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Time To Cross the Bridge: Factor Investing in Credit Markets

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

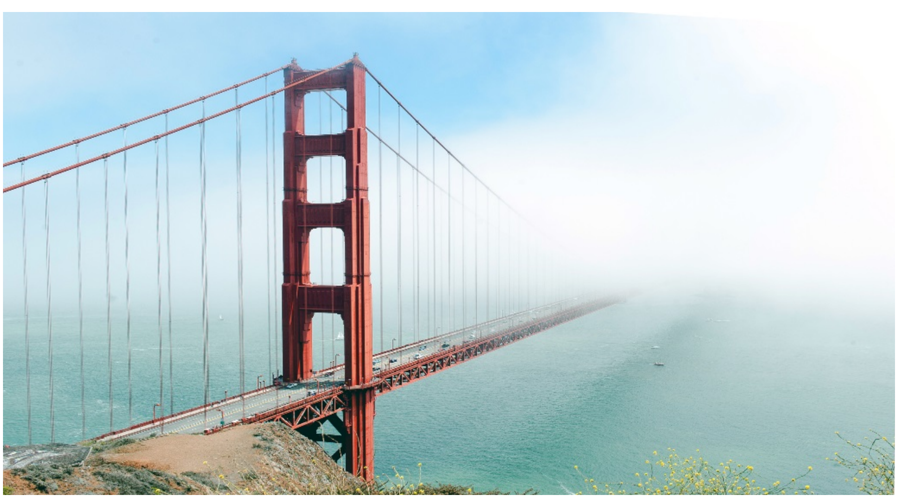
This Quantcraft report connects factor investing and Corporate Credit markets. It provides a bridge to the systematic investor seeking to exploit one of the final frontiers of factor investing. It also introduces the Credit investor to the art and science of quant investing.

To tackle the challenges of frontier markets, we had to adapt. We used credit default swaps instead of corporate bonds, for reasons including liquidity, standardisation, position symmetry and their unfunded nature. We also applied innovative transaction cost management techniques to slow turnover where needed.

In our factor harvesting process, we employed tools that are unique to the asset class. We used duration-times-spread as a risk measure, distance-to-default as a signal-generating variable and duration to uncover structural inefficiencies.

We have found six investable factors - divided into market-related and company-specific. Some involve following the crowd, but others go distinctly against it. We believe that "reaching for yield", for example, is often an unrewarded practice. As a result, some of our strategies are notably defensive - a welcome characteristic given the number of hidden risks in the asset class.

Time To Cross the Bridge



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Time to Cross the Bridge: Factor Investing in Credit Markets

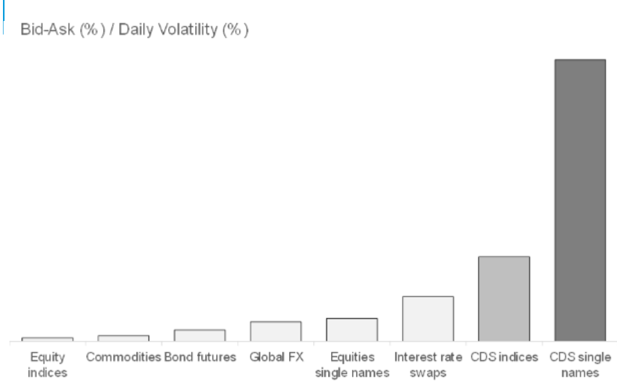
1. Introduction

Credit markets have been paradoxical to the quant investor. On one hand, the breadth of instruments, markets and idiosyncratic features – regulatory and structural – make them ripe for alpha capture.

On the other hand, it is also – for various reasons – one of the most under-researched asset classes for the factor reader. The data lacks breadth and depth, owing partly to poor liquidity and its OTC nature. Credit markets are heterogeneous, and varying seniority, maturity, optionality and covenant profiles make it hard to compare corporate bonds with each other. Further, trading costs are often at a different level relative to other publicly traded asset classes.

The advent of liquid credit default swap markets in the early 2000s ameliorated much of the above. Standardized CDS contracts allow for better cross-sectional comparisons, and liquidity on the 5-year tenor is higher than that of most corporate bonds. But trading costs are still well above those of other asset classes, as we show in Figure 1.

Figure 1: Transaction Cost Comparison Across Asset Classes



Source: Deutsche Bank

This *Quantcraft* sheds light on the asset class, thereby tackling one of the final frontiers in factor investing. Following the recipe from our recently published FX Cookbook, we conduct a thorough review of systematic investing in Credit with different investment applications. We pay particular attention to trading costs, with various implications for how signals are aggregated and turned into viable portfolios.

This *Quantcraft* is organized as follows:

- Section 1 develops the case for using CDS contracts instead of corporate bonds in factor investing. It also describes our investable universe and data sources.
- Section 2 uses econometrics to identify returns and explores how they interact over time.
- Section 3 describes the methodology used to construct portfolios, weight positions and neutralize signals.
- Section 4 introduces our investment factors, at both the single name and aggregate index levels.
- Section 5 shows how we combine different factor strategies into a multi-factor portfolio and develop a novel approach to reduce the impact of transaction costs.
- Finally, Appendix A illustrates a step-by-step process to create a return series from CDS spreads.

1.1 CDS contracts and data

We focus on the US Corporate Credit market given the higher liquidity, and CDS contracts instead of corporate bonds. These choices afford the following advantages:

- CDS spread quotes constitute a straight measure of credit risk, as opposed to bond yields. Corporate bond yields require particular treatment to strip the credit component from the quoted yield. There are different ways to do so, each with its own advantages and disadvantages. CDS spreads save the trouble of selecting the methodology and the step of turning bond yields to credit spreads. The CDS spread is a direct and straightforward price of credit risk.
- CDS contracts have standard maturities. This means that all issuers have contracts with the exact same maturity, allowing for a direct cross sectional comparison of credit spreads. Corporate bond

maturities are highly diverse and the cross sectional comparison of credit spreads requires further consideration. Not all credit issuers have bonds with similar maturities.

- Standard CDS contracts are, on average, more liquid than typical corporate bonds. Liquidity is concentrated in the 5Y tenor, which is also the implementation vehicle for most strategies shown in this report.
- CDS contracts allow the investor to go short a credit name - to "buy protection" - in as straightforward a manner as going long - "selling protection". This allows us to design long-short strategies, as is paramount to the factor investor. In contrast, going short credit through corporate bonds is far more challenging - borrowing is costly and inventories can be scarce. Therefore, implementing long short bond portfolios on a systematic basis is far less realistic.

The investable universe used in this *Quantcraft* comprises corporate issuers that are part of the NA Investment Grade CDS index (CDX.IG) and the High Yield CDS index (CDX.HY)[1].

Since CDS index constituents change over time, our universe also changes periodically. In total, we use data from over 400 credit names starting in January 2004 and ending in December 2018 - 15 years.

The CDS data for the January 2004 - December 2005 period has been sourced from Deutsche Bank internal databases. From January 2006 onwards we use Markit; as per industry practice.

2. Identifying the Investment Factors

We begin our study by identifying the return factors of the asset class – in other words, by uncovering the persistent drivers of future Credit returns, using multiple time horizons.

We use two standard tools: principal component analysis (PCA) and panel regressions. PCA allows us to understand the commonality of contemporaneous returns, and to an extent connect them to tangible market and macro-economic measures. Panel regressions in turn take each tangible variable and evaluate its contribution to future asset class returns, both in absolute terms and relative to other drivers, as well as how that varies over time.

2.1 Principal Component Analysis (PCA)

In line with our approach in other asset classes, we begin by applying PCA to our Credit return streams to analyze the common variations of the asset class.

PCA assists us in distilling large datasets into a small set of endogenous variables that explain the main variations of the asset class. While endogenous, these variables – the principal components – can then be compared to tangible market measures through simple co-movement analysis. This ultimately allows us to understand what drives contemporaneous returns.[2]

2.1.1 Cross Sectional PCA

We ran our PCA exercise on a dataset containing over 400 different credit names, focusing on 5-year CDS returns, using the whole history from 2004. We repeated the analysis over different return frequencies, from weekly to annually, to evaluate the impact that these have on the overall results.

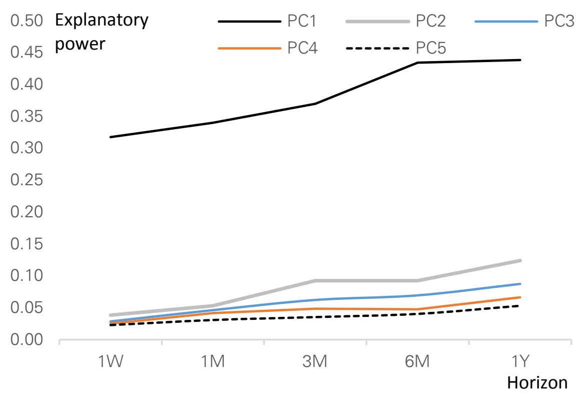
In Figure 2 the first principal component explains approximately 38% of the asset class variations, a number far higher than any of the other components. Its explanatory power steadily grows as we move to lower frequencies – i.e. longer periods. This can be linked to the noisiness and randomness of short-term returns.

Importantly, this profile is similar to what Capra et al. (2018) found in equity markets, arguably the most comparable asset class. The reader may find that the quantity explained by PC1 is somewhat low, especially if compared to other asset classes as done in Natividade et al. (2013) and Natividade et al. (2018), but it also raises the possibility that company-specific, residual momentum can be captured in Credit just as it is in Equities.

[1] The CDX.IG is an index contract with 125 constituents, the most liquid North American credit entities with investment grade credit ratings. The CDX.HY is an index contract with 100 constituents, the most liquid North American credit entities with non-investment grade credit ratings. Both indices weight their constituents using an equal weights approach. As of January 2019, the index contracts roll over semi-annually. On roll-over dates new series are issued and a review is carried for the inclusion of new credits in the index. Single name CDS contracts follow the same series and rollover pattern as that of the indices.

[2] This is a standard approach in quant studies. An example of such exercise is carried by Anand et. al. (2019) where the authors find strong correlation between the PC1 of a set of 27 different currencies and the USD. This allowed the authors to interpret the PC1 as representative of the US dollar factor.

Figure 2: Explanatory power by principal component across data snapping frequencies



Source: Deutsche Bank

Having crystalised the main source of return variations into one time series, our next step is to relate it to tangible variables to better understand the drivers of the asset class.

Figure 3 shows that PC1 correlates heavily with global equities and commodities – two key proxies for global growth. Likewise, it correlates very negatively with our Global Sentiment Indicator (GSI), a proxy for market sentiment and volatility, and very positively to the main credit market indices. We can therefore conclude that this "market factor" is heavily pro-cyclical.

These findings are intuitive, as the literature on corporate bond returns narrows the drivers down to interest rates, growth and volatility[3]. With interest rates being largely removed by construct, the other two factors prevail in our analysis.

Figure 3: Long-term correlations – Credit PC1 and other market variables

	PC1
GSI	-0.34
US Nowcast Growth	0.03
US Nowcast Inflation	0.02
Global Treasuries	-0.32
Global Equities	0.58
USD/FX	-0.47
Global Commodities	0.39
CDS Indices	0.85

Source: Deutsche Bank. Correlations are calculated using weekly non-overlapping percentage changes between PC1 and Market/Economic Measure. The final value is the average of non-overlapping series with 5 different start dates. See Natividade et al. (2015) for our nowcasters.

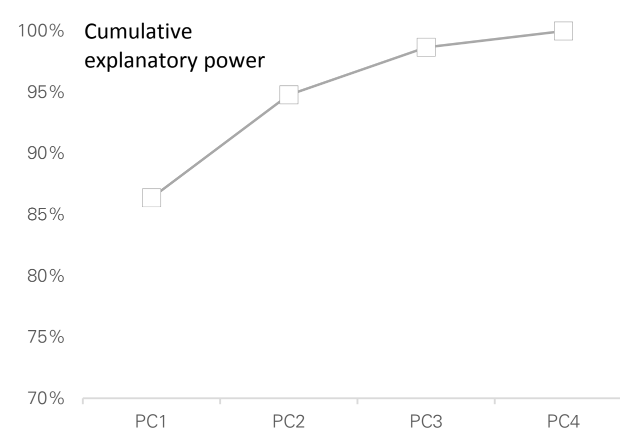
2.1.2 Term Structure PCA

So far our PCA work has focused on the 5-year tenor as it is the most liquid. But any analysis of Credit markets would be incomplete without accounting for the rest of the term structure as well, as contracts with other maturities are also traded.

We next conduct principal component analysis on a basket of 3Y, 5Y, 7Y and 10Y CDX NA IG and HY indices, equally weighted. We chose indices instead of single name CDS to capture dynamics of the market as a whole, as opposed to individual names, especially given that the prior exercise suggested the market factor is most relevant.

We applied PCA to weekly returns using the same 15 years of data. As shown in Figure 4, the first principal component now accounts for some 86% of the common return variations in the Credit term structure. The inclusion of the second and third principal components increases the explanatory power to approximately 99%. Such findings are similar to those of related exercises done using interest rate swap rates[4].

Figure 4: Credit term structure principal components



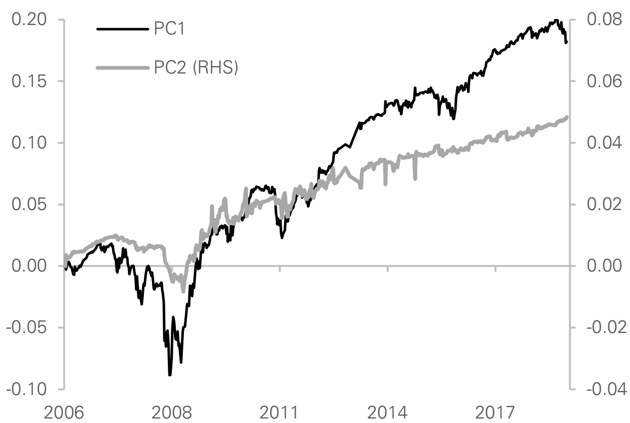
Source: Deutsche Bank

Figure 5 shows the historical progression of both PC1 and PC2 series from the term structure exercise above. Both series rise over the long run, suggesting that exposure to both is rewarding.

[3] Thiagarajan et al (2016) find that rates, economic growth expectation and volatility explain 80% of the returns in a representative set of fixed income indices.

[4] Rebonato (2018),using data for over 30 years on the US Treasury market term structure, finds that the first principal component accounts for 90% of the observed variance, adding the second PC increased the explanatory power to 95% and the three first principal components explain 99% of the of the total variance

Figure 5: Term structure PCs – cumulative progression

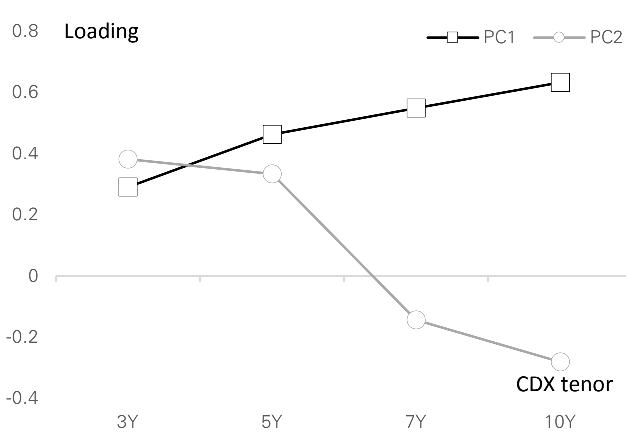


Source: Deutsche Bank

The loadings of each component in Figure 6 indicate that exposure to PC1 is achieved through similar long-only exposures on different points of the curve – as is normally the case with "level" factors[5].

On the other hand, PC2 loadings are distinctly different. Exposure to this component requires taking long positions - "selling protection" - on shorter tenors and short positions on longer-dated tenors. In other words, PC2 mimics a curve steepener trade.

Figure 6: Term structure PC loadings per CDX tenor



Source: Deutsche Bank

That it is also a rewarding factor, and uncorrelated to PC1 over the long sample, indicates that PC2 deserves further attention – as given in Section 4 in the context of our Low Duration factor.

2.2 Panel Regressions

Panel regressions complement PCA analysis by adding more tangible variables to the mix of drivers, and by focusing on predicting future returns as opposed to explaining current returns.

Our work follows Anand et. al. (2019): we selected a mix of fundamental and market data that have been linked to the predictability of credit returns, based on our review of the literature[6]. The goal was to calculate the marginal explanatory power of each driver, across future return horizons, in the context of a panel regression.

