Invesco

Risk & Reward

Research and investment strategies

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Risk & Reward #01/2023

Marty Flanagan
President and CEO
of Invesco Ltd.

The Q1 2023 edition of Risk & Reward is dedicated exclusively to one of Invesco's key strengths – factor investing. Based on data analysis and proven correlations, factor theory is a highly systematic and rational basis for investing. We believe that current advances in computing power, data availability and artificial intelligence promise to make this approach more powerful than ever.

For the first time in more than a decade, fixed income investments are offering competitive coupon returns. Our colleagues seized on this moment to thoroughly examine the efficacy of factor investing in the bond space. They have analyzed what metrics can be used, how a fixed income factor portfolio could be implemented in practice and how performance should be analyzed and monitored. Risk & Reward also spoke to the Invesco Quantitative Strategies team to find out more about their convictions and their approach.

Next, we compare different models for the systematic incorporation of equity signals – simple linear models as well as more complicated non-linear ones – which would be impossible to run without machine learning (ML) technologies. Read to learn how ML facilitates the gathering of information but, as our results show, is no substitute for sound, human economic reasoning.

Finally, my colleagues from our Factor Investing teams have tried something new: applying the bond momentum factor to equity portfolios – and vice versa – to discover what useful information the correlations between them can offer for asset managers. This may sound odd at first, but actually has a sound economic basis – and yields interesting results.

We hope you enjoy this edition of Risk & Reward!

Best regards,

Marty Flanagan
President and CEO of Invesco Ltd.

A research-based approach to fixed income factor portfolio implementation

By Jay Raol, Ph.D., Amritpal Sidhu, Benton Chambers, Reed McDonnell, Nancy Razzouk and Bin Yang

Does factor investing work for fixed income? To answer this and other questions, we review motivations for factor investing, describe the implementation of a multi-factor portfolio with turnover and risk constraints, and present a framework for return attribution and monitoring.

In their popular paper on the Norwegian Government Pension Fund Global, Chambers et al. (2012) develop a set of criteria for fund investing, which became known as the Norway Model. These criteria include sufficient diversification and capacity, low-cost implementation, and transparency. But can they be fulfilled by a fixed income factor strategy?

We believe so, provided implementation of the factor strategy is as robust as the factors themselves. But, since the starting point of any factor strategy lies in the factors, we will first discuss the ones we consider most important for fixed income: low volatility, value and carry. Our analysis is based the Bloomberg Barclays US Investment Grade index on US investment grade corporate bonds, with data from January 2002 to December 2021.

For each factor, we divide our investment universe into five factor quintiles, with quintile 1 having the lowest and quintile 5 the highest factor exposure. When regressing the factor exposures on monthly credit returns, we control for spread volatility as measured by duration times spread (DTS) to reduce noise.[1]

Low volatility

The low volatility factor explains the higher risk-adjusted return of low volatility bonds.[2] Table 1 shows the results of our regressions for the five factor quintiles. The intercept, i.e., the excess return of the factor quintile over the investment universe, is statistically significant. It is positive for quintile 5 (highest exposure to low volatility) and decreases continuously to quintile 1 (lowest exposure), where it is strongly negative. Sharpe ratio and information ratio against the capitalization-weighted index are also much better for lower volatility bonds.

Since we control for DTS, the spread volatility is similar in all quintiles. But there are clear differences in the higher moments: Quintile 5 has a significant negative skew – i.e., a median above the mean – which implies many small positive monthly returns. But the kurtosis of quintile 5 is also elevated, indicating a significant left tail and infrequent, but large, losses. This return pattern significantly deviates from the other quintiles and cannot be explained by spread volatility. Furthermore, quintile 1

Table 1
Regression of low volatility on credit returns and other risk summary metrics

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

Source: Invesco. Quintile 1: lowest exposure to low volatility; quintile 5: highest exposure to low volatility. Intercepts and spread volatility in bps/month. Monthly data from January 1, 2000 to December 31, 2021.

has a statistically significant negative intercept, meaning that removing just the 20% most volatile bonds can result in significantly better portfolio returns.

Value
The value factor explains the higher risk-adjusted return of bonds with spreads above those of other bonds with similar characteristics. We have chosen a simple definition that selects bonds with the highest options-adjusted spread (OAS) within their respective industry and rating groups.

Table 2 summarizes the results. The intercept (i.e., excess return), Sharpe ratio and information ratio all improve with higher factor exposure. Volatility clearly rises with exposure to the value factor, even though all five quintiles have similar DTS. Thus, portfolios with higher value exposure are likely to exhibit higher returns, but also risks not captured by spread volatility.

Carry
The carry factor explains the higher risk-adjusted returns of the bonds with highest option-adjusted spread.

Table 3 summarizes the results. Again, we see a strong relationship between factor exposure and excess return; the intercepts are statistically significant. Sharpe ratio and information ratio both increase with higher carry exposure. Finally, the top quintile portfolio has significantly higher spread volatility, skew and kurtosis. Risk and return also increase with carry exposure. Like low volatility and value, the carry factor is statistically significant for quintile 1. This implies that removing the 20% of the universe with the lowest carry exposure can result in better returns.

The factors are robust to fixed income risk and liquidity
We now control for other characteristics beyond DTS to see whether any hidden loadings on common risk factors can explain excess factor returns. Table 4

Table 2
Regression of value on credit returns and other risk summary metrics

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

Source: Invesco. Quintile 1: lowest exposure to value; quintile 5: highest exposure to value. Intercepts and volatility in bps/month. Monthly data from January 1, 2000 to December 31, 2021.

Table 3
Regression of carry on credit returns and other risk summary metrics

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

Source: Invesco. Quintile 1: lowest exposure to carry; quintile 5: highest exposure to carry. Intercepts and volatility in bps/month. Monthly data from January 1, 2000 to December 31, 2021.

Table 4
Intercepts for long/short factor portfolios when controlling for different characteristics

Sort	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	(6.70)
Maturity	12.5	(1.52)	4.9	(2.95)	22.3	(5.24)
Rating	6.8	(0.82)	11.6	(2.14)	15.5	(2.62)
Age	7.7	(0.91)	12.0	(2.36)	13.5	(2.40)
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)

Source: Invesco. Intercepts for long/short factor portfolios when controlling for different characteristics. Volume is based on TRACE data, size is the amount outstanding. Monthly data from January 1, 2000 to December 31, 2021.

shows the intercepts of long-short portfolios formed by taking the top quintile factor portfolios and subtracting the respective bottom quintile factor portfolios. This isolates the return and risk of the respective factor.

As we see, our three factors earn consistent excess return irrespective of sorting controls. Not only do they work across a large part of the corporate universe, but also across sectors, rating classes and maturity buckets. Therefore, we should expect fixed income factors to be as scalable as equity factors.

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When controlling for size (amount outstanding), transaction volume in the preceding month and age of the bond, we see that the factors still have positive excess returns.

In addition to traditional factors, we look for liquidity characteristics to understand whether the factors can be traded at costs similar to the overall universe. When controlling for size (amount outstanding), transaction volume in the preceding month and age of the bond, we see that the factors still have positive excess returns.

Factor allocation

To construct targets with multiple factor exposures, we now combine the single factor targets using a simple weighting mechanism. The weights are based on empirical correlations, seeking to provide consistent performance and risk in different macro environments and roughly equal risk contributions from each factor. Indeed, there is significant diversification potential between low volatility and the more risk loving factors value and carry. Table 5 shows the correlations of factor excess returns for US investment grade and high yield bonds. We seek an asset allocation scheme that allows us to utilize the diversification offered between the various factors to produce a multi-factor target intended to perform well across various market environments.

We have analyzed five different asset allocation methods: equal drawdown allocation, equal standard deviation allocation, the efficient frontier portfolio method, equal contribution to risk (risk parity) and risk targeting:

- **Equal drawdown allocation** measures the drawdown of each factor and allocates based on equal contributions to historical drawdown.
- **Standard deviation allocation** computes standalone factor volatility, allocates based on this metric and does not account for correlations among factor returns.
- The **efficient frontier portfolio (a.k.a. mean-variance optimization)** is the tangency portfolio in the traditional Markowitz model.
- The **risk parity method** computes the covariance of factor returns and allocates weights to achieve equal contributions to risk while also accounting for correlation among the factors.
- **Risk targeting** is the most complicated method, further expanding on the equal contributions achieved using the risk

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Note: We refer to simulated portfolios as *targets* or *target portfolios*. These are constructed based on the historical holdings of various Bloomberg Barclays indexes, such as the US Investment Grade Corporate Index and US High Yield 2% Issuer Capped Index.

Table 5
Correlation of excess returns

		Carry	Low Volatility	Value
US Investment Grade	Carry	1.000	-0.330	0.754
	Low Volatility	-0.330	1.000	-0.208
	Value	0.754	-0.208	1.000
US High Yield	Carry	1.000	-0.530	0.784
	Low Volatility	-0.530	1.000	-0.399
	Value	0.784	-0.399	1.000

Source: Invesco. Monthly data from January 1, 2000, to December 31, 2021.

Table 6
Information ratios of five different asset allocation methods

	Macro period	Equal drawdown	Equal standard deviation	Mean variance	Risk parity	Risk targeting
US IG Target (LEH CORP Index)	**Full period**	**0.707**	**0.744**	**0.995**	**0.745**	**0.767**
	Depressed US credit returns	-0.693	0.358	-1.453	0.034	0.537
	Weak USD currency	0.714	0.430	1.505	0.532	0.400
	Depressed SP 500 returns	-0.632	0.164	-0.897	-0.089	0.314
	High VIX Index	-0.244	0.439	-0.297	0.225	0.648
	Average across stress periods	**-0.213**	**0.348**	**-0.286**	**0.176**	**0.475**
US HY Target (LHY2ICAP Index)	**Full period**	**0.179**	**0.185**	**0.252**	**0.180**	**0.179**
	Depressed US credit returns	-0.078	0.106	0.151	0.102	0.236
	Weak USD currency	0.235	0.164	0.261	0.156	0.122
	Depressed SP 500 returns	-0.039	0.121	0.181	0.115	0.229
	High VIX Index	0.094	0.194	0.279	0.187	0.268
	Average across stress periods	**0.053**	**0.146**	**0.218**	**0.140**	**0.214**

Source: Invesco. Information ratio of excess return across various macroeconomic conditions as measured by forming quartiles on the percentage change of the underlying macroeconomic variable. Monthly data from January 1, 2000, to December 31, 2021. Allocations for the multi-factor target are static but periodically reviewed.

