Introducing the Cluster-Momentum Portfolio in Alternative Risk Premia Investing

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Abstract: Managing alternative risk premia (ARP) portfolios is a challenging task, due to the complexities of these types of investments. In this article, we present a purely quantitative approach that relies on performance persistence among ARP strategies while ensuring diversification by classifying the ARP indices using unsupervised hierarchical clustering. This cluster-momentum portfolio shows a superior performance when compared to a set of internally built benchmarks and also of existing ARP asset manager funds. It seems that persistence in performance can be capitalized in ARP, while the clustering technique achieves its objective of risk-reduction due to portfolio diversification. Moreover, the cluster-momentum portfolio appears to be resilient to parameter modifications.

1 INTRODUCTION

Alternative Risk Premia (ARP) are a type of liquid alternative investments that expose investors to sources of risk and return different from traditional long-only equities and fixed income assets. Typically, these pockets of returns are captured in a rule-based long-short format, with the aim of achieving market neutrality to these traditional assets (equities and bonds), and expand to other asset classes such as commodities and exchange rates (FX). Investors and asset allocators can get exposures to ARP strategies either by building their own ARP or by allocating to investment bank (IB) ARP through total return swaps (TRS). IBs publish rule-books, where the construction and rebalancing process of each ARP is detailed, as well as daily data of a representative index, whose returns are exactly the ones from the TRS, provided the same leverage.[1]

The surge of ARP and growth in popularity among the asset management industry originates from the emergence of the Arbitrate Pricing Theory (APT) and factor investing research. Fama and French (1993) identified the market, size and value as common risk factors in equities, and maturity and default risk as common factors in fixed income. Carhart (1997) added the momentum factor in equities. Fung and Hsieh (2004) decomposed hedge fund returns using a 7-factor model.[2]

ARP products offer, in theory, exposures to these same risk factors, and others that have been "discovered" at later stages, but in a liquid, transparent, systematic and cost-effective manner. Investors do not need to pay the high fees of alpha providers, as with ARP they are simply getting compensated (i.e. earning a risk premium) to carry the different risk factors efficiently.[3]

In practice, ARP investing is not a straightforward task. Capturing risk premia internally involves high

[1] There are a few exceptions of ARP IB indices in which, due to their construction, data is published at a weekly or monthly frequency only.

[2] ARP can also be seen as natural extensions of hedge fund replicators better known as hedge fund clones.

[3] In the long-only format, it is equivalent to the smart beta mutual funds or exchange traded funds (ETFs), that provide exposure to the market (also known as beta exposure) and also to some of these factors (e.g. size, momentum, value) systematically. Therefore, these products do not charge the high fees of traditional active mutual funds.

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trading costs and vast resources, making it unviable or unfavourable for most asset managers, who will prefer to build their own portfolios using IBs ARP products. Yet, not all banks offer the same risk premia and, for the same strategy, each has its own "cooking recipe". Naya and Tuchschmid (2019) found a high degree of heterogeneity among the indices from different providers that supposedly capture the same risk premium. Kuenzi (2020) identified 8 sources of return dispersion that can explain this phenomenon. On the other side, Scherer (2020) noted that some ARP strategies suffer from a "contagion" effect: different ARP strategies that are uncorrelated during normal times can become highly positively correlated during market drawdowns, losing the benefits from portfolio diversification. Finally, many of those ARP, whose risk premium is backed by extensive research and backtested performance, appear to underperform once they become *live* and available to investors. Both Suhonen et al. (2017) and Naya and Tuchschmid (2019) quantified the *backtesting bias* in ARP and proposed performance haircuts of at least 75% as a rule of thumb, unveiling the risks of working with backtested data.

With all these complexities, asset managers must build and manage the ARP portfolios. Typically, they will limit their exposures to asset classes or strategies, in order to ensure diversification, and select and allocate to the strategies and indices based on some quantitative or qualitative (or a combination of both) process.