The predictive factors chosen are:

- A *price action factor*: the signal is defined as the n-period future returns of the single name CDS, where the lookback window is the same as the forecast horizon. This is in line with the evidence shown in academic literature.[7]
- A *credit ratings factor*: we use S&P long-term credit ratings to bucket single name credits into three categories: high, medium and low quality. The quality groups are introduced into the linear regression as dummy variables.[8] We include this factor in our regressions to assess the predictability of a potential quality signal on future returns.
- A *value factor*: following Brooks et al. (2018) we define the Value signal as the residual between the market spread and a fair value estimation. The spread fair value is the result of a cross-sectional regression between CDS spreads and Merton's distance to default.[9]
- A *spread factor*: we add credit spreads as a control variable. Credit spreads are a tangible measure of expected returns, as they represent the return on a CDS contract if held to maturity and in the absence of a credit event.

[5] The way credit PC1 loads in the credit market is similar to PC1 in the interest rate market. Traditionally this has been described as the "level" factor.

[6] Jostova et al (2013), Haessen et al.(2012), Howeling et al. (2017), Israel et al. (2017) are some key works in Credit factor investing that explore the predictability of credit returns.

[7] For instance Jostova et al (2013) studies the momentum phenomenon. Later publications on factor investing such as Howeling et al (2017) and Israel et al. (2017) find evidence documenting the economic significance of Momentum.

[8] The high-quality group is composed of credit ratings between A- and AAA, the medium-quality group is formed by credits rated between BB- and BBB+ and the low-quality bucket groups credits rated between D and B+.

[9] Different from Brooks et al. (2018) we do not incorporate duration as a regressor. The reason is that we are analyzing 5Y credit default swap spreads with little dispersion in duration values. In the case of Brooks et al. (2017) incorporating duration as a regressor is a key element since their data set is composed of bonds with different maturities. Later in the paper we expand on how to calculate Merton's distance to default.

- *Market betas*: the betas are a generic proxy for risk in our set of regressors. We focus on two betas: that to the US Credit market, proxied by the average of CDX NA IG and CDX NA HY indices, and that to the US Equity market, proxied by the S&P 500.[10]
- A *fundamental Credit factor*: We selected four indicators, as suggested by DB's Fundamental Credit Research team, all based on corporate accounting data: interest coverage, free cash flows to debt, net debt to EBITDA and EBITDA margin. These financial ratios, commonly used to assess a company's credit quality, are standardised by their respective GICS sector and linearly aggregated per company, providing us with a single, final fundamental factor reading per company.

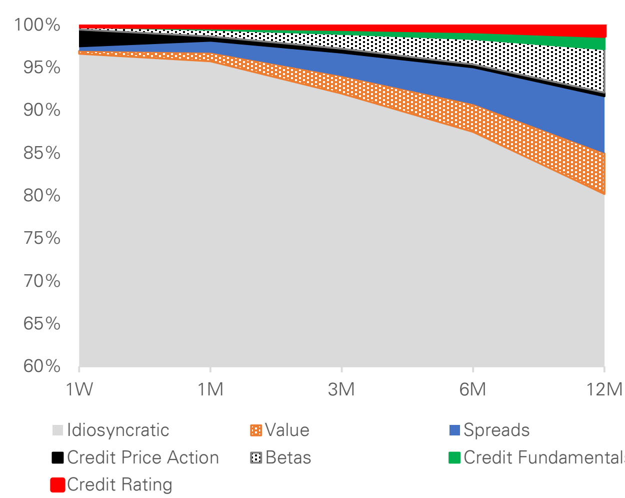
Having chosen our explanatory factors, the next step was to run panel regressions to evaluate the contribution of each to future returns in the asset class. We corrected for multicollinearity through the use of forward step-wise regressions where all permutations were applied. Further, we evaluated multiple horizons, ranging from 1 week to 1 year to attain a more holistic view.

For a given horizon, the steps are as follows:

1. We set future single-name 5Y CDS returns (from current to the next horizon date) as the dependent variable, and the current value of each of the regressors above as explanatory variables.
2. We apply cross-sectional standardization. All variables - dependent and independent- are subject to inverse z-score cross-sectional standardization, as per Natividade et al. (2014), to reduce the effect of outliers and bring them to the same scale[11].
3. For each permutation, we start by taking the first factor and using it as a regressor against Credit returns. We record the R-squared and regression residuals.
4. The residuals are then used as the dependent variable in a new linear regression with the next factor in the permutation as the only regressor. We record the R-squared and repeat the same exercise until we reach the last factor in the permutation.
5. At the end, we take the R-squared recorded on all possible permutations and average the values per factor to obtain our final estimate of explanatory power.

We use time series of non-overlapping returns in our regressions to avoid autocorrelation. But since this approach introduces discretization error[12], our panel regressions were repeated over different start dates. For instance, when calculating 1Y returns, we repeated the forward step-wise panel regression 251 times using 251 different start dates. The final result is the average outcome from different repetitions of our panel regressions.

Figure 7: Marginal explanatory power per driver, per forecast horizon



Source: Deutsche Bank

Figure 7 summarises our results, showing the marginal R-squared values plotted over different time horizons. We draw the following observations:

- A large portion of the systematic returns in Credit is not predicted by our choice of factors. While this vindicates the significant presence of active managers in the asset class, the portion explained by our chosen factors is similar to that in Equities, and higher than what we find in foreign exchange - thus not ruling out systematic factor investing in Credit[13].

[10] More explicitly an equally weighted index of CDX.IG and CDX.HY indices.

[11] The inverse z-score standardization consists of ranking signal values, taking the numeral and dividing it by the total number of signals plus 1. This guarantees that the values are between 0 and 1 (without being 0 or 1). This value is interpreted as a near-percentile, which is mapped to a z score in the normal distribution. The z-score becomes the standardized signal value.

[12] Discretization error refers to the variability of results as a consequence of selecting different start dates. The idea is to diminish key-date risk and spread it over several start dates.

[13] For further details we refer to Capra et al. (2018) on Credit versus Equities, and Anand et al. (2019) for FX.

- The predictive power of our regressors increases over time in most cases. This is not unexpected, as longer frequency data is less noisy.
- Credit spreads are the most important driver across all time horizons. However, other drivers such as betas and Value become increasingly important the further we move in the time horizon scale.

Now that we better understand both contemporary and predictive drivers of the asset class, we can start building a systematic, factor-based portfolio of strategies.

We divide our factors into two categories: (1) market-neutral, cross-sectional factors that trade single-name CDS contracts, and (2) market-directional factors that trade CDX (market-aggregate) instruments instead and take on time-varying positions on the asset class as a whole.

The following variables will be directly or indirectly covered:

- Price action: these will be covered by our Momentum factor, as per Section 4.5.
- Credit ratings and company fundamentals: these will be covered in our Quality factor, indirectly through *distance-to-default*. Our Quality factor is covered in Section 4.1.
- The term structure's second principal component will be covered in Section 4.2, as part of our Low Duration factor.
- Distance to fair value: this will be covered in our Value factor in Section 4.3.
- The market betas: these will be covered in market-neutral form, as part of our Low Beta factor, in Section 4.4.

These factors should *complement* a long-only, static exposure to the asset class, which will not be covered further in this report. For that reason we do not implement factors directly linked to CDS spreads either, such as a potential Carry factor, despite the notable predictive power of Credit spreads in our panel regressions. The Carry factor exhibited a strong, time-homogenous link to the static Credit premia under all configurations attempted.

3. Credit and Factor Investing

Factor investing is based on the argument that investors earn a premium in compensation for exposure to factor risk. Factors - in other words, drivers - can be exploited for both return and risk models, depending on whether they are a key source of portfolio volatility, future economic returns or both.

Factor investing involves multiple steps. While it is central to identify the drivers of the asset class, as we have in Section 2, these are just "rough" representations of a given factor and need to be processed before turning into tradable decisions. Indeed, the researcher may even need to replace variables to attain a more efficient – if not purer – representation of that driver.

Once the representative variables have been chosen, these need to be transformed in a way that maximises entropy and minimises noise, typically through standardisation and neutralisation tools. These transformed variables - the signals - can then be scrutinised for value-add in a portfolio context, where their predictive power, decay speed and diversification are thoroughly assessed.[14]

Finally, signals can be tuned further to remove unwanted structural exposures and be ultimately transformed into portfolio weights, which are rebalanced to generate equilibrium between signal entropy and trading costs.

We now walk the reader through how we followed this "cookbook" approach to Credit.

3.1 The RAMIC concept

Factor strategies are broadly categorised into those that take a directional view on the asset class and those that do not. Broader drivers typically fall in the first category while niche drivers fall in the second, though there are exceptions which carry an element of both. We dub them *market factors* and *company-specific factors*, respectively.

The two types of factor signals are normally built in distinctly different form so that the resulting return streams complement one another. That said, the steps taken throughout the construction process are typically the same.

The first step is to build signals from the original factor. As will be shown in Section 4, a signal is the "message" that the factor has about a given asset, having controlled

[14] Tulchinsky (2015) provides a generic overview on the steps behind alpha generation and factor investing.

for noise and having ensured that the factor's information content is optimally used.

The next step is to evaluate the predictive power of that signal, which we do by estimating its information coefficient. In other words, we evaluate the relationship between current position levels as dictated by the signals and future position returns. For that we introduce the Risk Adjusted Modified Information Coefficient (RAMIC), a metric defined below.

RAMICs differ from standard information coefficient metrics in that they account explicitly for each asset's risk profile. This is particularly important when there are significant differences in both explicit and hidden risks within the investable pool, as is the case with corporate Credit. For instance, the historical returns on AAA credit names are on a distinctly different scale from sub-investment grade returns.

We estimate two RAMIC versions: time series and cross sectional. Both are evaluated across multiple horizons h to evaluate the term structure of a signal's predictive power. As we will explain in Section 3.2, we use *duration-times-spread* (DTS) as a risk measure.

The time series RAMIC applies to our market-based signals. At a given evaluation date t, it is calculated as follows:

$$RAMIC_{t,h} = \frac{E\left[s_t^{mkt} \times \frac{r_{t+h}^{mkt}}{dts_t^{mkt}}\right]}{h} x252$$

where: s_t^{mkt} is the signal value for the market, $dts_t^{mkt}$is its DTS estimate *, and* r_{t+h}^{mkt} represents the average of daily future returns from t to $t + h$. [15] Individual signals have also been adjusted for DTS as part of their construction process, as will be shown later in this report.

The cross-sectional RAMIC is used in our company-specific signals. For a given asset i, it is calculated as follows:

$$RAMIC_{t,h} = \frac{E\left[\tilde{s}_t^i \times \frac{r_{t+h}^i}{dts_t^i}\right]}{h} \times 252$$

$$\tilde{s}_t^i = \begin{cases} 1 \ \ if & p_t^i \le 0.10 \\ 0 \ \ if & 0.10 < p_t^i \le 0.90 \\ -1 \ \ if & p_t^i > 0.90 \end{cases}$$

$$p_t^i = percentrank(s_t^i, \boldsymbol{s}_t)$$

where $\tilde{s}_t^i$ is a binary signal and $\boldsymbol{s}_t$ is a vector containing signals for all assets in the pool at time t.

We now separate between cross-sectional and time series implementations.

3.2 Cross sectional implementation

Cross-sectional implementation dictates that the direction of an asset position is based on how attractive that underlying is relative to other assets according to the same factor lens. The factor may be bearish a credit name, but if it is to go short, it needs to be more bearish on that asset than most other assets in the portfolio.

The value-add in such implementation comes from relativity - the names on which the factor is bearish should weaken relative to the names on which it is bullish. Market neutrality is therefore key for cross-sectional portfolios, and common practice is to assume "dollar neutrality" - the notional capital allocated to short positions (the "short leg") is equal to that of the "long leg".

This practice is faulty when the dispersion of risk levels among assets is high, as dollar-neutral portfolios will not be market neutral. Credit markets are notorious for that[16].

We opt instead for using duration times spread (DTS) as a measure of risk for neutralising our long and short legs against the market[17]. We find it a more appropriate measure than dollar neutrality, volatility neutrality, or even the market beta itself, as DTS is both highly adaptive and accounts for hidden risks - such as when CDS spreads are high but spread volatility is low. Therefore, our cross-sectional portfolios achieve market neutrality by having equal aggregate DTS[18] levels in both short and long legs. The DTS weights allocated to

[15] When carrying such analysis in this paper – to reduce discretisation error - we apply the same statistical averaging to estimate our RAMICs. In other words, when evaluating future cumulative returns using a 1-month horizon we use 20 different start dates and therefore calculate 20 RAMIC statistics, which are then averaged.

[16] For instance, Israel et al. (2018) argue that the dispersion of risk in credit markets is much larger than that of equity markets.

[17] The measure was first introduced by Ben Dor et al (2007). The authors show that changes in credit spreads do not occur in parallel; instead, they are linearly proportional to the spread. Wider spreads experience larger spread variation than tighter spreads. This helps further explain the large dispersion of risk in the asset class. For instance, a long-dated instrument trading at a spread of 600bp shows a beta that is orders of magnitude higher than that of a short dated instrument trading at a spread of 20bp.

[18] In our implementation we set the DTS level of risk to 612.5 units. This is the result of 4.9 (duration) x 125bp (credit spread). These numbers were set such that the USD notional sizes on both long and short legs averaged 100%. Working with a different level should not affect the results, if analyzed on a risk-adjusted basis.

each underlying name in the basket are also adjusted for DTS[19] just as CTA programmes adjust trend-following positions for asset volatility.

The DTS weight for asset i at rebalancing date t is calculated as follows:

$$w_{i,t} = \frac{\overline{dts}/n}{dts_{i,t}}$$

where $\overline{dts}$ is the pre-defined DTS target for both long and short legs, $dts_{i,t}$ is the DTS for asset i at date t and n is the number of positions in the portfolio. While this implies unequal dollar exposures, it is also a more prudent risk measure[20].

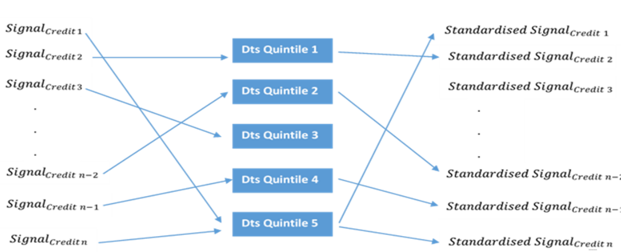
As for the construction of the long-short weights[21] across assets, for each factor portfolio, we start from the original signals but pre-process them to remove structural exposures.

Given the significant dispersion of spread levels - and therefore risk exposures - in the asset class, we separate signals according to five buckets, each representing a DTS quintile. The signals are then transformed in each bucket, and mapped into a $(-1,1)$ continuous interval according to the following formula:

$$\hat{s}_t^i = \frac{s_t^i - \bar{s}_t^k}{s_t^{k,max} - s_t^{k,min}}$$

where $k \in \{1,2,3,4,5\}$ is the quintile bucket comprising asset i at rebalancing date t. $s_t^{k,min}$, $\bar{s}_t^k$ and $s_t^{k,max}$ represent the minimum, mean and maximum signal values for that DTS bucket.

Figure 8: Signal DTS standardization



Source: Deutsche Bank

Transforming from signals to weights is a straightforward process, as we go long the top decile and short the bottom decile of assets according to signal ranking.

By construction, both long and short legs will have a breadth of low and high DTS names, as per discussion above, further reducing structural exposures.[22] That said, some credit names had to be separately removed for other structure-related reasons, as will be highlighted in the Value and Quality sections.

Once each factor portfolio has been defined, we apply two final adjustments to ensure optimal implementation.

The first step is to decide when each portfolio should be rebalanced, and we opt for either semi-annual or annual frequencies. While these may look too infrequent at first, they strike a balance between cost reduction and the long cycle of predictive power in the signals evaluated - as our RAMICs show in the next section.

The second step is *tranching*, where we create sub-portfolios, each carrying an equal proportion of total portfolio risk but rebalanced two weeks apart from the others.

Therefore, an annually-rebalanced factor portfolio will have 26 sub-portfolios, each carrying 3.85% (1/26) of total portfolio risk and rebalanced two weeks apart from the other. If rebalanced semi-annually, we implement 13 sub-portfolios, each also rebalanced two weeks away from the other but carrying twice the amount of portfolio risk. Tests using weekly rebalancing produced similar results.

Tranching contributes with two aspects: *adaptivity*, as the final portfolio rebalances far more often than the original ones, and *less "pin risk"*, as it accesses the market on a far more frequent basis.

Figure 9 illustrates the tranching procedure.

