TALOS

ANALYSIS

Performance Attribution for Crypto Sectoral Indices

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PERFORMANCE ATTRIBUTION FOR CRYPTO SECTORAL INDICES

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ABSTRACT: In this paper we'll show how portfolio managers are usually evaluated through performance attribution. As an example, we'll introduce the Brinson–Fachler model. Instead of evaluating a portfolio manager, we'll use it to explore DACS, the token taxonomy introduced by CoinDesk. Our objective is to see if using sectoral diversification there's value to be uncovered. The same methodology can be used to compare crypto VCs investing in liquid tokens to see if their out- or under-performance is due to asset selection, sector allocation, or the interaction of the two.

INTRODUCTION

Models in the Performance Attribution group give us a quantitative way of identifying the sources of excess returns, usually as compared to a benchmark portfolio. Just comparing Portfolio Managers (PM) based on summary metrics like the Sharpe ratio is not enough, as we also want to see where the alpha is coming from. One type of Performance Attribution model relies on Risk Factors, i.e. models we've discussed recently. With those models, we want to see if the returns are coming from certain risk premia, or if they are simply beta related. Today we'll discuss Brinson attribution, which focuses on a PM's ability to select the winning tokens and overweight the outperforming sectors. Brinson can be also used to reveal a PM's investment style and whether her particular style is detrimental in certain periods.

Here's some notation for the Brinson–Fachler model, from Lu and Kane. Note though that the interaction effect in the paper is not well defined (there's a missing term, we'll leave this to the reader as an exercise).

*Cloudwall and the technology behind its Serenity System were acquired by Talos in April 2024.

	Benchmark	Portfolio
weight of security i	w_i^B	w_i^P
weight of category j	$W_j^B = \sum_{i \in j} w_i^B$	$W_j^P = \sum_{i \in j} w_i^P$
return of security i	r_i	r_i
return of category j	$R_j^B = \sum_{i \in j} w_i^B r_I$	$R_j^P = \sum_{i \in j} w_i^P r_i$
overall exposure, individual security level	$R_B = \sum_{i=1}^{n} w_i^B r_i$	$R_P = \sum_{i=1}^{n} w_i^P r_i$
overall exposure, category level	$R_B = \sum_{j=1}^{n} W_j^B R_j^B$	$R_P = \sum_{j=1}^{n} W_j^P R_j^P$

Table 1: Brinson-Fachler model notation.

Now, the focal point of Brinson is that it breaks down the portfolio returns into four parts:

1. **Asset Allocation:**

$$r^A = \sum_{j=1}^{N} W_j^P R_j^B - \sum_{j=1}^{N} W_j^B R_j^B$$

This part answers the question of whether a PM's sector selection was successful if compared to the benchmark. The intuition here is that the portfolio would perform differently with different sectoral weights, (i.e. benchmark weight W_B vs portfolio weight W_P for the category j), while still containing the same assets (i.e. keeping the returns for the category j equal between the two portfolios). If this is positive, the PM either allocated less to an underperforming sector or allocated more to an outperforming sector.

We can also define:

$$R_A = \sum_{j=1}^{N} W_j^P R_j^B$$

as the allocation return, i.e. the PM's sector allocation decisions that exclude any individual security selection decision.

2. **Asset Selection**

$$r^S = \sum_{j=1}^{N} W_j^B R_j^P - \sum_{j=1}^{N} W_j^B R_j^B$$

This represents the amount of value that a PM added weighting certain tokens within a category differently with respect to a benchmark. Similar to asset allocation, the intuition here is that the portfolio would perform differently with different tokens while keeping sectoral weights constant. Thus, the selection return measures the difference in portfolio performance due to the selection of tokens. Here we define:

$$R_B = \sum_{j=1}^{N} W_j^B R_j^P$$

as the portfolio return due to selection, i.e., the PM's token selection decisions that exclude any sector allocation selection considerations.

3. **Active Return**

$$R_{active} = R_P - R_B$$

This measures the out or under performance of the PM's portfolio vs a benchmark

4. **Interaction effect**

$$R_{interaction} = R_P - R_A - R_S + R_B$$

This is any return that is unaccounted for by allocation and selection. Rather than a residual, the interaction effect captures the effect of the combination of allocation and selection effects. We'll have more insights on this later in the article.

BUILDING THE BENCHMARK & PORTFOLIO

The DACS (or Digital Asset Classification Standard) taxonomy by Coindesk is part of a growing set of digital asset classification taxonomies (if there's interest, we can publish a review of the main ones). A classification taxonomy provides us with a standardized method to determine sector and industry exposure, as well as easily conduct our portfolio attribution using the above-mentioned Brinson model. Here's a table with the Top 5 tokens for each of the five sectors (excluding stablecoins).

