Fixed income factor portfolios for institutional investors

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The "Norway Model" and the benefits of factors

Chambers, Dimsom and Ilmanen[1] describe the governance and investment objectives of the Norwegian Government Pension Fund Global (GPFG) in their 2011 paper. As the authors point out, the fund is one of the largest and most well-run funds in the world. They analyze the characteristics of the fund and distill several key principles which have been the key to its success.

First, there is an emphasis on risk control through diversification using liquid publicly traded securities. Second, the fund relies on a long-term investment horizon with little need for marketability. Third, the long-term horizon makes the fund tolerant of return volatility and short-term loss.

Fourth, given the fund's size, it only looks to invest in strategies with large capacity. Fifth, given the long-term investment horizon with stable risk preferences through time, the fund focuses on serving as an opportunistic liquidity provider through contrarian strategies. Finally, the fund focuses on low cost strategies with a transparent investment process.

Factor investing has been adopted by GPFG to improve diversification and returns as stated in their latest annual report[2]. The key reason being that factor investing fulfills the necessary criteria outlined by Chambers, Dimsom and Ilmanen. Factors have relatively low long-term correlation which ensures the fund can manage risk through diversification. They are scalable and come at a relatively low cost. In their most recent review of the portfolio's risk and return characteristics, the Norges Bank (2020)[2] which administers the GPFG reported the coefficient betas from multivariate regressions of their external manager's active returns. The estimated coefficients can be interpreted as exposures to factors over the analysis period while the intercepts can be attributable to manager value creation over and above the exposure of the factors. The Norges Bank uses 5 factors in equities including the market and four style factors: size, value, profitability and the investment factors from Fama and French (2015)[3] . The number of factors used reflects the substantial academic work behind equity factors. In the same report, the Norges Bank only uses credit and term in their regression for fixed income managers which is consistent with the two factors for bonds used by Fama and French (1993)[4].

The credit and term factors have more in common with the equity market factor than the style factors. 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 a maturity matched higher rated security. A corporate bond's yield and return can be decomposed into two sources – interest rate and spread. The interest rate risk is directly related to the bond's duration. The spread is the yield of the corporate bond above a maturity matched treasury and represents the higher returns associated with owning a riskier security than a treasury bond. While term may suffice to describe the interest rate exposure of a bond, the credit factor may not. In a way, it is the "CAPM" equivalent in corporate bonds. By only using the credit factor, investors are making an assumption that the spread return of the bond is due to its exposure to systematic credit risk. In diversified portfolios, this single factor suffices to explain the risk and return of the portfolio.

This concept of a single factor has been rejected in equities, there is no reason why multiple factors should not exist in corporate bonds as well.

Fixed income factors can offer similar benefits as equity factors

We will review several factors used in the literature and evaluate if factor investing can sufficiently fulfill the criteria laid out by Chambers, Dimson and Illmanen.

Specifically, do the factors provide strong diversification? Do the factors have capacity? Can they enable the fund to act as an opportunistic liquidity provider? Can it be implemented at low cost in a transparent way?

We focus on three factors – low volatility, value and carry - to demonstrate the efficacy of a factor-based approach. Our choice of factors is not exhaustive and does not represent of a set of orthogonal factors to explain the returns of the credit universe. Our goal is to only show that factors can be applicable to institutional investors. We included those most commonly used in the literature. In addition, we believe these three factors are of significant practical importance as well.

A recent survey of investors finds a majority of them would consider using value, carry, quality/low volatility and liquidity with a minority of survey participants willing to consider momentum.5 Therefore, we concentrate on the three factors that have more broad consensus among investors with consistent definitions in the literature.

We will show that the fixed income factors reviewed here do indeed have strong diversification benefits. The factor premiums are persistent in a large diversified cross-section of the corporate bond universe. While all of these historical simulations argue factors should be implementable at low cost, the positive factor exposures of existing managers demonstrate that they have positive premiums after transaction costs. Finally, in the spirit of transparency, a key criterion, we use simpler definitions of factors relative to those found in the literature where possible. Finally, as a concrete example of an implementable solution for large institutional clients, we employ a unique buy and hold technique to build portfolios with positive factor exposures while introducing very little trading and turnover. This technique is mostly applicable to investment grade securities and we shall confine our discussions of factors to this particular credit sector for the remainder of the paper.