In this article, we propose and test the cluster-momentum (CMOM) portfolio, a purely quantitative method. With the prior believe that ARP strategies show some degree of performance persistence, we test whether a diversified portfolio that chases past winners can outperform a set of benchmarks. Diversification is achieved by using unsupervised hierarchical clustering at each rebalancing period.

After a brief literature review in Section 2 and a presentation of the ARP dataset in Section 3, in Section 4 we introduce the portfolio construction process and the backtesting methodology. Then, in Section 5 we present the results of these backtests and compare the performance of our CMOM portfolio with a set of internally built benchmarks and of existing ARP asset manager funds. Section 6 concludes by discussing the main findings and provides direction for further research.

2 LITERATURE REVIEW

The rise of ARP IB products and asset manager funds over the last 15 years has allowed professional investors and researchers to study more in depth the ARP industry, its realized performance and risk, its impact into traditional portfolios, as well as its own specificities and complexities, some of them already mentioned in the Introduction section.

Jorion (2021) analysed the performance of ARP IB products for the 2010-2020 decade and found positive returns within equities, rates and credit but not FX strategies. Commodities ARP showed mixed results. He also observed that these fully investible IB products explain better the performance of hedge funds than the classic 7-factor model from Fung and Hsieh (2004). Monarcha (2019) focused on ARP asset manager funds and identified a negative average funds' return and a negative alpha for 75% of the sample, which was on average -2% annualized. The same author in Monarcha (2020) investigated the performances of ARP strategies during the Covid-19 equity drawdown in February-March 2020 and found a limited impact in most strategies, which was most severe for short volatility and mean reversion strategies, especially in the equities asset class. Gorman and Fabozzi (2022) revealed that the disappointing returns of ARP for the period 2018-2020 is in line with long-term expectations. Naya, Rrustemi and Tuchschmid (2023a) studied both ARP IB products and asset manager funds during the 2015-2020/05 period and concluded that well-diversified portfolios of ARP as well as most funds provided very low or even negative returns to investors and failed to bring the desired benefits from diversification during equity market drawdowns. However, some non-equity strategies showed risk-return profiles that could help mitigate the losses of a balanced portfolio during equity risk events. Suhonen and Lennkh (2021) examined the realised performance of ARP strategies over the 2008-2020/05 period. They found mixed results and concluded that including non-equity strategies to a 60/40 equity-bond portfolio would have added value, but the opposite is true for equity ARP. A similar result was found by Naya, Rrustemi and Tuchschmid (2023b). They compared the incorporation of a set of ARP strategies and portfolios with competing alternative assets and concluded that a systematic allocation to ARP with no equity exposure or correlated to equity risk could improve the return-risk relationship of a traditional balanced 60/40 portfolio. More recently, Suhonen and Vatanen (2023) propose trend strategies and the commodity cluster as the best candidates to achieve diversification in the balanced portfolio. For a comprehensive introduction to ARP, we refer to Hamdan et al. (2016), Gorman and Fabozzi (2021a) and Gorman and Fabozzi (2021b).

Regarding asset allocation in ARP, Bruder, Kostyuchyk and Roncalli (2022) proposed a risk parity model that takes into account skewness risk. Blin et al. (2021) introduce real-time macro, sentiment and valuation indicators to dynamically manage ARP exposures and show that these indicators improve a passive risk-based allocation. To the best of our knowledge, no previous research exists on the possible use of performance persistence in ARP for allocation purposes or of unsupervised clustering techniques as a way to achieve portfolio diversification, let alone on the combination of these both methods. Our article proposes this novel, untested approach to ARP allocation.

3 DATA

The dataset of ARP indices is part of a proprietary database (DB) from Investcorp-Tages. It represents one of the most comprehensive and actualized DBs in the ARP industry. For this study, only USD-denominated indices are considered. Indices that report at a frequency lower than daily (e.g. weekly or monthly) and "hedge", "long volatility", "multi-factor" or "multi-asset" indices are excluded. For each index, only its live period is considered. After all this data filtering and cleaning, we end up with 234 ARP indices from 14 different IBs. Table 1 reports the number of indices per asset class and main strategy.

