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4 **Taking advantage of momentum spillover**

Nikunj Agarwal, Yuxiao (Angelica) Dai, and Sergey Protchenko

Firms within the same economic cluster frequently see correlated share price movements. Using two distinct approaches for grouping companies, we explore how these interconnected dynamics can be harnessed to boost investment performance.

10 **Market-neutral investing: a systematic factor-based approach**

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Factor-based market-neutral strategies can outperform other market-neutral alternatives in terms of risk-adjusted returns. They provide transparency and cost-efficiency, making them even more attractive for investors seeking diversification beyond conventional market exposures.

17 **Managing currency exposures in multi-asset portfolios with constraining investment guidelines**

Carsten Becker, Alexandar Cherkezov, and Dr. David Happersberger

Diversified global portfolios come with foreign exchange risks and opportunities. We compare different currency management approaches, with and without investment constraints, to find out which is most suitable for a world with regulatory and other limitations.

Stephanie Butcher
Senior Managing Director and
Co-Head of Investments

Tony Wong
Senior Managing Director and
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Technological advancements have long been a catalyst for progress in the field of investment management. Quantitative investing, for instance, would have remained in the realm of theory without the computing power necessary to process vast datasets. Today, it's AI and machine learning that promise to drive yet another quantum shift in professional investing.

Our first article explores the 'delayed spillover effect' – a phenomenon in which a price change in one stock can influence the prices of other stocks after a time lag. For investors who know how to identify these linked stocks, this effect presents a compelling opportunity. Our team tested two quantitative methods to uncover these connections and developed a promising linkage signal.

Next, we turn our attention to market-neutral investing. These strategies are known for their ability to deliver pure alpha, independent of market movements. But our research suggests that combining the market-neutral concept with a factor-based component can enhance its effectiveness, particularly within a broader asset allocation framework.

In our third article, we examine currency management, comparing risk-based and factor-based approaches. While the factor model has a strong theoretical appeal, our findings suggest that a risk-based minimum variance strategy can often produce better results when dealing with real-world investment constraints. This outcome underscores the continued relevance of traditional techniques in certain contexts.

We hope you enjoy this edition of Risk & Reward.

Best regards,

Stephanie Butcher
Senior Managing Director and
Co-Head of Investments

Tony Wong
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Taking advantage of momentum spillover

By Nikunj Agarwal, Yuxiao (Angelica) Dai, and Sergey Protchenko

Firms within the same economic cluster frequently see correlated share price movements and are characterized by delayed momentum spillover. Using two distinct approaches for grouping companies – sell-side analyst coverage and industry classification – we explore how these interconnected dynamics can be harnessed to boost investment performance.

No security exists in complete isolation – each is directly or indirectly linked to others. A common explanation for the occurrence of delayed momentum spillover is the 'limited attention hypothesis': When facing an influx of information about a particular stock, individuals struggle to process the information fully and may need time to realize its relevance for other, related stocks.[1] As a consequence, these may underreact initially, creating opportunities out of past information.

The strength of linkage signals lies in their ability to offer additional insights beyond what is available from conventional information sources. Unlike conventional data, which is often limited to a specific region, sector, industry, or market-cap group, linkage signals draw from a broader range of contexts. They encapsulate information absent from traditional momentum signals and offer a distinct perspective that can enhance predictive accuracy.

We'll construct two alpha signals based on analyst coverage and industry classification, which show strong performance across various markets, both individually and in combination. The analyst coverage signal captures stocks that are connected

through shared coverage by sell-side analysts, while the industry classification signal identifies stocks based on their classification within the same industry. The two signals are constructed using a comprehensive global dataset from December 1996 to March 2023 and cover a significant portion of the global large-cap market.[2]

The analyst coverage signal

First, we use the Institutional Brokers' Estimate System (I/B/E/S) detailed file to identify stocks that are related through shared analyst coverage. At the end of each month, we classify two stocks as 'connected' if at least one analyst covers both of them. Our sample includes 3913 stocks, representing 94% of total market capitalization and 91% of the total number of stocks in the universe (table 1).

We then identify connections between stocks based on shared analyst coverage. To ensure that the connections are meaningful, we filter out analysts covering an excessively large number of stocks, as these connections may distort the results. No additional restrictions are imposed, and stocks are allowed to span different sectors and regions. This introduces new information by incorporating insights from outside a stock's immediate industry or country.

Next, we assign weights to these connections based on their strength, which is assessed via two criteria: the number of common analysts and the specificity of their coverage. For instance, a connection supported by five common analysts is considered stronger than a connection supported by just one. Moreover, a connection is deemed more robust if the common analyst exclusively covers the two stocks in question rather than a wider range. Thus, a connection supported by an analyst who focuses solely on a few stocks is valued higher than one involving a generalist analyst.

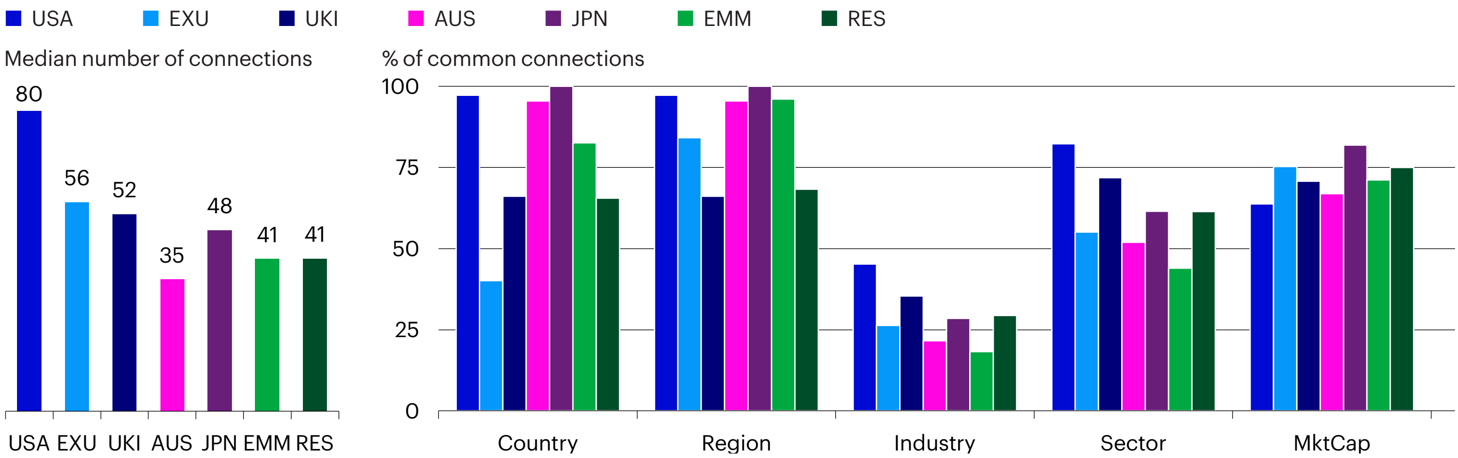
Finally, we determine the underlying information from the connected stocks. In accordance with the network effect and the momentum spillover hypothesis, we construct the analyst coverage signal based on the previous 12 months' returns of connected stocks. To ensure robustness, we also assess alternative measures, such as shorter-period returns, idiosyncratic momentum, and earnings momentum, all of which show consistent performance.

Table 1
Market coverage of our analyst coverage signal

	Number of stocks	% of market capitalization	% of number of stocks
USA (United States)	1210	98	97
EXU (Europe ex UK)	516	93	94
UKI (United Kingdom)	270	98	96
AUS (Australia)	114	97	96
JPN (Japan)	629	96	91
EMM (Emerging Markets)	866	85	84
RES (Rest of the World)	309	92	89
Total/Average	3913	94	91

Source: Invesco IQS research based on I/B/E/S data. Data as of December 1996 to March 2023.

Figure 1
Connections according to analyst coverage signal in detail



Source: Invesco IQS research. Data as of December 1996 to March 2023.

The analyst coverage signal is calculated as the weighted average of the 12-month returns of all stocks connected through analyst coverage:

$$AnalystCoverage_{i,t} = \sum_{j=1}^{k} w_{j,t} \times r_{j,t1\text{-}t12}$$

where i is the target stock, $w_{j,t}$ is the weight assigned to connected stock j, and $r_{j,t1\text{-}t12}$ is the cumulative 12-month return of connected stock j.

Depending on the region, the median number of connections varies from 35 to 80, with the United States having the highest number of connections (figure 1). Furthermore, about 40% to 99% of connections involve stocks from the same country, 65% to 99% from the same region, 18% to 45% from the same industry, 45% to 80% from the same sector, and 64% to 82% from the same market-cap group.

