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Keep Calm and Stay Market Neutral

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This is the twenty-fourth edition of our Quantcraft series. This periodical outlines new trading and analytical models across different asset classes.

This Quantcraft report outlines a framework for building market neutral portfolios across asset classes. It focuses on two pillars: confidence and diversification.

Confidence relates to whether or not the projected statistics of a strategy prior to launch can be trusted on, and - if not - what adjustments must be made to it. It also relates to strategy sizing and portfolio sizing, as both go live.

Diversification relates to the incremental value-add of each return stream relative to others. Candidate strategies should be assessed and aggregated according to that principle.

Our work utilises a combination of techniques from classical and modern statistical theory, and our conclusions rely upon thousands of trials from datasets that, albeit simulated, were calibrated onto real-world data. We conclude that:

- All information pertaining to strategy development should be recorded so that the investor can project future returns more efficiently.
- Strategies that are uncorrelated by design should be aggregated with simple risk-based methods. Should there be a strong covariance structure, however, the investor should favour methods that are less dependent on estimation error.
- Investors should favour a somewhat Bayesian approach to strategy sizing. Compare the updated performance with its prior and re-size the strategy accordingly.
- Investors should also favour dynamic portfolio sizing. Such may lead to lower Sharpe ratios, but a far better drawdown profile.

Figure 1: Keep calm and stay market neutral

Source: Deutsche Bank.

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Keep Calm and Stay Market Neutral

1. Introduction

When building portfolios, investors typically target two features: convexity and market neutrality. At times they will focus on one or the other, and at times on both.

Our prior research has focused on convex portfolios; specifically, those that maximised left-hand-side convexity. We argued in Anand et al (2019) that portfolios that combined systematic strategies with a protection goal should be comprised of naturally convex inputs, and that the aggregation process should focus on minimising *bleed* and *basis risk* while also maximizing *convexity*. Needless to say, defensive portfolios have been recently rewarded.

Today's *Quantcraft* report focuses on the other type – the market-neutral portfolios. When it comes to those, convexity is less of a priority as convex strategies take on big market-directional exposures - the very thing the market neutral investor wants to avoid. Our targets are now distinctly different; we look for stable, uncorrelated returns. And to achieve them, our aggregation process will focus on maximising *return confidence* and *diversification*.

This report evaluates return confidence in Sections 2 and 4, first focusing on construction robustness and later on capital allocation in light of differences between expected and live performances. Concepts such as overfitting risk and factor momentum will be used extensively in these sections. Section 3 assesses different algorithms aimed at enhancing diversification, thus defining our preference on how to aggregate the starting capital to each candidate strategy. Section 5 addresses portfolio sizing with drawdown limits and Section 6 concludes.

2. Assessing confidence in a strategy

"Confidence" is about what to expect from future performance. It is often confused with *timing* the strategy, which we believe is wrong. Confidence methods do not assess the likely performance in light of external conditions, as timing does, and instead they focus on the risk of strategy overfitting or that the inherent alpha has ceased to exist.[1]

This section addresses construction robustness, and introduces techniques that show a more holistic (and realistic) picture about future performance. We discuss 3 techniques:

- Probability of overfitting: the likelihood that the "alpha" actually exists. It can be used to validate an investment factor, or a market pattern. The method requires some knowledge of the research process, though it does not need live returns data.
- Sharpe ratio p-value: the "alpha" may exist, but our implementation may have been overfit. It evaluates the stability of our return stream in relation to number and type of trials, or versus a prior expectation. While this technique does not require live data, it requires detailed knowledge of the signal generation process. A related statistic – the *probabilistic Sharpe ratio* – can however be estimated without knowledge of the process.
- Probability of divergence: how out-of-sample performance compares with the in-sample. We project the distribution of cumulative returns applicable to each out-of-sample date in the future, and compare it with the actual progression of out-of-sample (or live) returns. This approach does not require any knowledge of the actual research process, but needs some live – or true out of sample – data on the strategy.

These techniques are additive and generic enough to apply to any potential return stream. But before going into each in detail, we first outline our test environment. We opt for a controlled dataset – in other words, simulated data – as it allows us to best measure the efficacy of these methods under different assumptions.

We simulate 2 systematic strategies:

- A time series momentum strategy. Albeit simple, the characteristics are similar to other CTA strategies in regards to construction and parameterisation. While it would be controversial to include it in market

[1] Timing methods, for instance, assume the strategy has been built using best practices and that its return characteristics are unlikely to structurally change.

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neutral portfolios, we add it to this section to illustrate the power of the techniques above.

- A cross-sectional strategy based on generic signals, which is both long and short baskets of assets in order to achieve market neutrality.

2.1 Simulating a trend following strategy

We start with a simulated trend following strategy, motivated by the fact that price action data often produces "mirages"; in other words, that random walks often appear to exhibit a trend structure.

The trend strategy is applied to 50 simulated assets, all assumed to be uncorrelated to one another. The 1-month returns of each follow a first order autoregressive process:

$$r_t = a + b \times r_{t-1M} + e_t$$

where there is no natural 1-month return drift ($a = 0$), asset volatility is set to 10% per annum, and returns are Gaussian. Each simulation assumes 2,500 datapoints, which is equivalent to 10 years of daily data. The 1-month returns are converted to daily returns through a Brownian bridge process[2].

As the reader may suspect, the parameter b is key to our analysis. It decides whether or not the subsequent series trends naturally, and therefore whether or not to trust the results from a trend following strategy applied to it. We set b as follows:

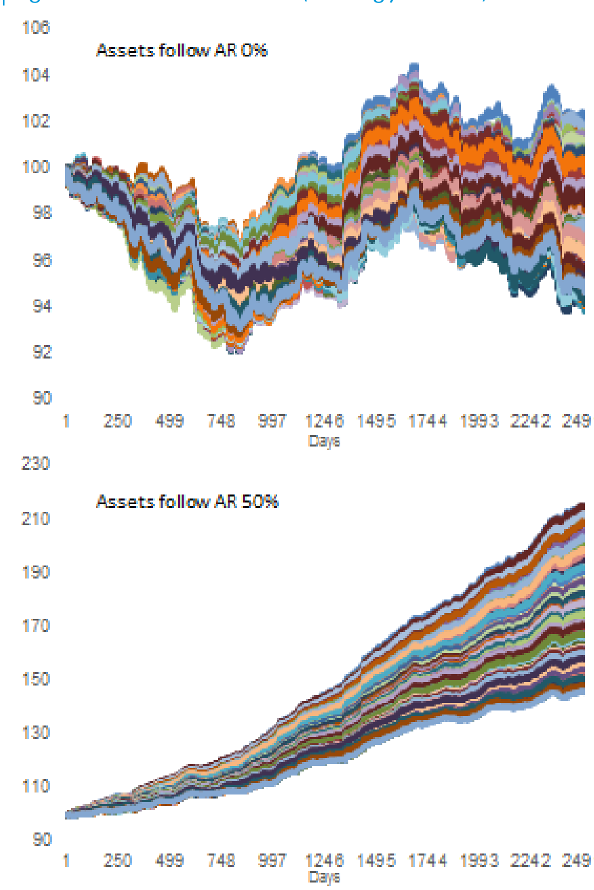
- $b = -0.5$: asset returns are mean-reverting over a 1-month horizon. A trend following strategy applied to this configuration, if focused on identifying the parameter set that maximises returns, should be overfitted and its backtest returns are unlikely to persist in the future.
- $b = 0$: asset returns are neither mean-reverting, nor exhibit momentum. A trend following strategy applied to this stream should also be overfitted.
- $b = 0.5$: asset returns exhibit strong trendiness over a 1-month horizon. As this asset is naturally trending, strategy returns should not be overfitted.

As for the strategy itself, we apply a simple moving average (MA) cross-over model based on 2 parameters: a short-term MA and a long-term MA. The strategy buys when the short-term MA is at or above the long-term equivalent, and sells otherwise. The short-term MAs range from 3 days to 3 months, whereas the long-term MA windows range between 9 and 12 months.[3]

For a given autodependency profile, we build multiple strategies by iterating through all possible cross-over MA combinations. This provides us with 3,776 combinations – i.e. trials – for each value of b.

The trend following portfolio is comprised of 50 independent trading strategies, each applied to an individual asset and with equal risk allocation to each. The portfolio is rebalanced on a daily basis.

Figure 2: Simulation trials (strategy wealth)



Source: Deutsche Bank

[2] A Brownian bridge is a continuous-time stochastic process B_t whose probability distribution is the conditional probability distribution of a Wiener process w_t subject to the condition that the process is pinned at the edges. Following are the steps to convert monthly to daily prices.

1. Convert annualized 1M volatility to daily volatility, $\sigma^D = \sigma^A / sqrt(252)$..
2. Estimate average daily return from monthly prices, $\mu^D = ({P_t^2}/{P_t^1} - 1)/21$.
3. Sample returns from a Normal distribution, $W_t = N(0,1) * \sigma^D$.
4. Adjust the returns to match the daily average, $B_t = W_t - \overline{W_t} + \mu^D$.
5. Convert daily prices from daily returns, $P_t^B = P_t^1 \prod_{t=0}^{t=20}(1 + B_t)$.
6. Equate the past price to the monthly price. $P_{21}^B = P_t^2$

where P_t^1 and P_t^2 are monthly prices, and σ^A is the annualised volatility.

[3] These boundaries have been set such that the average lookback does not deviate significantly from 1 month – the calendar period of interest in our simulated series.

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Figures 2 and 3 display the simulated trading strategy results.

2.2 Simulating a generic cross-sectional strategy

Simulating cross-sectional strategies is less straight forward, though equally important as these lie at the core of long-short factor investing and alternative risk premia strategies.

The simulation exercise is distinctly different from that of Section 2.1. Here we introduce 2 sets of variables: asset returns, and the factor score for each asset. They relate to one another through the rank correlation coefficient – in other words, the non-linear correlation between *current* factor score and *future* asset returns.

We define the two as per following processes:

$f_t = z_t^{(1)}$ is the asset exposure to a given factor at time t;

$r_{t+1M} = \sigma_{r_{t+1M}} \times \left(z_t^{(1)} \times \rho + z_t^{(2)} \times \sqrt{1-\rho^2}\right)$ represents the asset return one month into the future.

f_t and r_{t+1M} are related through a bi-variate Gaussian distribution, as calibrated by the parameter $\rho = 2 \times \sin(\rho^* \times \pi/6)$[4]. Most importantly, this allows us to set ρ^*, the Rank Information Coefficient, as the governing parameter in our simulated dataset. $z_t^{(1)}$ and $z_t^{(2)}$ are both Standard Normal variables.

