Are There Fences in the Global Factor Zoo?

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Abstract

We revisit the established dominance of local factors in international asset pricing by examining the predictability anomalies through the lens of factor momentum signals. Differing from previous results for asset pricing models where local factors are typically seen as superior to regional and global factors, our research reveals that regional and global signals surpass local signals in forecasting factor risk premiums. Strategies formed on non-local signals generally outperform strategies formed on local signals in all considered metrics. This outperformance is more pronounced for factors and regions with high structural integration. Non-local factor predictability potentially improves leading asset pricing models. Moreover, non-local signals revive momentum investing in markets previously thought to lack momentum opportunities, such as Japan.

Keywords: International Asset Pricing, Factor Timing, Factor Momentum, Return Prediction

JEL Classification: C52, G11, G15, G17.

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1 Introduction

For decades, international asset pricing models have been a cornerstone at the intersection of asset pricing and international finance, endeavoring to explain the variation in returns across a spectrum of markets. Central to this area of study is the investigation into whether asset prices are influenced primarily by local or global factors, a question deeply intertwined with the broader issue of market segmentation/integration. This field of financial literature is well-established, with notable reviews such as those by Karolyi and Stulz (2003) and Lewis (2011), which have significantly contributed to our understanding.

Amidst ongoing globalization, there's a general anticipation of advancing market integration. Bekaert and Harvey (1995) have shown that, although market integration is increasing, it exhibits considerable variation across different countries. More recent studies present a nuanced view, with evidence on the integration of international markets showing varied results. While there are indications highlighting the importance of global factors on asset prices, there are also contrary findings. Fama and French (1998) and Hau (2011) have emphasized the critical role of global factors in determining asset prices. Griffin (2002) and others (Fama & French, 2012, 2017; Hollstein, 2022) have found that global and regional asset pricing models do not adequately capture the time-series properties of characteristic sorted portfolios in comparison to local factor models.

Although these observations hold for modeling contemporaneous returns, the scenario could shift dramatically when examining the development of *time-varying expected returns*. We adopt the perspective of an investor seeking to forecast factor premiums to leverage time-varying differences in expected returns. The potential to time risk factors carries significant implications for asset pricing. Ehsani and Linnainmaa (2022) show that common asset pricing models like the Fama and French (2018) 6 factor model can be improved when integrating factor return predictability. However, factor return predictability may have spatial aspects that are yet unexplored. This paper aims to address this research gap by probing the question:

RQ: Is factor premium predictability driven by local, regional, or global forces?

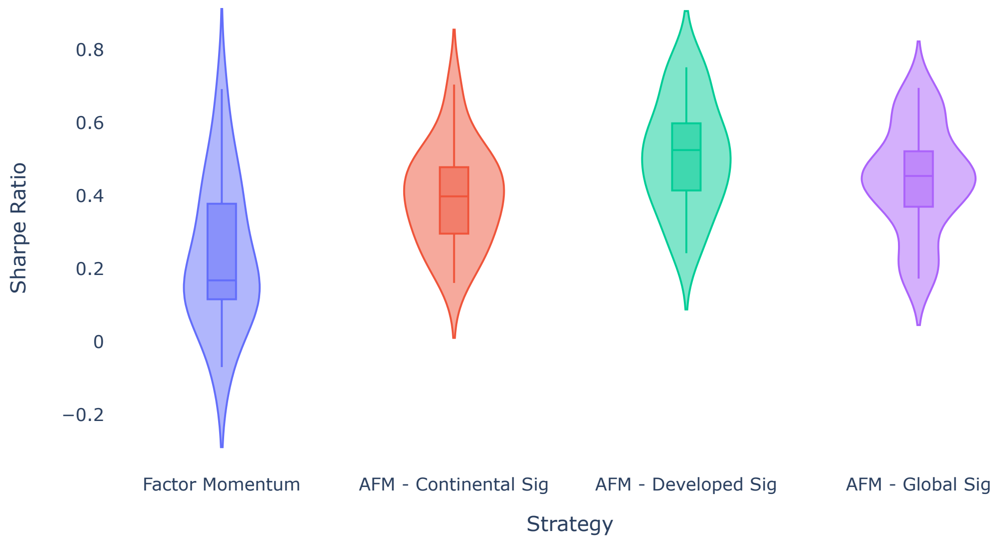
We address this inquiry by employing straightforward factor momentum signals identified as the most robust factor-level predictors in prior research (Neuhierl et al., 2023). Our method is streamlined to concentrate on the foremost predictor of factor premiums. Should the predictability reflect country-specific nuances as seen in most current asset pricing studies, then country-level factor momentum signals would emerge as the most powerful predictors, maximizing investor's utility and achieving the highest Sharpe ratios. Conversely, if the predictability is derived globally, investors would benefit more from incorporating non-local factor momentum signals into their local factor strategies.

While the creation of local and global factor momentum signals is straight forward, developing a regional signal presents an additional challenge: what is the optimal level of regionality? Should regions include only the neighboring countries, or encompass entire continents? We face this challenge with the following argument. If the underlying mechanics of a factor are determined by non-local influences, we can expect the returns of this factor to exhibit some degree of co-movement among countries, as they are driven by the same underlying forces. The extent of this cross-country integration might vary across different factors and regions. However, if such non-local influences exist, they could help define the optimal regional scope for implementing factor momentum strategies. Therefore, we first analyze international co-movement of factor returns before developing local, regional, and global factor momentum strategies.

Our findings show that international factor returns exhibit co-movement, with its strength varying across different factor themes and countries at different stages of development. Developed countries generally exhibit stronger cross-country co-movement than emerging markets, leading us to conclude that the optimal regional grouping should be based on the development status. Building on these insights to generate optimal factor momentum strategies, we find that while local signals effectively predict future factor returns, as shown in the previous literature, regional and global models outperform local ones in terms of predictability. By leveraging non-local (i.e., developed market) signals for forecasting local factor returns, an investor can double his portfolio's Sharpe ratio. The predictability derived from non-local signals is more consistent and results in strategies characterized by a lower standard deviation, greater skewness, and less severe maximum drawdowns. We show that as formulated by the hypothesis above, the superior performance of the non-local models is driven by leveraging the co-movement of factors that have high structural cross-country integration and are thus likely driven by non-local forces. Furthermore, we present evidence that regional aggregation based on development status, as aligned with the comovement argument, leads to a maximization in non-local predictability.

Our main result is illustrated in Figure 1. The left-most violin shows the distribution of Sharpe ratios of standard local factor momentum strategies in 23 countries, while the next three violins depict annualized Sharpe ratios from our Advanced Factor Momentum (AFM) strategies that are not formed based on the past 1-month performance of the local factor but of the aggregate equally weighted continental, developed market and global past 1-month factor performance. So, while we invest in a factor when its own history is among the top 50% factor signals and short the other 50%, in the AFM strategies we invest in a local factor when the aggregate past factor performance is among the top 50% aggregate factor signals. The resulting Sharpe ratios for the standard strategy are not only significantly lower on average than all the AFM strategies, as can be seen in Table A.3, but also more dispersed and heavily skewed to the left. Strategies utilizing non-local signals surpass those based on local signals in performance, with the developed market signal being the clear winner for developed countries. We show later that the superior predictability of non-local signals is strongest in markets where factor returns are more integrated. Interestingly, non-local signals have the potential to revive momentum investing in markets previously thought to lack momentum opportunities, such as Japan as shown in Table A.3.

Predictability is important for investors and academics alike. Timing of risk factors can improve portfolio performance. Furthermore, Ehsani and Linnainmaa (2022) show that factor momentum is crucial in understanding (an partially explaining) stock momentum and the cross-section of stock returns. Additionally, incorporating factor momentum can improve the explanatory power and predictive accuracy of asset pricing models. From an international asset pricing perspective we confirm the fact



Annualized Sharpe ratios	Mean	Std	Min	Q25	Median	Q75	Max
Factor Momentum	0.24	0.19	-0.07	0.12	0.17	0.37	0.69
AFM - Continental Sig	0.40***	0.13	0.16	0.31	0.40	0.48	0.70
AFM - Developed Sig	0.51***	0.15	0.24	0.42	0.53	0.59	0.75
AFM - Global Sig	0.44***	0.14	0.18	0.37	0.44	0.51	0.69

Figure 1: Violin plots for Sharpe ratios of different (advanced) factor momentum strategies: This figure depicts violin plots for 23 Sharpe ratios corresponding to the performance of country-level factor momentum strategies that are formed based on four different signals. All strategies are based on cross-sectional 1-month historical factor performance sorts and formed based on a median breakpoint that leading to a strategy that invests in 50% of a country's factors and shorts the other 50%. The four strategies are (i) a standard factor momentum strategy sorting on the past 1-month factor return within the country, and three *A*dvanced *F*actor *M*omentum (AFM) strategies that are formed based on the aggregated signal of a factor's past performance, where aggregation happens over (ii) all countries within a continent (continental signal), (iii) all developed markets (developed signal) and (iv) all markets (global signal). While the figure shows violin plots of annualized Sharpe ratios of all 23 countries considered in this sample, the table below gives corresponding descriptive statistics for these 23 Sharpe ratios (mean, standard deviation, skewness, minimum, 25-, 50-, and 75-quantile as well as the maximum). Additionally, we depict significance stars for a paired two-sample t-test of AFM strategies' Sharpe ratios against the standard factor momentums' Sharpe ratios. Significance values are given at the usual levels of 90% (*), 95% (**) and 99% (***).

that factors in countries are serially correlated (they have a factor momentum characteristic) but additionally observe, that they are strongly cross-autocorrelated to regional/global factors. This cross-autocorrelation is most pronounced in more integrated factor-themes, i.e. in factors that have strong non-local components. Our findings indicate that while local factor models play a role in the immediate pricing of assets, the essence of factor predictability is predominantly driven by non-local signals.

This introduces a fresh perspective and broadens the focus of the current body of research, which has predominantly focused on the contemporaneous connections between factors and returns, without exploring the predictive dimensions of factor dynamics. These insights can enhance the construction of asset pricing models, improve portfolio diversification strategies, and offer a more nuanced understanding of global financial markets.

Our work is related to prior studies examining the integration of international capital markets. Despite the ongoing globalization, Bekaert et al. (2009) finds no sign of increased integration in developed markets when investigating comovements (except in the Euro zone). Even though there are strong international components in stock portfolios like in value stocks (Fama & French, 1998), international or regional factor models underperform their local versions (Fama & French, 2012, 2017; Griffin, 2002). Hou et al. (2011) compare local and global empirical asset pricing models and find superior pricing performance of local models using 7 anomalies. Hollstein (2022) expands this analysis to 134 anomalies in 48 countries. Lastly, by comparing the performance of different asset pricing models Huber et al. (2023) show that no asset pricing model is superior to another but that the performance is largely sample and context-dependent.

Our paper further contributes to the factor momentum literature. Avramov et al. (2017) show that factor premiums are autocorrelated and can be timed in factor momentum strategies. Gupta and Kelly (2019) show that factor momentum is both prevalent in a vast amount of market anomalies and in international markets. Arnott et al. (2023) show that industry momentum is rooted in cross-sectional factor momentum. Ehsani and Linnainmaa (2022) argue that stock momentum is not a distinct risk factor but stems from autocorrelation in factor returns - factor momentum. They show that replacing the stock momentum factor with a factor momentum portfolio in the Fama-French (2018) 6-factor model improves the models' pricing accuracy.

Neuhierl et al. (2023) investigate factor return timing capabilities of different predictive signals and find factor momentum to be the most dominant predictor.[1] Hellum et al. (2023) utilize non-local signals to augment training data for predictive machine

[1] With inverse volatility as a significant twin-predictor.

learning models and find that non-local signals can help in estimating the desired mapping function. Instead of utilizing non-local data to fit models to find a robust mapping function in cross-sectional regressions, we directly use the non-local signals to predict local factor returns. We thus do not improve the modeling step but unveil nested factor predictability in international equity markets.

The structure of the remaining article is as follows: Section 2 introduces the data and the methodological setup of our analysis. Section 3 investigates the cross-country integration of international factor returns. Section 4 contains the analysis of how the insights on the integration can be used to predict factor returns in international markets. Section 5 concludes and lays out the implications of our work. The appendix holds supplementary material such as additional tables and figures.