The industry classification signal

We now employ the industry classifications provided by the Global Industry Classification Standard (GICS) to identify stocks that are related through their industry affiliations. The GICS sub-industry classification encompasses approximately 160 to 200 sub-industries over time. At the end of each month, we consider two stocks to be 'connected' if they fall within the same sub-industry. To ensure robustness, we exclude sub-industries comprising fewer than three companies, as these may not provide reliable data. Our sample includes 4186 stocks, representing 97% of total market capitalization and 97% of the total number of stocks in the universe (table 2).

The methodology followed is similar to that of the analyst coverage signal: Stocks within the same GICS sub-industry group are deemed connected, regardless of their country or market-cap group. Next, we develop a weighting scheme based on the market capitalization of the connected stocks, assigning greater weight to stocks with larger market caps. Again, the final linkage signal is computed as the weighted average of the 12-month returns of all the other stocks within the same GICS sub-industry group:

$$IndustryClassification_{i,t} = \sum_{j=1,\, j\neq i}^{k} w_{j,t} \times r_{j,t1\text{-}t12},$$

where i is the target stock, $w_{j,t}$ is the weight assigned to connected stock j, and $r_{j,t1\text{-}t12}$ is the cumulative 12-month return of connected stock j.

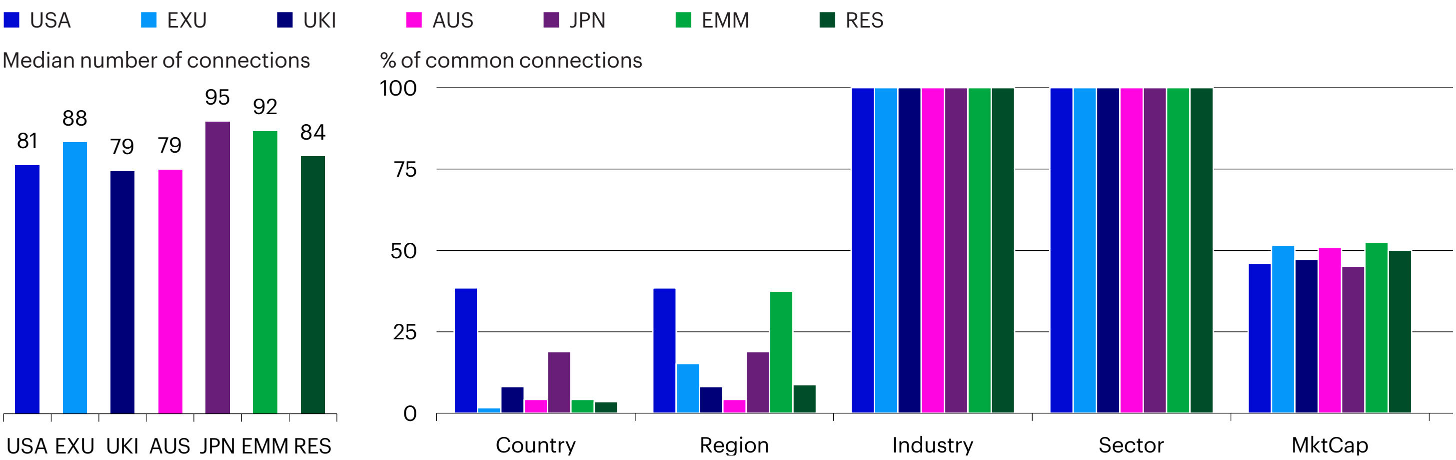
The median number of connections varies from 79 to 95, depending on the region,

Table 2
Market coverage of our industry classification signal

	Number of stocks	% of market capitalization	% of number of stocks
USA (United States)	1222	99	98
EXU (Europe ex UK)	533	95	96
UKI (United Kingdom)	275	99	97
AUS (Australia)	115	98	97
JPN (Japan)	680	98	99
EMM (Emerging Markets)	1029	96	97
RES (Rest of the World)	333	97	97
Total/Average	4186	97	97

Source: Invesco IQS research based on I/B/E/S data. Data as of December 1996 to March 2023.

Figure 2
Connections according to industry classification signal in detail



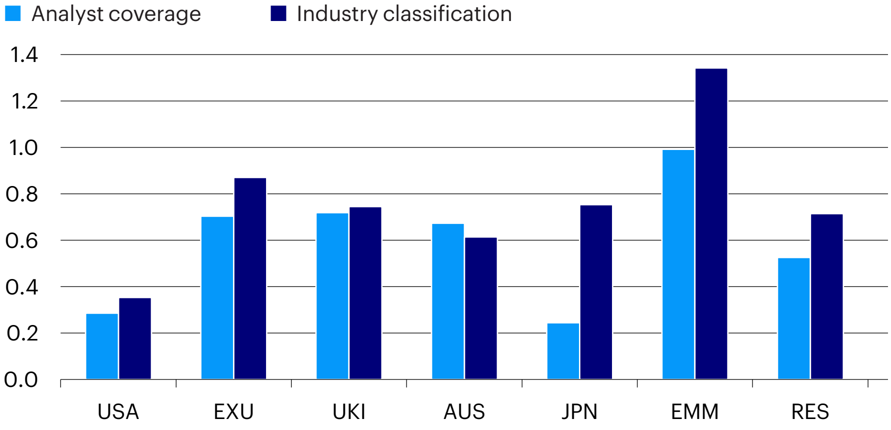
Source: Invesco IQS research. Data as of December 1996 to March 2023.

with Japan having the highest number of connections (figure 2). About 2% to 39% of connections involve stocks from the same country, 5% to 40% from the same region and 45% to 53% from the same market-cap group. Since we define connections strictly between stocks within the same sub-industry, all connections are within the same industry or sector.

Signal portfolios

The signal portfolios are a monthly rebalanced 100% long and 100% short market-neutral portfolio. The signal score is standardized and capped at ±3. The portfolios are then constructed based on these standardized scores, taking long positions in securities with positive scores and short positions in those with negative scores. We also implement appropriate risk controls such as beta neutralization.[3] We begin with separate portfolios for the two signals.

Figure 3
Information ratios of analyst coverage and industry classification signals



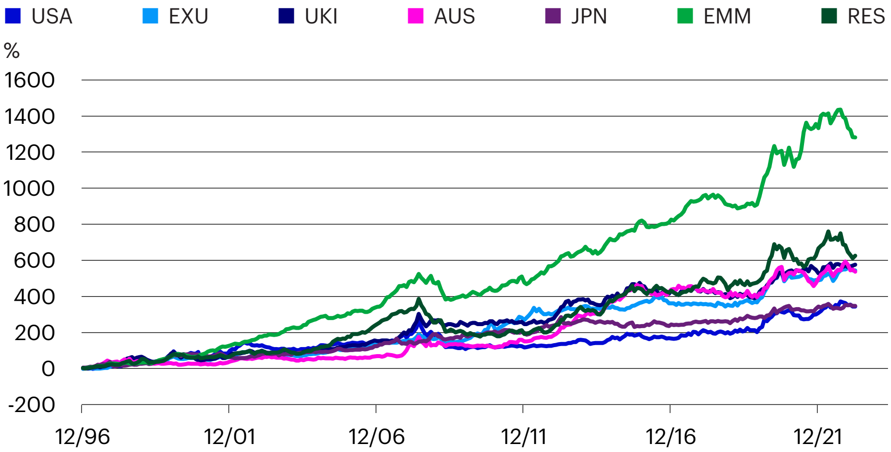
Source: Invesco IQS research. Data period December 31, 1996 – March 31, 2023.

Table 3
Hypothetical backtested performance statistics of combined linkage signal

	Return p.a. (%)	Std.dev. p.a. (%)	IR	Turnover p.a. (%), two way
USA (United States)	4.0	11.6	0.34	485
EXU (Europe ex UK)	7.3	8.5	0.86	469
UKI (United Kingdom)	7.6	9.6	0.80	483
AUS (Australia)	8.2	11.3	0.72	503
JPN (Japan)	4.9	8.9	0.55	502
EMM (Emerging Markets)	10.1	7.5	1.33	470
RES (Rest of the World)	7.6	10.7	0.71	485

Source: Invesco IQS research.

Figure 4
Simulated cumulative return of combined signal



Source: Invesco IQS research. Data period December 31, 1996 – March 31, 2023. **There is no guarantee that the simulated performance will be achieved in the future.**

Table 4
Correlation

	Momentum (%)	Quality (%)	Value (%)
United States	66	-5	-43
Europe ex UK	51	2	-20
United Kingdom	42	13	-27
Australia	28	1	-11
Japan	51	4	-19
Emerging Markets	58	20	-23
Rest of the World	41	-2	-22

Source: Invesco IQS research. Data period December 31, 1996 – March 31, 2023.

