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## Fixed Income Factors: Theory and Practice

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# Fixed Income Factors:
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### KEY FINDINGS

- Simple factor definitions for carry, value, momentum, and quality produce robust returns, and offer diversification benefits to investors. A trade cost aware multi-factor portfolio constructed from the US High Yield index produces an information ratio of 0.68, with a highly significant multi-factor signal.
- While some fixed income managers consider factors in their investment process, many have yet to take advantage of the additional risk premia and diversification benefits of factors.

### ABSTRACT

Fixed income markets present unique considerations that many believe make the space prohibitive to factor investing. Examples include high transaction costs, limitations on shorting instruments, and the highly diverse set of constraints credit portfolio managers often consider during construction—potentially "washing out" any factor exposures. Despite these challenges, the authors document significant performance for style factors created using simple construction rules applied across US investment grade, US high yield, and emerging market bonds. The authors conclude with two case studies that investigate the level of factor exposure for active fixed income funds to demonstrate a success story and highlight opportunities for funds that lack factor exposure.

Similar to the market factor in CAPM, Fama and French (1993) measure two corporate bond factors which encapsulate systematic market risk: credit and term. The term factor is the return of longer maturity Treasuries relative to shorter maturity Treasuries. The credit factor is the return of lower rated securities over maturity matched government bonds. Recent research has expanded on these two systematic factors with many proposed style factors. We focus our research on some of the most studied style factors in literature that all have extensive empirical evidence: Value, Carry, Quality, and Momentum. We show that simple model-free implementations of these style factors provide robust performance in long-only credit portfolios, offer compelling diversification, and can be incorporated into long-only credit portfolios that observe constraints such as sector, rating, or maturity neutralization. Additionally, we find that few US High Yield bond strategies have significant exposure to these factors.

First, in order to assess factor performance with limited market influence, we conduct a standard quintile portfolio test by forming "beta neutral" long-short factor portfolios and compute their monthly alphas in multivariate regressions on the systematic term, credit, and equity factors, as well as known equity style factors. Next, focusing on long-only factor portfolios and the diversification potential they may offer, we review their specific behaviour across different periods of market stress, as measured by monthly changes in the VIX, the Standard and Poor's 500 index, and US industrial production. To help us understand the usefulness and flexibility of credit factors in portfolio management, we neutralize factor portfolios along numerous dimensions such as age, size, sector, and rating. Applying such controls allows us to determine if factors can generate returns through portfolio construction constraints, which are common in credit portfolio management. We also document the persistence of the multi-factor signal over numerous months to test if the signal conveys useful information for extended periods.

Second, building on our assessment of factors, we showcase a long-only multi-factor portfolio constructed using all four factors in the US High Yield index. We aim to demonstrate that a multi-factor portfolio can overcome implementation costs, efficiently capture interaction effects of factor exposures, and deliver favorable returns. To this end, we calculate a simple but conservative transaction cost estimate using data compiled in Harris (2015) to generate a trade cost aware multi-factor portfolio.

Finally, we present two specific case studies that provide practical examples of the use of fixed income factors in practice. In the first case study, we assess style factor exposure for the Norwegian Government Pension Fund Global (GPFG) and discuss performance implications. In our second case study, we conduct a similar analysis on a broad universe of active US High Yield strategies to assess active skill.

## FACTOR DEFINITIONS

We have intentionally chosen simple factor definitions to allow the economic intuition behind each factor to be the key determinant of returns. By avoiding complexity wherever possible, we seek to limit the likelihood of presenting overfitted or cherry-picked results. While more complicated implementations of these factors could likely yield better results, simplicity allows for a clearer exposition of factor characteristics. Documenting robust and consistent performance from nearly identical implementations of simple strategies across three vastly different universes is a more convincing argument in support of fixed income factors than showcasing more complicated versions of factor implementations that might exhibit better performance. Below we provide definitions of the factor implementations we will use and highlight key research that supports the concepts behind each one.

### Value

Value, from a high level, is built on the concept of mean reversion, or that a security will converge to its intrinsic value. A common example of a simple value characteristic often used in equity investing is the book-to-value ratio. Within fixed income, the nuances of the value definition have varied in research. In Houweling and van Zundert (2017), for example, the authors rely on a cross-sectional regression to produce a model estimate of spread that is compared to the market spread to rank value. Israel et al. (2017) uses market spread per unit of default risk as measured by two different default models.

In this article, we compute value by ranking the option-adjusted spread (OAS) of bonds among similar "peer" bonds. Peer bonds are bonds that are in the same sector group, rating group, or country grouping (if relevant). These groupings organize the universe based on key fundamental characteristics, allowing us to rank bonds in like groups from cheap to expensive. More specifically, we define value as follows:

1. For corporate indices, bonds are ranked by OAS within Bloomberg Class 3 sectors and index credit rating groups. Higher ranked OAS bonds in each peer grouping receive higher ranks than lower ranked OAS bonds in the same peer group.
2. For the emerging market index, OAS is ranked within broad index rating (i.e., AA, A, BBB) and country code. In cases where only one bond is present in that grouping, meaning a relative value rank cannot be produced, then a broader grouping based on Rating, and Bloomberg Class 2 sector classification is used. Falling back on a broader peer group for countries that have few bonds in the index offers a more objective alternative to arbitrary data choices such as excluding them, or populating ranks with a 0 designation.

### Carry

Carry is the return an investor receives for holding a bond to maturity, assuming current market conditions persist. Recent research on carry includes Koijen et al. (2018), which studies carry across many asset classes, including fixed income. For our carry factor, we define carry simply as a rank on spread (OAS) as this is the return an investor will realize if market conditions remain unchanged.