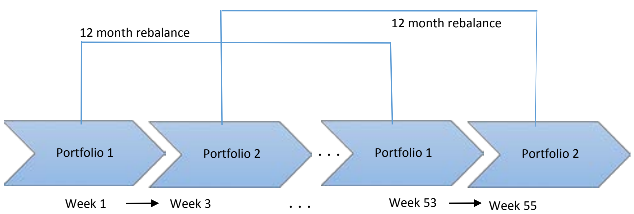
[19] The weighting methodology is straightforward. We take the pre-defined DTS level of risk and divide it by the number of credits in the portfolio, providing a DTS target for each position. The nominal amount is calculated as a function of it.

[20] This addresses a shortcoming seen in portfolios that weight individual positions equally. In such cases, performance is more heavily influenced by riskier credits.

[21] We follow Israel et al (2018) in the use of DTS groups to standardise signal values.

[22] Different from common approaches taken in the equity space, we do not standardise our signals according to sectors. Credit ratings are generally agreed as the best grouping metric even if research analysts often cover corporate sectors. Given the direct relationship between credit ratings and spread levels, categorizing by DTS not only reflects ratings but it also makes it more adaptive. Another practical argument against standardizing by sectors is the small number of credits in the investable universe. As there is a maximum of 225 names at any point in time, and 11 sectors, sector standardization would involve too few names.

Figure 9: Tranching procedure (12-month rebalancing example)



Source: Deutsche Bank

Finally, we comment on the estimation of asset betas to the Credit market, applicable to two cross-sectional portfolios – Low Beta and Residual Momentum. Our beta estimates come from a co-variance matrix of 3-day non-overlapping returns and 5-year (rolling) history. The main diagonal is exponentially smoothed using a 1-year half-life, while the off-diagonals use a 3-year half-life decay.[23]

We calculate three separate co-variance matrices from the above – each with a different start date – and three beta estimates as a result. Our final beta estimate is an average of the three.

3.3 Market implementation

As noted before, market factor portfolios capture market-wide drivers. The signal is based on the average[24] of signals among assets in the pool as that captures the broad market view.

Market signals are distinctly different from time series signals. While both are based on information exclusive to that asset, such as its past returns, the latter does not go against signal entropy while the former may. For instance, the time series implementation will go long all assets with a positive score and short all with a negative score, while the market implementation goes long or short depending on the average score. Hence it can go short assets with a positive score as long as that is a minority, and vice-versa.

Two of our investment factors are implemented in market form, a choice based on cost and liquidity characteristics relative to the equivalent time series implementation. As such, some of the adjustments from cross-sectional implementation – such as DTS neutralisation – are not required.

4. Credit Factors

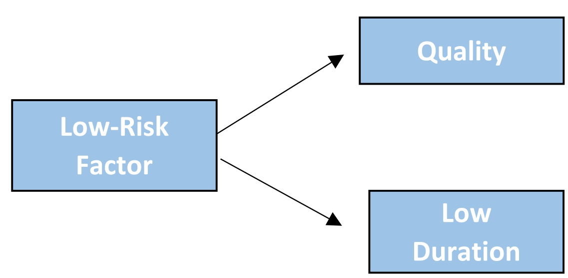
We now describe each of our factor portfolios in detail. We describe how each signal is designed, the term structure of its predictive power, the effect of different rebalancing dates and, ultimately, the economic significance. The results in this section exclude transaction costs; those are addressed later in Section 5.

4.1 Quality

Quality investing is based on the premise that higher-quality companies deliver higher risk-adjusted returns than low-quality names. As most other fundamental factors, the Quality factor was first explored in equity markets[25], where profitability ratios, combined with efficiency and balance sheet strength, are typical ranking metrics.

In Credit, the Quality factor is normally viewed in isolation; instead, the literature uses it as an input to define a broader Low Risk factor[26]. The rationale is to favour high-quality-low-duration bonds over low-quality-high-duration bonds, which can be interpreted as combining Quality and Low Duration factors.

Figure 10: Low Risk: Quality + Low Duration



Source: Deutsche Bank

4.1.1 Signal generation: Quality

Our Quality signal is based on a market-driven measure of corporate default risk: the *distance to default* (DTD). Pioneered by Merton (1974), the DTD model equates the bondholder's position to that of being short a put option on the underlying assets of the firm, with a strike price equal to the company debt. It assumes that if the value

[23] See Ward et al. (2016) for a discussion on the topic.

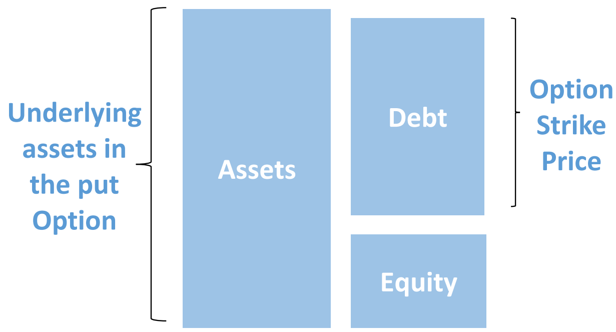
[24] Or weighted average, if the index is not formed using arithmetic averaging of its constituents.

[25] Asness et al (2017) study the quality-minus-junk (QMJ) factor in Equities. The authors show evidence that a portfolio that buys high quality stocks and sells poor quality stocks earns significant risk adjusted returns across 24 different equity markets.

[26] For further details see Houweling et al. (2017) and Israel et al. (2018).

of assets falls below the strike price - the value of the company's debt - the company defaults.

Figure 11: Debt holder's short put position



Source: Deutsche Bank

The DTD can be intuitively interpreted as the number of standard deviations (of corporate asset returns) that the company is away from its point of debt default.

One input – the volatility of company assets – is not directly observable, thereby requiring approximations. As such, we apply the assumptions introduced in Bharath and Shumway (2004) to estimate this quantity[27], and follow Correia et al. (2012) to solve for a "naïve" estimate of distance to default[28]:

$$DTD = \frac{\ln\left(\frac{Assets}{Short\ Term\ Debt + \frac{1}{2} Long\ Term\ Debt}\right)}{\sigma_{assets} * \sqrt{Time}}$$

As alluded to earlier, we favour this metric relative to more traditional proxies based on the following rationale:

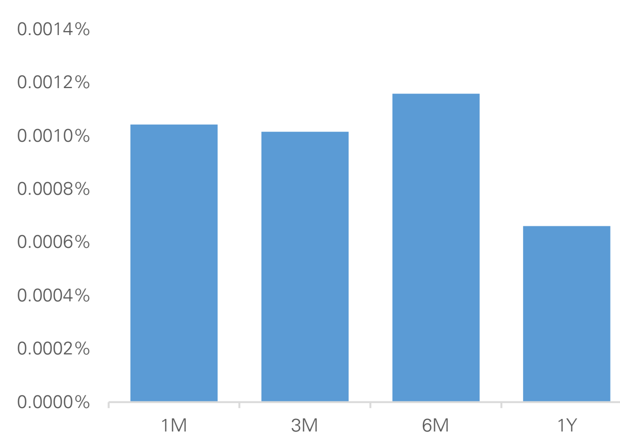
- Equity-related quality metrics do not address, as accurately, the company's ability to pay its debt. They focus instead on the company's ability to generate free cash flows to their shareholders.
- Credit ratings often lag the market at pricing default risk, and are far less adaptive than DTD.
- Our results using fundamental credit-related metrics were inconclusive. These included free cash flows to debt, interest coverage ratio, net debt to EBITDA and EBITDA margin. None of these metrics produced a return stream that was as defensive and economically significant as the DTD signal. Albeit not tested, we felt that common metrics from the equities literature – such as return on equity, gross profitability and firm leverage - would have been just as unsuccessful.
- The adaptivity benefit of DTD should not be understated, especially given Credit's opaque liquidity. The reader will find that we opt for highly adaptive variables wherever possible in Credit; jump-to-default and duration-times-spread are two other examples used in our portfolios.

Finally, we excluded financial companies from our Quality factor, as the high leverage makes our comparisons to less leveraged industries quite challenging. The leverage embedded in financial names implies structurally lower DTD measures relative to those of other corporate names, a structural bias we sought to avoid [29].

4.1.2 Signal predictive power: Quality

Figure 12 shows the term structure of predictive power of our Quality signal, as defined according to the risk-adjusted modified information coefficient (RAMIC). The signal shows persistency over time with some decay as we move towards the 1Y horizon.

Figure 12: RAMIC scores by horizon – Quality signal



Source: Deutsche Bank

[27] Bharath and Shumway (2004) test the accuracy of a default forecasting method based on Merton (1974) bond pricing model and compare it to the KMV-Merton model. The authors claim that their naïve approach retains both the functional form and basic inputs from the KMV-Merton default forecasting model. The proposed model achieves high and significant default forecasting ability. Their approach to estimate asset volatility consists of modeling it as a function of company leverage and equity volatility as per following formula:

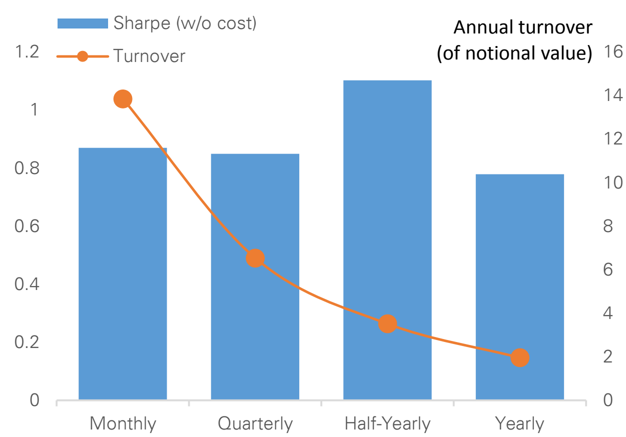
$$\sigma_{assets} = \frac{Equity}{Assets}\sigma_{equity} + \frac{Debt}{Assets} \times (0.05 + 0.25.\sigma_{equity})$$

[28] The original model from Merton (1974) uses the total value of debt as the firm default point as opposed to "short term debt + ½ Long Term Debt" as an input in the distance-to-default formula. The authors follow Moody's KMV approach in this sense. They also simplify the calculation by deliberately ignoring the drift term from the original distance-to-default formula.

[29] Chan-Lau and Amadou (2006) argue that the application of DTD measures to financial firms is not straightforward due to the difference between the liabilities of these institutions and those of non-financial corporations.

Figure 13 reiterates this message of stability, as it shows stable (pre-cost) Sharpe ratio backtest readings under less frequent rebalancing periods while turnover also drops. We ultimately chose to rebalance semi-annually, as the drop in turnover from semi-annual to annual rebalancing is not enough to compensate for the drop in risk-adjusted backtested returns. Section 5 will show this in more detail, as we add costs.

Figure 13: Results per rebalancing frequency – Quality factor

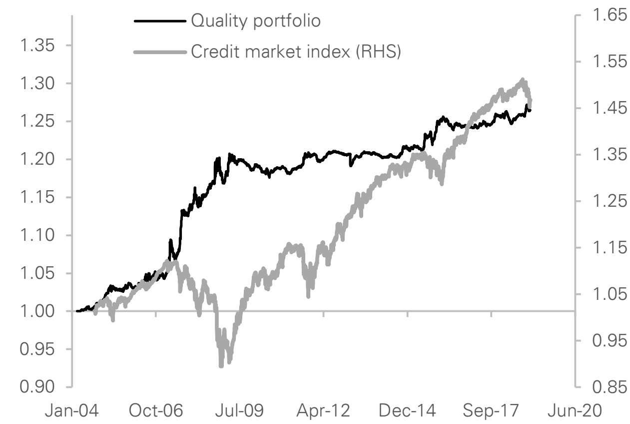


Source: Deutsche Bank

4.1.3 Backtested performance: Quality

Figures 14 and 15 show how pre-cost returns in the Quality factor relate to CDX market returns [30]. The defensive nature of this return stream is made clear by both the rolling correlations and historical performance during countercyclical periods in the Credit market. These results are intuitive and in line with what is observed in Equities.

Figure 14: Backtested cumulative returns



Source: Deutsche Bank

Figure 15: Quality – 1Y rolling correlations to CDX market

Source: Deutsche Bank

4.2 Low Duration Factor

As noted earlier, the literature often points to short-dated fixed income outperforming long-dated fixed income instruments by being more defensive; short-dated instruments are less volatile and carry less risk. It is no wonder, therefore, that discussions of this nature are often made under the label Low Risk[31], as mentioned in Section 4.1.

At the same time, active fixed income investors tend to naturally prefer longer-dated, higher-yielding bonds under the perception that the higher duration exposure

[30] We define the market as an equal-weighted composite formed by CDX.IG and CDX.HY indices. Among different choices (such as equal risk), we decided to follow an equal weights approach for its simplicity and to be consistent with how CDS indices are built individually. We also showed in Section 1 that the PC1, extracted from a pool containing all the credits in our sample, was highly correlated to this index definition.

[31] We refer the reader to Houweling et al. (2017) and Israel et al. (2018) for further details on the Low Risk Factor.

will lead to outperformance over the benchmark[32]. That Credit curves are typically upward sloping further supports the argument[33].

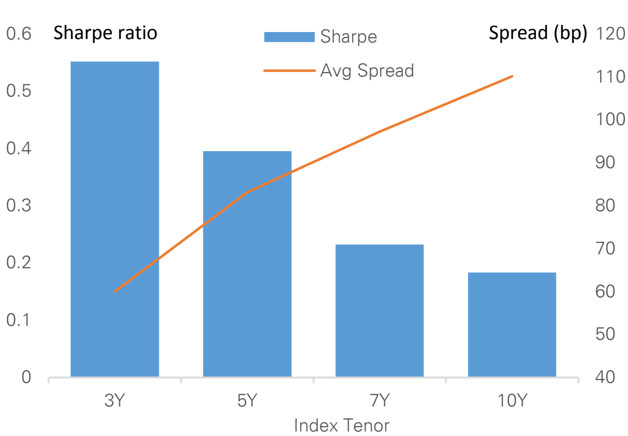
Such an invariant disconnect between the two is attributed to leverage constraints; it is not feasible for funded investors to match the duration - and volatility - profiles of the benchmark via short-dated bonds. They would need significant leverage to do so.

Therefore, the anomaly - that short-dated instruments outperform long-dated instruments on a risk-adjusted basis - has persisted over time and will likely continue to do so as long as funded investors remain leverage constrained.

That said, the existence of CDS markets also allows the risk premia investor to tackle the anomaly and harness its respective returns. Their unfunded nature allows the investor to capture the extra premia that shorter-dated Credit tenors have over longer-dated maturities while matching the same risk exposure.

This allows us to capture the second aspect of Low Risk: the Low Duration factor. Low Duration is a behavioural premium captured by taking a long Credit exposure in short-dated CDS instruments and a short Credit exposure in long-dated instruments.

Figure 16: 15-year long-only CDX IG performance by tenor and average CDS spread



Source: Deutsche Bank

This return driver is manifested in the second principal component of the CDX term structure, and, as shown in Section 2.2, it rewards the investor over the long run.

Figure 16 illustrates our argument by plotting backtested Sharpe ratios for long-only exposures to different CDX IG index tenors. They show that shorter tenors clearly outperform on a risk-adjusted basis, even though the term structure is typically upward sloping.

The Low Duration factor has five key characteristics:

1. It is a market-wide factor of returns, and not a company-specific factor. While the risky DV01 embedded in a CDS contract is influenced by spread levels, which are company-specific, the maturity of the contract plays a far more important role in defining this measure of risk. Therefore, on aggregate, shorter-dated CDS contracts outperform longer-dated CDS contracts on a risk-adjusted basis.

2. As a market factor, it should be captured through CDX indices, and not through single-name CDS contracts. As we argued earlier, market-wide factors should be captured using market-wide instruments. That liquidity in short-dated, single-name CDS contracts is scarce further validates our argument.

3. It is a pro-cyclical factor, and therefore not defensive. By taking unequal risk notionals in short and longer-dated CDX contracts, the investor is naturally exposed to *jump-to-default* (JTD) risk - the risk that any of the corporate names it is exposed to incur a credit event without warning, so that the risk was not reflected in that name's CDS spreads[34]. Such risk, also manifested through flatter or inverted CDS curves, is higher during economic downturns but lower during periods of robust growth, making it a cyclical factor. Figure 5 illustrates that by showing how the PC2 series also suffers during periods of market stress.[35]

4. It is typically carry positive. Despite being a "curve steepener" in term structures that are already steep, the risk-weighted notionals allocated to each leg compensate for that, as will be shown in Section 4.2.1. Such characteristic is in sync with pro-cyclical factors in other asset classes, and with the positive

[32] Frazzini et al (2012) find evidence that leverage constrained agents prefer to invest capital in risky assets across a range of asset classes, which include fixed income. The study uses bond duration to define risk in the fixed income market.

[33] The fixed income reader may, for instance, be familiar with expressions such as "yield to beach" and "reach for yield", which illustrate our argument.

