Deutsche Bank
Markets Research

Global

Quantitative Strategy
# Quantcraft

Date
17 August 2017

# Protect, Diversify or Track Your Core


Vivek Anand
vivek-v.anand@db.com

Caio Natividade
caio.natividade@db.com

Jacopo Capra
jacopo.capra@db.com

Spyros Mesomeris, PhD
spyros.mesomeris@db.com

Andy Moniz, PhD
andy.moniz@db.com

James Osiol
james.osiol@db.com

Aris Tentes, PhD
aris.tentes@db.com

Paul Ward, PhD
paul.ward@db.com

North America: +1 212 250 8983
Europe: +44 20 754 71684
Asia: +852 2203 6990



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

Already a pillar of quantitative investing, portfolio construction has become even more important in the age of *cross-asset* risk premia investing.

While the standard approach is to focus on the right combination of cross-asset *strategies*, this report focuses instead on the right combination of *assets* while still capturing the information content from the strategies.

This involves, first and foremost, estimating and predicting the covariances between assets across asset classes, and not between strategies. Further, it also involves directly targeting correlations to the investor's strategic portfolio.

Today's *Quantcraft* outlines 3 construction methods that benefit from this approach, each targeting a different objective; protection, diversification and tracking. The results suggest more stable, predictive covariances, more accurate targeting of beta exposures and better handling of asset exposure constraints.

We also outline shortcomings from this approach, in addition to the sensitivity of our results to changes in how the covariances are estimated.


Figure 1: Protect, Diversify or Track Your Core

*Source: Getty Images.*

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# Protect, Diversify or Track Your Core

## 1. Introduction

Portfolio optimisation in the age of cross asset risk premium investing typically involves estimating the optimal mix between separate systematic strategies. This follows the premise that if asset returns are driven by common factors, and if these common factors have well established characteristics, then the construction of efficient portfolios should focus solely on the combination of factors that target a certain objective - typically a portfolio return profile that is either cyclical, counter-cyclical, or cycle-independent.

While investors ultimately buy and sell assets - not strategies – in this context the target weights for each underlying are derived ex-post, as the standard approach combines the optimised weight for the chosen strategies with their exposure to that underlying asset.

This report invites the reader to consider an alternative approach for portfolios typically comprised of futures markets across asset classes: optimise for target asset exposures directly, while deciding on strategy weights exogenously. After elaborating our argument in Section 2 and defining our test environment in Section 3, we outline optimisation routines that create systematic overlay portfolios with distinct goals in mind: hedging the original portfolio (Section 4), achieving maximum diversification against the original portfolio (Section 5), and replicating the original portfolio (Section 6). Finally, Section 7 addresses covariance estimation, and Section 8 concludes.

## 2. Covariance between assets and strategies

We start by outlining the case for modeling asset covariances instead of strategy covariances.

First and foremost, we focus on the cross-asset investment pool, whose number of underlying assets is far smaller than that of the single stock universe. This removes much of the dimensionality reduction requirements seen in equities.

Second, our analysis of the risk factors that drive cross-asset variations suggests that most drivers are static, and not dynamic in nature. Static factors – typically regions or sectors [1] - are ultimately long-only asset groupings, and therefore further validate our premise.

Third, while asset covariances can be heavily sensitive to the exogenous sentiment environment, such regimes can be modeled through sentiment indicators and ultimately be an input to our covariance estimates, as per Natividade et al. [2017].

As such, we believe opting for asset covariances often allows for better risk estimation, and potentially better risk prediction. Strategies are comprised of dynamic (often long-short) baskets, whose composition can be volatile and therefore lead to covariance estimates with less predictive power. The relative stability of asset-by-asset covariances, on the other hand, often translates into better covariance predictions.

We illustrate our argument with an example. We assume a pool of 80 underlying assets across equity indices, commodities, currencies and Treasuries - shown in Figure 2 – with daily returns starting in the 1990s. We focus on the 5 systematic portfolios launched last year, all based on prior *Quantcraft* research: trend following, carry, value, sentiment and macro factor investing.

[1] The factors of risk identified in our study were: inflation, developed market equities, EM equities, USD/G10 FX, USD/EM FX, each major commodity sector (energy, metals and agriculture), global Treasuries, Momentum and Carry. 8 out of 10 are long-only factors.

Figure 2: List of assets used in the protection portfolio

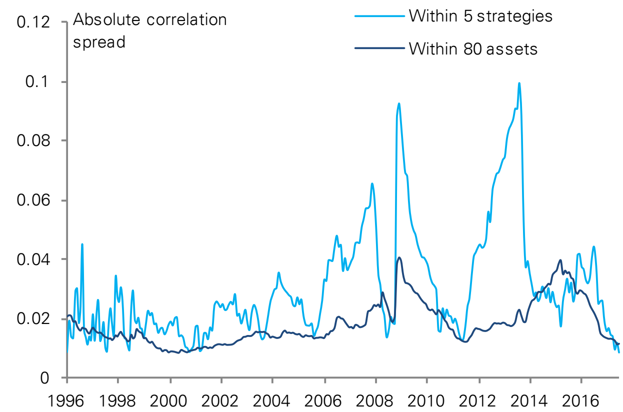
| Asset class | Underlying assets | | |
|---|---|---|---|
| Equity index futures | S&P 500 (US) | Nikkei 225 (JP) | ISE (TU) |
| | Eurostoxx 50 (EU) | OMX (SW) | TOP40 (SA) |
| | DAX (EU) | RDX (RU) | Kospi (KO) |
| | CAC (EU) | SMI (SZ) | Nasdaq |
| | Hang Seng (HK) | TSX (CA) | FTSE 100 (UK) |
| | IBEX (EU) | TAIEX (TA) | WIG (PO) |
| | ASX 200 (AU) | Bovespa (BR) | Bolsa (MX) |
| FX/USD | EUR | HUF | PHP |
| | GBP | IDR | PLN |
| | AUD | ILS | RON |
| | NZD | INR | RUB |
| | BRL | JPY | SEK |
| | CAD | KRW | SGD |
| | CHF | MXN | THB |
| | CLP | MYR | TRY |
| | COP | NOK | TWD |
| | CZK | PEN | ZAR |
| Commodity futures | Aluminium | Gasoil | Silver |
| | Brent | Heating Oil | Soybeans |
| | Cocoa | Led | Sugar |
| | Coffee | Natural Gas | Wheat |
| | Copper | Nickel | WTI |
| | Corn | Palladium | Zinc |
| | Cotton | Platinum | |
| 10Y Treasury futures | Australia | Japan | Switzerland |
| | Canada | Mexico | UK |
| | Germany | New Zealand | US |

*Source: Deutsche Bank, Bloomberg*

Figure 3 plots the median absolute spread between actual and predicted pairwise correlations between constituents in two sets: one comprised of our 5 *strategies*, and one comprised of our 80 underlying *assets*. The dispersion in the former is notably greater, and so is the average root square error: 0.051, versus 0.031 in the latter.[2] In both cases, the "predicted" correlation is estimated using a 5-year lookback window, smoothed using a 2-year half life, whereas the actual correlation is the correlation realised 1 month into the *future*.

[2] Strictly speaking, we must acknowledge that this is not a like-for-like comparison as any statistic will face more estimation error when using a smaller sample size. In other words, the average of 5 observations is likely to be less efficient than that of 80 observations, by default. We partly address that by using the *median* spread instead of the *mean* spread, as it reduces outlier risk. The best alternative would have been to compare the correlations of 80 (or 5) strategies with that of 80 (or 5) assets, but neither is an accurate reflection of the typical relationship between assets and strategies in a cross-asset portfolio.