### Quality

The quality factor selects securities with defensive characteristics, such as low leverage, measures of macroeconomic sensitivities, or distance to default. In fixed income, implementations of defensive or high-quality approaches have been reviewed in Frazzini and Pedersen (2014), Ilmanen et al. (2021), and Israel et al. (2017). This research shows that strategies as simple as being short duration with a tilt to higher rated credit can generate economically significant risk-adjusted returns. Drawing on this research, our quality factor ranks the shortest duration bonds within each credit rating group higher than longer duration bonds. We conduct the ranking within each credit rating group to ensure our quality signal is credit risk neutral vs the broader index.

### Momentum

While the benefits of momentum investing have been recognized for some time, the momentum premium was first documented in the academic literature by Jegadeesh and Titman (1993). It has since been studied in global bonds by Asness et al. (2012) and documented in corporate bonds by Jostova et al. (2013), among others. The momentum effect is the tendency of recent winners to continue to perform well and recent losers to continue to perform poorly. In this study, we define momentum as the trailing nine-month excess return with the most recent monthly return excluded from the formation period to avoid short-term reversals.

### Multi-Factor Strategy

We construct a multi-factor strategy by ranking securities using a simple average of the four individual factor ranks. Multi-factor strategies have been shown to generate robust performance, while also capturing diversification benefits over the individual factor portfolios. As stated in Henke et al. (2019), multifactor portfolios are thought to benefit from interaction effects that single factor implementations fail to capture.

Using factor definitions similar to those in this article, all four of these factors and multifactor implementations were studied in both long-short and long-only portfolios for US corporate bonds by Israel et al. (2017), and in global bonds over a century of data by Ilmanen et al. (2021).

## DATA AND METHODOLOGY

### Bond Data Filtering

We form three filtered universes based on the Bloomberg US Investment Grade, High Yield 2% Issuer Capped, and Emerging Market USD denominated indices. All data is monthly from January 2001 to July 2023. Total returns and excess returns are provided by Bloomberg. Total return is the full return realized by an investor, and excess return is total return less the impact of interest rates. Measuring performance in excess returns is common in fixed income, as it separates interest rate impacts from more security-specific impacts.

We then apply a price filter to remove highly distressed bonds, or those already in default, from the data. We assign numerical scores to both Standard and Poor's and Moody's ratings, ranging from 1–24. The highest rating of AAA receives a score of 1, AA+ receives a score of 2, etc. Scoring extends to D ratings, which represent defaulted or unrated securities and are assigned a rating number of 24. Bonds priced under $40 are excluded, and bonds rated 'D', in default, or not rated are excluded. Additionally, since highly distressed bonds at sufficient maturity evade simple price filters, bonds in the bottom 1% in terms of price when compared with peers of similar maturity are also excluded. Finally, we enforce one simple liquidity consideration: the smallest 10% of bonds, as measured by the outstanding issuance for the bond on each date, are removed. In Exhibit 1, we present a statistical summary of the data studied. These metrics are market value weighted, computed monthly, and then averaged over the full sample period.

### Portfolio Construction

After filtering and preparing the bond data, we then construct single factor portfolios. In fixed income markets, the cross-section of securities has very diverse exposures to systematic risks, which makes constructing long-short zero beta portfolios for performance measurement difficult, as the long and short sides of the portfolios may have very different betas. This can complicate the process of isolating and measuring "alpha." Ben Dor et al. (2007) found that duration times spread (DTS) is a superior metric for assessing and controlling a portfolios systematic exposure to duration and credit risks. It is simply the product of a bond's credit risk, or spread (OAS), and a bond's duration; the same two systematic risk components discussed earlier. Israel et al. (2017) utilize this measure in a control for systematic exposure in their study of style factors. We apply similar DTS controls to value, momentum, and the multi-factor signal. This control is not applied to the carry and quality factors, given that the factors use duration or spread, the two components of DTS, to rank holdings.

For the DTS-controlled factors, we construct signal-based portfolios by forming scaled ranks of each characteristic, then apply this DTS control across the five quintiles. The index is ordered by DTS and broken into five buckets ranging from low to high DTS. Factor characteristics are then re-ranked within each DTS quintile. These DTS controlled ranks are then used to form five equally weighted factor portfolios, with