[34] The default of Lehman Brothers is a classic example to illustrate the concept. The default occurred before the market had time to price in the increased default risk in credit spreads. At the time of the default, Lehman's 5Y CDS contract was trading close to 350bp. This level has not historically being associated with a company on the brink of default.

[35] This statement does not strictly contradict the literature, wherein the low risk factor is referenced without duration-matching short and long-dated bonds.

influence that spreads have on future Credit returns, as alluded to in Section 2.

5. It should only be captured using investment grade indices. High yield indices exhibit higher jump-to-default risk and low liquidity outside the 5Y tenor. Even if JTD risks were to be compensated, the lack of liquidity makes HY implementation prohibitive.

4.2.1 Signal generation: Low Duration

Our Low Duration factor is implemented as a time-homogenous steepener position on CDX NA IG indices. We sell 1 unit of protection on CDX using the 3-year contract and buy DV01-weighted units of protection on CDX using the 10-year contract. In other words, we go long Credit using the 3-year instrument and short the DV01-adjusted amount of Credit using the 10-year instrument. On average, we go short 0.35 units of the 10-year leg for every 1 unit that we go long the 3-year leg - a 2.8x ratio.

The reader may question why we chose DV01 as our risk unit. This choice combines market practice, practical similarity to other measures - such as volatility weights or beta weights - and improved risk profile relative to DTS weights. The latter choice would have implied an average ratio of 5.6x, further magnifying JTD risk. Volatility and beta weights showed average hedge ratios of 2.6-2.8x, similar to DV01 weights. Figure 17 shows the impact of different risk units as weighting schemes.

Figure 17: Low Duration weighting schemes

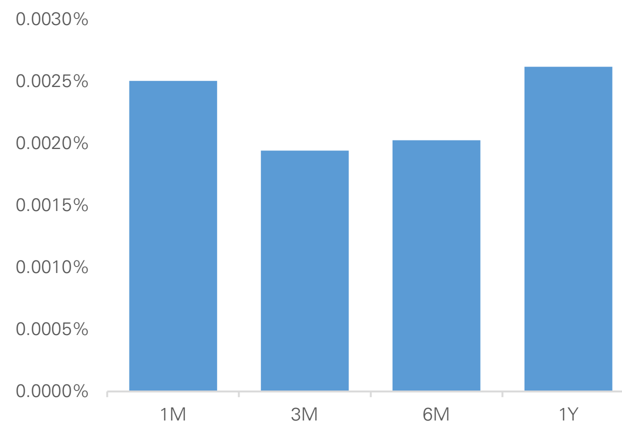
	DTS Weighted	DV01 Weighted	Volatility Weighted
Annual Return	0.84%	0.76%	0.70%
Annual Standard deviation	1.15%	1.06%	1.09%
Max DD	-3.3%	-2.4%	-3.2%
Sharpe Ratio	0.73	0.72	0.64
Average Long	1	1	1
Average Short	-0.18	-0.35	-0.38
Leverage	5.6	2.8	2.6

Source: Deutsche Bank

4.2.2 Signal predictive power and rebalancing choices: Low Duration

Figure 18 displays the risk-adjusted modified information coefficient (RAMIC) associated with our Low Duration signal. Albeit quasi-static, the signal has stable predictive power across holding periods, analogous to pro-cyclical signals across other asset classes.

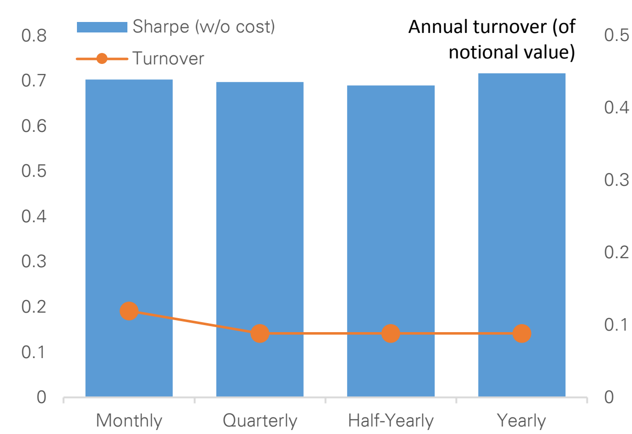
Figure 18: RAMIC scores by horizon – Low Duration



Source: Deutsche Bank

Figure 19 shows the sensitivity of our results to different rebalancing frequencies. The close similarity in the output is no surprise, given the quasi-static nature of the signal.

Figure 19: Results per rebalancing frequency – Low Duration factor

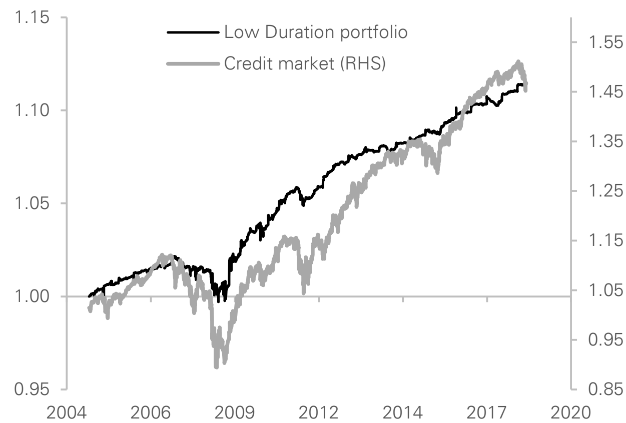


Source: Deutsche Bank

4.2.3 Backtest results: Low Duration

Figure 20 shows the backtested performance of our Low Duration factor, gross of transaction costs. While attractive, the reader should also observe its significant *underperformance* during periods of general market stress, as also seen in the CDX market series itself. This reiterates the pro-cyclical nature of this investment factor.

Figure 20: Backtested cumulative returns (pre-cost) – Low Duration



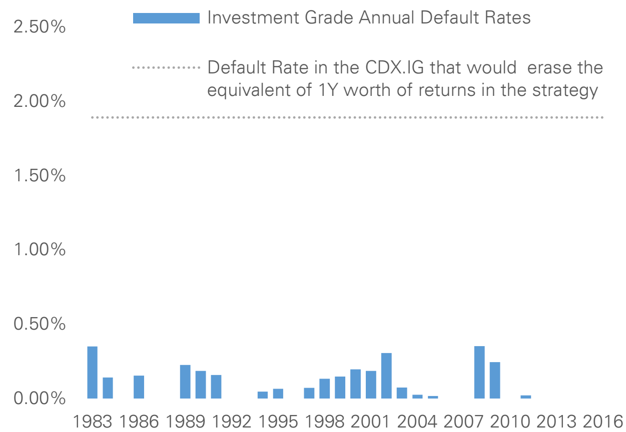
Source: Deutsche Bank

We also highlight that jump-to-default risk - the key concern with this particular investment factor - has not been properly witnessed over the course of our backtest. The CDX NA IG on-the-run series, for instance, has not experienced default in any of its constituents during the time studied[36].

That said, our estimates indicate that a hypothetical default on one of the index constituents would have erased the equivalent of circa five months of factor returns[37], thereby rewarding further attention.

To assess this risk in more detail, we further extend our analysis of default risk. Figure 21 provides historical perspective on investment grade default rates, showing data from 1983. On average, 0.10% of the credits in the investment grade universe defaulted on an annual basis over the 1983-2016 period. Ilmanen (2011) further estimates that long-run average default rates reside between 0.08% and 0.15% between 1920 and 2010. The dotted line in Figure 20 represents our estimate of the required default rate in CDX NA IG to erase a whole year's worth of returns in the Low Duration strategy (1.9%)[38].

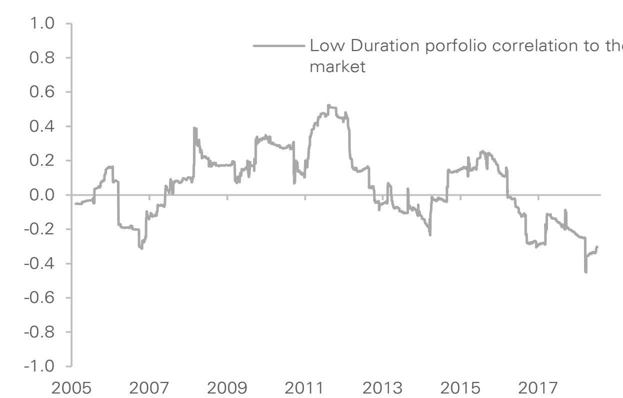
Figure 21: Investment grade annual default rates



Source: Deutsche Bank

Finally, Figure 22 shows the rolling, annualised correlations between the Low Duration factor and market returns. Correlations are tame over the long run, as expected given that this investment factor is linked to the second principal component of the asset class while the market represents PC 1. But joint dependencies rise significantly during counter-cyclical periods, as Credit curves flatten or invert. Those periods also coincide with the highest ex-ante carry, or highest ex-ante signal intensity, as is normally the case with mean-reverting and pro-cyclical strategies. Figure 23 shows the (ex-ante) carry profile of this investment factor over time.

Figure 22: Low Duration – 1Y rolling correlations to CDX market



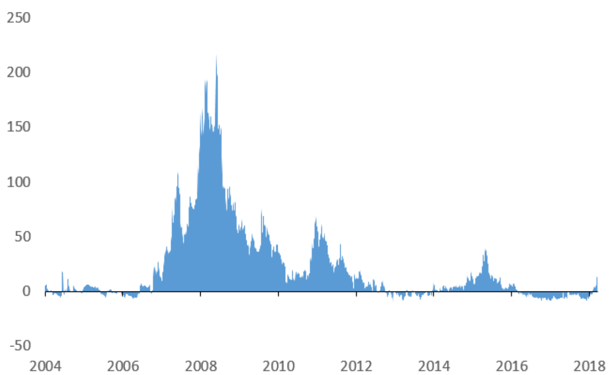
Source: Deutsche Bank

[36] This is the case for on-the-run contracts. There have been defaults recorded on CDX.IG off-the-run contracts. Particularly notorious is the case of defaults in the 2008-2009, which occurred on a series that had just become off-the-run.

[37] An intuitive way to quantify the P&L effect of a default is as follows. The weight of each constituent in the CDX.IG index is 0.833%. On this basis, the average net exposure to a single name is 0.54%, i.e. $1 \times 0.8333\% - 0.35 \times 0.8333\% = 0.54\%$. Assuming a recovery rate of 40%, the loss in the event of a default would be 0.324%. This is approximately equivalent to five months' worth of average historical returns according to Figure 16.

[38] The calculation follows a similar logic to the one shown in the previous footnote. The exact value of the referenced default rate is 1.89%. Given that CDX.IG comprises 120 names, it would be the equivalent of 2.27 names.

Figure 23: Low Duration – ex-ante carry profile (bp)

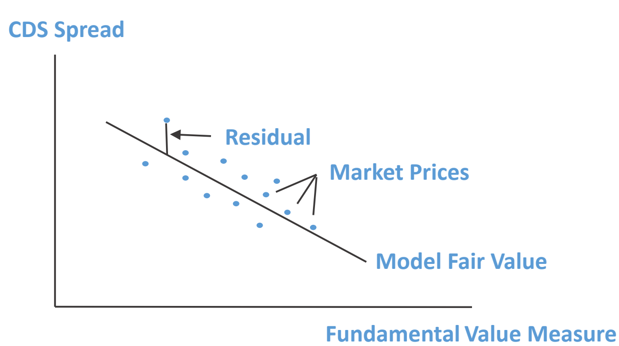


Source: Deutsche Bank

4.3 Value investing

Value investing is based on the premise that "cheap" assets will outperform "expensive" assets over the long run. Therefore, signals from this factor are typically based on the spread between current asset prices and a fundamental anchor that represents fair value.

Figure 24: Value proxy



Source: Deutsche Bank

Value models are also known for being contrarian, in that the signals are naturally designed to go against recent market direction. The more that current prices are rising further away from and above their fundamental anchor, the more that the Value strategy will go short, and likely do so with increasingly larger positions.

Such pre-disposition to be short regime breaks can be concomitant to pro-cyclicality when dealing with companies[39]. Asness et al. (2013), for instance, argue that the fundamental nature of Value signals lead to opposite positions during liquidity shocks and market sell-offs, with the downside that the strategy is exposed to short-term trend continuation and, more importantly, to regime changes that have an impact on company fundamentals[40].

4.3.1 Signal generation: Value

Our Value signal is based on the distance between market-observed CDS spreads and fair value spreads[41]. Our fair value model consists of a linear regression of log-scaled single name CDS spreads against distance to default, a metric defined in Section 4.1. That said, we differ from the literature in two key respects:

- We use univariate time series regressions, instead of multi-variate cross-sectional regressions, to define the signal. Our choice is solely based on the decay speed of the two signal types. Signals based on cross-sectional regressions using log values may be more adaptive and potentially more entropic, but they decay too fast for systematic investing in single name CDS. The time series construct, on the other hand, also produces correlated, reversal-like signals that decay far slower.
- We omit duration as a regressor in our fair value model. The univariate nature of our time series construct, coupled with the standardised nature of 5-year CDS contracts, makes duration a redundant variable for signal generation purposes[42].

Our Value signal for asset i at evaluation date t is therefore built as follows:

1. We transform both DTD and CDS spread series to log scale. Under this scale we can use linear regressions to estimate fair value spreads[43].

[39] In other asset classes cyclicality takes on different forms. Anand et al (2019) find an opposite, counter-cyclical behaviour in FX Value. Natividade et al. (2014) found no evidence of pro-cyclicality in Commodity Value and Rates Value.

[40] This information is usually only captured with a lag by the fundamental anchor. This is because fundamental anchors are usually based on information derived from corporate financial statements, which cover past information.

[41] This is in line with the literature. Houweling et al. (2017), for instance, compare the fitted fair value bond spreads from a theoretical model with actual spreads and use the residual as the signal.

[42] The latter argument can also be used cross-sectionally, explaining why we omitted duration from the cross-sectional tests as well. This is in opposition to, for instance, Houweling et al. (2017), who estimate fair value through the use of a cross-sectional regression of credit spreads on credit ratings, past three months' spread changes and duration.

[43] This is similar to the approach taken by Frieda and Richardson (2016), but the authors use logged credit spreads and probability of default as regression variables.

2. We run time series linear regressions on every name, using observations from the last 90 days.[44]

$$\hat{l}_t^i = \log(CDS_t^i) = \alpha_t^i + \beta_t^i \times \log(d_t^i)$$

where CDS_t^i is the CDS spread and d_t^i is our estimate of distance to default.

3. We extract the fair value spread - after scaling back the regression results - and take the difference with the market spreads. Such residual becomes our raw value signal:

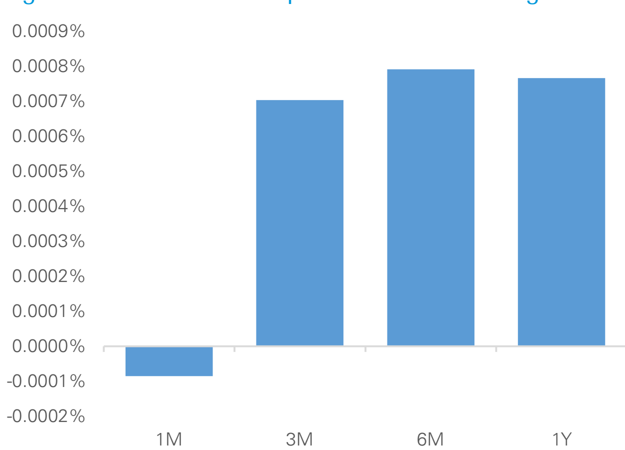
$$s_t^i = 10^{\hat{l}_t^i} - CDS_t^i$$

4. The final signal is calculated after standardizing the raw signal from Step 3 by DTS buckets, as per Section 3.2.

4.3.2 Signal Predictive Power and Rebalancing: Value

Figure 25 plots the term structure of signal predictive power, as measured according to our risk-adjusted modified information coefficients (RAMIC). RAMIC values are low - even negative - in the short term, but gradually grow over longer horizons. This is in line with our goal of designing a signal that captures slow-moving mispricings, and is consistent with Anand et al. (2019) on FX Value and Asness et al. (2013) on cross-asset Value[45].