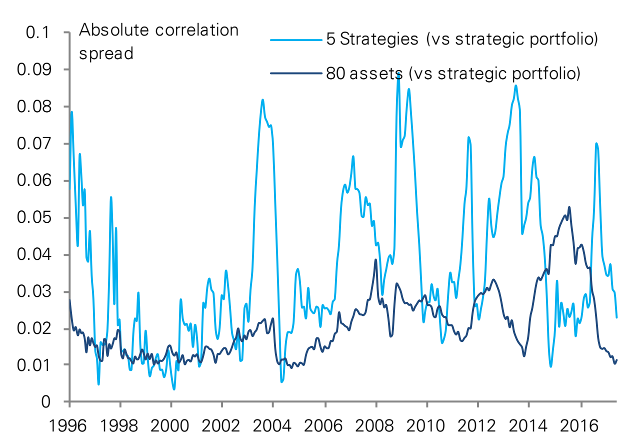
Figure 3: Median of absolute spread between 1-month predicted and 1-month (future) realised correlations within strategies and within assets




*Source: Deutsche Bank, Bloomberg.*

To further reiterate our argument, we also plot the average absolute spread between actual and predicted pairwise correlations between our strategies and a chosen portfolio, and between our assets and a chosen portfolio. For the latter we use a proxy US pension fund portfolio, described in more details in Section 3. As Figure 4 shows, the difference in predictive power between asset correlations and strategy correlations is even more significant.

Figure 4: Median of absolute spread between 1-month predicted and 1-month (future) realised correlations between a strategic portfolio and our strategies & assets




*Source: Deutsche Bank, Bloomberg.*

These general results have implications for portfolio construction. For instance, *using asset-based covariances may allow us to design overlay portfolios whose ex-post beta to a given benchmark is closer to the target specified in the optimisation routine*. Not only our covariance estimates are more accurate using this approach, but the optimisation process benefits from greater input breadth as there are more assets than there are strategies.

Another benefit of the asset covariance approach to portfolio construction is that it is more flexible in capturing certain investor constraints, specifically when it comes to boundary exposures to an asset or asset class. This allows for better control of risks linked to concentration and liquidity.

Strategy covariances may also be estimated using point-in-time portfolios; that is, by using the returns of a strategy whose asset composition is static and equal to that of the rebalancing date. While we agree that this approach leads to better covariance estimation, the approach still lacks input breadth (there are less strategies than assets to optimise for) and does not control for asset exposure boundaries explicitly.

Sections 4-6 will illustrate our argument in more detail.

## 3. Our test environment

We now outline 3 portfolio construction methods. Each of them addresses a distinct need: *protection*, *diversification*, and *replication*. For ease of reading, we first clarify our testing environment:

- Our *strategic* portfolios represent the investor's initial exposure, typically a funded portfolio. We use four: (1) a proxy US pension fund portfolio[3], (2) a proxy US fixed income portfolio[4], (3) a proxy global equity portfolio[5], and (4) a proxy risk parity portfolio that groups global equities with US fixed income[6].
- Our *overlay* portfolios are derived from the portfolio construction exercises done below. They are comprised of unfunded positions in 80 assets across currencies, commodities, Treasuries and equity indices - as outlined earlier.
- Our *final* portfolios are an aggregate of both strategic and overlay portfolios. For simplicity, we allocate equal weights to both. Figures 6 and 7 look at the sensitivity of our results to that, in the context of portfolio protection.
- Position boundaries in the overlay portfolios are capped at either 5% of the full portfolio or 2% of each asset's average daily volume, assuming a portfolio size of USD 500mn.
- Our *alpha* portfolio is an aggregate of the 5 systematic portfolios we have published in recent years: trend following (Natividade et al. [2013]), carry (Anand et. al [2014]), value (Natividade et al. [2014]), sentiment and macro factor investing (Natividade et al. [2015]). We allocate equal risk capital to each. While the alpha portfolio is built to maximise risk-adjusted returns, we use a risk-based aggregation function instead of a return-based function as we believe none of the aggregate strategies can be timed. A warning: we use the term "alpha" loosely in this report.
- Our overlay portfolios rebalance once a week, and positions are executed at the close of the following business day. We assume fixed transaction costs equal to a multiple of the historical average.
- Covariances are estimated using an EWMA approach with different decay profiles. In the case of the protection overlay, we use a 5-year rolling window of daily returns, decayed exponentially with a 2-year half-life. In the case of the diversifier and tracker portfolios, we use a 1-year rolling window with a 100-day half-life. Section 7 goes through our choices in more detail. We have also recently introduced a new risk estimation and forecasting approach, which incorporates our new risk factor model, the relevance of scheduled events in jump estimation, and volatility regimes. See Natividade et al. [2017] for details.

## 4. Building a protection portfolio

In our view, a good *protection* overlay solution possesses 2 properties: (a) stable, highly negative correlation to the strategic portfolio, and (b) non-negative returns over the long run. The framework outlined below, first introduced in November last year (see Anand et al. [2016]), aims to address both aspects. The first property comes via the objective function - a minimum correlation portfolio - while the second is addressed by using the predictive power from our alpha portfolio.

The steps are as follows:

Step 1: Solve for the initial weights $w$ such that the following loss function is minimized:

[3] 52% US Equities (<SPXT Index>), 20% US fixed income (<LBUSTRUU Index>), 7% Global inflation-linked bonds (<BXIIEUG2 Index>), 8% global commodities (<SPGSCITR Index>), 7% global hedge funds (<HFRXGL Index>) and 6% US real estate (<IYR US Equity>).

[4] Bloomberg Barclays US Agg Total Return Unhedged Index (fixed rate, investment grade bonds): <LBUSTRUU Index>.

[5] MSCI World Index (<NDDUWI Index>).

[6] 20% US Equities (<NDDUWI Index>) and 80% US fixed income (<LBUSTRUU Index>). The weights were chosen based on an in-sample, long-term lookback window for volatility estimation.

$$\sum_{i}^{N+1}\sum_{j}^{N+1} w_i w_j \rho_{i,j} \qquad (4.1)$$

subject to the following constraints:

a. $w_S^L = w_S^U = 0.5$ (constant with a high value[7])

b. $w_i^{U*} = if\,(w_i^a > 0, w_i^{U*} = w_i^U, 0)$
$w_i^{L*} = if\,(w_i^a < 0, w_i^{L*} = w_i^L, 0)$

c. $\sum_{i=1}^{N} |w_i| = 1$

d. $w_i^{L*} \le w_i \le w_i^{U*}$

where:

$w_i^U = \min(0.05, ADV_i \times 0.01), w_i^L = -w_i^U$ (thus addressing liquidity and concentration risk)

$$w_i^a = \sum_{q=1}^{Q} w_i^q$$

For clarity, $w_i$ is the weight of an asset, $w_i^U$ and $w_i^L$ are the upper and lower boundaries of an asset based on its liquidity. ADV is an estimate of the average daily volume of an asset, $w_i^{U*}$ and $w_i^{L*}$ are the upper and lower boundaries of an asset respectively after incorporating the information from our cross-asset systematic portfolios. Also, $w_S^L$ and $w_S^U$ are lower and upper bounds of the strategic portfolio, and $w_i^a$ is the weight of an asset in the aggregated portfolio of systematic strategies. Step 1 ultimately produces the target weight $\tilde{w}_i$ for each asset.

