# Can active credit managers generate alpha through single name selection?

## Tabula Capital Discussion Paper

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**Executive Summary**

For most investors, the concept of active management in credit markets is centered on fundamental analysis and single name selection, with large teams of analysts responsible for in-depth analysis to determine the issuers whose debt will outperform or underperform the market. To this extent, credit is often thought of as a "micro" asset class, along with equities.

In this discussion paper, we aim to quantify the potential for active managers to generate alpha from fundamental analysis and cross-sectional single name selection (which we term "single name alpha"). We ignore the impact of portfolio biases from factors such as market timing, investing in off-benchmark securities or overweighting higher beta names. In our view, this potential to generate single name alpha can be simply thought of as a function of two things:

1. *The skill of the active manager* – i.e. is the active manager talented at identifying mispriced individual credits?

2. *The opportunity set in the market, net of transaction costs* – i.e. does the structure of the market provide for enough mispricing and inefficiency such that there is some net alpha to extract for a talented manager once transaction costs are accounted for?

We take no position on the single name selection skills of active credit managers, but instead investigate the opportunity set that is available to these managers to generate single name alpha using more than 15 years of data for the global investment grade and high yield corporate bond markets.

Our results show that the characteristics of credit as an asset class, (in particular the fact that single name transaction costs are much higher relative to volatility than in equities) means that in the vast majority of market conditions it is extremely difficult for active credit managers to select a diversified long-only portfolio of corporate bonds that will outperform a benchmark on a net basis without resorting to additional loading on other risks (such as investing in off-benchmark securities or increasing credit beta). Active credit managers can improve their chances of generating net single name alpha by investing in more concentrated portfolios with lower numbers of securities, but this comes at the expense of lower diversification and the potential for greater dispersion of returns.

Overall, we believe that credit is much more of a "macro" asset class than investors appreciate, Active credit managers will find it difficult to outperform passive indices through single name selection without taking additional risk or exposure to off-benchmark securities.

## 1. Introduction

Active credit managers who are aiming to outperform a benchmark often look to achieve this through a combination of different approaches, including:

1. Overweighting or underweighting securities compared to their benchmark weights based on fundamental or technical views;
2. Including securities that are not present in the benchmark (for example, new issues prior to benchmark inclusion or adding BB-rated bonds to an investment grade portfolio).
3. Changing the macro risk profile of the portfolio relative to the benchmark (for example, taking more credit risk).

A number of previous academic studies have investigated the alpha that active managers in fixed income have been able to generate relative to their benchmarks, These studies[1] showed that while headline active fixed income funds generate significant alpha relative to their benchmark, the vast majority of this outperformance can be explained by the manager taking risks beyond that of the benchmark, i.e. the second and third approaches highlighted above. When the impact of this extra risk-taking is removed, very little of the original alpha remains and there appears to be little meaningful contribution from the first approach discussed above.

On the back of this result, we found ourselves asking the question: why do active fixed income managers struggle to generate alpha while tracking their benchmarks[2]? Many active managers market themselves on their ability to deeply understand companies at a fundamental level with large teams of experienced credit analysts, and the large number of securities within corporate bond benchmarks should provide ample raw material for generating alpha from this first approach, which we term "single name alpha".

To help answer this question, we find it useful to explain the alpha that active credit managers can generate from single name selection as a function of two factors:

1. *The skill of the active manager* – i.e. is the active manager talented at identifying mispriced individual credits?
2. *The opportunity set in the market, net of transaction costs* – i.e. does the structure of the market provide for enough mispricing and inefficiency such that there is some net alpha to extract for a talented manager once transaction costs are accounted for?

In this paper we take no view on the skill of individual active credit managers, but instead look to quantitatively measure and explain how large the "single name alpha" opportunity set is for corporate bonds in both investment grade and high yield, as well as in equities, to provide a relative comparison.

**"Single name alpha"**

We define single name alpha as the amount of outperformance (for example relative to a benchmark) that an active credit manager generates from overweighting or underweighting individual securities from the benchmark within their portfolio, while keeping the overall risk factors of their portfolio in line with those of the benchmark.

## 2. Measuring the single name alpha opportunity set

To measure the opportunity set for generating single name alpha we build a theoretical distribution of potential active manager returns for a given benchmark. We do this for a given month by randomly selecting a number of bonds from the benchmark, calculating the excess return of that portfolio of bonds relative to the benchmark, and then repeating the exercise until we build up enough of a representative distribution.

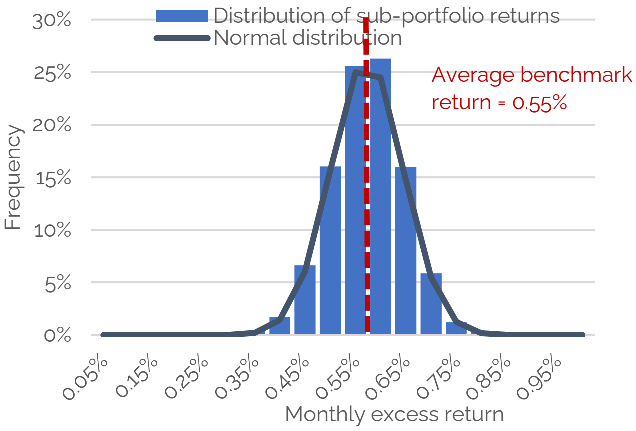
For example, at the start of December 2021 the ICE Global Corps Index (a global investment grade corporate bond index) contained more than 17,000 bonds from approximately 2,400 unique issuers. By randomly selecting 200 bonds out of the benchmark over a large number[3] of simulations we can build up a distribution of potential returns for an active manager choosing such a 200-bond subset. The distribution of returns for these subsets for December 2021 is shown in Figure 1.