2 Methodology and Data

2.1 Data and Sample

This study examines a comprehensive dataset of 153 monthly factor returns from January 1998[2] to December 2022, covering 25 years of a total of 47 countries[3]. The data is provided by Jensen et al. (2023).[4] The precise start date differs between factor-country pairs. Especially for less developed countries the data tends to become available later than for more developed countries. Figure 2 depicts the number of factors used in our study over time. At the beginning of the sample (January 1998), there are 4362 factors from 13 different themes[5] in our cross-section. The total number of factors increases to 6807 by the end of 2022. The factor returns are expressed in US Dollars, as conventional in international asset pricing (e.g. Baltussen et al., 2021; Cakici et al., 2024; Fama & French, 2012, 2017).

[2]As factor data before 1998 outside the USA is sparse we restrict our analysis to this timeframe.
[3]The countries are listed in Table A.2.
[4]The data can be retrieved through their website https://jkpfactors.com.
[5]Jensen et al. (2023) cluster the 153 factors into the following 13 themes. The mapping of the factor themes and descriptions of the individual factors are provided in Table A.1

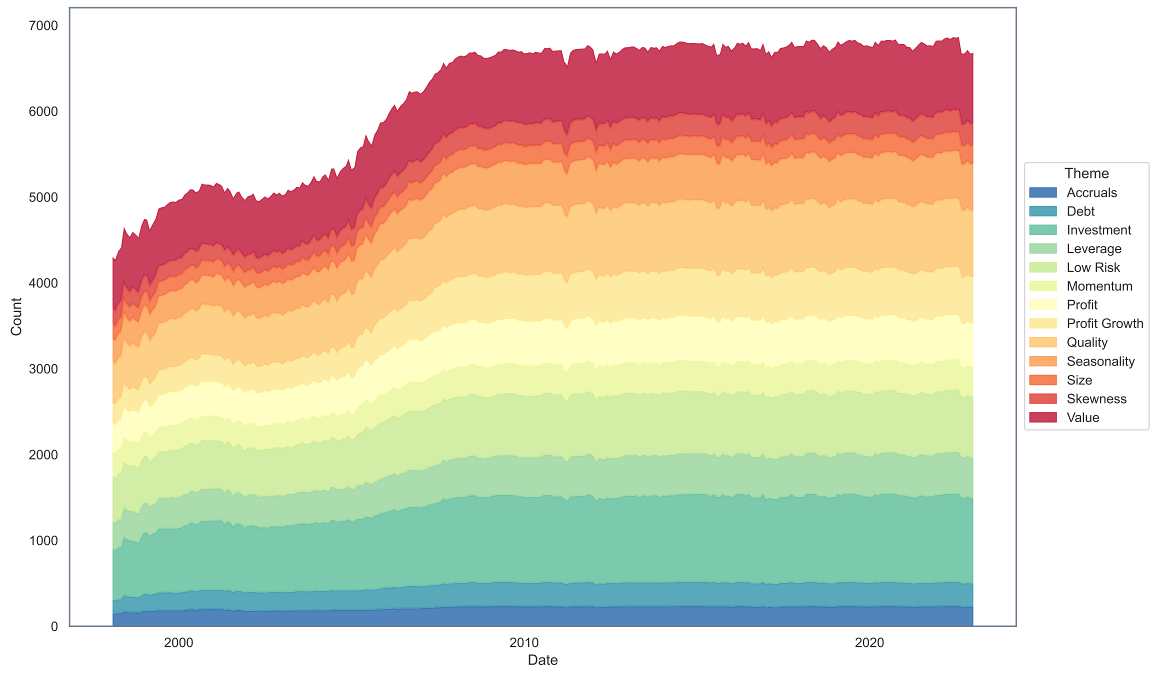


Figure 2: Number of factors over time: This figure depicts the number of factors available in our sample over time, visually categorized according to the 13 themes defined by Jensen et al. (2023). The sample consists of 153 factors in 47 (23 developed and 24 emerging) countries. Our sample spans the time period from January 1998 to December 2022.

2.2 Identification of Structural Integration

We start our analysis by examining the systematic co-movement of factor returns across countries. This rational stems from the argument that if country-level factors are driven by non-local forces, we can expect these forces to manifest in contemporaneous returns (through expectations) before influencing future realizations of factor returns (which are most likely driven by Sentiment (see Ehsani & Linnainmaa, 2022)). Understanding non-local forces and their impact on return expectations is crucial to understand regional effects in factor predictability.

For this analysis we follow Traut (2024) who analyzes the regional integration of Fama and French (2018) 6 factor model returns and finds that the strength of the regional integration is heterogeneous among different factor types.

For this part of the analysis, we focus on the factor themes defined by Jensen et al. (2023) who cluster the 153 factors into 13 factor themes.[6] Following Jensen et al. (2023), we define the return of a factor theme as the average return of the factors included within that theme. We focus on the themes as within themes the correlation

[6]The mapping of the factors and themes is outlined in Table A.1.

between factors is relatively high and between themes correlations are relatively low, implying that factors within a theme pick up on similar return premiums.[7]

We start the structural analysis by calculating the complete Pearson correlation matrix, $\mathbb{C}$, for all country-wise factor theme returns. The calculation of the correlation matrices requires to have complete time series data for each country. Some of the smaller countries in our sample have missing values such that we have to reduce our sample to 39 countries[8] for the structure detection part of the analysis. However this restrictions does not influence our implications for predictability but are merely required for the definition of suitable regions.

To assess the strength of the structural integration within factor themes we employ principal component analysis (PCA) using an eigendecomposition of the correlation matrices. Further, we assess systematic co-movement by calculating within theme return correlations.

2.3 Factor Momentum Strategy Formation

For the development of our factor momentum signals we follow a methodology that is similar to that of Gupta and Kelly (2019). We develop one-month cross-sectional factor momentum strategies that aim to identify factors that have demonstrated robust performance in the preceding month, with the expectation that they will maintain their superior performance in the near term.[9] Typically, for each country, this strategy purchases the top 50% (those above the median) of factors that exhibit positive one-month momentum and sells the bottom 50% (those below the median) of factors that show negative one-month momentum.[10]

[7]A correlation matrix of global factor theme returns supports these claims and can be found in Figure A.1.

[8]These countries are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Russia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, and the United States of America.

[9]This method is termed cross-sectional factor momentum. The cross-sectional factor momentum implementation allows us to double-sort factors in a later exercise. To allow cross-sectional comparison in double-sorts, a cross-sectional implementation is necessary. However, our results are robust to time-series factor momentum implementations.

[10]Using a 1-month formation period is rooted in Neuhierl et al. (2023), who find that shorter formation periods like 1, or 3 months succeed in factor timing, while longer formation periods like 12 or 9 months fail in outperforming a buy-and-hold benchmark. For robustness, we reproduce our results using formation periods between 3 and 12 months. Furthermore, to address the criticism that

Let $F_{i,t}$ represent the return of factor $i \in I$ in country $c \in C$ at time t.

Based on a momentum signal $M_{i,t} = F_{i,t-1}$, we classify factors into winners and losers within the defined scope (country, region, global). We additionally add a superscript A to depict, whether the momentum signal $M_{i,t}^A$ was formed using the local, the regional, or the global factor aggregate, where factor aggregation is a simple equally weighting of the local signals.

For each country $c \in C$ and signal formation area A, factors are sorted into winners $W_{c,t}$ and losers $L_{c,t}$, where:

$$W_{c,t}^A = \{i \in I | M_{i,t}^A > median(M_{.,t}^A)\}$$

$$and$$

$$L_{c,t}^A = \{i \in I | M_{i,t} \leq median(M_{.,t}^A)\}$$

The return of a momentum strategy portfolio in a country c, for formation region A at time $t+1$, denoted by $F_{c,t+1}^A$is calculated as the difference between the average return of the winners $W_{c,t}^A$ and the losers $L_{c,t}^A$:

$$P_{c,t+1}^A = \frac{1}{|W_{c,t}^A|} \sum_{i \in W_{c,t}^A} F_{i,t+1} - \frac{1}{|L_{c,t}^A|} \sum_{i \in L_{c,t}^A} F_{i,t+1}$$

So, to explore the predictability stemming from regional and global signals, above we modify the standard factor momentum strategy by adjusting the criteria for selecting factors to buy and sell. Instead of relying solely on country-specific signals, we expand our selection process to include factors based on their performance within broader regions and on a global scale. This approach allows us to compare the effectiveness of factor momentum strategies guided by local (country-specific), regional, and global signals. To differentiate our non-local method from the common local methodology, we refer to the non-local as "Advanced Factor Momentum" (AFM).

factor momentum strategies benefit from factors with large unconditional premia instead of timing factor returns, we follow Leippold and Yang (2021) and construct our factor momentum strategies for demeaned factor momentum signals. These robustness checks can be found in Figure A.2 to Figure A.6.

Additionally to the Sharpe ratio, as suggested by Barillas et al. (2020), we calculate several key performance metrics for the resulting return time series of each factor momentum strategy (country-specific, regional, and global). These metrics include annualized versions of:

- Mean Return: The average return generated by each strategy: $\mu = \frac{1}{T}\sum_{t=1}^{T} P_{c,t}$
- Standard Deviation: The variability of returns: $\sigma = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(P_{c,t} - \mu})^2$
- Sharpe Ratio: The risk-return tradeoff: $\frac{\mu}{\sigma}$
- Skewness: Asymmetry of the return distribution: $\sigma = \frac{\sum_{t=1}^{T}(P_{c,t}-\mu)^3}{T*\sigma}$
- Maximum Drawdown: The largest peak-to-trough decline in the portfolio's value: $MD = \frac{TV-PV}{PV}$

By examining these metrics across the different variants of factor momentum strategies, our objective is to determine which strategy most effectively leverages factor momentum. This evaluation entails scrutinizing the performance of different factor momentum strategies for each country in our study. Through this extensive examination, we aim to discover whether factor momentum strategies that integrate regional and global signals surpass those that rely exclusively on signals specific to individual countries. Should factor predictability originate from local sources, then strategies utilizing non-local signals would not be expected to exceed the performance of the conventional factor momentum strategy.

3 Structural Analysis

To display the degree of systematic co-movement in our factor data, we start the structural analysis by visually analyzing the correlation matrices of the 13 factor themes that are illustrated in Figure 3. In addition to the factors, we include a matrix of market returns that are defined as the value-weighted return of stocks within a country. The market returns serve as a benchmark for the interpretation of the results of factor returns. We order countries with respect to their development status, with developed countries being located at the upper left corner of the matrices and emerging countries in the lower right corner of the matrix.

Some factor themes like investment, low leverage, low risk, momentum, and value show co-movement, which is limited to developed markets. Factor themes like accruals, debt issuance, and seasonality show no sign of international integration in developed markets. Overall co-movement can be found in developed markets, while emerging markets show no sign of systematic co-movement.