Step 2: Re-adjust the preliminary weights to account for asset volatility. Solve for the final weights $w^f$ such that the following function is minimized.

$$\arg\min_{w^f} (w^f - \overline{w}^f)^T (w^f - \overline{w}^f)$$

subject to the following constraints:

a. $sign(w_i^f) = sign(w_i)$

b. $w_i^L \le w_i^f \le w_i^U$

c. $\sum_{i=1}^{N} |w_i^f| = 1$

where:

$$\overline{w}_i^f = \frac{\tilde{w}_i / \sigma_i}{\sum_{j=1}^{n} |\tilde{w}_j| / \sigma_j}$$

$w_i^U = \min(0.05, ADV_i \times 0.01), w_i^L = -w_i^U$ (thus addressing liquidity and concentration risk)

For clarity, $w_i^f$ is the final weight of an asset, and $\overline{w}_i^f$ is the initial weight of an asset after adjusting for its volatility, $\sigma_i$.

Figure 5 shows the results of this approach applied to the 4 strategic portfolios mentioned above. Each row shows our results for 4 strategic portfolios: (1) global equities, (2) a US pension fund proxy, (3) US fixed income, and (4) equity-bond risk parity.

In order to single out the effect of exposure boundaries brought by our alpha portfolio, we also include a *naive* minimum correlation portfolio; in other words, one that excludes Step 1.b.

The following observations stand out:

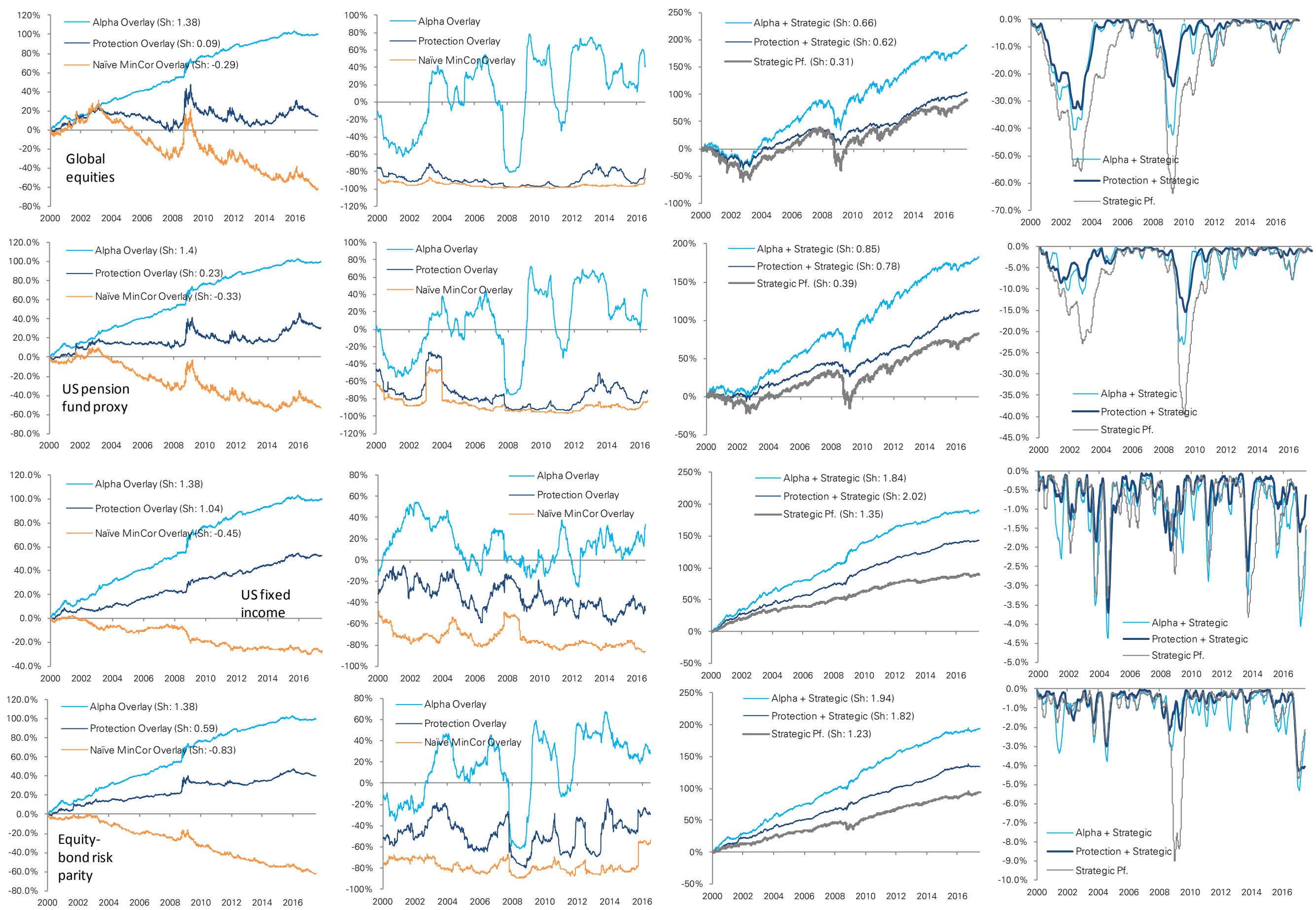
- In all instances, the protection overlay is much more negatively correlated (to the strategic portfolio) than the alpha overlay. The best results are in equity-heavy strategic portfolios, which we primarily attribute to their bigger drawdowns and hence greater need for protection, but also due to the breadth coming from our pool of signals and assets to diversify that exposure.
- The desired drop in correlations did not result in significantly worse performance in most instances, as shown in the first column. As we compare the overlay portfolios with the *naive* minimum correlation portfolio[8], we find that only the proposed protection overlay maintains a similar correlation profile while not "bleeding" as much over time. We attribute this to the second constraint (b.) in Step 1 of our optimisation exercise, which ensures all asset exposures in the protection overlay are in the same direction as those of our "alpha" portfolio.
- As expected given the findings above, the drawdown profile has also improved (relative to the alpha overlay) in all instances, as shown in the fourth column.

The benefits of a stable, highly negative correlation profile must not be understated. The more that this profile is observed, the more *capital efficient* the overlay portfolio is. In other words, even a small allocation to the overlay generates a significant impact in stabilising the volatility and, more importantly, improving the drawdown profile of the final portfolio. This should be key to the large institutional investor, who often faces insurance solutions that are not scalable.

[7] We opted for 0.5 as it implies equal focus, but the weight choice is completely discretionary. High weights are likely to increase concentration risk, while lower weights reduce the protection nature of the overlay.

[8] The naive minimum correlation overlay is built using the same process as that of the protection overlay, except that it does not account for the second constraint (b.) in Step 1; in other words, it does not utilise the predictive power inherent in the "alpha" portfolio.

Figure 5: Columns: (1) overlay portfolio performance, (2) 1Y rolling correlation to the strategic portfolio, (3) final portfolio performance, (4) final portfolio drawdowns. Rows: (1) strategic pf. = global equities, (2) strategic pf. = US pension fund proxy, (3) strategic pf. = US fixed income, (4) strategic pf. = equity-bond risk parity.