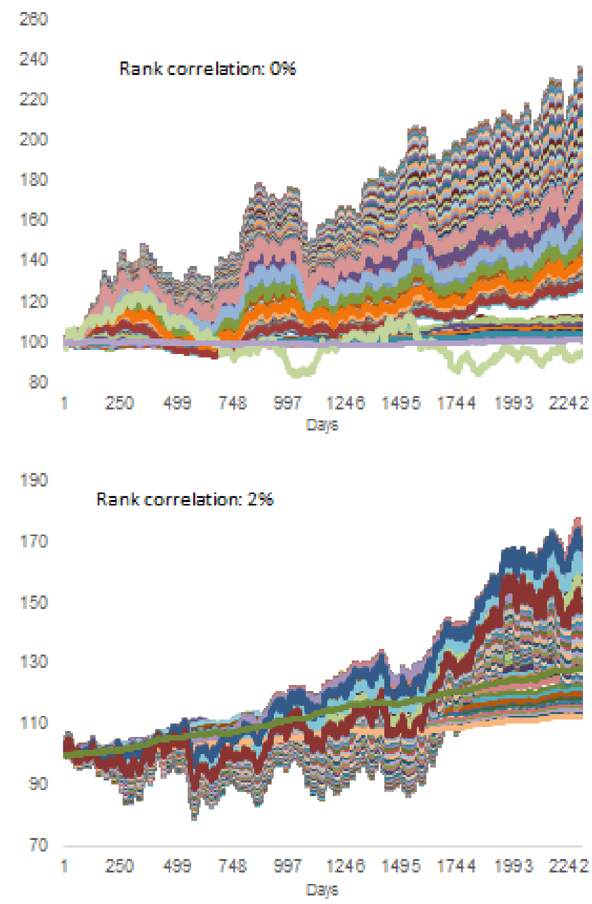
Asset returns are uncorrelated to one another and are also normally distributed with 10% annualized volatility and zero drift. We simulate 1,000 assets and 2,500 time steps in each.[5]

The trading strategy ranks assets according to factor score, as standard in a cross-sectional strategy. As before, we generate strategy trials by looping through the values of 2 parameters, though in this context they are distinctly different:

- N: the number of assets in each long and short basket, ranging from 1 to 500.
- λ: a decay factor that defines the weight allocation across assets inside each basket. In other words, $w_{i,t,} = 0.5^{n \times \lambda}$, where $n = [1, \ldots, N]/N$ and where $\lambda \epsilon [0,1000]$ in 7 steps.

This produces 3,500 trials for each ρ^* value. The factor portfolio is long the basket of top ranked assets and short the opposite basket, and it rebalances at every time unit – in other words, every month.

Figure 3: Simulation trials (strategy wealth)



Note: used ranked correlation of 0.1% instead of 0% so as to get a greater quantity of simulations with high Sharpe ratios. Source: Deutsche Bank

Having defined our simulated environment, it is now time to introduce our testing techniques.

2.3 Technique #1: Probability of Backtest Overfitting (PBO)

As noted before, this technique focuses on whether or not the "alpha" exists. If a strategy configuration that systematically outperforms other configurations in-sample (IS) continues to do so out-of-sample (OOS), the probability of backtest overfitting is low.[6]

Importantly, this technique allows for the best in-sample strategy configuration to change at every trial. Therefore, if the best configuration at every possible trial systematically underperforms other configurations once it goes out-of-sample, one should question whether the "alpha" we want to capture really exists.

[4] See Croux and Dehon (2010).
[5] Equivalent to 10 years of daily data.
[6] Introduced by Bailey and Lopez de Prado (2015).

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The first step to quantify the PBO is to build a sampling procedure denoted by Bailey and Lopez de Prado (2015) as *combinatorically symmetric cross validation* (CSCV). It works as follows:

1. We build a matrix M of order $T \times N$ by collecting returns from each trial. There are N trials and T is the length of each full backtest.

2. We partition M across rows, into an even number S of disjoint sub-matrices of equal dimensions, i.e. T/S rows and N columns in each submatrix. S is chosen as a balance between number of partitions – the more, the better – and autodependency risk between blocks – the less, the better. We opt for $S = 16$ as per authors.

3. We form blocks comprised of in-sample and out-of-sample sets. Each set is comprised of $S/2$ (i.e. 8) sub-matrices, where the constituents of the OOS set are complementary to those of the IS. All combinations are evaluated, thereby leading to ' S choose $S/2$ ' (12,870) blocks[7], each of which containing one in-sample and one out-of-sample set.

4. We find, in each training set, the strategy configuration that yields the highest Sharpe ratio. We then calculate its ranking relative to other configurations in the out-of-sample set and standardise that ranking: $w = r/(N+1)$.

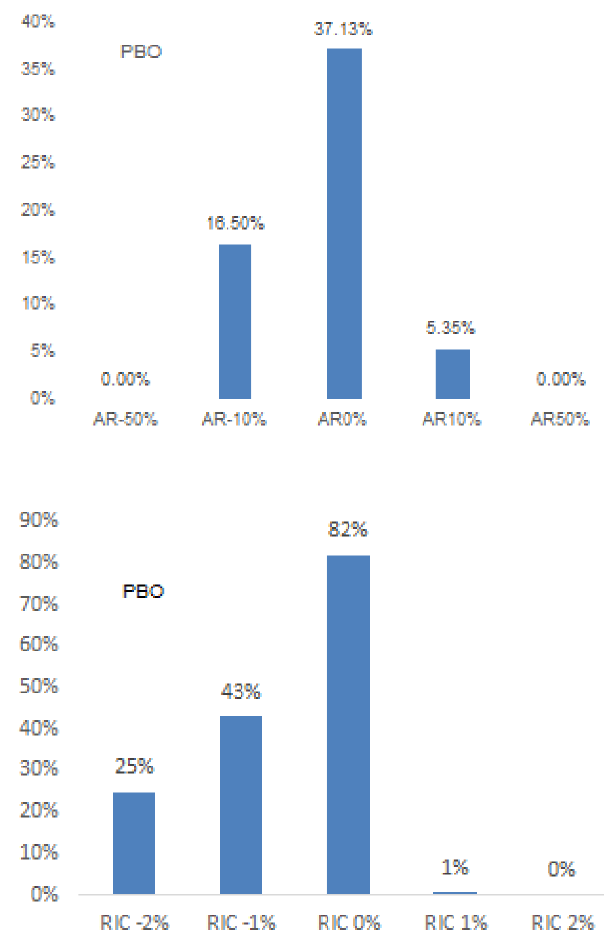
5. We compute the logit value associated with each IS-OOS combo in Step 4 as $\lambda = \log w/(1-w)$. High logit values imply consistency between IS and OOS performance, which suggests low risk of overfitting.

6. We form a distribution of logit values from Step 5, which we then use to calculate the probability of backtest overfitting[8]. As per Lopez de Prado (2015), we interpret it as the probability associated with in-sample optimal strategies that underperform out-of-sample. It is calculated as the number of instances when λ was below zero divided by the total number of λ observations. In other words, *the percentage of instances when the best in-sample strategy ranked among the worst half in the out-of-sample period.*

Figure 4 plots our results for both time series and cross-sectional strategies. We note the following:

- In the former, the higher the b coefficient, the more likely that asset returns are positively autocorrelated and hence the more likely that there is "alpha" in trend following. The probability of backtest overfitting drops as b rises.
- The higher the ranked correlation between current factor score and future asset returns, the more likely that there is "alpha" to be harnessed in the factor strategy. The probability of backtest overfitting drops as the ranked correlation rises.

Figure 4: Probability of overfitting – time series and cross-sectional strategies



Source: Deutsche Bank

2.4 Technique #2: Sharpe Ratio P-Value (SRP)

This technique provides an estimate of confidence on the reported Sharpe ratio based on available information about the backtest process. As the reader may suspect, it estimates a distribution of Sharpe ratio values and compares the backtest against it. The more that the estimate lies at the far right of the distribution, the lower

[7] 16-choose-8.
[8] $\phi = \int_{-\infty}^{0} f(\lambda) d\lambda$

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the p-value and therefore the lower the likelihood that our parameters have been overfitted.

While this technique favours using all backtest trials from the research process as inputs, it is also generic enough to accept instances when that information is not available. We therefore start with the latter case - when all we know is the time series of strategy returns - and utilise the approaches taken by Lo (2002) and Bailey and Lopez de Prado (2014).[9]

As standard when estimating p-values, we must first define the "null" hypothesis and, from there, estimate how likely our statistic is to vary from it. Our null hypothesis is that the strategy's true Sharpe ratio is zero[10], and the likely variation is defined as a function of the reported Sharpe and the number of observations used in order to calculate it. Given the relevance of higher order moments in financial data, we also estimate skewness and kurtosis from our backtest returns. The steps are:

1. We calculate the Sharpe ratio of returns using the highest data frequency available; in the case of daily returns data, we calculate the *daily* Sharpe ratio.

2. We subjectively define the *null* hypothesis that our Sharpe ratio is zero, i.e. $SR_0 = 0$.

3. We calculate our threshold value as:
$$\widetilde{SR} = \frac{(SR - SR_0)\sqrt{T-1}}{\sqrt{1 - \gamma_3 SR + \frac{\gamma_4 - 1}{4} SR^2}}$$
where T is the number of observations used to estimate the reported Sharpe ratio – in our case, the number of business days, γ_3 is the skew of (daily) returns, and γ_4 represents kurtosis.[11]

4. We calculate the p-value associated with this threshold as: $SRP = 1 - \Phi[\widetilde{SR}]$, where $\Phi[x]$ is the cumulative Standard Normal distribution.[12] The p-value can be interpreted as usual; a p-value below 0.05 indicates that the risk of overfitting from the current backtest configuration is low.

