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Risk & Reward #04/2023

Andrew Schlossberg
President and CEO
of Invesco Ltd.

Invesco has always been a multi-asset, multi-style investment manager, with a strong focus on quantitative techniques and factor investing. We use our quarterly journal, Risk & Reward, to present innovative and timely analysis from our quantitative investment teams – seeking to improve forecasting, risk management, and portfolio performance across the asset management landscape. This winter 2023 issue of Risk & Reward is no exception.

Factor investing continues its rapid integration into the mainstream – largely due to its simplicity, transparency, and rules-based approach. But details matter, and a key differentiator between various investment managers rests in the definitions they use for their factors. At Invesco, we believe investors should diversify not only across factors, but also across the signals within those factors. A neutralized multi-signal factor approach may have several advantages. Learn why inside.

China's A-share market has a reputation for being particularly inefficient, making it an ideal hunting ground for active managers. But how should an investor go about finding the right portfolio mix? Which is better – qualitative plus fundamental or quantitative and model-driven? As is often the case, the answer lies somewhere between the extremes – and there may just be such a thing as an optimal allocation between styles. Find out more in our second article.

Turning to ESG, the plethora of benchmarks in this space can be confusing, and ESG indices often come with a high tracking error versus traditional benchmarks. Is there perhaps a better alternative to strategies that closely track common ESG benchmarks? Our article presents different indices and an ESG-oriented factor strategy that could eliminate some of the problems navigating the ESG benchmark maze.

Finally, we look at a little-regarded issue that can profoundly impact portfolio composition: modeling of non-trading days in risk forecasting. While common practice is to introduce bias, we've tested several alternatives and come to a very clear conclusion about how the reality of days without live pricing can be reflected in risk modeling.

We hope you enjoy this issue of Risk & Reward!

Best regards,

Andrew Schlossberg
President and CEO of Invesco Ltd.

Leveling up factor performance: a multi-dimensional approach

By Satoshi Ikeda, Sergey Protchenko and Viorel Roscovan, Ph.D.

Factor investing has revolutionized the way investors construct their portfolios – through a simple, transparent, rules-based approach that relies on factors to manage key drivers of risks and returns. But naïve implementation of factor strategies may prevent investors from unleashing a factor's full potential. We show how investors can potentially improve factor premiums by diversifying across signals and removing exposures to unrewarded risks.

A factor investor should, first and foremost, take a stand on which factors to harvest.[1] But, the factor view shouldn't stop there, as subtle differences in factor definition can profoundly impact performance. A crucial decision to make is whether to rely on a single or multiple signals. This choice is central to the success of a factor-based strategy and warrants careful consideration – alongside market and industry neutralization.

In this article, we'll explore how investors can enhance their factor investing strategies by diversifying across multiple correlated factor characteristics and effectively managing unrewarded market and industry risks.[2] We provide stylized examples and evidence pertaining to the benefits of such an approach for single and multi-factor investors.

Simple and multi-dimensional factor views compared

Capturing a factor through a single signal may be sufficient to generate absolute returns, but it is not optimal from a risk-return perspective. As factor behavior is complex and multidimensional, there is no one perfect signal that can explain it in full. Rather, a single signal merely serves as an approximation of what a factor should encapsulate.

When aggregating multiple signals to capture factor behavior, we adopt a portfolio-oriented approach, diversifying across signals. The signals we use should adhere to several principles: Firstly, they should align with a singular economic rationale, such as the idea that undervalued stocks tend to outperform their overvalued counterparts. Additionally, these signals may exhibit strong positive – yet still imperfect – correlations among themselves, allowing the potential for some extra alpha. This collection of signals may provide diversification benefits, notably in terms of risk and drawdown reduction.

It's important to note that, while combining correlated signals to a factor can offer advantages, the diversification benefits may not be as evident as when combining negatively correlated factors, such as value and momentum. To truly appreciate the value of diversification, one must extend beyond the simplified example of just two signals and delve into the realm of incorporating numerous signals, a practice commonly employed by practitioners in the field. In doing so, the true potential of diversification becomes apparent and reinforces the wisdom of adopting a multifaceted approach to factor investing.

We will now show why combining multiple signals makes sense using the value, momentum and quality factors in a simplified setting.

Value

Value investing strategies involve the selection of stocks that, considering their fundamental characteristics, are priced more attractively than their peers. This approach is rooted in the findings of Fama and French (1992), who show that cheaper stocks tend to outperform more expensive stocks on a risk-adjusted basis. Investors can use various metrics to find stocks that are priced below their fundamental value, which is the essence of value investing. Fama and French themselves used the book yield. However, instead of the valuation, we can also look at a company's ability to generate cash flows. Foerster, Tsagarelis and Wang (2018), for example, show that firms with a higher cash flow-to-price ratio tend to outperform on a risk-adjusted basis.

Rather than looking at a firm's valuation or cash flows separately, a prudent strategy may be to diversify across multiple imperfectly but positively correlated characteristics to help mitigate the risk associated with a single signal. Individual characteristics, although positively correlated, might still exhibit different sensitivities to various market environments and thus not perform consistently across all market conditions. By combining them, investors can create a more robust definition of value that is less susceptible to the idiosyncrasies of any one metric and helps identify genuine value opportunities across various market scenarios.

Momentum

Momentum investing revolves around the pursuit of stocks that exhibit discernible trends in their price movements. It draws upon the notion that market sentiment can often resemble the wisdom of crowds, where investor behavior can sway collectively, resulting at times in either irrational exuberance or inexplicable pessimism. Academic studies have corroborated the phenomenon that stocks displaying upward momentum tend to sustain their ascent in the short to medium term, while – conversely – a similar persistence can be observed in downward-moving stocks. Momentum strategies therefore assess stocks based on their recent performance, typically gauged over a period of 3 to 12 months (Jagadeesh and Titman, 1993).

While past price trends can be somewhat indicative of the future, alternative momentum factor definitions propose evaluating individual firm characteristics, such as idiosyncratic momentum in prices or earnings, as key expected return drivers. Combining standard momentum characteristics with such alternative facets of momentum could potentially create a more nuanced factor that considers both price-based and fundamental firm-specific information. A combined approach acknowledges that price movements may not always capture all relevant information about an asset's prospects and seeks to integrate additional sources that might help determine price trending behavior.

Quality

Quality investing strategies are geared toward identifying stocks with superior earnings quality. This entails seeking out stocks that exhibit profitability, a solid management and a track record of consistent earnings over an extended period. In essence, quality investing is the pursuit of companies that use their capital resources efficiently. Quality investors seek to optimize the value they receive for their investments, although their primary focus is on the earnings the companies generate.

An overly simplistic way to define the quality factor relies on a firm's return on equity to measure its financial health and gauge how efficiently it uses shareholder equity to generate returns. Alternative characteristics, such as gross profitability (as proposed by Novy Marx, 2013), use the core operational profitability of a firm, highlighting its competitive strengths. Combining return on equity and gross profitability creates a multifaceted quality factor definition that captures both a company's financial efficiency and its operational prowess. This holistic approach provides a more comprehensive view of a company's overall quality, enabling investors to identify firms with strong profitability, prudent financial management and competitive advantages, making it a robust strategy for quality-focused investing.

Multiple signals

We now compare the risk and return characteristics of factors based on one signal to those of factors based on multiple signals (two in our case). Our equity return data comes from Datastream and comprises both developed and emerging markets, with our regional definitions closely following the MSCI classification. For each company in our sample, we use quarterly balance sheet data from Compustat US (for the US) and Worldscope (for all other countries). Our sample runs from January 1996 to June 2023.

For each factor, we now create value-weighted tercile long-short factor portfolios based on two factor signals – a standard and an alternative one – as well as a combination of both.

More specifically:

- for value, we use book-to-market equity ratios (B/P) and, alternatively, cash flow-to-price ratios (CFY);

> Irrespective of the factor – adding the alternative signal may result in higher risk-adjusted returns.

- for momentum, we use prior 12 to 1-month return (12-1Mom) and, alternatively, a residual return post orthogonalization on a market factor model, also known as idiosyncratic momentum (iMom);
- for quality, we use return on equity (ROE) and, alternatively, gross profitability to total assets (GPA).

For developed as well as emerging markets, table 1 shows the return correlations between different specifications of the factor portfolios; table 2 shows their performance characteristics.

For each factor, the correlation coefficients are positive, confirming that our alternative factor signals capture similar dimensions to the conventional ones. However, although significantly positive, the correlations are imperfect, highlighting the complementary nature of our signals. Since the positive correlation is significantly lower in emerging markets, we expect more diversification benefits even with just a two-signal combination.[3]

As for the key performance statistics, our results show that – irrespective of the factor – adding the alternative signal results in higher risk-adjusted returns (IRs) and lower drawdowns.

Our examples, though certainly simplified, nevertheless show that a multidimensional approach is better than relying solely on a common signal with high conviction. Investors may expand their factor views by considering other signals that are correlated to B/P, 12-1Mom and ROE while still adding alpha and improving the risk-return profile.

Compensated and uncompensated factor risks

Despite these promising results, even dedicated factor investors would be unwise to disregard the uncompensated risks that come along with standard factor investing approaches. Harvesting factor premiums, whether based on single or multiple characteristics, may inadvertently create strong sector and regional biases, as well as unwanted exposures to market movements.

Such uncompensated risks are particularly prominent in single-factor approaches, but also exist in multi-factor portfolios. For example, value investors might focus on traditional industries such as retail, while momentum investors might prefer more dynamic industries like information technology.

By maintaining neutrality to sectors, regions and/or market movements, investors seek to isolate the pure effect of the targeted factor. This ensures that the factor's impact on portfolio returns remains distinct from the influence of sector or market-wide fluctuations. Industry neutrality prevents unintended sector bets, reducing the vulnerability of portfolios to industry-specific risks or economic cycles. In the same vein, region/country neutrality prevent unintended country bets, thus reducing the portfolio exposure to geopolitical risk. Finally, market neutrality ensures that the factor's performance isn't merely a reflection of broader market trends and enables a more precise assessment of its ability to deliver consistent risk-adjusted returns.

To address these concerns, we have developed enhanced versions of all the above factor strategies, based on industry/region and beta-neutral signals.[3] Table 3 shows the results.

Compared to our earlier results, the industry/region and market-neutral portfolios exhibit lower risk, significantly higher IRs and significantly lower

Table 1
Correlations of value, momentum and quality signals

	Developed markets			Emerging markets		
Value	**B/P**	**CFY**	**Combination**	**B/P**	**CFY**	**Combination**
B/P	100.0%	-	-	100.0%	-	-
CFY	73.5%	100.0%	-	48.5%	100.0%	-
Combination	93.5%	91.3%	100.0%	93.5%	69.6%	100.0%
Momentum	**12-1Mom**	**iMom**	**Combination**	**12-1Mom**	**iMom**	**Combination**
12-1Mom	100.0%	-	-	100.0%	-	-
iMom	84.8%	100.0%	-	69.1%	100.0%	-
Combination	94.8%	93.8%	100.0%	90.5%	86.9%	100.0%
Quality	**ROE**	**GPA**	**Combination**	**ROE**	**GPA**	**Combination**
ROE	100.0%	-	-	100.0%	-	-
GPA	78.7%	100.0%	-	58.3%	100.0%	-
Combination	94.5%	92.8%	100.0%	83.2%	88.6%	100.0%

Source: Invesco. Correlation coefficients between various value-weighted tercile long-short factor portfolios based on single and multiple factor signals. Data from January 1996 to June 2023. Factor strategy returns in USD and gross of fees and transaction costs.