Currency	BTC	DOGE	XRP	LTC	SHIB
Smart Contract Platforms	ETH	BNB	ADA	DOT	SOL
DeFi	UNI	CAKE	AAVE	MKR	YFI
Entertainment	MANA	AXS	SAND		
Computing	ICP	LINK	FIL	HNT	

DATA

Our time-series data is extracted from the Top 50-token universe based on market cap, with daily frequency, and over the period May 2021 — March 2022. You can refer to our previous research article on stylized facts, wherein we've also built a market cap-weighted index from the top 5 assets in each sector. In addition to that, we've constructed an aggregate index by taking equal weights on each sectoral index. Let's call this latter the Equal Weighted Sectoral Index (EWSI).

What do we want to see now? Well, we want to have an indication of whether the indices built based on a certain sector taxonomy shows any value for active investment management. Here our active portfolio will differ just by the fact that we allocate equally between sectors, while the capital weighted benchmark doesn't offer the same harmony.

And here's what the weight distributions for our "active" portfolio (EWSI) and for our cap-weighted Benchmark look like.

EWSI

W_j^P	20%		20%		20%		20%		20%	
	Computing		**Currency**		**DeFi**		**Smart Contract Platforms**		**Entertainment**	
		$w^P_{i \in comp}$		$w^P_{i \in curr}$		$w^P_{i \in defi}$		$w^P_{i \in scp}$		$w^P_{i \in ent}$
	ICP	11.72%	BTC	17.47%	UNI	10.00%	ETH	13.98%	MANA	14.81%
	LINK	5.30%	DOGE	1.06%	CAKE	3.01%	BNB	2.99%	AXS	2.92%
	FIL	2.62%	XRP	0.85%	AAVE	2.82%	ADA	1.63%	SAND	2.27%
	HNT	0.36%	LTC	0.41%	MKR	2.66%	DOT	1.05%		
			SHIB	0.20%	YFI	1.50%	SOL	0.35%		

BENCHMARK

W_j^B	3.81%		59.95%		1.99%		34.10%		0.15%	
	Computing		**Currency**		**DeFi**		**Smart Contract Platforms**		**Entertainment**	
		$w^B_{i \in comp}$		$w^B_{i \in curr}$		$w^B_{i \in defi}$		$w^B_{i \in scp}$		$w^B_{i \in ent}$
	ICP	2.23%	BTC	52.38%	UNI	1.00%	ETH	23.84%	MANA	0.11%
	LINK	1.01%	DOGE	3.17%	CAKE	0.30%	BNB	5.09%	AXS	0.02%
	FIL	0.50%	XRP	2.56%	AAVE	0.28%	ADA	2.78%	SAND	0.02%
	HNT	0.07%	LTC	1.24%	MKR	0.26%	DOT	1.79%		
			SHIB	0.60%	YFI	0.15%	SOL	0.60%		

Table 3: Weights distribution between EWSI and the benchmark portfolios.

PERFORMANCE ATTRIBUTION

Now we compute the allocation, selection, and interaction effects. As a reminder, the allocation effect measures how well a portfolio manager weighted groups relative to their benchmark. The selection effect shows how well the manager picked tokens with respect to the benchmark composition. The interaction effect is often summed with the selection effect, because mathematically if we combine these two effects in the Brinson model, we'll have a multiplication between the active (portfolio) weight of a group of tokens with the active (portfolio vs benchmark) return, i.e. it shows a **benefit of active portfolio management**. Splitting the two effects can also help. For instance, if the portfolio manager selected better components (more weight) vs benchmark, but underweighted the category, then we'll have a negative interaction effect (and a much larger selection effect). This can help the manager to understand if she should recalibrate her sector allocation strategy while leaving the selection strategy intact. Let's see the results for the single-period Brinson model:

	W_j^B	R_j^B	W_j^P	R_j^P	$W_j^B \cdot R_j^B$	$W_j^P \cdot R_j^B$	$W_j^B \cdot R_j^P$	$W_j^P \cdot R_j^B - W_j^B \cdot R_j^B$ **(returns allocation)**	$W_j^B \cdot R_j^P - W_j^B \cdot R_j^B$ **(returns selection)**
Currency	59.95%	-30.02%	20%	-9.10%	-18.00%	-6.00%	-5.46%	12.00%	12.54%
Smart Contract Platforms	34.10%	-15.51%	20%	-8.18%	-5.29%	-3.10%	-2.79%	2.19%	2.50%
DeFi	1.99%	-2.82%	20%	-26.78%	-0.06%	-0.56%	-0.53%	-0.51%	-0.48%
Entertainment	0.15%	0.17%	20%	18.25%	0.00%	0.03%	0.02%	0.03%	0.27%
Computing	3.81%	-10.12%	20%	-44.49%	-0.38%	-2.02%	-1.69%	-1.64%	-1.31%
Total								12.07%	13.28%

Table 4: Brinson-Fachler performance attribution for EWSI (click to enlarge). Color key: overweight (or overperforming) is green, underweight (or underperforming) is red.