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> Over the full 20-year period, however, classic mean-variance optimization is clearly preferable.

parity approach and further optimizing allocation weights over time such that the final portfolio is DTS-neutral to the broader investment universe.

Table 6 shows the information ratios of the different methods over the full period as well as during times of market stress for our US investment grade universe as well as for a US high yield universe. As the table shows, the various forms of risk parity may add value in times of stress, a result that is confirmed by several studies.[3] Over the full 20-year period, however, classic mean-variance optimization is clearly preferable.

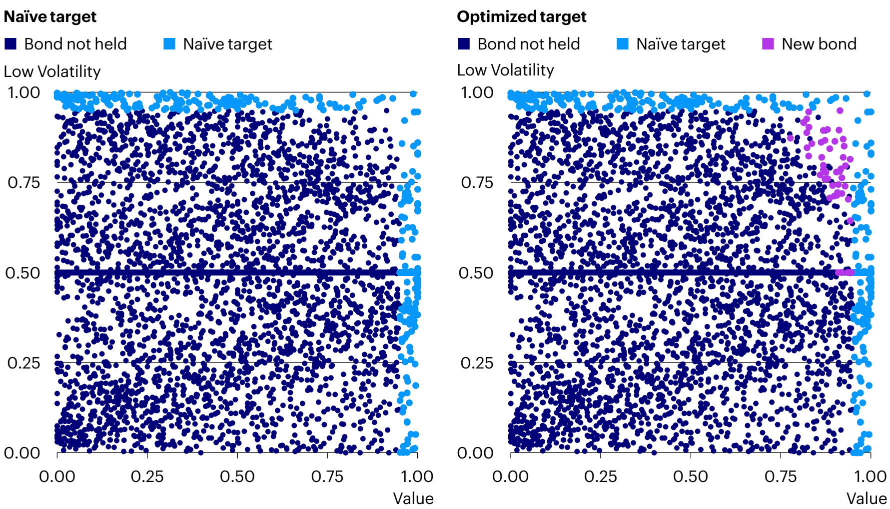
Portfolio optimization

Factor targets have two kinds of active risk: (1) active factor exposures (intentional) and (2) residual risk exposures (unintentional). The unwanted residual risk exposures, which are the consequence of simple factor definitions or construction methodologies, should be minimized so that the major active risk exposures come from factor tilts.[4] Optimization allows us to explicitly set deviation constraints for these residual active risks (such as issuer, sector, OAS, DTS) while still prioritizing bonds with high factor exposures.

Building on the simple multi-factor target based on the allocation framework described above, which constructs a naïve multi-factor target portfolio by blending several single factor target portfolios, we utilize an optimization step to take final risk constrains, portfolio bond count limitations, and turnover into account. This allows us to generate a smaller target portfolio that fulfills certain risk constraints while still having high exposure to multiple factors.

We seek to find an optimized target exhibiting high holdings overlap with the

Figure 1
Scatter plots of hypothetical two-factor portfolios



Source: Invesco. Hypothetical factor portfolio (low volatility and value) with constraints.

Table 7
Return attribution of a hypothetical US investment grade factor portfolio

Factor sleeve	Market value (average)	Portfolio excess return	Portfolio excess return contribution	Index excess return	Active excess return contribution
Full portfolio	100%	7040	7040	2208	4833
Low volatility	45%	2599	1167	2208	174
Value	36%	12574	4567	2208	3772
Carry	9%	13261	1083	2208	885
Tracking error control	10%	2229	223	2208	2

Source: Invesco. Data from January 1, 2000 to December 31, 2021. For illustrative purposes only. Portfolio excess return, portfolio excess return contribution, index excess return and active excess return contribution are stated in basis points

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The performance of a multi-factor target portfolio can be cleanly attributed to the various factor sleeves.

naïve multi-factor target (in terms of positions) and risk characteristics similar to those of our naïve target and benchmark. Figure 1 visualizes the optimization process. Each chart shows a scatter plot of value and low volatility factor scores for the individual bonds from the US investment grade universe on September 30, 2020. The light blue dots represent the bonds included in our naïve multi-factor target, whereas the dark blue dots represent those not included because of low factor scores. The naïve multi-factor target is on the left, the optimized target is on the right.

In a naïve target, by definition, we would simply select bonds in the top-most and right-most rectangles with factor scores higher than 0.95 (for illustrative purpose, we show only two factor dimensions here). The optimized target, on the other hand, also includes bonds from the upper-right corner, which do not fall into our factor rectangles. The optimized target selects them to satisfy the constraints on active risk exposures with respect to countries, sectors, duration etc.[5]

Rebalancing and attribution

Rebalancing can be based on TRACE data, Bloomberg dealer runs, market access data etc. To control turnover whenever trading a factor portfolio, we use a sampling approach: We sample tradable bonds from our optimized target and portfolio being traded while controlling for other risk factors such as sector, rating and maturity. The main advantage here is that it allows for explicit security selection while minimizing turnover. From our experience, a classic optimizer-only approach not only produces higher turnover, but also results in portfolios with factor exposures different from those of the target portfolio. The automated rebalancing process can ensure that sampling occurs effectively across any construction dimension, e.g., sector, maturity bucket or rating without having to trade to explicitly match an optimized target holding for holding, all while producing a final entity that has high factor exposures.

Here, ex-post attribution analysis is also helpful to ensure that a portfolio's return is generated by the intended drivers rather than unintended bets. If the attribution approach is flexible and built around a faithful implementation of how the portfolio is constructed and traded, it has great potential to identify shortcomings and improve future portfolio management decisions.

The performance of a multi-factor target portfolio can be cleanly attributed to the various factor sleeves, as in the example in table 7. Over the past 20 years, the index achieved a return of over 200% percentage points. Therefore, as expected, value and carry would have performed well – as they usually do in up markets. Low volatility, on the other hand, may have been the largest allocation, but would have contributed comparatively little to the overall performance, again as expected.

When markets are rising, factors like carry and value should perform well. In our example, they account for 1083 bp and 4567 bp return contribution, i.e., for almost the entire return of the blended-factor target portfolio.

Conclusion

Credit factors have provided statistically significant alpha over credit benchmarks, and properly constructed single and multi-factor factor portfolios that are tradeble and take turnover and bond liquidity into account can achieve their targets in terms of risk controls and factor exposure, in particular when supplemented by optimization and automated trade generation techniques as well as performance attribution.

Notes

1 Technique developed by Fama and French (1993) and further refined by Bai (2018).
2 The low volatility effect has been observed in various asset classes; see Brinson (1986).
3 E.g., Litterman (2015) and Korajczyk (2011).
4 In theory, one should seek to find new factors that are orthogonal to the existing risk factors and thus represent unique risk dimensions. But, in our pure factor construction, not all risks are explicitly controlled.
5 These bonds are not the only possible solution for correcting unwanted active risk biases. Solutions can include combinations of bonds from any part of the factor grid. In this case, we intentionally tilt towards bonds with high factor exposures to raise efficiency.

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About the authors (Fixed Income Systematic and Factor Investing Group)

Jay Raol, Ph.D.
Head of Fixed Income

Jay and his team research and manage systematic and factor-based strategies in global fixed income and currency markets.

Amritpal Sidhu
Senior Quantitative Analyst

In this role, Amritpal is focused on building and implementing systematic strategies in global credit, rates, and FX.

Benton Chambers, FRM
Quantitative Analyst

In this role, Benton works on research for credit factor signals, portfolio construction, and factor-based performance and risk attribution.

Bin Yang, CFA®
Quantitative Analyst

Bin is focused on factor research, portfolio construction in credit and currency markets, and works extensively to develop research and production infrastructure.

Reed McDonnell
Quantitative Analyst

Reed works closely with the software engineers to manage and develop our code-driven investments process designed by the research and portfolio management teams. In addition to quantitative development work, he also conducts factor research and assists the portfolio managers with rebalances.

Nancy Razzouk, CFA®
Quantitative Analyst

In this role Nancy is responsible for factor and ESG research and is involved in implementing credit strategies in close coordination with the portfolio management team and executing factor-based trade rebalance processes.

“Fixed income factors and equity factors share similar foundations”

Interview with Jay Raol, Amritpal Sidhu, Benton Chambers, Bin Ying, Reed McDonnell and Nancy Razzouk

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Factor research is open-ended and encourages equal input from all team members.

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In equities and in bonds, the value factor often relies on mean reversion.

Risk & Reward spoke to the Invesco Systematic and Factor Investing Group, co-authors of our study on fixed income factor portfolios.

Risk & Reward
How do fixed income factors compare with equity factors? Do they share any underlying economic drivers? Are they just as scalable?

Systematic and Factor Investing Group
Fixed income factors and equity factors share similar foundations. Think of concepts such as risk and return, supply and demand, and performance expectations in up or down markets. Many bond factors have the same economic rationale as their equity counterparts. In bonds – as in equites – value seeks to purchase assets that are cheap relative to their peers, and low volatility seeks less volatile bonds as well as less volatile equities. Fixed income factors are also scalable, and when controlled for size and liquidity metrics they can provide robust risk-adjusted returns in different market environments. Nevertheless, there are some implementation challenges, in particular in long-short portfolios.

Risk & Reward
Can you give an example of a bond factor constructed along similar lines as the corresponding equity factor?