This distribution of returns is very close to a normal distribution, with the mean of the distribution (0.552%) virtually identical to the monthly benchmark returns (0.548%). The fact that the means are in line supports the idea that the random sampling does not, on average, select portfolios that are meaningfully more or less risky than the benchmark.

[1] Most notably *Active Fixed Income Illusions, Brooks, Gould and Richardson, Journal of Fixed Income, Spring 2020.*
[2] i.e. only selecting securities from, and keeping the overall risk profile of the portfolio consistent with, the benchmark.

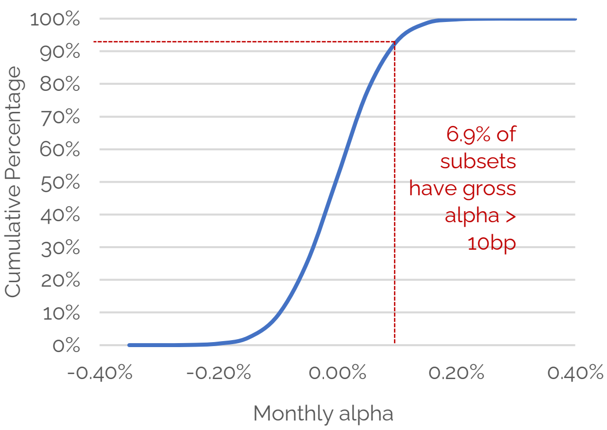
[3] We use 25,000 different samples and include some additional constraints on the selection of names to better align the high level characteristics of the subset and the benchmark, see Appendix I for more details.

*Figure 1: Distribution of December 2021 monthly excess returns for randomly generated 200 bond sub-portfolios of the IG benchmark.*




This distribution of the monthly excess returns of the sub-portfolios then gives us an indication of the range of possible single name alpha that can be generated by an active manager; we plot the cumulative distribution of this alpha in Figure 2.

*Figure 2: Cumulative distribution of December 2021 monthly gross alpha versus benchmark for randomly generated 200-bond sub-portfolios of the IG benchmark.*




The advantage of this approach is that, without taking any view on the *skill* of active credit managers, we can quickly obtain an idea of what the realms of possibility are for an active manager to generate single name alpha within a given time period. For example, the distribution in Figure 2 suggests that in December 2021 it was challenging, but possible, for an active credit manager benchmarked to the ICE Global Corps Index to generate more than 10bp of single name alpha before transaction costs; 6.9% of the subset portfolios showed an alpha higher than this. However, it would be very challenging for an active manager to generate more than 20bp before transaction costs that month with a portfolio containing 200 line items; only 0.24% of possible subsets showed an alpha exceeding this level.

The fact that single name alpha is very close to normally distributed (with a mean of zero), helpfully means that we can track how this distribution of potential single name alpha has changed through time purely by analysing the standard deviation of the distribution; given that the number of scenarios that exceed a given level of *x* bp will increase as this standard deviation increases we can also view this standard deviation as a rough proxy for the size of the single name alpha opportunity at any point in time.

In Figure 3, we show the historical time series of this cross-sectional standard deviation on a monthly basis from January 2004 to December 2021 for an active portfolio of 200 bonds chosen from the ICE Global Corps Index. We convert the standard deviation of returns from monthly to annual by multiplying by the square root of twelve.

*Figure 3: Annualised standard deviation of single name alpha distribution for randomly generated 200-bond subsets of the IG benchmark.*

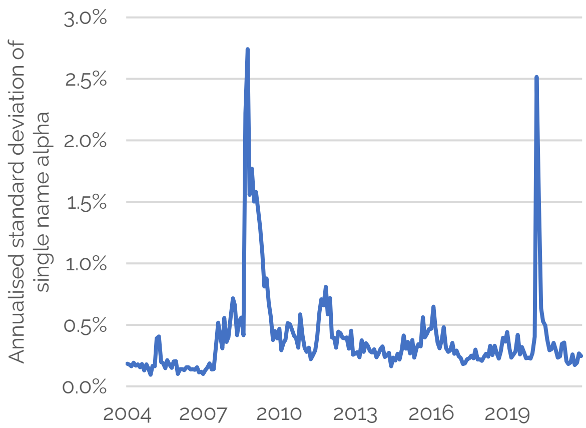



Figure 3 clearly shows that the opportunity set for generating single name alpha has changed dramatically through time for global investment grade corporate bonds. As intuitively expected, the opportunity set is materially higher during times of market stress, most notably during the 2008-09 global financial crisis and the 2020 Covid crisis. We can also run the same historical analysis for global high yield corporate bonds and global equities. The results of this are shown in Figures 4 and 5 below[4], while Figure 6 compares the standard deviations through time for the three different asset classes

[4] For global high yield corporate bonds we use the ICE Global High Yield Constrained Index and for global equities we use the Stoxx Global 1800 Index.