Figure 1 below shows the number of live and delisted ARP indices over time. It clearly shows that the ARP industry was most developed during the 2010-2017 years. After 2017, the trend changed. The number of newly launched indices decreased, while the number of delisted indices started to rise, shrinking the amount of available ARP indices in these most recent years. This effect might be due to the underperformance of the ARP industry during this period, which made institutional investors lose interest in these investment products and strategies.

Table 1: Number of ARP indices by asset class & strategy.

	EQ	CO	FI	FX	All
Carry	1	29	10	19	59
Vol Carry	19	5	14	6	44
Value	9	10	3	10	32
Momentum	9	10		7	26
Trend	5		14		19
Other	11				11
Reversion	5	1	1	3	10
Low Risk	9				9
Credit Carry			7		7
Merger Arb	6				6
Quality	6				6
Size	5				5
All	85	55	49	45	234

EQ: equity; CO: commodities; FI: fixed income; FX: foreign exchange. "Other" englobes varied strategies that do not fall in any of the categories (e.g. sector rotation, FCF/invested capital, ROE).

As benchmarks, we have the daily data of 8 ARP asset manager funds. The USD share class is taken.

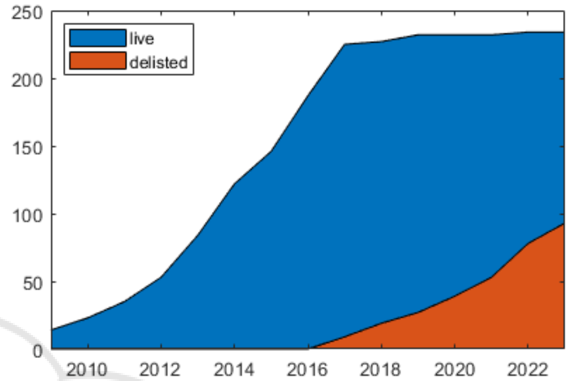

Figure 1: Number of live and delisted ARP indices.

4 METHODOLOGY

In this section, we describe the portfolio construction process and the out-of-sample backtesting method. The sample period spans from January 1st, 2016 to September 28th, 2023. We begin in 2016 to assure that enough indices are included in the sample. First, we need to define a set of parameters, mainly the learning window $\tau = 12$ months, the rebalancing frequency $\upsilon = 1$ month, the number of clusters formed at each rebalancing date $\theta = 10$ and the performance measure that will be used to rank the underlyings in each cluster and to choose the "winner" over that period. We use the Sharpe ratio, calculated over τ. Also, we leverage the ARP indices such that all of them have a target volatility $\bar{\sigma} = 10\%$ annualized.

The cluster-momentum (CMOM) portfolio construction process is as follows. At each time-step t, we first select all ARP indices with data available for the learning period $[t - \tau, t)$. Note that the universe of available indices varies over time, as they can become *live* or *delisted* at any date. Using this learning period, we classify the indices into θ clusters. We apply the unsupervised hierarchical clustering method (with the Ward distance), as the purpose is to group the ARP indices using an agnostic approach, not relying on the providers' classifications or any prior information except their past returns. The clustering technique should classify the indices according to the rule "as similar as possible within each cluster and as distant as possible between clusters". The number of components (nodes) in each cluster varies from one group to another and also between time-steps.

The second part of the process is to find, in each cluster, the best performer, that is the index with the highest Sharpe ratio, over the same learning period. Figure 2 below exemplifies the process for the first time-step $t = 0$, May 1st, 2017.

Then, we build the portfolio composed by θ indices that are the "winners" of each cluster. The portfolio is equally weighted. Finally, we run the portfolio for the out-of-sample period $[t, t + \upsilon]$ and store the realized returns.

This process is repeated every υ, in our base case monthly, until the end of our sample period.