Table 2
Performance characteristics of value, momentum and quality signals

	Developed markets			Emerging markets		
Value	**B/P**	**CFY**	**Combination**	**B/P**	**CFY**	**Combination**
Return (ann.)	0.5%	7.3%	4.9%	4.7%	11.7%	8.8%
Standard deviation	11.3%	12.3%	12.3%	11.9%	10.1%	11.8%
Information ratio	0.04	0.60	0.39	0.40	1.16	0.75
Average drawdown	-22.2%	-8.0%	-11.9%	-12.5%	-5.1%	-7.7%
Momentum	**12-1Mom**	**iMom**	**Combination**	**12-1Mom**	**iMom**	**Combination**
Return (ann.)	4.8%	6.8%	6.4%	6.7%	11.6%	11.2%
Standard deviation	15.1%	10.8%	13.8%	16.3%	12.5%	14.0%
Information ratio	0.32	0.63	0.46	0.41	0.93	0.80
Average drawdown	-18.6%	-8.3%	-13.7%	-24.7%	-6.0%	-10.7%
Quality	**ROE**	**GPA**	**Combination**	**ROE**	**GPA**	**Combination**
Return (ann.)	4.9%	7.8%	7.3%	2.7%	5.4%	4.7%
Standard deviation	9.9%	7.2%	8.9%	8.8%	8.5%	8.5%
Information ratio	0.50	1.08	0.83	0.31	0.64	0.55
Average drawdown	-13.9%	-7.2%	-10.1%	-7.7%	-4.2%	-4.7%

Source: Invesco. Performance characteristics of various value-weighted tercile long-short factor portfolios based single and multiple factor signals. Data from January 1996 to June 2023. Factor strategy returns in USD and gross of fees and transaction costs. **There is no guarantee these views will be realized. See Simulated performance disclosure at the end of the article.**

drawdowns. These improvements show the potential payoff of disentangling from rewarded and unrewarded factor risks.

Implications

To show the possible advantages of using neutralized multi-signal factors in a multi-factor portfolio, table 4 makes clear how factors (as opposed to signals within factors) exhibit negative or very low correlations to one another.[4]

We now evaluate the performance characteristics for an investor who combines value, momentum and quality factors with equal weight (QMV). In the standard case, each factor is based on a single characteristic (B/P for value, 12-1Mom for momentum, and ROE for quality). In the enhanced case, the alternative factor signals (CFY, iMom and GPA) are added and the factors are neutralized against market and industry

Table 3
Performance characteristics of industry and market-neutral value, momentum and quality signals

	Developed markets			Emerging markets		
Value	**B/P**	**CFY**	**Combination**	**B/P**	**CFY**	**Combination**
Return (ann.)	2.0%	6.6%	5.9%	1.7%	5.6%	5.3%
Standard deviation	5.3%	4.3%	5.9%	8.3%	7.1%	6.7%
Information ratio	0.37	1.56	1.00	0.20	0.79	0.79
Average drawdown	-4.7%	-1.6%	-2.5%	-10.7%	-5.7%	-4.6%
Momentum	**12-1Mom**	**iMom**	**Combination**	**12-1Mom**	**iMom**	**Combination**
Return (ann.)	2.9%	4.1%	4.8%	4.7%	7.0%	7.9%
Standard deviation	9.5%	6.2%	8.5%	8.3%	5.6%	7.7%
Information ratio	0.31	0.67	0.56	0.56	1.25	1.02
Average drawdown	-12.9%	-5.5%	-8.1%	-8.1%	-5.0%	-5.8%
Quality	**ROE**	**GPA**	**Combination**	**ROE**	**GPA**	**Combination**
Return (ann.)	3.8%	4.9%	4.4%	1.2%	4.0%	3.7%
Standard deviation	5.7%	5.4%	5.2%	6.2%	5.9%	6.0%
Information ratio	0.67	0.90	0.85	0.20	0.67	0.61
Average drawdown	-8.7%	-5.9%	-9.6%	-10.8%	-5.0%	-5.7%

Source: Invesco. Performance characteristics of various value-weighted tercile long-short factor portfolios based on single and multiple factor signals. The signals are industry/region and market beta-neutral. Sample from January 1996 to June 2023. Factor strategy returns in USD and gross of fees and transaction costs. **See simulated disclosure at the end of the article.**

Table 4
Factor correlations in standard and enhanced multi-factor strategies

	Developed markets			Emerging markets		
Standard	**Value**	**Momentum**	**Quality**	**Value**	**Momentum**	**Quality**
Value	100.0%	-	-	100.0%	-	-
Momentum	-64.3%	100.0%	-	-53.2%	100.0%	-
Quality	-22.3%	50.8%	100.0%	-59.6%	32.0%	100.0%
Enhanced	**Value***	**Momentum***	**Quality***	**Value***	**Momentum***	**Quality***
Value*	100.0%	-	-	100.0%	-	-
Momentum*	-53.4%	100.0%	-	-43.3%	100.0%	-
Quality*	-41.6%	51.7%	100.0%	-30.0%	18.8%	100.0%

Source: Invesco. Correlation coefficients between various value-weighted tercile long-short factor portfolios based on single and multiple factor signals. Standard portfolios based on B/P (value), 12-1Mom (momentum) and ROE (quality). The enhanced factors (*) add the alternative factor signals (CFY, iMom and GPA) and are industry and market neutralized. Sample from January 1996 to June 2023. Factor strategy returns in USD and gross of fees and transaction costs.

Table 5
Performance characteristics of standard and enhanced multi-factor strategies

	Developed markets		Emerging markets	
Model	**Standard (QMV)**	**Enhanced (QMV*)**	**Standard (QMV)**	**Enhanced (QMV*)**
Return (ann.)	4.0%	5.1%	5.4%	5.8%
Standard deviation	6.1%	3.4%	5.2%	3.1%
Information ratio	0.65	1.49	1.04	1.84
Average drawdown	-5.3%	-2.2%	-4.0%	-1.2%

Source: Invesco. Performance characteristics of various value-weighted tercile long-short multi-factor portfolios based on single and multiple factor signals. Standard portfolios based on B/P (value), 12-1Mom (momentum) and ROE (quality). The enhanced (*) characteristics are industry/region and market beta neutral. For the enhanced portfolios, the alternative factor signals (CFY, iMom and GPA) are added and factors are industry and market neutralized. Factors (quality, momentum, value) are equally weighted. Sample from January 1996 to June 2023. Factor strategy returns in USD and gross of fees and transaction costs.

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The enhanced factor portfolio (QMV*) comes with higher returns, significantly lower risk, significantly higher IR and significantly smaller drawdowns.

risks, as discussed above (QMV*). Table 5 shows the results.

According to these findings, a multi-factor combination delivers better results than any single factor component presented earlier. Moreover, the enhanced factor portfolio (QMV*) comes with higher returns, significantly lower risk, significantly higher IR and significantly smaller drawdowns than the standard portfolio (QMV).

Conclusion

We have shown that, due to the intricate and multifaceted nature of factor behavior, investors are better off embracing a multi-signal approach to defining factors. Diversifying factors across signals not only bolsters risk-adjusted returns but also curtails portfolio drawdowns. We have also underscored the importance of industry/region and market beta neutrality in the quest to remove unrewarded factor risks. By preserving neutrality to sectors, regions and market fluctuations, investors can isolate the core influence of the targeted factor, thereby reducing susceptibility to sector-specific perils and economic cycles. When combined, these two controls lead to an enhanced factor model that may outperform standard models across markets.

Notes

1 Gupta, Raol and Roscovan (2022) provide a comprehensive framework depicting how investors can select the factors that best align with their preferences and investment objectives.
2 Diversification does not ensure a profit or protect against loss.
3 There is no guarantee these views will be realized.
3 Our industry/region and beta neutralization is performed in two steps: In the first step, for each company and at every point in time, we subtract the average region/industry score from the raw score. In a second step, we orthogonalize the resulting score against industry dummies and market beta.
4 The correlation pattern tends to persist across regions that go beyond those considered in our study, although some time variation is possible.

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Simulated performance: Performance shown is hypothetical/simulated for educational and informational purposes only. The simulation presented here was created to consider possible results of a strategy not previously managed by Invesco for any client. It does not reflect trading in actual accounts and is provided for informational purposes only to illustrate the factor results during specific periods. There is no guarantee the model/ hypothetical results will be realized in the future. Invesco cannot assure the simulated performance results shown for these strategies would be similar to the firm's experience had it actually been managing portfolios using these strategies. In addition, the results actual investors might have achieved would vary because of differences in the timing and amounts of their investments. Simulated performance results have certain limitations. Such results do not represent the impact of material economic and market factors might have on an investment advisor's decision-making process if the advisor were actually managing client money. Simulated performance also differs from actual performance because it is achieved through retroactive application of a model investment methodology and may be designed with the benefit of hindsight.

Quantitative strategies to optimize Chinese A-share allocation

By Andrew Tong

Numerous studies indicate significant inefficiencies in China's A-share market, and asset owners who want to exploit them have historically turned to fundamental active managers. In recent years, however, model-driven quantitative strategies have gained more attention. We compare the performance of the two styles, explain some of the differences and derive the optimal quant share in a multi-manager A-share portfolio.

Fundamental active managers are often credited with in-depth company and industry knowledge, while quantitative active managers are credited with stable performance – which is particularly relevant in volatile markets. Given the conceptual differences between the two styles, their excess returns are not highly correlated. Thus, additional diversification benefits can be garnered when they are combined.

We examined the performance differences between fundamental and quantitative strategies for Chines A-shares based on 12 years of mutual fund returns (December 31, 2010 to December 31, 2022). To ensure that the results are benchmark agnostic, the first step was to calculate every fund's active monthly returns against its own official benchmark. Then, we constructed return time series for a "median fundamental manager" and a "median quant manager" using the median active monthly returns for the two groups. This allows us to quantify and compare the return and risk of these two styles while accounting for the growing number of funds over the study period.

Methodology

- Our sample covers 707 China-domiciled A-share mutual funds (as of December 31, 2022) that pursue either an active fundamental or active quantitative investment style.
- To avoid survivorship bias, the historical monthly returns of terminated funds are included in our sample.
- To allow benchmark-agnostic comparison, each fund's active return is calculated relative to its own official benchmark, which is usually a weighted composite of an equity index and the risk-free rate (for example, 95% x CSI300 Index + 5% x bank deposit interest).
- Fund returns are net of fees.
- Active risk or tracking error is the annualized standard deviation of active returns.

The median quant manager outperformed the median fundamental manager.

Performance compared

In our sample, the median quant manager outperformed the median fundamental manager (figure 1) and delivered positive active returns every year (figure 2). The median fundamental manager, on the other hand, experienced greater outperformance in some years and larger drawdowns in others. Furthermore, the share of quant managers with positive alpha is higher.

Figure 1
The median quant manager outperformed the median fundamental manager
(active return, cumulative, p.a.)

	2010 to 2022
All managers (median)	3.33%
Median quant manager	3.86%
Median fundamental manager	3.13%

Sources: WIND, Invesco analysis. Mutual fund data from December 31, 2010 to December 31, 2022. **Past performance is no guarantee of future results.**

Higher risk-adjusted returns and more persistent alpha

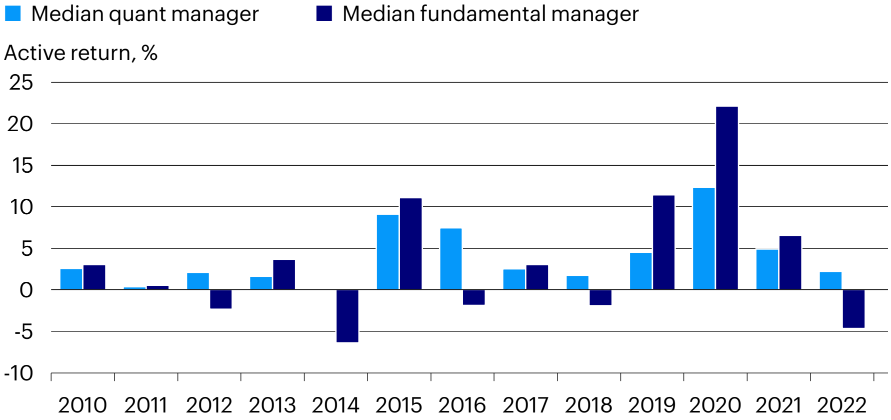
For Chinese A-shares, quant managers' returns are typically less volatile. In our analysis, the active risk (tracking error) of the median quant manager is less than half the active risk of the median fundamental manager (around 2% to 3% p.a. as compared to around 2% to 12% p.a.). Consequently, the median quant manager's information ratio (IR) is better (figure 3). The aggregate IR of the median quant manager is three times as high as that of the median fundamental manager.