*Figure 4: Annualised standard deviation of single name alpha distribution for randomly generated 200-bond subsets of the HY benchmark.*

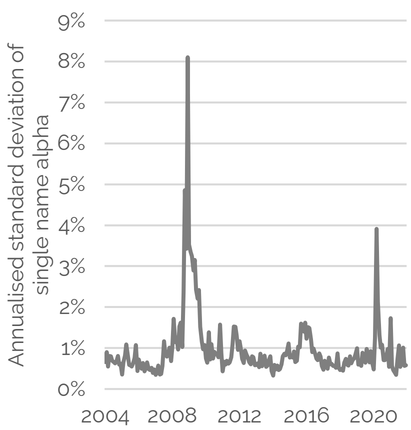



*Figure 5: Annualised standard deviation of single name alpha distribution for randomly generated 200-stock subsets of the equity benchmark.*

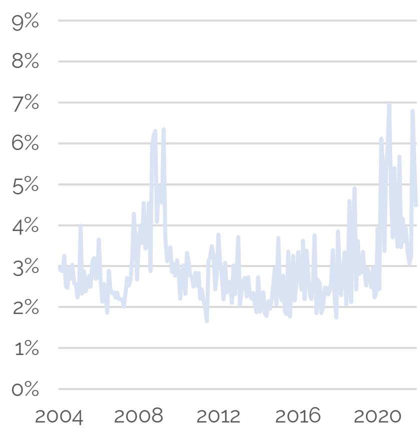
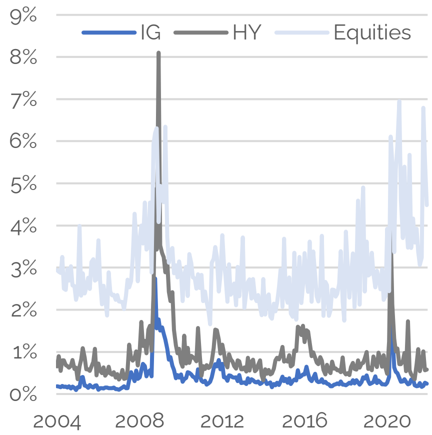



*Figure 6: Comparison of standard deviations of single name alpha across IG, HY and equities.*




Several trends are quickly apparent. Firstly, the standard deviation of the single name alpha is almost always highest in equities, followed by high yield credit and then investment grade. This is largely explained by the lower volatility of credit relative to equities, but the more concentrated weights of equity benchmarks also plays a part (see Appendix II for more details on the factors explaining the single name alpha distribution).

Secondly, the standard deviation of single name alpha shows considerably more variation in credit than in equities. For example, the maximum standard deviation in investment grade credit is 2.74%, equal to 9.2 times the median value of the standard deviation at 0.30%. In high yield this ratio is 10.9x, while in equities this ratio is only 2.5x.

This analysis already suggests that the single name alpha opportunity in credit is already far smaller than the comparable opportunity in equities in the vast majority of market conditions, as well as less consistent through time. This is even before the transaction costs – notoriously high in many single name credit instruments – that will be encountered when trying to capture any potential single name alpha. Fund management fees also further eat into any outperformance generated from single name alpha.

To illustrate the impact of transaction costs and fund fees on the single name alpha that can be generated in each asset class we first make an assumption of "typical" costs and fees in each asset class; these are shown in Table 1.

*Table 1: Assumed transaction costs, durations and fund management fees per asset class.*

| Asset Class | Assumed Bid-Offer (bp) | Assumed Duration | Assumed Fund Mgmt. Fee | Annual T-Cost & Fee Impact |
|---|---|---|---|---|
| IG credit | 5 | 5.9 | 0.15% | 0.45% |
| HY credit | 20 | 3.9 | 0.50% | 1.28% |
| Equities | 8 | 1 | 0.50% | 0.58% |

Source: Tabula Capital. Annual impact assumes 1x portfolio turnover per year. Assumed durations are average modified duration to worst from Jan 2004 to Dec 2022 for ICE Global Corps and ICE Global HY Constrained.

We appreciate that transaction costs and fund fees are highly subjective and will vary greatly depending on a large number of factors including market conditions as well as the security, fund or market participant in question. With this in mind, these costs and fees are intended to be broadly indicative of the market in question and we would encourage readers to plug in their own estimates of transaction costs and fees if they prefer; the calculation for the annual cost impact is given in Appendix I.

For each asset class we build a "typical" distribution of potential levels of single name alpha across active portfolios using the median standard deviation through time discussed above (0.30%, 0.75% and 2.76% for IG, HY and equities respectively). We then compare this distribution to the projected annual impact of transaction costs and fund fees shown in Table 1; these results can be seen in Figure 7 to Figure 9 below.

*Figure 7: Median distribution of gross single name alpha in global IG corp bonds compared to cost impact*

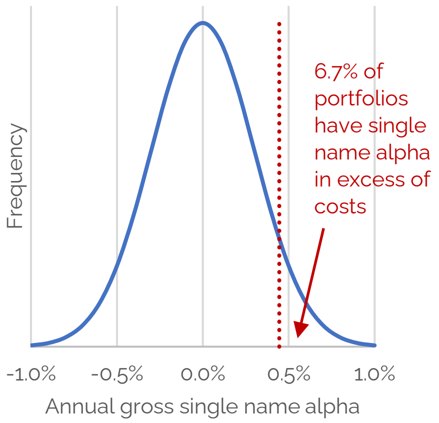



*Figure 8: Median distribution of gross single name alpha in global HY corp bonds compared to cost impact*