Data and methodology

For corporate bond data, we rely on monthly quoted bond prices and analytics from the Bloomberg Barclays US Investment Grade Index and the Bloomberg Barclays US High Yield Index starting from January 1, 2000 and ending on December 31, 2019. For each bond, the data includes the monthly total return as well as the excess return, or duration-hedged return using quoted prices. The excess return is calculated by taking the total return of the bond and subtracting the total return of a maturity matched US Treasury bond. This return isolates the impact of spread return from interest rate return. In addition to return information, the data contains offering amount, offering date, maturity date, coupon rate, coupon type, bond rating, issuer and sector information. Using quoted bond prices instead of transactions has several draw backs. In particular, the pricing of less liquid bonds maybe stale and could affect the actual implementation of factor strategies. To address these concerns, our analysis will specifically look to control for common liquidity characteristics to see their impact on historical results. While we believe these results hold more generally across global

investment grade corporate bonds, we only demonstrate our approach with USD denominated corporate bonds.

Credit factor descriptions

In order to study the significance of different factors to the cross-section of corporate bond returns, we form bivariate quintile portfolios each month starting from January 1, 2000 to December 31, 2019 by sorting on each factor while controlling for duration times spread (DTS)6 . Briefly, DTS is a measure of the credit factor exposure of a portfolio. By controlling for DTS in our factor analysis, we are removing variations in risk and return driven by differences in exposure to the credit factor. Quintile portfolios are formed every month from January 1, 2000 to December 31, 2019 by first sorting the corporate bonds based on DTS; then within each quintile portfolio, bonds are sorted further into five sub- quintiles based on their factor rank. The bonds are value weighted by amount outstanding in each sub-quintile. Finally, five portfolios are formed by combining sub-quintiles across all of the quintiles.

This methodology, under each DTS-sorted quintile, produces portfolios with similar DTS but with dispersion in factor exposures. We report the average monthly excess, or duration-hedged, returns of the portfolios. In addition, while our double sorts reduce any DTS bias in the signals, there can still remain deviations that could potentially impact the estimates of the factor premium. Therefore, we show the intercepts (alphas) from the regression of the quintile excess returns on the credit factor to adjust for any beta bias. We use the excess return

of the Bloomberg Barclays US Investment Grade Index as our credit factor return. Since all of these returns are duration- hedged, we exclude the term factor from our regressions.

To explore if the results are robust to other potential explanations of the factor premium, we conduct bivariate sorts that follow the same methodology as mentioned above for each factor on size, age and TRACE volume to capture liquidity7 effects. To capture more traditional sources of fixed income risk, we also control for rating, sectors based on Bloomberg Barclays (Lehman) Class 4 and maturity.

Maturity should capture any residual term effects not captured in duration hedging.

LOW VOLATILITY

The low volatility factor explains the higher risk-adjusted returns associated with holding low volatility bonds, as is widely observed in the academic literature across several asset classes.[8] Low volatility can be a noisy measure when using monthly realized returns. As a simple proxy, we rank bonds by maturity with a credit quality of BBB+ or better. Our construction is like others who focus on definitions which emphasize short duration and higher rated bonds.9

Table 1 show the bivariate analysis of low volatility when controlled for DTS. The intercept from regression against the credit factor is statistically significant and positive for quintile 5 with the highest exposure and decreases monotonically to quintile 1 with the lowest exposure.

Table 1. Statistics – low volatility factor

Quintile	Intercept	T-Stat	Volatility	Skew	Kurtosis	Sharpe	Information ratio
1	-7.89	-4.45	143	-1.03	9.55	0.01	-0.28
2	-2.96	-1.71	135	-1.03	9.59	0.03	-0.12
3	0.50	0.32	130	-1.20	10.65	0.06	0.00
4	4.31	3.37	130	-0.65	8.25	0.10	0.19
5	6.73	1.86	161	-2.34	25.22	0.11	0.14

Table 1 shows the statistics for the bivariate quintile sorts of low volatility while controlling for DTS. Shown in the table are the intercepts from regression against the credit factor in bps/month, their associated t-stats, the volatility in bps per month, skew, kurtosis, Sharpe and Information ratio. The Information ratio is the average active excess return of the portfolio relative to the market value weighted index divided by the tracking error. Source: Bloomberg Barclays US Investment Grade Index, Invesco calculation from January 1, 2000 – December 31, 2019.