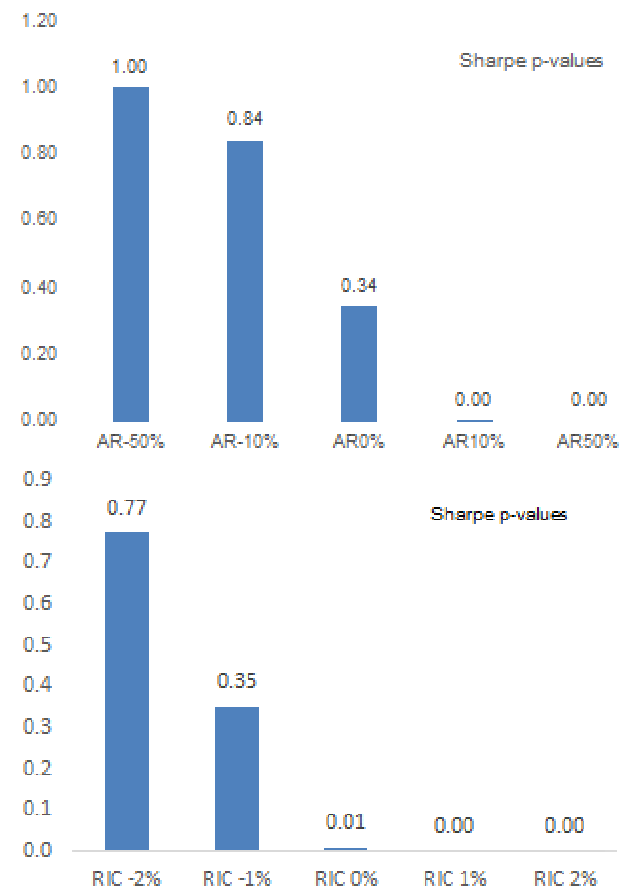
While the procedure above is an appropriate starting point, it can be further improved if one has access to all backtest variations used when building the strategy. In this case, the *null* Sharpe ratio from Step 2 can be modified as follows:

$$SR_0 = \sqrt{V[\{SR_N\}]}\left((1-\gamma)\Phi^{-1}\left[1-\frac{1}{N}\right] + \gamma\Phi^{-1}\left[1-\frac{1}{N}\right]e^{-1}\right),$$

where γ is the Euler-Mascheroni constant,[13] $\Phi^{-1}[x]$ is the inverse Normal cumulative distribution function, and N is the number of *independent* trials attempted when building the strategy.

All other steps used to estimate the p-value are the same as per first technique, and so is the interpretation of the SRP.

Figure 5: Sharpe p-values for time series and cross-sectional strategies



Source: Deutsche Bank

[9] Bailey and Lopez de Prado (2014) define this as the Probabilistic Sharpe Ratio. In fact, the SRP measure is a slight modification of two techniques used by the authors: Probabilistic Sharpe Ratio and Deflated Sharpe Ratio.

[10] One can subjectively define the null hypothesis.

[11] If we assumed that strategy returns are Gaussian, the equation simplifies to a simple z-score, i.e. $\widetilde{SR} = \frac{SR-SR_0}{\sigma_{SR}} = \frac{SR-SR_0}{\sqrt{\frac{1+0.5\times SR^2}{T}}}$.

[12] We apply the Standard Normal Distribution as Sharpe ratios are assumed to be asymptotically Gaussian, as per Lo (2002). This also helps explain the inclusion of skew and kurtosis to our standard error estimate and not elsewhere.

[13] The difference between the harmonic series and the natural logarithm. $\gamma = 0.58$ when estimated to the second decimal place.

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While potentially more powerful, this second approach[14] has its own challenges.

First, it relies upon access to all backtest attempts – which is often hard to come by.

Second, the approach originally focuses on independent trials. Such focus raises two questions: how to estimate independence, and whether we should also include correlated trials. We favour hierarchical clustering to address the first question, as per Lopez de Prado (2016), which is consistent with hierarchical risk parity and therefore contains similar benefits.[15] As for the latter question, we favour subjectively assessing the sensitivity of our p-value to the number of trials assumed. Such approach allows the researcher to form an informed view on the likely p-value of a given test.[16]

Figures 5 and 6 show our p-value estimates, according to different approaches, applied to the simulated strategies introduced in Section 2.1 and 2.2. As with Section 2.3, the results are in line with intuition.

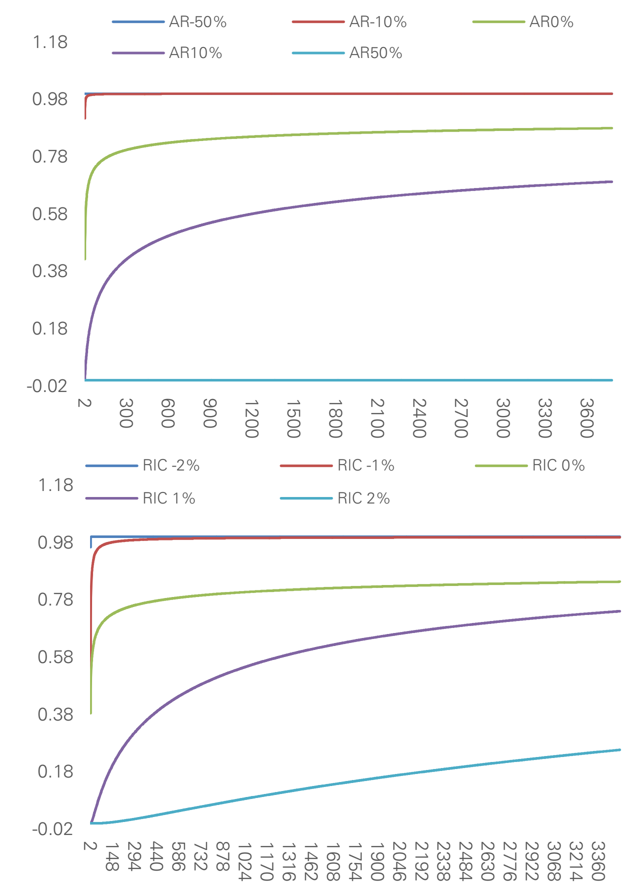
In Figure 6, we plot the p-value of a strategy with different null Sharpe ratios as measured by varying the number of trials but using the same variance estimated from all strategy trials.

2.5 Technique #3: Probability of Divergence (PoD)

The Probability of Divergence is our third and final technique. It applies to instances when we have no access to the research process – in other words, we only have one series of cumulative strategy returns with both backtest and live (or true out of sample) data.

In short, this technique evaluates how a sequence of observations relates to its original distribution. It doesn't diagnose over-fitting per se – as divergence could come from other culprits[17] – but it can be used in conjunction with other techniques.[18]

Figure 6: Deflated Sharpe ratio p-values (Y-axis) according to number of trials (X-axis) for different AR(1) assumptions



Source: Deutsche Bank

The process is as follows:

1. We first cut the returns data into two samples: backtest and live.[19]

2. We transform the backtest returns from daily to weekly, non-overlapping. Weekly returns strike a balance between more quantity and less noise, thereby still preserving the desired memory effects.

3. We fit an $AR(p)$ model to the returns from Step 2, so as to correct for auto-dependencies.

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[14] Defined as Deflated Sharpe Ratio, following Bailey and Lopez de Prado (2014).

[15] The number of clusters represents the number of independent trials.

[16] One idea is to separately calculate the p-value statistic using 3 assumptions: (a) independent trials, (b) all trials and (c) all trials whose average pairwise correlation to the rest is below a given threshold – say, 0.5.

[17] Examples include the time-varying nature of strategy returns, "alpha" decay and structural market changes.

[18] As per Lopez de Prado (2013), this technique was originally designed to assess fund manager performance versus the benchmark.

[19] Alternatively, the live period can be replaced by true out of sample.

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4. We fit a Gaussian Mixture model (GMM) with 2 Gaussian distributions to the *residuals* of the $AR(p)$ model above.[20] We use the Variational Bayesian method to fit the GMM, which outputs marginal distributions of first moment parameters and a joint distribution of the second moment parameter. In other words, we get 2 marginal mean distributions and 2 marginal variance distributions, and ultimately calculate the 2 marginal Gaussians through variational inference (see Appendix 1). These are sampled separately and blended through a mixing parameter, π. Mathematically we have

$$p(\mathrm{x}) = \sum_{\mathrm{z}} p(\mathrm{z})p(\mathrm{x}|\mathrm{z}) = \sum_{k=1}^{K} \pi_k N(\mathrm{x}|\mu_k, \sigma_k^2),$$

where $p(\mathrm{x})$ denotes the marginal distribution of data x, z is a binary variable in which a particular element z_k equals to 1 and all other elements equal to 0, and K corresponds to the number of Gaussian components.

5. We sample 10,000 trials from the GMM distributions defined in Step 4, where each trial contains the same number of observations as the live period, added up. Each observation is sampled from the GMM distributions using the $AR(p)$ model from Step 3. In other words:

$r_t^* = \sum_i b_i r_{t-i} + e_t$, where the first observation r_{t-1} is sampled randomly from the in-sample data set and e_t is sampled from the GMM described earlier. r_t^* relates to projected (simulated) returns from the start of the live period onwards, hence the different notation.