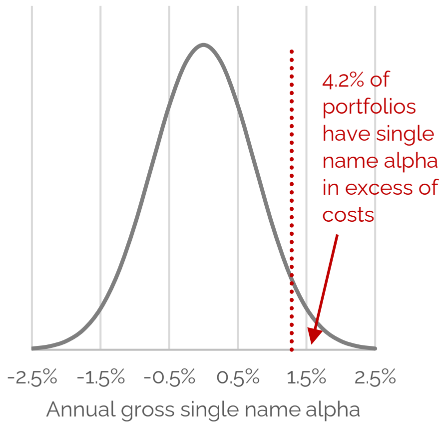
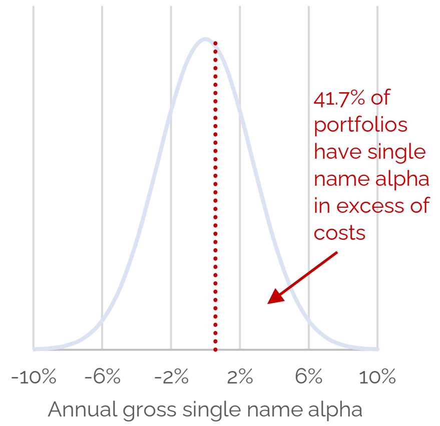



*Figure 9: Median distribution of gross single name alpha in global equities compared to cost impact*




Assumes 200 bonds or stocks in active portfolio

The results are striking; in credit only a tiny portion of the universe of potential active portfolios show positive single name alpha once transaction costs and fees are accounted for, whereas in equities the relatively lower costs compared to the more broadly distributed single name alpha means that almost half of the possible portfolios have positive alpha after costs.

This picture improves partially for IG and HY credit if we consider more concentrated portfolios with a smaller number of securities: Table 2 shows the results of repeating the analysis conducted above with more concentrated portfolios of 25, 50 and 100 securities (as opposed to 200 above) on the standard deviation of the single name alpha, while Table 3 expresses this in terms of the percentage of scenarios where the alpha exceeds our assumed transaction costs and fund fees. The impact of halving the number of securities results in an increase in the percentage of scenarios where net alpha is positive by around 7-8% for both IG and HY, but also rapidly reduces the diversification of the portfolio.

This analysis assumes that the active portfolio is only turned over once per year (on top of any benchmark turnover), but the high transaction costs of credit mean that turning over the IG and HY portfolio more only further diminishes the likelihood of generating net alpha. By comparison, in equities the low transaction costs relative to the standard deviation of the single name alpha mean that it can be advantageous to turn the active portfolio over multiple times a year (see Figure 10).

Appendix I gives more details on the methodology used in this section, including the analysis of increased turnover.

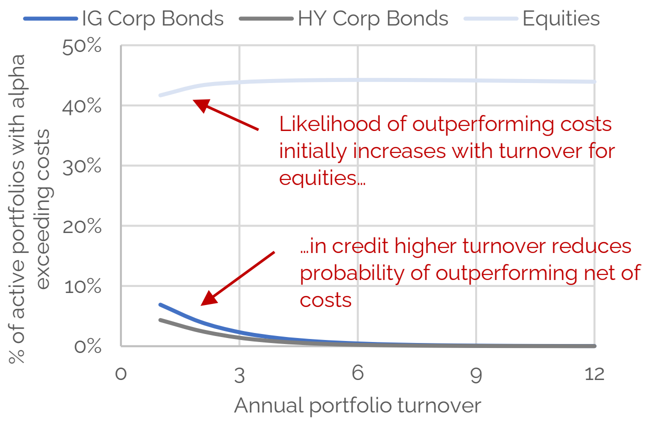
*Table 2: Standard deviation of single name alpha as function of number of securities in active portfolio*

| Asset Class | Number of securities in active portfolio 25 | 50 | 100 | 200 |
|---|---|---|---|---|
| IG | 0.82% | 0.58% | 0.42% | 0.30% |
| HY | 2.08% | 1.49% | 1.06% | 0.75% |
| Equities | 7.11% | 5.26% | 3.86% | 2.76% |

*Table 3: Percentage of scenarios where single name alpha exceeds transaction costs and fund fees*

| Asset Class | Number of securities in active portfolio 25 | 50 | 100 | 200 |
|---|---|---|---|---|
| IG | 29.3% | 22.3% | 14.2% | 6.7% |
| HY | 26.9% | 19.4% | 11.3% | 4.2% |
| Equities | 46.8% | 45.6% | 44.0% | 41.7% |

*Figure 10: Impact of portfolio turnover on likelihood of being able to generate positive net single name alpha*



## 3. Conclusion: credit as a macro asset class

We have often heard investors classify credit as a "micro" asset class along with equities, meaning that individual single name selection is key and dominates returns when building portfolios. The common narrative presented by credit managers – many of whom market their credit strategies on the basis of strong fundamental research capabilities – is certainly in keeping with this.

However, Brooks, Gould and Richardson (2020) demonstrated that, after accounting for additional exposure to "macro" risks there remains very little meaningful alpha in existing actively managed credit funds. This suggests that the actual single name alpha that active credit managers have been able to generate has been negligible, but does not answer whether this is a "skill" or an "opportunity" problem. For example, it may have been the case that the potential does exist in credit for active managers to generate meaningful net single name alpha, but so far managers have on average not demonstrated a good track record at doing so. In this state of the world, new investing techniques – for example applying factor investing to credit - could have theoretically unlocked this single name alpha potential.