Systematic and Factor Investing Group
Take value, for instance: In equities and in bonds, the value factor often relies on mean reversion. In equities, it identifies stocks that are trading at a price below their fundamental value, such as earnings or book value – the idea being that the price will eventually return to the intrinsic value of the security, generating returns if you purchased them at a discount. In fixed income, the value factor can be constructed by identifying bonds that are trading at a discount. They may have a higher yield or a lower price than other bonds in a similar rating class, maturity segment or industry sector. In both equities and fixed income, the value factor seeks to capture the long-term return premium associated with buying low and selling high.

Risk & Reward
Can you briefly describe the research process? How do you evaluate new ideas?

Systematic and Factor Investing Group
Factor research is open-ended and encourages equal input from all team members. In regular meetings we set goals and evaluate ideas based on their relevance. It’s important that a concept works in different markets, for efficiency reasons but also as proof of its economic rationale. We use a variety of data sources and market insights, and we thoroughly assess potential risks and limitations.

Risk & Reward
What is your underlying factor philosophy? How do you deal with complexity, and what do you do to facilitate implementation?

Systematic and Factor Investing Group
Simplicity and an ease of implementation are central to the approach. Complex factors may sometimes appear smart and promising, but in practice they often cause problems. They can require more data and analysis, which leads to higher costs and more uncertain results. More complex factors may also be harder to trade and monitor – so that maintaining a consistent investment strategy over time can become quite a challenge. Ultimately, successful factor investing requires a strategy that is grounded in sound economic principles yet is also straightforward and easy to execute.

Risk & Reward
How do you evaluate the statistical robustness of a factor? And does this offer insight into its scalability and liquidity?

Systematic and Factor Investing Group
We seek factors with similar performance across different asset classes, for example US high yield or European investment grade debt – we think such factors are more robust. We control for credit rating or issue size, and we prefer factors with a robust alpha when controlled for numerous metrics. In addition, we analyze their performance under various market conditions using macroeconomic data. Not only do we aim for high alpha, we also compare the factor performance with our expectations because a factor that should theoretically perform well in an up market shouldn’t perform poorly when the index is rising.

An optimizer can sometimes be a bit of a black box.

Portfolio blending means better transparency and interpretability.

Risk & Reward
What risk controls and constraints can be applied, and what is the role of optimization?

Systematic and Factor Investing Group
Multiple risk controls can be applied to ensure that factor portfolios are well-diversified and appropriately balanced. For instance, factors can be ranked across numerous control buckets, with index weights allocated to selected dimensions, like country or maturity. This helps ensure broad diversification over risk factors. Then, a light-touch optimization can help achieve more nuanced controls while reducing the number of bonds in the portfolio. Generally, we think optimizers should be used as little as possible to improve clarity. Indeed, an optimizer can sometimes be a bit of a black box.

Risk & Reward
One final question: I know it is not part of your most recent study, but it's no secret that you prefer portfolio blending to signal blending in multi-sector factor portfolios. Why?

Systematic and Factor Investing Group
Indeed we do – and for various good reasons. First, portfolio blending allows for a more straightforward rebalancing. Each asset class-specific factor portfolio is constructed separately before the individual portfolios are combined. This simplifies rebalancing since we can adjust the individual portfolios' weights without having to modify the signal combination itself. Second, portfolio blending allows use of existing attribution methods such as Brinson to monitor portfolio performance through a factor lens. Portfolio blending means better transparency and interpretability. The individual factor contributions to the overall portfolio are easier to understand.

Risk & Reward
Thank you very much!

Can Machine Learning enhance systematic incorporation of equity signals?

By Tarun Gupta, Ph.D., David Mischlich and Yifei Shea, Ph.D.

In theory, an investor can achieve above-market performance by obtaining better information or having a better process to distill relevant information from the available data. We conduct an experiment to evaluate whether machine learning (ML) can enable better inference of future returns from stock characteristics such as earnings yield, profitability, and momentum. Our findings suggest that while employing a non-linear ML model may lead to improved signal processing, thoughtful transformation of raw signals potentially further enhances information extraction of the ML model.

In the world of systematic and factor investing, the quest for informational advantage has led to an increasing number of predictive stock characteristics being 'discovered'.[1] As such traditional signals become more commoditized, researchers are looking for alternative alpha, for example by analyzing earnings call transcripts or credit card transaction data.[2]

But how should the available signals be incorporated in an investment model? Machine learning (ML) techniques have drawn significant attention, as they are generally well suited for dimension reduction and signal combination.[3] Additionally, they may capture potential non-linear relationships between signals and future returns as well as interaction effects among the signals.

There are, however, caveats associated with applying ML methods for return forecasting. For instance, stock characteristics such as earnings yield are known to be weak predictors of future stock returns; in other words, the signal-to-noise ratio is rather low. This and the dynamic nature of markets are challenges for any statistical modeling technique, but with increased model complexity there is increased concern of overfitting. Allowing non-linearities also makes the results more

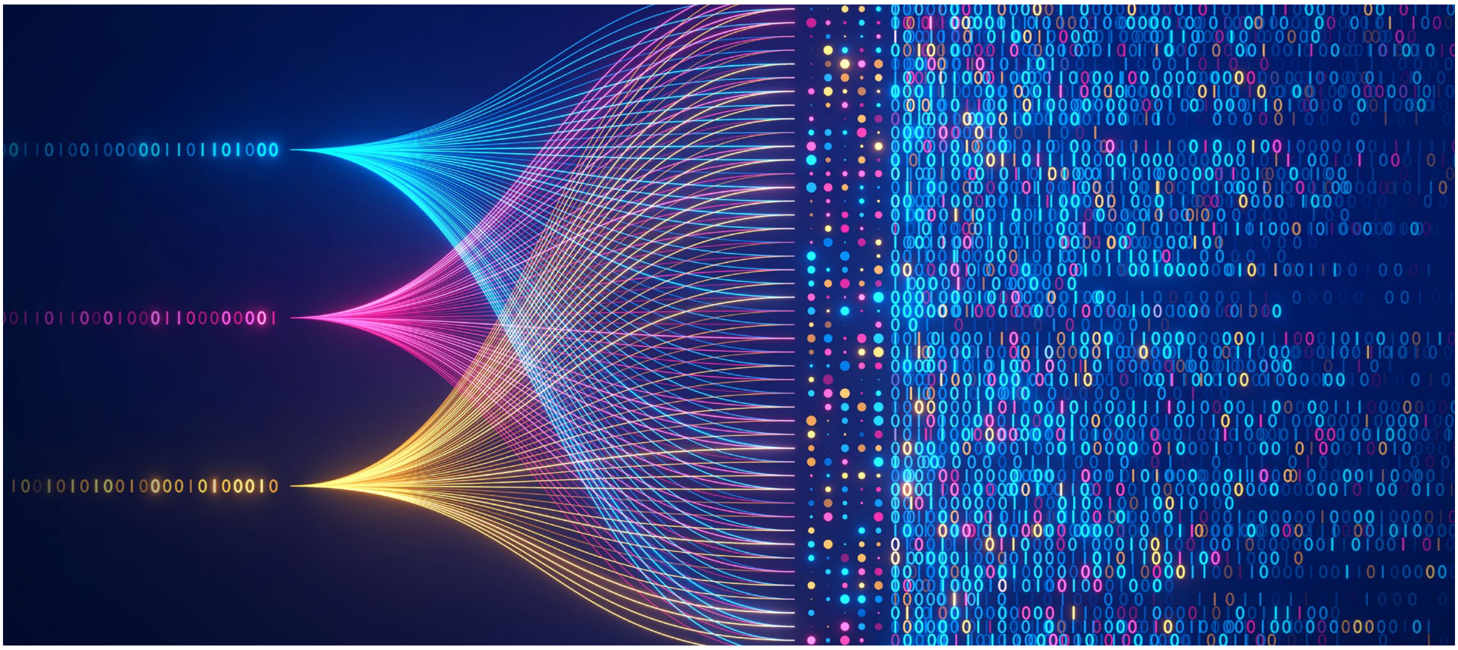
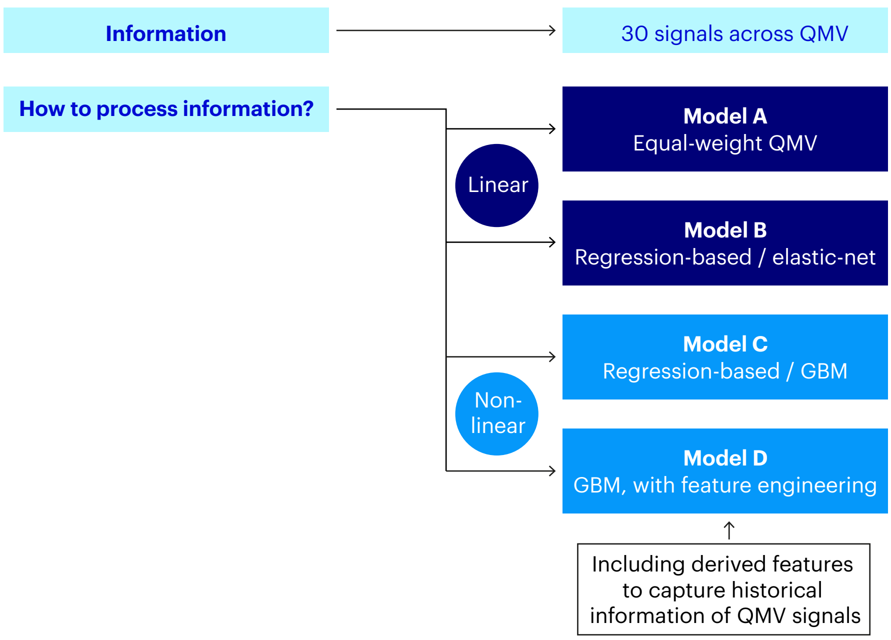


Figure 1
Four predictive models for extracting signal information



Source : Invesco.

difficult to interpret, necessitating additional tools for performance monitoring and attribution.