We also gauged the persistence of outperformance, based on the average percentage of months a manager beats the benchmark every year. A higher percentage reflects a more even return stream. We find that the median quant manager shows greater persistence, outperforming the benchmark around 66% of the time – i.e., for roughly eight months a year.

Diversification benefits

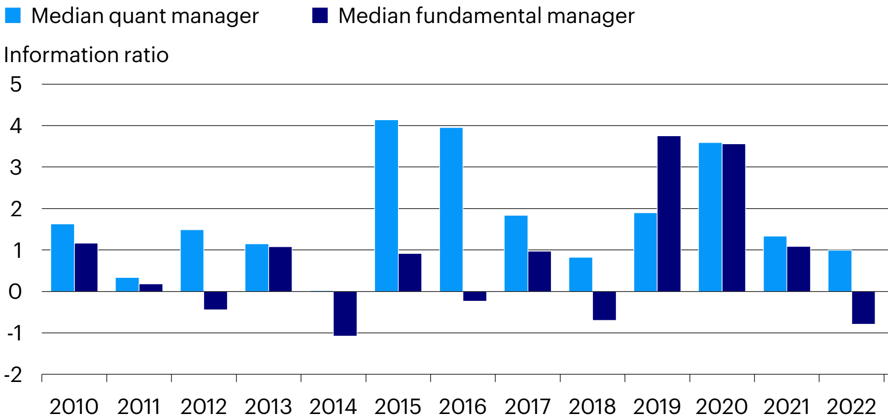
Finally, we analyzed the correlation between the monthly active returns of the two median managers. Over the full study

Figure 2
The median quant manager outperformed the benchmark every year



Sources: WIND, Invesco analysis. Mutual fund data from December 31, 2010 to December 31, 2022. **Past performance is no guarantee of future results.**

Figure 3
The median quant manager achieved a higher information ratio



Sources: WIND, Invesco analysis. Note: IR is calculated using median active return. Mutual fund data from December 31, 2010 to December 31, 2022. **Past performance is no guarantee of future results.**

period, we find a relatively low correlation of 0.467, suggesting that the quant manager's alpha is relatively uncorrelated with that of the fundamental manager. Accordingly, adding quant funds to a fundamentally managed A-share portfolio may improve diversification effects.

The strengths of quant managers...
The relatively strong performance of quant managers may be attributed to their differentiated investment process and competitive edge in information processing. Most quantitative managers adopt a systematic process that minimizes the subjective biases of their portfolio managers. With such a disciplined risk approach, it is unsurprising that quant managers had highly repeatable performance.

Quant managers' ability to analyze large datasets swiftly is also a significant advantage in the A-share market – which now includes over 5,000 listed companies. While, due to resource constraints, most fundamental managers and brokerage firms limit their research to just a fraction of the entire stock universe, quant models can sift out asset mispricing from the entire market.

Quant managers' ability to analyze large datasets swiftly is a significant advantage in the A-share market.

Market inefficiencies in China can arise from factor risk premia, retail trading behavioral bias and even top-down policy effects. Quant strategies can utilize these diversified alpha sources because of their capacity to more quickly process and analyze information.

... and the optimal quant allocation
So, what allocation to quant strategies would be optimal in an A-share portfolio? We examine this from the perspective of a hypothetical asset owner who has selected both a fundamental manager and a quant manager. To disentangle manager selection from weight allocation effects, we'll analyze two cases: one based on median-performance managers ("base case") and another based on top-quartile managers ("high performance case"). In

Figure 4
Hypothetical portfolio weights

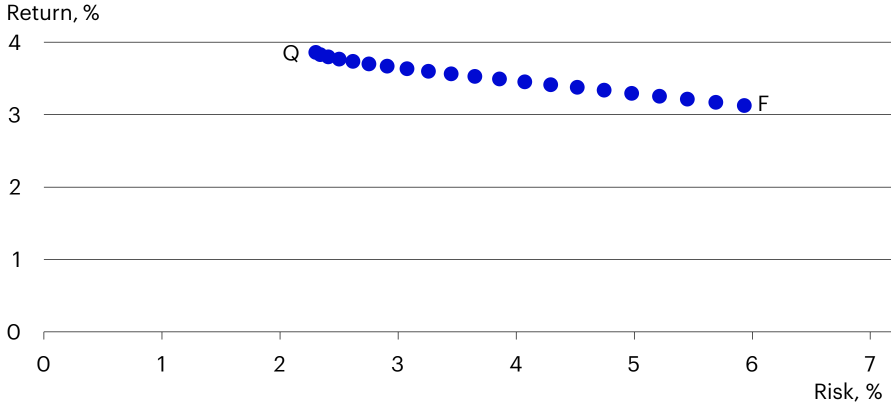
Portfolio	Quant manager	Fundamental manager
P1 (F)	0%	100%
P2	5%	95%
P3	10%	90%
P4	15%	85%
P5	20%	80%
P6	25%	75%
P7	30%	70%
P8	35%	65%
P9	40%	60%
P10	45%	55%
P11	50%	50%
P12	55%	45%
P13	60%	40%
P14	65%	35%
P15	70%	30%
P16	75%	25%
P17	80%	20%
P18	85%	15%
P19	90%	10%
P20	95%	5%
P21 (Q)	100%	0%

Source: Invesco analysis.
For illustrative purposes only.

both cases, we construct an efficient frontier plot representing 21 portfolios of varying manager weights (figure 4) and rebalance them every month. In each plot, F represents the portfolio that is 100% allocated to the fundamental manager, while Q represents the portfolio that is 100% allocated to the quant manager.

The base case
In the base case, we assume that that the asset owner cannot forecast manager performance – implying that the selected managers can be approximated by the two

Figure 5
Base case: The median quant manager achieves higher returns with lower risk
Efficient frontier (base case)



Sources: WIND, Invesco analysis. Annualized cumulative monthly median returns from December 31, 2010 to December 31, 2022. **Past performance is no guarantee of future results.**

Figure 6

Base case: Larger allocations to the median quant manager tend to improve the information ratio

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21
2010	1.17	1.24	1.32	1.41	1.51	1.62	1.75	1.89	2.05	2.21	2.38	2.52	2.63	2.66	2.62	2.51	2.35	2.16	1.97	1.79	1.63
2011	0.18	0.19	0.19	0.20	0.20	0.21	0.21	0.22	0.23	0.24	0.25	0.25	0.26	0.28	0.29	0.30	0.31	0.32	0.33	0.33	0.34
2012	-0.44	-0.42	-0.39	-0.36	-0.33	-0.29	-0.25	-0.21	-0.16	-0.10	-0.03	0.04	0.13	0.23	0.35	0.48	0.64	0.83	1.03	1.26	1.49
2013	1.08	1.09	1.11	1.12	1.14	1.15	1.17	1.18	1.20	1.22	1.23	1.25	1.26	1.27	1.28	1.28	1.28	1.26	1.24	1.20	1.15
2014	-1.08	-1.07	-1.06	-1.06	-1.04	-1.03	-1.02	-1.00	-0.98	-0.96	-0.93	-0.89	-0.85	-0.80	-0.74	-0.66	-0.57	-0.45	-0.31	-0.15	0.02
2015	0.92	0.96	1.00	1.05	1.10	1.16	1.22	1.30	1.38	1.47	1.58	1.71	1.86	2.04	2.25	2.51	2.82	3.17	3.56	3.93	4.14
2016	-0.23	-0.18	-0.13	-0.07	-0.01	0.07	0.15	0.25	0.36	0.48	0.63	0.80	1.01	1.25	1.53	1.87	2.27	2.72	3.19	3.63	3.96
2017	0.97	1.00	1.04	1.08	1.12	1.16	1.21	1.26	1.31	1.37	1.42	1.48	1.55	1.61	1.67	1.73	1.78	1.82	1.84	1.85	1.84
2018	-0.70	-0.65	-0.60	-0.55	-0.49	-0.42	-0.36	-0.28	-0.20	-0.12	-0.04	0.05	0.14	0.24	0.33	0.42	0.51	0.59	0.68	0.75	0.82
2019	3.76	3.77	3.77	3.77	3.77	3.75	3.73	3.69	3.64	3.57	3.49	3.39	3.27	3.14	2.99	2.82	2.65	2.46	2.28	2.09	1.90
2020	3.56	3.58	3.60	3.62	3.64	3.66	3.68	3.70	3.72	3.73	3.75	3.76	3.77	3.77	3.77	3.76	3.75	3.72	3.69	3.65	3.59
2021	1.08	1.10	1.12	1.14	1.16	1.18	1.20	1.21	1.23	1.25	1.27	1.29	1.30	1.32	1.33	1.34	1.34	1.35	1.34	1.34	1.33
2022	-0.79	-0.76	-0.74	-0.70	-0.67	-0.63	-0.59	-0.54	-0.48	-0.42	-0.35	-0.27	-0.18	-0.07	0.05	0.18	0.33	0.49	0.66	0.83	0.99

Sources: WIND, Invesco analysis. **Past performance is no guarantee of future results.**

median managers. Since, over the full study period, the median quant manager (Portfolio Q) achieves a higher return with lower risk, the overall information ratio of this manager is also higher. Therefore, the efficient frontier is a monotonic decreasing function, favoring a 100% allocation to the quant manager (figure 5).

Even though the median fundamental manager achieved a higher return in most years, the higher drawdowns associated with this manager lead to lower returns overall, and a very high tracking error. Therefore, in most years, larger allocations to the quant manager lead to a higher information ratio (figure 6).

The high performance case

In the high performance case, we assume that the asset owner can forecast manager returns fairly accurately and only selects managers from the top performance quartiles of both investment styles. We therefore construct return time series for a "top-quartile fundamental manager" and a "top-quartile quant manager". Rather than median monthly returns of the full sample, we now use the top 25th percentile monthly return – and then follow the same procedure as in the base case. Again, we construct 21 hypothetical portfolios with varying weights allocated to the two managers (figure 7).

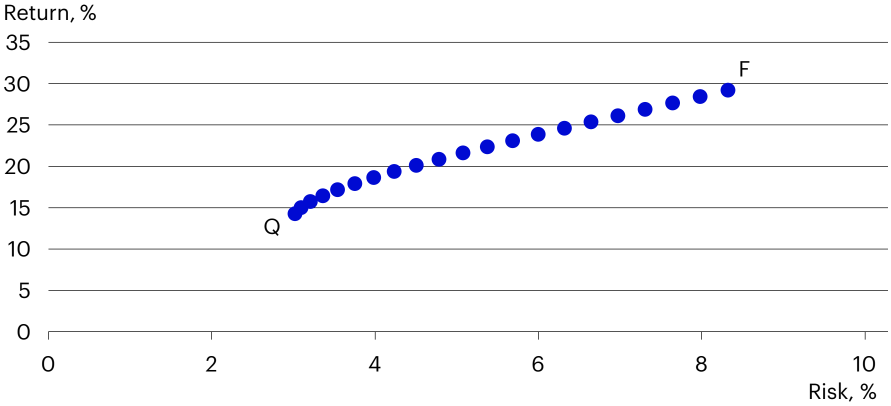
Unlike the base case, there is now a clear trade-off between risk and reward (figure 7). Over the full study period, Portfolio F, which is 100% invested in the fundamental manager, has the highest return but also comes with the highest risk. As the portfolio allocation shifts to the quant manager (towards the bottom left of the efficient frontier), portfolio return and risk decrease monotonically until we reach Portfolio Q, which has the lowest return but also the lowest risk.