Table 5
Spanning test

	Momentum (%)	Quality (%)	Value (%)	Multi factor (%)
United States	3.1*	7.2***	7.8***	4.2**
Europe ex UK	4.6***	9.0***	9.7***	5.4***
United Kingdom	6.5***	8.2***	8.7***	6.1***
Australia	8.3***	10.2***	10.5***	8.3***
Japan	3.1*	5.5***	6.8***	3.3*
Emerging Markets	3.9***	9.7***	13.1***	4.9***
Rest of the World	2.9	9.6***	11.0***	5.0**

Statistical significance: * at the 10% confidence level, ** at the 5% confidence level, and *** at the 1% confidence level.
For the spanning test, the linkage portfolios' monthly returns are regressed on the market portfolio and M/Q/V/Multi-factor portfolio. The intercept is then annualized.
Source: Invesco IQS research. Data period December 31, 1996 – March 31, 2023.

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Both the analyst coverage and the industry classification signal yield robust and statistically significant results.

Both the analyst coverage and the industry classification signal yield robust and statistically significant results. Figure 3 shows their information ratio across regions, which are always positive. With information ratios between 0.35 and 1.34, industry classification exhibits better performance than analyst coverage, which has information ratios between 0.24 to 0.99.

We now construct a composite factor by averaging the analyst coverage signal and the industry classification signal, each receiving a weight of 50%.

$CombinedLinkage_{i,t} =$
$0.5 \times AnalystCoverage_{i,t} +$
$0.5 \times IndustryClassification_{i,t}$

Table 3 shows the backtest performance statistics of this combined signal, figure 3 its cumulative return. The signal achieves an annualized return of 4.0% to 10.1%, at an annualized standard deviation of 7.5% to 11.6%, yielding an information ratio of 0.34 to 1.33, depending on the region. The annualized portfolio turnover is around 470% to 500% and thus consistent with other price momentum signals. The portfolios experienced a significant drawdown during the Global Financial Crisis, followed by a robust recovery.

Additional alpha?

Finally, we'll examine the combined linkage signal's correlation with the factors in the Invesco IQS model and its ability to generate additional alpha. The proprietary model comprises three factors: momentum, value, and quality – each constructed from multiple proprietary signals and then formed into factor portfolios.[4]

Over the sample period, the combined linkage signal exhibited a correlation of 28% to 66% with the momentum factor, and a correlation of -11% to -43% with the value factor (table 4). In the spanning test, the signal generates a positive and statistically significant alpha over the momentum, value, and quality factor portfolios, as well as the multi-factor portfolios, across almost all regions (table 5). This indicates that the signal enhances the model in every region.

Conclusion

When two firms are economically linked or share similar fundamentals, information about one firm is also pertinent to the other. If investors or analysts fail to fully react to relevant news about a connected firm, this can lead to predictability in returns across firms, a phenomenon referred to as 'momentum spillovers'. The two alpha signals – analyst coverage and industry classification – capture interfirm connections and utilize these spillovers effect to generate additional alpha.

Both signals show strong performance across all regional equity markets. Combining them creates a combined linkage signal, which delivers statistically significant backtest results. This signal provides positive information ratios that are consistent and robust across regions. The combined signal is positively correlated with momentum and negatively correlated with the value factor. In the spanning test, it produces a positive and statistically significant alpha over the multi-factor portfolios in nearly all regions. This suggests that the signal is not subsumed by the model.

Notes

1 Peng and Xiong (2006), Hirshleifer et al. (2011).
2 Previous research has explored related areas – such as industry momentum (Moskowitz, 1999), customer momentum (Cohen and Frazzini, 2006), and shared analyst coverage (Ali and Hirshleifer, 2019). Here, we examine these phenomena from a practitioner's perspective.
3 For a detailed description of the construction method, see Feng et al. (2024).
4 For a detailed description of the methodology, see Ikeda et al. (2023).

References

Ali, Usman and David Hirshleifer (2020): Shared analyst coverage: Unifying momentum spillover effects, Journal of Financial Economics 136.3, pp. 649-675

Cohen, Lauren and Andrea Frazzini (2008): Economic links and predictable returns, The Journal of Finance 63.4, pp. 1977-2011

Feng, Xihao, et al. (2024): Control and Transparency in Factor Portfolio Implementation, Journal of Beta Investment Strategies 15.1

Hirshleifer, David, Sonya S. Lim, and Siew Hong Teoh (2011): Limited investor attention and stock market misreactions to accounting information, The Review of Asset Pricing Studies 1.1, pp. 35-73

Ikeda, Satoshi, et al. (2023): Leveling up factor performance: a multi-dimensional approach, Risk and Reward #4/2023, pp. 4-8

Moskowitz, Tobias J.,and Mark Grinblatt (1999): Do industries explain momentum?, The Journal of finance 54.4, pp. 1249-1290

Peng, Lin and Wei Xiong (2006): Investor attention, overconfidence and category learning, Journal of Financial Economics 80.3, pp. 563-602

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Market-neutral investing: a systematic factor-based approach

By Sergey Protchenko, Viorel Roscovan, Ph.D., and Jerry Sun, Ph.D.

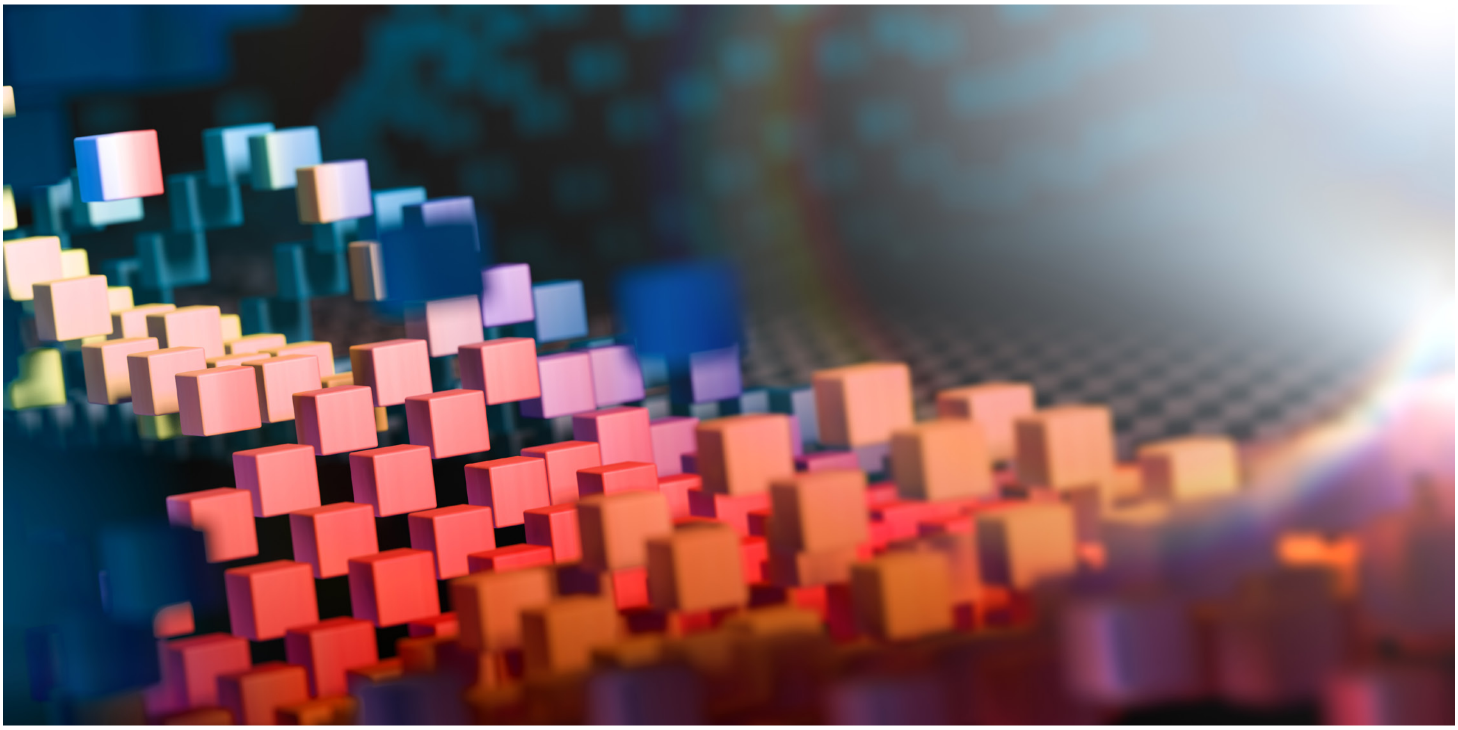
Market-neutral strategies enable alpha generation while mitigating systematic risk through long and short positions. Meanwhile, factor-based market-neutral strategies can offer more attractive risk-return tradeoffs then other market-neutral alternatives. They also provide transparency and cost-efficiency, making factor-based strategies even more attractive for investors seeking diversification beyond conventional market exposures.