In this article we evaluate whether a non-linear ML model performs better than a linear combination of stock selection signals, and if feature engineering – the thoughtful transformation of raw inputs – can further improve the ML model's performance. To this end, we present our experiment set-up, backtest results and examples of the application of Interpretable Machine Learning (IML) tools.

The predictive models and their rationale

We construct and compare four predictive models (figure 1) based on a global developed market large cap stock universe.[4] Our information set includes 30 well-established Quality, Momentum and Value (QMV) equity signals with good economic intuition.[5] To keep signal selection parsimonious, we restrict data to non-financial sectors, given certain fundamental signals are less applicable to financial stocks. Our sample includes monthly signals and one-month forward returns from December 31, 1997 to December 31, 2020. On average, there are 2,490 stocks each month during this period.

For processing the inputs, Model A applies equal weighting of the signals within each of the three buckets: Quality, Momentum and Value and then equal weights the three factors. In comparison, Model B is based on the estimated statistical relationship between the current month's signals and next month's stock returns. We use a regularized linear regression model called elastic-net (or e-net for short), often used to reduce overfitting and to make the model easier to interpret.

Both Models A and B are linear combination of the 30 signals; they serve as benchmarks for evaluating Models C and D, which apply a non-linear ML algorithm (Gradient Boosting Machine, or GBM). GBM is a well-performing tree-based model which efficiently combines a large number of weak predictors into a strong one. It has also been applied and discussed in Leung et al. (2021).

In ML, better information extraction does not only happen at the modeling stage but can also be achieved by transforming raw signals before supplying them to the model. This process is called feature engineering, since signals are called 'features' in ML. Thus, while Model C uses the same inputs as Models A and B, in Model D, we extract 48 additional features based on the 30 QMV signals to capture their historical evolution and use all original and derived features as GBM inputs. An example of a derived feature is the trailing percentile of the earnings yield (figure 2).[6] Whereas earnings yield is one of the most popular Value factors, and

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Both Models A and B are linear combination of the 30 signals; they serve as benchmarks for evaluating Models C and D, which apply a non-linear ML algorithm (Gradient Boosting Machine, or GBM).

What is GBM?

GBM (Gradient Boosting Machine) is a popular machine learning technique to create a strong learner from multiple weak learners using shallow regression trees. It builds the model recursively by adding regression trees sequentially to an ensemble, with each one correcting its predecessor. In each stage, the model attempts to correct the errors of the previous stage by fitting a new tree to the residual error. More specifically, we apply stochastic gradient boosting (Friedman, 2002) which selects random subsamples of the training data to fit each tree in the ensemble. The use of subsamples allows for faster training and can improve the model's ability to generalize to new data. In contrast, traditional gradient boosting trains each tree on the full training set.

Figure 2
An example of a derived feature: trailing 3-year percentile of analyst forecast earnings yield

3-year trailing percentile calculation based on a 38-month look-back window to account for potential reporting lag.
Source: Invesco. For illustrative purposes only.

useful for gauging the 'cheapness' of a stock relative to its peers, its trailing percentile provides incremental information regarding whether a stock is cheap relative to own history.

The idea that historical evolution of stock characteristics, such as earnings yield, is useful for future return prediction is supported in previous research. For instance, Pani and Fabozzi (2021) show that trend in various Value factors are potent return forecasting signals. A well-known Quality signal, Piotroski's F-score[7], also includes several components based on year-over-year change in selected financial metrics. Instead of devising an economic rationale for each signal, Avramov, Kaplanski and Subrahmanyam (2022) suggest that a neglection of historical fundamentals is a manifestation of 'anchoring',[8] and they utilize deviation of 93 stock fundamentals from historical mean to forecast drifts in prices. Similarly, our intuition is over-arching, such that we think there is a general under-utilization of historical signal information. This allows us to mitigate potential bias in feature selection yet only supply sensible inputs in Model D.

The backtest framework and results

When setting up the models, we use a ranking-based standardization for pre-processing of the input signals and

Table 1
Backtest results of different models and regions

Region	Model	Return p.a.	Standard deviation p.a.	Information ratio	Max. drawdown	Turnover
US (average number of stocks: 972)	A (Equal-weight QMV)	1.5%	4.2%	0.36	-30.0%	3.84
	B (Linear / elastic-net)	1.6%	4.2%	0.38	-29.6%	5.29
	C (Non-linear / GBM)	2.7%	3.8%	0.70	-22.6%	6.96
	D (GBM, with historical information)	3.8%	3.8%	0.98	-20.9%	8.10
Japan (average number of stocks: 568)	A (Equal-weight QMV)	3.0%	4.5%	0.67	-21.5%	4.25
	B (Linear / elastic-net)	3.7%	4.7%	0.78	-23.2%	5.66
	C (Non-linear / GBM)	4.9%	4.4%	1.12	-15.4%	7.39
	D (GBM, with historical information)	6.4%	4.4%	1.47	-10.1%	8.61
EU ex UK (average number of stocks: 394)	A (Equal-weight QMV)	4.4%	3.7%	1.20	-21.2%	4.46
	B (Linear / elastic-net)	4.4%	3.7%	1.19	-14.8%	5.76
	C (Non-linear / GBM)	4.0%	3.7%	1.07	-14.4%	7.72
	D (GBM, with historical information)	5.0%	3.6%	1.39	-11.4%	8.77
UK (average number of stocks: 213)	A (Equal-weight QMV)	3.8%	4.9%	0.77	-14.1%	4.22
	B (Linear / elastic-net)	4.3%	5.3%	0.81	-11.7%	5.70
	C (Non-linear / GBM)	3.8%	5.5%	0.70	-12.0%	7.63
	D (GBM, with historical information)	3.8%	4.9%	0.76	-11.9%	8.56

Results for large cap universes of main developed regions, excluding financials, December 2002 to January 2021. The signals from each model are transformed into market and industry-neutral portfolios within each investment region. All portfolios are rebalanced monthly from December 31, 2002 to December 31, 2020. Turnover figures are one-way, annualized. Back-tested performance is not a guide to future returns. Model doesn't take into account fees.
Source: Invesco.

To avoid the pitfall of 'research through backtesting', we spend much time building and employing Interpretable ML tools for all estimated models.

returns to ensure industry and region neutrality. Accordingly, our model forecasts represent the outperformance or underperformance of a stock relative to its peers.

While Model A uses no statistical tools, we train return prediction models using an expanding window for Models B, C and D; the first estimation models are based on features and forward returns from December 31, 1997 to November 30, 2002, then applied on inputs as of December 31, 2002 to obtain following-month return predictions. In this manner, we generate out-of-sample following-month return forecasts based on each model from December 31, 2002 to December 31, 2020.[9]

Next, we transform the monthly forecasts of each model into dollar, market and industry-neutral long and short portfolios for every region.[10] Table 1 shows the backtest performance of the four models in key developed market regions. The main performance metric is Information Ratio (IR), which measures the risk and reward trade-off of a strategy. We find, using the original information set of 30 signals, that the performance of non-linear model C is mixed relative to the two linear models A and B, even though Model C outperforms in the two regions with larger cross-section of stocks, US and Japan.

The more consistent performance improvement is observed once we additionally include features derived from original signals to capture their historical information, as manifested in the higher IRs from Model D compared to Model C. In unreported results, we find that Model D generally provides alphas beyond traditional QMV factors, mainly due to the derived features. In addition, table 1 shows lower or similar drawdown for the non-linear vs. the linear models.

However, one of the caveats of the non-linear models is the higher portfolio turnover. In the backtest period, the average turnover across regions is twice as high for Model D as for the equal-weight Model A. Smoothing the investment signals from Model D would result in reduced turnover while incurring decay in signal efficacy.[11] Therefore, net of transaction costs, it may be difficult to translate Model D signals into a profitable strategy, especially in the presence of various portfolio constraints such as long-only.

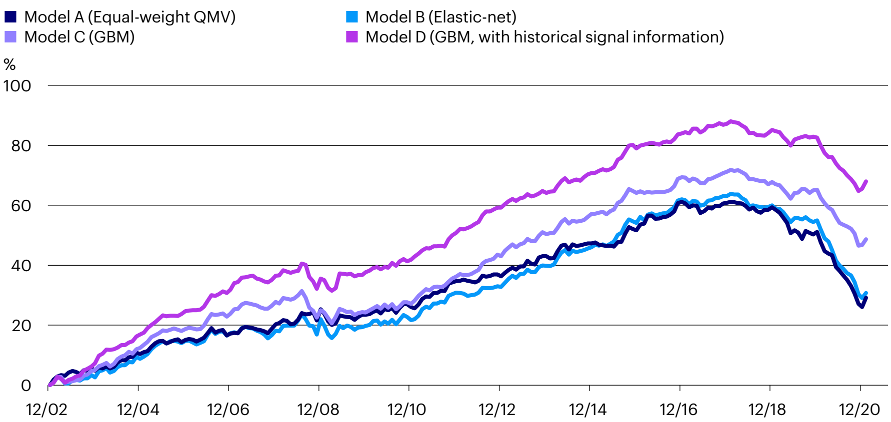
Next we examine the backtest performance through time for the four models. Figure 3 shows the cumulative returns in US large cap universe, excluding financials. The annualized return differential between Models D and B per annum is 2.1%, which can be further broken down to 1.1% from including derived features to capture historical signal information (proxied by the return differential between Models D and C), and 1% from allowing non-linearity (proxied by the return differential between Models C and B). In addition, we note the return contribution from including signal evolution information is more stable over time and across regions, compared to the contribution from purely adopting GBM instead of linear regression. This seems to confirm that, although the non-linear modeling technique may help, information can potentially be more reliably extracted in the feature engineering stage of ML – though caution is required, as our observations are essentially based on one historical realization.