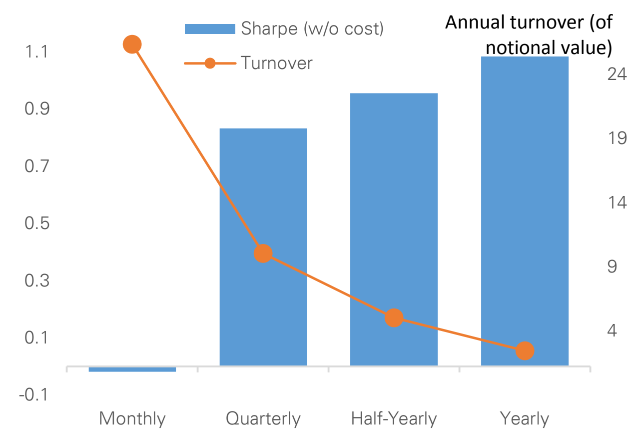
Figure 25: RAMIC scores per horizon – Value signal



Source: Deutsche Bank

Figure 26 shows performance sensitivity to different rebalancing windows for each sub-portfolio as described in Section 3; the 1-year frequency is optimal in expected economic returns and turnover.

Figure 26: Results per rebalancing frequency – Value factor



Source: Deutsche Bank

4.3.3 Backtest results: Value

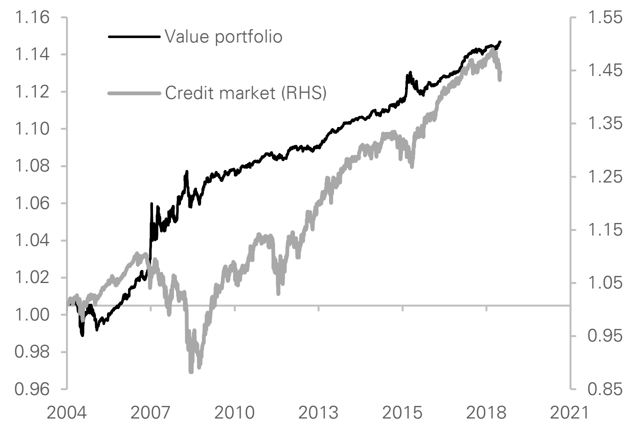
Figures 27 and 28 display our pre-cost backtested results and rolling correlations to the Credit market.

Three observations stand out. First, the pre-cost Sharpe ratio is high, in line with other strategies that are structurally short regime shifts. Second, correlations to the Credit market tend to be positive over time, in line with the pro-cyclicality of fundamental Value strategies in equities. Finally, the strategy outperformed in 2008 and 2015, which goes against long-term pro-cyclicality but is in line with the performance of price reversal strategies during those periods.

[44] Our results are robust to the use of different lookback windows. We tested different configurations in the range of 60-180 days without observing significant changes.

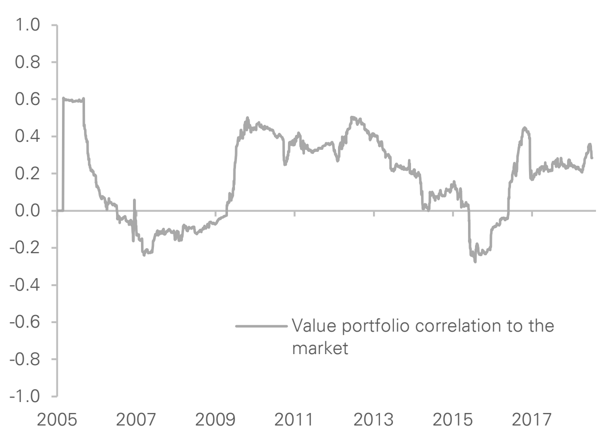
[45] For instance, Asness et al (2013) utilize Value signals based on the negative of the past five year returns on different asset classes.

Figure 27: Backtested cumulative returns (pre-cost) – Value



Source: Deutsche Bank

Figure 28: Value – 1Y rolling correlations to CDX market



Source: Deutsche Bank

4.4 Low beta investing

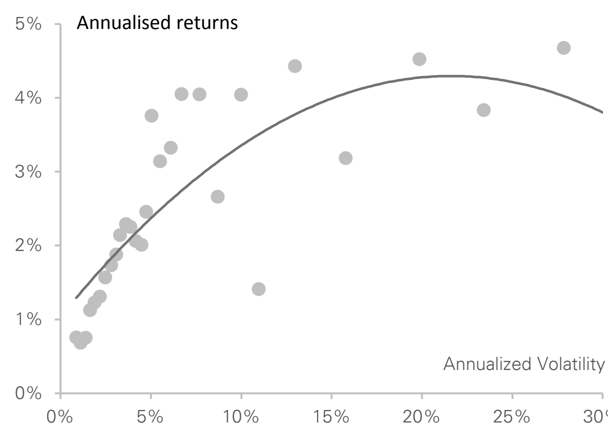
The Low Beta investment factor is based on the premise that riskier assets underperform their less risky counterparts on a risk-adjusted basis. In other words, the level of risk embedded into the asset is one of its return drivers, as we showed in Section 2.2.

As with Low Duration, this return factor is also borne out of leverage constraints affecting the Credit investor. As pointed in Ang (2014), leverage-constrained investors prefer corporate bonds with built-in leverage as, according to our interpretation, they are seen as exhibiting higher total return potential than both the benchmark and safer bonds. Such demand leaves these assets relatively overpriced.

The phenomenon is also manifested in a Markowitz-like context by observing that, while there is a positive relationship between return and volatility, this relationship flattens as asset volatility rises. In other words, for a one unit rise in historical asset volatility, historical asset returns rise by less than unity.

As such, the riskier the asset, the lower the historical Sharpe ratio. Figure 29 illustrates that argument using long-term data for our pool of single-name corporate CDS returns.

Figure 29: CDS historical risk-return relationship



Source: Deutsche Bank. Annualized volatility and annualized returns observations of single name CDS contracts over the period 2004-2018 with a minimum of 500 observations. The data was grouped in 30 buckets according to the annualized volatility values. The data shown is the average annualized returns and volatility of each group.

Further, the Low Beta factor has been studied on different asset classes. Frazzini and Pedersen (2012), for instance, found evidence that market-neutral portfolios, holding low beta assets and shorting high beta assets, produce positive excess returns across different asset classes. More specific to our case, the authors show evidence of the phenomenon's existence in the US corporate bond market.

4.4.1 Signal Construction: Low Beta

Our signal is defined as the (rolling) beta of asset returns against the CDS market[46]

$$r_t^i = \alpha_t^i + \beta_t^i \times r_t^{CDX} + e_{i,t}$$

$$s_t^i = \beta_t^i$$

[46] We define the market as an index that equally weights the on-the-run 5Y CDX IG and 5Y CDX HY.

As alluded to in Section 3, the covariance matrices used for beta estimation are based on 3-day non-overlapping returns and 5-year lookback windows, where values are decayed with a 1-year half-life in the main diagonal and a 3-year half-life in the off-diagonal elements.

Further, we opted for beta as a risk measure because we take the view that correlation risk – the extra feature that differentiates beta from outright volatility or DTS – is not rewarded and should therefore be penalised[47].

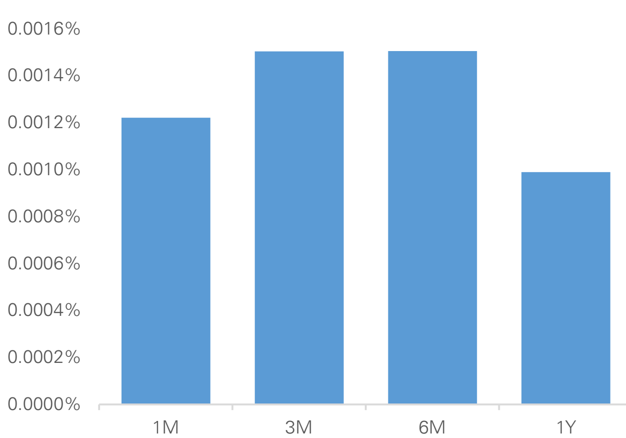
4.4.2 Signal predictive power and Rebalancing: Low Beta

Figure 30 shows stability in the predictive power of our Low Beta signal across multiple horizons; a stability that is maintained as we evaluate performance on different rebalancing frequencies.

This naturally raises the question of unrelated - and unrewarded - structural exposures that this factor portfolio may have incurred given that we do not apply sector or industry neutralisation. The reader may argue, for instance, that the market beta of utility companies should be consistently lower than that of technology companies and that the strategy could therefore be consistently short one industry and long another.

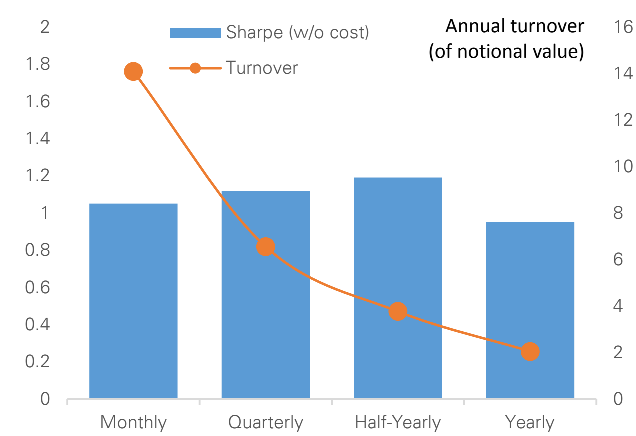
But as we argue in Section 3, this is not the case as DTS neutralisation solves for much of these potential structural imbalances. As such, the rebalancing and - more importantly - turnover profile of the Low Beta strategy are very similar to those of our other "slow" signals (Momentum and Quality). We opt for semi-annual rebalancing, with sub-portfolios tranched weekly.

Figure 30: RAMIC scores per horizon – Low Beta signal



Source: Deutsche Bank

Figure 31: Results per rebalancing frequency – Low Beta factor

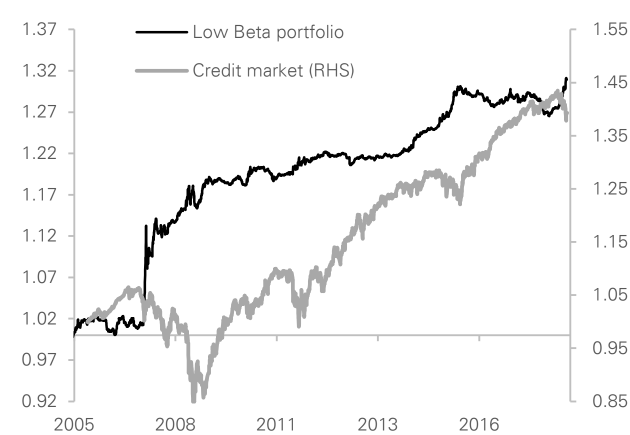


Source: Deutsche Bank

4.4.3 Backtest Results: Low Beta

Figure 32 shows the backtested returns of our Low Beta factor, pre-cost. As is the case in Equities, the strategy is highly defensive. This is no surprise as safer (riskier) assets, which the strategy is long (short), outperform (underperform) during periods of market aversion.

Figure 32: Backtested cumulative returns (pre-cost) – Low Beta



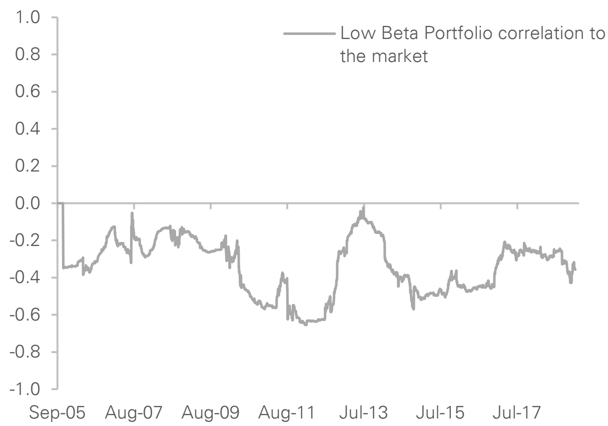
Source: Deutsche Bank

[47] Mathematically:

$$Beta = Correlation * Asset\ Volatility\ /\ Market\ Volatility$$

Therefore, assets with higher market correlation are seen as riskier by our signal.

Figure 33: Low Beta – 1Y rolling correlations to CDX market



Source: Deutsche Bank

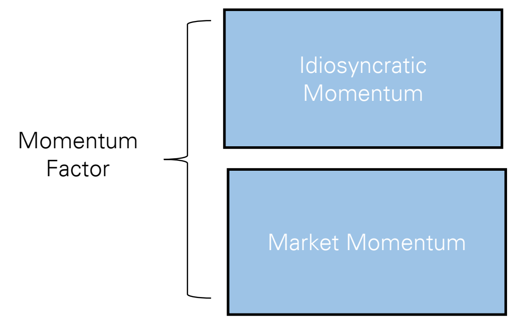
4.5 Momentum investing

Momentum - the propensity of future returns to resemble past returns - is one of the most widely studied return factors across asset classes. Its presence in Credit markets has been documented academically, with Gebhardt et al. (2005) and Jostova et al. (2013) being key references. Their combined work, which focused on US corporate bonds since the 1970s, concludes the following:

- The Momentum phenomenon is more clearly observed in sub-investment grade bonds relative to investment grade. It is also shown that on a broad sample of corporate bonds, including both investment grade and high yield names, the momentum phenomenon is significant, as also noted in Israel et al. (2018).
- Momentum in debt returns can be complementary to Equity Momentum, as positive news for the equity holder may be bad for the bond holder at certain times, and vice versa. For instance, Jostova (2013) argues that the impact of corporate events such as dividend cuts, debt reduction, equity issuance, etc. imply wealth transfers between equity and bondholders. Therefore Credit and Equity markets can react in opposite directions to such events.
- While acknowledging the previous point, Equity Momentum may also spill over into Credit Momentum, as information diffuses more slowly in the latter asset class. Gebhardt et al. (2005) for instance, views equity spillover momentum as a fixed income factor in its own right.

We take a fresh approach to the topic, bringing some tools from our experience with this investment factor in other asset classes. A key difference in our approach is the direct separation between market-related momentum and residual momentum.

Figure 34: Momentum factor breakdown



Source: Deutsche Bank

Corporate CDS returns are influenced by both market and idiosyncratic momentum, but the former component is most optimally exploited through market indices, while the latter can only be captured through single-name CDS contracts.

Further, we remove the market effect when assessing idiosyncratic momentum by concentrating on residual returns. In other words, we regress daily single-name CDS returns against the market, and use the residual to assess idiosyncratic momentum.

Before moving to signal generation, it is important to understand the impulse-response dynamics of the asset class, and we do so by focusing on the direction of both past and future Credit returns. We carry the analysis using sequential dependencies, as a simplification of the Counting Continuation and Reversals Test[48]. Our metric (κ) is built as follows:

1. We multiply the sign of past returns with the sign of future returns across multiple non-overlapping periods[49].
2. We sum the individual $\{-1,1\}$ readings and divide them by the total number of readings, thereby obtaining a final value κ inside the continuous space $\kappa \in [-1,1]$.
3. κ scores below zero indicate reversal properties, while numbers above zero indicate momentum.

[48] See Natividade (2012).

[49] As in prior analysis, we repeat the exercise using different start dates, so as to reduce discretisation error.

We favour this nonparametric measure over other, regression-based metrics due to its lower sensitivity to outliers.

