2022c) and Suhonen and Lennkh (2021), analyze the recent underperformance of ARP products, at strategy level and asset manager funds of funds level, and their potential factors. Our current study aims first at distinguishing performance between allocation strategy and picking ability and at quantifying how much alpha can be delivered..

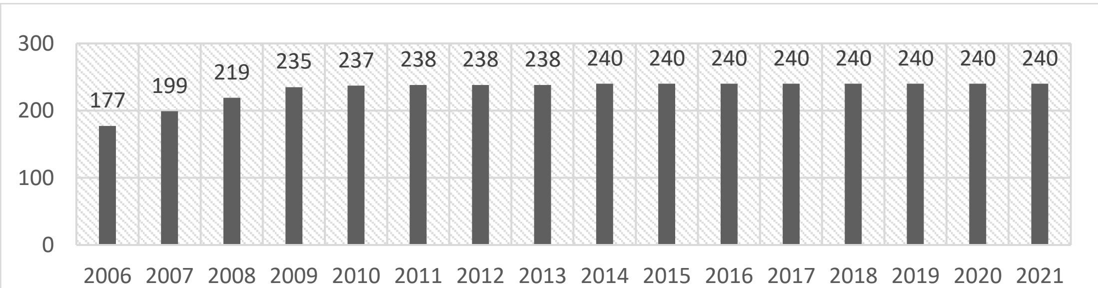
On that basis, this study is divided into two parts. After a brief description of the dataset in Section 2, in Section 3 we compare the performance of different allocation techniques commonly used, to answer the question of whether these techniques have an impact on performance compared to a naïve, diversified portfolio. In Section 4, we analyze the effect of picking ability. To do so, we model and simulate picking ability, both at individual index level and at strategy level, and then analyze the subsequent performance. We finally look at the performance of different ARP funds to contextualize the results of our findings. Section 5 concludes.

Data

The dataset combines observations provided by two different sources in the ARP industry. In total, our ARP dataset is composed of 240 different indices. The indices are grouped into 4 main strategies: Momentum, Carry, Hedge and Value. For each index, we have information regarding the live data, the asset class, the currency, the strategy and the sub-strategy. To extend our sample period as much as possible, we take both backtested results and live data, even if it is well-documented that there are selection and overfitting biases in using data that are made available before live data (e.g. see Suhonen, Lennkh and Perez, 2017 or Naya and Tuchschmid, 2019). However, here we study managers' abilities to pick and to allocate and we compare results. Hence, biases should have no impact on the comparison analysis.[1]

We fix the start date in 2006 to include enough indices. As can be seen in Figure 1, the number of indices amounts to 177 in 2006 and increases to reach its maximum in 2014 with 240 indices. From the 240 available indices, 14 were excluded due to frequencies other than daily, or to missing observations.

Figure 1: Number of available indices from 2006 to 2021



[1] At most, one should carefully factor in these biases if one wants to analyze performance and raw returns individually or separately.

Allocation techniques and portfolio performance

To analyze the performance of allocation strategies, we proceed as follows. Starting in 2006 we pick 20 ARP indices randomly and estimate their covariance matrix using a one-year window. We then use two standard unconditional allocation techniques, that is, Global Minimum Variance (GMV) and Equal Risk Contribution or risk parity (ERC), to build portfolios. For GMV portfolios, we also add Ledoit and Wolf (2003) proposed shrinking estimates (L-W). [2] After three months, we rebalance the portfolios, that is, we use a one-year window to update the parameters and the GMV, ERC and L-W optimizers to obtain a new set of allocation. Using one year of observations, note that the allocation period starts in 2007 and stops in May 2021 when we reach the end of our sample period. As a natural benchmark, we use a “naïve”, equally-weighted portfolio (EW). EW uses the same approach, that is, it is made up of the same 20 APR indices and rebalanced every quarter. This process is repeated 1000 times, that is, for each of the four allocation strategies, we calculate the performance of a thousand portfolios that randomly picked 20 ARP indices and then take the mean of those thousand portfolios. To ensure that our results reflect industry practice, we introduce the following constraints: no short-selling, a 4% annualized volatility target, minimum and maximum weights of 2% and 15% and no more than 40% of a portfolio in one of the main strategies (momentum, carry, value, hedge). Summary statistics are presented in Table 1. As a point of comparison, Table 2 shows the same statistics for unconstrained portfolios.

Table 1: Performance of allocation techniques with constraints

Constrained Portfolios	EW	ERC	GMV	L-W
Avg. Return (Ann.)	6.29%	7.21%	6.98%	6.96%
Volatility (Ann.)	5.00%	4.90%	4.95%	4.93%
Skewness	-3.32	-2.39	-2.77	-2.81
Kurtosis	177.05	106.76	136.46	135.72
CVaR	-0.68%	-0.70%	-0.70%	-0.69%
Max DD	18.97%	19.66%	19.59%	18.89%

Avg. Return (Ann.) and Volatility (Ann.) refer to annualized return and annualized volatility. CVaR is the Conditional Value-at-Risk at 95% level and expressed in daily returns. Max DD stands for the maximum drawdown from peak to trough. The coefficients are the average values of the 1000 bootstrapped portfolios.