## EXHIBIT 1

### Summary Statistics for Filtered Index Universes

| | Metric | Mean | Std. Dev. | Percentile 5% | 10% | 25% | 50% | 75% | 90% | 95% |
|---|---|---|---|---|---|---|---|---|---|---|
| US Investment Grade | Age (years) | 3.8 | 0.3 | 3.2 | 3.3 | 3.7 | 3.9 | 4.1 | 4.2 | 4.3 |
| | Amount Outstanding (Mil) | 1,256 | 232 | 808 | 1,004 | 1,066 | 1,298 | 1,486 | 1,520 | 1,526 |
| | Bond Count | 3,978 | 1,332 | 2,326 | 2,434 | 2,812 | 3,483 | 5,065 | 5,997 | 6,392 |
| | DTS | 9.9 | 4.6 | 3.4 | 3.7 | 6.9 | 10.0 | 12.2 | 14.4 | 16.2 |
| | Excess Return (bps) | 7.8 | 143.5 | –176.2 | –117.4 | –38.1 | 17.2 | 58.8 | 123.2 | 187.3 |
| | OAD (years) | 6.7 | 0.9 | 5.6 | 5.7 | 5.9 | 6.7 | 7.2 | 7.8 | 8.5 |
| | OAS (bps) | 148.8 | 74.1 | 85.5 | 90.2 | 102.8 | 134.3 | 165.8 | 208.2 | 253.1 |
| | Rating | 7.8 | 0.4 | 7.2 | 7.3 | 7.5 | 8.0 | 8.1 | 8.2 | 8.3 |
| | Total Return (bps) | 40.0 | 175.2 | –246.0 | –140.1 | –46.3 | 52.3 | 135.3 | 239.7 | 299.0 |
| | Years to Maturity | 10.5 | 0.7 | 9.5 | 9.6 | 10.1 | 10.5 | 10.9 | 11.7 | 12.1 |
| | Yield to Maturity (%) | 4.4 | 1.6 | 2.2 | 2.8 | 3.2 | 4.2 | 5.6 | 6.4 | 7.5 |
| US High Yield | Age (years) | 3.0 | 0.3 | 2.4 | 2.5 | 2.7 | 3.0 | 3.3 | 3.4 | 3.5 |
| | Amount Outstanding (Mil) | 836 | 211 | 472 | 491 | 727 | 901 | 1,018 | 1,060 | 1,070 |
| | Bond Count | 1,525 | 306 | 906 | 1,017 | 1,347 | 1,602 | 1,779 | 1,878 | 1,920 |
| | DTS | 18.5 | 7.6 | 10.0 | 11.0 | 12.9 | 16.6 | 22.6 | 27.6 | 30.9 |
| | Excess Return (bps) | 23.1 | 282.7 | –394.9 | –239.7 | –76.0 | 36.7 | 136.7 | 318.6 | 449.6 |
| | OAD (years) | 4.2 | 0.4 | 3.5 | 3.7 | 4.0 | 4.2 | 4.6 | 4.7 | 4.7 |
| | OAS (bps) | 481.2 | 197.2 | 274.4 | 297.1 | 335.4 | 432.6 | 581.9 | 702.7 | 781.1 |
| | Rating | 15.1 | 0.3 | 14.6 | 14.7 | 14.9 | 15.1 | 15.3 | 15.4 | 15.5 |
| | Total Return (bps) | 53.6 | 252.4 | –323.4 | –200.0 | –53.8 | 75.3 | 164.3 | 290.3 | 412.6 |
| | Years to Maturity | 6.9 | 0.8 | 5.7 | 5.9 | 6.3 | 6.7 | 7.7 | 8.1 | 8.3 |
| | Yield to Maturity (%) | 8.1 | 2.3 | 5.3 | 5.7 | 6.3 | 7.6 | 9.0 | 11.4 | 12.0 |
| Emerging Market | Age (years) | 4.1 | 0.3 | 3.6 | 3.8 | 3.9 | 4.1 | 4.3 | 4.5 | 4.7 |
| | Amount Outstanding (Mil) | 2,160 | 478 | 1,589 | 1,634 | 1,683 | 2,173 | 2,659 | 2,791 | 2,876 |
| | Bond Count | 871 | 668 | 221 | 231 | 263 | 464 | 1,665 | 1,804 | 1,846 |
| | DTS | 18.6 | 6.6 | 9.2 | 12.4 | 15.0 | 17.2 | 20.6 | 29.2 | 33.9 |
| | Excess Return (bps) | 25.2 | 249.0 | –331.4 | –213.2 | –70.9 | 44.9 | 158.1 | 254.1 | 335.9 |
| | OAD (years) | 5.9 | 0.7 | 4.4 | 4.8 | 5.6 | 6.0 | 6.3 | 6.7 | 6.9 |
| | OAS (bps) | 318.7 | 155.0 | 133.0 | 177.2 | 244.5 | 279.8 | 341.0 | 549.6 | 669.3 |
| | Rating | 11.6 | 1.3 | 10.3 | 10.3 | 10.6 | 11.5 | 13.0 | 13.7 | 14.0 |
| | Total Return (bps) | 57.5 | 262.8 | –321.0 | –189.9 | –60.3 | 71.5 | 187.4 | 324.1 | 429.5 |
| | Years to Maturity | 10.7 | 1.3 | 8.8 | 8.9 | 9.2 | 10.8 | 11.6 | 12.4 | 12.8 |
| | Yield to Maturity (%) | 6.3 | 2.4 | 3.7 | 3.9 | 4.4 | 5.8 | 6.9 | 10.8 | 11.6 |

**NOTES:** Market value weighted averages for each month were computed for the filtered universes from January 2001 to July 2023. Sample consists of 284 monthly periods, with 1,129,629 periods for US Investment Grade, 247,316 for Emerging Markets, and 433,216 for US High Yield.

**SOURCES:** Invesco, Bloomberg.

the top quintile having the highest factor ranks and the bottom quintile the lowest. For the long-short portfolio, the portfolio is long the top quintile and short the bottom quintile, resulting in a net zero-dollar portfolio. The long-only portfolio is long the top quintile of bonds.

For the multi-factor strategy, we first compute the average of the four factor ranks, and then apply the DTS control to the combined signal. This DTS controlled multi-factor signal is then used to form equally weighted quintile portfolios. For carry and quality, quintiles are formed using the non-DTS controlled ranks.

All portfolios are rebalanced monthly.

### Multi-Factor Portfolio with Trade Costs

To test if returns are significant after transaction costs, we apply a heuristic-based approach on bond rating, portfolio turnover values, and a reasonable assumption about portfolio size.

1. First, as mentioned in the bond data overview, we apply a filter that removes the smallest 10% of bonds by issuance size from each index, which Harris (2015), shows are more expensive to trade than larger issues.
2. We then assume our hypothetical portfolio is of average size for a credit mutual fund, $500 million to $1 billion, allowing it to trade easily in lot sizes of half a million or more. Harris (2015) presents many analyses of average dealer spread along metrics such as issue size, trade size, and rating type (for example, investment grade versus high yield).
3. With the above considerations, we estimate the trade cost to be three times the index rating number of a bond. For example, a BBB bond would have an index rating number of 10 and, consequently, a trade cost of (3 × 10), or 30 basis points for a large trade.