Figure 35: Sequential dependency scores (κ) on CDX market returns

Lookback Window \ Lookahead Window	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
1M	0.10	0.10	0.13	0.17	0.19	0.20	0.21	0.20	0.21	0.18	0.17	0.18
2M	0.19	0.18	0.23	0.28	0.29	0.30	0.30	0.28	0.29	0.26	0.26	0.25
3M	0.15	0.28	0.32	0.31	0.32	0.33	0.34	0.33	0.33	0.29	0.29	0.29
4M	0.24	0.24	0.34	0.31	0.30	0.33	0.34	0.33	0.32	0.30	0.29	0.30
5M	0.37	0.32	0.32	0.34	0.34	0.36	0.37	0.34	0.35	0.33	0.34	0.35
6M	0.23	0.24	0.40	0.42	0.37	0.38	0.37	0.37	0.38	0.35	0.35	0.37
7M	0.47	0.48	0.42	0.38	0.38	0.41	0.43	0.44	0.44	0.42	0.42	0.41
8M	0.17	0.19	0.44	0.47	0.43	0.39	0.43	0.45	0.44	0.41	0.40	0.39
9M	0.55	0.26	0.31	0.34	0.34	0.39	0.42	0.43	0.42	0.40	0.38	0.37
10M	0.28	0.41	0.45	0.46	0.42	0.35	0.34	0.35	0.36	0.37	0.35	0.34
11M	0.21	0.25	0.24	0.11	0.17	0.21	0.30	0.34	0.34	0.33	0.33	0.32
12M	0.13	- 0.01	0.12	0.14	0.19	0.28	0.34	0.39	0.38	0.35	0.31	0.30

Source: Deutsche Bank

Figure 36: Sequential dependency scores (κ) on residual returns* (single name CDS)

Lookback Window \ Lookahead Window	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
1M	0.10	0.10	0.09	0.09	0.08	0.09	0.10	0.10	0.10	0.10	0.10	0.10
2M	0.11	0.10	0.10	0.09	0.09	0.10	0.10	0.11	0.11	0.11	0.11	0.11
3M	0.10	0.10	0.09	0.09	0.09	0.10	0.11	0.11	0.11	0.11	0.11	0.11
4M	0.12	0.09	0.09	0.09	0.10	0.10	0.11	0.11	0.12	0.12	0.12	0.12
5M	0.07	0.11	0.10	0.10	0.10	0.11	0.11	0.12	0.12	0.12	0.12	0.12
6M	0.13	0.12	0.10	0.10	0.11	0.12	0.12	0.13	0.13	0.13	0.13	0.13
7M	0.09	0.12	0.11	0.11	0.11	0.12	0.13	0.13	0.13	0.14	0.13	0.14
8M	0.10	0.10	0.12	0.12	0.13	0.13	0.13	0.13	0.13	0.14	0.14	0.14
9M	0.11	0.09	0.12	0.15	0.14	0.13	0.12	0.13	0.13	0.14	0.14	0.15
10M	0.14	0.14	0.13	0.12	0.12	0.13	0.13	0.13	0.13	0.14	0.14	0.15
11M	0.10	0.13	0.11	0.08	0.09	0.10	0.11	0.13	0.14	0.15	0.15	0.15
12M	0.16	0.10	0.07	0.05	0.06	0.09	0.11	0.13	0.14	0.15	0.15	0.15

Source: Deutsche Bank * Residual returns refers to the residuals from a regression between CDS returns and market returns

Figure 35 and Figure 36 display the results of our measure of sequential dependencies, first using an aggregate of CDX NA IG and CDX NA HY index returns, and then using single-name CDS residual returns. Shorter formation periods were omitted as we find short-term Momentum a separate signal in its own right. To get a more holistic view, we looped through formation windows (the rows) and future return periods (the columns).

The resulting heat maps indicate the following:

- There is momentum in both market returns and residual returns, though it is more significant in the former.
- There are no patterns suggesting an optimal formation window to assess momentum in market returns. This is in line with our findings when following trends in macro, CTA markets.
- Single-name residual momentum exhibits a slow pattern, in terms of both formation windows and potential holding periods, supporting the view that information diffuses slowly in corporate Credit markets. It also supports the view that residual momentum is generally slower, as highlighted by Gutierrez and Pirinsky (2007) and Blitz et al. (2018).

Finally, previous authors [50] have highlighted that traditional momentum – that is, the sum of market and residual momentum – is more pertinent in High Yield relative to Investment Grade corporate bonds. We carried out a similar analysis but focused exclusively on residual returns on corporate CDS, which pointed to momentum in both IG and HY universes[51].

These findings, which we identify using the full CDS dataset available, set the basis for our signal generation process.

4.5.1 Signal generation: Momentum

Our Momentum signals are built under the premise that signal direction, unlike signal magnitude, carries the most predictive power for future asset returns. The former should therefore be used for signal generation, while the latter should be used for noise control[52]. We use this premise in defining both Market Momentum and Residual Momentum factors, whose asset pools differ:

- Market Momentum uses 5Y CDX NA IG and CDX NA HY as a combined instrument, as these indices are a liquid representation of the "market" concept.
- Residual Momentum uses 5Y single-name corporate CDS as investment instruments.

At a given rebalancing date t, the Market Momentum signal for asset i (the market) is calculated as follows:

[50] See, for instance, Avramov (2007) and Jostova (2013).
[51] The sequential dependency results for HY and IG separately resemble those seen in Figure 36 - which contain information for a broader set comprising both IG and HY names. This further illustrates the existence of momentum when trained under different formation windows.
[52] For further details, we refer the reader to Natividade et al (2013) and Natividade et al (2016).

1. We observe the cumulative CDX returns using multiple start dates and ending at the close of the previous business day. The first lookback window starts 252 business days ago and the last starts 21 business days ago. As such, we have 232 observations of historical returns - each with a start date one day apart from the other. More formally, we calculate returns between $t-h$ and t, where $h \epsilon [21{,}252]$.

2. We record the sign of each of the 232 values above, therefore building a vector of -1 and +1 values.

$$\hat{s}^i_{t,h} = 1 \;\; if \;\; r^i_{t-h,t} > 0$$
$$and$$
$$\hat{s}^i_{t,h} = -1 \;\; if \;\; r^i_{t-h,t} < 0$$

   where $r_{t-h,t}$ relate to instrument returns during the lookback period.

3. The raw signal value is the average of the vector of values from Step 2. We also record the vector's standard deviation, a measure of dispersion that will be used for noise control.

$$\bar{s}^i_t = \frac{1}{251-32}\sum_{h=32}^{251} \hat{s}_{t-h,t}$$

4. Once the raw signal has been created, we control it for noise to generate the final signal. Our method, shown in Anand et al. (2019), is based on hysteresis: if the absolute value of the raw signal falls below a "noise" threshold, we keep the old signal value. We set the threshold to 1/3, in line with Anand et al. (2019), thereby also improving the turnover profile.

$$\tilde{s}^i_t = \quad if \; |\bar{s}^i_t| \geq \frac{1}{3}$$
$$and$$
$$\tilde{s}^i_t = \tilde{s}^i_{t-1} \;\; otherwise$$

5. Finally, we further control for noise by deflating the signal by its dispersion, as recorded in Step 3. This gives us the final signal.

$$s^i_t = \frac{\tilde{s}^i_t}{\sigma_{\hat{s}_t}}$$

The Residual Momentum signal for asset i (single name CDS) at rebalancing date t is calculated as follows:

1. We calculate the raw residual signal[53]:

$$e^i_{t,h} = r^i_{t-h,t} - \beta^i_t \times r^{mkt}_{t-h,t}$$

   where $r_{t-h,t}$ represent cumulative returns for individual assets and the market, and β_t is the beta coefficient estimated in Section 3.2.[54]

2. We observe the cumulative residual returns using multiple start dates and ending at the last business day's close. While the first lookback window also starts 252 business days ago, the last starts 126 business days ago, in line with the slow nature of this signal. We therefore record 126 return values between $t-h$ and t, where $h \in [126{,}252]$.

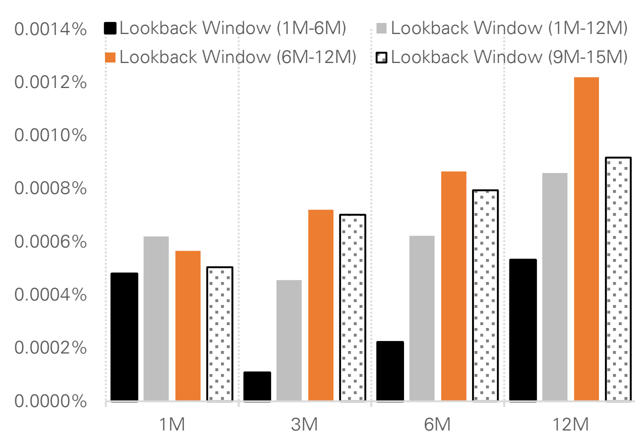
3. The remaining steps for the raw signal follow Steps 2, 3, 4 and 5 in Market Momentum.

Finally, as highlighted in Section 3, the Market Momentum signal is implemented using a time series construct while the Residual Momentum signal is implemented using a cross-sectional construct.

4.5.2 Signal predictive power: Momentum

Having defined our Momentum signals, we now evaluate how well they predict future asset returns over different horizons. Figures 37 and 38 display our results using the risk-adjusted modified information coefficients (RAMICs) defined in Section 3.1.

Figure 37: Residual Momentum – RAMIC scores per horizon under different training windows



Source: Deutsche Bank

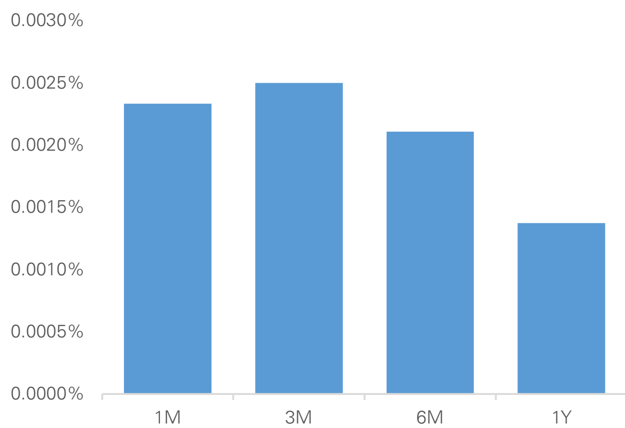
[53] Our residual momentum signal is derived from modeling asset returns as $r_{i,t} = \alpha_{i,t} + \beta_{i,t}\, r_t + e_{i,t}$. We do not include $\alpha_{i,t}$ (also known as Jensen's alpha) in our residual calculation because the alpha contains idiosyncratic information that we wish to capture in our signal.

[54] The reader may note a difference in frequencies between beta estimation (3-day returns) and cumulative returns in the Residual Momentum signal (21-252 day cumulative returns). We opted for this approach, as opposed to the matched-frequency approach from Anand et al. (2019) to further reduce estimation noise. This approach is also consistent with what is often implemented in Equities. The two approaches do not exhibit notable differences in results.

We highlight two important findings:

- Slowing our Residual Momentum signal was a valid decision; faster versions - which use shorter formation windows - have lower predictive power across multiple horizons.
- The Market Momentum signal also decays slowly.

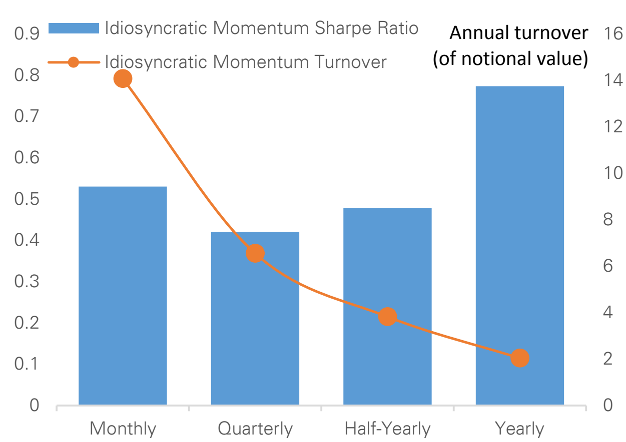
Figure 38: RAMIC scores per horizon – Market Momentum signal



Source: Deutsche Bank

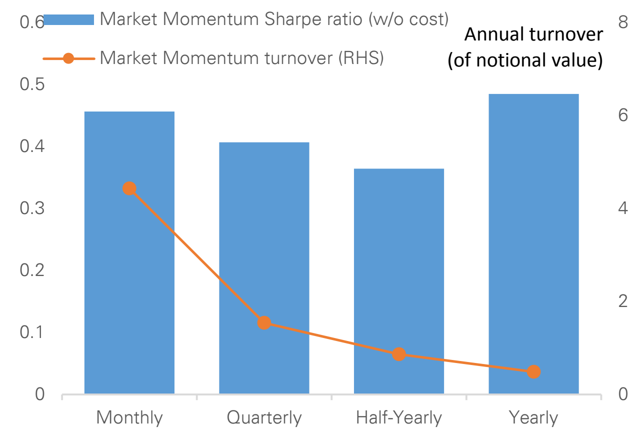
Figures 39 and 40 also show the sensitivity of our factor results to different rebalancing frequencies. It is no wonder that the results favour rebalancing the Residual Momentum factor slowly, as prior results leaned in that direction. But the U-shape display in Figure 41 is more intriguing.

Figure 39: Results per rebalancing frequency – Residual Momentum



Source: Deutsche Bank

Figure 40: Results per rebalancing frequency – Market Momentum



Source: Deutsche Bank

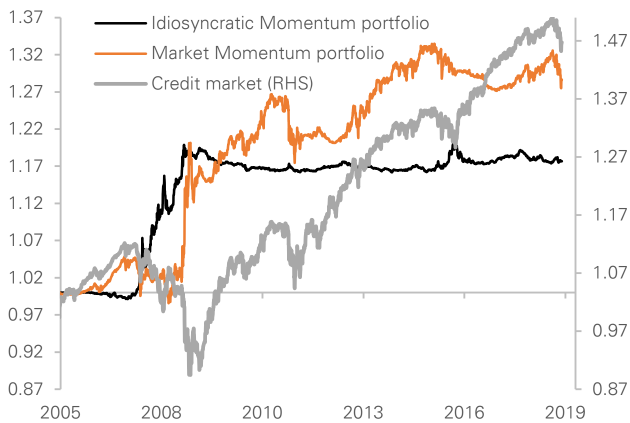
The reader may ask whether the positive predictive power, slow signal decay and positive strategy results are simply due to the multi-year rally in the asset class since 2004, when our dataset starts. While we are data-constrained, there are a few arguments that point to this not being the case:

- The Residual Momentum factor is mostly market neutral, and therefore the secular market rally plays a small role (if any).
- The long bias in the Market Momentum strategy – 76% of the positions are long the market – simply reflects the multi-decade rally in the asset class. More importantly, the strategy is adaptive, as seen by the short positions during drawdowns as per Figure 42.

4.5.5 Backtest results: Momentum

Figures 41 and 42 illustrate the defensive nature of our Credit Momentum strategies, as is expected given how this factor manifests itself in other asset classes.

Figure 41: Backtested cumulative returns (pre-cost) – Market Momentum and Residual Momentum

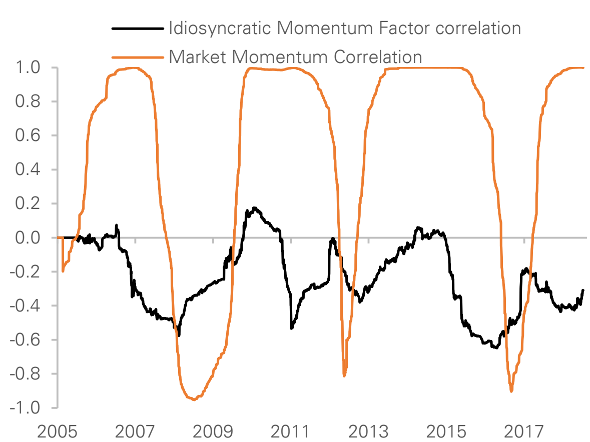


Source: Deutsche Bank

A few observations are worth highlighting:

- The Residual Momentum strategy is notably defensive in nature, with generally negative and somewhat stable correlations to the market index.
- Both strategies exhibit positive convexity during protracted market drawdowns, as expected with momentum strategies across asset classes.
- The two strategies complement one another, as shown in both Figures; the factor investor should therefore consider both as part of a multi-factor Credit portfolio.

Figure 42: Momentum – 1Y rolling correlations to CDX market



Source: Deutsche Bank

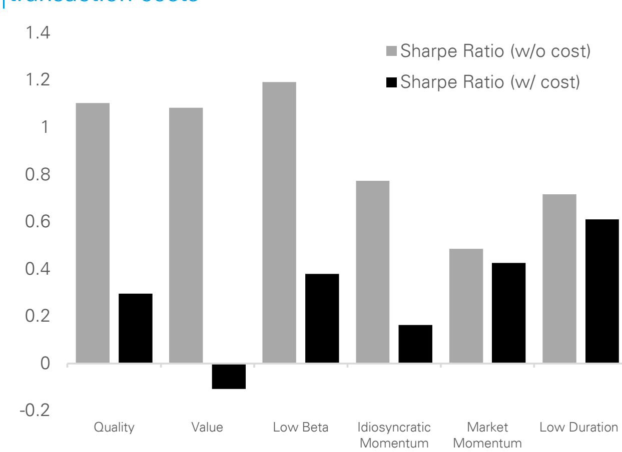
5. Factor Aggregation and Applications

Having defined our investment factors, we now combine them with two distinct applications: as an *absolute return portfolio* and as an *active overlay portfolio*. In each case, we combine the company-specific and market factors separately as sub-portfolios[55], and bring them together later. The absolute returns portfolio is a simple aggregation of both components, whereas the active overlay further combines it with a benchmark bond market index.

5.1 Sub-portfolio 1: company-specific factors

The company-specific factor sub-portfolio combines Value, Residual Momentum, Quality and Low Beta strategies. Each strategy is given equal risk allocation as we do not take a view on relative performance. Single name (asset) weights are further netted to minimise the impact of transaction costs. Such netting is crucial to this implementation. Figure 43 shows the reason for it. Most factors are unattractive if implemented independently after introducing transaction costs.

Figure 43: Backtested Sharpe ratios – before and after transaction costs



Source: Deutsche Bank

Figure 44 defines our transaction cost assumptions for 5-year CDS contracts, sourced internally.[56]

[55] The company-specific factors are Quality, Value, Low Beta and Residual Momentum. The market factors are Low Duration and Market Momentum.

