Fund Report
Asset Allocation Workshop

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1 Relative performance analysis:

First period: 22/09 - 7/10

In the first period of analysis our portfolio had an amazing performance in all the fields of our interest. Indeed it registered a strong growth of +3.20%. The contribution given by each class was :

- **Equity**: $r = 6.36\%$
- **Bonds**: $r = 0.38\%$
- **Commodities**: $r = 8.20\%$
- **Crypto (ETH)**: $r = 14.61\%$

The **Information Ratio** was 0.6527.

Second period : 8/10 - 21/10

In the second period our portfolio had a more consistent equity part at expense of the bond one. We justify the choice of reducing by the 10% the bond part by the fact that some important central banks started to increase the interest rates in order to counteract the rise of inflation. By this way our portfolio still obtained a positive growth, even though less marked than the first period. The performance was of +1.42% with the following contribution per class:

- **Equity :** $r = 2.96\%$
- **Bonds :** $r = -0.42\%$
- **Commodities :** $r = 1.83\%$
- **Crypto (ETH) :** $r = 10.69\%$

The **Information Ratio** for the considered period was 0.0273.

Third period : 22/10 - 3/11

During the last period of observation our portfolio kept performing well. Indeed, its total return was of +1.76%. More in detail we have the following class contribution:

- **Equity :** $r = 3.62\%$
- **Bonds :** $r = 0.41\%$
- **Commodities :** $r = -1.10\%$
- **Crypto (ETH) :** $r = 16.34\%$

We observe that the best class is, once again, the Crypto one, followed by the equity asset class. Bond funds have now registered a positive growth while the

commodities had an opposite trend now. Indeed they got a negative return of 1.10%.

The **Information Ratio** for this last period was 0.0479.

Exchange impact

Our investments were mainly focused in the United States (with some minor exceptions such as Ethereum, quoted also in EUR) thus we were exposed to the volatility of the exchange market.

Analysing separately the effect of this factor, we understood this was a good moment to invest in USD products: indeed, despite some minor setbacks, the USD became stronger during the workshop time, improving our position.

Therefore, the USD-EUR exchange was definitely involved in our fund success, earning us about 40,000 euros.

Contribution of rebalancing and transaction costs

To estimate the impact of the transaction costs, we simulated what would have happened if we did not change the initial composition or if we performed only the first rebalancing. The returns in each scenario are:

1) No rebalancing = 4.7%

2) First rebalancing only = 5%

3) True fund return = 5.6%

These are the true returns already considering the transaction costs of all the different scenarios. We can say that each rebalancing was justified and yielded an increase in the total return.

2 Absolute Performance Analysis

Here are reported the total returns of the different asset classes:

	Fund	Benchmark
Equity	9.05%	1.01%
Bond	0.37%	-0.86%
Commodities	8.55%	\
Crypto	47.58%	\
Entire investment	5.58%	0.69%

In the overall period we obtained an **Information Ratio** of 26.4%. We observe that the top performer is (by far) the Crypto asset class; one cause of this may have been the introduction on the New York stock exchange of the first Future Bitcoin ETF. However we believe that our choice of limiting the weight of this asset class in our portfolio was correct due to its notorious high volatility. On the contrary the worst performer was the bond asset class. Indeed the fixed income products were negatively affected by the increase of interest rates which were raised by many Central Banks as a way to contrast the growth of inflation. Therefore our analysis of the situation and the negative consequences we predicted on the bond class were correct.
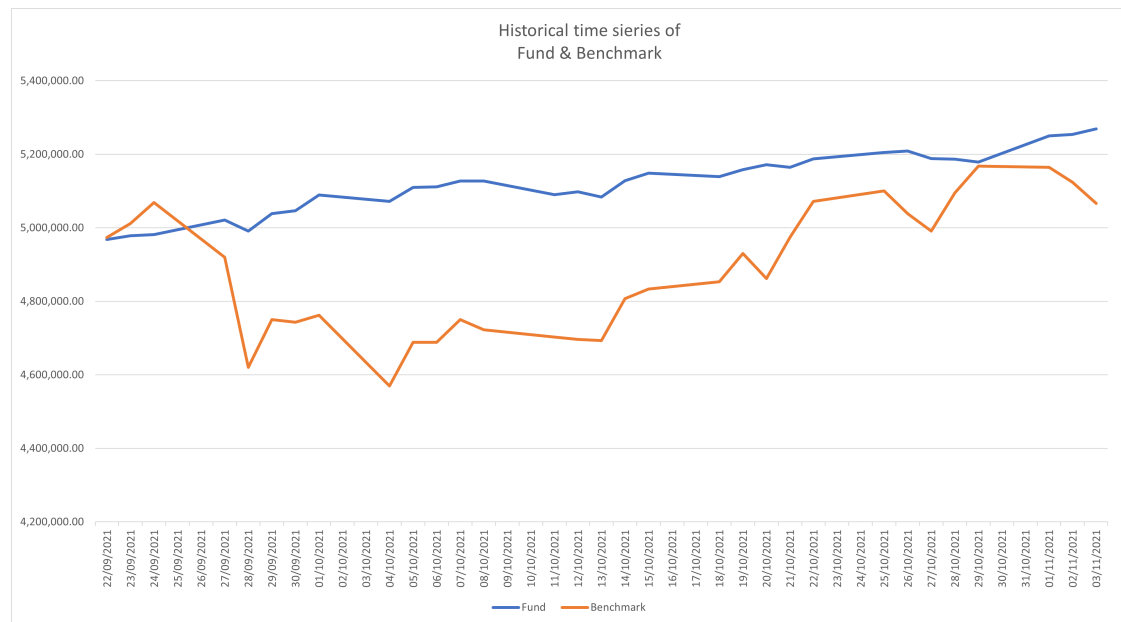
3 Comment on Performance Attribution