This trade cost multiplier was selected to produce a range of trade costs along each rating group that is slightly higher and more conservative than costs reported in studies such as Harris (2015), or Chen et al. (2007), who found the average trade cost for BBB-rated bonds in large trades to be 22 basis points. We compute total portfolio trade cost as the sum of the turnover value for each bond multiplied by its trade cost estimate. This cost is then subtracted from the portfolio's returns.

## RESULTS

### Long-Short and Long-Only Portfolios

To provide support for fixed income factors, we present the standard "portfolio test" common in econometric studies. This test helps determine if a factor is "real" or just "noise." The monthly alphas of long-short and long-only factor portfolios are computed in multi-variable regressions for each factor. The more significant a factor portfolio's alpha is, as measured by the t-stat of the alpha term, the more likely the factor is a "real" return premium.

Exhibit 2 presents the monthly alphas and t-statistics from two different regression models. The first, indicated as Model 1, uses systematic return proxies for credit, term, and equities. The second, indicated as model 2, supplements the first model with the Fama-French (2015) size (SMB), value (HML), quality (RMW), and investment (CMA) equity factors.

With the long-short portfolio, we see mixed results for carry, where significance is only exhibited in US investment grade bonds. Momentum exhibits significance in US High yield bonds, but is not significant in investment grade bonds, in line with Jostova et al. (2013) and other studies. Quality lacks significance across all three asset universes. Value and the multi-factor signal are highly significant in both models and across all indices.

With the long-only portfolio, we see the same results with Carry as we did for the long-short portfolio, with carry only remaining significant in the US investment grade universe. Likewise, momentum displays significance with US high yield bonds, but is not significant in investment grade bonds. Contrary to the long-short portfolio, the long-only quality factor portfolio is modestly significant in US corporate bonds, but not in emerging markets. Value and the multifactor signals are highly significant for both models in all indices.

## EXHIBIT 2
### Quintile Test for Long-Short and Long-Only Portfolios

| | Model | Metric | US Investment Grade Long-Short | US Investment Grade Long-Only | US High Yield Long-Short | US High Yield Long-Only | Emerging Markets Long-Short | Emerging Markets Long-Only |
|---|---|---|---|---|---|---|---|---|
| Carry | 1 | Intercept (α) | 18.0 | 13.9 | 14.7 | 4.9 | –6.6 | –13.0 |
| | | t-statistic | *2.8* | *2.8* | *0.9* | *0.4* | *–0.3* | *–0.7* |
| | 2 | Intercept (α) | 17.0 | 12.7 | 16.6 | 5.0 | –8.0 | –13.2 |
| | | t-statistic | *2.6* | *2.5* | *1.0* | *0.4* | *–0.4* | *–0.7* |
| Momentum | 1 | Intercept (α) | –9.0 | –1.9 | 30.4 | 23.7 | 19.3 | 12.7 |
| | | t-statistic | *–2.1* | *–0.9* | *3.6* | *4.6* | *2.0* | *2.6* |
| | 2 | Intercept (α) | –9.6 | –2.7 | 28.1 | 19.9 | 19.4 | 12.4 |
| | | t-statistic | *–2.2* | *–1.2* | *3.2* | *3.8* | *2.0* | *2.6* |
| Quality | 1 | Intercept (α) | 4.6 | 3.6 | 1.0 | 12.9 | 1.1 | 1.9 |
| | | t-statistic | *1.1* | *1.9* | *0.2* | *3.3* | *0.2* | *0.5* |
| | 2 | Intercept (α) | 6.1 | 3.6 | 2.8 | 11.9 | 6.1 | 3.7 |
| | | t-statistic | *1.4* | *1.9* | *0.5* | *3.0* | *0.9* | *0.9* |
| Value | 1 | Intercept (α) | 25.2 | 14.7 | 35.3 | 24.8 | 40.9 | 15.5 |
| | | t-statistic | *10.0* | *6.6* | *6.1* | *5.0* | *5.1* | *3.1* |
| | 2 | Intercept (α) | 24.3 | 13.9 | 32.2 | 21.1 | 41.0 | 15.3 |
| | | t-statistic | *9.5* | *6.0* | *5.4* | *4.2* | *5.0* | *2.9* |
| Multi-Factor | 1 | Intercept (α) | 20.6 | 13.0 | 39.8 | 28.2 | 34.7 | 20.3 |
| | | t-statistic | *6.1* | *5.2* | *5.4* | *4.9* | *4.7* | *3.9* |
| | 2 | Intercept (α) | 19.5 | 12.3 | 37.3 | 25.0 | 36.0 | 21.1 |
| | | t-statistic | *5.6* | *4.7* | *5.0* | *4.3* | *4.8* | *3.9* |

**NOTES:** Monthly alpha and t-statistic regression output for top quintile minus bottom quintile long-short and long-only top quintile portfolios using data from January 2001 to July 2023. Excess returns are regressed using two separate models. The independent variables for each model are as follows:

Model 1: Term, credit, and equity systematic returns.
Model 2: Model 1 variables plus the Fama-French SMB, HML, RMW, and CMA equity factor returns.

**SOURCES:** Invesco, Standard & Poor's, Bloomberg.

In aggregate, all of the credit factors are effective across each index, especially for the multi-factor signal.