By maintaining aggregate long and short positions of equal size, market-neutral strategies aim to neutralize systematic market risk (beta) and capture alpha independent of market movements. This setup allows managers to take full advantage of their insights and create portfolios that profit from both outperforming stocks (through long positions) and underperforming stocks (through short positions). In contrast, long-only strategies typically focus only on securities expected to outperform.[1]

In market-neutral strategies, losses from the short positions are offset by gains in long positions when markets rise, and vice versa in a decline. This approach offers several advantages:

- **Beta Reduction:** Market-neutral strategies reduce market exposure, eliminating systematic risk and leaving alpha as the primary driver of returns. This makes them appealing for investors seeking diversification without additional market risk (Frazzini and Pedersen, 2013).

- **Diversification:** Because, by design, they tend to have a low-correlation to traditional long-only equity and



> Factor-based market-neutral approaches which offer an effective, transparent, and cost-efficient alternative.

fixed income portfolios, market-neutral strategies provide valuable diversification benefits, helping to reduce overall portfolio volatility (Agarwal and Naik, 2004).

- **Risk Mitigation:** These strategies offer a natural hedge against adverse market movements, as short positions can yield positive returns in bear markets, providing a degree of protection against market downturns.

- **Alpha Generation:** The long-short structure opens up a broader opportunity set, allowing portfolios to benefit from both rising and falling asset prices. Empirical research shows the superior alpha generation potential of market-neutral strategies, especially in volatile equity markets (Jagannathan et al., 2010).

- **Scalability and Flexibility:** Market-neutral strategies are adaptable to different investor requirements and risk tolerances across various asset classes and market environments, enhancing their utility in multi-asset portfolios (Pedersen, 2015).

Figure 1 compares the HFRX Equity Market Neutral Index, a common benchmark for market-neutral equity strategies investing in the US, to the MSCI USA Index and a 60/40 portfolio. On average, the HFRX Index demonstrates lower risk and drawdowns, with strong diversification benefits (approximate -10% correlation to the market).

However, there are challenges: While the HFRX Index does exhibit lower risk, it also has considerably lower returns, resulting in an Information Ratio (IR) of just 0.3 – well below that of the MSCI USA Index (0.58) and the 60/40 portfolio (0.69). Furthermore, from 2014 onwards, the HFRX experienced the largest and longest drawdowns of the three, raising questions about its ability to consistently generate alpha. This is partly due to its reliance on discretionary strategies, which can lead to unpredictable results. The lack of transparency, coupled with the high fees associated with the 2/20 model (2% management fee, 20% performance fee), significantly reduces net returns of typical market-neutral hedge funds. To overcome these drawbacks, investors could consider factor-based market-neutral approaches which may offer an effective, transparent, and cost-efficient alternative.

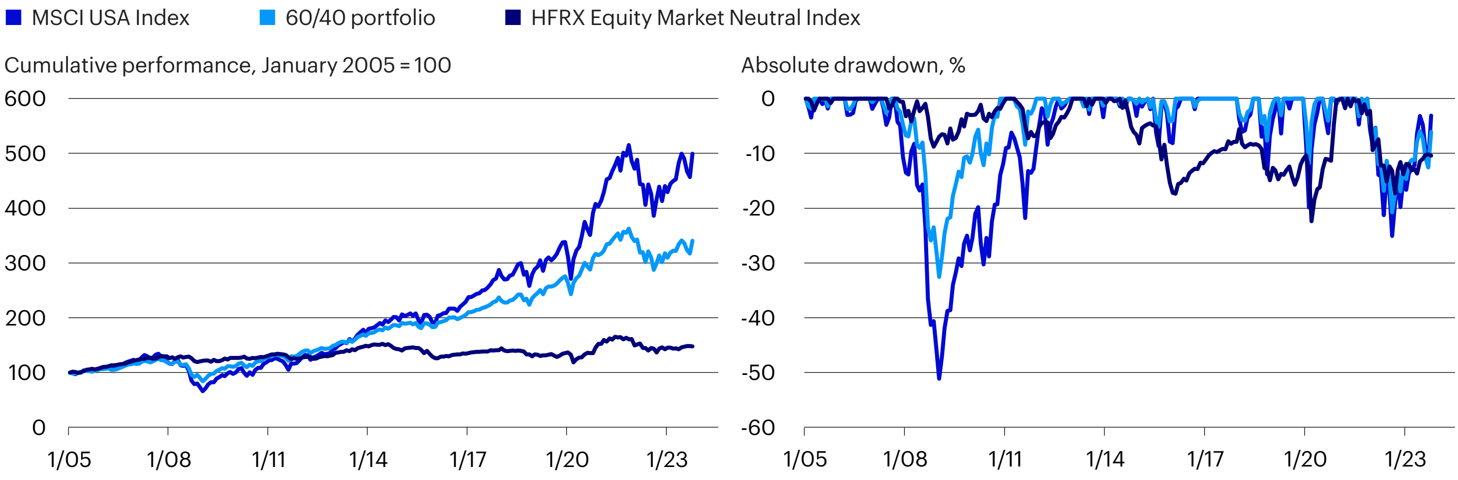
Factor-based market-neutral strategies

Empirical evidence suggests that factor premia deliver positive risk-adjusted returns over the long run (e.g., Fama and French, 1993; Jegadeesh and Titman, 1993; Novy-Marx, 2013). We see three key components underpinning an effective factor-based market-neutral strategy: investment philosophy, a factor-based alpha engine, and portfolio construction/risk management.

Investment philosophy

A factor-based approach should be grounded in evidence-based factors, supported by strong academic and industry research. The factors used should

Figure 1
Cumulative performance and absolute drawdowns of market-neutral strategies in comparison



	MSCI USA Index	60/40 portfolio	HFRX Equity Market Neutral Index
Return p.a. (%)	9.0	6.8	2.1
Standard deviation (%)	15.4	9.8	7.0
Information Ratio	0.58	0.69	0.30
Max. drawdown (%)	-51.1	-32.5	-22.4
Correlation to MSCI USA (%)	–	98.4	-9.1

The HFRX Equity Market Neutral Index measures the performance of market-neutral equity strategies investing in the US. The MSCI USA Index measures the performance of US equities. The 60/40 portfolio is assumed to consist of 60% MSCI USA Index and 40% Bloomberg US Aggregate Bond Index.
Source: Invesco Quantitative Strategies with data from Morningstar, Bloomberg, and MSCI. Monthly data from January 2005 to December 2023; returns, including dividends, in USD and gross of fees. **Past performance is not a guarantee of future results.** An investment cannot be made directly into an index.

Factor-based market-neutral approaches offer four distinct advantages.

demonstrate robust risk and return characteristics over time, across regions and asset classes. Studies and experience have shown that value, momentum, quality, and low volatility meet these requirements (e.g., Gupta, Raol, and Roscovan, 2022) and offer compelling long-term risk-adjusted returns. Given its natural beta tilt (low beta minus high beta), low volatility has been excluded, leaving value, momentum, and quality as the relevant factors in this model.

Alpha generation

These three factors – value, momentum, and quality – act as the alpha engine and are the fundamental drivers of risk and return in the factor-based market-neutral portfolio. While effectively capturing them is challenging, we use a diversified signal approach, which equally weights multiple correlated signals to capture the multifaceted nature of each factor[2] and equal risk-weights factors to create a diversified multi-factor portfolio.

This equal risk-weight approach, as outlined by Gupta, Sun, and Zou (2023), maximizes diversification and minimizes turnover while preserving the core factor characteristics. The model also ensures that the portfolio remains market-neutral, dollar-neutral, and sector-neutral, enabling a long-short market-neutral structure that closely tracks factor-specific alpha and provides an ideal representation of factor performance.

Portfolio construction and risk management

Constructing market-neutral portfolios hinges on effectively balancing long and short factor exposures while maintaining market neutrality. A compelling approach, outlined by Feng, Gupta, Protchenko, Roscovan, and Sun (2024), uses a multi-factor model portfolio structured as a 100% long and 100% short market-neutral portfolio, which serves as a target for the final, implementable portfolio.

The final portfolio is optimized to mimic the model portfolio subject to various investment constraints, addressing diversification benefits, risk mitigation, and implementation concerns. The main advantage of this approach is that it provides an anchor portfolio that could be held in the absence of other investment constraints.