To test whether the clustering technique brings diversification benefits in our CMOM portfolio, we build a benchmark portfolio (MOM) that invests, at each time-step t, to the θ indices that performed best over the entire universe of available indices during the same learning period $[t - \tau, t)$, equally-weighted. We expect this MOM portfolio to be highly concentrated into one or a few ARP strategies at each time-step, as the indices from different providers that capture the same risk premium should perform similarly, at least in theory.

In order to test if the performance persistence adds value, we also build as benchmark the EW portfolio: at each time-step, the ARP indices are classified into the θ clusters as in CMOM. Then, we equally-weight all the components of each cluster to build θ (in our case 10) representative subindices. Finally, we invest, again equally-weighted, into these subindices. Note that, in this case, each cluster has the same weight, regardless of the number of indices that compose it.

Additionally, we build 1,000 random portfolios: starting at $t = 0$, at each time-step t, each portfolio selects, at random, θ ARP indices from the universe available. Then, it invests equally-weighted on them during the same out-of-sample period $[t, t + \upsilon]$. This random selection is performed with υ frequency until the end of our sample September 28th, 2023. To make the results more comparable to existing, investible products, we simulate a 0.15% transaction cost every time that a portfolio disinvests from an index between two time-steps (i.e. if an index is present at $t - 1$ but not at t).

In a second test, we compare the results of the CMOM, MOM and EW portfolios with 8 existing ARP asset manager funds. In this case, we leverage the portfolios' weights at each time-step to achieve a

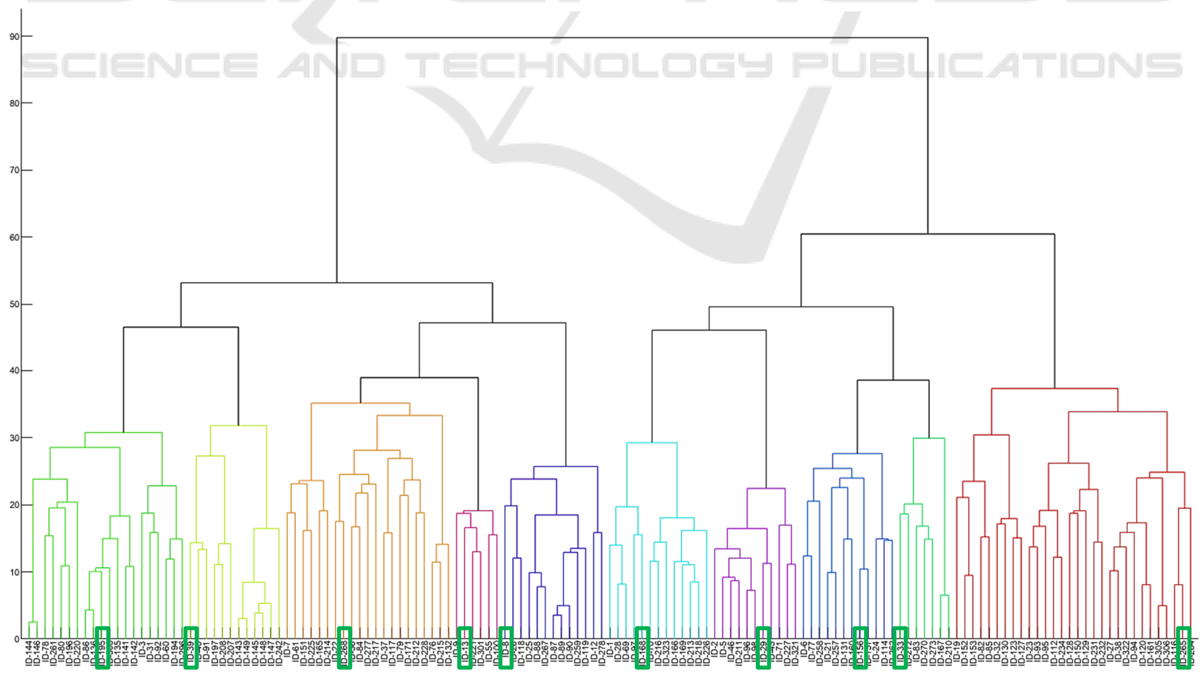

Figure 2: Cluster-momentum portfolio construction process at $t = 0$ (May 1st, 2017).

target volatility of $\bar{\sigma}_p = 7\%$ annualized, similar to the funds' average volatility.[4]

Finally, for robustness tests, we build the CMOM, MOM and EW portfolios and re-run the out-of-sample backtests but modifying τ, or υ, or both.