We believe that the results set out in this discussion paper answer this question, and that the apparent lack of positive net single name alpha is best explained by the characteristics of the asset class (and in particular the size of transaction costs relative to the alpha opportunity), rather than due to the skill (or lack thereof) of active managers. This is in some ways a more depressing result than the case where there is single name alpha on offer for managers talented enough to capture it, given that it suggests that irrespective of skill and resources thrown at the challenge the odds are very much stacked against a positive alpha outcome. This is in contrast to equities, where the minimal transaction costs of that asset class mean that there is at least the *potential* for single stock selection to generate meaningful net alpha in diversified portfolios.

The one route that we can see where active credit managers in search of true single name alpha can meaningfully improve their chances is to invest in far more concentrated portfolios with fewer securities. However, this comes at the risk of lower diversification and it still appears to be considerably more difficult to generate meaningful single name alpha in concentrated credit portfolios than diversified equity portfolios.

Given that generating single name alpha in a diversified portfolio is so challenging, it makes sense that active credit managers should turn to other ways to generate alpha, including those highlighted by Brooks, Gould and Richardson (2020). These strategies, which often involve taking on one or more additional risks, include:

1. **Macro loading,** by increasing the exposure of the active portfolio to one or more market risk factors, for example taking more credit risk than the benchmark.
2. **Off-benchmark securities**, for example investing in new issues prior to entering the benchmark or holding onto fallen angels after benchmark exit.
3. **Illiquidity/complexity**, where the manager overweights or adds securities (or loans) which offer an illiquidity or complexity premium relative to the benchmark[5].
4. **Market timing**, where the manager changes the positioning (and exposure to other alpha strategies) of the active portfolio through time in line with their market views.

While there is no doubt a "micro" element present in selecting illiquid assets or off-benchmark securities, we would argue that each of these alternative approaches is fundamentally "macro" in nature; i.e. they typically involve altering the risk profile of the portfolio relative to the benchmark, either from a market risk, liquidity or product standpoint.

Ultimately, we believe that credit should be primarily viewed as a "macro" asset class, with portfolio construction and high-level risk factors primarily responsible for determining outperformance, rather than a "micro" asset class where single name selection drives returns.

[5] We previously highlighted allocating to CDS indices as a way of generating alpha relative to corporate bonds, This can be seen as an example of a complexity premium. See *Comparing credit indices: are CDS indices a better investment than corporate bonds?* Tabula Capital Discussion Paper, 17 May 2021.

## References and further reading

Brooks, Jordan, Gould, Tony and Richardson, Scott, Active Fixed Income Illusions (December 17, 2019), published in *Journal of Fixed Income, Spring 2020*.

J.P. Morgan, European Credit Strategy Mid-Year Outlook (June 3, 2014)

Kakwani, Nanak and Podder, Nripesh, On the Estimation of Lorenz Curves from Grouped Observations (1973).

## Appendix I: Methodology for sampling realised distributions of single name alpha

In section 2 we generate a distribution for single name alpha on a monthly basis for three asset classes: global investment grade corporate bonds, high yield bonds and equities. For investment grade corporate bonds we use two ICE indices as our universe for investment grade and high yield corporate bonds, namely the ICE Global Corps (G0BC) Index and the ICE Global High Yield Constrained (HW0C) Index. More information on these indices can be found at https://www.theice.com/market-data/indices/fixed-income-indices. For global equities we use the Stoxx Global 1800 Index as our universe; more information on this index can be found at https://www.stoxx.com/index-details?symbol=SXW1E.

For a given month and index, a distribution of single name alpha is constructed by randomly selecting a sample of *n* securities (*n* is initially set to 200 but is later reduced in Table 2) from the index constituents over 25,000 iterations. The likelihood of a security being selected is proportional to its weight in the index and the constituents chosen for inclusion in the subset are then also weighted in proportion to their benchmark weights. Additionally, for the corporate bond indices the overall weight of each security in the subset is scaled by the ratio of the average benchmark DTS (i.e. duration times spread) to the average subset DTS to ensure a broadly equivalent level of credit risk between the benchmark and subset.

Next, the subsequent monthly return is calculated for both the benchmark index and the subset portfolio; for the corporate bond indices this return is the excess return over treasuries so as to exclude any return attributable to interest rate risk[6]. The single name alpha for this individual sample is equal to the subset return minus the benchmark return.

Later in section 2 we examine the "net" single name alpha, i.e. the remaining single name alpha after transaction costs and fund fees have been subtracted. For an active manager who is able to achieve the *p*th percentile of the single name alpha distribution, this net single name alpha can then be expressed as:

$$\alpha_{Net}(p) = \Phi^{-1}(p)\sigma_\alpha\sqrt{\tau} - S \times D \times \tau - F \tag{1}$$

Where $\sigma_\alpha$ is the standard deviation of the single name alpha distribution, $\tau$ is the annualised portfolio turnover (in excess of any benchmark turnover), *S* is the bid-ask spread in basis points, *D* is the modified duration (equal to one for equities) and *F* is the annual fund management fee. Here we assume that doubling the turnover allows a manager to achieve a given alpha twice as often but decreases the standard deviation of the alpha over six months by the square root of two compared to that over a year.