To avoid the pitfall of 'research through backtesting', we spend much time building and employing Interpretable ML tools for all estimated models. Our aim is to ensure a good understanding of the relationship between input features and model forecasts before evaluation of performance. In the next section, we show examples of such IML applications.

Illuminating the black box

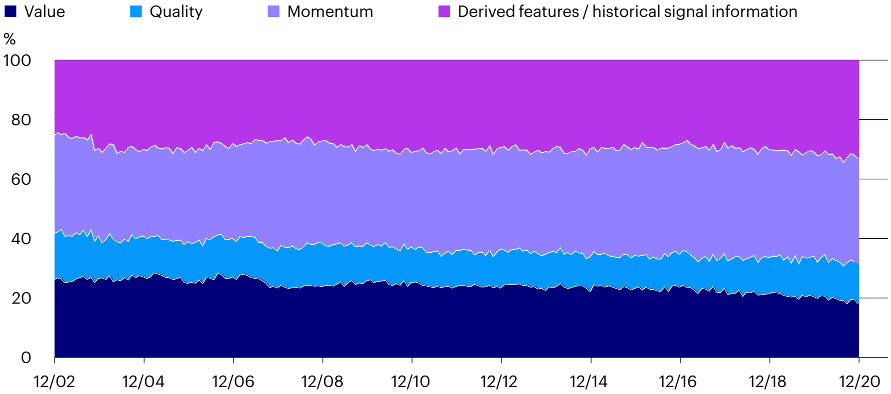
One of the most popular statistics used to shed light on non-linear ML models is called variable importance, which

Figure 3
Backtest performance: Cumulative returns of four models in US large cap universe, excluding financials



The portfolios are rebalanced monthly from December 31, 2002 to December 31, 2020. Backtested performance is not a guide to future returns.
Source: Invesco.

Figure 4
Variable importance through time by feature group



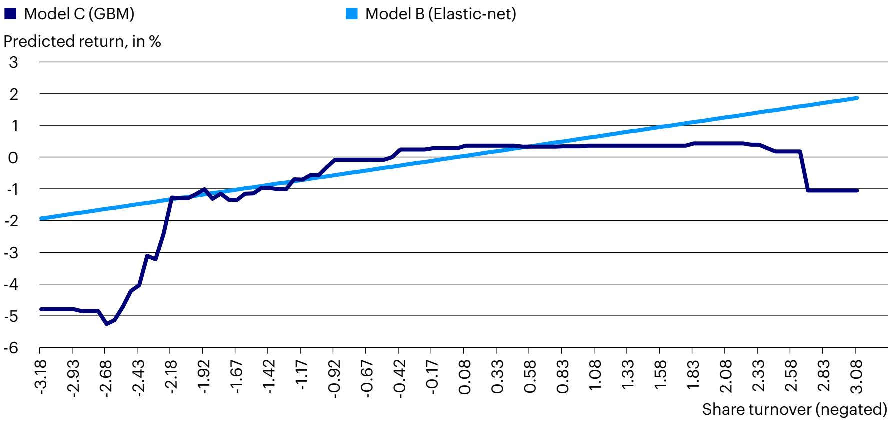
Relative variable importance is computed on signal level then aggregated by group. On December 31, 2002, the variable importance is based on GBM estimated using signals and 1-month forward returns from December 31, 1997 to November 30, 2002. An expanding window is used for each subsequent month of estimation.
Source: Invesco.

measures to the relative importance of each feature in the model.[12] Figure 4 shows the variable importance of feature groups over time based on Model D. We can see the relative importance of each feature group remains stable over time; on average, the importance of Value, Quality, Momentum and derived features is 24%, 12%, 34% and 29%, respectively.

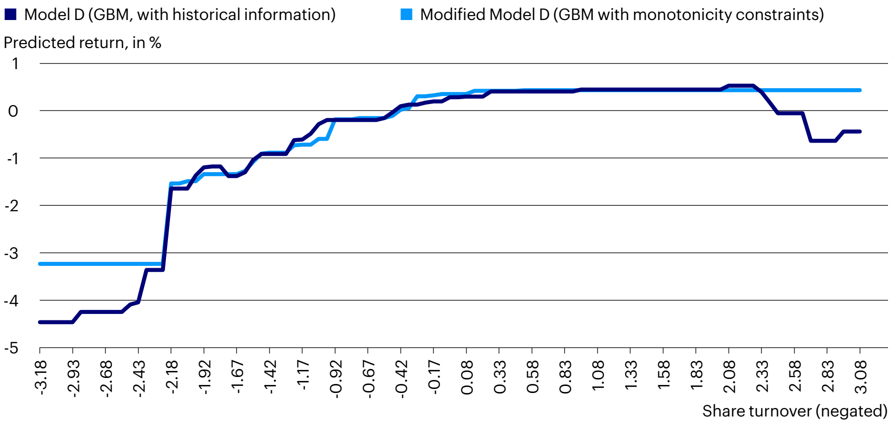
On the individual feature level, share turnover[13] emerges as highly important in non-linear models C and D, but does not rank high when measured by its correlation with return forecasts (a metric to capture linear relationship). Thus, it is interesting to inspect how the predicted returns change with share turnover (holding values of other model features constant) based on either a linear or a non-linear model.

Figure 5
Partial dependence plots (PDPs) of share turnover

Panel A: PDPs of linear and non-linear models



Panel B: PDPs of GBM models with or without monotonicity constraints



Based on models estimated using standardized signal and one-month forward returns from December 31, 1997 to November 30, 2020.
Source: Invesco.

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Thoughtful transformation of input signals to capture their historical evolution, coupled with using GBM to efficiently incorporate such information, may be advantageous.

We use Partial Dependence Plots (PDPs)[14] to visualize such marginal effects and give an example for share turnover in figure 5. As shown in panel A, the non-linear Model C can detect certain non-linearities a linear model cannot. More specifically, for assets with a high turnover, it predicts lower forward returns compared to the linear model while suggesting little difference for assets with below average turnover. This is consistent with our intuition that high turnover can be an indication for stock underperformance, whereas low turnover does not necessarily precede better returns.

Additionally, PDPs can be useful to visualize constraints in the ML model. To alleviate overfitting concerns, in one of our robustness studies, each input to Model D had to have a monotonic relationship with forward returns consistent with our prior. Panel B of figure 5 shows the impact of such monotonicity constraints.

Summary

We have designed experimental models to test whether non-linear ML models, when applied for systematic equity investing, improve the distillation of signal information compared to traditional linear models. Broadly, the answer is yes: According to our results, thoughtful transformation of input signals to capture their historical evolution, coupled with using GBM to efficiently incorporate such information, may be advantageous.

However, we need to be aware of the hurdles, as we show in backtesting. First, non-linear ML models have a high turnover, so the net gain will depend on portfolio constraints and implementation. Also, using non-linear technique makes the model harder to interpret. We think work towards illuminating interactions among signals and their historical evolution, as well as linking ML forecasts with stock fundamentals, could bring additional insights.

Notes

1 E.g. Cochrane (2011), and more recently, Bartram, Lohre, Pope and Ranganathan (2021).
2 E.g. Gupta and Shea (2022); Gupta, Leung and Roscovan (2022).
3 E.g. Rasekhschaffe and Jones (2019); Avramov, Cheng and Metzker (2022); Leung, Lohre, Mischlich, Shea and Stroh (2021); Nagel (2021).
4 The universe includes stocks from global and regional equity indexes: MSCI, FTSE, S&P, and STOXX. To alleviate investability concerns, we exclude stocks with very small free-float market capitalization, applying a 95% free-float market-capitalization percentile threshold per region and date.
5 There are 10 signals in the Quality bucket, including metrics to measure accrual and profitability; 11 signals in the Momentum bucket, including various price and earnings momentum signals; and 9 signals in the Value bucket, such as earnings yield and free-cash-flow yield.
6 Earning yield is defined as the ratio of consensus analyst forecast of next year EPS and stock price.
7 Piotroski (2000).
8 Tversky and Kahneman (1974).
9 The elastic-net and GBM models are implemented using the open-source ML platform H2O-3 including its pre-set of default hyperparameters. We also tested hyperparameter tuning following the training, validation and testing framework outlined in Leung et al. (2021), and noted limited added value given our sample size.
10 We use own industry definitions which closely follow GICS classifications, as well as predicted betas based on own calculations.
11 Another route for reducing turnover is to use longer horizon such as 6 -month forward returns in the estimation models, as discussed in Leung et al. (2021).
12 Hastie, Tibshirani and Friedman (2017). While we have constructed multiple measures of variable importance, in this section we use the definition from H2O for GBM (see https://docs.h2o.ai/h2o/latest-stable/h2o-docs/variable-importance.html#variable-importance-calculation-gbm-drf), such that the importance of a feature is determined by whether it was selected to split on during the tree building process, and how the squared error (over all trees) improved (decreased) as a result.
13 Share turnover is defined as the median of standardized industry-neutral trade dollar volume per shares outstanding (monthly) over last 12 months. The values are then negated so that higher scores represent lower share turnover.
14 Hastie et al. (2017).

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About the authors

Tarun Gupta, Ph.D.
Managing Director, Global Head of Research & Investment Technology
Invesco Quantitative Strategies
Tarun Gupta is a member of the Invesco Quantitative Strategies management team and leads the build-out of customized and tax-managed equity capabilities.

Yifei Shea, Ph.D., CFA®
Senior Quantitative Research Analyst
Invesco Quantitative Strategies
Yifei Shea conducts research into quantitative models that drive the investment decisions for multi-factor equity products. Her current focus includes equity factors, machine learning and natural language processing.

David Mischlich, CFA®
Research Analyst
Invesco Quantitative Strategies
David Mischlich conducts research into quantitative models that drive the investment decisions for multi-factor equity products. His current focus includes equity factors, machine learning and natural language processing.