The model portfolio also helps measure portfolio implementation success and alignment with investor objectives. Specifically, one may evaluate how well factor exposures in the final portfolio align with those in the model portfolio. The model portfolio approach facilitates transparency via unambiguous attribution of realized exposures and returns and can help with purposeful evaluation of factor models.

Four distinct advantages of factor-based market-neutral strategies

Factor-based market-neutral approaches offer four distinct advantages:

1. Solid empirical foundation: Decades of academic research confirm the persistence and robustness of factor premia.

2. Survivorship bias mitigation: Factor-based investing avoids the overstated performance of some market-neutral indices by not excluding the results of failed discretionary managers from performance analyses (Carhart, 1997).

3. Diversification and risk management: Factor-based market-neutral strategies offer diversification benefits through systematic portfolio construction, ensuring market-neutrality and resilience to market fluctuations.

4. Transparency: Factor-based strategies follow clearly defined rules and selection criteria, making them easier to monitor and evaluate (Harvey et al., 2016).

Shorting is a necessary component of market-neutral portfolios, and it poses certain challenges, including borrowing costs, liquidity constraints, and the risk of short squeezes. These risks, however, can be mitigated through prudent risk management and portfolio construction to ensure the strategy's sustainability (Asness et al., 2015).

Market-neutral strategies compared

To assess the effectiveness of factor-based market-neutral strategies, we compare the factor-based approach to the HFRX.

Table 1
Performance characteristics of Factor-Based Market-Neutral US strategy and the HFRX US Equity Market Neutral Index

	MSCI USA Index	HFRX Equity Market Neutral Index	Factor-based market-neutral US strategy
Return p.a. (%)	9.0	2.1	4.4
Standard deviation (%)	15.4	7.0	4.7
Information Ratio	0.58	0.30	0.94
Max. drawdown (%)	-51.1	-22.4	-21.1
Correlation to MSCI USA (%)	–	-9.1	-13.9

The HFRX Equity Market Neutral Index measures the performance of market-neutral equity strategies in-vesting in the US. The MSCI USA Index measures the performance of US equities.
Source: Invesco Quantitative Strategies with data from Morningstar, Bloomberg, and MSCI. Monthly data from January 2005 to December 2023; returns, including dividends, in USD and gross of fees.

Table 1 compares the risk and return characteristics of the factor-based market-neutral strategy and the HFRX Index to the MSCI USA from January 2005 to December 2023. The factor-based market netural strategy and the HFRX both exhibit lower risk and negative correlations to the MSCI USA. Both show significantly lower drawdowns, with an average of around -22% compared to a much steeper -51% for the MSCI USA, highlighting the valuable diversification and risk mitigation benefits of market-neutral approaches.

The key distinction, however, lies in the risk-return tradeoff: The factor-based approach outperforms the HFRX Index, delivering an Information Ratio of 0.94 versus HFRX's 0.30, demonstrating a more efficient return per unit of risk. In contrast, the MSCI USA achieves an IR of 0.58. The considerably lower IR of the HFRX is driven by both lower alpha and a lesser reduction in volatility. It seems the factor-based model may be far more effective at delivering consistent returns than other market-neutral strategies.

Further analysis through Fama-French regressions (table 2) sheds light on the specific factor contributions to returns and risk for both the factor-based market-neutral strategy and the HFRX Index.

While both strategies exhibit positive annualized alphas, the factor-based strategy exhibits a stronger economic alpha of 3.9%, significant at a 1% p-value, compared to HFRX's 3%, which is only significant at 10%. Both approaches maintain beta neutrality, though HFRX has a slight negative beta bias, also significant at 10%.

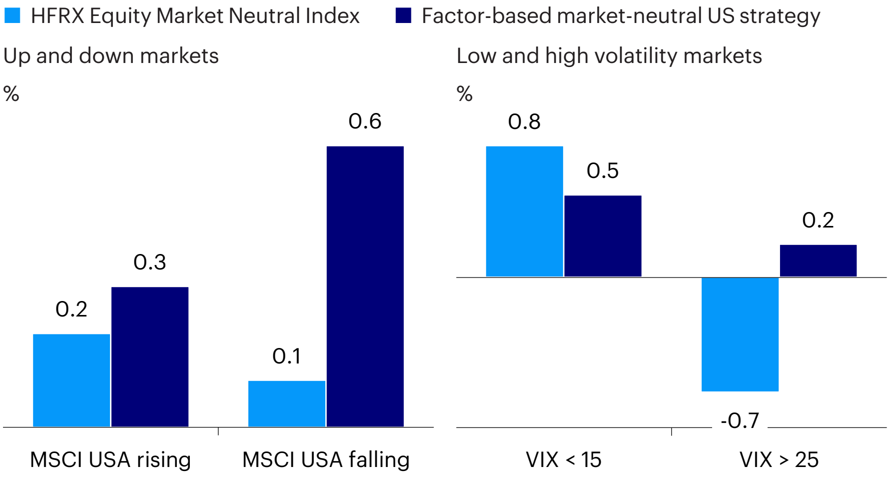
Notably, no significant factor drivers are identified for the HFRX Index, highlighting

Table 2
Key performance drivers in comparison

	HFRX Equity Market Neutral Index	Factor-based market-neutral US strategy
Alpha (annualized, %)	3.0*	3.9***
Beta market	-0.05*	-0.01
Beta SMB	0.10	-0.09***
Beta HML	0.05	0.17***
Beta RMW	-0.01	0.18***
Beta CMA	-0.08	-0.03
Beta WML	0.04	0.08***
R-sq (%)	2.9	37.4

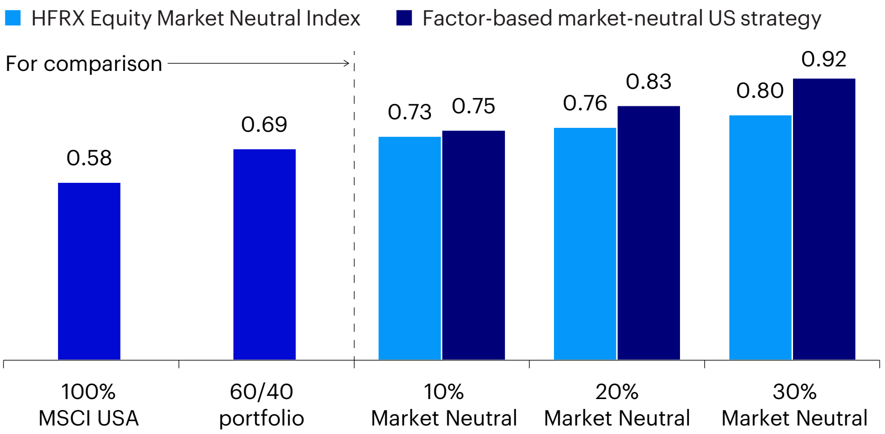
Coefficient estimates of a Fama-French 6 factor model regression. Dependent variable: return of the HFRX Equity Market Neutral Index (measuring market-neutral equity strategies investing in the US) and of the factor-based market-neutral US strategy. 6 Factors: the market, size (SMB), value (HML), profitability (RMW), investments (CMA), and momentum (WML); ***, **, and * denote significance at 1%, 5%, and 10% levels.
Source: Invesco Quantitative Strategies with data from the Ken French database, Morningstar, and MSCI. Monthly data from January 2005 to December 2023; returns, including dividends, in USD and gross of fees.

Figure 2
Performance in different market scenarios compared



Average monthly returns of the HFRX Equity Market Neutral Index and the factor-based market-neutral US strategy in up and down markets (as measured by the MSCI USA Index) as well as in low and high volatility markets (as measured by the VIX).
Source: Invesco Quantitative Strategies with data from Morningstar, MSCI, and CBOE. Monthly data from January 2005 to December 2023; returns, including dividends, in USD and gross of fees.

Figure 3
Information Ratios in comparison



The HFRX Equity Market Neutral Index measures the performance of market-neutral equity strategies in-vesting in the US. The MSCI USA Index measures the performance of US equites. The 60/40 portfolio is as-sumed to consist of 60% MSCI USA Index and 40% Bloomberg US Aggregate Bond Index.
Source: Invesco Quantitative Strategies with data from Morningstar, Bloomberg, and MSCI. Monthly data from January 2005 to December 2023; returns, including dividends, in USD and gross of fees.