It is worthwhile noticing that performance metrics differ significantly between Table 1 and 2. As expected, the unconstrained portfolios with a level of volatility that gravitates around 1.8% shows lower returns than the constrained portfolios whose volatility has been set at 4%. More interesting is the fact that adding constraints seems to help the allocation techniques to perform better than the naïve EW portfolio. We can also notice that ERC is doing slightly better than the other strategies. Differences are still marginal. The relative underperformance of the EW portfolios can be explained by the fact that the EW composition is often altered so as to respect the 40% maximum allocation in one strategy class. The excess proportion is then redistributed evenly to the other classes. This process appears to impact significantly the average annualized return. EW comes first in Table 2 with no constraint and a slight increase in volatility but then last in Table 1 with volatility still slightly higher than that of the other allocation strategies. In that regard, one should note that the volatility

[2] The shrinkage method of Ledoit and Wolf (2003) aims at reducing estimation errors in the covariance matrix and thus at improving the out-of-sample results of GMV portfolios.

target of 4% is not satisfied. All portfolios have on average overshot. That result stems from the chaotic conditions that prevailed in February and March 2020, which brought a high level of variability in markets and, therefore, in valuation of ARP indices.

Table 2: Performance of allocation techniques without constraints

Unconstrained Portfolios	EW	ERC	GMV	L-W
Avg. Return (Ann.)	3.50%	3.09%	2.96%	2.96%
Volatility (Ann.)	1.94%	1.79%	1.71%	1.71%
Skewness	-3.55	-1.86	-1.75	-1.81
Kurtosis	156.78	66.55	59.12	59.87
CVaR	-0.34%	-0.26%	-0.24%	-0.24%
Max DD	8.09%	6.90%	6.85%	6.80%

Avg. Return (Ann.) and Volatility (Ann.) refer to annualized return and annualized volatility. CVaR is the Conditional Value-at-Risk at 95% level and expressed in daily returns. Max DD stands for the maximum drawdown from peak to trough. The coefficients are the average values of the 1000 bootstrapped portfolios.

In terms of risk metrics, one should also note that differences are negligible across all portfolios. CVaR and drawdown are almost the same. Only the EW portfolios show negative skewness on average higher than the others. To summarize, allocation techniques do not seem to produce significant differences compared to a naïve, diversified portfolio. Somehow, it confirms the results of a previous study (see Naya and Tuchschmid, 2018). If there is an exception, it should be seen under annualized returns. Out-of-sample, optimized portfolios with constraints tend to do better than the EW portfolio. But the difference is a matter of a few basis points. If backtested returns were to be excluded, the ranking might not change but the differential should be unperceivable. [3]

Estimation risk and covariance matrix

"In-sample portfolios" are obtained when the optimal weights are estimated inside the allocation period as opposed to the out-of-sample portfolios. In-sample, the portfolios do not suffer from estimation risk, as all parameters are estimated within the sample and the weights obtained are applied in the same return sample. More precisely, at each rebalancing date, instead of using the previous 12 months to estimate the covariance matrix, we will use the next 3-month period. As expected, due to an elimination of estimation risk, the performance increases when looking at the in-sample portfolio, compared to the out-of-sample. Tail risk is also reduced by a large margin when looking at kurtosis, or to a lesser extent, at CVaR. The reason as to why the equally weighted increase in performance in-sample compared to out-of-sample can be explained by the decrease of estimation risk due to using the covariance matrix when setting the 4% target volatility. The weights applied with 4% target volatility change whether we applied them in-sample versus out-of-sample. The least

[3] Kurtosis values are quite high, some in the range of 200. The high values are explained by the Covid-19 market drawdown in February-March 2020. Similar levels of kurtosis can be found in FX, when looking for examples at EUR/CHF exchange rates beginning of 2015 when the Swiss National Bank removed the EUR-CHF 1.20 cap. Moreover, we give in the Tables averages based on 1000 out-of-sample returns. These averages are skewed by a few large outliers. When taking the median, the kurtosis is usually divided by 6. We illustrate these findings in the Appendix, Table A.1.

affected method is L-W. Performance out-of-sample or in-sample does not change as noticeably as with the ERC or GMV methods, where performance increases by 1.4% in both cases.

More importantly, in both Tables 1 and 3, the allocation strategies increase the performance of the portfolios compared to the naïve strategy. This leads us to conclude that allocation methods do help in performance when setting these specific sets of constraints. In other words, more than the optimization method, the success of an allocation strategy does seem to greatly depend on the set of constraints that are set.