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Theory to practice: Bond momentum for equities – and equity momentum for bonds

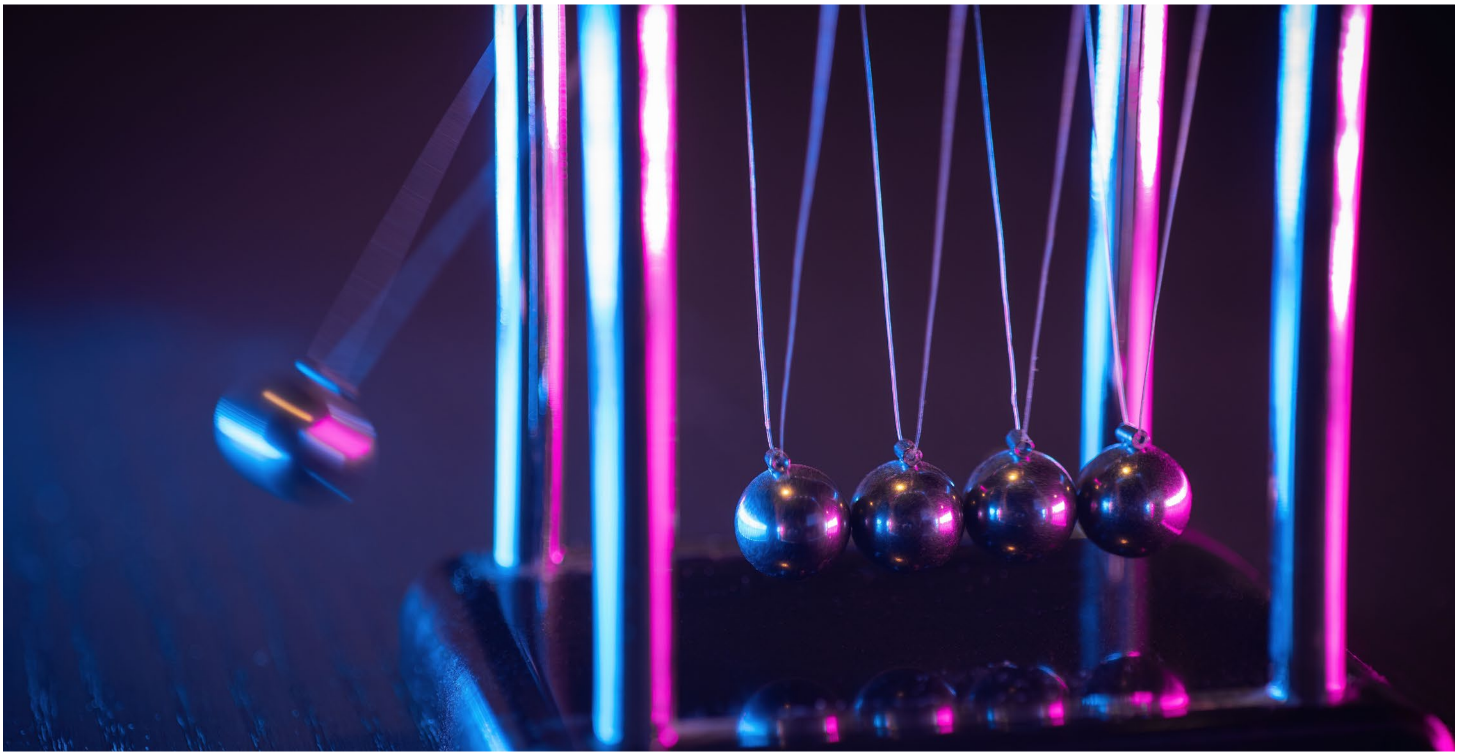
By Angelica Dai, Sergey Protchenko, Jay Raol, Ph.D., and Bin Ying

Factor investors use characteristics to explain asset risk and returns and for harvesting factor premia. The "characteristics" can be generalized as factors and are used to form investment portfolios. The academic literature is full of factors that claim to explain risk and return, but as documented by "factor zoo" (Cochrane 2011), not all factors are created equal.

A recent paper on "Factor Investing: From Theory to Practice" (Gupta, Raol and Roscovan) established a mechanism to navigate the factor zoo. We can parsimoniously evaluate factor existence within traditional asset classes. The approach is anchored by four pillars: Economic Theory, Robust Risk and Return Evidence, Cross-Asset and Across-Region Validation and Implementability. As an application of this framework, we look at momentum by examining the efficacy of bond momentum in equities and equity momentum in bonds. First, we review the economic rationale for momentum and theory behind the potential efficacy of momentum across assets.

Economic rationale

Momentum is the tendency for assets that have performed well (poorly) in the recent past to continue to perform well (poorly) in the future. (Jegadeesh and Titman [1993]). In addition to equity market momentum, the factor has been observed in currency and commodities markets (Gorton, Hayashi, and Rouwenhorst (2013)) as well as fixed income market (Jostova et al. (2013) and Barth, Scholz, and Stegmeier (2017)).



Matching a firm's equity and bond data is a challenge.

There are two competing explanations for this phenomenon. The risk premia school explains momentum with: industry, beta, business cycle, market microstructure and stock-specific effects (Blitz, Huij, and Martens (2011)). The behavioral finance school explains it with the irrational behavior of investors who simply follow the crowd (Barberis, Shleifer, and Vishny (1998)). Whichever the driver, the empirical evidence is clear that within each asset class, momentum works.

But how does momentum work across asset classes? Why should bonds and equity momentum be linked? The Merton Model developed in 1974 provides strong intuition on the relationship between credit and equity markets. The model relates equities to corporate debt by linking the value of the equity as a call option on the value of the company whose strike is equivalent to its liabilities or debt payments. This would imply that shocks to the value of assets should be valuable information for both debt and equity investors. Indeed, empirical studies have indeed observed a strong relationship between the default rates of corporate bonds and the value of stocks. Giesecke et al. (2011) look at 150 years of corporate bond defaults and potential drivers. Consistent with the Merton model, they find that both a fall in equity prices and an increase in equity volatility are associated with higher corporate bond default rates.

Matching equity and bond data

For the cross-asset class momentum portfolios, we used (1) a proxy for Russell 3000 universe and (2) the outstanding bonds in the Bloomberg US Investment Grade and Bloomberg High Yield indices from January 2000 to September 2022. For our analysis, we had to link the constituents of the two bond indices with those of the equity universe.

Matching a firm's equity and bond data is a challenge. First of all, firms typically have a single class of common shares, but may have multiple outstanding bonds with different maturities, seniorities, ratings and other structural differences. Sometimes, bonds are issued by different entities within the same firm. In addition, the equity and bond markets lack a common firm identifier. Even though identifiers such as CUSIP and ISIN can bridge these two markets to some extent, corporate actions such as mergers, acquisitions, spin-offs and name changes can break such links.

To create the equity and bond linking table, we first combined all bonds by the same issuer and mapped them to the corresponding equities by their exchange tickers. Next, we identified all the unmatched cases from merging using exchange tickers and attempted to join those via CUSIPs. According to CUSIP Global Services, a CUSIP is a 9-character code that identifies a financial security in the US and Canada. In addition, the first 6 characters uniquely identify the issuing entity. Hence, we could join the bond and equity data through their common first 6 characters of the CUSIPs. The resulting linking tables can match the majority of the constituents of both the equity and bond universes.

Table 1 shows the results achieved by the linking table on the US equity universe. It can match 54% of the large cap and mid cap universe, which represent 78% of total market capitalization. In addition, most constituents of the S&P 500 and Russell 1000 indices can be matched by the linking table (78% and 60%, respectively), which represent 85% and 80% in terms of market capitalization.

Table 2 shows the coverage results from the perspective of a fixed income investor. On average, we can match 82% in the US Investment Grade Index and 66% in the High Yield Index, which represents 80% and 69% in terms of market value. In general, we see that the match rate in the High Yield Index is meaningfully lower than the Investment Grade Index. This is

Table 1
Coverage of different US equity universes in the US Investment Grade and High Yield bond indices

	S&P500	Russell 1000	Large & mid cap	Small cap	All cap
By number of stocks	78%	60%	54%	18%	28%
By market capitalization	85%	80%	78%	31%	74%

Source: Invesco. Based on data from January 2000 to September 2022. Backtested data.

Table 2
Coverage of different US bond universes in a proxy for Russell 3000 universe

	US Investment Grade	US High Yield
By number of bonds	82%	66%
By market capitalization	80%	69%

Source: Invesco. Based on data from January 2000 to September 2022.

because the High Yield Index consists of more private issuers which do not have an associated equity identifier.

Additional work is warranted in order to improve the matching results. In constructing the linking table, we primarily relied on the index providers to model mergers, acquisitions, spin-offs and name changes, all of which can be a source of noise. To tackle these issues, manual matching may be necessary. Furthermore, some constituents of the equity universe have outstanding bonds that are not covered by the linking table because they do not meet the inclusion requirements of the US Investment Grade or High Yield indices. In addition, some constituents of the bond universe are not covered because their issuing entities are private companies which are not included in the Russell 3000 universe.

> We constructed a bond momentum factor and analyzed its performance in the equity market.

Bond momentum in the equity market
In a four-step process, we then constructed a bond momentum factor and analyzed its performance in the equity market.

1. We first computed the aggregated bond return for each firm by aggregating all its outstanding bonds' excess returns based on market cap. We used excess return (in excess of duration-matched Treasury returns) rather than total return, because this more accurately represents changes in the issuing firms' credit risk and underlying fundamentals.

2. Then, we formed the bond momentum factor by cumulating the aggregate bond returns during the formation window of three months, including the most recent month (three-month momentum). The factor was then ranked and standardized.

3. From the standardized scores, we finally constructed a long-short bond momentum factor portfolio with a 100% long position in the top half and a 100% short position in the bottom half. We controlled for a selected number of risk factors such as beta and industry exposures. Consequently, the bond momentum factor portfolio is beta and industry neutral.