Despite the higher returns, a 100% allocation to the top-quartile fundamental manager would be optimal in less than half of the years – because a balanced

Figure 7

High performance case: A trade-off between risk and reward

Efficient frontier (high performance case)



Sources: WIND, Invesco analysis. Annualized cumulative monthly median returns from December 31, 2010 to December 31, 2022. **Past performance is no guarantee of future results.**

Figure 8
High performance case: A balanced allocation tends to improve the information ratio

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21
2010	3.61	3.68	3.76	3.84	3.92	4.01	4.10	4.19	4.28	4.37	4.46	4.53	4.59	4.63	4.65	4.63	4.57	4.47	4.33	4.15	3.94
2011	2.67	2.74	2.83	2.92	3.03	3.14	3.27	3.42	3.58	3.76	3.97	4.20	4.46	4.73	5.01	5.28	5.49	5.58	5.52	5.27	4.87
2012	2.76	2.80	2.84	2.88	2.93	2.99	3.04	3.10	3.17	3.24	3.32	3.41	3.50	3.60	3.70	3.81	3.91	4.01	4.08	4.13	4.13
2013	3.80	3.84	3.88	3.92	3.98	4.03	4.09	4.16	4.24	4.33	4.42	4.53	4.65	4.78	4.92	5.08	5.23	5.36	5.45	5.45	5.30
2014	2.64	2.72	2.81	2.90	3.01	3.12	3.24	3.37	3.52	3.67	3.84	4.01	4.19	4.37	4.53	4.67	4.77	4.80	4.76	4.63	4.43
2015	4.00	4.06	4.14	4.22	4.31	4.42	4.54	4.68	4.84	5.03	5.25	5.51	5.83	6.20	6.65	7.19	7.81	8.47	9.02	9.16	8.62
2016	3.29	3.41	3.53	3.67	3.82	3.98	4.15	4.33	4.52	4.74	4.96	5.20	5.46	5.73	6.02	6.31	6.61	6.90	7.17	7.41	7.60
2017	7.22	7.29	7.35	7.41	7.47	7.52	7.56	7.58	7.59	7.58	7.55	7.49	7.40	7.28	7.12	6.92	6.69	6.43	6.14	5.83	5.50
2018	5.70	5.86	6.02	6.17	6.33	6.47	6.61	6.73	6.83	6.90	6.94	6.95	6.91	6.83	6.71	6.55	6.35	6.13	5.89	5.63	5.37
2019	9.29	9.40	9.50	9.61	9.71	9.81	9.90	9.97	10.02	10.04	10.01	9.93	9.79	9.57	9.27	8.89	8.43	7.90	7.32	6.71	6.08
2020	7.57	7.59	7.60	7.62	7.64	7.67	7.69	7.72	7.75	7.78	7.81	7.83	7.86	7.87	7.88	7.88	7.86	7.81	7.74	7.62	7.45
2021	5.68	5.68	5.68	5.67	5.67	5.66	5.65	5.64	5.62	5.59	5.55	5.51	5.45	5.38	5.29	5.18	5.05	4.90	4.72	4.53	4.30
2022	4.07	4.15	4.23	4.33	4.43	4.54	4.66	4.79	4.94	5.09	5.26	5.44	5.63	5.82	6.01	6.18	6.31	6.38	6.34	6.19	5.92

Sources: WIND, Invesco analysis. **Past performance is no guarantee of future results.**

“We believe that long-term investors should not ignore the diversification benefit of lower-risk quant strategies.

allocation to both managers is more likely to lead to a higher information ratio and satisfy the overall portfolio objectives (figure 8).

Conclusion

We have analyzed the long-term performance of actively managed fundamental and quantitative portfolios of Chinese A-shares. In our sample, the median quant manager achieves higher active performance and a higher information ratio. Although the median fundamental manager’s active return is higher in most years, this is offset by larger and more frequent drawdowns.

We then provide a dual-case framework to help investors determine their optimal allocation to a quant strategy. In the case of a hypothetical investor who cannot forecast manager performance, we find that a higher allocation to the quant strategy better satisfies the overall return and risk objectives. On the other hand, if the investor has a consistently strong forecasting ability, there is a trade-off between return and risk. Then, on average, return objectives are better satisfied through higher allocation to the fundamental manager, while risk objectives can be better achieved through higher allocation to the quant manager. However, the gradient of the trade-off function varies significantly each year, suggesting that higher-risk portfolios are not consistently well compensated. Hence, we believe that long-term investors should not ignore the diversification benefit of lower-risk quant strategies, which can smooth out their portfolio return streams and improve the portfolio information ratio.

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Investment risks: The value of investments and any income will fluctuate (this may partly be the result of exchange rate fluctuations) and investors may not get back the full amount invested. When investing in less developed countries, you should be prepared to accept significantly large fluctuations in value. Investment in certain securities listed in China can involve significant regulatory constraints that may affect liquidity and/or investment performance.

With contributions from Monica Uttam, Thought Leadership and Insights, Asia Pacific
This is an abridged version of the whitepaper “What is the optimal allocation to quant strategies for China A-share investors?”, May 2023.

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ESG: Navigating the benchmark maze

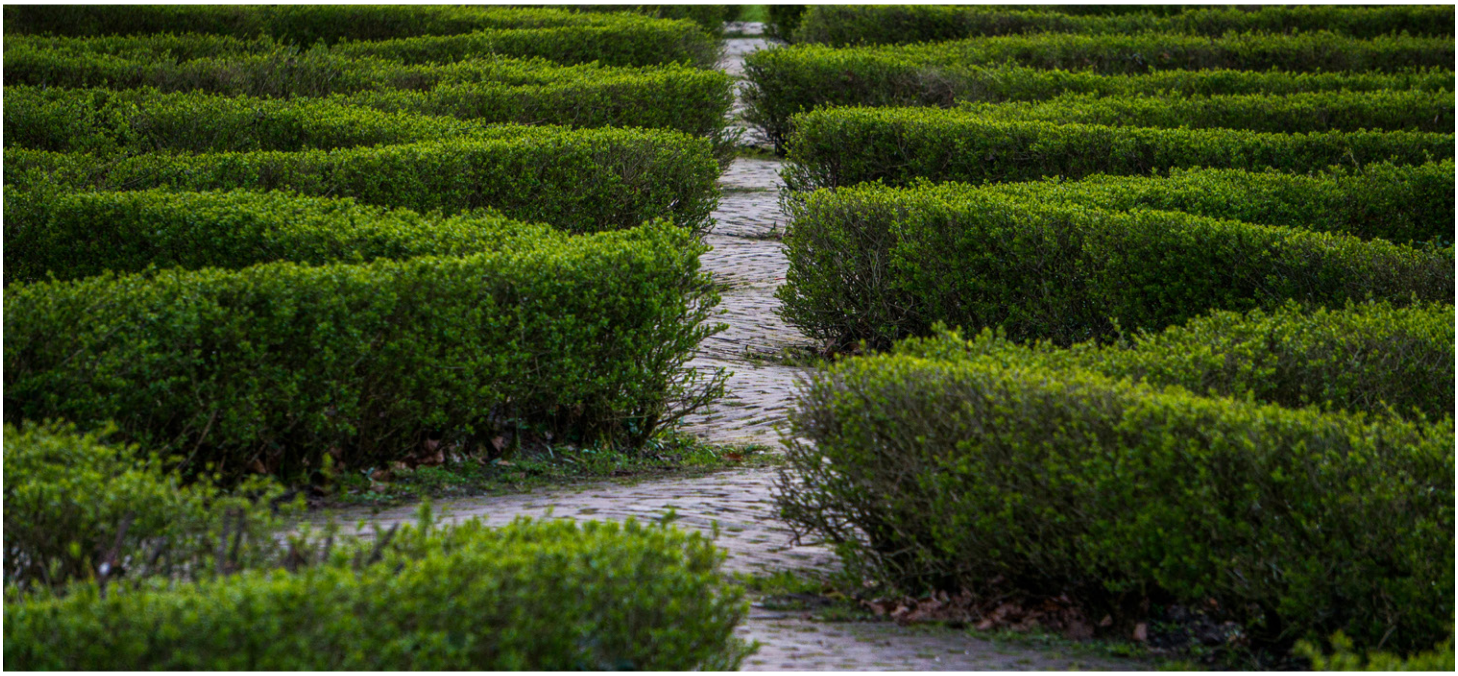
By Julian Keuerleber, David Mischlich and Alexander Tavernaro

We've analyzed popular global and regional ESG indices, looking at their past performance and factor patterns, as well as comparing them to traditional capitalization-weighted indices. We also looked at ways to mitigate the risks inherent in the individual ESG benchmarks and present an alternative that may successfully address some of their shortcomings.

Investors face a plethora of ESG benchmarks, making for a landscape that is often confusing and fraught with uncertainty about which one to choose – especially for those favoring a passive investment strategy. We feel the time has come to seek greater clarity.

When choosing a non-traditional benchmark, a natural first step is to investigate alternative indices that best reflect an investor´s non-financial objectives. Popular index providers offer a wide range: MSCI Inc., for example, claims to be the world's largest provider of ESG indices, with more than 1,500 equity and fixed income ESG indices to help institutional investors manage, measure and report on ESG mandates.[1]

In our analysis, we will compare four global indices – the MSCI World SRI[2] Index, the MSCI World Climate Paris Aligned Index, the MSCI World ESG Leaders Index and the MSCI World ESG Universal Index. These indices include large and mid-cap stocks across 23 developed market countries, as defined by MSCI. There are differences in the index construction methodologies to achieve the target outcomes. We'll also compare the indices' European counterparts.



> Since their inception, the four MSCI ESG indices have slightly outperformed their parent indices.

An abundance of choices ...

The **MSCI World SRI Index** is a capitalization-weighted index that excludes companies whose products have negative social or environmental impacts. Stock selection is based on proprietary MSCI research with the objective of achieving a diversified SRI benchmark comprised of companies with a strong sustainability profile. Companies that do not meet these criteria are excluded. The index has approximately 400 constituents.

The **MSCI World Climate Paris Aligned Index** is designed to exceed the minimum standards of the EU Paris-Aligned Benchmark by incorporating the recommendations of the Task Force on Climate-related Financial Disclosures. The index is a common benchmark for investors seeking to reduce their exposure to physical climate risks and to transition to a lower carbon economy. The index comprises approximately 600 constituents and is the only index in our sample that uses an optimization approach to arrive at index weights; the other indices apply heuristics.

The **MSCI World ESG Leaders Index** is designed to represent the performance of companies based on environmental, social and governance criteria. The sector exposures are closely tied to the parent index, the MSCI World Index. The index targets 50% free float-adjusted market capitalization coverage of each sector. Stock selection of constituents is based on criteria, including the MSCI ESG Rating, its trend and individual companies' industry-adjusted ESG score, as well as each company's involvement in specific business activities and exposure to controversies. The index comprises approximately 700 constituents.

The **MSCI World ESG Universal Index** is designed to reflect the performance of an investment strategy that seeks exposure to companies with a robust – and improving – ESG profile. The index tilts away from free float market cap weights, but uses only very basic exclusions. The index comprises approximately 1,500 constituents.

... with different return characteristics ...