Table 3: Performance of allocation techniques without estimation risk

Unconstrained Portfolios	EW	ERC	GMV	L-W
Avg. Return (Ann.)	7.61%	8.73%	8.46%	8.00%
Volatility (Ann.)	4.02%	4.02%	4.02%	4.02%
Skewness	-0.44	-0.33	-0.37	-0.42
Kurtosis	5.42	4.20	4.55	5.06
CVaR	-0.58%	-0.56%	-0.56%	-0.57%
Max DD	10.39%	10.19%	9.95%	9.93%

Avg. Return (Ann.) and Volatility (Ann.) refer to annualized return and annualized volatility. CVaR is the Conditional Value-at-Risk at 95% level and expressed in daily returns. Max DD stands for the maximum drawdown from peak to trough. The coefficients are the average values of the 1000 bootstrapped portfolios.

Picking ability and portfolio performance

To model the picking ability of an asset manager, we proceed as follows: At time t_0 we rank the 226 ARP indices by their next three-month return and split them into two quantiles. The first half is made of indices that have outperformed the second half. To introduce picking ability, we vary the number of indices that are randomly picked within these two quantiles and analyze the subsequent performance of the four portfolio allocation techniques implemented in the previous section, applying the same constraints, on the next three-month period, i.e. the same period used to rank the indices. For example, we assume that the manager has been able to pick 11 indices from the first half and 9 from the second. The process is then repeated every quarter and one thousand times. The benchmark here is a portfolio made of 10 indices from the first half and 10 from the second half. It represents the performance of an asset manager who would have shown no picking ability. Hence, comparing the 11-9 portfolio to the 10-10 portfolio must allow us to assess how much picking ability can bring in terms of alpha. We initially study the 10-10, 11-9 and 12-8 portfolios. We then increase the number of scenarios and possibilities so as to have a more detailed idea of the picking ability's impact on the portfolio performance.

Table 4 presents the first set of results. Increasing the manager's ability from 10-10 to 11-9 and to 12-8 naturally increases the performance. The changes can be quite impressive. Across the different allocation techniques, performance tends to increase by an average of 1.5 % per annum. No allocation strategy seems to increase more than the others. Similar to the results in the previous section, when introducing some degree of picking ability, optimizing portfolios also adds to the performance (around 0.8 %) compared to a simple, equally weighted portfolio. [4]

Table 4: Performance of portfolios with different picking abilities and allocation techniques (with constraints)

Strategies	EW	ERC	GMV	L-W
Panel A. 10-10 Portfolios				
Avg. Return (Ann.)	6.29%	7.21%	6.98%	6.96%
Volatility (Ann.)	5.00%	4.90%	4.95%	4.93%
Skewness	-3.32	-2.39	-2.77	-2.81
Kurtosis	177.05	106.76	136.47	135.72
CVaR	-0.68%	-0.70%	-0.70%	-0.69%
Max DD	18.97%	19.66%	19.59%	18.89%
Panel B. 11-9 Portfolios				
Avg. Return (Ann.)	7.92%	9.00%	8.73%	8.70%
Volatility (Ann.)	5.05%	4.98%	5.05%	5.06%
Skewness	-3.21	-2.55	-2.89	-2.95
Kurtosis	191.58	128.42	160.08	162.76
CVaR	-0.678%	-0.686%	-0.686%	-0.686%
Max DD	16.422%	16.533%	16.719%	16.153%
Panel B. 12-8 Portfolios				
Avg. Return (Ann.)	9.64%	10.84%	10.54%	10.52%
Volatility (Ann.)	5.05%	4.97%	5.00%	4.99%
Skewness	-3.00	-2.24	-2.53	-2.52
Kurtosis	197.73	126.83	150.97	152.19
CVaR	-0.66%	-0.67%	-0.67%	-0.67%
Max DD	13.91%	13.66%	13.74%	13.20%

Avg. Return (Ann.) and Volatility (Ann.) refer to annualized return and annualized volatility. CVaR is the Conditional Value-at-Risk at 95% level and expressed in daily returns. Max DD stands for the maximum drawdown from peak to trough. The coefficients are the average values of the 1000 bootstrapped portfolios.

In Table 5, we show the performance of an 11-9 "momentum strategy." The latter simply ranks the ARP indices based on the previous year returns. We randomly choose 11 from the upper quantile, and 9 from the lower quantile, similarly to the 11-9 portfolios. Yet, the quantiles here are based on past data and therefore out-of-sample. If the results are better than the 10-10 portfolio, they are not as good as the 11-9 portfolios of Table 4. A classic momentum strategy could thus help to improve performance but it does not replace what could be brought by a manager's picking ability if we can assume the latter does have any.

Table 5: Performance of the "11-9" momentum strategy

11-9 Momentum	EW	ERC	GMV	L-W
Avg. Return (Ann.)	6.47%	8.73%	8.46%	8.00%
Volatility (Ann.)	5.45%	4.02%	4.02%	4.02%
Skewness	-7.38	-0.33	-0.37	-0.42
Kurtosis	336.63	4.20	4.55	5.06
CVaR	-0.74%	-0.56%	-0.56%	-0.57%
Max DD	22.21%	10.19%	9.95%	9.93%

Avg. Return (Ann.) and Volatility (Ann.) refer to annualized return and annualized volatility. CVaR is the Conditional Value-at-Risk at 95% level and expressed in daily returns. Max DD stands for the maximum drawdown from peak to trough. The coefficients are the average values of the 1000 bootstrapped portfolios.

