ALKEN FUND

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Convertible Bond Funds:
Breaking down the universe and creating simple peer groups

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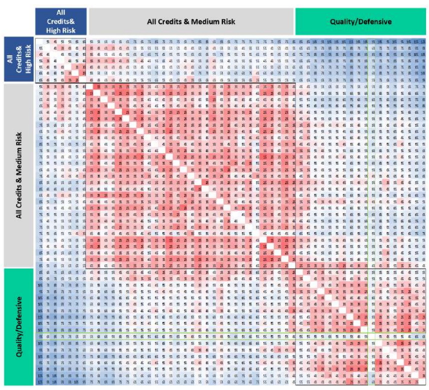
SUMMARY

After launching our product 3 years ago, we have been asked many times what makes our fund different and how it should be compared with the existing products. This document is an attempt to address that issue and to answer the most challenging question asked by fund investors: how can you really differentiate one convertible bond fund from another?

To that end, we grouped funds for comparison and have found generally that this was, as expected, not a straightforward exercise. What follows is an account of the different paths we followed and how we arrived at our own groups based on some qualitative choices of the most important criteria with a data-based validation stage.

We find that while most of the funds have their own idiosyncrasies, true diversification can only be achieved by combining funds from different groups. In particular, our analysis shows that combining funds from within the same group - especially from within the traditional all credit quality/balanced space - provides limited diversification benefit.



OUR APPROACH

The first stage consisted of gathering all the funds that operate in a similar way to ours; in other words, those that are global and hedge their FX exposures. All the available data about their official benchmarks and the returns of the funds for the last two years were collected.

We analysed 54 funds for a total of USD 43 billion AUM (i.e., the majority of the investment universe for fund selectors).

When combining funds, we went beyond taking the official benchmarks at face value. Indeed, a first look at the data revealed that the official benchmarks are not always the most representative. For more than a third of the funds, we found a lower tracking error to another benchmark of the same family, as compared to the 'official' benchmark. This is not necessarily that surprising, as is the fact that PMs are active and steer their risks in different directions from time to time - but it could also suggest that PMs decide sometimes to use a different reference index when building their exposure, effectively helping them to generate a higher tracking error vs their official benchmark. This analysis gave us an idea of the actual regional bias and credit type that the funds favoured beyond what the official benchmark was.

These are the dimensions that we considered to help us group the funds:

- Absolute Risk: What sort of drawdown did they have, for example?
- Relative Risk to the benchmark: How high or low is the tracking error?
- Strategy: Is the fund trying to adopt a defensive strategy (credit or Delta)?
- The type of Credit risk according to the benchmark: Quality (IG and Crossover) or All types?
- The regional tilt that they seemed to have: Was the "effective" benchmark more tilted towards the US, for example?

We have not included ESG as a dimension because it is a prime factor, which does not dictate the risk characteristics and the style of the fund itself.

We reviewed a number of potential methods to group the funds (see Appendix). The main issue with purely statistical methods, such as hierarchical clusters based on correlations, for example, is that the result is nearly always meaningless. This is not to say that such an approach is 'wrong' or not useful, but they are meaningless because, once the algorithm gives you the groups, you are then left to wonder what the groups represent by trying to find which dimensions are more present in each group. Of course, one can be lucky, and the groups look obvious when you look at the characteristics of the funds, but it is almost never the case.

We ran the algorithms, analysed the data many times and thought about what should really differentiate the funds. Although we had a precise idea of how we could differentiate the groups, one outcome from the analysis was that there was quite often a large middle group. Hence, we decided that there could not be as many groups as we had believed at the beginning. In the end, we concluded that the simpler 'Credit Quality vs Absolute Risk' dimensions would be sufficient and carry more meaning. The Absolute Risk could be Medium / High, and the Credit qualities could be ALL or just "Quality /Defensive" (i.e., pure IG and crossover, with a limit on HY).