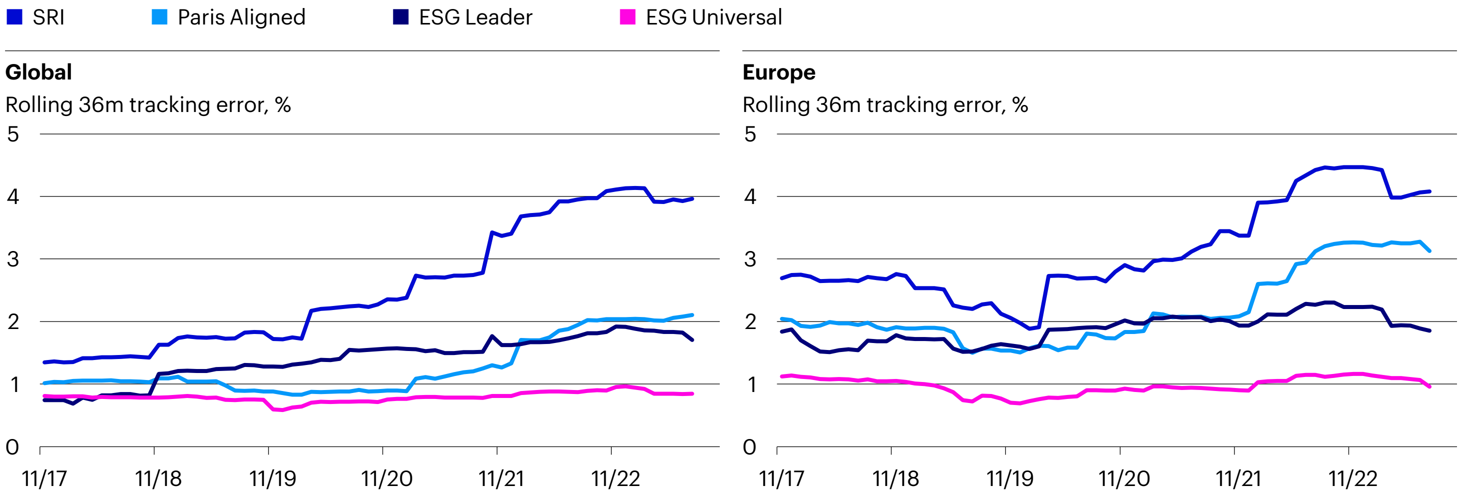
Since their inception almost nine years ago, the four MSCI ESG indices have slightly outperformed their parent indices, while performance over the short and medium term has been mixed. This is true for the

Figure 1
Annual relative performance of ESG indices vs. their parent indices

	Global indices vs. MSCI World				European indices vs. MSCI Europe			
	SRI	Paris Aligned	ESG Leaders	ESG Universal	SRI	Paris Aligned	ESG Leaders	ESG Universal
1 year	0.21	-1.64	-0.06	-0.10	-2.37	-2.18	-0.80	-0.20
3 years	-0.11	-1.16	0.16	-0.37	-1.83	-1.19	-1.35	-0.29
5 years	1.64	0.14	0.47	0.31	1.44	0.93	0.85	0.84
Since inception	1.42	0.62	0.04	0.12	1.53	0.82	0.52	0.59

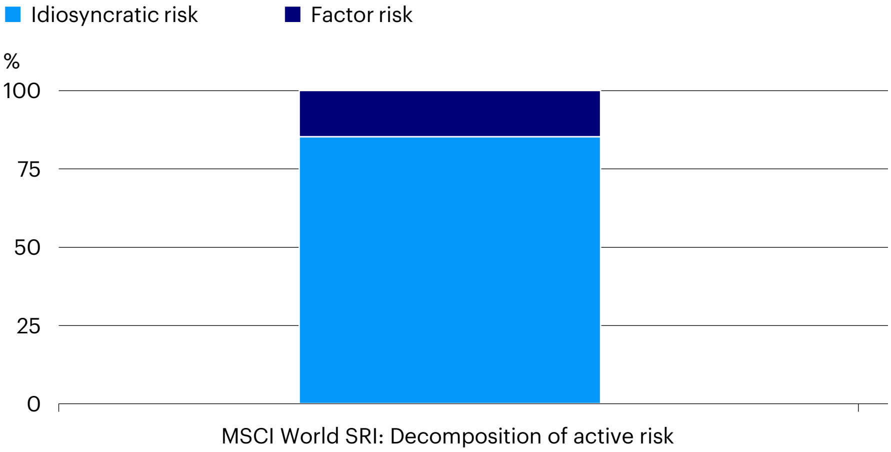
SRI: MSCI World SRI Index/MSCI Europe SRI Index; Paris Aligned: MSCI World Climate Paris Aligned Index/MSCI Europe Climate Paris Aligned Index; ESG Leaders: MSCI World ESG Leaders Index/MSCI Europe ESG Leaders Index, ESG Universal: MSCI World ESG Universal Index/MSCI World ESG Universal Index.
Source: MSCI, Invesco calculations. Relative performance p.a. from Novemer 30, 2014 (common index inception) to July 31, 2023. **Past performance is not indicative of future results.** An investment cannot be made directly in an index.

Figure 2
Tracking error of ESG indices vs. their parent indices



SRI: MSCI World SRI Index/MSCI Europe SRI Index; Paris Aligned: MSCI World Climate Paris Aligned Index/MSCI Europe Climate Paris Aligned Index; ESG Leaders: MSCI World ESG Leaders Index/MSCI Europe ESG Leaders Index, ESG Universal: MSCI World ESG Universal Index/MSCI World ESG Universal Index.
Source: MSCI, Invesco calculations. 36-month tracking error from November 30, 2017 to July 31, 2023.

Figure 3
Tracking error of the MSCI World SRI Index vs. its parent index



Source: MSCI, Invesco calculations. MSCI World SRI Index as of July 31, 2023.

“

Almost all of the tracking error was attributable to idiosyncratic stock-specific risks.

“

All ESG indices exhibit higher turnover.

global indices as well as their European versions. The ESG indices have outperformed their respective market capitalization-weighted parent indices over the full period and over 5 years. Interestingly, ‘stricter’ ESG indices have outperformed their less strict counterparts both in Europe and globally. On the other hand, relative performance over the most recent 1-year and 3-year periods has been lackluster, seeing global indices performing in line with and European indices underperforming their non-ESG counterparts. The MSCI Climate Paris Aligned Index has underperformed in both regions.

... and sometimes considerable active risk

The realized tracking error of ESG indices over their parent indices can range from 0.5% to over 4.0% (figure 2). While active risk has remained stable for the MSCI ESG Leaders and MSCI ESG Universal Screened index suites, it has increased significantly for the MSCI Climate Paris Aligned and MSCI SRI indices. For passive or enhanced index investors, this poses a challenge, as changes in active risk profiles can distort overall asset allocation. This can lead to increased monitoring costs and, in the case of asset allocation changes, increased turnover costs as well.

But where do these high levels of active risk come from? As an example, we have decomposed the tracking error of the MSCI World SRI Index into various components: elements of active risk that can be explained by common factors (e.g., sectors, countries, value factor, etc.) and a residual element that captures idiosyncratic stock-specific risks (figure 3). In July 2023, almost all of the tracking error was attributable to idiosyncratic stock-specific risks (86%). This is not surprising given the high concentration of this index; for example, Microsoft alone accounts for 16%.[3] The second largest contributor was the different sector structure (7%), primarily due to the considerable overweight in technology. This is followed by market sensitivity; i.e., beta (2%), as the SRI index’ beta is estimated to be around 1.05. Factors such as momentum, quality and value share the remaining 5%, with each accounting for only a negligible portion of total active risk.

Turnover, concentration ...

All ESG indices, for both Europe and the world, exhibit higher turnover, ranging from 10% to 28% p.a. – compared to 2% for the parent indices (figure 4). The ESG indices also appear to be more concentrated: While the number of index constituents could still indicate a reasonably well-diversified portfolio, the weight of the largest and the ten largest stocks indicate a significantly higher concentration risk, especially for the SRI index.

Figure 4
Turnover and concentration in comparison

	Global indices					European indices				
	SRI	**Paris Aligned**	**ESG Leaders**	**ESG Universal**	**MSCI World**	**SRI**	**Paris Aligned**	**ESG Leaders**	**ESG Universal**	**MSCI Europe**
Turnover p.a.	22%	11%	13%	13%	2%	28%	12%	27%	10%	2%
Number of stocks	407	607	724	1494	1512	199	260	206	421	428
Largest weight	16%	6%	8%	5%	5%	11%	3%	6%	4%	3%
Top 10 weight	34%	22%	26%	18%	20%	45%	22%	37%	26%	23%

SRI: MSCI World SRI Index/MSCI Europe SRI Index; Paris Aligned: MSCI World Climate Paris Aligned Index/MSCI Europe Climate Paris Aligned Index; ESG Leaders: MSCI World ESG Leaders Index/MSCI Europe ESG Leaders Index, ESG Universal: MSCI World ESG Universal Index/MSCI World ESG Universal Index.
Source: MSCI, Invesco calculations. Turnover data from December 31, 2014 (index inception) to July 31, 2023; all other data as of July 31, 2023.

Figure 5

Relative factor loadings of ESG indices vs. their parent indices

SRI: MSCI World SRI Index/MSCI Europe SRI Index; Paris Aligned: MSCI World Climate Paris Aligned Index/MSCI Europe Climate Paris Aligned Index; ESG Leaders: MSCI World ESG Leaders Index/MSCI Europe ESG Leaders Index, ESG Universal: MSCI World ESG Universal Index/MSCI World ESG Universal Index.
Source: MSCI, Invesco calculations. Relative factor loadings from June 30, 2017 (index inception) to July 31, 2023.

> A multi-factor ESG strategy can be effective in achieving not only risk and return objectives, but also sustainability goals.

... and factor loadings

In addition, there are different (and potentially unwanted) factor loadings. Through the lens of the Invesco Quantitative Strategies model, the relative momentum exposure (measuring both price and fundamental momentum), fluctuates considerably. The relative quality exposure, on the other hand, remains unchanged – or rises. This is plausible since certain governance elements might be related to the quality concept. The value exposure is consistently below that of the parent index, indicating that ESG indices are invested in more expensive stocks.[4] While none of the indices target a specific factor profile, it is important to understand and monitor factor loadings regularly, as they can be a significant contributor to performance.

So, what is the alternative?

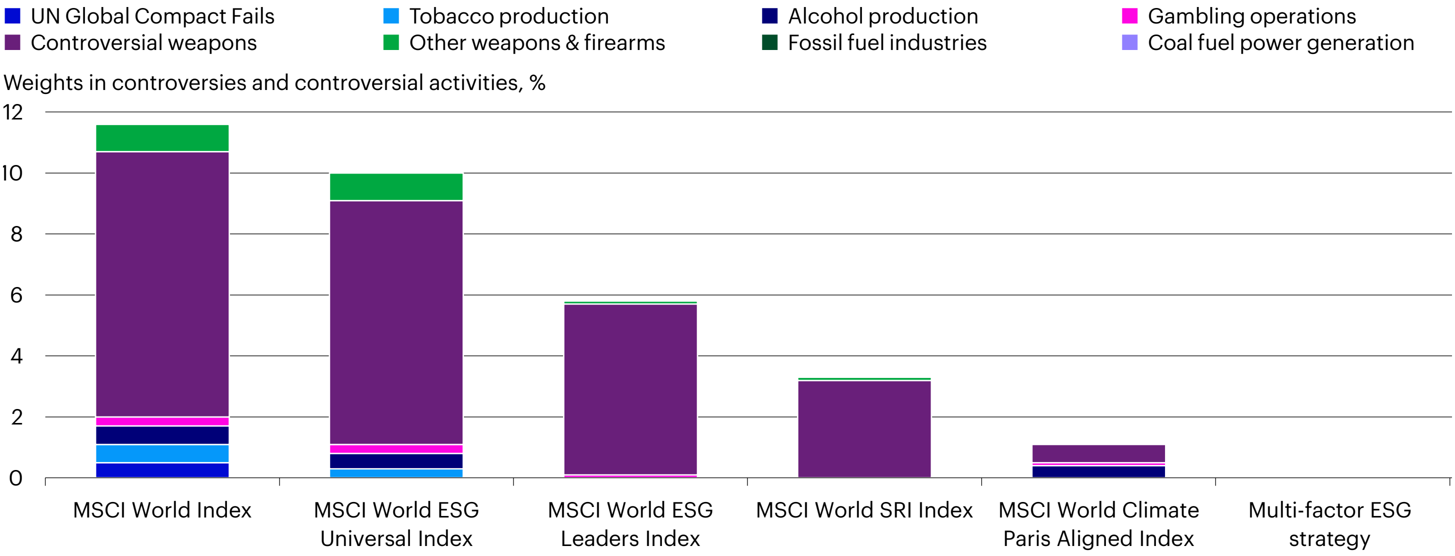
Having analyzed the characteristics and shortcomings of common ESG indices, we now turn to a possible alternative. In our view, a multi-factor ESG strategy can be effective in achieving not only risk and return objectives, but also sustainability goals. To illustrate this, we have constructed a hypothetical long-only strategy against the MSCI World Index based on Invesco's proprietary model portfolio approach.[5] The investable universe consists of global developed-market large and mid caps, Whereas some controversial companies and activities are still included in the ESG benchmarks, they are completely eliminated from our model portfolio.

filtered for ESG characteristics. To avoid companies involved in controversial business activities and controversies, we used a best-in-class approach and excluded the worst 51% of assets within each sector and region.