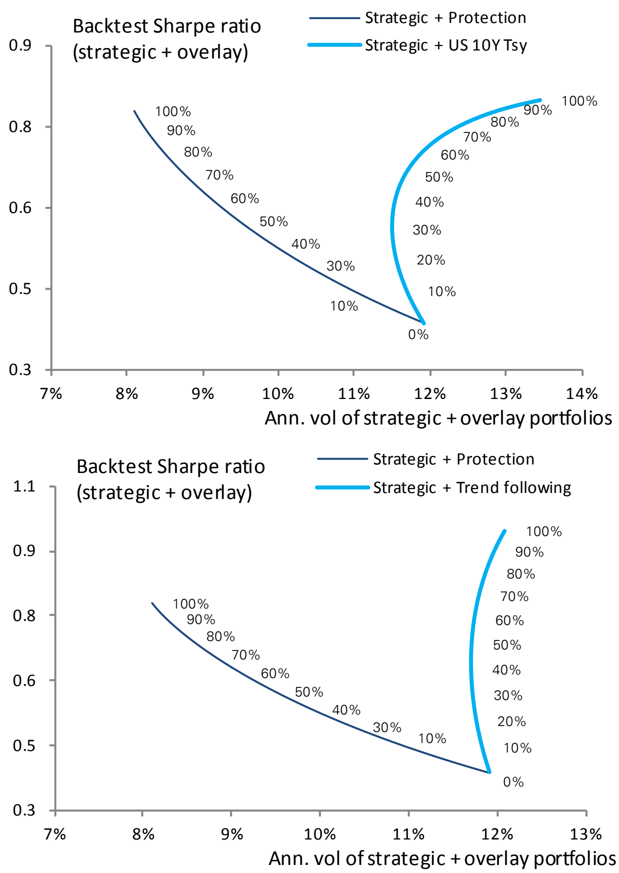

*The drawdowns are smoothed by a 3-month moving average. Source: Deutsche Bank, Bloomberg.*

Figures 6 and 7 illustrate this type of problem as they compares the impact that 3 overlay solutions - trend following, US Treasuries and our protection portfolio - have on the risk-reward of an aggregate portfolio (100% of capital in the strategic portfolio and varying allocation to the overlays).

We use the pension fund proxy as our strategic portfolio because it is often so large that no overlay can be invested into in equal size. Further, we use US Treasuries and trend following because they are often used as tail risk protection.

As the charts show, all 3 overlay alternatives lift risk-adjusted returns in the combined portfolio, but the value comes from distinctly different sources. US Treasuries and trend following lift returns, while the protection overlay reduces both drawdowns and overall volatility. This property of the protection overlay allows for even small allocation quantities to make a meaningful impact on the risk profile of the final portfolio. Figure 8 reiterates the argument by showing the protection overlay has a more stable and negative correlation to the pension fund proxy portfolio.

Figure 6: Sharpe ratio vs volatility of aggregate portfolios (pension fund proxy + overlay) according to varying allocation to the overlay




*Data since 2000. Source: Deutsche Bank, Bloomberg.*

Using USTs and trend following leads to more *alpha* risk, as it is their returns - and not their hedging capacity - that generate value. On the other hand, the protection overlay incurs more basis risk given that the protection benefit depends on how predictive our covariance estimates are.

Another important observation relates to how the objection function chosen - the *minimum correlation* portfolio - relates to its cousin function, the *minimum variance* portfolio. The latter is a slight modification of the former in that the new objective function to be minimised becomes:

$$\sum_{i}^{N+1}\sum_{j}^{N+1} w_i w_j \sigma_{i,j} \qquad (4.2)$$

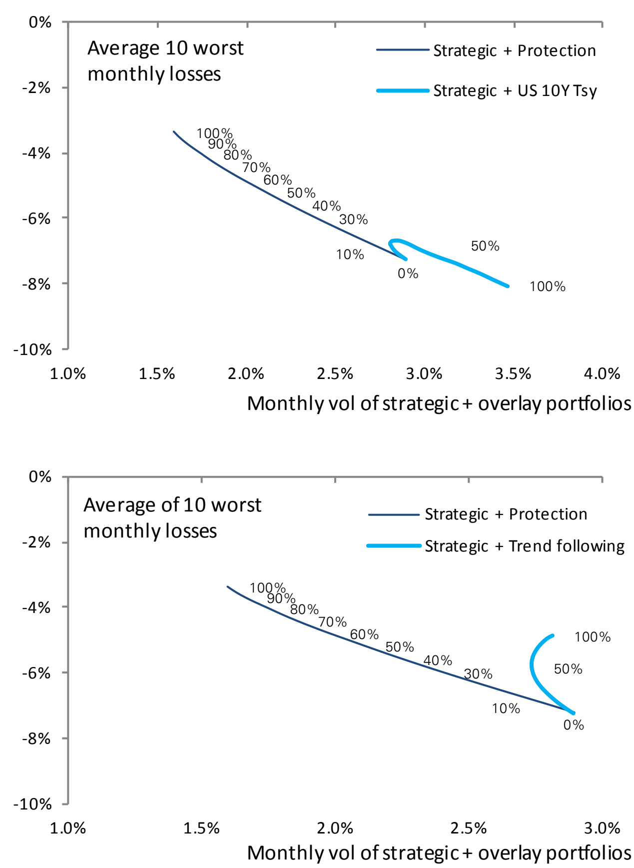
with the added condition that:

$$\sum_{i}^{N} w_i \beta_{i,Str} = -1, \text{ where } \beta_{i,Str} = \frac{\sigma_{i,Str}}{\sigma_{Str}^2}.$$

All other conditions are kept the same, and $\sigma_{i,j}$ represents the covariance between assets $i$ and $j$.

This second objective function benefits from 2 characteristics: (a) it is (arguably) more intuitive as it targets beta explicitly and (b) it removes an extra parameter (that $w_S^L = w_S^U = 0.5$) as highlighted earlier.

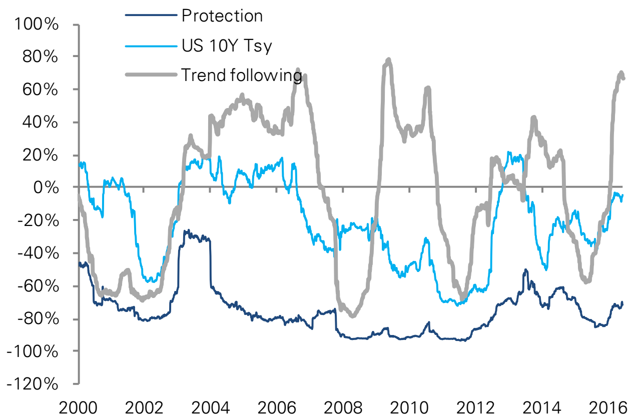
Figure 7: Shortfall vs volatility of aggregate portfolios (pension fund proxy + overlay) according to varying allocation to the overlay




*Data since 2000. Source: Deutsche Bank, Bloomberg.*

Figure 9 compares both functions in terms of how they correlate with each of our 4 strategic portfolios. The approach from Equation 4.2 may be convenient, but it also worsens our results. In all instances, the minimum correlation-based framework proposed above exhibits a more stable and negative correlation profile than the minimum variance approach. Further, the risk adjusted returns in the final portfolio were higher in 3 out of 4 cases – all except for when we used global equities as the strategic portfolio.

Figure 8: 1Y rolling correlations between overlay and pension fund proxy portfolios




Source: Deutsche Bank, Bloomberg.