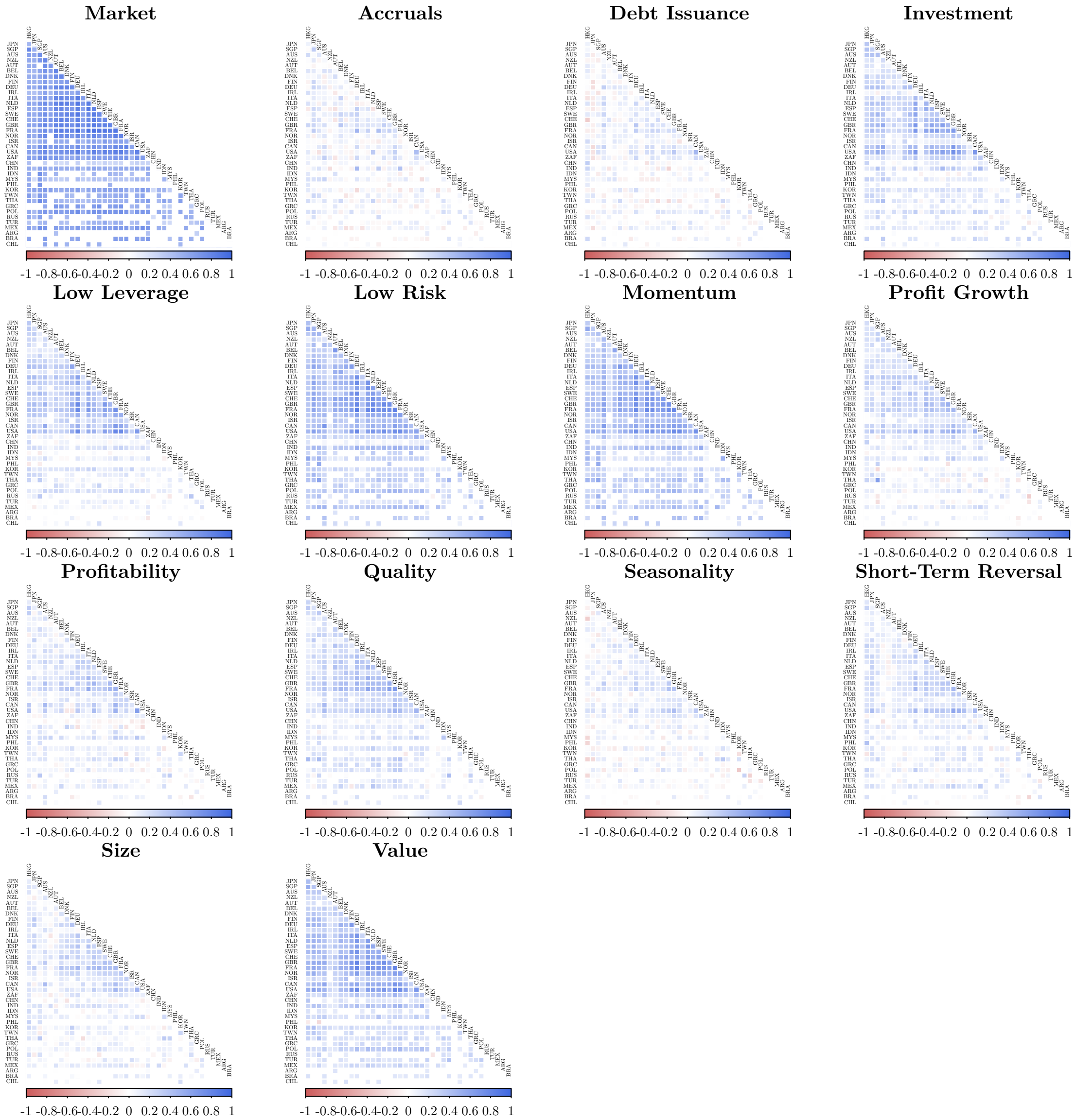


Figure 3: Correlations of international factor returns: This figure depicts correlation matrices for monthly international market returns and returns of the 13 themes defined by Jensen et al. (2023). The return of a factor theme is defined as the average return of all factors that fall into the respective theme. Our sample spans the time period from January 1998 to December 2022. The countries are sorted with respect to development status. Only correlations that are significant at 5% confidence are displayed.

To quantify the strength of the structural integration and to see whether a differentiation between developed and emerging countries is supported by the data, we perform an eigendecomposition of each correlation matrix and plot the eigenvectors v_1 and v_2

in Figure 4. The proportion of explained variance is noted on the respective axis. [11]

Consistent with the results of the correlation analysis which showed distinctive patterns for developed and emerging countries, the eigenvectors group countries according to their development status. We can further see that countries from similar geographic regions built clusters. The proportion of explained variance provides more evidence that the strength of the regional integration is heterogeneous among factors. Comparing theme returns to the market return benchmark, we find that the integration for momentum, low risk, and value is roughly 50% of the market benchmark level. For other factors like accruals, debt issuance, and seasonality this value is approximately 24% of that of market returns. Thus, we conclude that the borders (which are mainly driven by development status) for regional integration are relatively similar for all themes, but there is strong heterogeneity between different themes. Based on the above results, the divide between developed and emerging markets suggests that development status is an effective criterion for defining optimal regions.

Finally, we evaluate the integration strength of different factors in our two regions by computing the average correlations of country-specific factor theme returns in Table 1. It is striking that while there is some degree of cross-country correlation in developed markets, it is almost non-existent for emerging markets. Again, if we set the market returns as our benchmark and the within region correlation as our measure of factor integration, the most integrated factors like low risk, momentum and value achieve up to 65% of the market's integration for developed countries. For emerging countries this ratio is lower with up to 39%. Same as for the PCA analysis, accruals, debt issuance and seasonality show the lowest integration with up to 10% of the market's integration in developed countries and up to 6% in emerging markets.[12] Based on our results non-local forces should manifest in the low risk, momentum, value, low leverage, quality and investment themes, and lead to non-local factor predictability. We will investigate this prediction in the next chapter.

[11] We focus on the first two eigenvectors as it is found by Traut (2024) that only these carry sufficient information about the underlying structure of the data when controlling for noise.

[12] A similar result is obtained when regressing single-country factor/theme returns on regional aggregates and comparing average R^2 statistics.

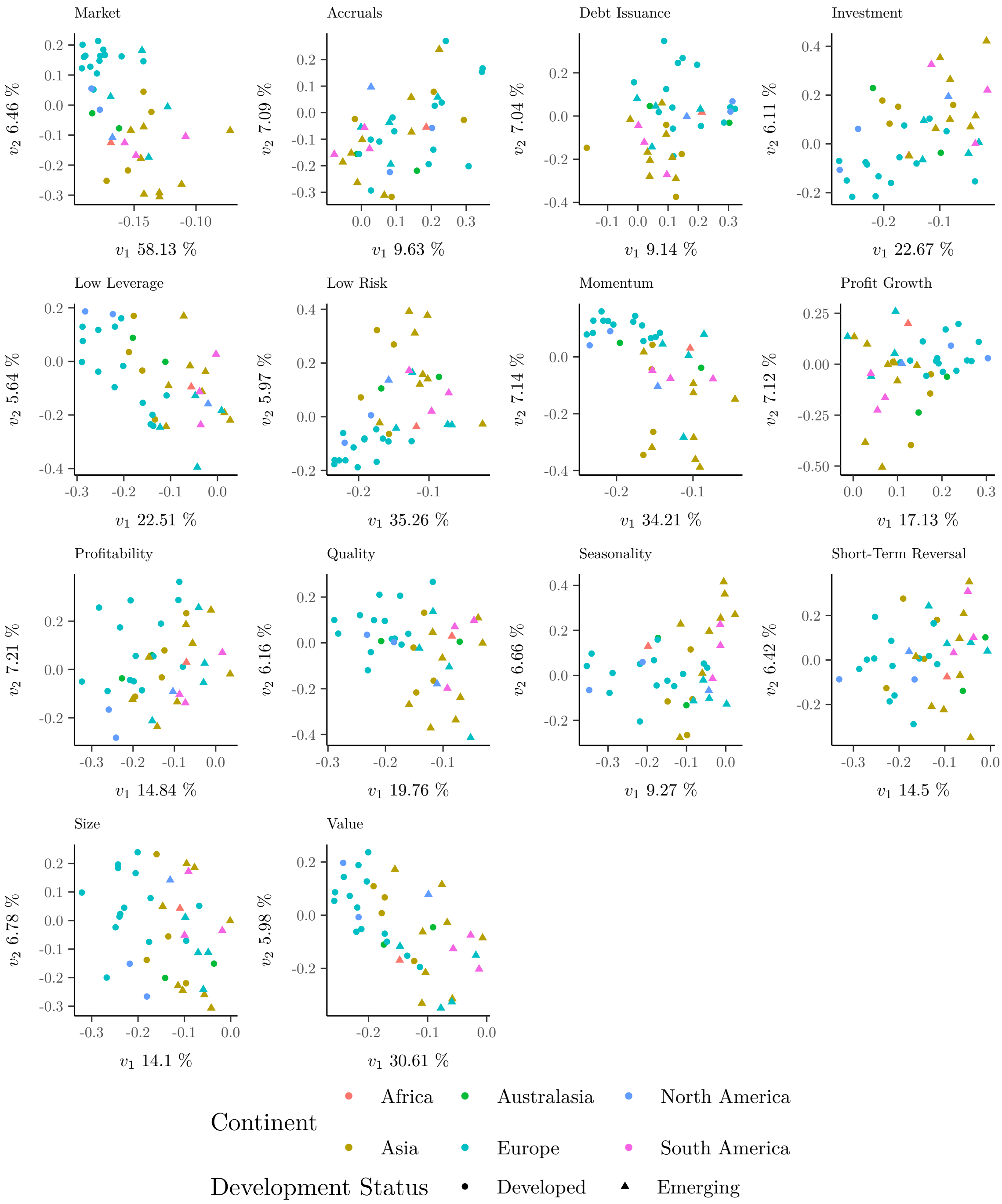


Figure 4: Principal component analysis of international factor returns: This figure illustrates the first two eigenvectors, v_1 and v_2 of correlation matrices for monthly international returns of market returns and returns of the 13 themes defined by Jensen et al. (2023). The return of a factor theme is defined as the average return of all factors that fall into the respective theme. Our sample spans the time period from January 1998 to December 2022. The percentages on the axes describe the portion of explained variance by the respective eigenvector. Development statuses are sourced from MSCI.

4 Factor Predictability in International Markets

This section discusses the efficacy of factor investing approaches incorporating predictive signals at the country, regional, and global levels. Following the results of

Table 1: Average within theme correlations: This table shows holds the within theme correlation for international market and factor returns. The 13 themes are defined by Jensen et al. (2023). Our sample spans the time period from January 1998 to December 2022. Development statuses are sourced from MSCI.

	Developed	**Emerging**
Market	0.69	0.46
Accruals	0.07	0.01
Debt Issuance	0.06	0.03
Investment	0.24	0.05
Low Leverage	0.30	0.04
Low Risk	0.45	0.16
Momentum	0.43	0.18
Profit Growth	0.20	0.02
Profitability	0.17	0.04
Quality	0.24	0.06
Seasonality	0.09	0.02
Short-Term Reversal	0.15	0.04
Size	0.17	0.06
Value	0.40	0.09
Total	**0.26**	**0.09**

Section 3 we expect the difference in performance between local and non-local signals to be larger for developed countries as we primarily find cross-country factor integration for developed countries. As a result, this section treats developed and emerging markets separately, with a more in-depth focus on the former.

4.1 Developed Markets

Driven by our results of the structural analysis, we develop four AFM strategies for each country. A local/standard approach, which buys (sells) the best (worst) performing factors in each country, as well as continental, development-based and global approaches, that buy (sell) country-level factors conditional on momentum extracted from continental-, developed markets-, and global (all countries) signals. The continental strategy is more nuanced than the development status strategy because it differentiates between six continents[13] compared to just two development statuses.

All advanced factor momentum strategies demonstrate superior performance compared to the standard factor momentum strategy, in terms of Sharpe ratios. As depicted by the violins in Figure 1, the variability (standard deviation) of the Sharpe ratios across countries is reduced for advanced strategies compared to the standard approach. The underlying complete country-wise evaluation can be found in Table A.3 in the appendix. Also, we show in Figure A.2 to Figure A.6 that the results are robust to different formation periods and are not driven by unconditional differences in risk premia (Leippold & Yang, 2021).

Table 2 presents the fundamental portfolio metrics for all four strategies, with the columns representing specific portfolio metrics and the rows showing a statistical summary of the strategies across the developed countries in our sample. The third column reflects the findings shown in Figure 1. Advanced strategies exhibit several advantageous features: they yield higher returns, exhibit lower volatility, achieve greater Sharpe ratios, have higher skewness, and experience less severe maximum drawdowns. Moreover, across all metrics (portfolio skewness being the exception), advanced factor momentum strategies display reduced cross-sectional variability (std). In summary, Table 2 indicates that beyond the Sharpe ratio, advanced factor momentum strategies surpass the standard factor momentum strategy in key portfolio metrics that are relevant for international investors.

When comparing the three non-local strategies among one another, we can see that the strategy that focuses on development status performs the best concerning average return, Sharpe ratio, positive skewness, and drawdown reduction. This shows that as expected by our structural analysis, factor integration is strongest between countries of similar development status and thus results in the highest predictability. Compared to the developed-markets strategy, the continental strategy may pick too few and/or the wrong countries whereas the global strategy may incorporate too many countries.[14]

[13]The continents are Africa, Asia, Australasia, Europe, North America, and South America.