Table 2. Statistics – value factor

Quintile	Intercept	T-Stat	Volatility	Skew	Kurtosis	Sharpe	Information ratio
1	-9.33	-6.41	132	-1.00	7.95	-0.00	-0.43
2	-4.65	-4.58	131	-1.21	9.90	0.02	-0.31
3	-1.05	-1.36	134	-0.99	9.70	0.05	-0.10
4	3.13	3.27	142	-0.82	9.66	0.08	0.22
5	11.36	6.15	152	-0.76	12.39	0.13	0.39

Table 2 shows the statistics for the bivariate quintile sorts of value while controlling for DTS. Shown in the table are the intercepts from regression against the credit factor in bps/month, their associated t-stats, the volatility in bps per month, skew, kurtosis, Sharpe and Information ratio. The Information ratio is the average active excess return of the portfolio relative to the market value weighted index divided by the tracking error. Source: Bloomberg Barclays US Investment Grade Index, Invesco calculation from January 1, 2000 – December 31, 2019.

Similarly, the Sharpe ratio of each quintile and the information ratio against the market value weighted index also show a strong monotonic relationship with factor exposure. While the volatility of the quintiles does not seem different, there is clear difference in higher moments. Specifically, the top low volatility quintile, 5, has a significant negative skew (the median is larger than the mean) which implies many small positive monthly returns. The kurtosis is very elevated which indicates that the distribution has a significant large left-tail (infrequent but large negative loss). This return pattern significantly deviates from the other quintiles. Since all quintiles have similar DTS with similar exposure to the credit factor, this implies that the credit factor is not capturing tail risks in the low volatility factor. It is important to note that quintile 1 on its own has a statistically significant negative intercept and excess return. This means that by only removing the bottom 20% of the entire credit market, the low volatility factor still has a significant return over the credit factor.

VALUE

The value factor explains the high risk- adjusted returns from owning bonds wither higher spreads than fair value. There have been several different definitions offered to define value. We have chosen a simple definition that selects bonds with the highest options adjusted spread (OAS) within their respective industry and ratings groups. On the surface, this differs from the approaches taken in the existing literature. Both Houweling and van Zundert (2017) and Israel e. al. (2018) 8 rely on a regression-based approach that uses rating, maturity, and other characteristics predict the spread of every bond in the universe. Value bonds are those with a high spread relative to predicted values. We choose our definition for its simplicity and believe it captures the same dynamic as the regression-based approach. Like low volatility, we control for credit beta by utilizing a bivariate sort on DTS. Table 2 summarize the results. With respect to different return measures, the intercepts from regression, Sharpe ratio and information ratio all show monotonic dependency of the returns to factor exposure. Just as in low volatility, even excluding the lowest value quintile and investing in 80% of the remaining securities by market value weight will result in statistically significant returns over the credit factor. From a risk perspective, volatility shows a clear dependency on value factor exposure. While all five quintiles have similar credit factor exposure, quintiles with higher value have more volatility.

Again, this emphasizes that portfolios with higher value exposure may exhibit higher returns and risk not captured by the credit factor.

CARRY

The carry factor explains the high risk- adjusted returns for investing in bonds with highest option adjusted spread. Relative to value and low volatility, there is less consensus in the literature around carry as a factor. Only Isreal et. al. (2018) 8 argue for it, among those who have looked at multi-factor models. We have decided to include it in this study since previous work have found carry to be a common factor in many other fixed income markets beyond credit.[10] Table 3 summarizes the historical results. As in low volatility and value, we see a strong relationship between increasing factor exposure and excess returns. Intercepts are statistically significant. The Sharpe ratio and Information ratio both increase with higher carry exposure.