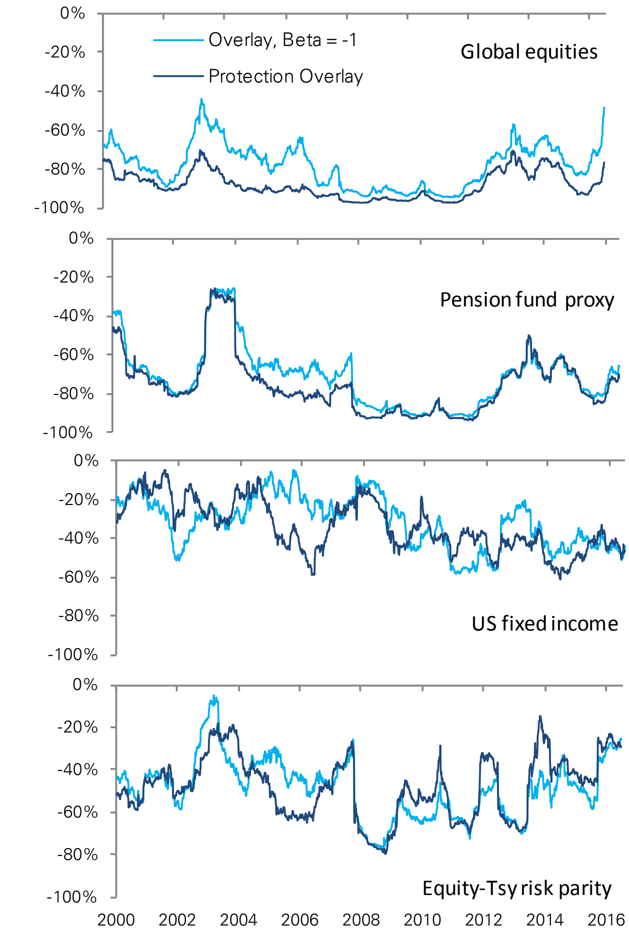
In our view, this is because a *minimum variance optimiser favours low correlation and low volatility assets alike*. Therefore, an asset with very low volatility can be given high weight despite also exhibiting undesirable correlation properties.

The beta constraint in the minimum variance approach may produce an overlay portfolio whose *unlevered* volatility better matches that of the strategic portfolio, but volatility matching is not our aim; minimising correlations is. Volatility matching can also be achieved later, by leveraging the overlay portfolio.

Finally, we also find it important to outline the potential risks to the portfolio construction approach outlined above. We highlight the following:

- Basis risk: the risk that the correlation (and covariance) estimates used differ significantly from what is verified in the future, eventually resulting in less protection. This risk is typical of overlay solutions that seek to combine protection and cost; it is not unique to the framework above.
- "Alpha" risk: the risk that the systematic strategies that define our original *alpha* overlay will underperform, therefore removing the value-add from the direction-based constraint in Step 1.
- Concentration risk: the risk that the protection overlay is too concentrated on a few positions. The more assets are added to the investment pool, the less that this is a concern.

Figure 9: 1Y rolling correlations between strategic portfolio and type of protection overlay (original and with beta=-1)




Source: Deutsche Bank, Bloomberg.

## 5. Building a diversifier portfolio

Our second portfolio construction algorithm lies at the core of liquid alternative risk premia (ARP) investing.

ARP portfolios are meant to be uncorrelated to traditional exposures, and the standard approach is to define the weight of each strategy such that the combination would have been historically *uncorrelated* to the investor's strategic portfolio. This approach is simple - hence, convenient - and produces favourable long-term results. That said, it also suffers from the issues highlighted in Section 2, namely lower short-term correlation predictivity due to unstable estimates and diminished control of asset and asset class boundary exposures.

We propose a different algorithm, which focuses instead on the diversification power of each *asset* while also accounting for the value of each *strategy*. While not all of the 5 strategies included here classify as classical ARP, the results suggest this method may achieve both diversification and positive expectancy more efficiently.

We minimise the following objective function:

$$\sum_{i}^{N}\left(w_i - w_i^{\alpha}\right)^2 \qquad (5.1)$$

subject to the following constraints:

a. $\sum_{i}^{N} w_i \beta_{i,Str} = 0$, where $\beta_{i,Str} = \frac{\sigma_{i,Str}}{\sigma_{Str}^2}$

b. $w_i^{U*} = if\,(w_i^a > 0, w_i^{U*} = w_i^U, 0)$
$w_i^{L*} = if\,(w_i^a < 0, w_i^{L*} = w_i^L, 0)$

Note that this constraint is less important than in the case of the protection overlay, as Equation 5.1 already seeks minimum tracking error. We keep it for noise control.

c. $\sum_{i=1}^{80+1}\left|w_i\right| = 1$

d. $w_i^{L*} \le w_i \le w_i^{U*}$

where:

$w_i^U = \min\left(0.05, ADV_i \times 0.01\right), w_i^L = -w_i^U$ (thus addressing liquidity and concentration risk) and

$w_i^a = \sum_{q=1}^{Q} w_i^q$

As before, $w_i$ is the weight of an asset, $w_i^U$ and $w_i^L$ are the upper and lower boundaries of an asset based on its liquidity. ADV is an estimate of the average daily volume of an asset, $w_i^{U*}$ and $w_i^{L*}$ are the upper and lower boundaries of an asset respectively after incorporating the information from our cross-asset systematic portfolios. Also, $w_S^L$ and $w_S^U$ are lower and upper bounds of the strategic portfolio, and $w_i^a$ is the weight of an asset in the aggregated portfolio of systematic strategies (Q strategies in total). The target weight $w_i$ is our final output.

This approach does not require redistributing the weights to account for asset volatility differences, as with Step 2 in Section 4, since that is already accounted for in the weights of the original overlay portfolio. Inter-asset correlations have also already been accounted for, and are therefore not explicitly covered in this objective function.[9] Our framework of choice is, in essence, similar to a benchmark error tracking function.

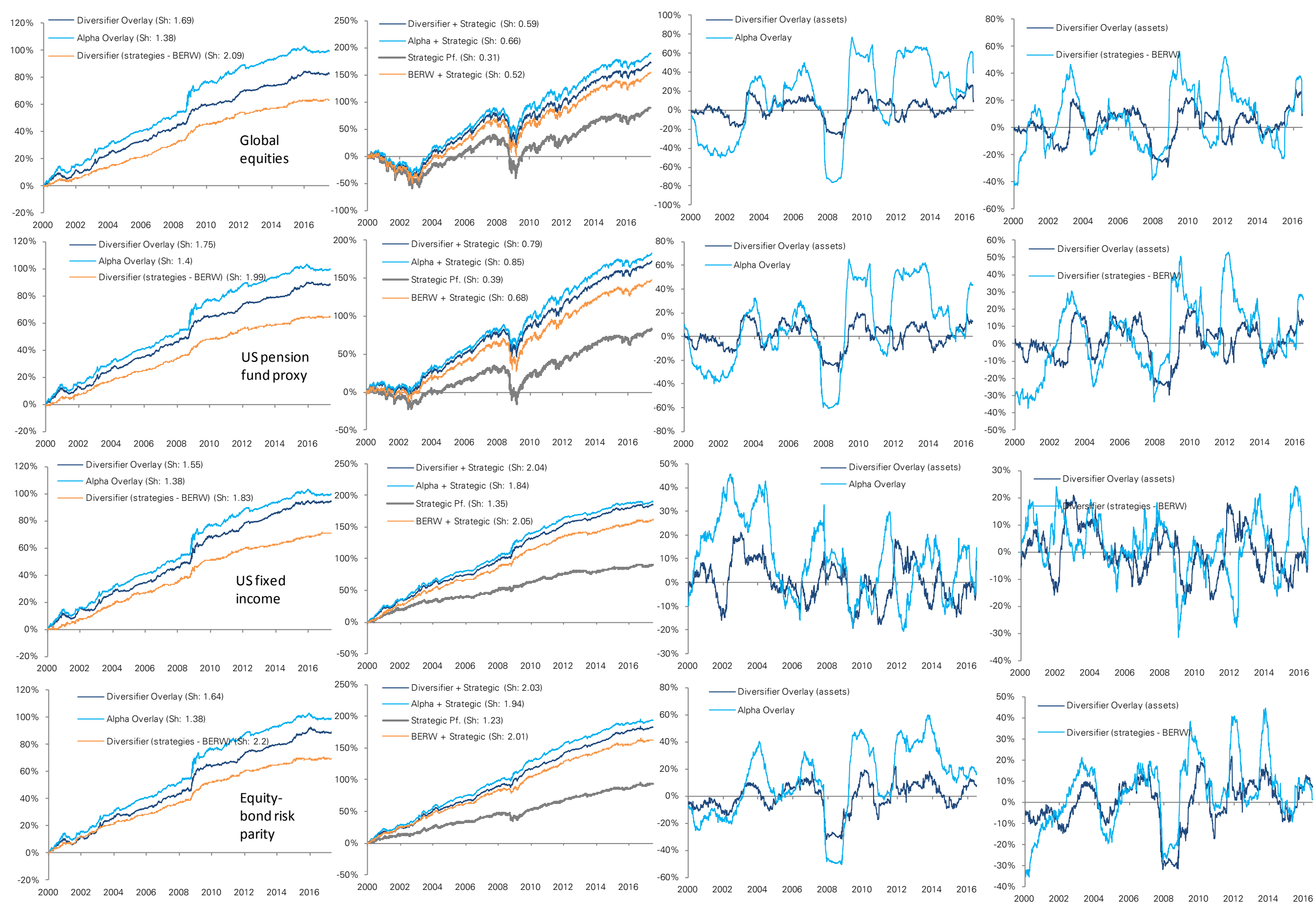
Figure 10 compares this approach with 2 other alternative overlay portfolios:

- Alpha overlay (SRW): we combined our 5 systematic strategies using equal risk allocation. This is the simplest approach; our *alpha* overlay.
- Beta-targeted, equal risk contribution weights (BERW): we solve for the equal risk contribution portfolio with a constraint that its beta to a given strategic portfolio is zero.[10] This is distinctly different from the approach outlined above in that here we optimise for optimal strategy weights, while earlier we optimised for asset weights. Strategy weights must be non-negative.

[9] An alternative procedure that further emphasizes covariances is to minimise the following function: $\sum_{j}^{N}\sum_{i}^{N}\sigma_{ij}\left(w_i - w_i^{\alpha}\right)\left(w_j - w_j^{\alpha}\right)$. We opted against it in this case because the original weights $w_i^{\alpha}$ from our *alpha* portfolio should have already accounted for asset diversification. Another approach considered was the minimum correlation portfolio with a target aggregate correlation of 0 to the strategic portfolio. We also opted against it as it would have captured less information content from the *alpha* portfolio.

[10] In other words, we minimise the following objective function $\sum_{r}^{R}\sum_{s}^{S}\left(w_r\sigma_{r,P} - w_s\sigma_{s,P}\right)^2$, subject to $\sum_{q}^{Q} w_q \beta_{q,Str} = 0$ and $w_q \ge 0$, where R, S and *Q* represent the number of available strategies and P represents the portfolio of strategies.

Figure 10: Columns: (1) overlay portfolio performance, (2) final portfolio performance, (3) and (4) 1Y rolling correlation to the strategic portfolio. Rows: (1) strategic pf. = global equities, (2) strategic pf. = US pension fund proxy, (3) strategic pf. = US fixed income, (4) strategic pf. = equity-bond risk parity.




*Source: Deutsche Bank, Bloomberg.*

We highlight the following observations:

- Targeting a neutral beta as extra constraint improves the correlation profile in all instances; both the diversifier overlay and the BERW generate lower correlations to our 4 strategic portfolios, as shown in the 3rd and 4th columns.
- In all instances, the proposed diversifier overlay displays more subdued correlations than the BERW overlay.
- This outperformance is reflected in higher risk-adjusted returns of the *final* portfolio, which combines the strategic exposure with overlay portfolios. The version with our proposed overlay outperforms the BERW overlay, as per second column, even though the latter outperforms the former when evaluated on its own (first column).

Using beta constraints to target exposure to assets – instead of exposures to strategies – benefits from giving the optimiser more freedom to identify an optimal solution. The optimiser may utilise more ingredients (i.e. "underlyings") and may target boundary constraints – asset and asset class – much more easily. Therefore it is no wonder that the diversifier overlay seems to outperform the BERW overlay in achieving lower correlations to the strategic portfolio.

*That said, one must also acknowledge that its implementation can be less practical.* It is often easier to bundle systematic strategies together with the aforementioned beta constraints instead of calculating the net asset weight from each strategy and re-weight asset exposures according to that beta target. Should the researcher opt for an approach similar to the BERW overlay, we advise enhancing the breadth of the pool of strategies to address the typical long-only exposure constraint to each strategy. Ideally one should seek *beta diversity* – in other words, include strategies with both negative and positive beta to the factor to be neutralised.

Another point to note is that one may target beta exposures to variables other than the strategic portfolio. Most notably, one can target beta exposures to risk factors. Natividade et al [2017] outline 11 factors of risk that help explain the variations of cross-asset returns, as well as how to estimate exposures as part of a holistic risk factor model. The diversifier overlay proposed in this section may also be applied in that context.

Finally, as with Section 4, this approach also suffers from concentration, basis and "alpha" risk.

## 6. Building a tracker portfolio

Our final algorithm is a portfolio *tracker*. It aims to replicate the return profile of a given benchmark - our strategic portfolios. This framework can be used as overlay to a strategic portfolio, which allows for better volatility targeting.

Our construction process is a slight modification from Navas-Palencia [2016] and Edirisinghe [2013]; In other words, we solve for the weights that minimise the output from the following objective function:

$$\frac{1}{2}\sum_{i}^{N}\sum_{j}^{N} w_i w_j \sigma_{ij} - \sigma_{Str}^2 \sum_{i}^{N} w_i \beta_{i,Str} \qquad (5.1)$$

subject to the following boundary constraint: $\sum_{i}^{N} w_i = 1$. Note that this is different from the *absolute* weight summation constraints in previous sections. Here we relax the constraint on absolute weights in order to better match the volatility of the benchmark portfolio, which also results in time-varying leverage.

We note that, unlike the original references, we chose not to add an extra constraint that targets tracking the first moment of the benchmark – i.e. $\sum_{i}^{N} w_i \mu_i = \mu_{Str}$. *We avoid targeting $\mu_i$ in most portfolio construction exercises as it is very difficult to predict.* The task is particularly challenging in this context because some of the benchmarks used are comprised of discretionary managers; their future investment decisions may be completely unrelated to past decisions. The primary use of this approach should be to target the volatility of funded portfolios.

If the investment goal is to replace an exposure that cannot be feasibly traded, however, the success of this approach will ultimately depend on the nature of the exposure.[11]

We have also omitted the alpha-based asset boundary condition (Step 1b in Section 4), which would have served as an *enhanced tracking* mechanism in this context. We do so as the tracker portfolio aims to mimic the benchmark, as opposed to outperform it.

Finally, we added liquidity-based boundary exposures ($w_i^{U*}$, $w_i^{L*}$) as done in Sections 4 and 5.