Here is reported the performance attribution (over the whole investment period).

	Asset Allocation	Stock Picking	Interaction Effect
Equity	-0.49%	3.86%	-0.43%
Bond	0.18%	0.87%	-0.25%
Commodities	0.00%	0.00%	0.91%
Crypto	0.00%	0.00%	1.43%
Liquidity	0.00%	0.00%	0.00%

- **Equity:** The Equity asset class has a positive stock picking index meaning that our portfolio had a greater return with respect to the benchmark. Instead the a.a. and the i.e. are negative since the equity class in our portfolio has had a lower weight across the whole period.

- **Bond:** Our portfolio also had a better performance than the benchmark in the bond asset class (s.p.$\geq$ 0), although much lower than the equity one: retrospectively it would have been better to lower the weight of the bond asset class and increase the equity one.

- **Commodities & Crypto:** these two asset classes were not represented in our benchmark. Therefore the a.a and s.p. indexes are equal to zero. The interaction effect is positive meaning that they both had a positive return across the whole period of investment.

4 Composition analysis

Initial composition

At the beginning of the workshop, we bought products following only the constraints linked to our fund type, namely: 50% bond funds, 27% equity funds, 10% commodities, 3% crypto currencies, 10% liquidity.
The idea behind this composition was the compromise between low risk assets and a more hazardous strategy. We believed we could move the main risk in the crypto field in order to have a free hand in the remaining part of the portfolio. Equity and commodities played the companion role of crypto in providing some major gain. The 10% liquidity was created so to be ready to face rapid market changes, either losses or unexpected market news.

First period: 22/09 - 7/10

The impressive results bestowed strength to our past choices. However we opted for two changes:

- Minimum investments cap: we had some concerns about the wealth concentrations in the best performing assets. Indeed it had been positive during the past two weeks since every asset gained value but it could have been tragic in the opposite scenario. Therefore we introduced a 2% minimum investment in every asset. This particular number was thought as guarantee for diversification and, on the other hand, not to be too restrictive.

- Major composition shift: news arising from the market hinted a rise of interest rates. This could pave the way for a price reduction of our fixed income products. Being exposed for the 50% to bond funds, we decided to cut involvement by shifting a 10% from the bond funds to the equity funds (+8% reaching 35%) and commodities (+2% reaching 12%).

Second period: 8/10 - 21/10

In these two weeks the rumors about increasing interest rates continued, causing a minor loss in the bond sector. Thus, our choice to limit the fund exposure to those products proved to be winning. Indeed we restricted the losses and could still have a positive performance in the two weeks period.
We pondered the idea of shifting again some wealth from the bond world to products less affected by the interest rates movements. Eventually we decided to preserve the status quo, not falling for some extreme solution and, if nothing else, avoiding to distort the initial spirit of the fund.
On the contrary, we decided to renew the safety thread by adding a VaR cap for our investments, avoiding to have a daily Value-at-Risk above 4%. This threshold was chosen to be not too harsh on our investment, aiming more to have a

known bound and eluding possible disrupting consequences rather than radically changing our composition.

Third period: 22/10 - 3/11

The bond market did not continue to decrease thus our strategy of not changing classes weights proved to be right. Furthermore the commodity market registered a setback which could have ruined our performance if we had invested more in that sector.

5 Modelling

The optimization of the weights of our portfolio across the whole investment period was based on the Markowitz model. It is a well known model, easy to use and to implement with constraints. However it has some major limitations:

- It is highly dependent on the parameters used, particularly on the mean estimator of the returns, making it very inefficient.