Figure 6 compares the ESG profile of the final optimized portfolio with that of the MSCI World Index and the four global MSCI ESG benchmarks. Whereas some controversial companies and activities are still included in the ESG benchmarks, they are completely eliminated from our model portfolio. This illustrates that a multi-factor ESG strategy is an effective method to account for an investor's sustainability preferences.

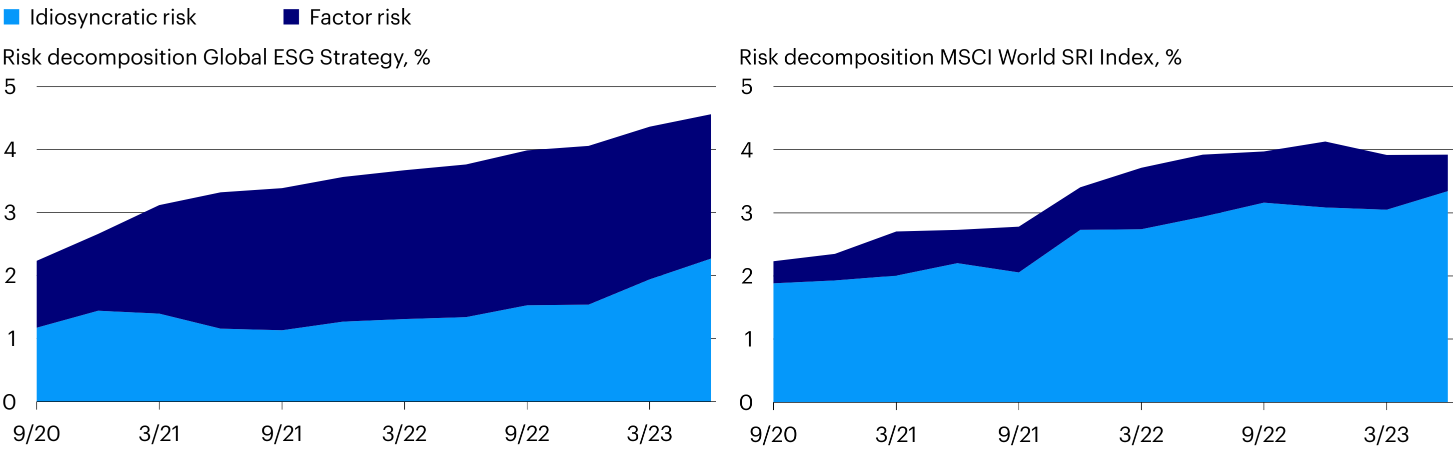
The multi-factor ESG model portfolio is less concentrated than the indices, with balanced tilts to rewarded factors and fewer unintended bets. Comparing its ex-post risk attribution to that of the MSCI World SRI Index (which, as shown above, is the strictest of the four MSCI ESG indices), we find that the residual risk is significantly lower while the contribution from factor risk is significantly higher through time (figure 7). This aligns well with our optimization target.

Figure 6
Revenues from controversial activities are eliminated from the IQS model portfolio, but not from the MSCI ESG indices
Controversies are eliminated in IQS model portfolio, ESG indices still show high exposures



Portfolios are rebalanced monthly using an optimization approach to maximize the sensitivity to an equal risk attribution portfolio of Quality, Momentum and Value factors. There are 11 signals in the Quality bucket, including metrics to measure accrual and profitability; 13 signals in the Momentum bucket, including various price and earnings momentum signals; and 8 signals in the Value bucket, such as earnings yield and free-cash flow yield. We keep portfolio betas, as well as sector, industry, region, country and currency exposures, close to the MSCI World benchmark. In addition, turnover is controlled during the monthly rebalancing. There are (on average) 239 assets in our portfolio over time and the number of top 10 single stock holdings is comparable to the MSCI World with a total weight of 20%. This results in a realized tracking error of about 3% p.a.
Source: Invesco, Moody's ESG Solutions. As of September 29, 2023. Moody's ESG Solutions business involvement data. Indicates portfolio/benchmark weight of holdings which derive revenue from this business activity above a threshold of 10%.

Figure 7
Less stock-specific risk, more factor risk in the model portfolio



Source: MSCI, Invesco calculations. Tracking error vs. MSCI World Index from September 30, 2020 to June 30, 2023.

Summary
When seeking to incorporate ESG, passive investors must be aware of the differences between the various ESG indices and their active risk over traditional capitalization-weighted indices. As it turns out, an ESG-oriented multi-factor strategy may sometimes be the better alternative, lowering exposure to controversial companies even below that of the strictest ESG benchmark and leading to a more balanced risk structure overall.

Notes
1 https://www.msci.com/our-solutions/indices/esg-indices
2 SRI = Socially Responsible Investment
3 MSCI also offers UCITS-compliant indices with capped weights.
4 This implies lower capital costs for more sustainable companies and may thus be desirable from a sustainability perspective. Nevertheless, it poses financial risks.
5 For more details see Quantitative Strategies Team (2022).

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Modeling non-trading days in risk forecasting

By Moritz Brand, Alexandar Cherkezov and Dr. David Happersberger

When forecasting daily market risk, a public holiday's zero return leads to a lower, and distorted, risk estimate. We tested different methods for imputing holiday returns and analyzed whether they smooth risk forecasts and reduce turnover in DPPI risk budgeting strategies.

Forecasting daily market risk involves several practical difficulties. For example: public or bank holidays, when exchanges are closed and prices do not change. To account for these, some risk models may assume a daily return of zero – which can potentially have a significant impact on the model output. In Copula-GARCH models, for example, which assign a significant weight to the most recent data, the zero-return assumption will result in a lower risk estimate.

For a risk budgeting strategy like Dynamic Proportion Portfolio Insurance (DPPI), a lower risk estimate can lead to a higher target exposure, potentially inducing a buy trade. This means that, when the market reopens, the price may rise disproportionately, leading to a higher risk estimate and a lower target exposure – and a sell trade. Thus, inadequate modeling of non-trading days may generate unnecessary turnover, and this effect is particularly pronounced when market risk is already high and risk management is at the forefront.

Modern risk modeling is guided by empirical patterns, which cannot be adequately captured with a conventional normal distribution assumption. Extreme events occur far more often than the normal distribution suggests. Volatility and correlations are not constant, and volatility clustering is not uncommon.

An effective method of understanding empirical risk is the Copula-GARCH model, as proposed by Patton (2006) or Jondeau and Rockinger (2006): In the first step, risk dynamics are measured by fitting univariate GARCH(1,1) models to the underlying return series. Assuming a return process $(r_{i,t})_{i \in N, t \in Z}$, the mean and variance equations are given by:

$$r_{i,t} = \mu_i + \varepsilon_{i,t}$$

$$\varepsilon_{i,t} = z_{i,t} \sqrt{\sigma^2_{i,t}}$$

$$z_{i,t} \sim D_i(0, 1, \xi_i, \upsilon_i)$$

$$\sigma^2_{i,t} = \omega_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i \sigma^2_{i,t-1}$$

where $\omega_i > 0$, $\alpha_i \geq 0$ and $\beta_i \geq 0$, $i = 1,\ldots, N$. Moreover, $r_{i,t}$ are the returns of the i^{th} portfolio asset at time t , and D_i reflects the skewed t-distribution with skewness parameter ξ_i and shape parameter υ_i according to Hansen (1994).

In the second step, a time-varying copula permits us to estimate the marginal distributions of the asset returns together with the dependence structure. In particular, the joint distribution of the NGARCH return processes can be expressed depending on an N-dimensional copula C:

$$F_t(r_t \mid \mu_t, \sigma_t) = C_t(F_{1,t}(r_{1,t} \mid \mu_{1,t}, \sigma_{1,t}),\ldots, F_{N,t}(r_{N,t} \mid \mu_{N,t}, \sigma_{N,t}) \mid F_{t-1})$$

where $F_1(\bullet),\ldots, F_N(\bullet)$ are the conditional marginal distributions of the return processes. The dependence structure of the margins is assumed to follow a Student's t-copula with conditional correlation R_t and constant shape parameter η. We opt for the Student's t-copula for modeling the dependence of financial assets, since the normal copula cannot account for tail dependence. The conditional density of the Student's t-copula at time t is given by:

$$c_t(u_{i,t},\ldots,u_{N,t} \mid R_t,\eta) = \frac{f_t(F^{-1}_{i,t}(u_{i,t} \mid \eta),\ldots,F^{-1}_{i,t}(u_{N,t} \mid \eta) \mid R_t,\eta)}{\prod^{n}_{i=1} f_i(F^{-1}_{i,t}(u_{i,t} \mid \eta) \mid \eta)}$$

where $u_{i,t} = F_{i,t}(r_{i,t} \mid \mu_{i,t}, \sigma_{i,t}, \xi_i, v_i)$ is the probability integral transformation of each series by its conditional distribution $F_{i,t}$ estimated via the first-stage GARCH process, $F^{-1}_{i,t}(u_{i,t} \mid \eta)$ represents the quantile transformation of the uniform margins subject to the common shape parameter of the multivariate density, $F_t(\bullet \mid R_t, \eta)$ is the multivariate density of the Student's t-distribution with conditional correlation R_t and shape parameter η and $f_i(\bullet \mid \eta)$ defines the univariate margins of the multivariate Student's t-distribution with common shape parameter η. Furthermore, we allow the parameters of the conditional copula to vary with time in a manner analogous to a GARCH model for conditional variance (e.g., Patton, 2006). Specifically, we assume the dynamics of R_t to follow an asymmetric generalized dynamic conditional correlation (AGDCC) model according to Cappiello, Engle and Sheppard (2006).

Based on the copula estimates, we then generate N sets of random pseudo-uniform variables and transform these into corresponding realizations of the error processes by using the quantile function of the margins. These simulated numbers are then used together with the conditional volatility forecast of the GARCH models to derive a Monte Carlo set of returns for each asset.[1]

Another matter to consider, in addition to the structure of the model itself, is that of an appropriate risk measure. Whereas many risk management approaches rely on value-at-risk (VaR), risk budgeting strategies naturally lend themselves to using expected shortfall (ES) to measure risk. In the case of VaR, it indicates the maximum possible loss at a given confidence level (usually 95% or 99%). However, VaR is silent with respect to the losses beyond the VaR threshold. Conversely, ES measures the expected loss in the event of a VaR violation. Hence, by means of the portfolio's weight vector, we can then compute a distribution of portfolio returns for t+1 which allows us to calculate VaR and ES forecasts.

There are different ways to avoid this kind of artificial back and forth: An intuitive and simple method would be to copy forward the risk estimate rather than the last price. But such an approach disregards what happens in the other (open) markets. In periods of high volatility, investors would prefer the risk forecast to increase rather than to remain constant. In this article, we will assess various methods that can tackle this problem.

Imputing returns of non-trading days

Forecasting returns, particularly daily returns, is extremely difficult (Rapach and Zhou, 2013). Fortunately, we are not interested in the exact return, but only in its magnitude. This will be the main driver of the final risk forecast, in particular since, in the GARCH model, the return is squared. Given the stylized facts of financial asset returns, such as volatility clustering and correlations between related markets, we opt for the following methodologies to generate the imputed return $\hat{r}_t$:

1. **Simple average:**

   $$\hat{r}_t = \frac{\sum^{t=-20}_{t=-1} r_t}{20}$$

   or the average return over the last 20 days (approximately one month of trading returns).