### Factors and Diversification

To better understand the diversification benefit of factors, we review the long-only factor portfolios during various periods of market stress. We partitioned the time series into quintiles along percentage monthly change in the S&P 500, VIX, and US Industrial Production. Exhibit 3 presents the information ratios (IR), as well as t-stats for a one-sided t-test where the mean active return for each grouping is greater than zero. Some clear patterns emerge for quality and carry across the VIX and S&P 500 quintile groupings. For example, during low VIX volatility periods, the quality factor has an IR of –3.48, but during high volatility periods it has an IR of 2.5. Carry exhibits the opposite behavior, with a low IR in times of higher market stress and a high IR in times of lower market stress. Value and the multifactor signals exhibit consistent performance across the various macroeconomic groupings.

The multifactor portfolio shows consistent performance across periods of stress with a test statistic for mean active return averaging over 2 across all 3 indices in the VIX and SP stress period. The average IR for the multifactor portfolio is .98 for all three asset classes.

## EXHIBIT 3

### Factor Diversification Test

| | | | Full Period | SPX Quintile | | VIX Quintile | | Production Quintile | |
|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 1 | 5 | 1 | 5 | 1 | 5 |
| US Investment Grade | Carry | Information Ratio | 0.38 | –1.50 | 2.78 | 2.17 | –1.46 | 0.16 | 1.38 |
| | | t-stat Active Ret. | *1.78* | *–3.15* | *5.95* | *4.64* | *–3.09* | *0.35* | *2.96* |
| | Momentum | Information Ratio | –0.34 | 0.14 | –1.86 | –2.11 | 0.86 | –1.09 | –0.36 |
| | | t-stat Active Ret. | *–1.61* | *0.30* | *–3.99* | *–4.52* | *1.82* | *–2.38* | *–0.77* |
| | Quality | Information Ratio | –0.06 | 3.04 | –3.21 | –3.48 | 2.50 | –0.27 | –0.09 |
| | | t-stat Active Ret. | *–0.28* | *6.40* | *–6.86* | *–7.45* | *5.29* | *–0.58* | *–0.20* |
| | Value | Information Ratio | 1.26 | 0.76 | 1.87 | 0.91 | 0.57 | 1.07 | 1.61 |
| | | t-stat Active Ret. | *5.99* | *1.60* | *4.01* | *1.94* | *1.21* | *2.34* | *3.44* |
| | Multi-Factor | Information Ratio | 0.90 | 0.94 | 0.68 | –0.07 | 1.44 | 0.09 | 1.67 |
| | | t-stat Active Ret. | *4.29* | *1.98* | *1.45* | *–0.14* | *3.06* | *0.20* | *3.57* |
| US High Yield | Carry | Information Ratio | 0.31 | –1.67 | 2.10 | 1.41 | –1.35 | 0.05 | 0.91 |
| | | t-stat Active Ret. | *1.47* | *–3.50* | *4.50* | *3.02* | *–2.87* | *0.10* | *1.95* |
| | Momentum | Information Ratio | 0.54 | 2.30 | –0.97 | –1.08 | 2.45 | 0.19 | 1.14 |
| | | t-stat Active Ret. | *2.58* | *4.83* | *–2.08* | *–2.31* | *5.19* | *0.41* | *2.43* |
| | Quality | Information Ratio | 0.36 | 3.71 | –2.60 | –2.51 | 3.32 | 0.15 | 0.28 |
| | | t-stat Active Ret. | *1.71* | *7.79* | *–5.57* | *–5.38* | *7.05* | *0.33* | *0.61* |
| | Value | Information Ratio | 1.13 | 1.41 | 1.13 | 0.44 | 1.19 | 0.89 | 1.55 |
| | | t-stat Active Ret. | *5.36* | *2.96* | *2.41* | *0.94* | *2.52* | *1.93* | *3.33* |
| | Multi-Factor | Information Ratio | 1.10 | 1.36 | 0.72 | –0.12 | 1.43 | 0.55 | 1.70 |
| | | t-stat Active Ret. | *5.22* | *2.87* | *1.55* | *–0.26* | *3.04* | *1.19* | *3.63* |
| Emerging Markets | Carry | Information Ratio | 0.19 | –1.11 | 1.52 | 0.99 | –1.64 | 0.43 | 0.10 |
| | | t-stat Active Ret. | *0.90* | *–2.34* | *3.25* | *2.12* | *–3.49* | *0.94* | *0.20* |
| | Momentum | Information Ratio | 0.32 | 1.05 | –0.20 | –0.38 | 1.55 | 1.10 | 0.15 |
| | | t-stat Active Ret. | *1.53* | *2.21* | *–0.42* | *–0.82* | *3.29* | *2.39* | *0.31* |
| | Quality | Information Ratio | –0.15 | 2.81 | –4.40 | –3.77 | 2.93 | –0.07 | –0.35 |
| | | t-stat Active Ret. | *–0.72* | *5.92* | *–9.41* | *–8.07* | *6.21* | *–0.16* | *–0.75* |
| | Value | Information Ratio | 0.78 | 1.52 | 0.26 | 0.00 | 1.37 | 1.57 | 0.32 |
| | | t-stat Active Ret. | *3.69* | *3.19* | *0.55* | *0.00* | *2.90* | *3.41* | *0.68* |
| | Multi-Factor | Information Ratio | 0.94 | 1.69 | 0.65 | 0.02 | 1.43 | 1.40 | 0.57 |
| | | t-stat Active Ret. | *4.49* | *3.54* | *1.39* | *0.05* | *3.03* | *3.05* | *1.21* |

**NOTES:** The excess returns of long top quintile factor portfolios for each characteristic are aggregated along ex-post quintiles of Standard and Poor's 500 less 3-month T-bills, monthly change in VIX, and the monthly change in US industrial production. Periods of market stress are indicated with red columns. Full period is comprised of 284 months, with approximately 56 periods in each quintile grouping. The information ratio is the mean active excess return divided by its standard deviation for all observations. Information ratios and t-statistics are shown where the mean active return for each grouping is greater than zero.