5 RESULTS

In this section, the results of the out-of-sample backtests are presented. First, we compare the performance of the CMOM portfolio with the MOM and EW benchmarks. We also include the 5th–percentile coefficients of various performance measures from the 1,000 random portfolios.

5.1 Portfolios' Performance

Table 2 exhibits the portfolios' out-of-sample descriptive statistics and Figure 3 the portfolios' path over time. It is noticeable that both the CMOM and MOM portfolios outperformed the EW passive benchmark, as well as more than 95% of the random portfolios, in terms of annual returns. MOM delivered better returns than CMOM. However, MOM also manifested more risk, in terms higher volatility, negative skewness, kurtosis, CVaR and maximum drawdown coefficients. [5] Consequently, this outperformance is not translated into the risk-adjusted measures. CMOM shows a lower Sharpe ratio than MOM (0.58 vs. 0.68), while the former exhibits a higher Calmar ratio (0.36 vs. 0.31). These results suggest that, first, there is added value that can be extracted from performance persistence in ARP (i.e. chasing the most recent winners), and second, that the clustering technique achieves its desired outcome: provide diversification to reduce the portfolio's risk.

5.2 Cluster-Momentum Strategy vs. ARP Asset Manager Funds

As a second set of benchmarks, we compare the results of our CMOM strategy and the MOM and EW portfolios with 8 existing asset manager ARP funds. As a reminder, the CMOM, EW and MOM portfolios are levered to achieve, at each rebalancing, a volatility target $\bar{\sigma}_p = 7\%$ annually. Interestingly, the out-of-sample, realized portfolio's volatility σ_p is slightly above 9% for CMOM and MOM, showing a large volatility "overshooting" impact, while it is of 6% for the EW case. The funds' volatility is, on average, 8.03%. In terms of annual return μ_p, the fund's average is of 1.87% only, likely below investor's expectations but above the naïve EW strategy. The CMOM and MOM strategies outperformed most funds, not only in terms of annual returns (only Fund 1 and Fund 3 are above CMOM, while no fund is above MOM), but especially in risk-adjusted terms, where only Fund 1 outperformed both strategies. In this case of levered portfolios, MOM shows a higher Sharpe ratio (SR) than CMOM but the latter still outperforms in terms of Calmar (CR).

It also exhibits lower (negative) skewness and kurtosis coefficients. Another interesting result is that, while the volatility of CMOM (9.36%) is larger than most funds (8.12% on average), its maximum drawdown (-15.40%) is lower, in absolute terms, than all funds except Fund 1 and Fund 2. This is not the case for MOM or even EW, whose *MaxDD* are around 10 pp. larger (in absolute terms). Once again, the benefits from diversification due to the clustering

Table 2: Portfolios' out-of-sample descriptive statistics

	μ_p	σ_p	SR	CR	$skew.$	$kurt.$	$CVaR_{95}$	$MaxDD$	$Start$	$Dur.$	$Rec.$
CMOM	2.33%	3.98%	0.58	0.36	-2.88	31.19	-0.63%	-6.47%	07.03.23	7	
EW	0.06%	2.47%	0.02	0.01	-2.71	20.55	-0.44%	-9.06%	05.01.18	573	
MOM	3.84%	5.61%	0.68	0.31	-3.50	45.40	-0.90%	-12.26%	05.01.18	266	669
5th–pct.	2.01%	3.23%	0.58	0.30	-	-	-0.50%	-5.85%	-	-	-