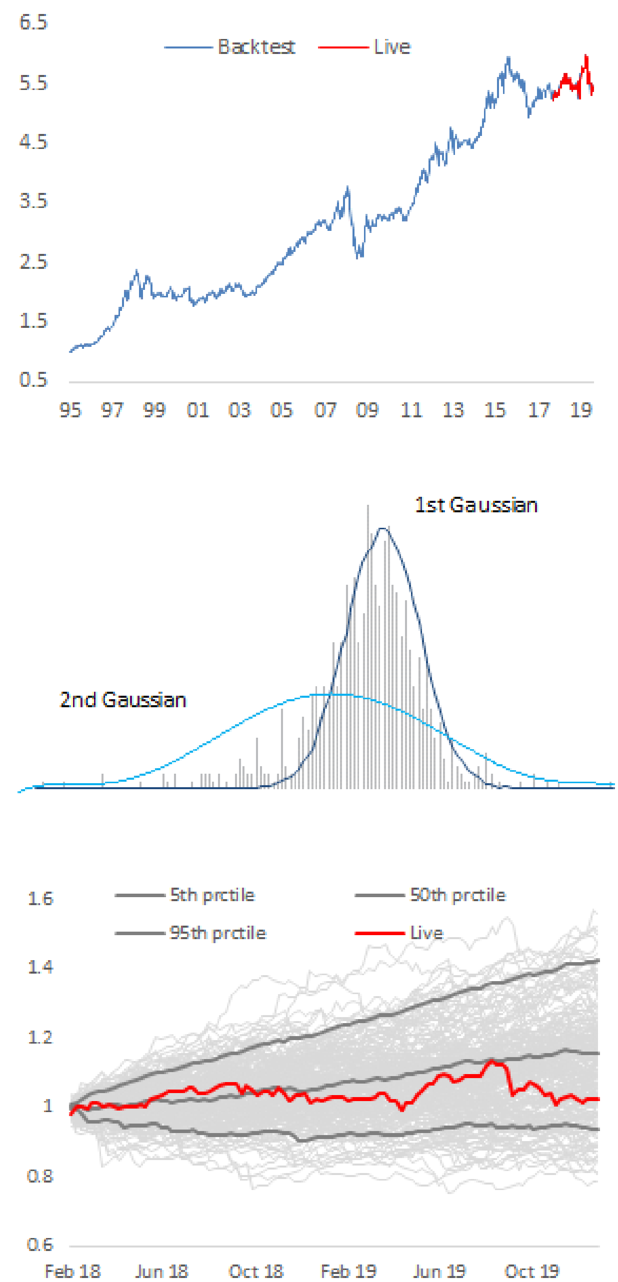
6. We calculate the Probability of Divergence according to the following formula:

$PoD_{R_t,t} = 2 \times |\Theta[R_t, t] - 0.5|$, where $\Theta[x, t]$ is the empirical cumulative density assessed at time t and R_t represents the actual cumulative returns from live date until t. In other words, $PoD_{R_t,t}$ *measures the live data's percentile rank relative to our projections from the backtest, and therefore its proportional departure from the median.*

Figure 7 illustrates the process. The cones represent the 5th and 95th percentiles of our projected distributions, re-calculated at every new point in time.

Needless to say, the PoD also benefits from attractive visual characteristics.

Figure 7: Probability of divergence



Source: Deutsche Bank

[20] We used 2 Gaussian distributions (and not more) for simplicity, as in line with Lopez de Prado (2013).

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3. Defining the initial strategy weights

We now move on to strategy sizing. We assume that all return streams used from here onwards have passed the robustness checks set out in Section 2, and focus on how to allocate the *initial* capital to each strategy as we launch our market neutral portfolio.

As highlighted earlier, diversification is a key pillar of market neutral portfolios. As we cannot infer which strategy will outperform in the future, the aggregation process should maximize the diversification potential that each qualifier brings. As such, we favour risk-based aggregation methods and will focus part of this section on comparing candidate algorithms.

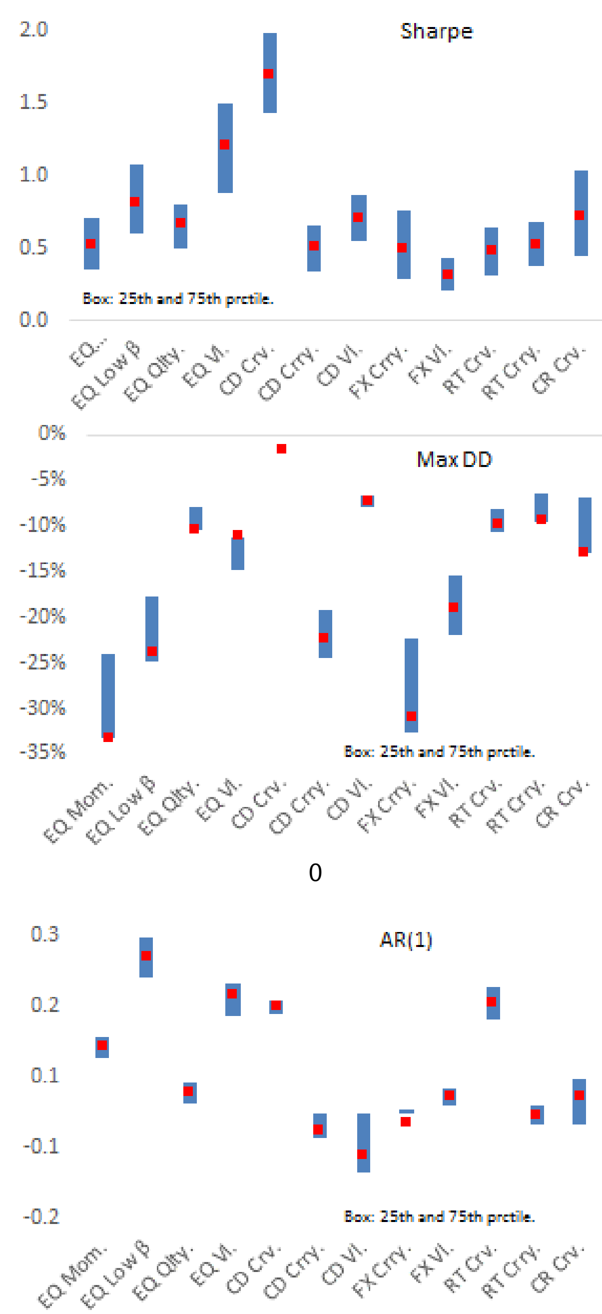
But prior to that, we must define the universe of qualifying strategies and our test environment. In order to be more realistic from this point onwards, we opted against the simulated strategies and selected 12 strategies from DB's live index suite instead. These are traditional return streams and primarily market neutral – either by nature or through beta neutralisation[21]:

- Cash Equities: Momentum, Low Beta, Quality and Value;
- Fixed Income: IRS Carry (cross-market and single market), and Credit Carry (single market);
- Foreign exchange: Carry and Value;
- Commodities: Carry (cross-market and single market) and Value.

Our trials will be based on *stationary bootstrapping*, a sampling technique designed by Politis and Romano (1994) that is largely applicable to weakly dependent time series. It uses blocks of random length to generate samples, where – as recommended by the authors – the average block size is 10% of the dataset. [22] The resampling procedure works as follows:

1. We randomly pick a start point in the data set.
2. We sample a number from the uniform distribution, and compare it to p, the main parameter governing the Geometric distribution of block sizes.[23]
3. If the number sampled in Step 2 is greater than or equal to p, we add a subsequent observation to the block started in Step 1; in other words, the block size expands by 1 observation. We then repeat Step 2.
4. If the number from Step 2 is less than p, we stop, thereby completing the current block size and starting a new one.

Figure 8: Distribution of Sharpe, Max DD, and AR(1) Coefficient



Source: Deutsche Bank

[21] For examples of the latter, see Anand et al. (2018).

[22] Stationary bootstrapping has two advantages. First, the sampling output is less sensitive to the block size, and it is therefore less subject to errors when estimating the auto-dependency structure of the data. Second, it allows for greater variation in the simulated drawdowns. These were key in our choice versus other bootstrapping methods available.

[23] In our case, $p = \frac{1}{0.1 \times N}$, where N is the number of datapoints in the whole set. When dealing with 20 years of daily data, $p = 0.02$.

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Figure 8 shows the distribution of 2,000 simulated paths using stationary bootstrapping for each of the 12 strategies above. We see that for all 3 statistics of interest – Sharpe ratio, maximum drawdown and AR(1) coefficient – the distribution of simulated statistics is centered around the values observed using the original data set. Note that, while we focused on backtested data, we also reach the same results when using live index data.

These results are reassuring; they suggest we can apply this approach to test our aggregation methods using far more than just backtested data. That said, we highlight two further observations:

- To ensure further stability, we removed trials whose maximum drawdown statistic sat outside the 25th – 75th percentile range, thereby narrowing it down to 1,000 trials.
- As the trials of each strategy are generated separate from those of other strategies, we are ignoring the observed co-variance structure of the 12 strategies. That said, we note that they were chosen partly due to low co-dependencies to start with, as we are after a market neutral portfolio, and hence this is less of a concern.

3.1 Risk-based capital allocation

We can now introduce 5 candidate aggregation algorithms suitable for market neutral portfolios. They are all risk-based methods; in other words, they focus on higher order return moments and not on expected returns. This is in line with our premise that strategy returns are hard to predict and that market neutral portfolios should focus on enhancing diversification instead. The algorithms are:[24]

- Inverse Volatility Weights (IVW): each strategy is weighted in inverse proportion to its empirical volatility. Lower allocations are given to high volatility strategies and higher allocations to low volatility strategies. This method ignores correlations.
- Maximum diversification (MD): this algorithm solves for strategy weights that maximise the distance between the (weighted average) volatility of each underlying portfolio and the overall portfolio volatility. It seeks to maximise diversification potential based on historical data, and therefore also accounts for strategy correlations.
- Equal risk contribution (ERC): ERC solves for individual weights such that all strategies contribute the same amount of risk to the portfolio. "Risk" is defined as empirical volatility and is estimated using past data. The method is similar to IVW, but different in that it also accounts for strategy correlations.
- Minimum Variance (MV): this algorithm solves for the weights that minimise the risk of the whole portfolio. It overweights strategies with lower volatility or correlations to the rest of the portfolio.
- Hierarchical risk parity (HRP)[25]: introduced by Lopez de Prado (2016), this is another variation of the risk parity concept. Crucially, it is free of optimization in its natural form[26] and is therefore less sensitive to co-variance noise. The algorithm uses hierarchical implementation of inverse-variance weights, separated according to clusters of similar strategies.[27] Capital is therefore first divided between groups of strategies, as opposed to between strategies at the outset.[28]

We applied these 5 portfolio construction techniques to build the long-only portfolios of 12 strategies – a total of 1,000 portfolios.[29] We rebalanced the positions quarterly, and included costs while calculating the P&L. We also attached an upper boundary of 20% to all strategies.

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[24] See Natividade et al. (2013) and Lou et al. (2013) for a summary of all formulae.

[25] See Lopez de Prado (2016).

[26] That said, one would require optimisation should there be weight constraints on individual strategies.

[27] A similar method, called *Handcrafting*, has also been proposed by Carver (2017) where inputs are allocated between clusters and also within clusters through equal risk allocation.