**SOURCES:** Invesco, Standard & Poor's, Bloomberg.

### Practicality and Persistence Tests

Next, we test practicality by applying controls to multi-factor portfolios along several common credit characteristics including Age, Bloomberg Level 3 Sector classification, Country, Distance to Par, One-Month Reversal, Issue Size, Years to Maturity, and Sovereign Issuer Rating.

Bai et al. (2018) examined several credit factors in corporate bonds and documented their performance after neutralizing along metrics such as size, age, one-month reversal, and ratings. These control sorts follow in the same manner as the DTS control sorts previously described. Controlling the factor portfolios along these dimensions neutralizes them relative to the index and simulates the types of constraints encountered when constructing credit portfolios. For example, a portfolio manager may wish to construct a rating neutral or sector neutral portfolio. In Panel (A) of Exhibit 4, we present alphas and test statistics for the multi-factor signal controlled along eight different characteristics. In all controls and across all indices, the multi-factor portfolio produces significant alpha.

Additionally, we investigated persistence of these signals by studying the predictive strength of the signal at 1-month, 2-months, and 3-months forward. A signal that quickly decays leads to high turnover and may be prohibitively expensive to trade in practice. The test statistics shown refers to the intercept over the systematic factors and Fama and French style factors. As shown in Panel (B) of Exhibit 4, the average annual IR is 1.01, and the test statistic averages 4.30 at the time of trade. Three months later, these signals still demonstrate predictive power, with a 0.55 IR and 2.48 test statistic, on average. The persistence of a signal for months after it is computed allows for factor strategies to be implemented with lower turnover.

## EXHIBIT 4

### Multi-Factor Long-Only Portfolio Characteristics

**Panel A: Alphas After Controls**

| | US Investment Grade | | US High Yield | | Emerging Markets | |
|---|---|---|---|---|---|---|
| **Control Metric** | **Alpha** | **t-Stat** | **Alpha** | **t-Stat** | **Alpha** | **t-Stat** |
| Age | 11.5 | 4.65 | 24.2 | 3.52 | 20.3 | 3.61 |
| Bloomberg Level 3 Sector | 9.8 | 3.76 | 19.2 | 2.87 | 23.0 | 4.23 |
| Country | 11.0 | 4.52 | 23.3 | 3.46 | 14.2 | 2.94 |
| Distance to Par | 9.7 | 4.22 | 21.8 | 4.13 | 17.5 | 3.48 |
| One-Month Reversal | 12.7 | 5.45 | 26.6 | 4.28 | 24.1 | 4.55 |
| Issue Size | 10.8 | 4.49 | 21.0 | 3.26 | 19.0 | 3.30 |
| Years to Maturity | 13.6 | 4.65 | 25.9 | 3.80 | 24.1 | 4.23 |
| Sovereign Issuer Rating | 11.2 | 4.62 | 23.9 | 3.53 | 18.6 | 3.73 |

**Panel B: Signal Persistence Test**

| | US Investment Grade | | | US High Yield | | | Emerging Markets | | |
|---|---|---|---|---|---|---|---|---|---|
| **Period** | **Alpha** | **t-Stat** | **IR** | **Alpha** | **t-Stat** | **IR** | **Alpha** | **t-Stat** | **IR** |
| Trade Date (0 Months) | 12.3 | *4.72* | 0.90 | 25.0 | *4.28* | 1.10 | 21.1 | *3.90* | 1.01 |
| 1 Month | 10.8 | *3.96* | 0.66 | 19.0 | *3.33* | 0.76 | 16.4 | *3.18* | 0.85 |
| 2 Months | 8.7 | *3.08* | 0.47 | 15.5 | *2.75* | 0.70 | 13.8 | *2.65* | 0.66 |
| 3 Months | 8.5 | *3.03* | 0.47 | 13.9 | *2.38* | 0.60 | 10.6 | *2.02* | 0.59 |

**NOTES:** Panel A: Long-only equally weighted quintile portfolios are formed by sorting using the multi-factor signal controlled across eight metrics. For numeric controls, five control groups are formed. Distance to Par is market price less par price and indicative of a bond's premium or discount. Monthly alphas and test statistics are reported for a regression of portfolio monthly excess returns onto equity, credit, term, and the Fama and French SMB, HML, RMW, and CMA factor returns. Panel B: Persistence of the "base" DTS controlled multi-factor signal. Results are reported for the trade date, 1-, 2-, and 3-month horizons. Monthly alphas and test statistics use the same regression described in Panel (A) above. Information ratios are annualized. Monthly data from January 2001 to July 2023. Persistence test portfolios are formed using the factor rank from n months prior and rebalanced monthly.

**SOURCES:** Invesco, Standard & Poor's, Bloomberg.

**EXHIBIT 5**

**Multi-Factor Trade Cost Aware Portfolio Results**

| Holding Period | Volatility | Average Return | Tracking Error | Average Active Return | Information Ratio |
|---|---|---|---|---|---|
| One Month – No trade costs | 10.18 | 6.82 | 3.10 | 3.40 | 1.10 |
| One Month – With trade costs | 10.18 | 5.54 | 3.10 | 2.12 | 0.68 |

**NOTES:** Summary statistics are presented for the long-only US high yield multi-factor portfolio with trade costs estimates applied. The one-month rebalance portfolio with no trade cost applied is shown for reference.

**SOURCES:** Invesco, Bloomberg.

### Long-Only Trade Cost Aware Multi-Factor Portfolio

Expanding on the high yield multi-factor results presented above, we incorporate trade cost estimates to probe the feasibility. Exhibit 5 presents the mean returns, volatilities, and information ratios for the multi-factor portfolio, including trade cost estimates. After accounting for trade costs, we report an information ratio of 0.68.