> The factor-based market-neutral strategy consistently outperforms HFRX due to its potential ability to generate more consistent alpha.

its reliance on discretionary alpha generation. In contrast, the factor-based strategy shows strong, statistically and economically significant exposure to size, value, momentum, and profitability; the slight large cap tilt, indicated by the negative size coefficient, is expected due to the broad Fama-French universe. Moreover, results show that the profitability effect largely drives the quality factor in the factor-based strategy, and the low R^2 of the HFRX Index versus the high R^2 of the factor-based strategy suggests that systematic factors are the primary drivers of factor-based performance, whereas the HFRX depends more on discretionary decision making unrelated to the Fama-French factors.[3]

In an up- and down-market comparison (figure 2a), both the factor-based strategy and the HFRX Index demonstrate positive returns regardless of market conditions. But the data shows a positive return trend with the factor-based strategy supporting our theory that it has the potential ability to enhance returns..

We also analyzed the performance in low- and high-volatility market scenarios (figure 2b): Both the factor strategy and the index show positive returns in periods of low uncertainty, though the returns of the index under stable conditions are higher. In high-volatility periods, however, the factor-based strategy continues to produce positive returns, whereas HFRX delivers negative performance. This suggests that HFRX's discretionary alpha generation performs best in stable environments, where discretion is arguably less valuable. Conversely, in volatile periods, when discretionary decisions should theoretically add the most value, HFRX disappoints with negative returns. The factor-based strategy, on the other hand, proves to be an all-weather approach, consistently delivering strong returns across varying market conditions, further highlighting its robustness and resilience.

Thus, with strong, statistically significant exposure to systematic factors like value, momentum, and profitability, the factor-based market-neutral strategy consistently outperforms HFRX due to its potential ability to generate more consistent alpha than the discretionary approach. The transparency with respect to factor drivers offers investors a clearer understanding of performance sources. Moreover, the factor-based approach typically comes with lower fees, as it relies on systematic processes rather than costly discretionary management. This enhances overall returns. Its resilience across various market conditions further reinforces the factor-based strategy's potential ability to be effective over the long term.

Factor-based market-neutral strategies in asset allocation

Given the advantages of factor-based market-neutral strategies, they are an interesting input to enhance traditional long-only approaches. Historically, hedge funds have provided investors with access to alternative strategies aimed at generating alpha. Factor-based strategies, however, present a more accessible and cost-effective option, providing similar benefits with lower fees and greater transparency (Agarwal et al., 2009).

One of the primary applications of market-neutral strategies is within portable alpha frameworks, where alpha generation is decoupled from beta exposure. These structures allow investors to combine market-neutral strategies with passive exposures to asset classes such as equities or fixed income as a way to enhance returns without increasing systematic risk (Kritzman and Page, 2003). Figure 3 shows how adding market-neutral strategies can improve a portfolio's Information Ratio – as well as how a factor-based approach can further improve IR.

We compare a pure 60/40 allocation to 60/40 portfolios to which market-neutral

Even modest allocations to a market-neutral strategy may lead to a meaningful improvement in IR.

strategies have been added, either through the HFRX Index or own factor-based market-neutral approach. Even modest allocations to a market-neutral strategy may lead to a meaningful improvement in IR. These improvements can be significantly more pronounced when investors consider the factor-based approach over the HFRX Index.

Conclusion

Market-neutral strategies offer a compelling approach to alpha generation without assuming market beta risk. Factor-based approaches enhance this potential through transparency, cost efficiency, and systematic factor exposures. Particularly in the context of asset allocation, this makes them an interesting tool for institutional investors and asset owners. As the asset management industry continues to evolve, factor-based market-neutral strategies may emerge as a valuable and scalable solution for modern portfolio construction.

Notes

1 Cp. Ang (2014). Equity market-neutral strategies should not be confused with long/short equity strategies, even though there are similarities (Nafia et al., 2023). In contrast to market-neutral strategies, long-short strategies typically share the equity market's fluctuations because managers often have unequal sums invested in their long and short positions, generally favoring long positions to participate in long-term market gains.

2 At this stage, investors could consider stripping out unrewarded risks such as market and sector/industry biases inherent in generic factors (see Protchenko, Ikeda, and Roscovan, 2023).

3 Although Fama-French factors can help to explain the performance of the factor-based market-neutral strategy, they still leave a significant amount of alpha unexplained.

References

Agarwal, V., Daniel, N. D., and Naik, N. Y. (2009): Role of managerial incentives in hedge fund performance, The Journal of Finance, 64(5)

Ang, A. (2014): Asset management: A systematic approach to factor investing, Oxford University Press

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013): Value and momentum everywhere, The Journal of Finance, 68(3)

Carhart, M. M. (1997): On persistence in mutual fund performance, The Journal of Finance, 52(1)

Fama, E. F. and French, K. R. (1993): Common risk factors in the returns on stocks and bonds, Journal of Financial Economics, 33(1)

Feng, X., Gupta, T., Protchenko, S., Roscovan, V., and Sun, J. (2024): Control and transparency in factor portfolios, Journal of Beta Investment Strategies, 15(1)

Frazzini, A. and Pedersen, L. H. (2013): Betting-against-beta. Journal of Financial Economics, 111(1)

Gupta, T., Raol, J., and Roscovan, V. (2022): Factor investing: from theory to practice, Journal of Beta Investment Strategies, 13(4)

Gupta, T., Sun, J., and Zou, H. (2022): Risk-based weighting for better factor investing, Risk and Reward #4

Jagannathan, R., Malakhov, A., NOVIKOV, D. (2010): Do hot hands persist among hedge fund managers? An empirical evaluation, The Journal of Finance, 65(1)

Jegadeesh, N. and Titman, S. (1993): Returns to buying winners and selling losers: Implications for stock market efficiency, The Journal of Finance, 48(1)

Kritzman, M. and Page, S. (2003): The hierarchy of investment choice: a normative interpretation, The Journal of Portfolio Management, 29(4)

Nafia, A., Yousfi, A., and Echaoui, A. (2023): Equity-Market-Neutral Strategy Portfolio Construction Using LSTM-Based Stock Prediction and Selection: An Application to S&P500 Consumer Staples Stocks, International Journal of Financial Studies, 11(2)

Novy-Marx, R. (2013): The other side of value: the gross profitability premium. Journal of Financial Economics, 108(1)

Pedersen, L. H. (2015): Efficiently Inefficient: How Smart Money Invests and Market Prices Are Determined, Princeton University Press

Ikeda, S., Protchenko, S., and Roscovan, V. (2023): Leveling-up Single Factor Performance, Risk and Reward #4

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Managing currency exposures in multi-asset portfolios with constraining investment guidelines

By Carsten Becker, Alexandar Cherkezov, and Dr. David Happersberger

Diversified global portfolios come with foreign exchange risks and opportunities. We compare different currency management approaches, with and without investment constraints, to find out which is most suitable for a world with regulatory and other limitations.

In two previous articles,[1] we introduced currency management approaches for global portfolios: the first focusing on risk, the second on factors. Now, we will look at these ideas through the lens of a practitioner confronted with investment guidelines imposed by clients or regulators – using a risk-based and a factor-based methodology.

Our risk-based methodology takes advantage of minimum-variance optimization to exploit the relatively stable correlations between currencies and asset classes (Figure 1). Certain currencies tend to act as a safe-haven asset when stock markets fall, most notably the Japanese yen and, to some degree, also the US dollar. Others, like sterling, the Canadian dollar and the Australian dollar, tend to be more procyclical. Technically, this strategy minimizes overall portfolio variance by holding asset class exposures fixed while varying currency hedge ratios.

The factor-based concept, on the other hand, is based on the finding that style factors (the most popular being carry, momentum, and value) tend to reliably predict currency returns over time:

- For a **carry** trade, an investor borrows funds from a country with a low-yielding currency to fund an investment in a country with a high-yielding currency.

- **Momentum** makes use of the fact that assets that performed well in the past tend to continue performing well in the future. There is evidence of FX momentum for various time periods. For our factor construction, we use three-month spot momentum.

- The **value** factor is used to distinguish between overvalued and undervalued currencies. It is often approximated by consumer price indices and the associated purchasing power parity. The idea is that goods should cost approximately the same in all countries.