Finally, the risk in the top quintile portfolio has significantly higher volatility, skew and kurtosis. Again, while all of these portfolios have similar exposure to the credit factor, their risk and return increase with carry

Table 3. Statistics – carry factor

Quintile	Intercept	T-Stat	Volatility	Skew	Kurtosis	Sharpe	Information ratio
1	-7.87	-3.77	114	-1.05	10.86	-0.00	-0.23
2	-3.45	-1.85	129	-1.01	11.58	0.03	-0.13
3	0.58	0.37	135	-1.16	11.00	0.06	0.01
4	4.40	2.56	140	-0.89	9.51	0.09	0.17
5	7.31	1.67	188	-1.95	18.96	0.11	0.13

Table 3 shows the statistics for the bivariate quintile sorts of carry while controlling for DTS. Shown in the table are the intercepts from regression against the credit factor in bps/month, their associated t-stats, the volatility in bps per month, skew, kurtosis, Sharpe and Information ratio. The Information ratio is the average active excess return of the portfolio relative to the market value weighted index divided by the tracking error Source: Bloomberg Barclays US Investment Grade Index, Invesco calculation from January 1, 2000 – December 31, 2019.

Table 4. Intercept for long/short bivariate quintile sorts of each factor

	Carry	Low volatility	Value
Sector	13.4 (2.39)	13.1 (2.96)	17.1 (2.97)
DTS	15.2 (2.45)	14.6 (2.91)	20.7 (6.7)
Maturity	12.5 (1.52)	4.9 (2.95)	22.3 (5.24)
Rating	6.8 (.82)	11.6 (2.14)	15.5 (2.62)
Age	7.7 (.91)	12.0 (2.36)	13.5 (2.4)
Volume	10.2 (1.41)	10.4 (2.39)	17.6 (3.42)
Size	5.8 (0.69)	12.4 (2.48)	12.6 (2.23)

Table 4 shows the intercepts for long/short bivariate quintile sorts of each factor while controlling for age, sector, DTS, maturity, rating, volume and size. Volume is calculated from TRACE data and size is amount outstanding. Shown in the table are the intercepts from regressions against the credit factor in bps/month along with the t-stats of the regressions in parenthesis below. Source: Bloomberg Barclays US Investment Grade Index, Invesco calculation from January 1, 2000.

exposure. Similar to low volatility and value, the carry factor has a statistically significant t-stat for quintile portfolio 1. This implies that investing in the 80% of the universe with the highest carry exposure will result in excess returns over the credit factor.

The factors are robust to fixed income risk and liquidity

Before proceeding further, we control for other factors beyond DTS to see if any hidden loadings on common risk factors can explain the factor excess returns. In the table 4 below, we report the intercepts from the long-short portfolio formed by taking the top bivariate quintile portfolio and subtracting the bottom bivariate quintile portfolio. This isolates the return and risk of only the factor to access if it is associated with excess return over the credit factor. We control common fixed income risk factors such as maturity, rating and sector. Table 4 shows that the factors earn a consistent excess return in the presence of these controls. We restate the results of the previous sections that showed the exclusion of the lowest ranked quintile, or only 20% of the universe, would result in positive excess returns for a factor portfolio formed on the remaining 80% of the universe. Not only do the factors work across a large part of the corporate universe but their efficacy is spread across sectors, rating and maturity. Therefore, we should expect fixed income factors to be as scalable as equity factors.

In addition to traditional factors, we look for liquidity characteristics to understand if the factors can be traded at costs similar to the overall universe. When controlling for size (amount outstanding), TRACE volume in the preceding month and age of the bond, we see that the factors still have positive excess returns. Therefore, the costs associated with factor exposures should be a function of the turnover. The historical returns we observe are not a result of trading in illiquid or poorly marked securities.

Diversification

Carry, value and low volatility offer strong diversification potential relative to the credit factor. Table 5 below shows the correlation between the long-short factor portfolios and the credit factor. Low volatility and value have very low correlation to the credit factor while carry has some positive exposure. The factors overall have medium to low correlation to each other except for carry which has a high correlation to low volatility and credit. First, this not totally unsurprising, since a DTS controlled portfolio of the highest carry quintile will have a natural bias towards lower duration bonds. Second, the highest carry quintile will still have a higher DTS bias even after double sorting. This is reflected in the higher correlation to credit. As a robustness check, we report here that the carry long-short portfolio when controlled for low volatility has an intercept of 17 bps per month and t-stat of 2.4.