[28] The algorithm works in three stages:
1. Hierarchical clustering: in this step, we group a set of strategies based on their correlation coefficients. It is a bottom-up procedure where strategies originally represent single clusters, and are sequentially joined into larger clusters until the full hierarchical structure is attained. We have used the *single-linkage* method to determine the hierarchical structure of inputs.
2. Quasi-diagonalization: this step uses the information obtained from Step 1 to rearrange the covariance matrix into a more diagonal representation. In other words, the rows and columns of the correlation matrix are re-organised such that similar strategies are placed together and dissimilar inputs are placed far apart.
3. Recursive capital allocation: in this final step, the weights of the strategies are calculated as the inverse-variance allocation between two clusters applied recursively by splitting the covariance matrix until only one input is contained in each cluster. The similarity between strategies is taken into account while deciding the border objects of the sub-clusters. Here, we use *maximum dissimilarity* – the allocation is performed exactly along the cluster dendrogram. For a visual example, see https://online.stat.psu.edu/stat555/node/86/.

[29] As we have 1,000 trials of each strategy, the total number of portfolios is also 1,000 for each portfolio construction method.

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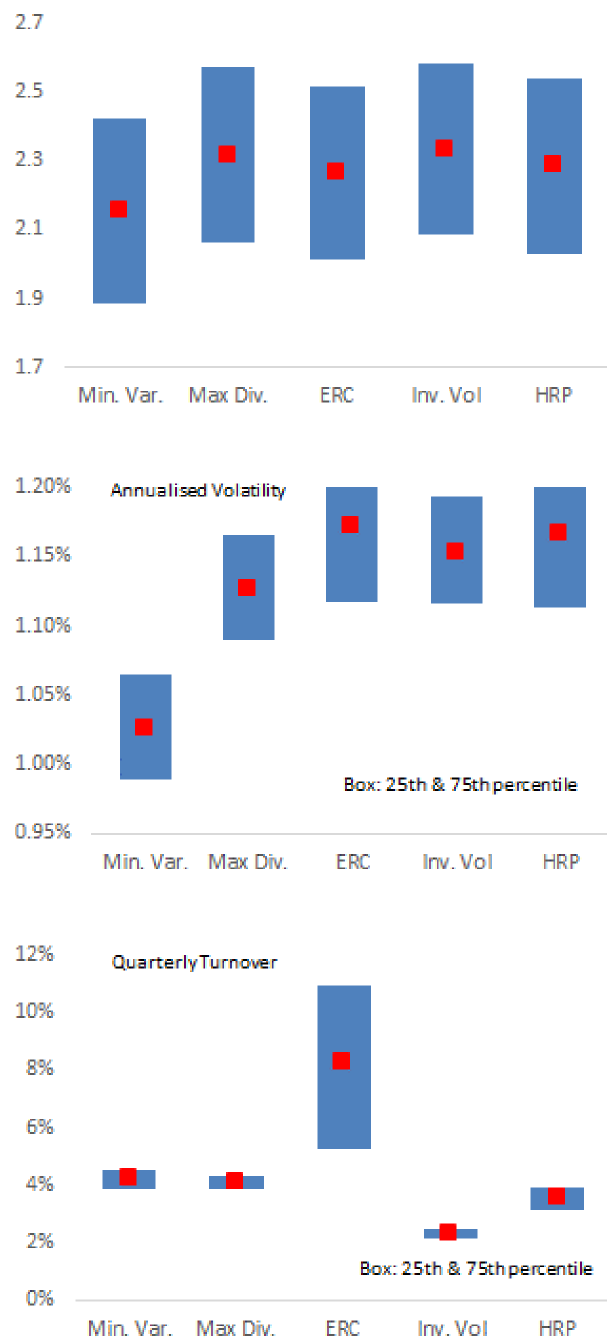
Figure 9: Sharpe, turnover, volatility of the 1,000 trials of the 5 techniques



Source: Deutsche Bank

Figure 9 display our results, with emphasis on how the main statistics are distributed across the 1,000 portfolio trials. We observe that:

- No method clearly outperforms the others. But IVW and HRP exhibit lower turnover and are, in natural form, free of optimization.
- Other aggregation methods are more sensitive to parameter estimation, therefore exhibiting higher turnover. This is maximized with ERC – the method that is most sensitive to how we estimate covariances.
- The minimum variance portfolio exhibits abnormally low volatility, as would have been expected.

The results above do not point to an obvious choice based on performance, but that is not a concern. As we target market neutral portfolios, the candidate strategies should exhibit low cross-correlation to begin with and therefore the differences are not significant.

That said, Sharpe ratios are only part of the story. Optimization-free methods also benefit from a much-desired lower turnover. Of those, IVW is the simplest method – and hence it is our choice in this exercise.[30]

4. Dynamic strategy sizing

We now cover sizing each strategy assuming the *portfolio* has gone live and the initial weights have been defined. Sticking to the original weights is not enough; we need to address risks including *alpha* erosion, changes in market structure and time-varying risk premia.[31]

Our approach is based on rewarding (penalizing) strategies with more (less) capital than the original defined in Section 3.1 based solely on how returns in the relevant period compare with expectations. "Relevant period", in this context, is when the portfolio has gone live – which is often much later than when the strategy went live.

The reader may be thinking *factor momentum* at this stage and, as such, will likely be concerned about any *factor reversal* properties among the candidate strategies discussed. Put simply, *if we are dealing with return streams that are robust enough to qualify from*

[30] That said, our tests favour the HRP method in instances where there is a strong correlation structure between inputs. It accounts for correlations as the optimisation-based methods do, but it is less sensitive to exact co-variance estimates and hence also keeps the turnover low.

[31] Citing some examples, we have seen that traditional trend- following strategies across asset classes have not performed well since global financial crisis and in our view, this underperformance is mainly due to the lack of medium-to-long term market trends – a shift in market dynamics. In addition, Equity Value has not performed in recent years due to its strong short position on high growth stocks – key outperformers. This is similar to what we have seen in the late 1990s, thereby illustrating the time varying nature of the fundamental factor premia.

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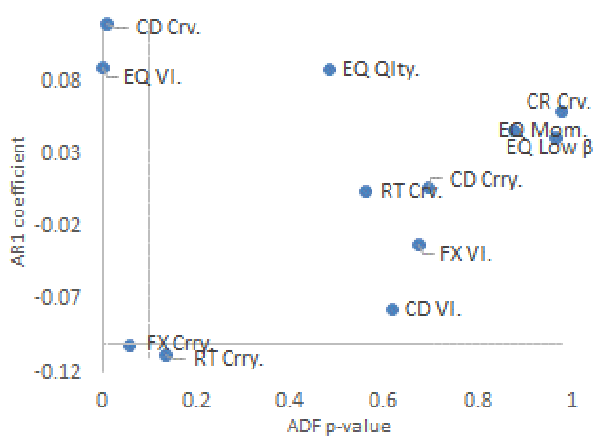
Section 2, should we not refrain from under-weighting recent losers as they are poised to be the upcoming winners?

That is a valid concern, and one that we tested extensively.[32] But contrary to standard theories of alternative risk premium, we were unable to find significant negative auto-dependencies in any of the strategies introduced in Section 3[33]. This implies that strategy returns either follow a random walk or, in some cases, a positive AR(p) process, as shown in Figure 10. Sizing strategies based on relevant past performance should therefore not be detrimental to the portfolio.

Figure 10: Estimating strategy autocorrelation properties



Note: data from 2000 onwards. Using weekly returns, but also checked on monthly and quarterly returns as these are the typical portfolio rebalancing frequencies. The longer the estimation frequency, the less significant our auto-dependencies. Source: Deutsche Bank

Our framework has four main considerations:

1. How to estimate the distribution of Sharpe ratios[34] that we expect for the relevant period?

2. How to estimate a performance statistic for the relevant period that can be compared to the aforementioned Sharpe ratio distribution in a way that does not simply add noise? In other words, how to *update* our understanding of how the strategy performs – our Updated Sharpe Ratio (USR)?

3. What should the boundaries be for leveraging and deleveraging our strategy weights? How much should we size exposure up or down based on posterior versus prior performances?

4. How fast should the above weights move towards the upper and lower boundaries?

We address each of these questions in steps.

4.1 Building the Sharpe Ratio distribution and estimating the Updated Sharpe Ratio (USR)

One can think of several methods to estimate the standard error of a strategy's Sharpe Ratio. Among the alternatives[35], we opted for the approach suggested by Lo (2002), where the (Gaussian) distribution parameters are defined as:

$$\mu^S = S^B$$

$$\sigma^S = \sqrt{\frac{1 + 0.5(S^B)^2}{T}}$$

where S^B is the Sharpe ratio prior to the relevant period and T is the length of that period.[36] This formula assumes strategy returns to be Gaussian and IID, which we do for simplicity, though this assumption can be relaxed.[37]

Estimating our USR is the next step. Sticking to the Sharpe Ratio of the relevant period – the portfolio's live history – is sub-optimal as this statistic will be very volatile if the relevant period is short.[38] We propose the following formula:

$$USR = \lambda S^B + (1 - \lambda) S^R$$

---

[32] We used 6 methods to examine the mean-reversion characteristics. They are: Augmented Dickey-Fuller (ADF) Test, Hurst exponent, Variance ratio, Autoregression (AR(p)) models, Ornstein–Uhlenbeck (OU) half-life, and the Mann-Kendall test.

[33] And neither with a much larger set of strategies from DB's QIS suite

[34] We opt for the Sharpe ratio as our performance metric because it can be modelled efficiently; it follows a normal distribution asymptotically even under real-world return assumptions. For more details, see Lo (2002).

[35] The methods include:
1. Varying the strategy parameters to generate various strategy trials. In the case of trend following, for instance, this implies varying the lookback windows to estimate trend, volatility and correlation.
2. Applying bootstrap techniques to generate various possible strategy paths, as done, for instance, with stationary bootstrapping in Section 3.
3. Perturbing the signals applied to each asset in the strategy by a small amount, before re-ranking so as to decide on the composition of each long and short basket. Anand et al. (2018) provide an example of that.
4. Calculating the Sharpe ratio's standard error using parametric means. The Sharpe ratio may be asymptotically normal, but strategy returns may not be. Aftab et al. (2008) show multiple ways of incorporating the higher moments of strategy returns into the Sharpe ratio standard error.

[36] As an example, a strategy whose data prior to the relevant period equals 10 years and posts a Sharpe Ratio of 1 would have a standard deviation of 0.3874.