μ_p: annual realized portfolio return; σ_p: annualized portfolio volatility; SR: Sharpe ratio; CR: Calmar ratio; $skew.$: skewness coefficient; $kurt.$: excess kurtosis coefficient; $CVaR_{95}$: Conditional Value-at-Risk at 95% confidence level; $MaxDD$: maximum drawdown; $Start$: maximum drawdown's start date; $Dur.$: drawdown's duration from peak to trough (in days); $Rec.$: drawdown's recovery duration from trough to previous peak (in days). 5th -pct. Refers to the 5th– percentile best coefficient of each measure. The out-of-sample investment period spans from 01.05.2017 to 28.09.2023.

[4] The average fund's realized volatility is 8.03%. We set the target volatility at 7% as we expect some degree of "volatility overshooting" out-of-sample. Anderson, Bianchi and Goldberg (2014) show that leverage has a negative impact on Sharpe ratio even without considering transaction costs, via the "covariance term".

[5] Another result not reported here is that MOM tends to show highly concentrated positions into the same ARP strategy, while this is not the case for CMOM.

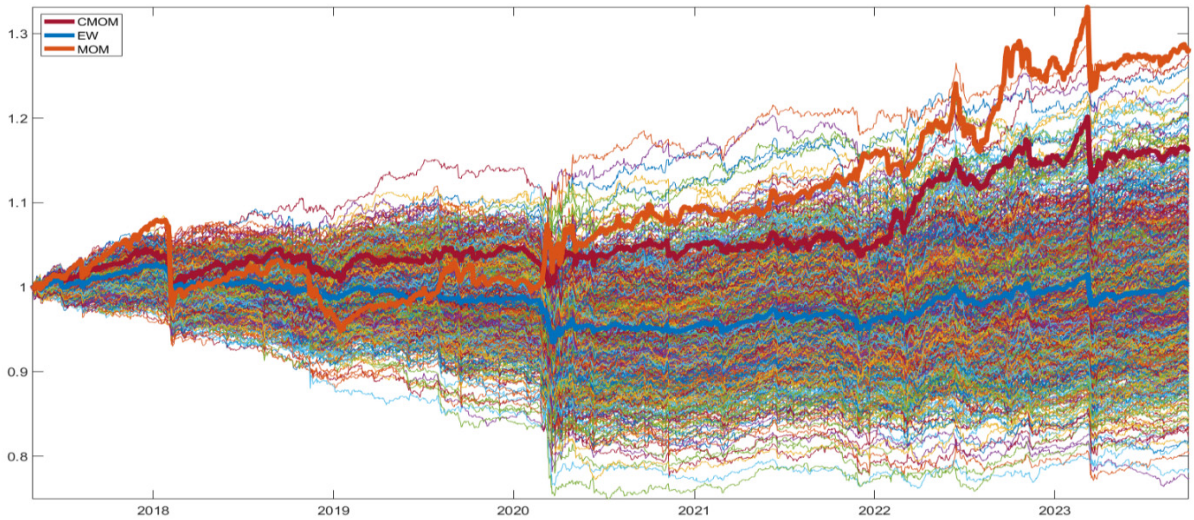

Figure 3: Portfolios' path over the out-of-sample period.

Table 3: Levered portfolios' and ARP asset manager funds' out-of-sample descriptive statistics.