Factors satisfy the key criteria for Institutional clients

DTS controlled factor construction allowed us to test whether the credit factor can explain the risk of the different factor portfolios. They all capture a dimension of risk not explained by beta. This finding leads us to infer that these factors capture a risk and return relationship in the corporate bond market. As such, we believe that these factors will be stable through time and will not be arbitraged away. Thus, they can be considered for investors with a long-term horizons. Their low correlations to the credit factor show they offer the potential to add excess return into a portfolio through diversification. Further, they exhibit strong efficacy across a large cross section of the corporate bond universe including across sectors, ratings and maturities making them very scalable. The excess returns are robust to` characteristics associated with liquidity including size, age and volume – meaning they are implementable. Finally, the definitions offered here are simple versions that allow for transparency and low costs.

Table 5. Correlation between the long/short DTS controlled factor portfolio and the credit factor

	Carry	Low Volatility	Value	Credit
Carry	1	0.75	-0.15	0.60
Low Volatility		1	0.03	0.013
Value			1	-0.19

Table 5 shows the correlation between the long/short DTS controlled factor portfolio and the credit factor. The correlation between factors and the credit factor are generally low with the exception of carry. Source: Bloomberg Barclays US Investment Grade Index, Invesco calculation from January 1, 2000 – December 31, 2019

Active portfolio already have factor exposures – that means they are implementable

For the final question of implementation, we turn to an important lens for analysis. In earlier work, we look at factor exposures of active bond managers in the US.11 We find that the majority have exposures to factors and that they explain a large percentage of the excess return generated by managers. Most managers have positive exposure to carry and value; and they have negative exposures to term. Factor exposures explained a majority of active returns for many managers. Our findings are consistent with several other studies who have looked at similar data12 . Since the returns used in this analysis include the transaction costs associated with factor exposures, the overall positive excess returns generated by many managers in our study indicates these factors are implementable. To make the example concrete, we analyze the GPFG fixed income portfolio and show that the carry, low volatility and value factors can explain a significant percentage of the excess returns generated by the portfolio over just the credit and term factors.

Motivated by these previous results, we take the time series of the GPFG portfolio and benchmark available at the Norges Bank Investment Management's website which reported monthly results from January 1, 2013 to December 31, 2019. We calculate the active returns of the portfolio and benchmark in US dollars. For these active returns, we regress the term and credit factor first and verify the results relative to those reported on the Norges Bank website. In the table below, we see that the intercept of the portfolio is 2.83 bps per month or approximately 33 bps per year. The exposure to term is slightly negative and significant at the 99th percentile and credit is close to zero.

Overall, credit and term explain 28% of the return variability. All numbers align very closely to the numbers reported on the website.

Next, we include carry, low volatility and value in the regression. The negative exposure to term stays negative. The credit factor gets a negative exposure while the carry factor gets a positive exposure at the 95% confidence level. Low volatility and value have low significance, but it is interesting that the exposure match very closely to the median fund manager from our analysis of US active bond managers. Specifically, the large exposure to carry, positive exposures to value and the negative to flat loadings on term and low volatility. Most importantly, the additional factors increase the explanatory power of the model to 44%. This parallels the reported explanatory power of the five-factor equity model which explains 40% of the return variability of GPFG's equity portfolio in the last ten years. Finally, the intercept falls to 1.56 bps per month.

Factor exposures to carry, value and low volatility account for close to half of the annualized excess return of the portfolio over the term and credit factors. Again, this mirrors the results found in our study of US active managers.

Buy and hold laddered factor portfolios

By looking at existing managers, we have some confidence that factors can be implemented for a large institutional fund like GPFG's. We will demonstrate how investors can harvest factor premiums with no turnover through a buy and hold approach. The basic building block is a fixed maturity factor portfolio. This is a portfolio with an overweight to securities with positive factor exposure within a defined maturity range. When a fixed maturity factor portfolio is first invested is has positive factor exposures that decay to zero without rebalance. In order to add exposure back, the buy and hold portfolio will consist of a series of different fixed maturity factor portfolios commonly known as a "laddered" portfolio. As the shorter dated portfolio matures, the cash is reinvested in longer dated maturities adding factor exposure back into the laddered portfolio. We first explain the construction, risk and return of a single fixed maturity factor portfolio before building the laddered portfolio. While the approach we take here is similar to previous work, it differs in implementing low volatility.[13]