4. Lastly, we tested the bond momentum factor portfolio for the US large cap and mid cap sub-universes from table 1.

Table 3 shows the backtest performance statistics. The bond momentum factor would have generated an annualized return of 0.6% and an annualized standard deviation of 4.5%, resulting in an information ratio of 0.139. The portfolio turnover of 157.9% would have been higher than for a typical momentum factor. The portfolio would have had a large drawdown during the global financial crisis (-15.5%) followed by a strong reversal from 2009 to 2013. During the sample period, the bond momentum factor was positively correlated with the momentum factor (61%), slightly positively correlated with the quality factor (5.5%) and negatively correlated with the value factor (-29.2%). In the spanning test, the bond momentum factor generated a positive and significant alpha on top of the value factor portfolio. It also generated a positive, but insignificant, alpha on the momentum factor portfolio, quality factor portfolio and on the quality, momentum and value multi-factor portfolios.

Why a three-month formation window?
We chose the three-month formation window based on theoretical support and empirical evidence. The theoretical background is that the momentum factor in the bond market is typically shorter-term. Evidence shows that 3-month bond

Table 3
Equities: Bond momentum factor portfolio analysis

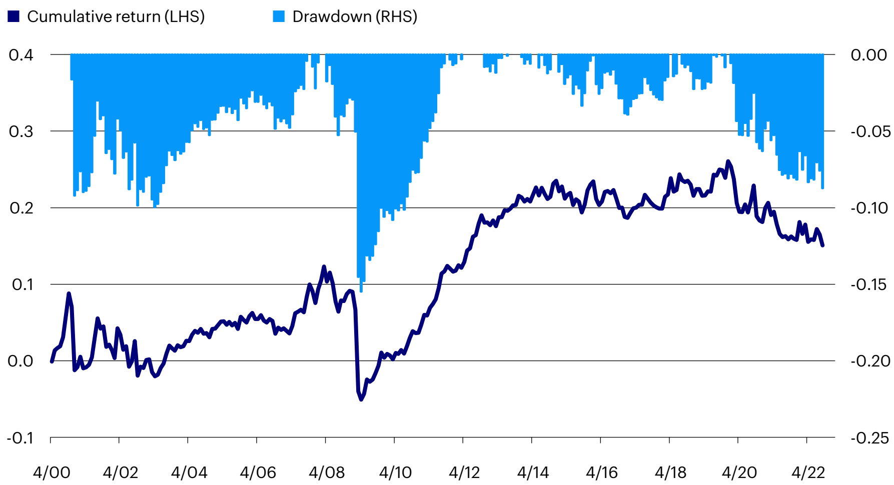
(A) Performance statistics	**Bond momentum**
Annualized return	0.60%
Annualized sd	4.50%
Information ratio	0.139
Realized beta	-0.084
Maximum drawdown	-15.50%
Turnover	157.90%

(C) Correlation	**Momentum**	**Quality**	**Value**
Return correlation	61.0%	5.5%	-29.2%

(D) Spanning tests

Market	Momentum	Quality	Value	Multi-factor
0.014	0.0002	0.0001	**0.018**	0.002
(1.516)	(0.024)	(1.44)	**(2.038)**	(0.203)

(B) Performance



Backtest results, based on data from April 2000 to September 2022. T-values in brackets. Backtested performance is not a guide to future returns. Source: Invesco.

Table 4
Equities: Performance of the bond momentum portfolio with different formation windows

	Formation window	Past 12 months	Past 9 months	Past 6 months	Past 3 months
Excluding month t-1	Information coefficient	0.01 (0.90)	0.01 (0.94)	0.00 (0.83)	**0.01 (2.30)**
	Spread return	-0.01 (-0.07)	0.02 (0.10)	0.00 (0.01)	**0.29 (2.05)**
	Information ratio	0.110	0.083	-0.019	0.172
	Annualized return	0.4%	0.4%	-0.1%	0.7%
	Annualized standard deviation	3.9%	4.3%	4.4%	4.2%
	Turnover	97%	107.9%	128.3%	189.6%
Including month t-1	Information coefficient	0.01 (1.16)	0.01 (1.21)	0.01 (1.12)	**0.01 (2.43)**
	Spread return	-0.01 (-0.03)	-0.01 (-0.08)	0.10 (0.57)	**0.33 (2.14)**
	Information ratio	0.155	0.151	0.091	0.139
	Annualized return	0.7%	0.7%	0.4%	0.6%
	Annualized standard deviation	4.3%	4.5%	4.7%	4.5%
	Turnover	91.9%	103.2%	119.9%	157.9%

Source: Invesco. Backtest results, based on data from April 2000 to September 2022. T-values in brackets.

We analyze how equity momentum can be informative in predicting a corporate bond's performance.

momentum works for both investment grade and high yield bonds, whereas longer-term bond momentum only works for high yield bonds. But our empirical results also supported a shorter formation window: We examined several possible formation windows, which varied by the length and the inclusion/exclusion of the most recent month. We found that performance generally decreased as the formation window extended from the past 3 months to the past 12 months, and the exclusion of the most recent month resulted in a significant decline in factor performance.[1]

Comparing bond and equity momentum factors

We now compare the performance of the bond momentum factor and the equity momentum factor for the US large cap and mid cap sub-universes (table 5). During the sample period, the bond momentum factor was substantially less volatile than that of the equity momentum factor (4.5% vs. 6.8%), but it also underperformed (0.6% vs. 2.1%). Taken together, this resulted in a lower information ratio for bond momentum than for equity momentum (0.139 vs. 0.314). On the other hand, the bond momentum factor portfolio suffered a smaller maximum drawdown (-15.5% vs. -20.7%). Lastly, the bond momentum factor portfolio had a turnover of 157.9%, which was higher than the equity momentum factor portfolio (86.1%).

Equity momentum in the bond market

We now analyze how equity momentum can be informative in predicting a corporate bond's performance. We used monthly historical data of Bloomberg US Corporate Investment Grade and High Yield indices from January 2000 to September 2022. We further limited our sample universe to those firms for which the bond-to-equity mapping table can find successful matches and the equity momentum data is present. To construct the bond factor based on issuer's equity momentum, we proceeded with the following steps:

1. We started with the equity momentum factor scores. To make the predictive power somewhat independent relative

Table 5
Equities: Bond and equity momentum factor portfolios in comparison

	Bond momentum factor portfolio	Equity momentum factor portfolio
Information coefficient	0.01 (2.43)	0.01 (2.67)
Spread return	0.33 (2.14)	0.29 (1.76)
Annualized return	0.6%	2.1%
Annualized standard deviation	4.5%	6.8%
Information ratio	0.139	0.314
Realized beta	-0.084	-0.155
Maximum drawdown	-15.5%	-20.7%
Turnover	157.9%	86.1%

Source: Invesco. Backtest results, based on data from April 2000 to September 2022. T-values in brackets. Backtested performance is not a guide to future returns.

to the length of the formation window, we combined multiple formation periods. That also helps to identify a cleaner trend and avoid riding on short-term reversals. Again, the factor scores were neutralized for market beta and industry exposure.[2]

2. At the beginning of each month, we ranked the bonds based on the equity momentum factor scores, breaking them into deciles. During the sorting process, we controlled for non-factor-driven risk exposures such as sector, rating and duration.

3. Finally, we took the bonds in the top decile and weighted them by market value to form a long-only factor. Again, we used excess return, defined here as returns in excess of duration-matched Treasury returns. We measured performance against the corresponding benchmark, i.e., the US Investment Grade Index and the US High Yield Index.

Table 6 shows the backtest performance summary for the equity momentum factor. In US investment grade, the factor would have actively outperformed the benchmark by 61 bp. p.a. – with a tracking error of 1.16% on average – leading to an information ratio of 0.53 (with an annualized alpha of 0.71% and a beta of 0.87). At 397%, the annualized turnover would have been fairly high compared to our normal factor portfolio turnover of around 130%. Similarly, in the high yield market, equity momentum would also have beaten the index with an active excess return of 182 bp p.a., an average tracking error of 3.58% and an information ratio of 0.51 (with an annualized alpha of 2.31% and a beta of 0.81).

What drives the outperformance?

Next, we examine whether the outperformance of the equity momentum factor can be explained by traditional bond factors, such as sector, rating, duration and liquidity, as well as our proprietary factors carry, low volatility and value.

Table 7 shows the active excess return correlations of equity momentum against our existing factor portfolios. We see that, over the full sample period measured by beta-adjusted excess return, momentum has negative correlations of -36.5%, -17.4% and -20.6% to carry, value and low volatility in US investment grade. In US high yield, we see a negative correlation of -26.2% to carry, a positive correlation of 27.96% to low volatility and a close-to-zero correlation to value. These results suggest that adding an equity momentum factor into the current factor pool could potentially bring more diversification.

Furthermore, we ran a spanning test to see if equity momentum has significant unexplained returns on top of the index and the fixed income factors. Table 8 shows

Table 6
Bonds: Equity momentum factor portfolio analysis

	US Investment Grade	US High Yield
Annualized excess return over US Treasuries	1.34%	4.38%
Annualized volatility	4.54%	8.88%
Sharpe Ratio	0.30	0.49
Skewness	-1.59%	-1.56%
CVaR	-3.18%	-6.41%
Maximum drawdown	22.14%	34.71%
Annualized active excess return over the index	0.61%	1.82%
Tracking error	1.16%	3.58%
Annualized alpha	0.71%	2.31%
Beta	0.87	0.81
Information ratio	0.53	0.51
Turnover	397%	375.57%

Source: Invesco. Backtest results, based on data from April 2000 to September 2022.