[4] An analysis of in-sample versus out-of-sample allocation results was also conducted, but the conclusions were the same as in Section 3: the EW performs better when looking at unconstrained portfolios.

To bring further results, Table 6 shows the performance of a standard, long-momentum strategy. More precisely, it invests equally in the best 20 performing indices ranked on the basis of their past yearly returns. It also displays the performance of a so-called “perfect momentum” strategy. The latter assumes perfect forecast. It invests equally in the best 20 performing indices over the coming three months. These different strategies serve as a comparison and benchmarks to understand the impact of picking abilities compared to other strategies.

Table 6: Performance of standard momentum and “perfect forecast” momentum strategies

	Standard Momentum	Perfect Momentum
Avg. Return (Ann.)	6.89%	30.24%
Volatility (Ann.)	5.50%	6.35%
Skewness	-6.84	4.45
Kurtosis	269.24	72.79
CVaR	-0.73%	-0.63%
Max DD	19.65%	7.66%

Avg. Return (Ann.) and Volatility (Ann.) refer to annualized return and annualized volatility. CVaR is the Conditional Value-at-Risk at 95% level and expressed in daily returns. Max DD stands for the maximum drawdown from peak to trough. The coefficients are the average values of the 1000 bootstrapped portfolios.

Comparing Tables 4 and 5 with Table 6, we can see the impact of picking ability on performance. Excluding perfect momentum, that obviously and greatly outperforms all other portfolios, “classic” momentum strategies display a return of 6.89% while the 11-9 portfolio displays much higher performances of around 8% to 9%. In terms of risk, the 11-9 portfolio shows lower risk measures compared to the momentum strategies, be it volatility, CVaR, or maximum drawdown. From the results above, the benefit of possessing picking ability is undeniable in terms of portfolio performance. Not only are the returns significantly improved compared to standard momentum strategies, but the risk seems to be reduced. The latter should stem from less concentrated portfolios in terms of ARP strategies.

Extension of the model

The results obtained so far provide a first indication of the impact of picking ability in ARP portfolios. The results might still depend on many factors, be they allocation strategy, investment constraints, picking ability, etc. It thus remains rather difficult to quantify and to clearly identify the impact of picking ability and overperformance by the manager. To extend the analysis, we slightly modify how picking ability is modelled. Instead of choosing 11 from the first quantile and 9 from the other, we choose only 1 index among the first half and let the others be randomly chosen. We then vary the number of indices selected in the first quantile from one to four so as to change the manager’s picking ability. We also vary the number of ARP indices in the portfolios, starting from 10 and then increasing by ten up to 40. Then, we proceed as in the previous section. We model different picking abilities and choose different portfolio sizes. But for each of them, we simulate one thousand times the randomly picked components.

To go one step further, we estimate alphas by regressing these one-thousand results of each portfolio against a benchmark that we constructed by simply computing an equally weighted portfolio of all the 226 ARP indices.

We then take the mean of those 1000 returns series and thus end up with 16 different returns series, one for each portfolio size (10, 20, 30, 40) and for each number of *good* ARP indices present in the portfolio (1,2,3,4). [5] The 16 different returns are then regressed against the benchmark to obtain the alphas as presented in Table 7.

Table 7: Alphas obtained from regressing ERC portfolios of different size and of different picking ability

portfolio size\No. of *good* ARP indices	**1**	**2**	**3**	**4**
10	2.72%	4.21%	5.85%	7.67%
20	2.19%	3.45%	4.36%	5.40%
30	1.83%	2.19%	2.93%	3.605%
40	1.37%	1.85%	2.32%	3.02%

The alphas are annualized using 252 business days.

Unsurprisingly, the more indices from the first half of ARP are included in the portfolio, the higher are the alphas. The latter tend to become small and to reach a limit as the portfolios are made of 60 components or more. It is also logical to find an inverse relationship between the alpha and the number of the ARP indices making up portfolios. Table 8 sheds further light on the previous results. Each annualized alpha is referred to the percentage of the first half ARP indices that compose the portfolios. Standard least square regression can then be run to analyze the relationship between picking ability and extra performance. The result is given in Equation (1) and shown in Figure 2.