Equation 1 can also be re-arranged and used to calculate the percentage of the distribution where the net single name alpha is positive by setting the net single name alpha in Equation 1 to zero and solving for $1 - p$:

$$\%\ of\ Scenarios\ with\ \alpha_{Net} > 0 = 1 - p = 1 - \Phi\left(\frac{S \times D \times \tau + F}{\sigma_\alpha\sqrt{\tau}}\right) = \Phi\left(-\frac{S \times D \times \tau + F}{\sigma_\alpha\sqrt{\tau}}\right) \tag{2}$$

[6] In particular, we calculate the mean of the individual bond-by-bond excess returns provided by ICE.

## Appendix II: A theoretical framework for the distribution of single name alpha

As an alternative to measuring the distribution for single name alpha using random sampling, we can use a theoretical model to proxy this distribution. In particular, the standard deviation of the gross single name alpha can be approximated as:

$$\sigma_\alpha = \sigma\sqrt{1-\rho}\sqrt{\left(\frac{2\lambda^2+2\lambda+1-e^{-2\lambda}}{4\lambda}\right)\left(\frac{1}{N}+\frac{1}{n}\right)-\frac{2}{N}} \tag{3}$$

Where $\sigma$ is the annualised percentage volatility of the underlying assets in the benchmark, $\rho$ is the average pairwise correlation between securities in the benchmark, $\lambda$ is a Kakwani-Podder parameter (see Equation 6) that describes the distribution of weights within the benchmark (with $\lambda = 0$ implying an equally distributed portfolio and increasing values of $\lambda$ indicating an increasingly uneven portfolio) and n and N representing the number of securities in the active portfolio and benchmark respectively. This builds upon an approach used in the J.P. Morgan 2014 European Credit Strategy Mid-Year Outlook, where the correlation and volatility of the European single name CDS market is used to build a proxy for the profitability of single name CDS relative value trades through time, in addition to using a "composition factor" as a third contributing term (i.e. the final $\sqrt{\phantom{x}}$ term).

Figure 11 to Figure 13 compare the standard deviation of the sampled single name alpha distribution discussed above with the theoretical standard deviation calculated using Equation 3. In each case, the standard deviations have been calculated for each calendar year (as opposed to each month as shown in the main body of this paper). The results show that the theoretical model presented in Equation 3 is in the vast majority of cases a very close proxy for the "real" distribution of single name alpha in each asset class, albeit with some increasing basis between the theoretical model and reality in recent years for global equities.

*Figure 11: Comparison of actual and theoretical single name alpha standard deviation for global IG corp bonds*

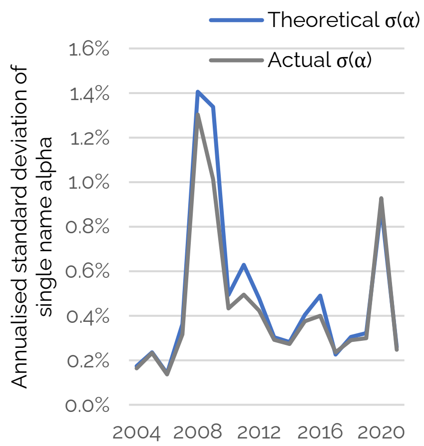



*Figure 12: Comparison of actual and theoretical single name alpha standard deviation for global HY corp bonds*

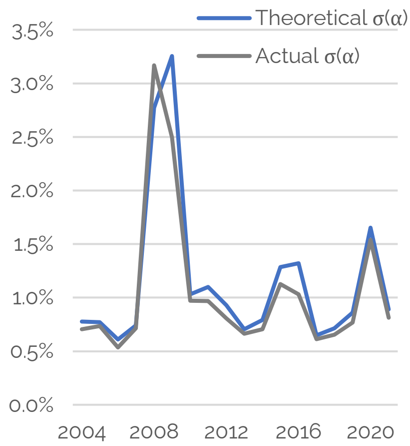
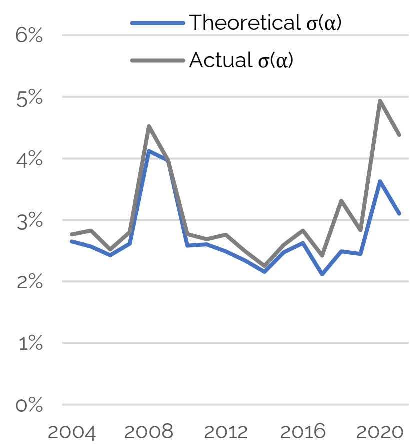



*Figure 13: Comparison of actual and theoretical single name alpha standard deviation for global equities*



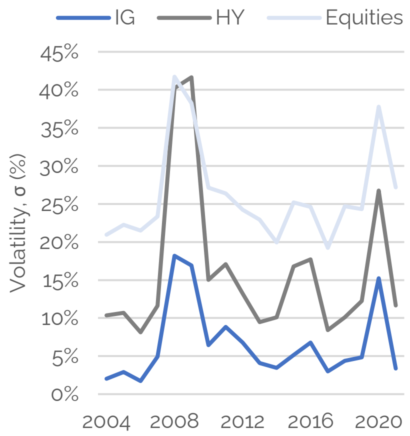

Assumes 200 bonds or stocks in the active portfolio

This theoretical framework for the distribution of single name alpha also allows us to understand which of the three contributing terms – namely volatility, correlation and composition – are responsible for the difference in the standard deviations across asset classes. Figure 14 to Figure 16 show the values of each of the three terms shown in Equation 2 (volatility, correlation and composition factor) across IG, HY and equities, calculated on an annual basis..