Currency management without constraints

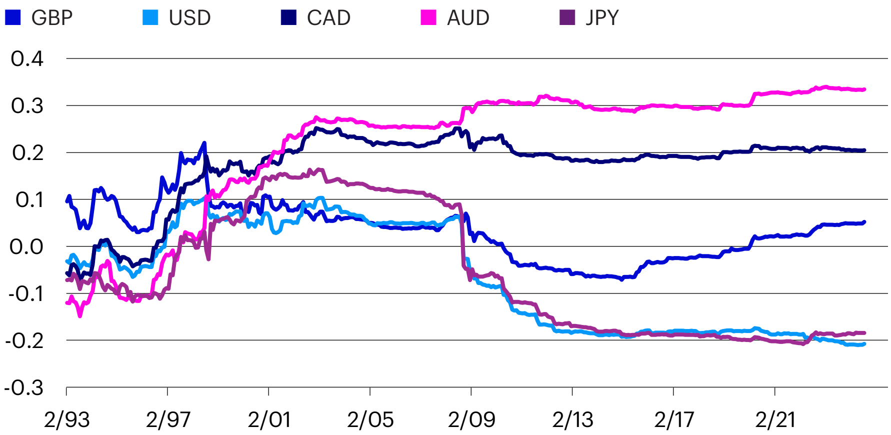
We compare four currency management concepts: unhedged, fully hedged, minimum-variance and currency style factors, the latter of which seeks not only to reduce risk but to enhance returns. Our analysis is based on a well-diversified portfolio comprising 28% global developed-market equities, 40% developed-markets government bonds, and 10% commodities.

From 1995 to 2024, a euro-based investor with unhedged currency exposure would have earned an annualized return of 6.47% (Table 1). However, this would have come with relatively high volatility, resulting in a Sharpe ratio of just 0.68. At the opposite end of the spectrum, fully hedging the currency risk results in lower returns but significantly lower volatility, leading to improved risk-adjusted return.

The third approach, the risk-based minimum-variance strategy, offers improvements over both the hedged and unhedged portfolios. Compared to a full hedge, this strategy provided higher returns and more importantly, lower volatilty, resulting in a potentially highly and more attactive Sharpe ratio. Notably, the minimum-variance portfolio places no restrictions on unhedged currency risk or tracking error.

Finally, we consider a multi-asset portfolio with a currency factor overlay. Thanks to the favorable correlation of currency factors with equities, bonds and commodities, and positive expected factor premia, this approach generates a significant increase in returns. Although it introduces some additional risk, the risk-adjusted return of the factor strategy is the highest of all four alternatives (though only slightly better than the minimum-variance approach). Thus, return-seeking investors may be able to benefit from incorporating currency factors.

Figure 1
Rolling 3-year correlations between the S&P 500 and different currency pairs



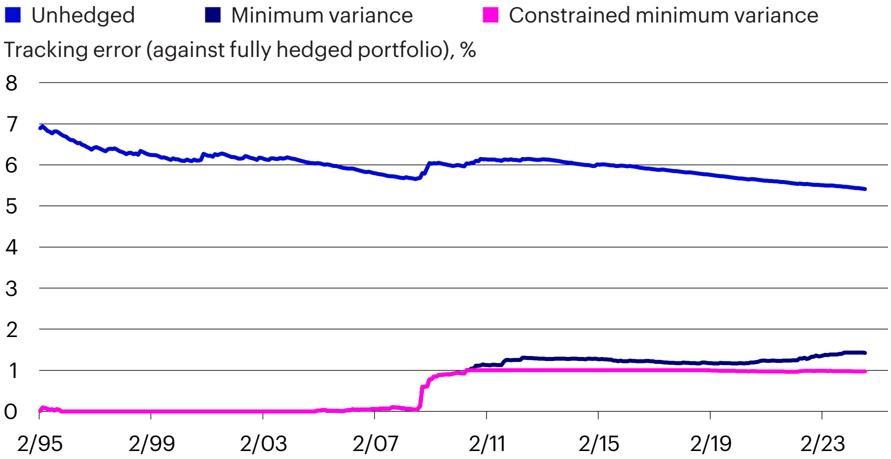
Source: Bloomberg, Invesco calculations. Data from February 28, 1993 to August 7, 2024.

Table 1
Risk and return characteristics of different currency management approaches

		Unconstrained			Constrained	
	Unhedged	Hedged	Minimum-variance	Factor overlay	Minimum-variance	Factor overlay
Return (%)	6.47	5.82	5.98	7.45	5.95	5.85
Volatility (%)	6.56	5.22	5.01	6.75	5.03	5.36
Sharpe Ratio	0.68	0.74	0.80	0.81	0.79	0.72

Long-only constraint for the factor overlay, 10% limit on open currency exposure and tracking error of max. 100 bps (compared to the hedged version) for the minimum-variance portfolio (which is, by definition, long-only). This analysis is based on backtested data based on fully funded index futures.
Source: Invesco calculations. Data from February 28, 1995 to August 7, 2024; EUR based.

Figure 2
Tracking error (against the fully hedged portfolio) in comparison



Source: Invesco calculations. Data from February 28, 1995 to August 7, 2024; EUR based.

Introducing constraints
A logical conclusion might be to utilize currency factors for currency management. However, real-world constraints complicate this approach. Most investors limit shorting and leverage due to either their own preferences or regulatory demands. A common restriction is the long-only constraint, which permits hedging currency exposures from fully funded equity, bond, and commodity positions but prohibits outright shorts. Outright long positions are also restricted, the maximum exposure to any single currency being limited to what is available from the underlying.

While the minimum-variance portfolio is inherently long-only, it may still fail to conform with client guidelines, especially when limits are imposed on open currency. In our example, we apply a realistic constraint of a maximum 10% open FX exposure and a tracking error capped at 100 bps compared to the hedged portfolio. Under these constraints, both return and volatility decrease only marginally, resulting in a Sharpe ratio that remains highly attractive – outperforming both fully hedged and unhedged currency exposures.

In contrast, the factor approach is significantly impacted by constraints. The long-only constraint notably reduces returns, while its effect on volatility is less pronounced. Consequently, the Sharpe ratio of the constrained factor approach falls below that of the fully hedged portfolio and the constrained minimum-variance portfolio.

In the presence of real-world constraints, managing currency exposure in multi-asset portfolios requires a more granular approach. While currency factors may initially appear attractive, they cannot reach their full potential in a constrained environment. The research indicates the minimum variance strategy may improve the Sharpe ratio by reducing volatility. This approach leverages the correlation structure between currencies and asset classes, adding value beyond the binary choice of full hedging and no hedging.

The minimum-variance portfolio in detail
One key question remains: What unintended characteristics might the minimum-variance portfolio exhibit? These portfolios are known for diverging significantly from

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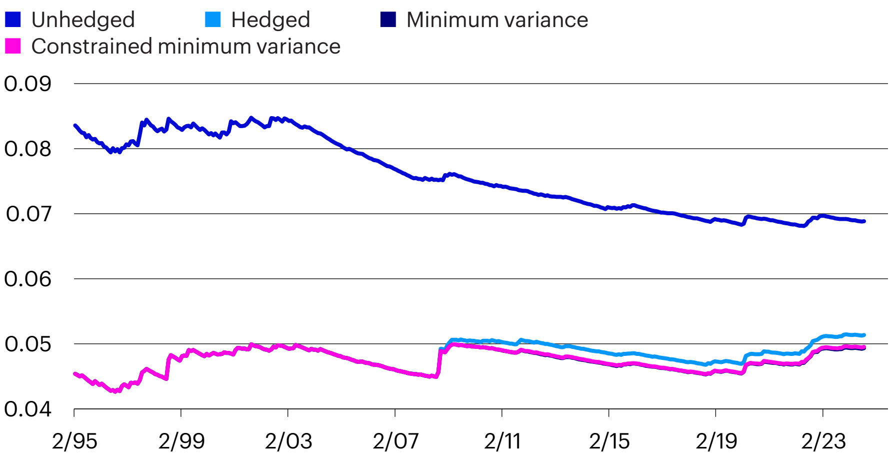
In the presence of real-world constraints, managing currency exposure in multi-asset portfolios requires a more granular approach.

Figure 3
Volatility in comparison



Source: Invesco calculations. Data from February 28, 1995 to August 7, 2024; EUR based.