[14]In not reported results we test for the influence of the USA on the developed predictability. While the USA contributes to the signal, dropping the USA from the sample does not change the view on

Table 2: Key performance metrics: This table aggregates key performance measures of 4 different factor momentum strategies in 23 developed countries. Panel A shows results for standard factor momentum strategies, while Panels B-D show results for Advanced Factor Momentum Strategies using a continental (B), developed (C) and global (D) signal. For each strategy, we calculate the return, standard deviation, Sharpe ratio, skewness, and maximum drawdown measures for every 23 countries separately (columns). We then describe these $23 \cdot 5$ metrics using their mean, standard deviation, minimum, 25-, 50-, and 75-quantile, and maximum (rows). Each value in the table is a descriptive statistic on 23 observations describing one certain aspect of a strategy (e.g. the Sharpe ratio). The third column mirrors the results in Figure 1. For all advanced strategies, we furthermore test the hypothesis that the average metric (first row in each panel (B-D)) is statistically significantly different from the average metric of the standard strategy (panel A). We report the t-statistic in brackets behind the mean statistic. Again, the statistics relate to the significance stars in the table depicted in the lower part of Figure 1. All metrics are annualized.

	Return	Std	Sharpe Ratio	Skewness	Maximum Drawdown
		Panel A: Standard Factor Momentum			
Mean	3.45	13.66	0.24	0.07	-0.40
Std	3.92	6.06	0.19	0.18	0.18
Min	-1.16	8.40	-0.07	-0.23	-0.94
Q25	1.23	10.55	0.12	-0.08	-0.48
Median	3.11	11.85	0.17	0.07	-0.37
Q75	4.26	15.24	0.37	0.16	-0.29
Max	17.89	35.38	0.69	0.45	-0.15
		Panel B: Advanced Factor Momentum - Continental Signal			
Mean	4.05 [0.81]	10.18 [-6.10]	0.40 [4.34]	0.17 [1.80]	-0.27 [5.96]
Std	2.05	4.07	0.13	0.30	0.13
Min	1.51	6.75	0.16	-0.20	-0.75
Q25	2.85	8.25	0.31	0.05	-0.28
Median	3.36	9.20	0.4	0.15	-0.25
Q75	4.68	10.37	0.48	0.26	-0.19
Max	10.85	27.23	0.70	1.09	-0.13
		Panel C: Advanced Factor Momentum - Developed Signal			
Mean	5.04 [2.49]	10.06 [-6.72]	0.51 [9.09]	0.21 [2.79]	-0.23 [8.54]
Std	2.21	4.11	0.15	0.25	0.14
Min	2.24	6.34	0.24	-0.29	-0.73
Q25	3.73	8.21	0.42	0.15	-0.27
Median	4.35	9.14	0.53	0.21	-0.20
Q75	5.47	10.19	0.59	0.31	-0.14
Max	11.89	27.2	0.75	0.73	-0.08
		Panel D: Advanced Factor Momentum - Global Signal			
Mean	4.14 [0.99]	9.61 [-6.58]	0.44 [6.12]	0.14 [1.68]	-0.25 [7.86]
Std	1.78	3.55	0.14	0.22	0.14
Min	1.47	6.28	0.18	-0.28	-0.67
Q25	3.13	8.02	0.37	0.03	-0.29
Median	3.91	8.74	0.44	0.14	-0.20
Q75	4.76	9.73	0.51	0.25	-0.16
Max	9.87	24.09	0.69	0.72	-0.10

Until now, we have demonstrated the advantage of utilizing non-local signals over local signals for predicting factor returns. However, this enhanced performance may originate from increased risk-taking, which necessitates risk adjustment. Table 3 displays the summary coefficients from time-series regression analyses of factor momentum strategy returns against the Fama French 3, Fama French 5, and Fama French 6 factor models. Across all models and strategies, these factor models account for only a minimal fraction of the returns, with average beta coefficients close to zero. Although the explanatory power (R^2) slightly increases with the addition of factors, it never surpasses 10%. Consistent with previous findings, the use of developed market signals in advanced factor momentum strategies results in the highest risk-adjusted returns for all strategies.

Incorporating factors such as investment, profitability, and momentum into the regression analyses does not diminish the strategies' average alphas. On average, advanced strategies exhibit a significantly higher number of countries with meaningful strategy alphas compared to the standard strategy. Specifically, the standard strategy does not achieve more than 9 significant alphas (out of 23 countries), whereas the developed signal strategy attains 21 significant and positive alphas (out of 23 countries) when adjusted using a Fama French 3 factor model. In summary, local factor models[15] fail to account for the superior predictive power of non-local signals, with the development status strategy yielding the highest alpha.

In principle, factor momentum strategies purchase factors that are performing well and sell those that are not. Consequently, these strategies require the establishment of four positions in long-short portfolios: two long and two short. Given that many international investors might encounter restrictions on short selling, the success of these strategies could primarily be attributed to arbitrage limitations, as suggested by Shleifer and Vishny (1997).

To explore this possibility, Table 4 breaks down the four suggested factor momentum strategies into four sub-positions. In Panel A, column (I) details the long component of the winning factor's long position (for example, the long side of the value portfolio in a

our results. Furthermore, the USA is itself better predicted by developed market signals than by the US signal which is shown in Table A.3

[15] Since we are pricing local assets/factors, it is advisable to use local factor models, as they have superior pricing capabilities over non-local models (Fama & French, 2012, 2017; Hollstein, 2022).

Table 3: Risk adjustment: This table reports average coefficients and the average r-squared statistic of time-series regressions of (advanced) factor momentum strategies on local factor models. Panel A shows the Fama French 3-factor model. Panel B shows the Fama French 5-factor model. Panel C shows the Fama French 6-factor model. For each strategy, we run 23 distinct time-series regressions (23 countries) of the respective factor momentum strategy return on its matching local factor model. Additionally, we report the number (#) of statistically significant (5%) alphas (based on Newey and West (1987) standard errors) in all 23 regressions.

	α [#]	β_{Mkt}	β_{HML}	β_{SMB}	β_{RMW}	β_{CMA}	β_{MOM}	R^2
Panel A: Local FF 3 Factor Model								
Factor Momentum	0.26 [9]	-0.06	-0.06	-0.07				0.06
AFM - Continental Sig	0.35 [16]	-0.05	-0.04	-0.07				0.06
AFM - Developed Sig	0.42 [21]	-0.04	-0.05	-0.04				0.05
AFM - Global Sig	0.35 [19]	-0.05	-0.04	-0.05				0.06
Panel B: Local FF 5 Factor Model								
Factor Momentum	0.23 [8]	-0.06	-0.10	-0.05	-0.04	0.01		0.08
AFM - Continental Sig	0.33 [18]	-0.04	-0.05	-0.03	-0.04	-0.03		0.08
AFM - Developed Sig	0.40 [19]	-0.04	-0.07	-0.03	-0.02	0.02		0.07
AFM - Global Sig	0.36 [17]	-0.05	-0.05	-0.04	-0.02	0.00		0.08
Panel C: Local FF 6 Factor Model								
Factor Momentum	0.19 [8]	-0.05	-0.08	-0.05	-0.02	0.01	0.05	0.10
AFM - Continental Sig	0.33 [16]	-0.04	-0.05	-0.04	-0.02	-0.01	0.01	0.09
AFM - Developed Sig	0.42 [18]	-0.04	-0.07	-0.02	-0.01	0.02	-0.01	0.08
AFM - Global Sig	0.34 [15]	-0.04	-0.04	-0.04	-0.02	0.01	0.01	0.09

winning value factor). Column (II) presents the long component of the losing factor's short position (for example, the value portfolio's long side in a losing value factor). Column (III) outlines the short component of the winning factor's long position (for example, the short side of the growth portfolio in a winning value factor). Column (IV) displays the short component of the losing factor's short position (for example, the short side of the growth portfolio in a losing value factor). The contributions of the first and fourth columns are positive to the strategy's overall performance, whereas the second and third columns negatively affect the total position.

In Panel B of Table 4 we highlight the return differences between advanced factor momentum strategies and the standard factor momentum strategy. Primarily, every sub-position contributes to the overall performance of the respective strategy. That means short positions do not fully explain the differences between the returns. Second, the short position (shorting factors that have performed below the median in the continent/developed markets/globally) contributes 0.97 ($0.48 + 0.49$), indicating that there is an asymmetry in predictability advances for winners/losers. Surprisingly it

Table 4: Dissecting advanced factor momentum: Panel A of this table reports the average annualized returns of long and short positions in four different factor momentum strategies (X_X). The first letter corresponds to the position in the factor momentum strategy. It indicates whether a long-short portfolio was a winning (L_), or losing (S_) portfolio in the past (macro-position). The second letter corresponds to the sub-portfolio in a position. It thus indicates whether a portfolio is the long- (_L) or the short (_S) leg in a factor (micro-position). For the value factor, the (second letter) short position would be the growth portfolio. L_L corresponds to a winnings factor's long portfolio. L_S corresponds to a winnings factor short portfolio. S_L corresponds to a losing factors long portfolio and S_S to a losing factors short portfolio. The brackets behind the sub-positions indicate the positive or negative contribution. For example: the long portfolio of a winning factor (L_L) has a positive contribution (the higher the average return, the higher the overall return of the strategy). Summing up the contributions of all 4 sub-positions ((I-II)-(III-IV)) (column 5) mirrors the first row per panel of column 1 in Table 2. To emphasize the contribution of each sub-position in advanced factor momentum strategies to the overall strategy, in Panel B we subtract its return from the sub-position returns of the standard factor momentum strategy.

	(I) L_L [+]	(II) S_L [-]	(III) L_S [-]	(IV) S_S [+]	(I-II)-(III-IV)
Panel A: Subportfolio performance					
Factor Momentum	9.30	5.53	7.45	7.13	3.45
AFM - Continental Sig	9.36	5.30	7.37	7.36	4.05
AFM - Developed Sig	9.6	5.05	7.12	7.61	5.04
AFM - Global Sig	9.40	5.30	7.32	7.36	4.14
Panel B: Difference of subportfolio performances vis-a-vis standard factor momentum					
	$I_{AFM} - I_{FM}$	$II_{FM} - II_{AFM}$	$III_{FM} - III_{AFM}$	$IV_{AFM} - IV_{FM}$	(I-II)-(III-IV)
AFM - Continental Sig	0.06	0.23	0.08	0.23	0.60
AFM - Developed Sig	0.29	0.48	0.33	0.49	1.59
AFM - Global Sig	0.10	0.23	0.13	0.23	0.69

is not a short-leg portfolio that has the lowest returns. With 5.05 annualized average return using the developed markets signal the long leg of the losing factors has the lowest average returns. This finding underscores the significance and feasibility of factor timing within international markets.

Until now, our research has focused on the benefits of utilizing continental, developed market, and global signals in factor momentum strategies, employing a straightforward 50-50 cross-sectional momentum approach. This method, naturally, results in high turnover, requiring investors to manage up to 153 factors simultaneously. Handling this many factors in a cost-efficient manner can be a difficult task. Because of this, we explore the impact of using more extreme quantile breakpoints for our strategies, which naturally reduces the number of factors to trade. In doing so, we examine the specific contributions of country-specific and non-local market signals to the strategy's effectiveness. We perform this comparative analysis solely for the local and developed market strategy as the latter proved to perform superior over the other non-local strategies.

As a first step, we compare the mean annualized returns for the two strategies when opting for more extreme breakpoint quantiles in Figure 5. The figure also breaks down the average annualized return to identify the contributions of signals that are common to both strategies (such as buying factors that are above the upper breakpoint and thus winners in both strategies and shorting those that are below the lower breakpoint and thus losers in both strategies), and those that are unique to the standard factor momentum (like purchasing factors that are top performers and above the upper breakpoint in a specific country but do not clear that breakpoint in developed markets, and selling factors that are below the bottom breakpoint in the country but do not fall below that breakpoint in developed markets).

The results show that shifting the quantile breakpoints towards more extreme values results in higher mean annualized returns for both strategies. We can further see that the performance gap widens in favor of the developed market factor momentum strategy. The highlighted contributions of the signals that are unique to each strategy suggest that, at these extreme levels, signals from non-local factors become increasingly predictive compared to local signals.