[37] Christie (2005) has derived the asymptotic distribution of Sharpe ratio that only assumes stationary and ergodic returns. It is interesting as it allows to assume returns to be more realistic i.e., non-normal, serially correlated and even non-IID. In this case, the standard error is defined as follows:
$\sigma^S = \sqrt{\frac{1+0.5(S^B)^2 - \gamma_3 S^B + \frac{\gamma_4 - 3}{4}(S^B)^2}{T}}$, where γ_3 and γ_4 represent skewness and kurtosis of strategy returns.

[38] High volatility implies higher portfolio turnover and therefore higher cost.

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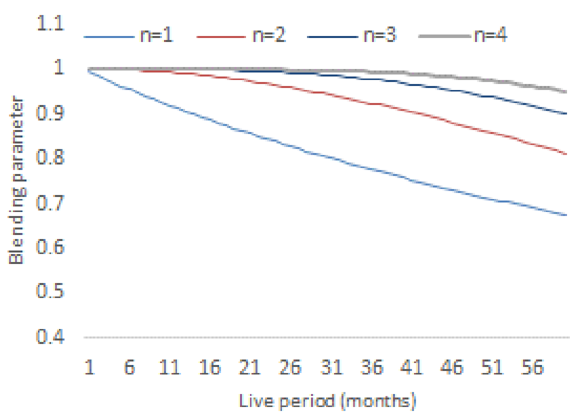
where S^R and S^B are Sharpe ratios calculated from the relevant period and prior to that, respectively, and λ is our blending parameter. We suggest:

$$\lambda = \frac{N^n}{(N^n + M^n)}$$

where n is a natural number governing the decay speed, and M and N are the respective lengths of the relevant and pre-relevant period. This blending factor therefore determines the speed with which new return information is incorporated into our USR. We define $n = 1$ in this study, though Figure 11 shows the effect from other specifications.

Figure 11: Blending parameter n as a function of live period (months)



Source: Deutsche Bank

4.2 Sizing the strategy

We now define the steps to adjust our strategy sizes based on how each performs in the relevant period. Crucially, we define sizing by comparing a strategy's recent performance versus *its own* history, and not relative to how other strategies are performing. This treatment – favouring absolute instead of relative – is supported by the fact that market neutral strategies often have distinctly different return profiles and should not be compared like-for-like. Our steps are as follows:

1. We calculate the Sharpe ratio and standard error using data prior to the relevant period, as defined in Section 4.1.

2. We calculate the USR by blending relevant and pre-relevant period data as per Section 4.1.

3. We calculate the USR's z-score as follows:

$$Z^{USR} = {(USR - \mu^S)}/{\sigma^S}$$

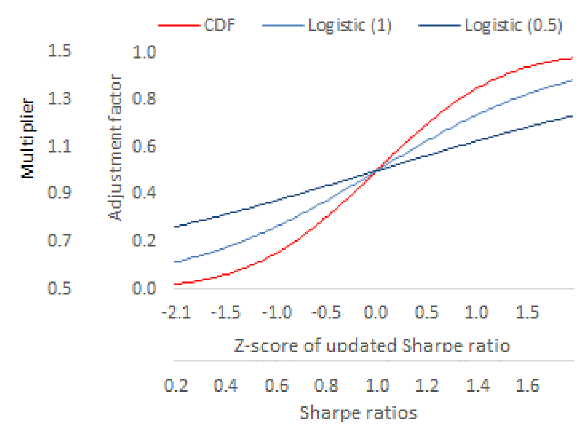
4. We transform the z-score value to an adjustment factor using an S-shaped function:

$$\varphi = f^s(Z^S), \qquad \varphi \in [0,1]$$

5. We calculate the sizing factor by linearly transforming the adjustment factor from Step 4 to a number between pre-specified leverage boundaries:

$m = lb + (ub - lb)\varphi$, where $lb = 0.5$, is the lower boundary for leverage and $ub = 1.5$ is the upper boundary. This means a strategy can be sized down to 0.5x the original defined in Section 3, or levered up to 1.5x the original. This ensures that *no strategies are turned off and therefore are given the opportunity to recover if needed*. Note that f^s can take various forms. While in this study we used the cumulative density function of the Normal distribution, Figure 12 shows our results using other S-shaped functions.

Figure 12: S-shaped functions



Source: Deutsche Bank

6. Having calculated the sizing factor for each strategy, we multiply it with the original strategy weights from Section 3 at every rebalancing date. If the sum of new strategy weights exceeds 100%, it is re-normalised back to that level; otherwise, the portfolio stays under-leveraged.[39] In other words:

$$w_i^S = m_i w_i$$

[39] In other words, if most strategies are underperforming in the relevant period versus the long history, we reduce our exposure to the portfolio as a whole.

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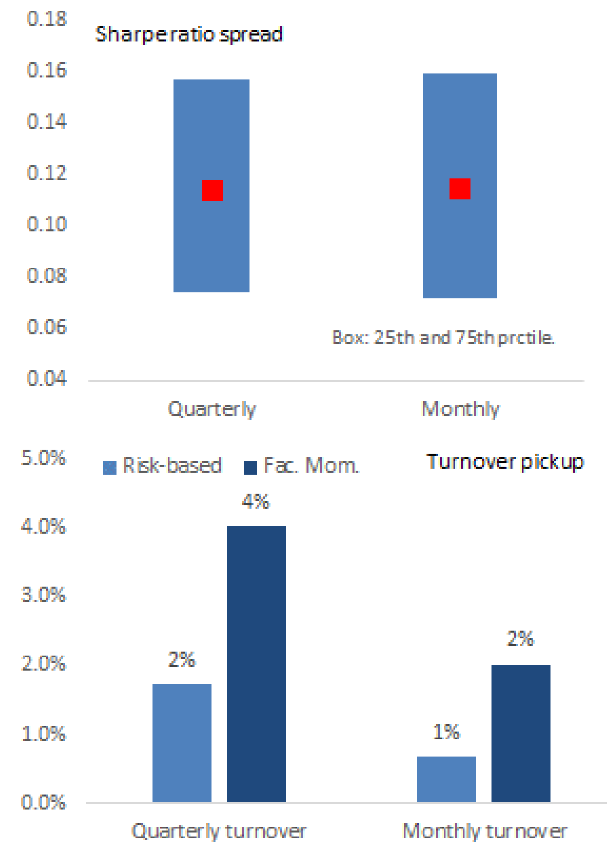
$$W_p = \sum_{i=1}^{N} w_i^S$$
$$If\ W_P > 1, w_i^{final} = \frac{w_i^S}{W_P}$$
$$If\ W_P < 1, w_i^{final} = w_i^S$$

where m_i is the sizing factor for strategy i calculated in Step 5, w_i is the original weight allocated to the strategy from Section 3, and w_i^{final} is the final strategy weight.

We tested the efficacy of this sizing method on the same set of 1,000 market neutral portfolios used in Section 3, assuming a portfolio live date of January 1st, 2018. In other words, the relevant period encompassed 2 years. We used inverse volatility weights as the original, and tested both monthly and quarterly rebalancing windows.

As shown in Figure 13, the incremental returns using the proposed method outperforms the original in excess of 96% of the 1,000 trials and leads to an average Sharpe ratio pickup of 0.1. The percentage of instances in which it outperforms the naive risk-based method is in excess of 97% for both monthly and quarterly rebalancing. However, it also leads to an average turnover (quarterly) increase of 2%.

Figure 13: Sharpe ratio, turnover pickup, and percentage of outperformance



Source: Deutsche Bank

5. Dynamic portfolio sizing

Having dealt with strategy validation and sizing, our final step is sizing the market neutral portfolio. We aim to control the risk profile of the programme as a whole, leveraging exposure up or down – against cash – based on the observed and target drawdowns.

As is likely to resonate with most portfolio managers, *our target is – first and foremost – to avoid hitting our drawdown limits*. And as we demonstrate below, the approach also carries attractive implications to the portfolio's likely long term growth rate.

5.1 Risk control methods and estimation

We consider three risk control methods: a stop-loss trigger, synthetic put replication and CPPI.[40]

Stop-loss triggers are as simple as the name implies; if cumulative returns drop below a pre-specified threshold, we remove all exposure to the portfolio. Such simplicity raises major questions, including:

- When does the investor re-scale back into the strategy?
- How does one model gap risk, and the *effective* stop-loss level in light of market depth?

As the reader may suspect, there are no deterministic answers to these questions; they are normally

[40] The reader may wonder why volatility targeting is not one of our risk control methods. It is common to assume that volatility is synonymous to risk, and therefore that one should size portfolio exposure such that observed volatility matches a pre-defined target. The literature supports this practice. For instance, Hocquard and Papageorgiou (2013), Harvey et al. (2017), Hallerback (2012) and Carver (2015) find that volatility targeting reduces the likelihood of extreme returns, and Perchet et al. (2015) find that this effect is even more pertinent during volatility clusters. To the extent that volatility can be predicted – and Christian, Robert and Bryan (2011) and Natividade et al. (2017) provide promising results – this can be an effective risk control method. Nevertheless, we have avoided it as volatility targeting does not explicitly target drawdown protection; it does so only indirectly.

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addressed with subjectivity. That said, one can innovate with the application of rolling stop-loss triggers – see, for instance, Natividade (2013) – and identifying the conditions that favour using stop triggers. Di Graziano (2014), for instance, argues that tighter stop triggers are better applied to risk averse investors and trend-like strategies.

In all, stop-loss triggers can be beneficial. As argued in Kaminski and Lo (2008), they provide positive premiums when applied to realistic return processes – i.e. those with serial correlation and multi-regime dynamics.[41] We therefore add it to our candidate methods.

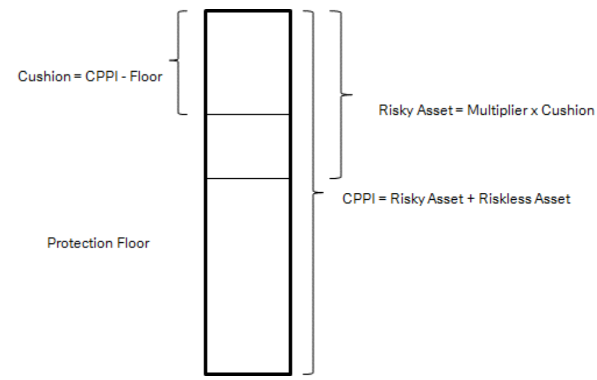
The *synthetic put strategy* is our second candidate method. We consider it a scaled-in version of the stop-loss trigger introduced earlier; in other words, our exposure drops gradually as the portfolio mark-to-market drops. If the drop continues, at some stage our exposure drops to zero.