	μ_p	σ_p	SR	CR	$skew.$	$kurt.$	$CVaR_{95}$	$MaxDD$	$Start$	$Dur.$	$Rec.$
CMOM	4.47%	9.36%	0.48	0.29	-2.51	31.78	-1.49%	-15.40%	15.12.17	583	1079
EW	-0.93%	5.97%	-0.16	-0.04	-2.62	19.00	-1.08%	-25.63%	05.01.18	573	
MOM	5.67%	9.26%	0.61	0.24	-4.00	58.67	-1.50%	-23.74%	05.01.18	266	939
Fund 1	5.56%	8.30%	0.67	0.41	-0.88	7.26	-1.35%	-13.44%	18.02.20	20	191
Fund 2	3.07%	7.33%	0.42	0.22	-0.93	7.19	-1.13%	-13.80%	17.01.20	45	209
Fund 3	4.85%	12.39%	0.39	0.12	-0.16	2.46	-1.82%	-41.25%	31.01.18	743	1113
Fund 4*	2.52%	6.44%	0.39	0.13	-1.07	7.23	-1.00%	-19.40%	25.01.18	726	1210
Fund 6	2.36%	10.81%	0.22	0.09	-0.50	3.52	-1.59%	-24.92%	17.12.19	228	
Fund 5	-0.02%	6.52%	0.00	0.00	-0.71	5.20	-1.06%	-25.80%	26.01.18	804	
Fund 7	-0.24%	7.79%	-0.03	-0.01	0.41	8.37	-1.11%	-31.00%	19.06.17	908	
Fund 8	-3.15%	5.40%	-0.58	-0.11	-0.70	5.97	-0.86%	-28.68%	15.12.17	592	

μ_p: annual realized portfolio return; σ_p: annualized portfolio volatility; SR: Sharpe ratio; CR: Calmar ratio; $skew.$: skewness coefficient; $kurt.$: excess kurtosis coefficient; $CVaR_{95}$: Conditional Value-at-Risk at 95% confidence level; $MaxDD$: maximum drawdown; $Start$: maximum drawdown's start date; $Dur.$: drawdown's duration from peak to trough (in days); $Rec.$: drawdown's recovery duration from trough to previous peak (in days). The out-of-sample investment period spans from 01.05.2017 to 28.09.2023. *Fund 4 start date is 18.10.2017.

classification are present in our CMOM strategy.

Another intriguing result is the high skewness, kurtosis and CVaR coefficients that our CMOM and MOM portfolios show with respect to the values from the funds.

Finally, it is worthwhile remembering that these 8 funds are all ARP asset manager funds that were launched before May 2017 (except Fund 4, whose start date is October 2017) and were still alive by September 2023. There were ARP asset manager funds that did not survive the 2018-2020 period of underperformance of the ARP industry. Therefore, there can be some "survivorship bias" in the sample of funds and, if those "dead" funds were to be included, it is likely that these ones would have also underperformed.

To sum up, both the CMOM and MOM strategies delivered very competitive results when compared to the existing, investible funds, while the CMOM still showed signs of risk-reduction with respect to MOM, especially in terms of drawdown.

5.3 Robustness Tests: Modifying τ and υ

As robustness tests, we build the same CMOM and MOM portfolios but modifying the learning window $\tau = \{3,6,12\}$ months and the rebalancing frequency $\upsilon = \{1,3\}$ months (i.e. monthly or quarterly rebalancing). Table 4 presents the results for all combinations. The results show that, not only modifying parameters does not worsen the performance of both the CMOM and MOM strategies but it improves it in almost all combinations. CMOM appears to be more resilient to parameter modifications, as the 3x1 MOM strategy is the only combination that suffers a negative annualized return. Another observation is that all quarterly rebalanced portfolios outperform their monthly rebalanced counterparts. Some combinations, such as the 3x3 in CMOM and MOM and the 6x3 in MOM achieve annualized returns above 10% with a similar level of volatility. These results suggest that the CMOM strategy is not negatively affected by the arbitrary choice of the learning window and rebalancing frequency parameters. In fact, the 12x1 base case seems to be the portfolio with worst returns among all combinations, and these ones were competitive when compared to the asset manager funds. The benchmark MOM portfolio seems to be more sensitive to parameter modifications.

6 CONCLUSIONS

The selection and allocation of ARP is a challenging task. IBs provide their own internal classifications which can be different from one to another. Moreover, each provider has its own cooking recipe for each specific strategy, making two ARP indices from the same strategy behave very differently in some cases. On the other side, ARP that are uncorrelated during quiet periods can become highly correlated during market drawdowns, showing a contagion effect. These and other complexities from ARP investments must be considered when building and managing portfolios.