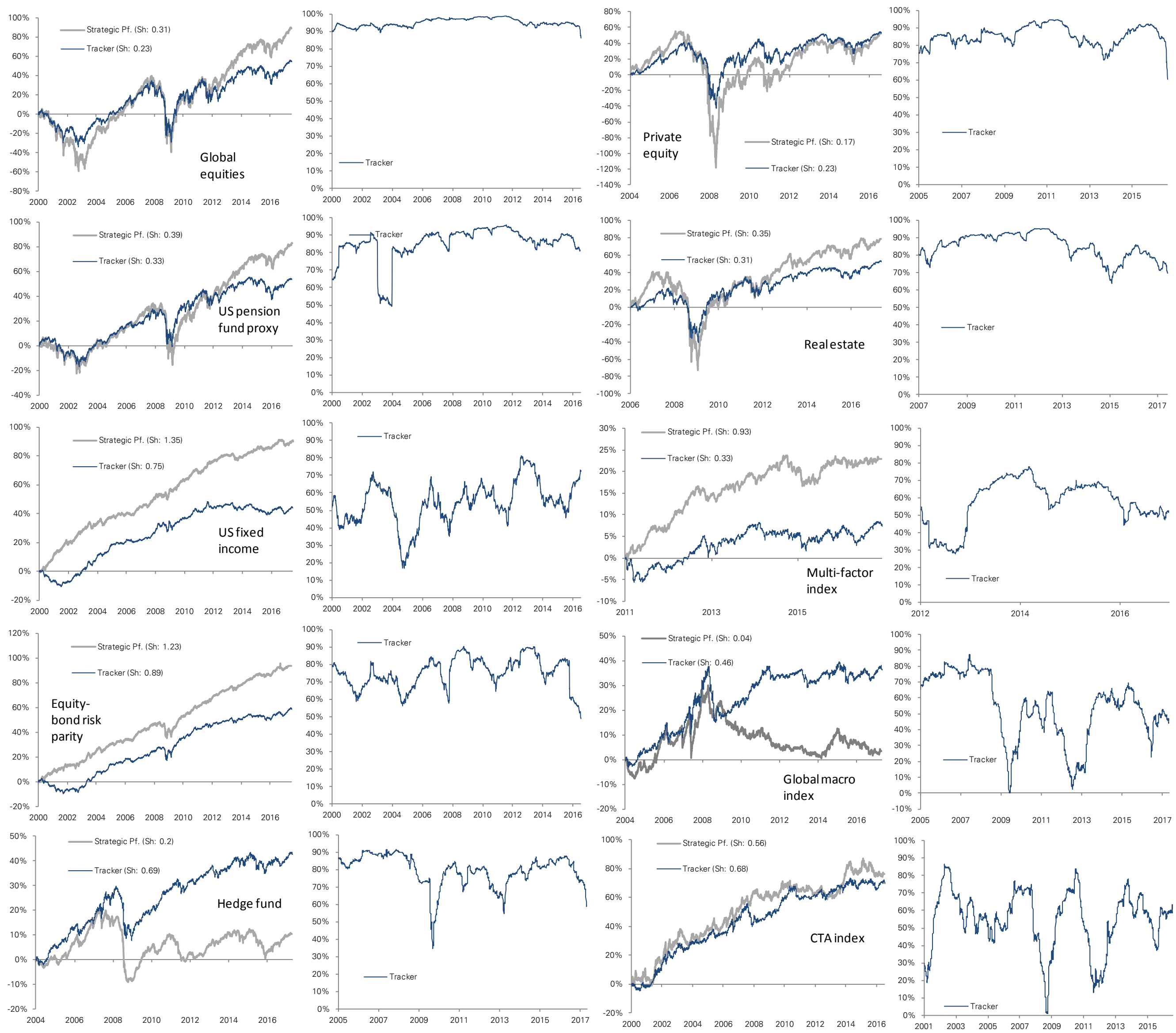
The tracker overlay portfolio was tested on 10 benchmarks in total. These are the original 4 strategic portfolios from Section 3, in addition to:

- A *private equity* index (<SPLPEQTY Index> on Bloomberg);
- A *real estate* index (<TENHGU Index> on Bloomberg);
- A *hedge fund replication* index (<HFRXGL Index> on Bloomberg);
- A *CTA-replication* index (<NEIXCTA Index> on Bloomberg);
- A *global macro* index (<HFRXM Index> on Bloomberg);
- A *multi-factor* index (<EHFI900 Index> on Bloomberg).

Figure 11 illustrates our results when applying the tracker framework to all 10 strategic portfolios. The primary finding relates to the correlations between our tracker portfolios and their respective benchmarks. While high, these correlations are not as positive and stable as the correlations in the protection portfolio (Figure 5) are negative and stable. This is due to lower breadth and weight constraints. In other words, our pool of 80 assets is not wide enough to replicate some of our benchmarks, and the boundary constraints attached to each asset keep the optimiser from achieving higher correlations. This is less of an issue when replicating equity benchmarks - as per first and second rows of Figure 11 - because our pool is largely comprised of investment assets. But it is a shortcoming when replicating risk-mitigating assets such as Treasuries.

[11] For completeness, we attempted the mean targeting constraint as per academic references. We used 2 approaches to estimate $\mu_i$: historical momentum and expected returns based on alpha aggregation, as per Natividade et. al [2017]. The benchmark mean $\mu_{Str}$ was always estimated using short-term historical momentum. We found better replicating results using static benchmarks, such as a long equities position, and worse results when using manager aggregates as benchmarks.

Figure 11: Columns: (1) and (3): performance of overlay and benchmark (strategic) portfolios, (2) and (4): 1Y rolling correlation to the strategic portfolio. Rows: strategic portfolios as per labels.




*Source: Deutsche Bank, Bloomberg.*

Figure 11 also highlights how challenging it can be to replicate benchmarks comprised of active managers. While the correlations are generally high, they also witness sudden drops - coincidental to when the benchmarks suddenly rise or drop.

That said, some result characteristics are positive. For instance, the volatility of our tracker portfolios generally matched that of our benchmarks - one of the goals of our objective function. Further, the leverage numbers in our tracker portfolios are realistic.[12] Finally, the results excluding weight constraints – that is, removing the condition that $\sum_i^N w_i = 1$ – generally yielded higher correlations.[13]

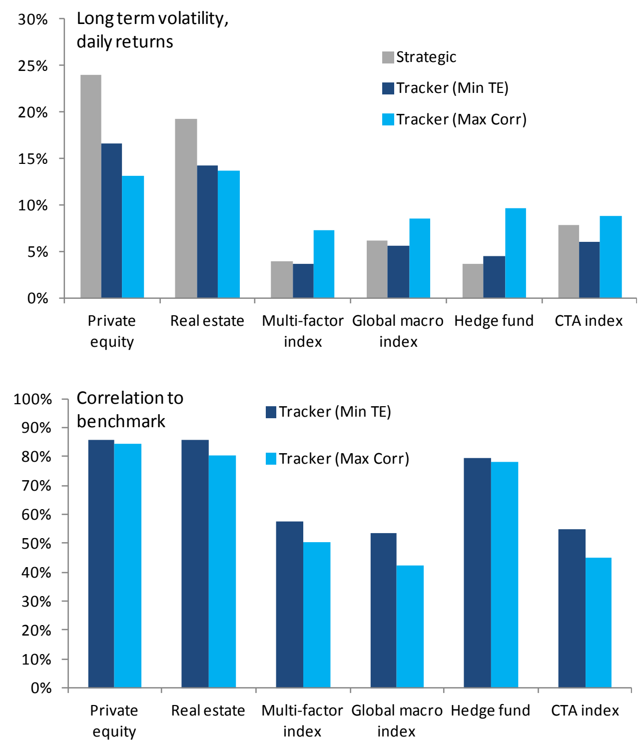
[12] In equity-linked benchmarks, the average leverage has been 2.2x and the standard deviation has been 0.2x over the past 17 years. The numbers are 1.7x and 0.2x in fixed income benchmarks, and 2.0x and 0.08x in active manager benchmarks, respectively.

[13] The results are mostly felt in fixed income-linked benchmarks. The average 1Y correlation (without constraints) has been 0.75, and the

Another important observation relates to our choice of objective function: we opted for a *minimum tracking error* portfolio, as opposed to a *maximum correlation* portfolio - the latter being the opposite of what was described in Equation 5.1.[14] Our choice relates to optimisation efficiency; both objective functions are convex, but maximising the latter is more likely to yield a corner solution - a problem less likely to occur when minimising the former. Further, the leverage target is already built into our chosen objective function; we do not need to address it separately as is the case under the maximum correlation portfolio. Finally, Figure 12 also shows that our primary choice provides a better benchmark replication profile in both correlation and volatility terms. We focus on active manager benchmarks as these are harder to replicate to begin with.