The speed through which this exposure changes is defined by replicating the delta of a put option struck on the value of the portfolio. As we combine our delta-one exposure with this synthetic put, *we ultimate replicate a call option on the portfolio*.

The method, introduced as a form of portfolio insurance in Rubinstein and Leland (1981),[42] supersedes the naïve stop-loss by addressing both shortcomings of the latter. The investor re-scales back into the portfolio using a delta replication algorithm, as opposed to by a subjective decision, and such gradual change in positions reduces gap risk and market impact.[43]

CPPI – Constant Proportion Portfolio Insurance – is our third candidate. A popular risk control method in insurance markets, it allocates capital between the portfolio and riskless (or low risk) assets based on performance. As with the other methods, it optimizes according to our drawdown limits and reduces capital exposure the more that the value of the portfolio edges closer to its drawdown limit. That said, it also provides the user with extra flexibility on the pace and magnitude with which positions are rebalanced.

Figure 14: CPPI illustrated



Source: Deutsche Bank

Figure 14 illustrates the scheme. It highlights 2 parameters – a constant multiplier and a floor – and their product defines our portfolio exposure. Of these, the multiplier provides most flexibility, as a leverage ratio that controls the dynamic allocation between riskless asset and our portfolio. Of these, we use two choices:

- Kelly leverage: designed to maximize the compounded rate of growth of one's wealth[44], it defines that the optimal leverage ratio for a portfolio of Gaussian-like returns is $f = {}^{\mu}/_{\sigma^2}$, where μ is the mean excess return and σ^2 is its return variance. Participants use the *half-Kelly* ratio or other variations,[45] including those based on optimization methods, in order to address the non-normal nature of most portfolio returns. In this report we investigate the half-Kelly method, estimated both deterministically – as per formula above – and through an optimization-based method.[46]
- Volatility leverage: another popular CPPI multiplier estimate is the inverse of the portfolio volatility. Often called *utilitarian leverage*, this choice is similar to volatility targeting – in other words, positions are sized up (down) according to drops (jumps) in volatility.

Figure 15 shows the historical progression of three multipliers, together with portfolio wealth over time. The half-Kelly methods assume a portfolio with annualized volatility of 5% and a Sharpe ratio of 2, and the multiplier is re-estimated using a rolling window of 3 years. The

[41] Note that transaction costs must be accounted for when modelling stop-loss triggers. As argued in Lo (2017), they make it such that very tight triggers can lead to underperformance versus buy-and-hold strategies.
[42] Dichtl, Drobetz and Wambach (2014) is another useful reference.
[43] Gap risk is reduced by not nullified – it will be present during large short-term shocks. One extra way of addressing such risk, in addition to the risk of a knee-jerk portfolio rally, is by capping the minimum and maximum portfolio exposure.
[44] See Kelly (1956).
[45] See, for instance, Carver (2015) and Chan (2013).
[46] We find the optimal leverage f via $\min_f -\sum_i \log(1 + f * R_i)/N$, where R denotes the returns and N is the sample size. This approach maximizes the expected value of the compounded growth rate using a non-Gaussian distribution of R.

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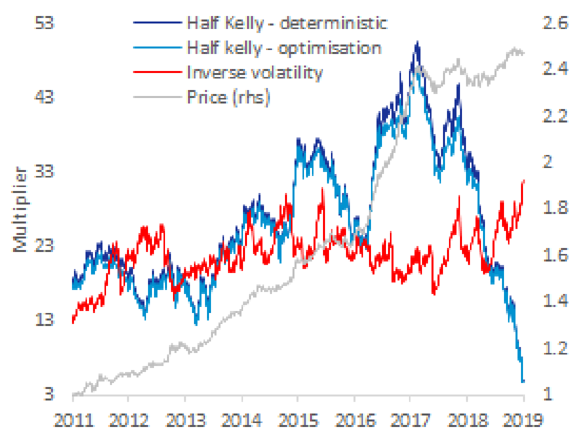
volatility leverage method estimates volatility using exponential decay.[47]

Figure 15: Historical progression for the 3 multipliers



Source: Deutsche Bank

As shown, the Kelly-based multipliers rise as the portfolio outperforms, and drop – often aggressively – as the portfolio stabilizes or underperforms. The volatility-based multiplier, on the other hand, is far more stable. Such difference is attributed to their targets; Kelly-based methods optimize for CAGR maximization, while the other method also accounts for time-varying volatility. A final, more subtle observation is that the small difference between the two Kelly-based multipliers comes to fore during highly volatile markets. This makes us favour the optimization-based approach, as it better accounts for non-Gaussianity in the data set.

Figure 16 describes the steps we use when estimating all 3 methods – the stop-loss, synthetic put and CPPI. As the reader can see, most steps apply equally to all of them.

Figure 16: Portfolio insurance – construction steps

Estimation Steps	Estimation Frequency	Stop-Loss	CPPI	Synthetic Put
1. Compute the floor value	(update daily or quarterly)	Floor value can be either predefined or determined by a drawdown limit, i.e. $floor_t = peak_t * (1 - drawdown)$ $where\ peak_t = \max(peak_{t-1}, portfolio\ value_t)$		
2. Compute the cushion	quarterly	$cushion = \frac{portfolio\ value - floor}{portfolio\ value}$		
3. Compute the portfolio weights	quarterly	$w_{portfolio} = 1\ if\ cushion > 0\ else\ 0$	$w_{portfolio} = m * cushion$	$K = (1 - cushion) \times (S + P(K))$ $w_{portfolio} = \frac{S \times N(d_1)}{S \times N(d_1) + K \times e^{-rT} \times N(-d_2)}$
4. set constraints on the portfolio weights	quarterly	$w_{portfolio} = \min(w_{portfolio}, 1$ $w_{portfolio} = \max(w_{portfolio}, 0$		
5. Compute value on the portfolio and cash	quarterly	$value_{portfolio} = w_{portfolio} * portfolio\ value$ $value_{cash} = (1 - w_{risky}) * portfolio\ value$		
6. Update the portfolio value on a daily basis	daily	$portfolio\ value_{t+1} = value^t_{portfolio} * \left(1 + r_{portfolio}\right) + value_{cash}$ $value^{t+1}_{portfolio} = value^t_{portfolio}\left(1 + r_{portfolio}\right)$		

Source: Deutsche Bank

Figure 17 provides an example of our methods at work. The reader may recognize similarities to replicating the delta of a call option on the underlying asset.

The closer we are to the maximum drawdown tolerated, the more the CPPI and synthetic put methods de-lever exposure – one in linear, the other in non-linear fashion. The stop-loss method, however, closes its entire exposure at once – resembling a binary option. Note that, in all 3 instances, the lines are derived by averaging all trials.

[47] In other words, EWMA volatility where $halflife = 252$

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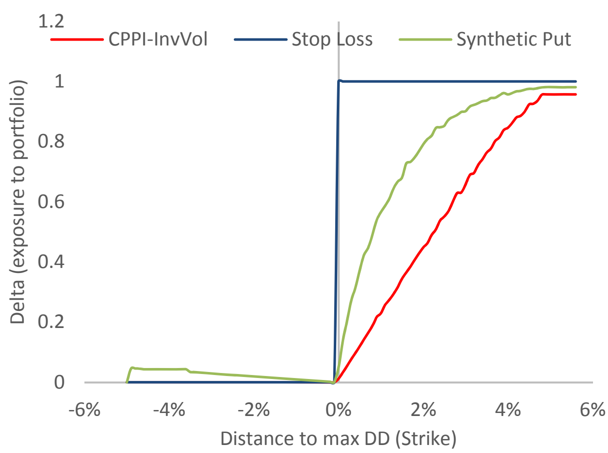
Figure 17: Portfolio insurance methods at work – sizing exposure according to distance to drawdown limits



Source: Deutsche Bank

5.2 Results

We now compare our risk control methods against the benchmark of no risk control – in other words, the case where we are always fully invested in the portfolio.

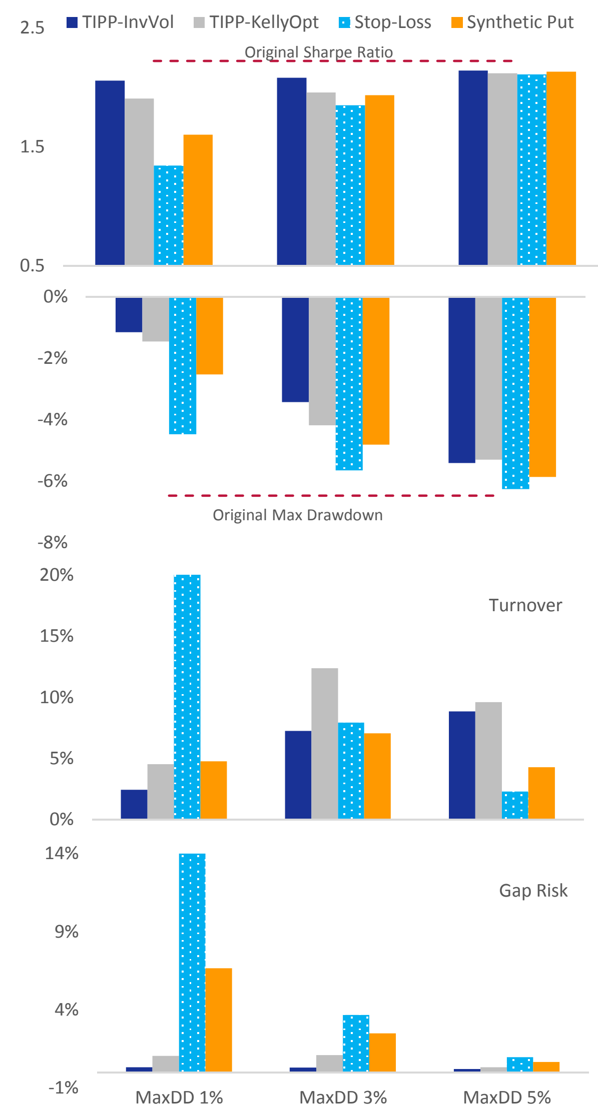
As before, our tests utilize stationary bootstrapping; we generated 1,000 simulated portfolio returns with 5% annualized volatility.