Table 8: Annualized alphas with their corresponding percentage of *good* ARP indices in the portfolio

Percentage of *good* ARP indices in the portfolio	Annualized alphas
10.0%	2.7%
5.0%	2.2%
3.3%	1.8%
2.5%	1.4%
20.0%	4.2%
10.0%	3.4%
6.7%	2.2%
5.0%	1.9%
30.0%	5.8%
15.0%	4.4%
10.0%	2.9%
7.5%	2.3%
40.0%	7.7%
20.0%	5.4%
13.3%	3.6%
10.0%	3.0%

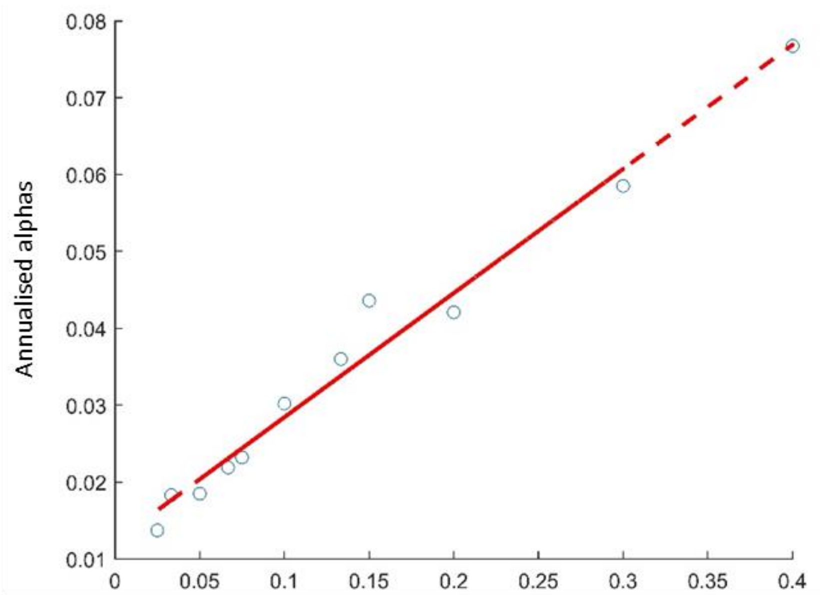
The alphas are annualized using 252 business days. The percentage of *good* ARP indices refers to number of *good* indices divided by the portfolio size of Table 7.

A 1 % picking ability thus translates into a 0.164% alpha according to Equation (1) and in Figure 2, one sees, for example, that correctly picking, for example 10% of ARP, generates an alpha of approximately 1.64%.

$$y = 0.164 * x + 0.013 \qquad (1)$$

[5] Here we use the portfolio returns series based on the ERC allocation technique.

Figure 2: Graphical representation of the relationship between picking ability and managerial performance (ARP)



Percentage of indices picked in the top quantile

Alphas of Table 7 and 8 look quite impressive but they could also be misleading. If we took as an example, the portfolios made of 2 ARP indices in the top quantiles among a total of 20, the alphas of the 1000 simulations range between -1.96% and 7.82% for an average of 3.45%. The latter illustrates well that even though a manager could indeed possess picking ability, he still can exhibit significant negative alphas, due to the other randomly selected indices present in his portfolio.

To shed more light on our previous results, we need a point of comparison. For that, we apply the same methodology on US equities. More precisely, we extracted the S&P 500 index composition of 2021. We used daily prices of the components, using the start date as that of the APR indices, that is 2006 and yields of the 1-month US T-Bill as proxy of the risk-free rate. Results for the stock portfolios are provided in the Appendix, Tables A.3, A.4 and Figure A.1. Our results indicate that a manager that correctly picks 10% of his portfolio would increase alpha by 2.9%, compared to 1.6% of the ARP portfolios. Stated otherwise, picking ability seems to be more effective for stocks.

Reasons for the difference between the two classes can be numerous, yet we believe that part of the explanation certainly has to do with the dispersion of returns among stocks and among ARP respectively. ARP components display lower cross-sectional volatilities compared to the S&P 500 components (6.8% vs. 30% respectively), results are found in Appendix, Table A.3. Picking ability should thus pay more in equity than in ARP.

Strategy vs. individual index picking ability

When looking at the results derived from picking ability, a question arises: does the increase in performance result from picking individual indices, or is it due to the fact that the best performing strategy is picked more often? To answer this question, we replicate the study of the previous sections but, instead of picking individual indices, we rank the best performing strategy over the next allocation period (i.e. hedge, momentum, carry and value strategies), and increase its exposure by 5% or 10%, whereas we equally reduce the other strategies' exposure. In Table 9, we show only the results of the equally weighted portfolios. Interestingly, we observe that a 10% increase in a strategy corresponds to an 11-9 portfolio in terms of performance and of mean and volatility (see Table 4). In other words, the results are very similar.

Table 9: Performance of EW portfolios when increasing the exposure to the best ARP strategies (0%, 5%, 10%)

EW	0%	5%	10%
Avg. Return (Ann.)	6.29%	6.91%	8.10%
Volatility (Ann.)	4.987%	5.06%	5.23%
Alphas	0.00%	0.69%	1.37%

Avg. Return (Ann.) and Volatility (Ann.) refer to annualized return and annualized volatility. The alphas are also annualized.