2. **Last day:** $\hat{r}_t = r_{t-1}$
   Here we assume that the best prediction for the magnitude of the next day's market return is simply the magnitude of the current return. This could be an alternative in the case of volatility clustering.

3. **Cross market:**

   $$\hat{r}_t = \frac{\sum^{i=n}_{i=1} r_{i_{t-1}}}{n}$$

   where i is a related market (e.g., same asset class) and n is the number of related markets. With this approach, we aim to capture information from open markets in a simple manner.

4. **VaR model:** $\widehat{r_t} = v + A_1 * r_{t-1}$,
   where $\widehat{r_t}$ is the vector of returns to impute, v and A_1 are the model coefficients and r_{t-1} gives us the returns from the previous period. We use 500 days of lagged returns to estimate the model coefficients.

5. **Linear regression model on open markets (Linear model):**

   $$\widehat{r_t} = a + \sum_{i=1}^{n} b_i * r_{i,t},$$

   where $\widehat{r_t}$ is the return to impute, i is a related open market, n is the total number of related markets, b_i reflects the coefficients with respect to related open markets and $r_{i,\,t}$ is the return of the open market for the same time period.

6. **Enhanced linear regression model (Enhanced LM):**
   The enhanced linear regression model follows the same logic as method 5, but attempts to capture autocorrelation and volatility clustering by including 20 lags of the same time series. The equation is as follows:

   $$\widehat{r_t} = a + \sum_{i=1}^{n} \mathrm{b_i} * r_{i,t} + \sum_{k=1}^{k=20} c_k * r_{j,t-k},$$

   where c_k reflects the coefficients with respect to the own lagged series j.

Finally, suppose a market was closed from Monday through Thursday – the Friday return will likely be very high (or low), since it reflects the information of the whole week (figure 1).

For this reason, we adjust the realized return after the market reopens using the imputed returns of the prior days, as in the following equation, and apply the adjusted return $\widehat{R_5}$:

$$\widehat{R_5} = \frac{1 + R_5}{(1+\widehat{R_1}) * (1+\widehat{R_2}) * (1+\widehat{R_3}) * (1+\widehat{\{R_4\}})} - 1$$

Forecasting capability

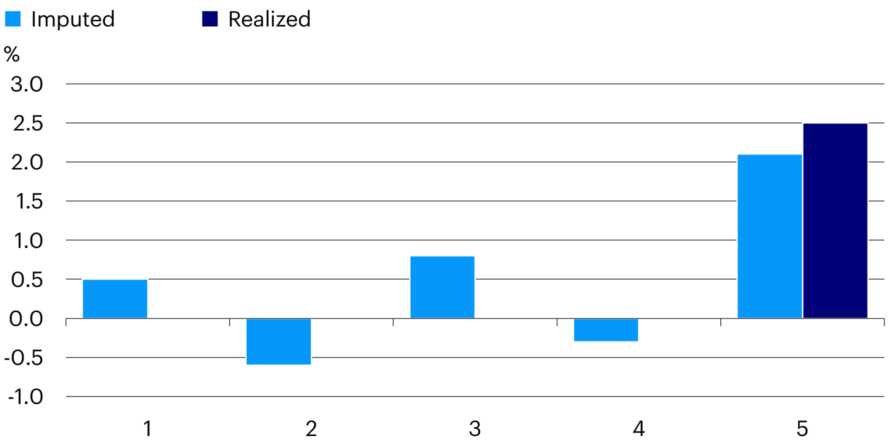
To assess the forecasting capability of the different methods using daily return data from March 20, 2001 to February 6, 2023, we first look at the methods' general forecasting power: We impute returns for all days (except for an initial estimation window) and then compare the imputed to the realized returns using the mean squared prediction error (MSPE) of each method. This will not include non-trading days (as no realized returns are observed on these days), but rather provides information on which method generally works best for predicting returns.

Table 1 shows the mean squared prediction errors for an asset universe of stock indices, government bonds, credits, commodities and foreign exchange. For each asset, the method with the lowest MSPE is shown in boldface. The Enhanced Linear Model delivers the smallest prediction errors in all but two cases, with US and Euro investment grade bonds the only exceptions.

To assess whether the differences in MSPEs between different methods are statistically significant, we perform modified Diebold-Mariano tests (Diebold and Mariano, 1995; Harvey, Leybourne and Newbold, 1997). In these tests, each model is tested against each other model to determine which of the pair has the better forecasting accuracy. Table 2 shows the p-values for the S&P 500. Again, Enhanced LM is best, providing better forecasts than each of the other four models. Then follows (in order) the Linear model, Cross market, Simple average and the VaR model. "Last day" comes in last.

In a second step, we repeat the analysis for the days with the most extreme market movements (see table 3). Getting these right is of particular importance. Again, the Enhanced Linear Model performs best in all but two cases, which is confirmed by the Diebold-Mariano tests, with the other models following in the same order as in the full dataset case.

Figure 1
Adjustment of a daily return after four consecutive days of the market being closed



Source: Invesco. For illustrative purposes only.

Table 1
General forecasting power of the models

Mean squared prediction errors (MSPE)		Simple average	Last day	Cross market	VaR model	Linear model	Enhanced LM
Stocks	S&P500	1.18%	1.78%	1.07%	1.31%	0.92%	**0.82%**
	EUROSTOXX50	1.41%	2.09%	0.99%	1.56%	0.69%	**0.66%**
	FTSE100	1.12%	1.64%	0.74%	1.23%	0.55%	**0.52%**
	MSCI EM	1.13%	1.48%	0.86%	1.04%	0.79%	**0.74%**
	TOPIX	1.35%	1.99%	1.38%	1.62%	1.14%	**1.09%**
Government bonds	AUS10Y	0.43%	0.64%	0.45%	0.55%	0.39%	**0.38%**
	CAN10Y	0.35%	0.50%	0.26%	0.36%	0.19%	**0.18%**
	US10Y	0.36%	0.52%	0.28%	0.38%	0.20%	**0.19%**
	JGB10Y	0.17%	0.26%	0.30%	0.20%	0.16%	**0.16%**
	UK10Y	0.40%	0.58%	0.30%	0.41%	0.24%	**0.22%**
	Euro Bund	0.34%	0.49%	0.24%	0.35%	0.19%	**0.18%**
Credits	EM sovereigns	0.47%	0.64%	0.44%	0.43%	0.39%	**0.36%**
	US IG	0.15%	0.16%	0.20%	**0.09%**	0.11%	0.09%
	US HY	0.40%	0.51%	0.33%	0.33%	0.29%	**0.27%**
	Euro IG	0.11%	0.14%	0.29%	**0.09%**	0.10%	0.09%
	Euro HY	0.36%	0.41%	0.33%	0.26%	0.28%	**0.24%**
Commodities	Agriculture	1.11%	1.60%	1.34%	1.13%	1.01%	**0.98%**
	Copper	1.61%	2.41%	1.54%	1.77%	1.41%	**1.36%**
	Oil	2.49%	3.67%	2.36%	2.65%	2.33%	**2.13%**
	Gold	1.06%	1.54%	1.44%	1.09%	1.00%	**0.96%**
Currencies	USDEUR	0.56%	0.82%	0.47%	0.59%	0.25%	**0.24%**
	GBPEUR	0.48%	0.69%	0.43%	0.49%	0.41%	**0.39%**
	JPYEUR	0.67%	0.98%	0.67%	0.71%	0.49%	**0.48%**
	AUDEUR	0.64%	0.93%	0.54%	0.68%	0.37%	**0.35%**
	NZDEUR	0.65%	0.94%	0.56%	0.69%	0.41%	**0.40%**
	CADEUR	0.56%	0.81%	0.44%	0.59%	0.38%	**0.37%**
	CHFEUR	0.44%	0.64%	0.52%	0.49%	0.41%	**0.38%**
	NOKEUR	0.50%	0.74%	0.51%	0.54%	0.40%	**0.38%**
	SEKEUR	0.42%	0.62%	0.47%	0.46%	0.36%	**0.34%**
	DKKEUR	0.02%	0.04%	0.33%	0.03%	0.02%	**0.02%**
	EMEUR	0.54%	0.84%	0.42%	0.64%	0.27%	**0.25%**

Source: Invesco calculations. Daily data from March 20, 2001 to February 6, 2023. In each row, the smallest value is in bold, indicating the best forecasting power.

Table 2
P-values of Diebold-Mariano tests

P-values	Simple average	Last day	Cross market	VaR model	Enhanced LM	Linear model
Simple average		0	0.9999185	0.00E+00	1	1.00E+00
Last day	1.00E+00		1	1.00E+00	1	1.00E+00
Cross market	8.15E-05	0		1.32E-12	1	1.00E+00
VAR model	1.00E+00	0	1		1	1.00E+00
Enhanced LM	0.00E+00	0	0	0.00E+00		9.16E-11
Linear model	0.00E+00	0	0	0.00E+00	1	

Source: Invesco calculations. The table should be read row-wise: for instance, “Simple average” delivers better forecasts than “Last day”, with a p-value of effectively 0 and worse forecasts than “Cross Market”, since the p-value approaches 1.

Expected shortfall

Using the Copula-GARCH model, we now compute expected shortfall (ES) forecasts for the S&P 500 as well as a multi-asset portfolio consisting of equity indices, government bonds, credits and commodities.[2] We analyze all available triplets of ES forecasts for the day before the non-trading day, the non-trading day itself and the day after – 151 triplets altogether.

In figure 2, panel A shows the mean of all 151 forecast triplets for the S&P 500. We see a pronounced V-shape for the no adjustment case, and less pronounced V-shapes for some of our six forecast models. Only the “Last day” method is clearly off: It’s risk forecasts for the day after the non-trading day are much too high. These findings are supported by the results for the multi-asset portfolio in panel B. In the no adjustment case, the V-shape is even more pronounced, stressing the need for an adjustment of some sort.

In both panels – and particularly panel B – risk forecasts in the no adjustment case fluctuate considerably, which is mitigated

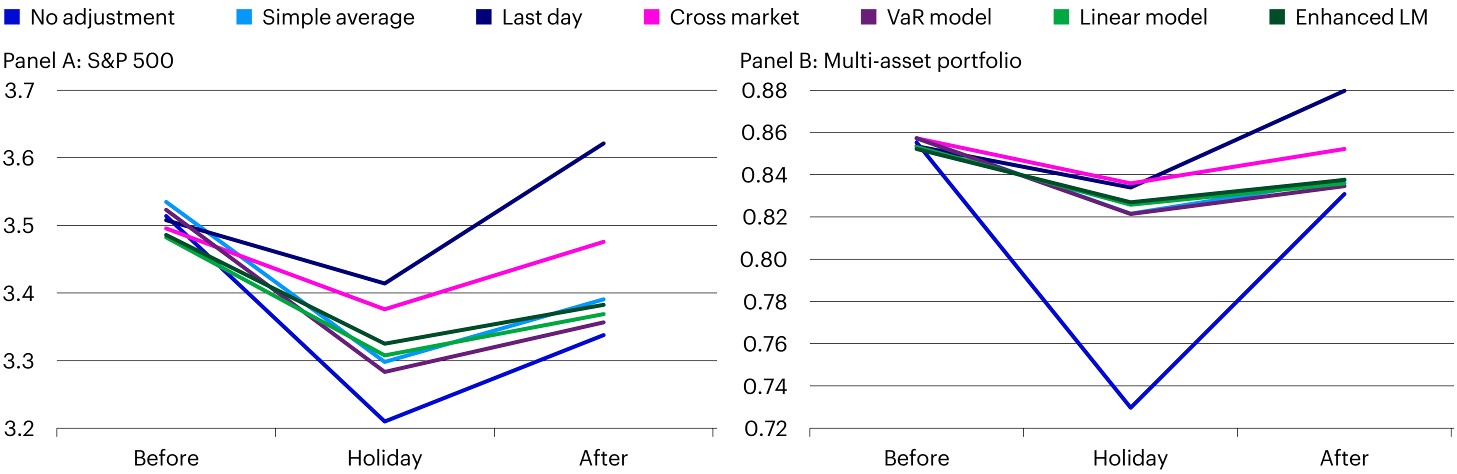
Table 3
Forecasting power of the models for extreme market movements (1% quantile)