As expected, the volatilities (Figure 14) are meaningfully different across each asset class, with the volatility of securities in IG corporate bonds significantly lower than that of HY corporate bonds and lower still on average than equities. We also see that the differing volatility of each asset class is responsible for the distribution of the single name alpha being far more variable in credit than in equities, with the volatility of equities far more stable in relative terms than either IG or HY corporate bonds.

By comparison, the intra-name correlations in each asset class (Figure 15) are broadly similar over time, with no asset class showing meaningfully higher or lower correlation over time. This suggests that there is no merit to an argument that higher intra-name correlations in credit are responsible for a lack of alpha opportunities in the asset class.

*Figure 14: Annualised volatility of securities in each of global IG, HY and equities.*




Assumes 200 bonds or stocks in the active portfolio

*Figure 15: Intra-name correlation of securities in each of global IG, HY and equities.*

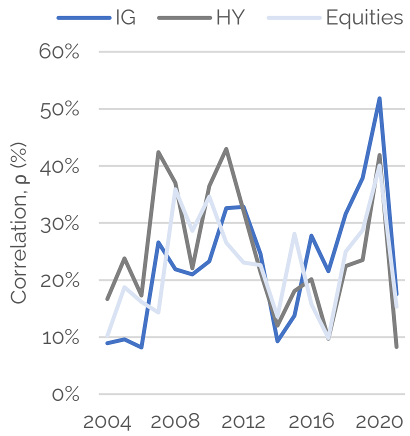
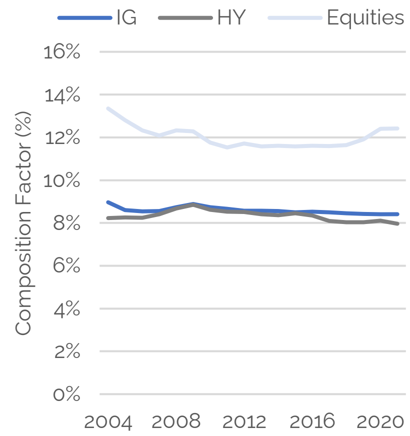



*Figure 16: Composition factor in each of global IG, HY and equities.*




Lastly, the composition factors (Figure 16) appear to widen the distribution of single name alpha in equities relative to credit. This can be explained by the much less equal distribution of weights of securities in typical equity benchmarks compared to corporate bond benchmarks; the mean value of $\lambda$ in the Kakwani-Podder function used in Equation 3 is 4.5 for global equities, compared to 1.6 and 1.7 for global IG and global HY respectively (see Figure 18). This makes intuitive sense in that you would expect to have a large difference between an active portfolio and a benchmark where a small number of mega-caps dominate the benchmark; simply not choosing those mega-caps (or underweighting them) will lead to an outsized difference versus the benchmark return.

**Deriving the theoretical framework**

The starting point for this theoretical framework is to assume that the benchmark index consists of *N* securities, where the return of each security $X_i$ is given by $X_i \sim N(\mu,\ \sigma^2)$ provided that the pairwise correlation, $\rho_{ij}$, between the return of two securities $X_i$ and $X_j$ is equal to $\rho$ if $i \neq j$ and one otherwise. The weight of each security in the benchmark is equal to $\omega_i^B$ such that $\sum_i \omega_i^B = 1$.

The active portfolio consists of *n* securities, each of which are present in the benchmark. The weight of each security in the active portfolio is denoted $\omega_i^A$ such that $\sum_i \omega_i^A = 1$. If a security *i* is not present in the active portfolio then $\omega_i^A = 0$.

The distribution of the return of the active portfolio minus that of the benchmark portfolio can be expressed as:

$$r_\alpha \sim N\left(0, \sum_{i=1}^{N}\sum_{j=1}^{N}\left(\omega_i^A\omega_j^A + \omega_i^B\omega_j^B - 2\omega_i^A\omega_j^B\right)\rho_{ij}\,\sigma^2\right) \tag{4}$$

The sum of the terms for which $i \neq j$ is equal to zero, leaving only the terms where $i = j$ as follows:

$$\sigma_\alpha^2 = (1-\rho)\sigma^2 \sum_{i=1}^{N} \left({\omega_i^A}^2 + {\omega_i^B}^2 - 2\omega_i^A\omega_i^B\right) \tag{5}$$

At this point it can be seen that the cross-sectional variance of alpha is already a function of three terms – namely a correlation term, a volatility term and a composition term – as we describe in Equation 3.

In a simplified case where both the active and benchmark portfolios are equally weighted, the weight of each security in the benchmark is equal to $1/N$ and the weight of each security in the active portfolio is equal to either $1/n$ or zero. In this case the third term reduces to $1/n - 1/N$. However, in reality most benchmark indices are not equally weighted and so we look for a simple way to parameterise the distribution of weights in a benchmark index. In particular, we use a single parameter function in line with that proposed by Kakwani, Podder (1973) as a way of expressing a Lorenz curve (which is used to represent income or wealth distribution) as shown in Equation 6. The cumulative distribution of weights under this function is expressed as:

$$L(x) = xe^{-\lambda(1-x)} \tag{6}$$

where $x \in [0,1]$ and $\lambda$ is a parameter ($\lambda > 0$) that describes the distribution of weights within the portfolio, with $\lambda = 0$ implying an equally distributed portfolio and increasing values of $\lambda$ indicating an increasingly uneven portfolio.