Finally, we reiterate the risks to this approach. Unlike in prior sections, there is no "alpha" risk as our systematic strategies are not part of the tracker framework. That said, one could argue that basis risk and concentration risk are magnified here. Replicating active managers can be particularly challenging, as shown in our results, given the nature of their decision making process. At the same time, our attempts to reduce the tracking error of fixed income heavy benchmarks using weight unconstrained portfolios prompted an over-allocation to other risk mitigating assets, therefore increasing concentration risk.

Figure 12: Tracker portfolios - volatility and correlation to benchmark




*Source: Deutsche Bank, Bloomberg. Correlation of daily returns, data from 2000 onwards depending on the benchmark.*

## 7. Covariance estimation and portfolio turnover

As is the case with all risk-oriented portfolio construction exercises, results can be heavily affected by how our covariances are estimated. This report utilises a standard approach, which benefits from simplicity: an EWMA covariance that utilises a rolling lookback window and half-life length equal to 2/5 of the full window. A more sophisticated approach introduced in Natividade et al. [2017] incorporates our new risk factor model, the relevance of scheduled events in jump estimation, and volatility regimes; that will be used in the future. We also refer the reader to Ward et al. [2016a] and Ward et al. [2016b] for a general overview of topics related to risk estimation, including model responsiveness.

This section addresses the sensitivity of our results to covariance estimation window. We address impact from 3 angles: portfolio turnover, Sharpe ratio and correlations to the strategic portfolio. We focus specifically on the proxy US pension fund portfolio as our strategic portfolio.

standard deviation has been 0.08. The respective numbers when weight constraints are added are 0.65 and 0.10 over the past 17 years. In equity-related benchmarks, both constrained and unconstrained versions produced similar results (0.9 correlation average, and 0.06 standard deviation).

[14] In other words, we maximise the following objective function:

$$\sum_{i}^{N+1}\sum_{j}^{N+1} w_i w_j \rho_{i,j}$$ , with the same constraints as highlighted in Steps 1 and 2 of Section 3. The variables here are also the same as highlighted in Section 3.

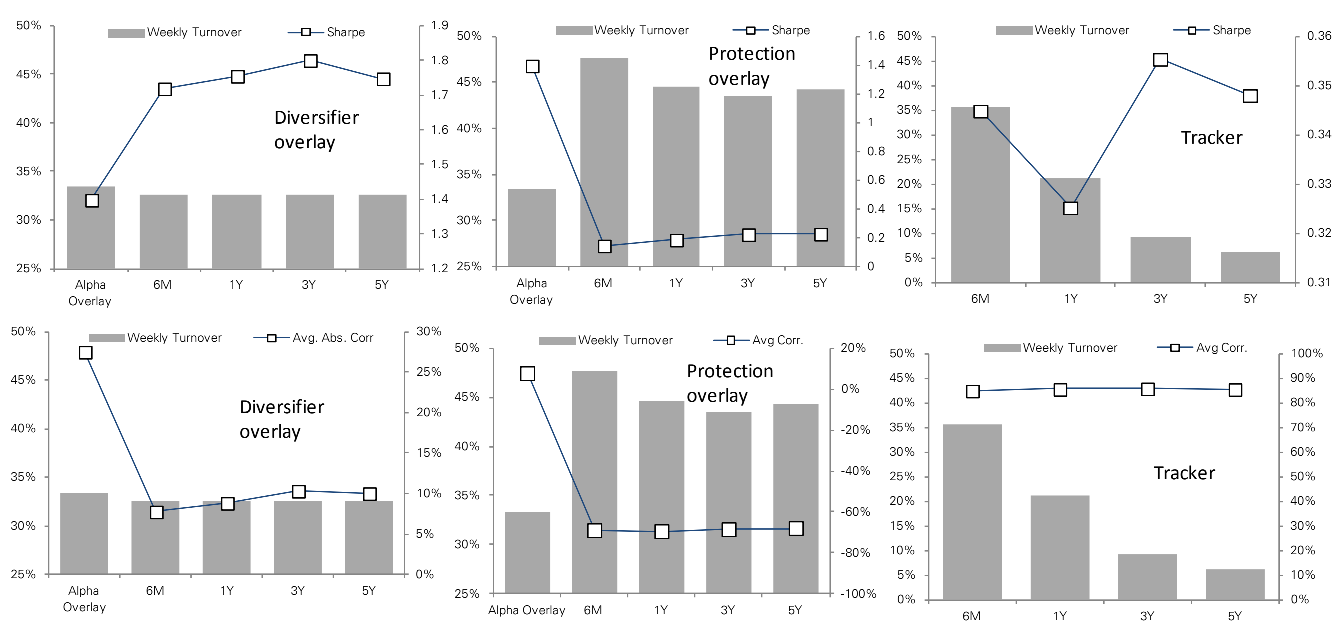
Figure 13 plots the impact of different covariance estimation windows on the overlay portfolio, measured according to its turnover, its average correlation to the strategic portfolio and its Sharpe ratio.

The charts show that the sensitivity of results to our covariance matrices is primarily dictated by the role that our *alpha* portfolio plays in the objective function, as follows:

- The covariance estimation windows have little impact in the turnover of the *diversifier* overlay from Section 5; as per objective function 5.1, both the direction and size of the final weights are primarily influenced by the alpha portfolio. Estimation windows play a larger role in the *protection* overlay from Section 4, as the *alpha* portfolio only influences the direction of the final asset weights while objective function 4.1 is entirely dictated by our correlation estimates. Finally, the estimation window plays the most significant role in dictating the turnover of the *tracker* portfolio from Section 6, as the *alpha* portfolio has no influence in either direction or size of the final asset weights.
- High turnover variation meant high impact on the Sharpe ratio of the *protection* overlay, just as the low variation meant low impact in the *diversifier* overlay - both being unlevered portfolios. As for the *tracker* overlay, whose framework allows for built-in leverage, the higher leverage brought by shorter estimation windows ultimately lifted the risk-adjusted returns and hence these were also stable. Figure 13 shows similar conclusions on the impact of changing turnover on correlations to the strategic portfolio.

These findings help justify our final choices for the lookback window when estimating our covariance matrices. The *protection* overlay, whose results suffer from shortening our sample lookback, utilises a longer lookback window - 5 years, with a 2-year half-life. The stability of these estimates ultimately improves the cost profile. The *diversifier* overlay, whose results are indifferent to our covariance estimation window, uses a shorter lookback window - 1 year, with a 100-day half-life. We ultimately favour its greater adaptivity. Finally, the *tracker* portfolio also utilises a shorter lookback window as its built-in leverage removed much of the negative impact from the higher turnover.

Figure 13: Result sensitivity to changes in lookback window for volatility estimation as measured by turnover, Sharpe ratio and correlation to the strategic benchmark




Source: Deutsche Bank, Bloomberg.

## 8. Conclusions

This report has outlined a framework for cross-asset portfolio construction that involves modelling the covariances between underlying assets across currencies, commodities, Treasuries and equity indices. It is different in that the standard approach is to model strategy covariances instead.

We outlined 3 portfolio construction methods that benefit from this approach, each targeting a different objective; protection, diversification and tracking. The results suggest:

- more stable, predictive covariances;
- more accurate targeting of beta exposures;
- better handling of asset exposure constraints.

We also outline shortcomings from this approach, in addition to the sensitivity of our results to changes in how the covariances are estimated.

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