[56] It assumes best execution practices and trade sizes not dissimilar to those regularly quoted by dealers, namely $5M for Investment Grade Names and $2M for High Yield Names.

Figure 44: Transaction cost assumptions* – per trade and per rollover

	Trade	Rollover
5y IG Single Name CDS	Max(2.5% * CDS Spread, 1bp)	Max (1.25%*Spread,1bp)
5y HY Single Name CDS	Max(2.5% * CDS Spread, 2.5bp)	Max (1.25%*Spread, 2.5bp)
	Trade	Rollover
IG Indices	Max(0.75% * CDS Spread, 1bp)	Max (0.75%*Spread, 1bp)
HY Indices	Max(0.75% * CDS Spread, 1bp)	Max (0.75%*Spread, 1bp)

*The table is based on the assumption that the single name CDS bid / offer spreads represent 5% of the CDS spread level. For instance, a 5Y CDS contract with a spread of 100bp (mid-price data) is assumed to be quoted 97.5 - 102.5. Therefore the transaction cost would be the price-to-mid difference (2.5%). In this example this is 2.5bp. Assuming a risky DV01 of 5.0 the actual price cost would be 2.5bp * 5 /10.000= 0.125% or 12.5bp on the traded notional. Source: Deutsche Bank

CDS market transaction costs are not a widely covered topic in the academic literature, with the valuable exception of Biswas et al (2014). The authors study effective CDS transaction costs on data from the Depository Trust and Clearing Corporation (DTCC)[57], with the following conclusions:

- During the studied period, effective half-spreads were on average between 12bp - 14bp of the notional traded amount, for trading sizes between $2.5M to $7.5M. For traded notionals between $7.5M and $12.5M the average half-spread was lower at 11.5bp.
- Indicative quoted spreads are twice as large as effective spreads. They find that 79% of the trades take place inside quoted bid-offer spreads[58].

The transaction cost assumptions from Figure 44, in the context of our strategy implementation, result in average costs of 25bp on the traded notional amount. While it is difficult to make direct comparisons[59], *our transaction cost estimates seem to err on the conservative side of Biswas et al (2014)*.

5.1.1 Combining the company-specific factors

We combine the four company-specific factors - Value, Low Beta, Quality and Residual Momentum - using an equal weights approach. Given that our individual portfolios were created targeting the same DTS level of risk, as highlighted in Section 3, equal weights is analogous to equal risk.

Further to it, we apply three weighting constraints while generating the target company-specific factor sub-portfolio:

- A maximum "dollar" exposure of 10% of the sub-portfolio in each position. This constraint ensures that our DTS-weighted aggregation does not lead to excessively high notional exposures to assets with very low CDS spreads. [60] This constraint also reduces jump-to-default risk in the sub-portfolio as a whole[61].
- A maximum spread level of 1000bp (at time of entry) on any single-name CDS exposure[62]. This reduces the risk of exposure to Credit names in distress.
- A minimum spread level, at the time of entry, of 40bp for investment grade contracts and 100bp for high yield contracts. We chose these levels in observance of the transaction cost table in Figure 44; with bid-ask spreads floored at 2bp and 5bp for IG and HY, these minimum spread constraints ensure that the floors are not hit and keep transaction costs at no more than 2.5% of the CDS spread at all times.

5.1.2 Transaction cost and risk disparity-based turnover controls

Turnover deceleration is common in expensive asset classes, but it must be done without significant entropy loss from the signals deployed.

Our newly introduced scheme strikes a balance between both by deciding on the aggregate amount of turnover and how it should be distributed among constituents.

The level of turnover is defined by a *transfer coefficient* threshold. Turnover distribution, in turn, is defined according to a risk budget. The transfer coefficient

[57] The authors estimate transaction costs for 851 single-name CDSs traded from August 2009 to May 2014. According to the study, this data covers 90% of the traded notional in the market during such periods.

[58] We arrive at the conclusion using intraday bid-offer quotes from Markit. This data vendor applies real time quote parsing algorithms to extract indicative OTC quotes from multiple dealer messages. The final bid-offer prices used are time weighted averages of the intraday quotes. The conclusions are made by comparing such bid-ask spreads with the transaction data sourced from DTCC.

[59] This is because the study does not model the estimation as a function of spread levels as we do.

[60] This type of constraint is common in portfolios that aggregate assets with distinctly different risk profiles using a risk-based metric. A good example is a typical CTA trend following portfolio, which uses equal volatility weights to combine assets with very low volatility, such as Asian bond futures, with assets with very high volatility, such as energy and base metals.

[61] Our results are also robust to the removal of this operationally-driven constraint.

[62] While the selection of this number is arbitrary, our implementation also is robust if we remove this cap. While we could have opted out of using any maximum limit, we believe it is a sensible measure to take for two reasons. The first is to avoid distress situations unseen in our data. The second, more pragmatic one relates to the illiquidity of distressed credits in the market and whose trading execution can be highly uncertain.

threshold is defined by the user, while the risk budget is the DTS spread between current and target portfolios. Crucially, positions with a higher DTS mismatch – the most "influential" exposures - are given first trading priority.

Puttin it differently, the scheme aims to reduce turnover as much as *feasible*.

At every rebalancing date, we observe the *target* portfolio – the one with target asset weights – and the *trading* portfolio, which implements positions. The former serves as a reference, and we use it solely to estimate the required change in positions.[63] The steps at a given rebalancing date are as follows:

1. We estimate the (theoretical) transaction costs from the latest rebalancing of our target portfolio. We call it our *transaction cost budget*, which defines the maximum turnover quantity allowed for the trading portfolio.

2. All asset positions are ranked by the difference between target risk and traded (current) risk. Larger risk disparities rank higher.

3. We estimate the *transfer coefficient*[64], defined as the Pearson correlation between asset weights in the target and traded portfolios. If the TC is above 0.95, we assume the traded portfolio tracks the target portfolio well enough, and therefore apply our cost reduction mechanism as per Steps 4-5.[65] If not, we trade more as per Step 6.

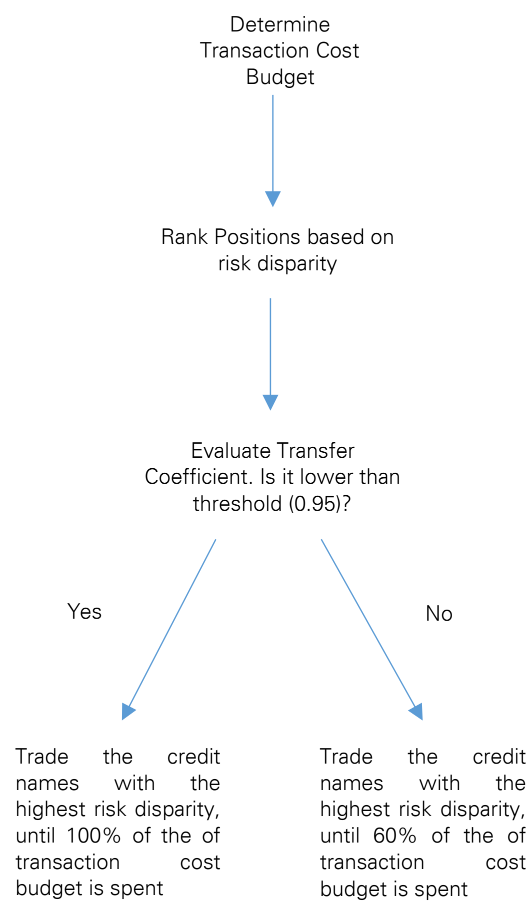
4. The cost reduction mechanism consists of "spending" 60% of the original transaction cost budget.[66]

5. The new transaction cost budget is spent by first trading the position with the largest risk disparity value. The trading of new positions continues until the transaction cost budget is fully spent. This implies that not all positions may be turned over at a given rebalancing date.

6. If the transfer coefficient is below 0.95, we spend 100% of the original transaction cost budget. In other words, we assume the tracking error between traded and target portfolios is high, and trade more to narrow the distance.

Figure 46 shows the transfer coefficient of the company-specific factor portfolio after applying the cost control mechanism. We clearly observe that the scheme stabilizes the transfer coefficient around 0.95.

Figure 45: Transaction cost management – flow chart



Source: Deutsche Bank

[63] In other words, the trading portfolio does not try to match the level of positions of the target portfolio. It tries to match the turnover of those positions. Note that both portfolios are the same in the first two years.

[64] This is the correlation between the weights in the trading portfolio and the target portfolio weights.

[65] The 0.95 threshold is arbitrarily set to be close to 1, to retain a portfolio that closely resembles the original. We tested our results using thresholds between 0.85 and 0.95, without observing significant changes.

[66] We selected 60% following detailed analysis. Values within the 50-80% range allow the transfer coefficient to stabilize around our target of 0.95 without significant fluctuations over time. While 50% also results in a larger cost reduction, we favored the use of 60% to have a safe margin of error.

Figure 46: Transfer coefficients – company-specific factors

Source: Deutsche Bank

Finally, Figure 47 compares performances between cost-controlled and uncontrolled company-specific factor portfolios. In essence, our cost control mechanism leads to a 30% improvement in our cost profile. Backtested returns also rise, despite the *alpha slippage* resulting from the scheme. Indeed, all performance metrics improve.

Figure 47: Company-specific factors – backtested performance with and without transaction cost control

	Without T/C Control	With T/C Control
Total Return	9.64%	11.35%
Annual Return	0.65%	0.76%
Annual Std	1.18%	1.13%
Max DD	-3.10%	-2.64%
Sharpe Ratio	0.55	0.67
Market Correlation	-0.28	-0.29
Annual Turnover	1.98	1.29
Annual Transaction Costs	0.57%	0.40%

Source: Deutsche Bank

5.2 Sub-portfolio 2: market factors

Our implementation of the market factors is more straightforward, owing to the small number of assets – 3Y, 5Y and 10Y CDX NA IG and 5Y CDX NA HY - and the friendlier cost profile.

These characteristics simplify our aggregation process; our market factors – Low Duration and Market Momentum – are aggregated using equal volatility weights.

Our positions in 3Y and 10Y CDX NA IG, which reflect Low Duration, and our positions on 5Y CDX IG and HY, which reflect Market Momentum, are therefore further weighted according to the relative volatility between the two strategies.

5.3 Factor aggregation and applications

We now describe two distinct applications of our Credit portfolios: absolute returns and active overlay.

5.3.1 The absolute returns portfolio

The *absolute returns portfolio* results from combining the market and company-specific sub-portfolios using equal volatility weights, in a process that is repeated on a bi-weekly basis. [67]

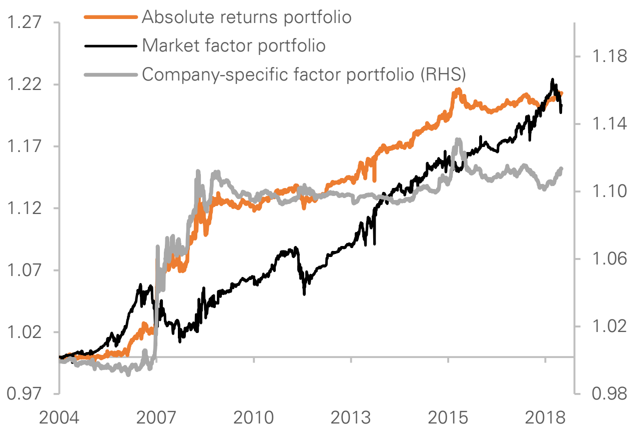
We do so by dynamically changing our exposure to the market sub-portfolio, which is far more liquid, to target the volatility of the company-specific sub-portfolio. This route improves our transaction cost profile as the company-specific portfolio weights are kept unchanged.[68]

Figures 48 and 49 shows the cumulative returns of both sub-portfolios, together with the absolute returns aggregate. The company-specific sub-portfolio exhibits a defensive nature, as is the case with three of its four inputs. The market sub-portfolio, on the other hand, varies in profile between defensive and pro-cyclical. As a result, the aggregate portfolio benefits from high diversification and a tame market correlation profile.

[67] Volatilities are estimated as per Section 3, and re-estimated on a bi-weekly basis.

[68] This is not to say that the capital (or "dollar") exposure to the idiosyncratic portfolio is constant. As shown before, each factor strategy has a DTS target that is equally applied to the long and short legs. Our capital exposure to each strategy, and to the sub-portfolio, varies to reach the DTS target.

Figure 48: Factor portfolio – backtested results (with costs)



Source: Deutsche Bank

Figure 49: Absolute return portfolio and sub-portfolio statistics

	Market Factors	Company-specific Factors	Absolute Returns Portfolio
Total Returns	20.3%	11.3%	21.3%
Annual Returns	1.3%	0.8%	1.4%
Volatility	2.0%	1.1%	1.6%
Sharpe Ratio	0.67	0.67	0.88
Market Correlation	0.27	-0.29	-0.01

Source: Deutsche Bank

5.3.2 The active overlay portfolio

We now illustrate how to apply our factor portfolios as overlay to an existing (long-only) corporate bond portfolio, with the aim to improve exposure to the asset class.

Given the multiple differences in: (1) the composition of funded corporate bond benchmarks[69], and (2) given the DTS-led differences in weights between CDX benchmarks and our multi-factor portfolios, the standard "smart beta" construction formulae does not apply. [70] Nevertheless, an overlay structure with targeted volatility can achieve comparable goals, and is therefore our preferred choice.

Our solution employs the following portfolios:

- A strategic portfolio (SP) comprising corporate bonds. This is represented by an equal weight combination of two cash bond indices covering the Investment Grade and High Yield universe[71]. We assume a static 100% capital allocation to this funded portfolio.
- The absolute returns portfolio (ARP) defined in Section 5.3.1. This overlay portfolio is unfunded, and has a static risk weight. Its historical volatility has on average been 0.3x that of the strategic portfolio.
- An index overlay portfolio (IOP) comprising equal weights between CDX NA IG and CDX NA HY, whose allocation will vary over time. This portfolio will be used exclusively to ensure that the observed volatility of the combined portfolio (SP + ARP + IOP) matches that of the original strategic portfolio[72]. Weights vary from long to short.
- A total portfolio (TP), which aggregates the three portfolios above.

This implementation [73] aims to improve investor exposure to the Credit asset class while also retaining the funded portfolio's original volatility. It also accounts for the lack of leverage potential in the strategic portfolio and scarce liquidity of the absolute returns portfolio by making it such that only IOP weights are adjusted at each rebalancing date. In essence, we target the original SP volatility by changing our allocation to the IOP.

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[69] There are several differences, including:

1. Bond benchmark indices have a much larger number of constituents than CDS indices.
2. Bonds indices contain bonds with different maturities, as opposed to CDS indices where all maturities are the same.
3. Cash bond indices are generally value-weighted and CDS indices are equally weighted.

[70] Our factor portfolios use a DTS approach to size their positions. The notional values allocated to lower risk components are larger than to those of higher risk names, sometimes by orders of magnitude. This creates difficulties in underweighting and overweighting positions subject to a non-shorting constraint, as is usually the case with smart beta solutions, because the CDS indices are equally weighted. While there are implementable mathematical solutions to that problem, the results (in our experience) distort the alpha generated by the factor portfolio. In short, the non-shorting constraint is too restrictive.

71 The first one is the Bloomberg Barclays US Corporate Total Return Value Index (Bloomberg ticker: LUACTRUU Index), which covers the Investment Grade Universe. The second one is the Bloomberg Barclays US Corporate High Yield Total Return Index Value (Bloomberg ticker: LF98TRUU Index), which covers the High Yield Universe.

[72] We considered an alternative Index Overlay Portfolio comprising not only the credit element (CDS indices) but also the rates component (via 5Y interest rate swaps, for instance). However, we disregarded this approach. The idea of the IOP is to correct for the volatility mismatch added by the ARP, which is free of the interest rate component, and therefore we opted for an index overlay that is also free of interest rate exposure.

[73] As analogous to Anand et al. (2019).

At a given rebalancing date, our steps are as follows[74]:

1. We combine the SP and ARP portfolios using the allocations described above.

2. We calculate the TP volatility target as the 1-year rolling volatility of the strategic portfolio. We also estimate 1Y rolling volatilities and 1Y rolling correlations for the individual components.