In that regard, results shown in Table 9 illustrate the difficulty to disassociate between picking the right indices or picking the right strategy. Performance appears to be close. The latter is, of course, not as surprising as it sounds. The two are connected. An ARP index belongs to a strategy and a strategy is made of ARP indices. The question of whether the increase in performance comes from choosing the correct individual components or whether the right strategy is obviously difficult to tackle. There is, however, a significant difference between picking a strategy versus picking a *good* index in this study: one is simulated, the other is not. Indeed, we obtained the results regarding picking the right index by repeating 1000 different simulations and then getting the average of these simulations, which does not show the extreme possible results. When picking the right strategy however, there is no simulation needed. The performance of that allocation technique is given as it is by the backtesting methodology. For instance, if we take the worst possible performance of no index picking ability by simulating 1000 10-10 EW portfolios, we find a performance of 2.9%, which is worse than the EW portfolio with no correct strategy picking ability (see Table 9).[6] This is a significant margin: 2.9% to 6.29%. In other words, it indicates that it is possible to perform much worse if one tries to correctly pick individual indices compared to correctly picking a strategy composed of a multitude of indices. To conclude, although it is difficult to disentangle the differences between picking the right strategy compared to picking the correct indices, it is noticeable that trying to pick the right strategy delivers less volatile and safer results than trying to pick the right index, a result that confirms somehow what has been shown by Suhonen et al. (2017) or Naya and Tuchschmid (2019).

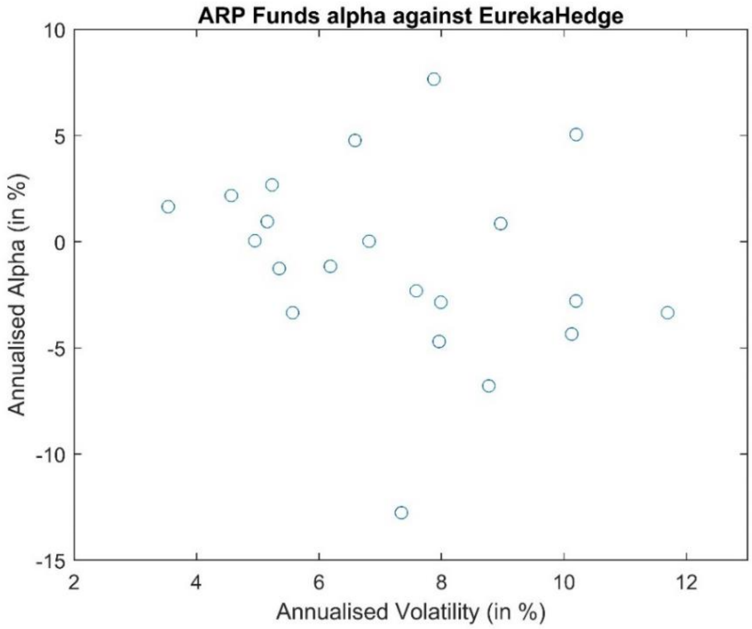
Performances of ARP funds in the market

If our previous results show that picking ability can be rewarded, verifying whether it has been truly the case is a different story. For that, we have selected 21 ARP funds of funds currently available for investors and use three different benchmarks, namely the EurekaHedge Multi-Factor Risk Premia index (EH MFRP), the SG Multi Alternative Risk Premia index (SG MARP), and an equally-weighted portfolio made of the 226 indices from our dataset. For each of the 21 funds, we regressed their returns since their inceptions against the benchmarks to

[6] The results of the experiment were as follows: the minimum return of the 10-10 EW portfolio was 2.9% while the maximum return was 8.1%.

estimate their annualized alphas. The inception dates of the 21 funds range from March 2009 to August 2019. For one of the benchmarks, the EH MFRP index, results are shown in Figure 3.[7] The average annualized alpha is of -0.35% for an average volatility of 7.27%. If the 21 funds of funds are representative of the industry, and assuming no market timing ability or limited ability, then these portfolio managers appear unable to generate abnormal returns. Stated otherwise, beating the ARP market net of fees appears difficult.[8] Although there are obvious additional returns that can be gained from correct picking abilities, the question of whether it can be really transformed into portfolio performance remains to be answered.

Figure 3: ARP fund performances against EH MFRP benchmark



Average Statistics of Funds' Performance

Statistics	
Mean Alpha	-0.35%
Volatility of the Funds	7.27%

[7] Results of the other benchmarks are given in Appendix, Figure A.2 for the SG MARP index and Figure A.3 for the EW benchmark.

[8] Of course, there are exceptions. One could also argue that the difference of performances in ARP funds of funds is somehow a "random" effect. In this sample period, the best performing managers might simply be the luckiest ones (Barras et al., 2010).

Conclusion

This study provides a new perspective on managers' performance and ARP. By separating allocation strategy and individual picking ability, one aims at obtaining a better view on what if any could drive the extra performance. Regarding the question on the impact of allocation methodologies, results are not clearcut. Whether GMV or ERC optimizers do provide better results than a naïve, equally weighted portfolio seems also to depend on the constraints that have been set on the portfolio strategy, which in turn will certainly depend on the choices made by the managers themselves. For instance, when setting the same target volatility, all optimized allocation strategies did perform better than the naïve strategy. However, the latter does not hold without constraints. A naïve, diversified, equally-weighted portfolio does better.