Table 7
Bonds: Active excess return correlations, beta-adjusted

	Carry	Low volatility	Value
US Investment Grade	-36.6%	-17.4%	-20.6%
US High Yield	-26.2%	28.0%	-0.4%

Source: Invesco. Backtest results, based on data from April 2000 to September 2022. T

Table 8
Bonds: Spanning test

	Market	Carry	Low volatility	Value	Multi
US Investment Grade	0.71 (3.548)	0.76 (4.070)	0.77 (3.893)	0.92 (4.480)	0.65 (3.346)
US High Yield	2.31 (3.626)	2.15 (3.510)	1.55 (2.463)	2.30 (3.626)	1.20 (2.006)

Source: Invesco. Backtest results, based on data from April 2000 to September 2022. T-values in brackets.

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The outperformance of equity momentum in both US investment grade and high yield is not driven by factor constellations, liquidity risk or the traditional fixed income risk factors alone.

the intercept and the corresponding t-stats when regressing equity momentum excess returns against different factors. In both US investment grade and high yield, we find significant alpha after regressing against the market, the standalone factors and a combination of all factors. Therefore, we can conclude that the equity momentum factor is an additional return source that is not driven purely by loading on market or factor risks.

Next, we need to test whether the unexplained return premium can be explained by other risk factors, such as liquidity and the common fixed income risk exposures. To this end, we ran double-sort tests by controlling for different types of risk exposures that can potentially drive the risk premium of equity momentum (figure 9). Specifically, we formed long-short equity momentum portfolios by first neutralizing the momentum scores on a specified risk exposure and subsequently taking a long position in the top-decile portfolio, as well as a short position in the bottom-decile portfolio. We used a bond's age, issuance size, trading volume and liquidity score as proxies for its liquidity. In addition, we also tested with the standard fixed income risk exposures such as rating, maturity, sector and DTS. For equity momentum factors in both the US investment grade and high yield universes, we found significant excess return alpha after residualizing these exposures. This further strengthens the argument that the outperformance of equity momentum in both US investment grade and high yield is not driven by factor constellations, liquidity risk or the traditional fixed income risk factors alone.

Comparing equity and bond momentum factors

As we did for equities, we also compared the performance of equity and bond momentum. For illustrative purposes, we chose 3-month cumulative returns as the signal and excluded bonds with missing mapping information or equity signals. Again, we took the top-decile portfolio by bond momentum scores, while controlling for sector, maturity and rating. Table 10 shows the performance summary; figure 1 shows the cumulative performance. In both markets, bond momentum underperformed equity momentum.

Table 9
Bonds: Double-sort test

	Controlled exposure	Annualized excess return (10th – 1st decile)	Sharpe ratio
US Investment Grade	Age	1.88 (2.59)	0.40
	Liquidity score	1.68 (2.35)	0.37
	Size	2.11 (2.88)	0.46
	Volume	1.94 (2.64)	0.42
	Sector	1.25 (4.11)	0.56
	Rating	1.84 (3.07)	0.45
	Maturity	1.97 (2.76)	0.43
	DTS	2.01 (2.89)	0.48
US High Yield	Age	4.69 (3.64)	0.41
	Liquidity score	4.61 (3.86)	0.42
	Size	4.12 (3.23)	0.34
	Volume	4.17 (3.49	0.36
	Sector	4.6 (4.1)	0.55
	Rating	3.78 (3.51)	0.41
	Maturity	4.86 (3.7)	0.40
	DTS	2.75 (3.11)	0.47

Source: Invesco. Backtest results, based on data from April 2000 to September 2022. T-values in brackets.

Table 10
Bonds: Bond and equity momentum factor portfolios in comparison

		Bond momentum factor portfolio	Equity momentum factor portfolio
US Investment Grade	Annualized excess return	0.05%	1.34%
	Annualized volatility	4.83%	4.54%
	Sharpe ratio	0.01	0.30
	Skewness	-2.05%	-1.59%
	CVaR	-3.67%	-3.18%
	Maximum drawdown	27.64%	22.14%
	Annualized active excess return	-0.68%	0.61%
	Tracking error	1.14%	1.16%
	Annualized alpha	-0.62%	0.71%
	Beta	0.92	0.87
	Information ratio	-0,59	0.53
	Turnover	618%	397%
US High Yield	Annualized excess return	2.73%	4.38%
	Annualized volatility	9.33%	8.88%
	Sharpe ratio	0.29	0.49
	Skewness	-0.95%	-1.56%
	CVaR	-6.56%	-6.41%
	Maximum drawdown	36.31%	34.71%
	Annualized active excess return	0.17%	1.82%
	Tracking error	3.35%	3.58%
	Annualized alpha	0.54%	2.31%
	Beta	0.86	0.81
	Information ratio	0.05	0.51
	Turnover	610%	376%

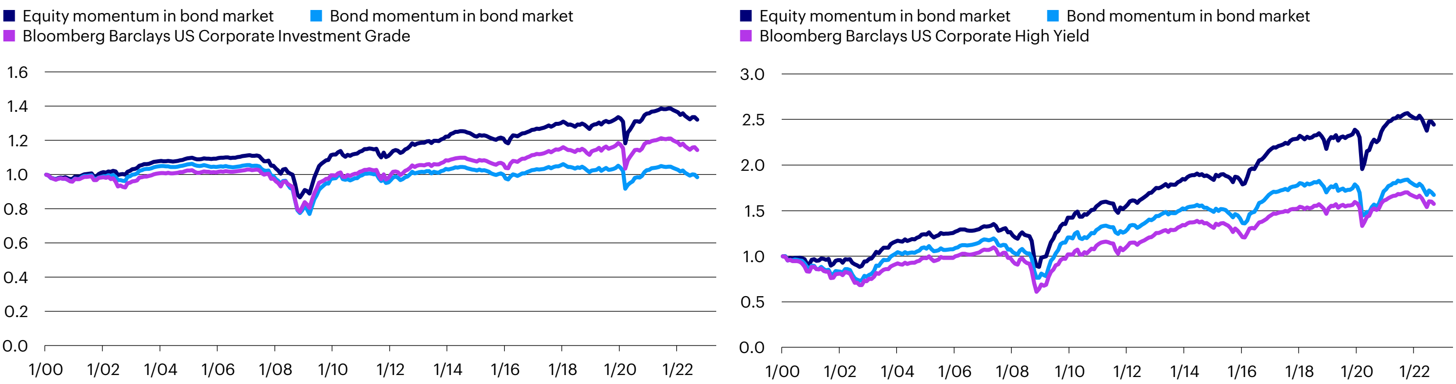
Source: Invesco. Backtest results, based on data from April 2000 to September 2022.

In US investment grade, the excess return tracking error of bond momentum is very close to that of equity momentum (1.14% vs. 1.16%). However, the active excess return is, on average, negative for bond momentum but positive for equity momentum (-0.68% vs. 0.61%). This results in a meaningful difference in information ratio, where bond momentum has -0.59 and equity momentum 0.53.

Similarly, in high yield the excess return tracking error of bond momentum is only slightly lower than that of equity momentum

Figure 1
Bonds: Cumulative performance

US Investment Grade **US High Yield**



Source: Invesco. Backtest results, based on data from April 2000 to September 2022.

Table 11
Bonds: Regression of equity momentum onto bond momentum

	Alpha	Beta	Correlation
US Investment Grade	0.88 (4.613)	0.28 (5.543)	31%
US High Yield	2.06 (3.655)	0.46 (8.528)	46%

Source: Invesco. Backtest results, based on data from April 2000 to September 2022. T-values in brackets.

Equity momentum shares similar risk characteristics with bond momentum but produces additional sources of return.

(3.35% vs. 3.58%), but the average active excess return of bond momentum is much lower than that of equity momentum (0.17% vs. 1.82%). Again, we find the information ratio for bond momentum to be significantly lower than that of equity momentum (0.05 vs. 0.51). Moreover, we also find excessive yearly turnover with bond momentum relative to equity momentum (618% vs. 397%), which points to implementation difficulties. As a result, we have been cautious in categorizing bond momentum as a risk premium factor for corporate bonds.

Merton revisited

We started with the Merton model, which suggests a fairly close correlation between equites and bonds of the same issuer, leading us to wonder whether equity and bond momentum may also be correlated. To this end, we performed a regression of equity momentum in the bond market onto bond momentum in the bond market using beta-adjusted excess return (table 11). In both investment grade and high yield, we see positive correlations, with 31% and 46%, respectively. Moreover, we find highly significant alpha of 0.88% and 2.06% p.a.

These results suggest that equity momentum shares similar risk characteristics with bond momentum but produces additional sources of return.

Conclusion

Navigating the factor zoo can be difficult. If one is trying to understand momentum through the lens of the behavior versus risk premia debate only, it can be daunting. However, going from theory to practice by looking at strong evidence across assets can build confidence in factors. It would be very difficult for a factor by chance to show some efficacy in a few assets classes. Momentum in an asset class helps to predict future returns. That has been known for some time. However, it would be even less likely that – by mere chance – equity momentum would help predict bond returns and the other way around. For this reason, we have strong conviction in momentum as a factor. We believe there should be more work to understand the potential drivers of these cross-asset dynamics. One thing is clear: building portfolios on momentum, whether in bonds or equities, can benefit investors.

Notes

1 Both observations are in line with the findings by Dor and Xu (2015) in their cross-asset class momentum study.
2 As a robustness test, we also experimented with equity earnings momentum, and the predictive power did not suffer.

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About the authors

Yuxiao (Angelica) Dai
Quantitative Research Analyst
Invesco Quantitative Strategies
Angelica specializes in multi-factor return and risk model, portfolio construction and optimization.

Sergey Protchenko
Senior Researcher
Invesco Quantitative Strategies
Sergey Protchenko specializes in factor investing research, portfolio construction and systematic equity investing.

Jay Raol, Ph.D.
Head of Fixed Income
Fixed Income Systematic and Factor Investing Group
Jay and his team research and manage systematic and factor-based strategies in global fixed income and currency markets.

Bin Yang, CFA®
Quantitative Analyst
Fixed Income Systematic and Factor Investing Group
Bin is focused on factor research, portfolio construction in credit and currency markets, and works extensively to develop research and production infrastructure.

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