We start with a universe of US investment grade corporate bonds with maturities from four and a half to five and a half years. From this universe of bonds, two portfolios will be formed – a factor portfolio and a passive portfolio . For the factor portfolio, the bonds

Table 6. Results of regression using a two-factor and five-factor model

	Two-factor model	Five-factor model
Intercept	2.83*** 5.767	1.56** 4.65
Term	-0.0055*** -4.3	-0.0043*** 1.21
Credit	0.00928 1.711	-0.073* -2.192
Carry		0.0745** 3.102
Low volatility		-0.068* -1.71
Value		0.056 1.65
R Squared	0.28	0.44

Table 6 shows the results of regression using a two-factor and five-factor model. The data was obtained from the Norges Bank Investment Management website (https://www.nbim.no/en/publications/reports/2019/return-and-risk-2019/). The significance levels of the coefficients are denoted by ***, ** and * for the 99th, 95th and 90th confidence levels. Source: Bloomberg, Norges Bank, Invesco calculation from January 1, 2013 – December 31, 2019.

Figure 1. Annualized active returns of the five-year portffolio over the market portfolio for different vintage years

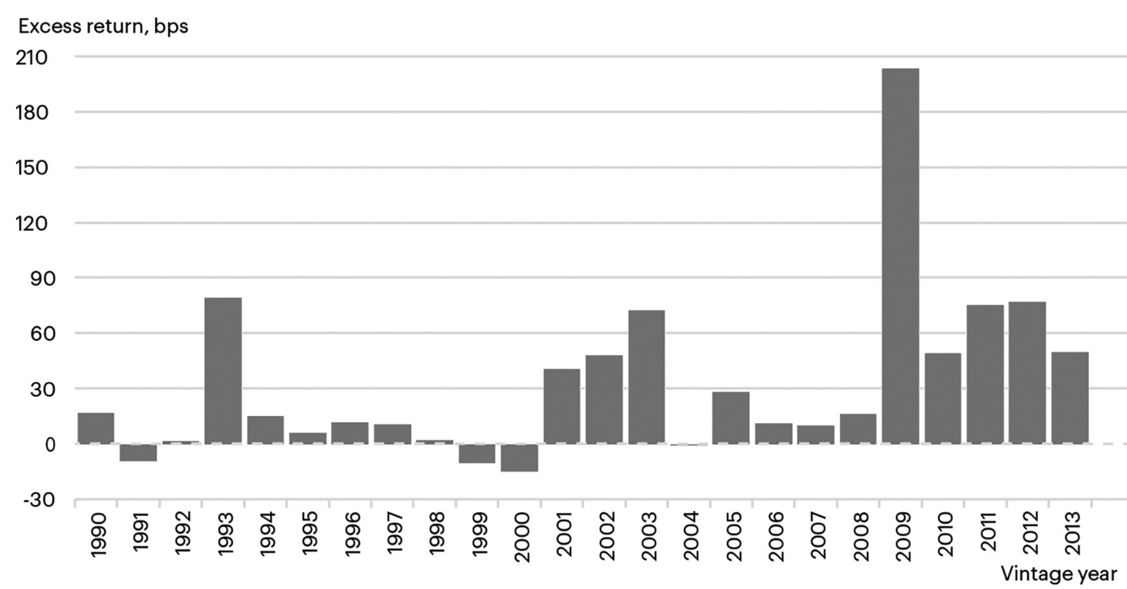

Figure 1 shows the annualized active (excess) returns of the five-year factor portfolio over the market portfolio for different vintage years. For example, the factor portfolio formed on 1 January 2009 outperformed the market value portfolio by 200 basis points annually over the subsequent five years. Source: Invesco calculations, Bloomberg L.P. Data from 1 January 1990 to 31 December 2017. **Past perfomance is not a guide to future returns.**

in this universe are ranked based on their exposure to the two factors: carry and value. Each bond is scored by carry and value separately and the bond's overall score is a 50/50 percent blend of these factor scores. Without embarking on a long analysis for the optimal weights of the factors, we chose an equal weight as a starting point to illustrate the benefits of buy and hold. In our previous work, we did include a small amount of low volatility, but found it's inclusion did not materially change the results. Since low volatility tends to create shorter duration portfolios, it doesn't impact a bullet portfolio's characteristics very much. The bullet portfolio is formed by taking half of the bonds in the universe (by market value weight) with the highest blended score and forming a market-value-weighted portfolio called the five year fixed maturity factor portfolio. The passive portfolio is formed by taking all of the bonds in the same maturity range and market value weighting them – the "market portfolio." Every year at the beginning of January, this process is repeated, so that we obtain a series of market and factor portfolios of different vintages.