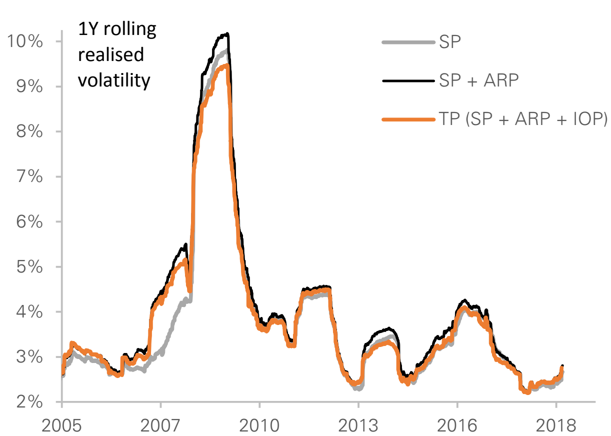
3. We solve for the IOP weight that - when combined with the static SP and ARP allocations – matches the volatility calculated in Step 2[75].

Figure 50: Volatility targeting portfolio – performance statistics

	SP	SP + ARP	TP (SP+ARP+IOP)
Total Retuns	119.2%	167.6%	155.8%
Annualized Returns	5.7%	7.2%	6.8%
Annualized Volatility	3.9%	4.1%	3.9%
Sharpe Ratio	1.46	1.73	1.74

Source: Deutsche Bank

Figure 51: 1Y rolling volatility – volatility target portfolios



Source: Deutsche Bank

We draw the following conclusions from Figures 50 and 51:

- The absolute returns portfolio adds value to the funded Credit investor. This an expected outcome given that the factor overlay strategy is uncorrelated to Credit returns.
- However, it is not a volatility-mitigating portfolio, especially given the often positive correlation between the market factor sub-portfolio and the strategic portfolio. The ARP contributes to both returns and volatility.[76]
- Adding the IOP helps reduce aggregate volatility without significantly affecting returns, thereby keeping risk-adjusted returns high.

Finally, we also highlight two main risks from this approach: *basis risk* and *alpha risk*. The *basis risk* arises when future volatilities and correlations differ from the historical estimates used in our portfolio construction. The *alpha risk* refers to the possibility of the factor overlay portfolio failing to add value in the future.[77]

6. Conclusion

This *Quantcraft* introduces our approach to systematic investing in Credit markets. We do so by first identifying the market drivers, then translating them into investable strategies, and ultimately grouping them together through absolute return and target volatility portfolios.

In this process, we have learned valuable lessons.

First, asset class drivers should be categorised as market-wide or company-specific, and their resulting factor strategies should be built differently.

Second, most of the alternative return drivers are borne out of structural or behavioural features, including slow information diffusion, peer benchmarking and the inability of active managers to apply leverage to their bond portfolios.

The latter two often drive excess demand for higher duration, higher carry and (often) lower quality exposures. We find these to be unrewarded and we often take on opposite positions through CDS markets. This may sound counter-intuitive to the average investor,

[74] We rebalance the IOP allocation quarterly. The rest (SP and ARP) rebalance as per usual.

[75] This implies solving the equation:

$$target\ vol = \sigma_{sp+arp}^2 . w_{sp+arp}^2 + \sigma_{iop}^2 . w_{iop}^2 + 2.\rho_{sp+fop,iop}.w_{sp+fop}.w_{iop}.\sigma_{sp+arp}.\sigma_{iop}$$

where the only unknown is w_{iop}.

[76] A version that excludes market factors from the absolute returns portfolio would, however, lead to a significant drop in aggregate volatility.

[77] *Concentration risk* is the third that we normally consider in optimization-based strategies, though in this case we empirically observed that the smallest number of assets in the company-specific factor portfolio has been 100 historically, which is not small.

but that is often what factor investing is about. *The factor investor often goes against the crowd.*

Third, trading costs may be the highest among public markets, but information diffusion is also the slowest. This allows Credit factor portfolios to rebalance at a much slower pace and therefore save on costs. The factor investor still needs innovative turnover management, which we cover in Section 5.

Fourth, Credit markets uniquely benefit from variables that aggregate fundamental and market measures, such as duration-times-spread and distance-to-default. These allow for portfolios to be based on fundamental drivers and be highly adaptive at the same time. Further, the same metric can have multiple uses. Distance-to-default, for instance, can be used as input to both Value and Quality signals even though the resulting factor strategies are negatively correlated to one another.

Last but not least, we must account for hidden risks even if the data does not show them. Jump-to-default risk is a good example of that. As such, we certainly welcome the defensive characteristics of most of our Credit factor strategies.

Appendix A: From CDS Spreads to Returns

This note is a reference guide to the calculation of credit default swap returns. It allows the reader to explore the key concepts involved and works as a "how to" guide to building CDS return indices. We assume certain familiarity with the CDS contract structure and its general terms.

A.1. Basic Concepts

As in most asset classes the return of a CDS is composed of two main components: mark to market changes and carry returns:

$$Returns = Change\ in\ MTM + Carry\ Return \qquad (1)$$

where:

$$Carry = Contract\ Spread\ x\ DayCountFraction \qquad (2)$$

The MTM calculation of a CDS contract is less intuitive than calculating the carry component. Different from other asset classes, the P&L cannot be directly calculated by taking the difference between quoted and historical prices. In the CDS case, it is necessary to use the term structure of survival probabilities and make a recovery rate assumption[78].

Let us use an example to illustrate the marking to market process of a CDS contract. Consider an investor that sells 5 year protection on an IG credit for 40bp. IG CDS contracts are written with a standard 100bp spread[79]. Therefore, the protection seller receives 100bp for the life of the contract. This is despite the market spread being 40bp.

Intuitively one can infer that the investor would need to economically compensate the protection buyer for earning a higher premium than that quoted in the market. The compensation amount is a function of the difference between the contract-specified spread (100bp) and the market quote of 40bp.

It follows that the CDS contact market value is the difference between the expected present value of periodic 100bp payments and the expected present value of periodic 40bp payments.

$$MTM = E[PV\ 100bp\ coupon] - E[PV\ 40bp\ coupon] \qquad (3)$$

It is an "expected present value" because the payments depend on the occurrence of default. If the reference entity defaults, premium payments comes to halt.

If we define the expected present value of 1bp paid on the premium leg as the Risky PV01, we can re-express the previous equation as:

$$MTM_t = RPV01_{t-1} * (100bp - 40bp) \qquad (5)$$

Continuing with our example, let us assume that 1 day passed and the CDS spread is now trading at 30bp. Our daily P&L can be calculated as:

$$Pnl_t = \overbrace{RPV01_{t-1} * (100bp - 40bp) - RPV01_t * (100bp - 30bp)}^{Change\ in\ MTM} + \underbrace{100bp * \frac{1}{365}}_{Carry} \qquad (6)$$

Generalizing, the Pnl of a CDS contract is given by:

$$Pnl = RPV01_{t-1} * (Spread - Entry\ Spread) - RPV01_t * (Spread - Current\ Spread) + Spread * DayCountFraction \qquad (7)$$

A.2. Creating a Return Index

Building up on the previous section it follows that a return index can be calculated in the following way:

$$R\ Index = CDS\ MTM + Value\ of\ Coupons\ Accrued \qquad (8)$$

Or if calculated on a daily basis, it can also be expressed as:

$$R\ Index = Intial\ Contract\ MTM + \sum Daily\ Change\ in\ MTM + \sum Daily\ Coupons \qquad (9)$$

However, this is the return index of a single contract. We are interested in calculating the returns of a contract with fixed maturity. Therefore one must take into account the contract rollovers and make the necessary adjustments to the return index.

To illustrate the rollover process let us use the case of the rollover of a 5Y CDS contract[80]. At a given rebalancing date it becomes the on-the-run contract with 5.25 years to maturity. After six months, it "rolls over": the 4.75-year contract is substituted by a new

[78] The market convention is to use a 40% recovery rate assumption for contracts specifying protection to senior unsecured debt, 20% for subordinate debt and 25% for emerging market debt (both senior and unsecured)

[79] Since 2009 CDS contracts follow market wide standards. Generally, IG contracts are written with a standard 10obp spread and HY contracts with a 500bp spread. Some exceptions apply.

[80] At the time of writing this report, CDS contracts rolled over twice a year following ISDA conventions

5.25-year contract, which becomes the new on-the-run CDS.

We define the index in the following way:

$$\text{R } Index\ = Notional_{t-1} * (MTM + \ Accrued\ Coupons\ ) \quad (10)$$

Or

$$R\ Index\ = Notional_{t-1} * (\text{ Intial } MTM\ + \sum \text{MTM } Change + \sum Coupons\ ) \quad (11)$$

With notional exposure equal to 1 on t=0. On roll over dates three actions take place:

1. The notional exposure is adjusted according to the equation below:

$$Notional = \frac{R\ Index}{1 + New\ Contract\ MTM} \quad (12)$$

2. The cumulative coupon and mark to market changes are reset to zero.

3. The initial CDS Contract MTM changes to that of the new on-the-run contract on the rebalance date.

A.3. Calculating the Risky PV01

The Risky PV01 summarizes the most important part of the CDS valuation in a single measure[81]. To understand the origin of this measure, we need to review the fundamentals of how to value CDS contracts. The valuation uses non-arbitrage principals. It equates the present value of the CDS premium leg (spread premium payments) to that of the protection leg (contingent payments in a default event).

A.3.1 Valuing the premium leg

The premium leg consists of a number of cash flows determined by the contract spread. Such payments depend on the occurrence of default. If the underlying entity defaults at any point during the contract life, the premium payments stop.

As a result, the cash flow valuation is directly linked to the probability of no-default-occurrences before the dates when premium payments take place. In other words, it is linked to the survival probability up to the date when cash flows are earned.

Ignoring accrued payments for the time being, the present value of the premium leg can be expressed as:

$$PVPremium = Spread * \sum_{i=1}^{n} DiscFactor_{t,i} * DayFrac_{t,i} * SurvivalProb_{t,i} \quad (13)$$

To account for the accrued payments, one must calculate the probability of survival for each premium payment date (as shown in Equation 13) and also the probability of default in the interval between such date and the next payment date. As a result, the previous formula needs the addition of an extra term to account for default events between premium payments.

$$PVPremium = \ Spread\ * \ \sum_{i=1}^{n}[\ DiscFactor_i * DayFrac_i * SurvivalProb_i + \int_{t_{i-1}}^{t_i} DiscFactor_{ti} * Day\ Frac_{t_i} * defProb_{t_i}\ ] \quad (14)$$

This expression can be approximated by the following formula[82]:

$$PVPremium = Spread * \sum_{n=1}^{n} Disc\ Factor_n * Day\ Frac_n * [SurvivalProb_n + \frac{1}{2} * (SurvivalProb_{n-1} - SurvivalProb_n)\ ] \quad (15)$$

The previous formula can be also expressed as:

$$PVPremium = Spread * RPV01 \quad (16)$$

With:

$$RPV01 = \sum_{n=1}^{n} DiscFactor_n * DayFrac_n * [SurvivalProb_n + \frac{1}{2} * (SurvivalProb_{n-1} - SurvivalProb_n)] \quad (17)$$

We have now defined the Risky PV01. As we previously mentioned, it is the main input into the valuation of CDS contracts. However, the previous formula is a function of the survival probabilities, which are unknown at this point. In section 3.3, we will review their estimation.

A.3.2 Valuing the Protection Leg

The protection leg values the contingent payment (1-recovery rate) on the occurrence of a default event. It can be expressed as follows:

$$PVProtection = (1 - RecRate) \sum_{n=0}^{n}(SurvivalProb_{n-1} - SurvivalProb_n) \quad (18)$$

[81] As we saw in the previous section, it is the key measure to be inferred to calculate the P&L of a CDS contract. Given the RPV01 importance, and the several steps needed for its computation, it is common to obtain historical time series from external providers.

[82] We follow O'Kane and Turnbull (2003) in approximating the integral solution to $\frac{1}{2} * (SurvivalProb_{n-1} - SurvivalProb_n)$.

A.3.3 Survival Probability

The survival probabilities can be modeled as a Poisson process[83] and account for the first occurrence of a credit event during a defined time interval and with a probability defined by:

$$P[\,\tau < t + \delta t \mid \tau \geq t] = \lambda(t)\delta t \qquad (19)$$

This is the probability of a default in the interval $(t, t + \delta t)$ given that no default has occurred before that period. This probability is equal to the product of $\lambda(t)$ (hazard rate) and the time interval δt. As a result, the probability of surviving in the interval $(t, t + \delta t)$ is equal to $1 - \lambda(t)\delta t$.

Finally, we have that the survival probability over a time period (t, T) when considering $\delta t \rightarrow 0$ is given by:

$$S.Prob_{t,T} = e^{-\int_t^T \lambda(s)\delta s} \qquad (20)$$

A.3.4 Hazard Rate Term Structure

The survival probability requires the estimation of hazard rates $\lambda(t)$. Therefore, the task is to infer hazard rates from market-observed CDS quotes. To do so, it is necessary to iteratively estimate (bootstrap) hazard rates and build a hazard rate term structure.

The process starts with estimating the hazard rate for the first period, and then plugging such value into the estimation of the second period hazard rate. The process continues to iterate up to the last term.

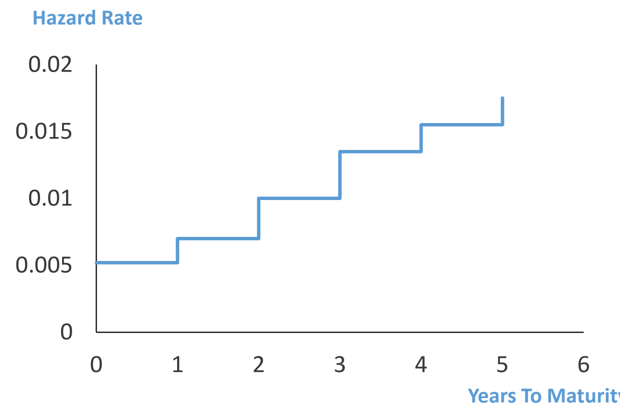
Assuming semi-annual premium payments and a piece-wise linear hazard rate term structure, the first period hazard rate can be obtained by solving the following equation[84]:

$$Spread * \sum_{n=0.5,1}^{n} DiscFactor_n * DayFrac * e^{-\lambda_{0,1}n} = (1 - RecRate) \sum_{n=0.5,1}^{n} (e^{-\lambda_{0,1}n-1} - e^{-\lambda_{0,1}n}) \qquad (21)$$

Using a numerical root-finding algorithm, such as the Newton-Raphson method, the first hazard rate $\lambda_{0,1}$ can be obtained. The process is then repeated for $\lambda_{1,2}$ and continues until the final maturity.

A typical hazard rate term structure is shown in Figure 52:

Figure 52: Term structure of hazard rates



Source: Deutsche Bank

Finally, if we discretized Equation 20, we have that:

$$S.Prob_{t,T} = e^{-(\lambda_{t,t+1} * DFrac_t + \,\ldots\, \lambda_{T-1,T} * DFrac_T)} \qquad (22)$$

A.3.5 Market Practice

In practice, market participants make the simplifying assumption that the CDS spread curve is flat[85]. As a result, only one point on the curve is needed to estimate the Risky PV01.

The latter means that the term structure of hazard rates becomes flat as well. In practical terms, this means that the need to bootstrap disappears. Therefore, instead of solving Equation (21) iteratively, we only now need to solve it once and find a unique hazard rate (λ) value.

$$Spread * \sum_{n=1}^{m} DiscFactor_{t_n} * DayFrac * e^{-\lambda t_n} = (1 - RecRate) \sum_{n=1}^{m} (e^{-\lambda * t_n} - e^{-\lambda * t_n}) \qquad (23)$$

A.4. Summary

We have reviewed the basics to transform CDS spread changes into return values. Equation (7) provides the formula to calculate the CDS P&L. The calculation key input is the risky PV01, which is estimated using survival probabilities. The survival probabilities require building the hazard rate term structure. The hazard rates can be inferred from market-quoted CDS spreads and the term

[83] A Poisson process is a stochastic process that counts the number of events and the time the events occur during a given a time interval. It assumes the time between two jumps (events) is independent and identically distributed.

[84] Left hand side of the equation is PV of the premium leg. The right hand side is the PV of the protection leg.

[85] This assumption is made to facilitate CDS contract trading. By assuming a flat spread curve, there is only the need to agree on a single tenor CDS spread. Otherwise, there would be a need to agree on spreads for multiple tenors.

structure can be bootstrapped. However, in practice, market participants make a simplifying assumption that makes the hazard rate term structure flat. As a result, a single hazard rate needs to be estimated. CDS return indices can be calculated using equation (11) and notional values must be reviewed on rebalance dates according to equation (12).

In summary:

1. Find hazard rate (λ) by solving Equation (23) through a root finding algorithm such as Newton-Raphson
2. Estimate survival probabilities using Equation (22)
3. Calculate Risky PV01 using Equation (17)
4. Calculate Pnl using Equation (7)
5. Calculate return index applying Equation (10) or (11) in conjunction with Equation (12)

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