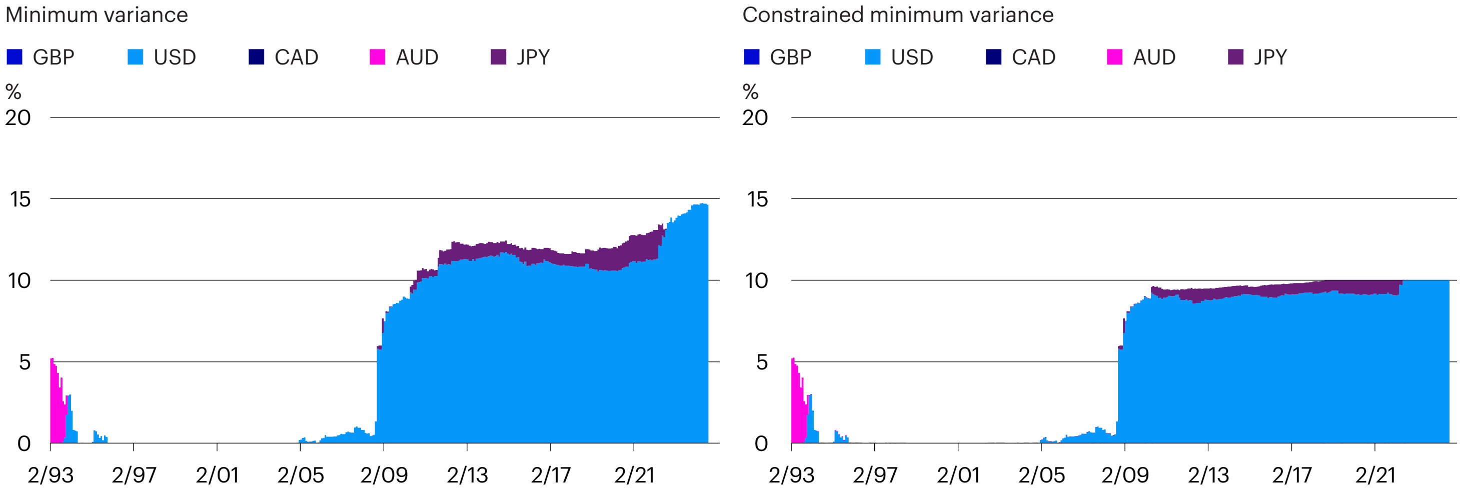
market-cap benchmarks or input portfolios. To explore this, we conducted a tracking error analysis. For the constrained minimum-variance portfolio, Figure 2 shows a low tracking error of around 1%, compared to an average of over 6% for the unhedged portfolio. Given the improvement in Sharpe ratios, we consider the tracking error budget to be well spent, without introducing unwanted active risk patterns.

A similar conclusion can be drawn regarding absolute volatility: As expected, the minimum-variance approach delivers the lowest ex-ante volatility, some 40% lower than that of the unhedged strategy (Figure 3).

The resulting currency exposures illustrate how risk reduction has been achieved (Figure 4). In the first half of the sample period, both the unconstrained and the constrained minimum-variance portfolio are predominantly hedged. However, in the second half, significant US dollar and Japanese yen exposures remain open. It's important to note that the underlying investments are primarily US dollar-denominated. Additionally, the effects of the constraints, such as the maximum 10% open currency exposure and the tracking error limit, are clearly visible.

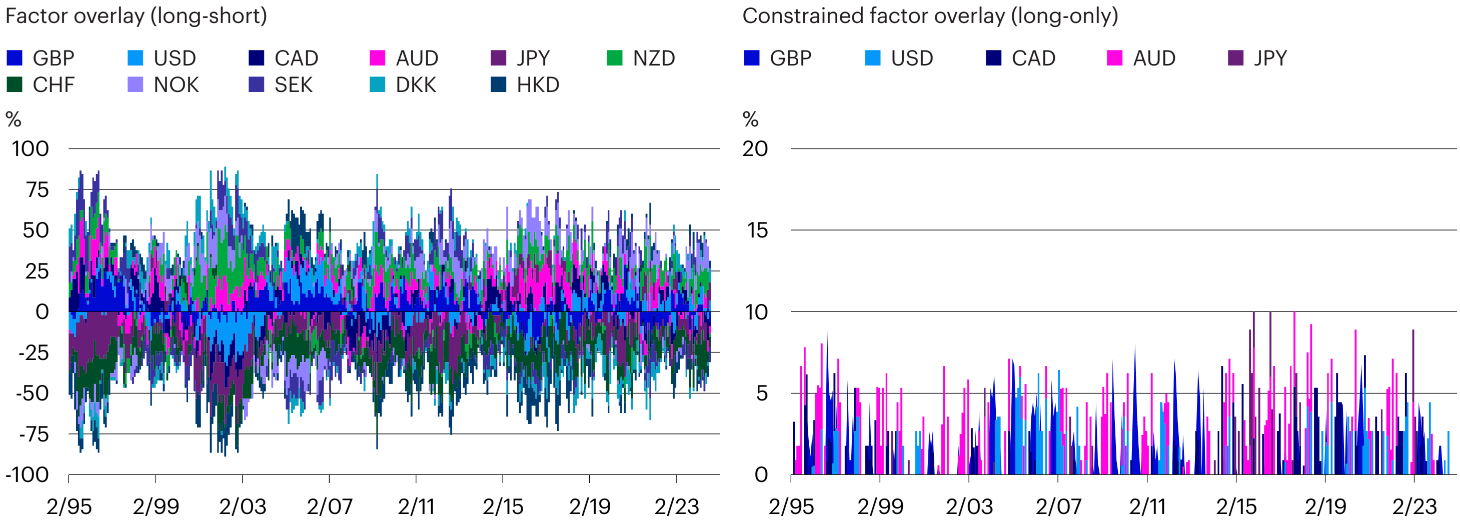
The currency exposures of the multi-factor overlays reveal the inherent strengths and weaknesses. The unconstrained long-short version requires a significant budget for outright long and shorts and completely disregards the currency structure of the underlying investments (Figure 5). The constrained long-only version respects those but can only partially capture the full benefits of the multi-factor currency model.

Figure 4
Open currency exposure in comparison



Source: Invesco calculations. Data from February 28, 1993 to August 7, 2024; EUR based.

Figure 5
Long-short and long-only currency exposures in comparison



Source: Invesco calculations. Data from February 28, 1995 to August 7, 2024; EUR based.

Table 2
Risk and return characteristics of different equity/bond allocations in comparison

		Unhedged	Hedged	Minimum variance	Constrained minimum variance	Factor overlay	Constrained factor overlay
100% equities	**Return (%)**	9.97	8.99	9.13	8.98	10.61	8.88
	Volatility (%)	15.19	14.83	14.49	14.65	15.78	14.92
	Sharpe Ratio	0.52	0.47	0.49	0.48	0.54	0.46
75% equities, 25% bonds	**Return (%)**	9.00	8.16	8.20	8.18	9.79	8.15
	Volatility (%)	12.11	11.09	10.86	10.94	12.15	11.23
	Sharpe Ratio	0.58	0.55	0.57	0.56	0.64	0.55
50% equities, 50% bonds	**Return (%)**	7.88	7.16	7.26	7.24	8.80	7.19
	Volatility (%)	9.43	7.62	7.49	7.50	8.84	7.76
	Sharpe Ratio	0.62	0.68	0.70	0.70	0.77	0.67
25% equities, 75% bonds	**Return (%)**	6.63	5.99	6.09	6.09	7.64	6.04
	Volatility (%)	7.59	5.02	4.96	4.96	6.37	5.11
	Sharpe Ratio	0.61	0.80	0.83	0.83	0.89	0.79
100% bonds	**Return (%)**	5.26	4.67	4.75	4.73	6.33	4.73
	Volatility (%)	7.25	4.92	4.90	4.90	5.92	4.90
	Sharpe Ratio	0.45	0.55	0.57	0.57	0.73	0.57

Equity Proxy: Market cap weighted portfolio is composed of Eurostoxx 50, FTSE 100, TOPIX, S&P 500.
Bond proxy: Equal weighted portfolio of US, German, Canada, Australia, Japan, UK 10 Year Government Bonds
Source: Invesco calculations. Data from February 28, 1995 to August 7, 2024; EUR based.

“

While currency factor models offer the greatest theoretical value, their potential is significantly limited in practice by restrictive investment constraints.

Does the portfolio structure matter?

Up to this point, our analysis has focused on a portfolio consisting of 28% in global developed-market equities, 40% developed-markets government bonds and 10% commodities. We now examine whether our findings can be generalized across equity and bond portfolios with varying allocations.

For a bond-only portfolio, currency volatility plays a crucial role, and we beliwve investors should consider some form of currency management. For a pure equity portfolio, on the other hand, equity market volatility overshadows currency risks, making currency management less critical over the long term (Table 2).

Overall, the findings from our base case are confirmed across all allocations – from 100% equities to 75%/25%, 50%/50%, 25%/75% to 100% bonds. As in the previous studies, a long-short factor overlay is found to generally add value – though much of this value is diminished under long-only constraints. While factor implementation has challenges, the minimum variance approach provides a more reasonable strategy to implement, with the greater share of the benefits realized after constraints are applied.

Conclusion

Our analysis demonstrates that, while currency factor models offer the greatest theoretical value, their potential is significantly limited in practice by restrictive investment constraints. Under such conditions, the minimum-variance approach proves to be the more effective strategy.

Note
1 Martin Kolrep and Harald Lohre (2017): Risk-based currency management, Risk and Reward #1/2017 . Martin Kolrep and Harald Lohre (2018): Currency Management with style, Risk and Reward #1/2018.

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