Looking at the benchmarks and the drawdown data, we manually attributed the funds to just 3 groups:

Category	Proportion	Assets
All Credits/High Risk	14%	27%
All Credits /Medium Risk	57%	57%
Quality/Defensive	29%	16%

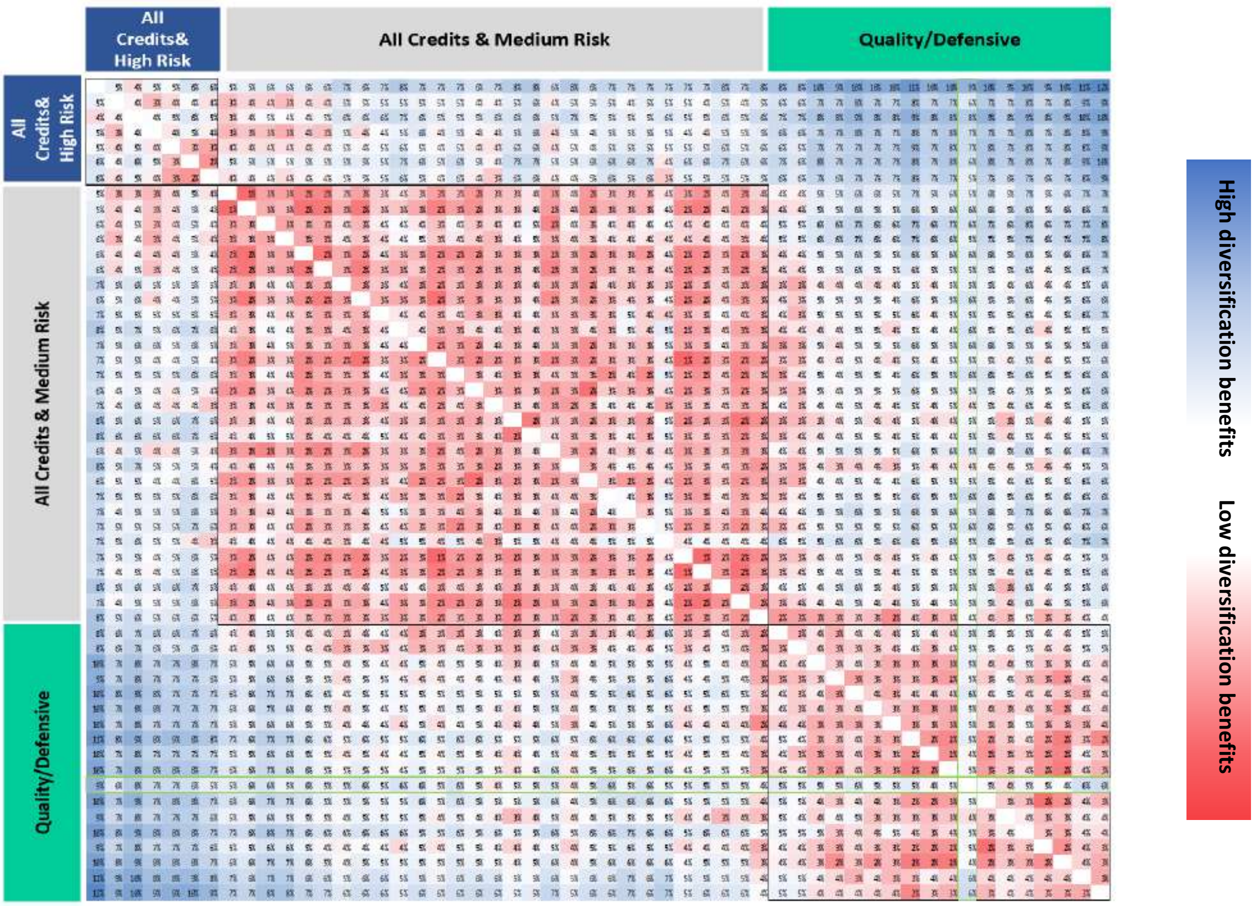
Source: Alken AM|Bloomberg

Our Fund invests primarily in bonds of investment grade quality, and as such is classified in the Quality/Defensive category.

We then sought to 'validate' this approach with data. This had the advantage that we brought a meaning/ explanation to the groups at the building stage, but we could still see if they would have looked reasonable using the same metrics used in statistical clustering.