In this article, we present a purely quantitative approach that uses unsupervised hierarchical clustering to achieve diversification, and then allocates to the best performers among each of the clusters, relying on some performance persistence among ARP. This portfolio is backtested out-of-sample and compared against a set of internal benchmarks and existing asset manager ARP funds.

The results suggest that such a strategy would have provided solid returns over the investment period with a limited risk thanks to the benefits from diversification achieved with the clustering technique. Moreover, this portfolio shows resilience to parameter modifications such as the learning window or the rebalancing frequency. Strong performance persistence appears to be present among ARP, from which investors can profit from. Furthermore, diversification through clustering ensures that the portfolio won’t be too concentrated into one or few ARP strategies, resulting into a reduced risk without resigning from long-term performance. These encouraging results should incentivise researchers and practitioners to explore further on the topic. For instance, it could be tested whether increasing the number of clusters to have more components in the portfolio, or picking more

Table 4: Out-of-sample descriptive statistics of portfolios with varied learning window and rebalancing frequency

	μ_p	σ_p	SR	CR	$skew.$	$kurt.$	$CVaR_{95}$	$MaxDD$	$Start$	$Dur.$	$Rec.$
CMOM											
12x1	4.47%	9.36%	0.48	0.29	-2.51	31.78	-1.49%	-15.40%	15.12.17	583	1079
12x3	6.75%	9.67%	0.70	0.42	-2.31	27.41	-1.58%	-15.96%	10.09.18	399	893
6x1	4.17%	9.24%	0.45	0.13	-2.67	22.78	-1.56%	-31.96%	13.09.18	390	919
6x3	8.18%	9.75%	0.84	0.29	-2.42	24.01	-1.57%	-28.31%	29.07.19	166	648
3x1	5.37%	9.12%	0.59	0.37	-1.95	20.90	-1.43%	-14.44%	07.03.23	7	137
3x3	12.39%	8.90%	1.39	0.65	-0.90	9.84	-1.36%	-19.10%	13.12.19	68	176
MOM											
12x1	5.67%	9.26%	0.61	0.24	-4.00	58.67	-1.50%	-23.74%	05.01.18	266	939
12x3	6.75%	9.67%	0.70	0.42	-2.31	27.41	-1.58%	-15.96%	10.09.18	399	893
6x1	6.66%	9.96%	0.67	0.29	-2.42	20.48	-1.66%	-22.82%	19.01.18	542	857
6x3	11.69%	9.78%	1.20	1.03	-2.02	18.41	-1.61%	-11.37%	19.01.18	14	377
3x1	-0.33%	9.73%	-0.03	-0.01	-2.17	20.32	-1.60%	-29.21%	19.01.18	549	
3x3	10.33%	9.65%	1.07	0.46	-1.16	13.74	-1.49%	-22.22%	22.01.18	354	581

μ_p: annual realized portfolio return; σ_p: annualized portfolio volatility; SR: Sharpe ratio; CR: Calmar ratio; $skew.$: skewness coefficient; $kurt.$: excess kurtosis coefficient; $CVaR_{95}$: Conditional Value-at-Risk at 95% confidence level; $MaxDD$: maximum drawdown; $Start$: maximum drawdown’s start date; $Dur.$: drawdown’s duration from peak to trough (in days); $Rec.$: drawdown’s recovery duration from trough to previous peak (in days). The out-of-sample investment period spans from 01.05.2017 to 28.09.2023. *Fund 4 start date is 18.10.2017.

than one index in each cluster for the same purpose, could add any value. In this article, we used hierarchical clustering with the Ward method, but other clustering techniques might be more appropriate. In the same vein, the performance measure to rank the underlyings could be another one than the Sharpe ratio that was used here. All these are just examples of many additional tests that can be done, but that are left for further research.

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