Secondly, we simulate a manager's picking ability by selecting ARP indices that will outperform their peers over the next rebalancing period. More precisely, we rank the ARP indices for the coming quarter according to their performance. We then divide them into two quantiles and simulate a picking ability by assuming that the portfolio manager can at least choose a pre-defined number of indices in the top quantile. We modulate this ability by changing the number of ARP indices that the manager is able to pick among the winners. Bootstrapping a thousand times for each possible scenario, we finally calculate an average annualized alpha. Our results show, for example, that a manager possessing an ability to choose 10% of his portfolio correctly, can expect to deliver an average 1.6% alpha. Knowing that the performance comes in addition to the allocation method is not insignificant.

Thirdly, we study whether any additional alpha stems from the right choice of individual indices or from an implicit exposure to strategies. Our results show that increasing exposure to the next period best performing strategy by 10%, for example, corresponds to an 11-9 portfolio with individual picking ability. Hence, it is clearly difficult to separate the two, that is, picking the right strategies or picking the right indices. However, one must stress that there is clearly less variability when choosing strategies than when picking ARP indices. This stresses once more that the choice of the provider matters. Two indices offering exposure to the same strategy do not deliver the same performance.

Finally, we analyze the performance of ARP funds of funds by comparing them to three different benchmarks. Their average annualized alpha is close to zero and even negative. These results once again highlight the difficulty to generate extra returns to cover costs and fees. Stated otherwise, net of costs, picking ability does not show up in the results.

In conclusion, to the question of whether managers do justify their fees, one could answer that there are indeed additional alphas that can be generated from the allocation method and from the right indices or from the right strategies. Yet here, too, consistently achieving positive alpha remains more the exception than the norm.

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Appendix

Table A.1: Kurtosis comparison between ARP indices and 10-10 ERC Portfolios

	Individual Indices	10-10 ERC Portfolios
Kurtosis mean	49.38	158.61
Kurtosis median	12.90	59.59
Kurtosis 90% quantile	75.60	370.93

Table A.2: Performance of portfolios based on the constraints, the allocation technique and estimation risk

Strategies	EW	ERC	GMV	L-W
Panel A. 12-8 In-sample portfolios with constraints				
Avg. Return (Ann.)	7.62%	11.13%	12.40%	12.05%
Volatility (Ann.)	4.02%	4.01%	4.02%	4.02%
Skewness	-0.44	-0.32	-0.28	-0.30
Kurtosis	5.39	4.88	4.04	4.33
CVaR	-0.59%	-0.55%	-0.54%	-0.54%
Max DD	10.33%	5.24%	5.26%	5.22%
Panel B. 12-8 Out-of-sample portfolios without constraints				
Avg. Return (Ann.)	3.40%	5.22%	4.56%	4.35%
Volatility (Ann.)	2.44%	2.33%	1.79%	1.70%
Skewness	-3.57	-1.83	-1.06	-1.01
Kurtosis	184.78	104.38	43.45	39.90
CVaR	-0.33%	-0.319%	-0.247%	-0.234%
Max DD	8.60%	5.263%	4.380%	4.328%
Panel C. 12-8 Out-of-sample portfolios with constraints				
Avg. Return (Ann.)	6.30%	9.64%	10.84%	10.54%
Volatility (Ann.)	4.96%	5.05%	4.97%	5.00%
Skewness	-3.34	-3.00	-2.24	-2.53
Kurtosis	177.65	197.73	126.83	150.97
CVaR	-0.68%	-0.66%	-0.67%	-0.67%
Max DD	18.97%	13.91%	13.66%	13.74%

Avg. Return (Ann.) and Volatility (Ann.) refer to annualized return and annualized volatility. CVaR is the Conditional Value-at-Risk at 95% level and expressed in daily returns. Max DD stands for the maximum drawdown from peak to trough. The in-sample portfolios demonstrate the benefit of applying allocation for a manager, compared to the out-of-sample portfolios. There is a definite increase in returns and decrease in risk when using allocation strategies compared to naïve strategies.