In summary, the four style factors and the multi-factor signal we have presented are significant predictors of returns, can survive being constrained across a host of dimensions, and still deliver compelling returns after trade costs are considered. Using simple definitions and no models or regressions, we can construct profitable portfolios with significant returns that also exhibit favorable diversification benefits in the long-only space, especially for the multi-factor portfolios. With that said, fixed income factors have yet to be widely adopted within portfolio management, unlike the case with equities.

## CASE STUDIES: FIXED INCOME FACTORS IN PRACTICE

### Overview

In this section of the article, we present two case studies that review corporate bond factors in practice. In each case study, we assess the impacts of factor exposures on the performance of active fixed income funds. For the first case study, we present the Norwegian Government Pension Fund Global (GPFG), an active fixed income fund that employs an investment strategy suitable for factor investing. In the second case study, we expand our analysis to a broader universe of actively managed US high yield funds. For each case study, we define three market betas: term, credit, and equity. Term and credit capture the main components of return for a corporate bond and the equity term is included for consistency. We also use our four style factors (carry, quality, value, and momentum) to capture the returns associated with factor exposures.

### Case Study 1: Norwegian Government Pension Fund Global

The Norwegian Government Pension Fund Global (GPFG) ranks among the largest and best-run funds worldwide. As discussed by Chambers et al. (2012), there is an emphasis in the fund on risk control through diversification using liquid, publicly-traded securities. The fund relies on a long-term investment horizon and has a limited need for short-term marketability. This long-term horizon perspective allows the fund to better manage fluctuations in returns and short-term losses. Furthermore, due to the fund's size, it only considers investing in strategies with large-scale capacity.

Lastly, the fund focuses on low-cost strategies with transparent investment processes. These investment objectives are well-aligned with factor investing. Systematic factor strategies are typically low-cost, and, by definition, transparent in their rules-based implementation.

For our analysis, we take the reported time series of GPFG monthly portfolio and benchmark returns from January 1, 2013 to December 31, 2022. We calculate active returns of the portfolio in USD and then regress the time series on the term, credit, and equity factors. For credit, the excess return of the Bloomberg Barclays US Investment Grade Index is used. For term, the interest rate component of return of that same index is used. The regression results are presented in Exhibit 6. This regression has an intercept of 2.16 bps per month, or approximately 26 bps per year. The exposure to term is slightly negative, while credit exposure is positive, and both are statistically significant. In contrast, the exposure to equity is insignificant. Overall, credit, term, and equity explain 35% of the variability of the active returns.

We then run a second regression, adding carry, quality, and value in the regression. The momentum factor is excluded due to its low statistical significance in the US investment grade universe. The term factor exposure remains slightly negative. The credit factor gets a negative exposure with low significance, while equity remains insignificant. Carry and value have positive exposure and quality has negative exposure. The three factors are all statistically significant. Most importantly, the additional factors increase the explanatory power of the model to 47%, as the intercept drops from 2.16 bps to 1.32 bps. Factor exposure to carry, value, and quality offer an additional 12% in explanatory power.

### Case Study 2: US High Yield Funds

In this case study, we broaden our analysis to a universe of active funds listed under the US High Yield Fixed Income product by eVestment. We filter the universe for funds that have a primary benchmark of Bloomberg US Corporate High Yield, Bloomberg US High Yield 2%, ICE BofA US High Yield, or ICE BofA US High Yield Constrained. The US high yield universe is considered specifically because active US high yield managers typically allocate a larger share of their assets to corporate bonds in comparison to their investment grade peers (Choi and Kronlund 2018). In total, there are 133 funds in the universe. The fund manager returns from eVestment are monthly total returns, net-of-fee, and range from January 2000 to June 2023.

In order to investigate the relationship of manager returns and corporate bond factors in our universe, we use three regression models. For each regression, we use the returns of the aggregate fund—an equal-weighted average return of all funds

## EXHIBIT 6

### Regression Results for GPFG Portfolio

| Model | Metric | Intercept | Credit | Term | Equity | Carry | Quality | Value | Adj. R-Squared |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Estimate | 2.16 | 0.017 | 0.005 | 0.000 | | | | 35% |
| | t-statistic | (6.4) | (3.9) | (1.9) | (0.3) | | | | |
| 2 | Estimate | 1.32 | 0.011 | 0.003 | 0.000 | 0.043 | 0.048 | 0.047 | 47% |
| | t-statistic | (3.1) | (1.0) | (1.4) | (0.2) | (2.3) | (1.7) | (2.5) | |

**NOTES:** This exhibit reports the regression results for the two-factor and the five-factor model for the first case study on GPFG. Data obtained from the Norges Bank Investment Management (2022) website . (https://www.nbim.no/en/publications/reports/2022/annual-report-2022/)