The bonds in these portfolios are held to maturity as long they maintain a rating higher than CCC. In other words, no change is made to the portfolios unless a bond approaches imminent default, at which time the bonds are sold and the cash proceeds kept in the portfolio.

Otherwise, cash from coupons is reinvested pro rata into the portfolio. Proceeds from securities that are called early or mature earlier than the overall portfolio are also kept as cash in the portfolio. While in practice cash accumulated in the portfolio would be reinvested, it suffices for our simulation to illustrate this approach.

Figure 1 shows the total returns of the five-year fixed maturity factor portfolios compared to those of the five-year market portfolios for different vintage years; the factor portfolios exhibits consistent outperformance against the market portfolios.

Next, we repeat the construction of portfolios with maturities of two through nine years. Table 6 summarizes key statistics and results: the excess returns of the factor portfolios are all positive; the tracking errors are small, but the information ratios (IR) are consistent across maturities.

The total return of any buy-and-hold strategy is a function of the starting yield less losses due to defaults, forced selling and any cash drag from the reinvestment of coupons, callability of bonds or recovery from default. To better understand the impact of defaults on portfolio returns, we determine the percentage of bonds that ended below a CCC rating during the life of each portfolio (see row labeled "Default rate"). Longer-maturity factor portfolios naturally have higher default rates since the cumulative default probabilities for any portfolio increase over time. The table also shows the active default rates (i.e. the factor portfolios' default rates in excess of the market portfolios' default rates) along with their yield impact. The advantage of the factor-based portfolios is that their higher yields more than offset the negative return impact from additional defaults. The findings are consistent with Eisenthal- Berkovitz et. al.14

Table 7. Performances and risk indicators of the factor portfolios vs the market portfolios.

	Portfolio maturity (years)							
	2	3	4	5	6	7	8	9
Total return (%)	3.83	4.67	5.08	5.66	5.97	6.28	6.71	6.52
Excess return (%)	0.15	0.21	0.20	0.33	0.17	0.22	0.33	0.06
Tracking error (%)	0.65	0.64	0.40	0.47	0.44	0.47	0.46	0.48
Information ratio	0.24	0.33	0.51	0.71	0.39	0.47	0.71	0.13
Starting yield (%)	5.32	5.66	5.91	6.41	6.80	7.04	7.26	7.19
Number of bonds	172	120	135	86	92	92	96	109
Default rate (%)	0.14	0.24	0.46	0.49	1.39	1.22	1.48	2.85
Active default rate (%)	0.08	0.06	0.07	-0.03	0.42	0.33	0.31	1.19
Yield loss from default (%)	0.04	0.05	0.07	0.06	0.14	0.11	0.11	0.20

Table 7 shows the excess returns, tracking errors and information ratios of the factor portfolios versus the market portfolios. Tracking errors and information ratios of the portfolios are averaged over the back-test period. Back-tested performance is not actual performance, but is hypothetical. Although back-tested data may be prepared with the benefit of hindsight, these calculations are based on the same methodology that was in effect when the index was officially launched. Past performance cannot guarantee future results. Source: Invesco calculations, Bloomberg L.P. Data from 1 January 1990 to 31 December 2017.