Let's take the Currency sector as an example. The benchmark weight is 3x our portfolio weight, and additionally, our sector composition outperformed the benchmark sector composition. This means that both the Allocation and the Selection effects are positive. If we consider instead the Computing sector, we have the opposite situation.

	Portfolio	Benchmark	Active (difference)
Currency	-1.82%	-18.00%	16.18%
Smart Contract Platform	-1.64%	-5.29%	3.65%
DeFi	-5.36%	-0.06%	-5.30%
Entertainment	3.65%	0.00%	3.65%
Computing	-8.90%	-0.38%	-8.51%

Table 5: EWSI vs Benchmark performance, with the active portfolio performance.

The Active return column suggests there are performance idiosyncrasies between different sectors, which leaves space for skilled active portfolio managers. We are not saying it would be easy, but from this analysis, we at least get a hint on some potential alpha out there, despite an overall negative market performance during the period. In general, it looks like just allocating more equally to each sector, without considering what risk factors are driving them, is not a very smart idea. Take into account that here we haven't considered any particular rebalancing strategy, we simply weight each period's return with pre-established weights.

	Allocation	Selection	Interaction
Currency	12.00%	12.54%	-8.36%
Smart Contract Platform	2.19%	2.50%	-1.03%
DeFi	-0.51%	-0.48%	-4.32%
Entertainment	0.33%	0.03%	3.59%
Computing	-1.64%	-1.31%	-5.56%
Total	12.07%	13.28%	-15.68%

Table 6: Allocation, selection, and interaction effects, by sector.

	Benchmark	Portfolio
weight of security i	w_i^B	w_i^P
weight of category j	$W_j^B = \sum_{i \in j} w_i^B$	$W_j^P = \sum_{i \in j} w_i^P$
return of security i	r_i	r_i
return of category j	$R_j^B = \sum_{i \in j} w_i^B r_I$	$R_j^P = \sum_{i \in j} w_i^P r_i$
overall exposure, individual security level	$R_B = \sum_{i=1}^{n} w_i^B r_i$	$R_P = \sum_{i=1}^{n} w_i^P r_i$
overall exposure, category level	$R_B = \sum_{j=1}^{n} W_j^B R_j^B$	$R_P = \sum_{j=1}^{n} W_j^P R_j^P$

Table 1: Brinson-Fachler model notation.

The summary of our results shows that the active return of the EWSI is 1.93%, which can be decomposed into allocation effect (2.41%), selection effect (2.66%), and interaction effect (-3.14%). If you followed the market in this past year, you would not be surprised by the outperformance of the Currency sector, followed by Entertainment and Smart Contract Platforms. Also not surprised by the DeFi and Computing underperformance. Note that we do observe a positive active return on the EWSI portfolio, indicating that there is a diversification benefit from sectoral decomposition, by holding the EWSI over a market-cap weighted portfolio of all assets. The performance attribution tells us that this portfolio had a similar Allocation and Selection effects, but the total interaction effect was negative. If we sum up the sectoral Selection and Interaction effects, we do see clearer impacts of sectoral differences due to our portfolio decision for EWSI. Here's a breakdown of the interaction effect by sector. Let's take the Currency sector as an example. The interaction effect here is negative because, despite the outperformance of our sector composition vs benchmark (-9% vs -30%), we considerably underweight this sector (20% vs 60%).

	W_j^B	R_j^B	W_j^P	R_j^P	$W_j^P - W_j^B$	$R_j^P - R_j^B$	$r_j^{interaction} = (W_j^P - W_j^B)(R_j^P - R_j^B)$
Currency	59.95%	-30.02%	20%	-9.10%	-39.95%	20.92%	-8.36%
Smart Contract Platforms	34.10%	-15.51%	20%	-8.18%	-14.11%	7.32%	-1.03%
DeFi	1.99%	-2.82%	20%	-26.78%	18.01%	-23.97%	-4.32%
Entertainment	0.15%	0.17%	20%	18.25%	19.85%	18.09%	3.59%
Computing	3.81%	-10.12%	20%	-44.49%	16.19%	-34.36%	-5.56%
Total							-15.68%

Table 8: Breakdown of the interaction effect, by sector.

Most of these interaction effects are due to the way we constructed the benchmark but notice how the Entertainment sector still stands out. Seems like there could be a Size risk factor driver. Or just the effects of major FOMO for Metaverses and NFTs. We'll see in our future analysis what factors are driving different types of portfolios.

CONCLUSIONS

In this exercise, we've shown how you could look at a Portfolio Manager's performance attribution. The objective of using a Brinson-Fachler model here was to try and get a sense on whether using a certain sectoral taxonomy for a simple capital weighted index would be helpful. Overall, it does seem that there's considerable space for active portfolio management, even if just based on market-weighted indices. We haven't experimented with any timing strategies or any portfolio optimization techniques, but we'll eventually share those results as well.

AUTHORS

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DISCLAIMER

[*] *Cloudwall and the technology behind its Serenity System were acquired by Talos in April 2024.*

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