**SOURCES:** Bloomberg, Norges Bank, Invesco calculation using data from January 1, 2013 through December 31, 2022.

## EXHIBIT 7

### Regression Results for Aggregate Active US High Yield Portfolio

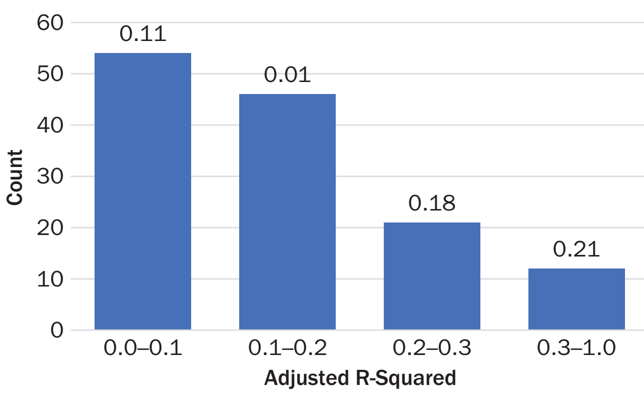
| Model | Metric | Intercept | Term | Credit | Equity | Carry | Quality | Value | Momentum | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Estimate | 0.012 | –0.174 | –0.176 | 0.035 | | | | | 60.0% |
| | t-statistic | (4.72) | (–5.58) | (–6.91) | (4.13) | | | | | |
| 2 | Estimate | 0.009 | –0.144 | –0.162 | 0.032 | 0.120 | –0.116 | –0.021 | 0.083 | 65.1% |
| | t-statistic | (3.16) | (–5.86) | (–6.27) | (3.96) | (2.38) | (–1.35) | (–0.20) | (2.47) | |
| 3 | Estimate | 0.011 | | | | 0.121 | –0.111 | –0.022 | 0.077 | 11.8% |
| | t-statistic | (4.52) | | | | (2.15) | (–1.89) | (–0.21) | (2.66) | |

**NOTES:** Output from the three regression models referenced in the second case study. In each regression, the aggregate fund is considered, returns are monthly, and the intercept is annualized. The input variables are the three market betas term, credit, and equity, and the four style factors Carry, Quality, Value, and Momentum. These style factors are the long-short, DTS-controlled corporate bond factors for US High Yield. The R-squared values are adjusted, and the t-stats are Newey-West adjusted. Model 1 regresses the active total returns of the fund on the three market betas. Model 2 expands on Model 1 by adding the four style factors. Model 3 regresses the fund's active total returns, in excess of market betas, on the four style factors.

**SOURCE:** Bloomberg, eVestment.

## EXHIBIT 8

### Distribution of Adjusted R-Squared for Selected US High Yield Funds




**NOTES:** Histogram of adjusted R-squared values from the third style-factor regression for all funds in the universe. Median information ratios are displayed above each bar in the histogram.

**SOURCE:** Bloomberg, eVestment.

in the universe. The regression results are presented in Exhibit 7. The first two models are the same as the GPFG case study. The third model regresses the active total returns of the aggregate fund, in-excess-of market betas, on the four style factors. The third model is then applied to the full fund universe.

For the first regression, 60% of the variation of the active total returns of the aggregate fund can be explained by the three market variables, term, credit, and equity, all of which are statistically significant. For the second regression, the adjusted R-squared increases marginally by 5.1% and the intercept reduces 21.8% from 121bps to 95bps. These changes in adjusted R-squared values and the intercept are significantly smaller than the changes observed in the first case study. For the aggregate fund, the style factors are less useful in explaining the active returns compared to the GPFG case study. These results are consistent with Palhares and Richardson (2020) and indicate that traditional active high yield managers provide alpha, in-excess-of market betas, that isn't effectively attributable to style factors. This represents an opportunity for investors to target additional sources of return and increase diversification in an overall active high yield mandate by combining a traditional active manager with a corporate bond factor strategy.

For the third regression, we regress the active total returns of the aggregate fund, in-excess-of market betas, on the four style factors. We use the coefficients from the first regression to compute the in-excess-of market betas performance. The third regression can help mitigate collinearity issues and provides us with a model that directly considers the performance in-excess-of market betas. This model has an adjusted R-squared of 11.8% and is consistent with the conclusion from the second regression: Style factors provide little explanatory power for the returns of the aggregate fund, in-excess-of market betas.

Lastly, we investigate the results of the third regression, but for all the funds in the universe. We present the distribution of adjusted R-squared values in Exhibit 8. Although the distribution of adjusted R-squared values is concentrated between 0 and 20%, 25% of funds (33 of 133) have values above 20%. The information ratios for the funds with adjusted R-squared values above 20% are higher than funds with adjusted R-squared values below 20%, although this difference is not statistically significant. These results suggests that some active managers do deliver performance, in-excess-of market betas, which can be partially attributed to style factor exposures. Investors should be wary of such active funds, as a portion of their alpha could be replicated with a lower-cost systematic corporate bond factor strategy.

## CONCLUSION

Fixed income factors, and their associated risk premiums, are real and exist across major fixed income asset classes like US investment grade, US high yield, and EM hard currency. Simple, model-free definitions can be used to implement factors, without added complexity, which offer a more direct link to underlying economic rationale. These risk premiums are robust after controlling for various fixed income variables and persist across different market regimes. Multi-factor portfolios can target multiple sources of risk premia simultaneously, while taking advantage of diversification benefits between factors. Although some active fixed income managers have adopted factors as part of their investment strategy, most have yet to take advantage of factor investing. Norges Bank serves as an example for an institutional investor whose investment strategy aligns with factor investing and active performance is partially attributable to corporate bond factors. With our US high yield case study, we reviewed the performance for a universe of active managers and discussed the low explanatory power of factor exposures on active performance. Factors can provide additional sources of return, even after accounting for trade costs and neutralizing traditional portfolio metrics. Furthermore, factors can be a low-cost complement to existing alpha strategies and provide increased diversification, as well as helping investors explore and justify performance.

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Detailed information about Bloomberg sector classifications can be found at: https://data.bloomberglp.com/professional/sites/10/Bloomberg-Barclays-Methodology1.pdf.

Exhibits 3 and 5: Based on Invesco calculation using data from January 2001 through July 2023.

Exhibits 7 and 8: Based on Invesco calculation using data from January 2000 through June 2023.

Fama/French factor data and details regarding size (SMB: small minus big), value (HML: high minus low), quality (RMB: robust minus weak), and investment (CMA: conservative minus aggressive) factors can be found at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html