To further investigate this insight, we continue to analyze the distinct contributions of local and non-local signals through double sorting. This method probes whether non-local predictability surpasses local predictability once the latter is controlled for. In Figure 6 we report the annualized returns of factors about which the two models disagree for increasingly extreme breakpoints. In red we depict returns of a portfolio formed based on winning factors according to the non-local signal but that are classified as losing factors according to the local signal, and vice versa in blue. The results show that at more extreme quantiles, when the models disagree, the non-local strategy consistently produces better predictions about future factor performance. In contrast, the predictive power of local factor momentum signals for these disagreed factors diminishes with increasing breakpoints, eventually turning negative in the most extreme cases.

Advanced factor momentum strategies involve purchasing winner factors and selling loser factors on a regional, or global scale. Our findings demonstrate that these advanced strategies surpass the performance of standard factor momentum. We believe

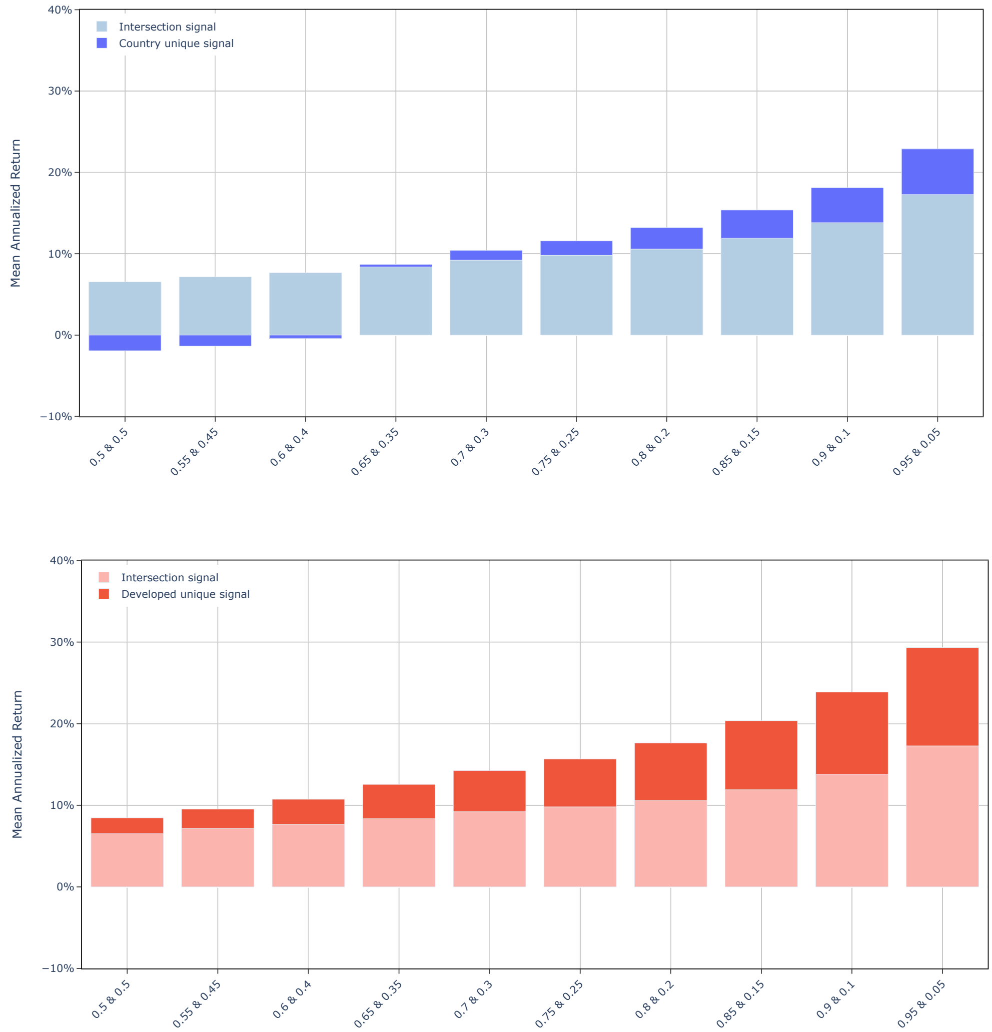


Figure 5: (Advanced) factor momentum strategy returns based on more exclusive breakpoints: This figure depicts mean annualized returns of factor momentum strategies for increasing breakpoint exclusiveness, disaggregated according to country/developed signal contribution. While the x-axis shows increasing (decreasing) breakpoint quantiles for the factor momentum portfolio sorts (the higher(lower) the quantiles, the fewer factors are traded, hence the more exclusive the strategies). Within both panels, the pale part of the bars highlight the performance stemming from factors that are selected simultaneously from the local as well as the developed signal (equal in both panels), the darker shade represents the performance contribution from the country-only (dark blue, upper panel) or developed-only (dark red, lower panel) signals.

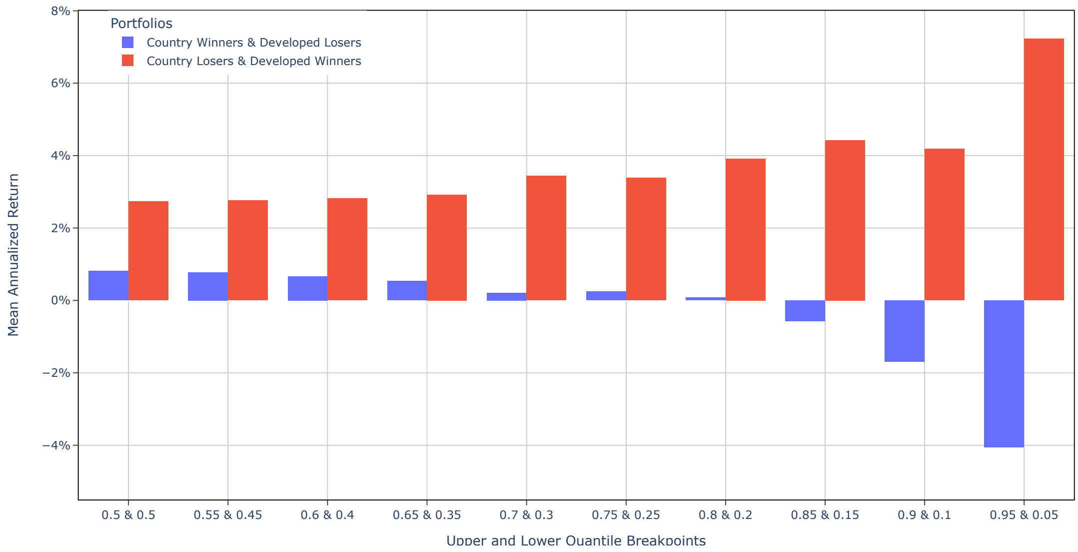


Figure 6: Annualized portfolio returns from a local/developed signal double sort for increasingly exclusive breakpoints: This plot is supposed to highlight the difference between the local signal and the developed signal when forming portfolios according to both signals. To this effect we depict average annualized factor returns form portfolios formed based on a misclassification from the local signal vis-a-vis the developed signal. In red we depict returns of a portfolio formed based on winning factors according to the developed markets signal that are loosing factors according to the country signal, and vice versa in blue. The difference of the blue and red signal for the median breakpoints translates to the dark bars of the median breakpoint based returns in Figure 5.

that the level of structural integration of factors is a driving force behind this increase. In Section 3 we show that the level of integration is heterogeneous among factors. Thus, if the enhancements seen in advanced strategies is linked to stronger regional integration of factors, it should be driven by themes that show high structural integration. Additionally, the effectiveness of the strategy should vary between different factor themes, depending on the themes' international integration.

To explore this hypothesis, we illustrate the breakdown of excess annualized returns by factor theme in Figure 7. We can see that the success of advanced factor momentum strategies is not confined to a single theme, but a broad phenomenon. However, the largest improvements are achieved among the the factors that we find to be most regionally integrated. Value (+0.59% contribution), Quality (+0.31%), Low Leverage (+0.22%), Investment (+0.15%), and Low Risk (+0.14%) are the themes with the highest explained variance ratio on PC1 (compare Figure 4). Likewise, the smallest contributors: Seasonality (-0.05% contribution), Accruals (-0.04%), Short-Term Reversals (+0.00%), Size (+0.00%), and Debt Issuance (+0.03%), are those five themes with the lowest explained variance ratio stemming from PC1. The only exception is the momentum theme, which only slightly improves using the developed signal. Anyhow, this is not surprising. Ehsani and Linnainmaa (2022) show that stock momentum, and factor momentum are strongly related. Furthermore, trading factor momentum on a stock momentum factor is not feasible.

When excluding the Momentum theme, the correlation between the average co-movement of a theme from Table 1 and the return increase from applying developed signals instead of local signals (as shown in the bottom panel in Figure 7) is 0.73. Therefore we conclude that factor predictability is a non-local phenomenon that is driven by the co-movement of the most integrated factors. We further show in Appendix B that the superior performance of advanced factor momentum strategies remains consistent over time and cannot be attributed to single performance spikes or outliers.

4.2 Emerging Markets

Following the results of our structural analysis, we do not expect the advanced factor momentum strategies to perform as well in emerging markets as they do in developed markets. However, given their distinct characteristics and dynamics—such as higher volatility, different regulatory environments, and varying degrees of market efficiency—it is crucial to test whether the observed benefits of advanced factor momentum strategies extend beyond developed economies. Accordingly, we replicate our methodology on a dataset encompassing factor returns from emerging markets over the same period.

Our analysis in emerging markets follows the same procedure as in developed markets, constructing factor momentum strategies based on local, continental, emerging markets, and global signals. The performance of these strategies is evaluated using the same portfolio metrics.

Figure 8 depicts the descriptive statistic of Sharpe ratios of the four different factor momentum strategies. Again, the advanced factor momentum strategies similarly outperform the standard country-specific factor momentum strategy in emerging markets. However, we can see that the differences between the local and non-local signals are not as pronounced as for the developed countries.