- It is a biased estimator. The efficient frontier is much more optimistic from the actual true frontier.

- The weights on the efficient frontier are discontinuous.

We tried to overcome these issues by implementing some statistical improvements on the methodology and on the estimators adopted. Below are reported precisely the constraints and methods used for each rebalancing period.

First period: 22/09 - 7/10

We used the standard unbiased mean and variance estimators and we computed the efficient frontier according to the following constraints on the weights:

- Equity class: $\sum_{i=1}^{n_{eq}} w_i = 0.27$

- Bond asset class: $\sum_{i=1}^{n_b} w_i = 0.50$

- Commodities class: $\sum_{i=1}^{n_c} w_i = 0.10$

- Cryptocurrencies class: $w_{Eth} = 0.03$

- Liquidity: $w_l = 0.10$

We want to point out that in order to implement the constraints above in our model, we couldn't resort to the default Matlab function, therefore we had to write a custom version of the same function taking into account the restrictions on the weights for the admissible portfolios. As a result our optimization takes quite some time to run (almost 28 seconds on a slow system), since our custom code relies heavily on the Matlab function `fmincon`.

Second period: 8/10 - 21/10

In the second period we used basically the same approach of the first optimization, changing slightly the constraints on the weights and adding a lower-bound of 2% for the weight of each asset of the portfolio:

- Equity class: $\sum_{i=1}^{n_{eq}} w_i = 0.35$

- Bond asset class: $\sum_{i=1}^{n_b} w_i = 0.40$

- Commodities class: $\sum_{i=1}^{n_c} w_i = 0.12$

- Cryptocurrencies class: $w_{Eth} = 0.03$

- Liquidity: $w_l = 0.10$

- $w_i \geq 0.02 \quad \forall i = 1, 2, ..., n_{pft}$.

Third Period: 22/10 - 3/11

[1] For the third optimization we implemented in our model two different techniques in order to improve the efficiency of our approach.

We performed a re-sampling on the dataset used for the optimization to mitigate the statistical error and to obtain a smoother frontier on the weights. Specifically we simulated multiple times the daily log-returns of our assets in the past using a normal distribution, and for each simulation we computed the efficient frontier. Finally we averaged across frontiers the weights of the corresponding portfolios. We also observed that our constraints (which are linear) are still satisfied by the averaged frontier. This procedure requires our custom function computing the efficient frontier to run multiple times, and as pointed out before, the computational cost to perform multiple optimizations could become prohibitive. For this reason we decided to lower the number of Portfolio in each frontier with respect to the previous deliveries. In this way our model was able to make multiple simulations and optimizations within a reasonable timeframe.

We also computed the efficient frontier from the real data using the Shrinkage estimators. For the Stein estimator we decided to put a target with negative return ($\mu = -0.1\%$) for the bond asset class since from our market analysis we expected the interest rates to rise as the Fed's tapering becomes closer. Instead we anticipated an high return on the short period for Ethereum ($\mu = 3\%$) [2], given that on the same week the First future Bitcoin ETF started trading on the New York stock exchange. Instead for the equity and commodities asset classes we set a target return of 0, since we don't have a clear view on the possible future performances. We observed however that we obtained a Stein estimator equal to the unbiased average; indeed the Shrinkage frontier is almost indistinguishable from the real one. For this reason we decided to implement our portfolio using the weights maximising the information ratio taken from the average frontier.

Moreover, we added a constraint for the VaR of the admissible portfolios when building the efficient frontier: we put an upper bound of 4% for the Value at Risk computed using the Historical Simulation. We tried using lower bounds but we observed that this constraint was becoming too restrictive and had some undesired effects on the efficient frontier.

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[1] Some parts are taken from 22/10 delivery

[2] value are taken arbitrarily but on the same order of magnitude of the past returns

6 Comments

Some improvements we thought at:

- A better benchmark to properly reflect the commodities-focused investments and the crypto currency. Indeed splitting the commodities investments into bond and equity for the benchmark purpose seemed at the end restrictive, especially when dealing with performance attribution.

- When deciding whether to change the classes of our funds we would have preferred some type of quantitative method, maybe involving with simulations or dealing with views from expert economists.

Some lucky strikes we enjoyed:

- Ethereum grew above the most optimistic expectations, gaining almost 50% in one month and a half!
  In general this was a florid period for crypto currencies but Ethereum enjoyed an exceptionally good result.

- The first two weeks our benchmark obtained an awful result whilst our fund got a moderate gain. Thanks to this period our information ratio skyrocketed and it could hold against the benchmark return of the following weeks.