Table A.3: Volatility analysis of S&P 500 Components and ARP Components

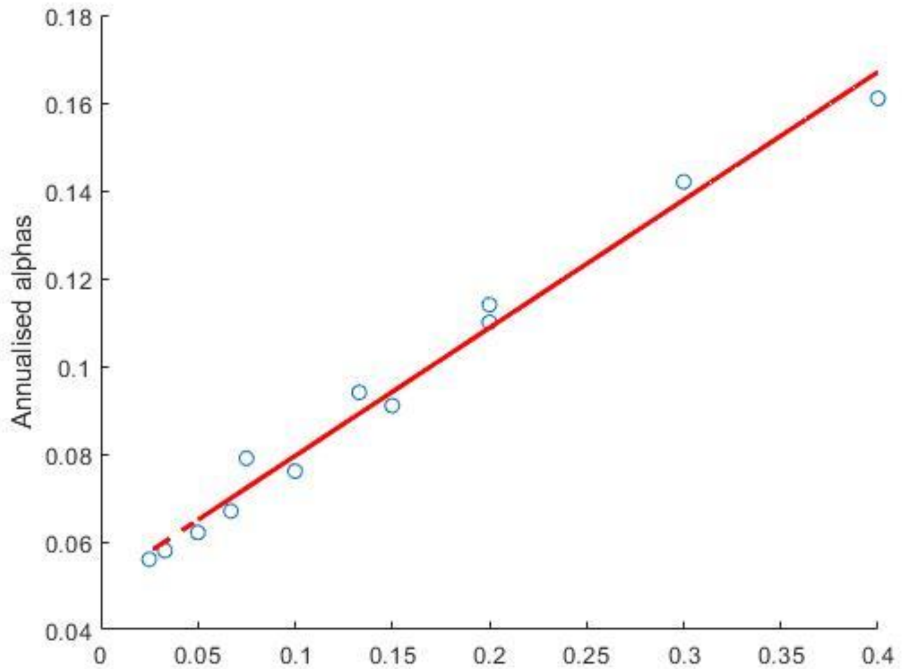
	Volatilities of S&P 500 Components	Volatilities of ARP Components
Mean	34.22%	6.80%
Standard Deviation	9.59%	4.04%
Min.	84.07%	34.11%
Max.	17.22%	1.08%

Table A.4: Alphas obtained from regressing portfolios with different size and picking ability with the S&P 500 index

portfolio size\No. of *good* stock	1	2	3	4
10	7.62%	11.05%	14.29%	16.12%
20	6.17%	7.61%	9.10%	11.44%
30	5.80%	7.24%	8.32%	9.41%
40	5.60%	6.21%	7.84%	8.43%

The alphas are annualized using 252 business days.

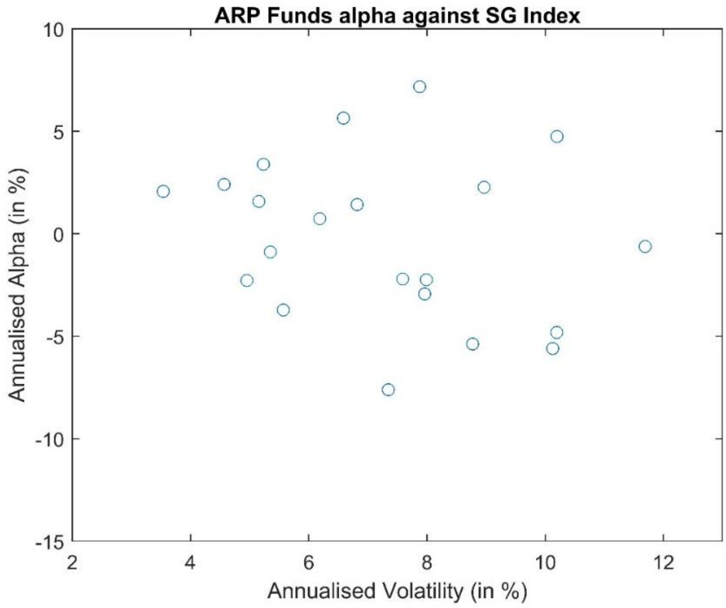
Figure A.1: Graphical representation of the relationship between picking ability and managerial performance (S&P 500)



Percentage of stocks picked in the top quantile

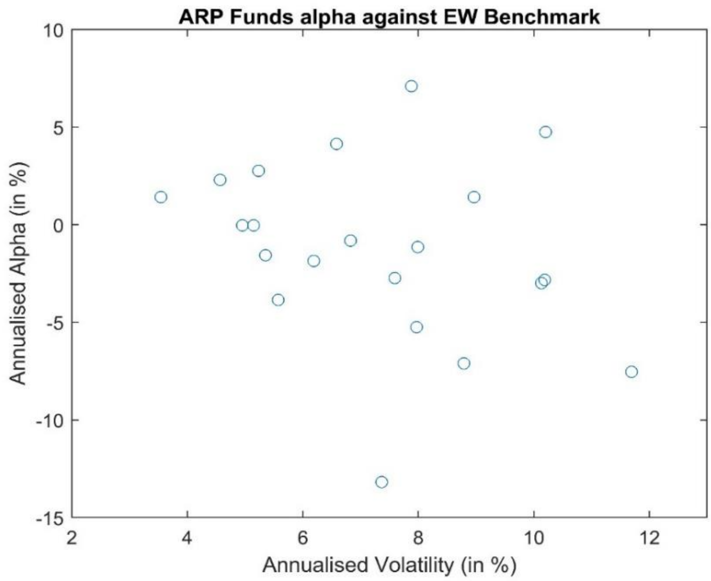
$$y = 0.291 * x + 0.0504$$

Figure A.2: ARP fund performances against SG MARP benchmark



Average Statistics of Funds' Performance	
Statistics	
Mean Alpha	-0.94%
Volatility of the Funds	7.27%

Figure A.3: ARP fund performances against an ARP EW benchmark



Average Statistics of Funds' Performance	
Statistics	
Mean Alpha	-1.29%
Volatility of the Funds	7.27%