Mean squared prediction errors (MSPE)		Simple average	Last day	Cross market	VaR model	Linear model	Enhanced LM
Stocks	S&P500	4.39%	5.52%	3.39%	5.60%	3.26%	**2.85%**
	EUROSTOXX50	5.25%	6.50%	3.11%	6.06%	1.65%	**1.44%**
	FTSE100	4.63%	5.32%	2.05%	5.70%	1.71%	**1.42%**
	MSCI EM	5.23%	5.90%	2.12%	4.60%	2.16%	**1.77%**
	TOPIX	6.09%	5.84%	3.78%	6.29%	3.39%	**3.13%**
Government bonds	AUS10Y	1.48%	1.80%	1.56%	1.92%	1.25%	**1.10%**
	CAN10Y	1.29%	1.79%	0.80%	1.41%	0.45%	**0.47%**
	US10Y	1.38%	1.27%	1.01%	1.55%	0.70%	**0.61%**
	JGB10Y	0.66%	0.78%	0.70%	0.90%	0.66%	**0.57%**
	UK10Y	2.38%	3.06%	2.04%	2.22%	1.62%	**1.40%**
	Euro Bund	1.27%	1.53%	0.85%	1.33%	0.63%	**0.56%**
Credits	EM sovereigns	2.22%	2.53%	1.86%	1.94%	1.21%	**1.13%**
	US IG	0.54%	0.28%	0.19%	0.24%	0.21%	**0.18%**
	US HY	1.79%	1.37%	0.93%	1.46%	0.88%	**0.74%**
	Euro IG	0.39%	0.37%	0.64%	0.30%	0.37%	**0.33%**
	Euro HY	1.80%	1.18%	1.31%	1.46%	1.43%	**1.15%**
Commodities	Agriculture	3.75%	4.47%	**2.80%**	4.15%	2.97%	2.83%
	Copper	5.99%	8.49%	4.42%	7.39%	4.52%	**3.86%**
	Oil	13.80%	15.49%	12.97%	14.10%	12.43%	**9.67%**
	Gold	4.37%	5.40%	3.47%	4.04%	2.97%	**2.76%**
Currencies	USDEUR	2.26%	2.22%	1.61%	2.18%	0.54%	**0.40%**
	GBPEUR	1.82%	1.78%	1.34%	1.86%	1.33%	**1.07%**
	JPYEUR	2.61%	3.58%	2.86%	3.06%	1.03%	**0.93%**
	AUDEUR	3.15%	4.52%	2.73%	3.40%	1.16%	**1.04%**
	NZDEUR	2.69%	3.36%	2.16%	2.95%	0.97%	**0.92%**
	CADEUR	2.12%	2.56%	1.17%	2.12%	**0.67%**	0.71%
	CHFEUR	1.33%	1.31%	1.50%	1.45%	1.02%	**0.92%**
	NOKEUR	2.34%	2.06%	2.07%	2.49%	1.47%	**1.13%**
	SEKEUR	1.51%	2.00%	1.40%	1.71%	1.20%	**0.99%**
	DKKEUR	0.08%	0.14%	1.51%	0.11%	0.07%	**0.03%**
	EMEUR	2.10%	3.22%	1.21%	2.12%	0.73%	**0.55%**

Source: Invesco calculations. Daily data from March 20, 2001 to February 6, 2023. In each row, the smallest value is in bold, indicating the best forecasting power.

by most of the six methods. This fluctuation is also visible in table 4, which shows the changes of the ES forecasts on the days before and after the non-trading day (first two columns) and the effect of the forecasting models (final two columns). Except for the "Last day" methodology in the S&P 500 case, the models lead to lower ES forecasts. They are particularly pronounced in the multi-asset case (see table 5).

Figure 2
Average ES forecasts for the 151 daily return triplets in our sample



Source: Invesco calculations. Daily data from March 20, 2001 to February 6, 2023.

Table 4
Fluctuations of average ES forecasts and forecasting model effects in the S&P 500 case

	Change of ES forecast since the previous day		Reduction of ES forecast due to the forecasting model	
	Day before	**Day after**	**Day before**	**Day after**
No adjustment	-7.29%	4.81%	-	-
Simple average	-6.15%	4.57%	-15.76%	-4.84%
Last day	-2.67%	7.79%	-63.44%	**62.12%**
Cross market	-2.67%	4.45%	-63.39%	-7.39%
VaR model	-6.24%	3.94%	-14.49%	-18.07%
Linear model	-4.44%	3.54%	-39.11%	-26.29%
Enhanced LM	-3.96%	3.23%	-45.72%	-32.77%

Source: Invesco calculations. Daily data from March 20, 2001 to February 6, 2023.

Table 5
Fluctuations of average ES forecasts and forecasting model effects in the multi-asset case

	Change of ES forecast since the previous day		Reduction of ES forecast due to the forecasting model	
	Day before	**Day after**	**Day before**	**Day after**
No adjustment	-13.45%	13.87%	-	-
Simple average	-3.41%	2.48%	-74.66%	-82.10%
Last day	-2.04%	5.93%	-84.80%	-57.24%
Cross market	-1.80%	2.38%	-86.59%	-82.83%
VaR model	-3.41%	2.09%	-74.64%	-84.94%
Linear model	-2.50%	1.80%	-81.38%	-87.03%
Enhanced LM	-2.27%	1.81%	-83.15%	-86.96%

Source: Invesco calculations. Daily data from March 20, 2001 to February 6, 2023.

The effects of our forecasting methodologies on a DPPI strategy
We now analyze the effect of our forecasting methodologies on a DPPI risk budgeting strategy. We assume a risk-averse investor who wants to limit portfolio drawdowns. In this approach, a certain drawdown limit is defined, which should not be exceeded in a specified period, typically a calendar year.

The target exposure depends not only on the risk forecast, but also on the available cushion C_t at time t. The cushion is the difference between the invested capital (W_t) and the net present value of the floor (F_t):

$$C_t = W_t - NPV(F_t)$$

Table 6
Turnover and turnover reduction for a DPPI strategy with different risk budgets: S&P 500 case

	Risk budget p.a.									
Turnover	**1%**	**2%**	**3%**	**4%**	**5%**	**6%**	**7%**	**8%**	**9%**	**10%**
No adjustment	8.49%	8.49%	8.49%	8.47%	7.81%	6.58%	5.87%	5.18%	4.48%	3.86%
Simple average	7.52%	7.52%	7.52%	7.50%	6.88%	5.73%	5.07%	4.42%	3.78%	3.32%
Last day	7.62%	7.62%	7.62%	7.59%	6.92%	5.81%	5.16%	4.41%	3.89%	3.28%
Cross market	7.56%	7.56%	7.56%	7.54%	6.89%	5.78%	5.06%	4.43%	3.79%	3.28%
VaR model	7.42%	7.42%	7.42%	7.39%	6.74%	5.53%	4.89%	4.26%	3.62%	3.12%
Linear model	7.11%	7.11%	7.11%	7.08%	6.40%	5.38%	4.77%	4.20%	3.56%	3.09%
Enhanced LM	7.03%	7.03%	7.03%	7.00%	6.36%	5.35%	4.75%	4.18%	3.56%	3.10%

	Risk budget p.a.										
Turnover reduction	**1%**	**2%**	**3%**	**4%**	**5%**	**6%**	**7%**	**8%**	**9%**	**10%**	**Average**
No adjustment	-	-	-	-	-	-	-	-	-	-	-
Simple average	11.43%	11.43%	11.43%	11.42%	11.95%	12.98%	13.61%	14.60%	15.56%	14.18%	12.86%
Last day	10.25%	10.25%	10.25%	10.39%	11.35%	11.70%	12.20%	14.80%	13.16%	15.22%	11.96%
Cross market	10.94%	10.94%	10.94%	10.99%	11.83%	12.20%	13.93%	14.46%	15.47%	15.08%	12.68%
VaR model	12.65%	12.65%	12.65%	12.69%	13.73%	16.02%	16.82%	17.72%	19.16%	19.26%	15.34%
Linear model	16.27%	16.27%	16.27%	16.42%	18.09%	18.25%	18.86%	18.96%	20.42%	19.97%	17.98%
Enhanced LM	17.20%	17.20%	17.20%	17.33%	18.61%	18.69%	19.16%	19.34%	20.43%	19.67%	18.48%

Source: Invesco calculations. For illustrative purposes only.

Table 7
Turnover and turnover reduction for a DPPI strategy with different risk budgets: multi-asset case

	Risk budget p.a.				
Turnover	**1%**	**2%**	**3%**	**4%**	**5%**
No adjustment	13.78%	7.81%	3.32%	1.26%	0.51%
Simple average	4.81%	3.32%	1.57%	0.66%	0.34%
Last day	4.96%	3.31%	1.61%	0.74%	0.43%
Cross market	4.84%	3.46%	1.73%	0.85%	0.37%
VaR model	4.55%	3.19%	1.50%	0.61%	0.30%
Linear model	4.56%	3.19%	1.51%	0.57%	0.25%
Enhanced LM	4.56%	3.21%	1.48%	0.53%	0.24%

	Risk budget p.a.					
Turnover reduction	**1%**	**2%**	**3%**	**4%**	**5%**	**Average**
No adjustment	-	-	-	-	-	-
Simple average	65.07%	57.53%	52.79%	47.43%	33.62%	51.29%
Last day	64.00%	57.60%	51.57%	41.19%	15.86%	46.04%
Cross market	64.85%	55.64%	47.81%	32.38%	27.87%	45.71%
VaR model	66.99%	59.19%	54.86%	51.27%	40.24%	54.51%
Linear model	66.89%	59.13%	54.52%	54.45%	51.32%	57.26%
Enhanced LM	66.88%	58.84%	55.44%	58.10%	52.10%	58.27%

Source: Invesco calculations. For illustrative purposes only.

To avoid losses in excess of the floor over the predefined time period, the target exposure e_t is a function of both the risk forecast and the available cushion at time t (C_t):

$$e_t = m_t * C_t,$$

The multiplier m_t is dynamic and a function of the risk forecast:

$$m_t = \frac{1}{\widehat{\rho_t} MDD}$$

where $\widehat{\rho_t}$ is the expected shortfall forecast at time t. Max drawdown days (*MDD*) is a risk aversion parameter, typically taking values between 1 and 5, which can be thought of as a linear extension of the number of days over which the drawdown can be suffered.

Tables 6 and 7 show the effect of our forecasting methodologies on the turnover of DPPI strategies, for both the S&P 500 case and the multi-asset case, for annual risk budgets from 1% to 10%. The turnover of an S&P 500 portfolio can be reduced by 18.48% (on average) in the case of the Enhanced LM methodology – but even "Last day" achieves an average reduction of 11.96%. In the multi-asset case, turnover reductions are also sizeable, with averages of up to 58.27%. Once again, the best result is achieved with the Enhanced LM methodology.

Conclusion

Not adjusting for non-trading days leads to higher risk forecast fluctuations and a higher portfolio turnover. We have tested different approaches for imputing non-trading day returns with the objective of ameliorating these problems. In most cases, all six methodologies deliver an improvement. Still, in our view, the Enhanced linear regression model (Enhanced LM) is the most appropriate choice given that it outperforms the other methods using a diverse set of evaluation metrics.

Notes

1 See Happersberger, Lohre and Nolte (2020) for further details on the applied risk model.
2 The multi-asset portfolio consist of 60% government bonds (German, UK, US, Canadian, Australian and Japanese; 10% each); 22% equities (S&P 500, EuroStoxx50, FTSE 100 and Topix; capitalization weighted), 10% commodities (2.5% oil, 5% gold, 2.5% copper), and 8% money market investments with practically no expected shortfall risk.

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