Figure 2. Factor-based laddered portfolio construction

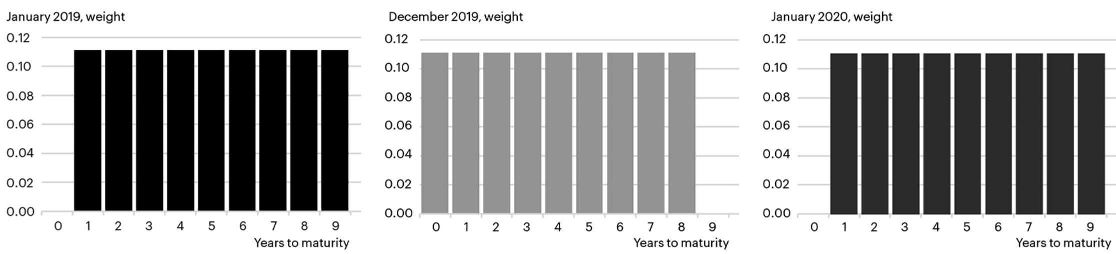

Figure 2, in the first panel, the portfolio is invested, in equal weights, in portfolios of maturities from one to nine years to target a five-year duration. The second panel shows how each portfolio has matured after one year. The cash generated from a maturing one-year portfolio is then used to buy a new nine-year portfolio, as shown in the last panel. In this way, the portfolio maintains a duration close to the desired five years, without incurring high trading costs. Source: Invesco calculations, Bloomberg. Data from 1 January 1990 to 31 December 2017.

Factor-based laddered portfolio construction

To extend the idea of utilizing factors in a zero-turnover portfolio, we use a laddered portfolio to create factor-based solutions whose characteristics look similar to broad-based, fixed income benchmarks. We construct the portfolio by buying an equal share of fixed maturity factor portfolios whose durations average the

chosen benchmark (figure 2). For example, to target a five-year duration portfolio, an equal-weighted portfolio is formed by investing in fixed maturity factor portfolios from one to nine years (targeting a five-year duration). At the end of each year, the proceeds of the maturing portfolio are used to buy a new nine-year portfolio. This is repeated each year to keep the duration within 0.5 years of the desired portfolio duration.

Years to maturity

The performance of the factor-based laddered approach relative to the similar ladder constructed with market bullets, or the benchmark, is shown below. When constructing a portfolio with similar duration as the benchmark and controlling for active sector and ratings exposure, we find that these portfolios can deliver 15 bps

Table 8. Risk and return of the laddered portfolio

Bullet range	Active excess return	Tracking error	Information ratio
1-9	15	107	0.14
1-8	33	52	0.63

of annualized outperformance with 107 bps in TE for an information ratio of 0.14.

Different from prior research, to implement the low volatility exposure in the portfolio, we skip its inclusion in the individual bullets, but instead we shorten the duration of the portfolio with a ladder only using 1-8 year bullets which lowers the spread duration of the portfolio. As shown in table 8, this results in a higher return and lower tracking error. This illustrates the diversification benefit of the low volatility. Finally, it should be noted that the results here are inline with the realized results of the Norwegian General Pension Fund General's fixed income sleeve. The buy and hold approach does offer a credible way to achieve outperformance for large investors.

Conclusion

Institutional investors should ask hard questions about their fixed income portfolios. Chambers, Dimsom and Ilmanen offer an excellent framework to judge the suitability of any strategy within a large portfolio. We find that factor investing can fulfill these criteria. They represent a fundamental risk and return relationship not explained by term and credit factors within the corporate bond market. Long horizon investors can take advantage of these factors by taking on the risks associated with the factors. The factors are scalable with efficacy across a large part of the market in different ratings, sector and maturities. Factor diversification can be used to target excess returns while controlling risk. Finally, the factors do not exhibit any exposure to typical liquidity metrics making their implementation costs similar to passive market value weighted portfolios. The simple definitions offer transparency of the investment process.

Finally, the potential to automate this investment process and bring the economies of scale mean they should come at extremely low cost. The buy and hold laddered portfolio can be extended in many intriguing ways. While they can be used to directly access factors, they can also be used as internal benchmarks to better measure manager value creation over and above factors. The simplicity of the design here can be expanded to include a dynamic trading model where bonds are held to maturity unless market conditions allow a fixed maturity portfolio to be traded into a similar portfolio trading at advantageous prices during periods of market disruption. This would allow investors to dynamical add some factor exposures such as value when they are rewarded for being opportunistic liquidity providers.

Important Information

United Arab Emirates. Regulated by the Dubai Financial Services Authority.

- Invesco Asset Management (Schweiz) AG, Talacker 34, 8001 Zurich, Switzerland.

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