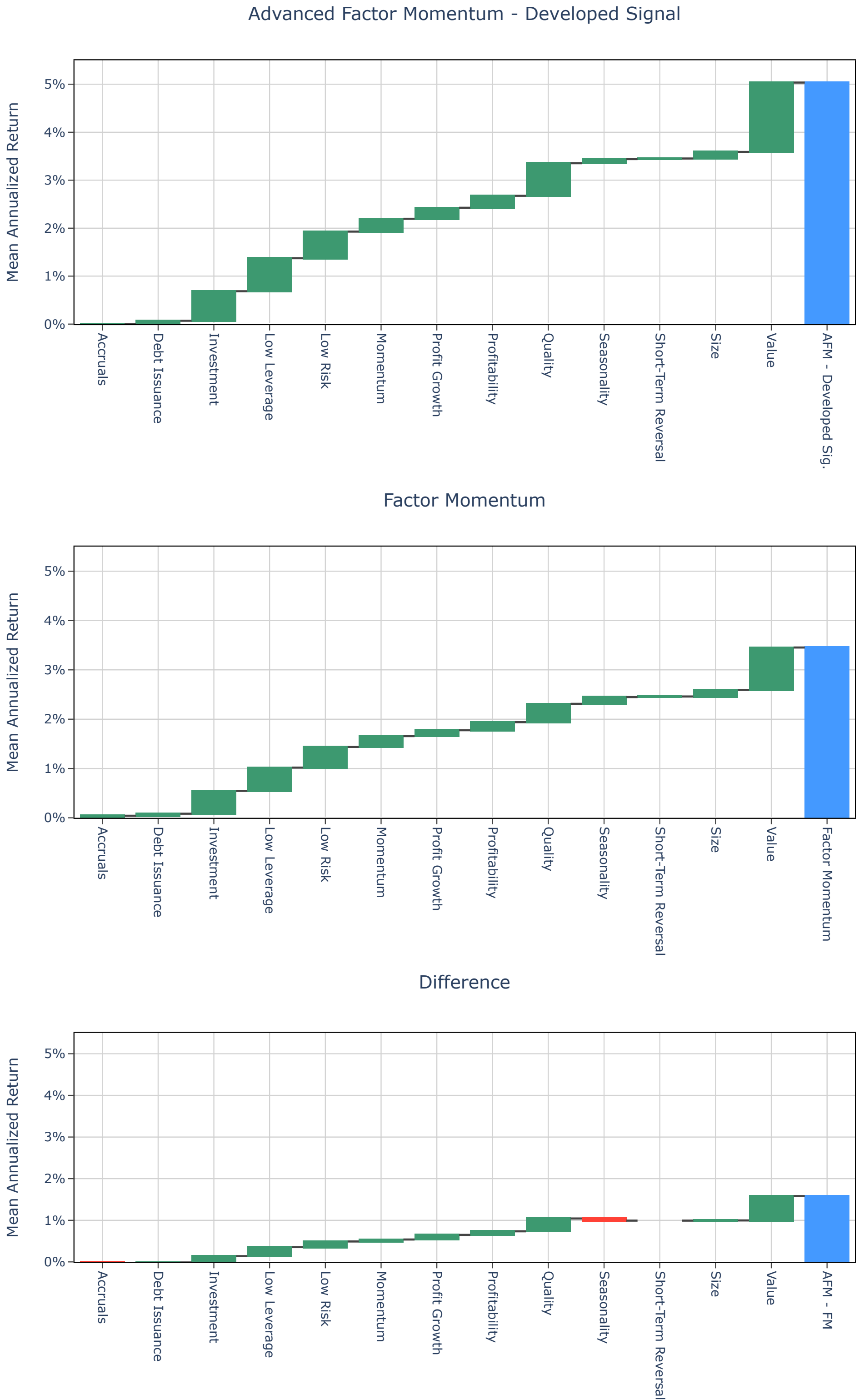
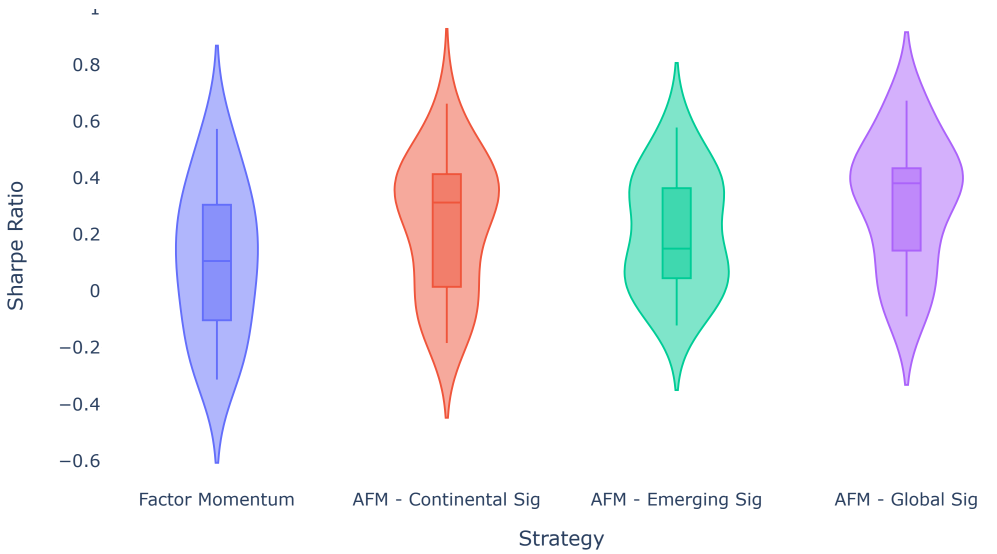


Figure 7: This figure depicts decomposed annualized excess returns of factor momentum strategies. Two factor momentum strategy returns (standard and developed sig) are decomposed into single-theme contributions. The waterfall chart shows each single theme's contribution to the average annualized return of the two strategies. The sum of all themes mirrors the performance of the respective aggregate shown in Table 2.



Strategy	Mean	Std	Min	Q25	Median	Q75	Max
Factor Momentum	0.11	0.26	-0.31	-0.08	0.11	0.3	0.57
AFM - Continental Sig	0.23***	0.24	-0.18	0.04	0.31	0.41	0.66
AFM - Emerging Sig	0.21*	0.2	-0.12	0.05	0.15	0.36	0.58
AFM - Global Sig	0.32***	0.22	-0.09	0.18	0.37	0.43	0.67

Figure 8: Violin plots for Sharpe ratios of different (advanced) factor momentum strategies in emerging markets: This figure depicts violin plots for 24 Sharpe ratios corresponding to the performance of emerging country-level factor momentum strategies that are formed based on four different signals. All strategies are based on cross-sectional 1-month historical factor performance sorts and formed based on a median breakpoint that leading to a strategy that invests in 50% of an emerging country's factors and shorts the other 50%. The four strategies are (i) a standard factor momentum strategy sorting on the past 1-month factor return within the country, and three Advanced Factor Momentum (AFM) strategies that are formed based on the aggregated signal of a factor's past performance, where aggregation happens over (ii) all countries within a continent (continental signal), (iii) all emerging markets (emerging signal), (iv) all markets (global signal). While the figure shows violin plots of annualized Sharpe ratios of all 24 emerging countries considered in this sample, the table below gives corresponding descriptive statistics for these 24 Sharpe ratios (mean, standard deviation, skewness, minimum, 25-, 50-, and 75-quantile as well as the maximum). Additionally, we depict significance stars for a paired two-sample t-test of AFM strategies' Sharpe ratios against the standard factor momentums' Sharpe ratios. Significance values are given at the usual levels of 90% (*), 95% (**) and 99% (***).

Table 5 presents all evaluation metrics for all four strategies. Same as before, the third column reflects the findings shown in Figure 8. The underlying complete country-wise evaluation can be found in Table A.4 in the appendix.

For emerging markets, all advanced factor momentum strategies show superior performance compared to the standard factor momentum strategy regarding higher average return, lower standard deviation, higher Sharpe ratio and less severe maximum drawdowns. Again, across all metrics (portfolio skewness being the exception), advanced factor momentum strategies display reduced cross-sectional variability (std). Except for skewness, we again receive the consistent picture that advanced factor momentum strategies outperform the standard factor momentum strategy in all key portfolio metrics.

Overall, the results from the performance analysis suggest that the benefits of incorporating broader market signals into factor momentum strategies are not limited to developed markets but are also applicable in the more volatile and unpredictable environments of emerging markets. This is remarkable as the average correlation within factor themes for emerging markets is only 0.09 (see Table 1). With such little cross-country correlation it is striking that non-local strategies that effectively harvest the continuation of cross-country co-movements yields an outperformance. The highest predictability is achieved when including developed markets in the signal (global signal). Thus, there attempts to be a strong global component in emerging market's factor predictability.

However, Sharpe ratios in emerging markets are, on average, lower than in developed markets, as aligned with our structural analysis on regional co-movement. Thus fewer economic gains can be achieved by incorporating non-local information into factor momentum strategies as there is less co-movement among factors that can be leveraged for making predictions.

Lastly, we demonstrate that despite not being as strong as for developed markets, advanced factor momentum signals still carry more information about future returns than local signals. To do so, we repeat the analysis that differentiates between more extreme breakpoints and the contributions of signals that are unique to the local and non-local strategy. To allow comparability between these results and the developed countries' results, we again employ the development status model as our non-local counterpart.

The results of this analysis are displayed in Figure 9. We can see that same as for developed markets, more extreme breakpoints result in higher mean returns for both strategies. Again, we see the pattern that with more extreme breakpoints, the relative economic gain of employing the advanced factor momentum strategy compared to using the standard factor momentum strategy increases. This highlights that investors

Table 5: Key performance metrics: This table aggregates key performance measures of 4 different factor momentum strategies in 24 emerging countries. Panel A shows results for standard factor momentum strategies, while Panels B-D show results for Advanced Factor Momentum Strategies using a continental (B), developed (C) and global (D) signal. For each strategy, we calculate the return, standard deviation, Sharpe ratio, skewness, and maximum drawdown measures for each of the 24 countries separately (columns). We then describe these $24 \cdot 5$ metrics using their mean, standard deviation, minimum, 25-, 50-, and 75-quantile, and maximum (rows). Each value in the table is a descriptive statistic on 24 observations describing one certain aspect of a strategy (e.g. the Sharpe ratio). The third column mirrors the results in Figure 8. For all advanced strategies, we furthermore test the hypothesis that the average metric (first row in each panel (B-D)) is statistically significantly different from the average metric of the standard strategy (panel A). We report the t-statistic in brackets behind the mean statistic. Again, the statistics relate to the significance stars in the table depicted in the lower part of Figure 8. All metrics are annualized.

	Return	Std	Sharpe Ratio	Skewness	Maximum Drawdown
Panel A: Standard Factor Momentum					
Mean	1.67	14.59	0.11	-0.06	-0.50
Std	3.76	5.06	0.26	0.31	0.20
Min	-4.41	7.61	-0.31	-0.88	-0.92
Q25	-1.26	11.38	-0.08	-0.14	-0.61
Median	1.48	13.49	0.11	0.01	-0.50
Q75	4.32	16.96	0.30	0.16	-0.32
Max	8.84	30.91	0.57	0.44	-0.23
Panel B: Advanced Factor Momentum - Continental Signal					
Mean	2.59 [-1.78]	11.37 [10.19]	0.23 [-3.02]	0.03 [-1.86]	-0.32 [-5.53]
Std	3.01	4.21	0.24	0.43	0.19
Min	-4.62	4.49	-0.18	-0.82	-0.89
Q25	0.33	8.67	0.04	-0.17	-0.34
Median	3.00	10.59	0.31	0.03	-0.26
Q75	4.86	13.18	0.41	0.24	-0.21
Max	7.71	25.16	0.66	0.94	-0.14
Panel C: Advanced Factor Momentum - Emerging Signal					
Mean	1.95 [-0.39]	10.04 [9.13]	0.21 [-1.85]	-0.11 [0.52]	-0.33 [-5.22]
Std	2.11	4.17	0.20	0.53	0.19
Min	-2.30	4.28	-0.12	-2.35	-0.78
Q25	0.61	7.45	0.05	-0.16	-0.41
Median	1.24	8.76	0.15	-0.07	-0.26
Q75	3.73	11.80	0.36	0.17	-0.21
Max	6.24	19.89	0.58	0.41	-0.14
Panel D: Advanced Factor Momentum - Global Signal					
Mean	3.37 [-2.47]	10.20 [8.23]	0.32 [-4.26]	0.00 [-1.00]	-0.28 [-6.38]
Std	2.80	3.68	0.22	0.34	0.15
Min	-1.52	4.74	-0.09	-1.07	-0.67
Q25	1.60	7.30	0.18	-0.13	-0.31
Median	2.82	8.98	0.37	0.09	-0.25
Q75	5.36	12.36	0.43	0.16	-0.19
Max	10.48	17.04	0.67	0.58	-0.12

can still significantly outperform standard factor momentum strategies by relying on models that incorporate non-local information into their predictions.