We assumed that any change in sizing would come at a cost of 5bp to the portfolio. We also fixed our exposure boundaries to be between 0% and 100% - in other words, our maximum exposure has to equal that of the benchmark approach. Further, we adjusted the portfolio's floor value according to its peak value as estimated on a quarterly basis. In other words, we apply a rolling floor.

Figure 18 displays our results assuming 3 distinctly different floor levels. We point out the following:

- The risk-controlled Sharpe ratios are moderately lower than the benchmark's, but the drawdown profiles are significantly better. If questioned about priorities, we go back to the original mantra: *first and foremost, avoid hitting the drawdown limits*.[48] The lower returns are primarily attributed to under-participation in early recoveries, though also to transaction costs at each quarterly rebalance.
- The CPPI-based methods typically outperform, while the stop-loss trigger underperforms unanimously. Our simulated portfolios are "cashed out" far more often in the latter case,[49] and the gap risk is also far more significant as we are fully invested going into the stop trigger.
- In the case of CPPI and put replication, quarterly turnover is generally low, and therefore so are the associated costs. Gap risk is also tame.

Figure 18: Performance, turnover and gap risk profile



Source: Deutsche Bank

[48] We repeated this exercise but updating the floor on a daily basis, instead of quarterly. Drawdown protection improved in all cases, but (again) at the cost of lower Sharpe ratios. We did not simulate results using daily rebalancing as we assumed transaction costs would have been prohibitive.

[49] The rolling stop loss approach assumes no re-entry back into the strategy – in other words, once we "cash out", the portfolio ends.

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6. Conclusions

This report outlines a framework for building market neutral portfolios. It evolves around two key pillars: *confidence* and *diversification*. In order to enhance the robustness of our results, we focus primarily on simulated data calibrated onto real systematic strategies.

We conclude that investors building market neutral portfolios should:

- *Record all information pertaining to the development of each strategy that is about to be launched*. The more we know about the research process, the more validation techniques can be applied and the better our projections will be for post-launch performance.
- *Favour simple aggregation*. As candidate strategies should already be less sensitive to market dynamics to begin with, simple approaches - such as inverse volatility weighting - perform at least as well as sophisticated methods and are less sensitive to parameterisation risk. Should strategies be correlated, however, we favour methods that are less dependent on estimation risk - such as Hierarchical Risk Parity.
- *Favour a Bayesian approach to strategy sizing*. Our exposure to a given strategy should reflect live performance versus pre-live expectations. *Updated* Sharpe ratios, which account for both live and backtest data, should be compared to their backtest-only *priors* and sizing should reflect that.
- *Favour dynamic portfolio sizing*. As most market-neutral portfolios are subject to drawdown limits, it is wise to consider portfolio insurance techniques - even if that comes at the cost of a lower Sharpe ratio. We favour dynamic portfolio sizing just as we favour dynamic strategy sizing, albeit with distinctly different techniques.

The authors of this report wish to acknowledge the contribution made by Robert Carver*, a lecturer, trader and independent consultant.*

7. Appendix 1: variational Bayesian for Gaussian Mixture Model

Mathematically, a mixture of Gaussians approximates a given probability density as

$$p(\mathrm{x}) = \sum_{\mathrm{z}} p(\mathrm{z})p(\mathrm{x}|\mathrm{z}) = \sum_{i=1}^{K} \pi_k N(\mathrm{x}|\mu_k, \sigma_k^2)\ ,$$

where $\mathbf{z}$ is a binary variable in which a particular element $\mathbf{z}_k$ equals to 1 and all other elements equal to 0., π_k is a mixing parameter and K corresponds to the number of Gaussian components. In Variational Bayesian, we often assign a joint Dirichlet distribution for the mixing parameters, and assume an independent Gaussian-Wishart prior governing the mean and precision of each Gaussian component, given by

$$p(\pi) = Dir(\pi|\alpha_0),$$
$$p(\mu, \Sigma) = p(\mu|\Sigma)p(\Sigma) = \prod_{k=1}^{K} N\left(\mu_k \middle| m, \beta\sigma_k^2\right) W(\Sigma_k|S, v),$$

where parameter α_0 is same for each of the components, β is a scaling factor and m is the hypermean of the mean distribution and $\Sigma_k = \sigma_k^{-2}$ denotes the precision. Note that the Wishart distribution $(\Sigma|S, v)$ is a conjugate prior for the inverse covariance matrix.

Given the above formulation, the joint distribution of all the random variables can be written as

$$p(\mathrm{x}, \mathrm{z}, \pi, \mu, \Sigma) = p(\mathrm{x}|\mathrm{z}, \mu, \Sigma)\mathrm{p}(\mathrm{z}|\pi)\mathrm{p}(\pi)\mathrm{p}(\mu|\Sigma)\mathrm{p}(\Sigma)$$

Using this factorization, we then sequentially update each variable by computing its expectation while keeping other variables constant. This iterative procedure maximizes the evidence lower bound (ELBO) to find parameters that give as tight a bound as possible on the marginal probability of x (see Chapter 10.2 in Bishop, 2006).

In this research, we fit a GMM with 2 Gaussians to the residuals of the $AR(p)$ model from which we get 2 marginal mean distributions and 2 marginal variance distributions, and ultimately calculate the two marginal Gaussian distributions. These are sampled separately and blended through a mixing probability. Note that, to draw samples from the marginal distribution $p(\mathrm{x})$, we firstly generate samples from $p(\mathrm{x}, \mathrm{z})$ and reshuffle the samples to ignore the ordering of z.

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8. Bibliography

Aftab, N., Jungwirth, I., Sedliacik, T., and Virk, N. (2008), “Estimate the Distribution of Sharpe Ratios”.

Anand, V., Ward, P., Natividade, C., and Gonzalez, J. (2019), “Playing Defense 2.0: New Tools for the Systematic Tail Risk Investor”, Deutsche Bank Quantcraft, 24 April 2019.

Anand V., Nativdade C., Sarvelos G. Gonzalez J., Gopal S., Grover R (2019). “FX Cookbook: A Recipe for Systematic Investing in Currency Market”. Deutsche Bank Quantcraft, 15 January 2019.

Bailey, D.H., Borwein, J., López de Prado, M., and Zhu, Q.J. (2015), “The Probability of Backtest Overfitting (February 27,2015)”, Journal of Computational Finance (Risk Journals), Forthcoming.

Bailey, D.H., and López de Prado, M. (2014), “The Deflated Sharpe Ratio: Correcting for Selection Bias, Backtest Overfitting and Non-Normality (July 31, 2014)”. Journal of Portfolio Management, 40 (5), pp. 94-107. 2014 (40th Anniversary Special Issue).

Bailey, D.H., and López de Prado, M. (2012), “The Sharpe Ratio Efficient Frontier (April 2012)”. Journal of Risk, Vol. 15, No. 2, Winter 2012/13.

Bishop, C. M. (2007), Pattern Recognition and Machine Learning, New York: SpringerVerlag.

Brownlees, C., Engle, R., and Kelly, B. (2011), “A Practical Guide to Volatility Forecasting through Calm and Storm”, J. Risk, vol. 14, no. 2, pp. 1–20.

Carver, R. (2015), “Systematic Trading”, Harriman House

Carver, R. (2017), Smart Portfolios: A Practical Guide to Building and Maintaining Intelligent Investment Portfolios, Harriman House, First Edition.

Chan, E., (2013), “Algorithmic Trading: Winning Strategies and Their Rationale”, John Wiley & Sons, Hoboken.

Christie, S. (2005),”Is the Sharpe Ratio Useful in Asset Allocations?”, MAFC Research Paper Nr.1, Applied Finance Center, Macquire University.

Croux, C, Dehon, C. (2010), "Influence Functions of the Spearman and Kendall Correlation Measures". Statistical Methods & Applications. 19(4):497–515.

Dichtl, H., Drobetz, W., and Wambach, M. (2017), “A Bootstrap-based Comparison of Portfolio Insurance Strategies”, The European Journal of Finance 23 (1), 31-59.

Graziano, G. D. (2014), “Optimal Trading Stops and Algorithmic Trading”.

Hallerbach, W.G. (2012), “A Proof of the Optimality of Volatility Weighting over Time”, Journal of Investment Strategies, vol. 1, no. 4, pp. 87–99.

Hocquard, A., Ng, S., and Papageorgiou. N. (2013), “A Constant-Volatility Framework for Managing Tail Risk”, The Journal of Portfolio Management 39 (2): 28–40.

Harvey, C. R., Hoyle, E., Korgaonkar, R., Rattray, S., Sargaison, M., and Hemert, O.V. (2018), “The Impact of Volatility Targeting”, The Journal of Portfolio Management, 45(1):14–33.

Kaminski, K., and Lo, A.W. (2007), “When do Stop-loss Rules Stop Losses?”, Preprint. MIT Sloan School of Management and National Bureau of Economic Research (NBER).

Lo, A. W., and Remorov, A. (2017), “Stop-loss Strategies with Serial Correlation, regime switching, and transaction costs”, Journal of Financial Markets, 24:1-15.

Leland, H.E., and Rubinstein, M. (1981), “Replicating Options with Positions in Stock and Cash”, Financial Analysts Journal, 37, pp. 63-72.

Lo, A. (2002), “The Statistics of Sharpe Ratios”, Financial Analysts Journal 58, 36-52.

Luo, Y., Wang, S., Cahan, R., Jussa, J., Chen, Z. and Alvarez, M. (2013), “DB Handbook of Portfolio Construction: Part 1”, Deutsche Bank Quantitative Strategy, 30 May 2013.

López de Prado, M. (2016), “Building Diversified Portfolios that Outperform Out-of-Sample (May 23, 2016)”. Journal of Portfolio Management.

Natividade, C., Mesomeris, S., Alvarez, M., Beceren, M. and Davis, C (2013), “Colours of Trend”, Deutsche Bank Quantcraft, 17 September 2013.

Politis, D.N., and Romano, J. P. (1994), “The Stationary Bootstrap”, Journal of the American Statistical Association 89, 1303-1313.

Perchet, R., and de Carvalho, R.L. (2015), “Constant Volatility Framework for Factor Investing”, France, Paris: BNP Paribas Investment Partners.

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