We used the pairwise tracking error to measure the 'distance' between the funds. This made a lot more sense than using correlations as correlations do not depend on the risk of the funds, which was an important dimension for us.

When we visualised the tracking error matrix of the funds in their assigned groups and used colours for the distance it immediately looked to us that the groups were meaningful.



Source: Bloomberg & Internal calculations based on 2 year monthly performance data |Fund categories have been defined looking at their benchmarks and management styles.

It remained to be seen whether the visual appearance could be corroborated with data.

To test whether our group made 'statistical' sense we decided to compare the average tracking error between the funds within each group vs the tracking error between the funds across groups. The result was the following:

Average Tracking Error between the fund categories

		1	2	3
	Group	**All Credit High Risk**	**All Credit Medium Risk**	**Quality/Defensive**
1	All Credit High Risk	**4.3%**	5.1%	7.5%
2	All Credit Medium Risk	5.1%	**3.2%**	5.2%
3	Quality/Defensive	7.6%	5.2%	**3.6%**

Source: Alken AM |Bloomberg

Here we see that the average tracking error is systematically lower between funds inside the same group vs those outside, which means that although we did not use a purely algorithmic method to group funds, we nevertheless identified groupings that make sense.

From an investment perspective this means these 3 groups bring you genuinely different risk / return profiles, and that it makes sense to combine funds which are not all in the largest, middle group - which constitutes the bulk of the global funds.

You may have multiple convertible funds within your portfolio, but our analysis suggests that if these are all traditional all-credit, medium risk funds, otherwise known as balanced or focus, they are unlikely to be providing you with the diversification that you desire. In this case, a fund - with a focus on investment grade credits and fundamental bottom-up analysis - could provide a greater level of diversification.

APPENDIX

Potential methods to group funds

Creating homogenous groups of funds can be done in general using two very different principles. We succinctly present the main choices that we found relevant:

1. **Method 1: You know the characteristics that matter.**

   This is never really the case because you will have limited information on the funds, and sometimes even the benchmark does not seem right, i.e., you will find funds which have a higher tracking error to their official benchmark than another available benchmark. You are left wondering whether this is just due to the period you have chosen or whether it is a more long-term issue. It will sometimes boil down to having met the portfolio manager and understanding his style to really be satisfied with a conclusion. Imagine you want to rely on the data: where do you put the tracking error limit that splits funds between active and passive? The choices say as much about the views of the person classifying the funds as about the funds themselves.

   The other issue, which is usually very well decided purely based on data, is how many groups of funds exist? For reasons of ease this will be a number between 2 and 10, but it is very difficult to argue definitively about say 4 vs 5, or 5 vs 6.

   a. You list characteristics, dimensions you want to use, for example:

      i. Which region / theme are they invested in?
      ii. What types of credit quality are they invested in?
      iii. Absolute risk: The volatility of the fund
      iv. Relative risk: How active is the fund vs its benchmark, what is its tracking error?

   b. You then use these to group the funds either:

      i. Manually, subjectively: You decide how important to the identity of the fund each characteristic is and create the groups accordingly.

      ii. You use a quantitative method such as k-means clustering:
      Each characteristic of the fund is a dimension in a space and the algorithm tries to identify clouds of data that are closer together.

      The problem with purely quantitative methods here is that they do not really make choices for you: they find compromises that enable the required number of groups to be created.

2. **Method 2: You have some characteristics for the funds, but you don't know which ones matter and you would like to "start from the end":**

   a. You decide on a metric that will ex-post decide how close the funds are. This is usually either:

      i. The correlation between the funds, or
      ii. The square of the difference between the returns. You could call this the tracking error between two funds. It is obviously the same between fund a and b and fund b and a.

You use a hierarchical clustering algorithm. It will start grouping together the funds that are the closest by the metric you have chosen, recalculate the metric between this new group and all the funds that have not been grouped yet (for example by averaging the metric of the funds that constitute the new group). The algorithm then finds the next two closest funds or groups and puts them together, until there is only one group left. You are again left to decide how many groups of funds there should be.