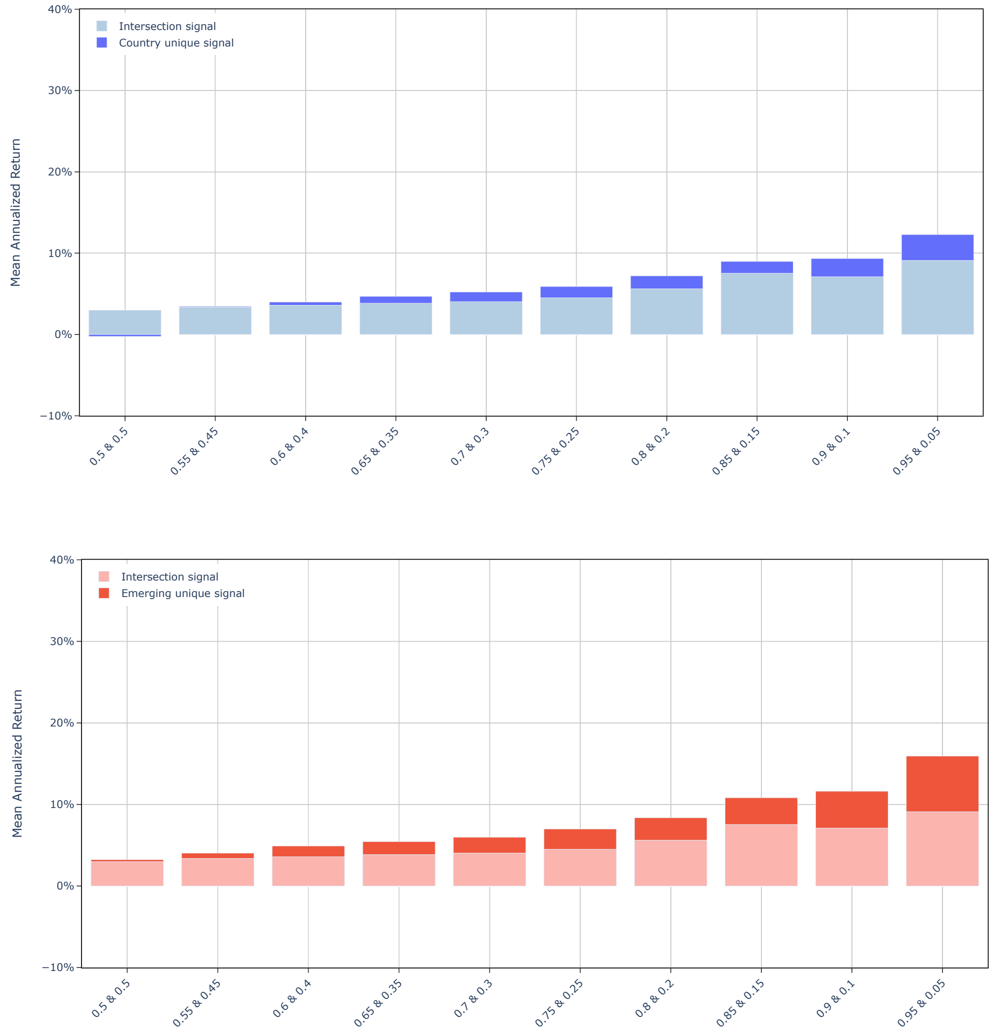


Figure 9: (Advanced) factor momentum strategy returns based on more exclusive breakpoints: This figure depicts mean annualized returns of factor momentum strategies for increasing breakpoint exclusiveness, disaggregated according to country/developed signal contribution. While the x-axis shows increasing (decreasing) breakpoint quantiles for the factor momentum portfolio sorts (the higher(lower) the quantiles, the fewer factors are traded, hence the more exclusive the strategies). Within both panels, the pale part of the bars highlight the performance stemming from factors that are selected simultaneously from the local as well as the developed signal (equal in both panels), the darker shade represents the performance contribution from the country-only (dark blue, upper panel) or developed-only (dark red, lower panel) signals.

5 Conclusion

In this study, we revisited the debate on the efficacy of local versus regional and global asset pricing models through the lens of factor predictability and momentum. By integrating factor momentum into our analysis, we demonstrate that regional and global signals exhibit superior predictive performance for time-varying expected returns, as evidenced by higher average Sharpe ratios and lower dispersion of these across markets. This simple, yet efficient method shows that factor predictability is a non-local phenomenon. Through a structural analysis, we provide evidence that the superiority of non-local models is likely attributable to cross-country factor co-movement. The outperformance of regional and global signals over local signals underscores the importance of considering cross-border mechanics in empirical asset pricing.

Notably, our findings reveal that regional and global factor signals not only offer a more robust framework for predicting asset returns but also have the unique ability to recreate momentum strategies in markets previously thought to be devoid of momentum opportunities, such as Japan. This suggests that the incorporation of regional and local country signals can unlock previously unidentified momentum-based investment opportunities, thereby enriching the arsenal of strategies available to international investors.

In conclusion, our research contributes to the ongoing discourse on international asset pricing by highlighting the superior performance and practical benefits of adopting regional and global predictive signals. These findings not only challenge traditional views but also pave the way for future research to explore the intricate dynamics between factor predictability, momentum, and asset pricing on a global scale. As markets continue to evolve, it becomes imperative for asset pricing models to adapt accordingly, embracing a more holistic view that captures the complexities of global financial markets.

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Appendices

A Additional Tables and Figures

Table A.1: Factor to Factor theme mapping: This table holds the factors used in the analysis and a short description. The mapping between factors and factor themes that is developed by Jensen et al. (2023) is indicated by the bold section headings.

Factor	Description
	Accruals
cowc_gr1a	Change in current operating working capital
oaccruals_at	Operating accruals
oaccruals_ni	Percent operating accruals
seas_16_20na	Years 16-20 lagged returns, nonannual
taccruals_at	Total accruals
taccruals_ni	Percent total accruals
	Debt Issuance
capex_abn	Abnormal corporate investment
debt_gr3	Growth in book debt (3 years)
fnl_gr1a	Change in financial liabilities
ncol_gr1a	Change in noncurrent operating liabilities
nfna_gr1a	Change in net financial assets
ni_ar1	Earnings persistence
noa_at	Net operating assets
	Investment
aliq_at	Liquidity of book assets
at_gr1	Asset Growth
be_gr1a	Change in common equity
capx_gr1	CAPEX growth (1 year)
capx_gr2	CAPEX growth (2 years)
capx_gr3	CAPEX growth (3 years)
coa_gr1a	Change in current operating assets
col_gr1a	Change in current operating liabilities
emp_gr1	Hiring rate
inv_gr1	Inventory growth
inv_gr1a	Inventory change
lnoa_gr1a	Change in long-term net operating assets
mispricing_mgmt	Mispricing factor: Management
ncoa_gr1a	Change in noncurrent operating assets
nncoa_gr1a	Change in net noncurrent operating assets
noa_gr1a	Change in net operating assets
ppeinv_gr1a	Change PPE and Inventory
ret_60_12	Long-term reversal
sale_gr1	Sales Growth (1 year)
sale_gr3	Sales Growth (3 years)
saleq_gr1	Sales growth (1 quarter)
seas_2_5na	Years 2-5 lagged returns, nonannual
	Low Leverage
age	Firm age
aliq_mat	Liquidity of market assets
at_be	Book leverage
bidaskhl_21d	The high-low bid-ask spread
cash_at	Cash-to-assets
netdebt_me	Net debt-to-price
ni_ivol	Earnings volatility
rd5_at	R&D capital-to-book assets
rd_sale	R&D-to-sales
tangibility	Asset tangibility
z_score	Altman Z-score

Table A.1: *(continued)*

Factor	Description
	Low Risk
beta_60m	Market Beta
beta_dimson_21d	Dimson beta
betabab_1260d	Frazzini-Pedersen market beta
betadown_252d	Downside beta
earnings_variability	Earnings variability
ivol_capm_21d	Idiosyncratic volatility from the CAPM (21 days)
ivol_capm_252d	Idiosyncratic volatility from the CAPM (252 days)
ivol_ff3_21d	Idiosyncratic volatility from the Fama-French 3-factor model
ivol_hxz4_21d	Idiosyncratic volatility from the q-factor model
ocfq_saleq_std	Cash flow volatility
rmax1_21d	Maximum daily return
rmax5_21d	Highest 5 days of return
rvol_21d	Return volatility
seas_6_10na	Years 6-10 lagged returns, nonannual
turnover_126d	Share turnover
zero_trades_126d	Number of zero trades with turnover as tiebreaker (6 months)
zero_trades_21d	Number of zero trades with turnover as tiebreaker (1 month)
zero_trades_252d	Number of zero trades with turnover as tiebreaker (12 months)
	Momentum
prc_highprc_252d	Current price to high price over last year
resff3_12_1	Residual momentum t-12 to t-1
resff3_6_1	Residual momentum t-6 to t-1
ret_12_1	Price momentum t-12 to t-1
ret_3_1	Price momentum t-3 to t-1
ret_6_1	Price momentum t-6 to t-1
ret_9_1	Price momentum t-9 to t-1
seas_1_1na	Year 1-lagged return, nonannual
	Profit Growth
dsale_dinv	Change sales minus change Inventory
dsale_drec	Change sales minus change receivables
dsale_dsga	Change sales minus change SG&A
niq_at_chg1	Change in quarterly return on assets
niq_be_chg1	Change in quarterly return on equity
niq_su	Standardized earnings surprise
ocf_at_chg1	Change in operating cash flow to assets
ret_12_7	Price momentum t-12 to t-7
sale_emp_gr1	Labor force efficiency
saleq_su	Standardized Revenue surprise
seas_1_1an	Year 1-lagged return, annual
tax_gr1a	Tax expense surprise
	Profitability
dolvol_var_126d	Coefficient of variation for dollar trading volume
ebit_bev	Return on net operating assets
ebit_sale	Profit margin
f_score	Pitroski F-score
ni_be	Return on equity
niq_be	Quarterly return on equity
o_score	Ohlson O-score
ocf_at	Operating cash flow to assets
ope_be	Operating profits-to-book equity
ope_bel1	Operating profits-to-lagged book equity
turnover_var_126d	Coefficient of variation for share turnover
	Quality
at_turnover	Capital turnover
cop_at	Cash-based operating profits-to-book assets
cop_atl1	Cash-based operating profits-to-lagged book assets
dgp_dsale	Change gross margin minus change sales
gp_at	Gross profits-to-assets
gp_atl1	Gross profits-to-lagged assets

Table A.1: *(continued)*

Factor	Description
mispricing_perf	Mispricing factor: Performance
ni_inc8q	Number of consecutive quarters with earnings increases
niq_at	Quarterly return on assets
op_at	Operating profits-to-book assets
op_atl1	Operating profits-to-lagged book assets
opex_at	Operating leverage
qmj	Quality minus Junk: Composite
qmj_growth	Quality minus Junk: Growth
qmj_prof	Quality minus Junk: Profitability
qmj_safety	Quality minus Junk: Safety
sale_bev	Assets turnover
	Seasonality
corr_1260d	Market correlation
coskew_21d	Coskewness
dbnetis_at	Net debt issuance
kz_index	Kaplan-Zingales index
lti_gr1a	Change in long-term investments
pi_nix	Taxable income-to-book income
seas_11_15an	Years 11-15 lagged returns, annual
seas_11_15na	Years 11-15 lagged returns, nonannual
seas_16_20an	Years 16-20 lagged returns, annual
seas_2_5an	Years 2-5 lagged returns, annual
seas_6_10an	Years 6-10 lagged returns, annual
sti_gr1a	Change in short-term investments
	Short-Term Reversal
iskew_capm_21d	Idiosyncratic skewness from the CAPM
iskew_ff3_21d	Idiosyncratic skewness from the Fama-French 3-factor model
iskew_hxz4_21d	Idiosyncratic skewness from the q-factor model
ret_1_0	Short-term reversal
rmax5_rvol_21d	Highest 5 days of return scaled by volatility
rskew_21d	Total skewness
	Size
ami_126d	Amihud Measure
dolvol_126d	Dollar trading volume
market_equity	Market Equity
prc	Price per share
rd_me	R&D-to-market
	Value
at_me	Assets-to-market
be_me	Book-to-market equity
bev_mev	Book-to-market enterprise value
chcsho_12m	Net stock issues
debt_me	Debt-to-market
div12m_me	Dividend yield
ebitda_mev	Ebitda-to-market enterprise value
eq_dur	Equity duration
eqnetis_at	Net equity issuance
eqnpo_12m	Equity net payout
eqnpo_me	Net payout yield
eqpo_me	Payout yield
fcf_me	Free cash flow-to-price
ival_me	Intrinsic value-to-market
netis_at	Net total issuance
ni_me	Earnings-to-price
ocf_me	Operating cash flow-to-market
sale_me	Sales-to-market

Table A.2: Country information: This table holds information about the developed, emerging, frontier, standalone and not rated country markets in our analysis. Country refers to the ISO-3 code of the respective country. Development statuses are MSCI classified.

Developed			**Emerging**		
Country	Continent	Full Name	Country	Continent	Full Name
ISR	Asia	Israel	ZAF	Africa	South Africa
HKG	Asia	Hong Kong	ARE	Asia	United Arab Emirates
JPN	Asia	Japan	CHN	Asia	China
SGP	Asia	Singapore	EGY	Asia	Egypt
AUS	Australasia	Australia	IDN	Asia	Indonesia
NZL	Australasia	New Zealand	IND	Asia	India
AUT	Europe	Austria	KOR	Asia	South Korea
BEL	Europe	Belgium	MYS	Asia	Malaysia
CHE	Europe	Switzerland	PAK	Asia	Pakistan
DEU	Europe	Germany	PHL	Asia	Philippines
DNK	Europe	Denmark	QAT	Asia	Qatar
ESP	Europe	Spain	SAU	Asia	Saudi Arabia
FIN	Europe	Finland	THA	Asia	Thailand
FRA	Europe	France	TWN	Asia	Taiwan
GBR	Europe	United Kingdom	GRC	Europe	Greece
IRL	Europe	Ireland	POL	Europe	Poland
ITA	Europe	Italy	RUS	Europe	Russia
NLD	Europe	Netherlands	TUR	Europe	Turkey
NOR	Europe	Norway	MEX	North America	Mexico
PRT	Europe	Portugal	ARG	South America	Argentina
SWE	Europe	Sweden	BRA	South America	Brazil
CAN	North America	Canada	CHL	South America	Chile
USA	North America	United States of America	COL	South America	Colombia
			PER	South America	Peru

Table A.3: Core performance of factor momentum strategies in developed countries: This table holds key performance measures of 4 different factor momentum strategies in 23 developed countries. The strategy forms long- short factor portfolios that are based on 1-month factor performance, using median breakpoints and equal weighting of factors. Panel A shows results for standard country-wise factor momentum strategies, while Panels B-D show results for Advanced Factor Momentum Strategies using continental (B), developed (C), and global (D) signals. For each strategy, we calculate the return, standard deviation, Sharpe ratio, skewness, and maximum drawdown measures for every 23 countries separately (columns). All metrics are annualized.