In Figure 17 we fit a Kakwani-Podder function to the composition of the ICE Global Corps Index in December 2021 in Figure 17 and the historical fitted values for the $\lambda$ parameter for IG, HY and equities in Figure 18; this fitting is done using a simple least squares method. It can be seen that the equity benchmark has a far less even distribution of weights than the corporate bond indices[7].

We can also obtain an estimate of how good a representation a Kakwani-Podder function is of the actual distribution in each benchmark using a simple sum of squared errors measurement. This analysis, shown in Figure 19, illustrates that the Kakwani-Podder function is typically a better fit for the IG and HY indices than for equities. Furthermore, the fitting error has noticeably increased in equities in recent years which matches the prior observation that the results of this theoretical approach have diverged somewhat from the actual results for equities in recent years.

*Figure 17: Example fitting of Kakwani-Podder function to benchmark weight distribution for global IG index in December 2021*

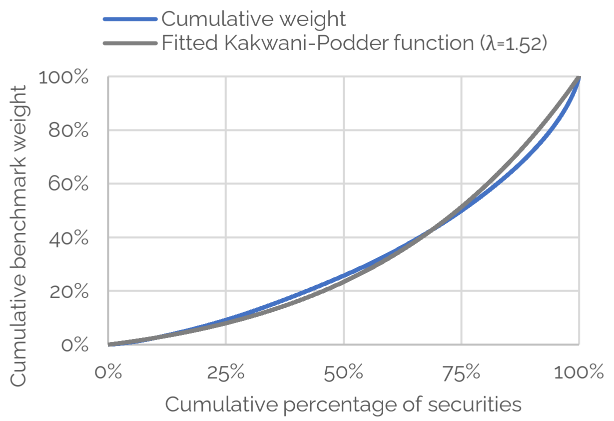
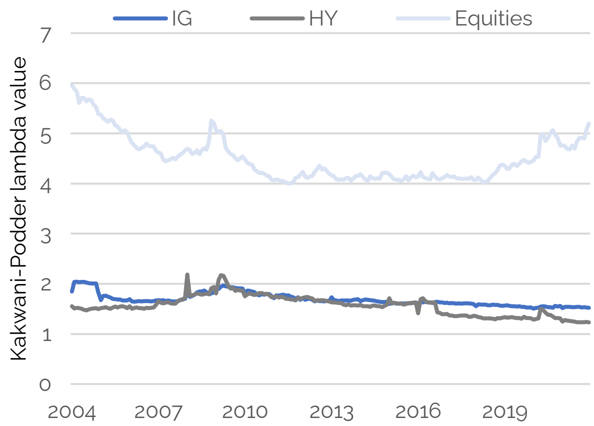
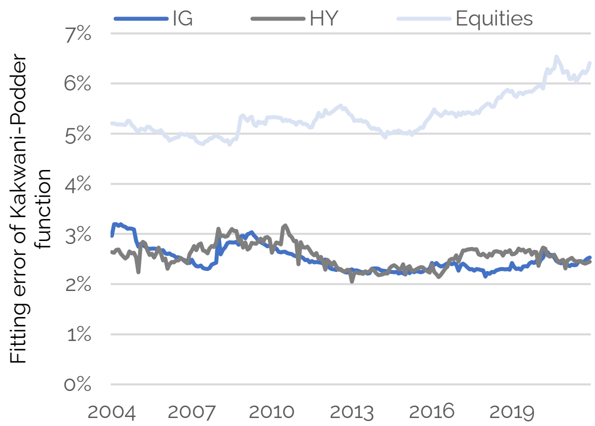



*Figure 18: Kakwani-Podder λ parameter values for IG, HY and equities through time*




[7] The high yield benchmark index is "constrained", meaning that the weights of the biggest issuers are capped at 2%. However, this has minimal impact on the benchmark composition and the Kakawni-Podder fitting. For example, in the December 2021 composition only one issuer (Pemex) exceeded the 2% weight cap, with the uncapped weight of 2.02% only marginally exceeding the 2% cap.

*Figure 19: Fitting error for Kakwani-Podder function for IG, HY and equities through time.*




Finally, we note that the weight of the security at the *x*th percentile of the benchmark index can be expressed as $L'(x)\,dx$ and then, using the assumption that the weights of securities in the active portfolio are proportional to their weights in the overall benchmark, re-express the third term of Equation 5 as follows:

$$\sum_{i=1}^{N}\left({\omega_i^A}^2+{\omega_i^B}^2-2\omega_i^A\omega_i^B\right)=n\int_0^1\int_0^1\left(\frac{L'(x)}{n}-\frac{L'(y)}{N}\right)^2 dxdy+\frac{(N-n)}{N^2}\int_0^1 L'(x)^2dx \tag{7}$$

Inserting $L'(x)=(1+\lambda x)e^{-\lambda(1-x)}$ we can then express Equation 5 as:

$$\sigma_\alpha^2=(1-\rho)\sigma^2\left[\left(\frac{2\lambda^2+2\lambda+1-e^{-2\lambda}}{4\lambda}\right)\left(\frac{1}{N}+\frac{1}{n}\right)-\frac{2}{N}\right] \tag{8}$$

which is equal to Equation 3 when taking the square root of both sides.

## About the authors

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## About Tabula Capital

Tabula Capital believes that credit investors should not have to compromise on fees, liquidity or default risk. Higher quality returns can be found by investing in liquid credit index instruments, using a core systematic approach combined with an active management overlay.

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