	Panel A: Local					**Panel B: Continental**				
Country	Return	Std	SR	Skew	Max. DD	Return	Std	SR	Skew	Max. DD
AUS	1.2%	8.4%	0.14	0.05	-27.0%	1.5%	7.1%	0.21	0.07	-24.0%
AUT	-0.6%	9.6%	-0.07	-0.09	-51.0%	1.9%	7.9%	0.24	0.12	-41.0%
BEL	5.7%	13.0%	0.44	0.05	-37.0%	4.6%	9.0%	0.52	0.10	-26.0%
CAN	3.1%	16.0%	0.19	0.40	-32.0%	2.1%	12.8%	0.16	-0.17	-27.0%
CHE	4.6%	11.8%	0.38	0.17	-17.0%	4.0%	9.2%	0.44	0.15	-16.0%
DEU	1.1%	10.6%	0.11	0.25	-44.0%	4.1%	8.0%	0.51	0.38	-13.0%
DNK	3.3%	12.2%	0.27	0.05	-48.0%	6.3%	8.9%	0.70	0.18	-16.0%
ESP	1.2%	11.4%	0.11	-0.11	-44.0%	2.2%	9.2%	0.24	0.23	-29.0%
FIN	17.9%	25.9%	0.69	0.45	-48.0%	6.8%	13.1%	0.52	0.72	-25.0%
FRA	1.1%	9.3%	0.12	-0.09	-29.0%	3.3%	8.2%	0.40	0.15	-19.0%
GBR	4.3%	9.0%	0.48	0.11	-15.0%	3.4%	7.5%	0.45	0.16	-15.0%
HKG	5.6%	13.0%	0.43	-0.23	-30.0%	3.2%	8.9%	0.36	-0.20	-32.0%
IRL	4.2%	35.4%	0.12	-0.23	-94.0%	10.8%	27.2%	0.40	-0.17	-75.0%
ISR	9.4%	16.5%	0.57	0.09	-28.0%	5.9%	9.6%	0.62	0.24	-28.0%
ITA	1.7%	11.9%	0.14	0.27	-51.0%	4.7%	9.9%	0.47	0.28	-28.0%
JPN	1.6%	9.2%	0.17	0.14	-30.0%	2.2%	6.8%	0.33	0.27	-19.0%
NLD	3.9%	14.6%	0.27	0.10	-45.0%	3.9%	11.3%	0.34	0.09	-24.0%
NOR	1.3%	10.9%	0.12	-0.06	-34.0%	3.2%	8.3%	0.38	0.17	-19.0%
NZL	1.2%	10.5%	0.12	0.31	-39.0%	2.5%	9.5%	0.26	0.34	-26.0%
PRT	-1.2%	16.9%	-0.07	-0.11	-63.0%	5.2%	10.8%	0.48	-0.19	-29.0%
SGP	4.0%	11.2%	0.36	0.15	-20.0%	4.7%	9.9%	0.47	1.09	-13.0%
SWE	1.2%	15.8%	0.08	-0.07	-61.0%	3.3%	11.7%	0.29	-0.19	-44.0%
USA	3.5%	11.3%	0.31	0.07	-25.0%	3.2%	9.3%	0.35	0.03	-24.0%
Mean	3.5%	13.7%	0.24	0.07	-40.0%	4.0%	10.2%	0.40	0.17	-27.0%
	Panel C: Developed					**Panel D: Global**				
AUS	3.8%	6.3%	0.60	0.21	-11.0%	3.6%	6.3%	0.57	0.23	-14.0%
AUT	2.2%	7.9%	0.28	0.14	-43.0%	1.5%	7.9%	0.18	-0.03	-46.0%
BEL	5.0%	8.9%	0.57	0.15	-30.0%	5.2%	8.4%	0.61	0.02	-28.0%
CAN	2.5%	10.2%	0.24	-0.29	-22.0%	2.3%	9.7%	0.24	-0.16	-21.0%
CHE	5.1%	9.6%	0.54	0.29	-18.0%	4.4%	9.0%	0.49	0.22	-17.0%
DEU	4.3%	8.2%	0.53	0.39	-14.0%	3.5%	8.1%	0.43	0.38	-20.0%
DNK	7.0%	9.3%	0.75	0.16	-18.0%	6.2%	9.1%	0.69	0.19	-17.0%
ESP	3.1%	8.8%	0.35	0.27	-23.0%	2.2%	8.7%	0.25	0.14	-30.0%
FIN	9.3%	14.3%	0.65	0.65	-30.0%	6.4%	13.5%	0.47	0.34	-41.0%
FRA	3.9%	8.5%	0.46	0.15	-20.0%	2.9%	8.3%	0.35	0.05	-20.0%
GBR	4.3%	7.7%	0.56	0.18	-10.0%	3.6%	7.4%	0.49	0.11	-12.0%
HKG	6.7%	9.1%	0.74	0.38	-15.0%	4.5%	8.6%	0.52	0.07	-18.0%
IRL	11.9%	27.2%	0.44	-0.07	-73.0%	9.9%	24.1%	0.41	-0.20	-67.0%
ISR	7.1%	9.4%	0.75	0.26	-21.0%	5.53%	9.2%	0.60	0.26	-16.0%
ITA	5.1%	10.2%	0.50	0.32	-24.0%	4.3%	9.8%	0.44	0.25	-26.0%
JPN	4.3%	7.3%	0.59	0.29	-12.0%	3.2%	7.1%	0.45	0.25	-14.0%
NLD	4.3%	11.3%	0.39	0.14	-21.0%	4.1%	11.3%	0.36	0.12	-22.0%
NOR	3.6%	8.8%	0.42	0.17	-18.0%	3.2%	8.4%	0.38	0.11	-24.0%
NZL	3.2%	7.4%	0.43	0.73	-10.0%	3.1%	7.2%	0.43	0.72	-10.0%
PRT	4.5%	10.8%	0.41	-0.14	-32.0%	3.9%	10.1%	0.39	-0.16	-33.0%
SGP	5.7%	8.2%	0.70	0.51	-8.0%	5.0%	7.7%	0.65	0.35	-10.0%
SWE	3.5%	12.0%	0.29	-0.24	-44.0%	2.3%	11.7%	0.19	-0.28	-43.0%
USA	5.2%	9.9%	0.53	0.25	-20.0%	4.5%	9.4%	0.48	0.24	-18.0%
Mean	5.0%	10.1%	0.51	0.21	-23.0%	4.1%	9.6%	0.44	0.14	-25.0%

Table A.4: Core performance of factor momentum strategies in emerging countries: This table holds key performance measures of 4 different factor momentum strategies in 24 emerging countries. The strategy forms long- short factor portfolios that are based on 1-month factor performance, using median breakpoints and equal weighting of factors. Panel A shows results for standard country-wise factor momentum strategies, while Panels B-D show results for Advanced Factor Momentum Strategies using continental (B), developed (C), and global (D) signals. For each strategy, we calculate the return, standard deviation, Sharpe ratio, skewness, and maximum drawdown measures for every 23 countries separately (columns). All metrics are annualized.

	Panel A: Local					**Panel B: Continental**				
Country	Return	Std	SR	Skew	Max. DD	Return	Std	SR	Skew	Max. DD
ARE	7.7%	19.2%	0.40	-0.88	-54.0%	3.0%	16.1%	0.19	-0.82	-51.0%
ARG	-4.4%	30.9%	-0.14	0.26	-92.0%	-4.6%	25.2%	-0.18	0.59	-89.0%
BRA	-1.0%	16.4%	-0.06	-0.09	-76.0%	-1.8%	13.0%	-0.14	0.03	-72.0%
CHL	-2.1%	7.6%	-0.27	0.02	-52.0%	-0.4%	4.5%	-0.08	-0.05	-14.0%
CHN	2.1%	10.3%	0.20	0.17	-24.0%	-0.2%	6.6%	-0.03	-0.15	-22.0%
COL	5.7%	18.7%	0.30	0.27	-36.0%	4.9%	13.8%	0.36	0.61	-33.0%
EGY	-1.9%	13.2%	-0.15	-0.13	-68.0%	-1.0%	11.8%	-0.09	-0.10	-59.0%
GRC	2.7%	21.5%	0.13	-0.16	-78.0%	7.0%	16.5%	0.42	-0.20	-52.0%
IDN	4.0%	15.1%	0.26	-0.53	-28.0%	5.4%	12.8%	0.42	-0.41	-25.0%
IND	8.8%	18.9%	0.47	0.44	-47.0%	7.7%	14.6%	0.53	0.59	-31.0%
KOR	1.0%	14.4%	0.07	0.18	-58.0%	3.7%	10.8%	0.34	0.49	-20.0%
MEX	-0.1%	8.3%	-0.02	-0.08	-34.0%	1.3%	7.1%	0.18	0.04	-19.0%
MYS	2.4%	9.4%	0.26	-0.16	-29.0%	3.8%	8.6%	0.43	-0.54	-21.0%
PAK	-2.8%	11.4%	-0.24	-0.08	-59.0%	3.0%	8.7%	0.35	0.13	-28.0%
PER	1.2%	14.2%	0.09	0.17	-40.0%	2.8%	9.4%	0.29	0.15	-23.0%
PHL	-3.3%	10.6%	-0.31	-0.61	-57.0%	0.5%	8.7%	0.06	-0.66	-19.0%
POL	6.4%	11.2%	0.57	-0.04	-29.0%	4.8%	9.4%	0.51	0.22	-16.0%
QAT	1.0%	13.5%	0.07	0.15	-45.0%	2.7%	10.4%	0.26	0.14	-28.0%
RUS	-1.0%	19.8%	-0.05	0.10	-82.0%	4.8%	14.5%	0.33	0.31	-27.0%
SAU	4.5%	13.5%	0.34	0.03	-36.0%	5.6%	8.5%	0.66	0.10	-18.0%
THA	6.7%	12.3%	0.54	0.13	-23.0%	4.9%	12.1%	0.41	0.94	-22.0%
TUR	-3.3%	13.0%	-0.26	-0.61	-70.0%	-0.3%	9.5%	-0.04	-0.50	-29.0%
TWN	1.7%	13.0%	0.13	0.02	-56.0%	0.6%	8.6%	0.07	-0.10	-38.0%
ZAF	4.2%	13.7%	0.31	0.01	-23.0%	4.2%	11.8%	0.35	-0.04	-23.0%
Mean	1.7%	14.6%	0.11	-0.06	-50.0%	2.6%	11.4%	0.23	0.03	-32.0%
	Panel C: Developed					**Panel D: Global**				
ARE	0.6%	19.9%	0.03	-2.35	-78.0%	0.1%	16.1%	0.06	-1.07	-63.0%
ARG	-2.3%	18.9%	-0.12	0.10	-77.0%	-1.5%	17.0%	-0.09	-0.15	-67.0%
BRA	0.8%	11.8%	0.07	-0.50	-60.0%	5.2%	12.3%	0.42	0.01	-38.0%
CHL	-0.2%	4.3%	-0.04	-0.21	-21.0%	-0.4%	4.7%	-0.08	-0.12	-24.0%
CHN	-0.0%	5.7%	0.00	-0.03	-28.0%	1.0%	6.2%	0.15	-0.12	-29.0%
COL	4.6%	13.3%	0.34	0.25	-26.0%	7.7%	12.6%	0.61	0.58	-19.0%
EGY	1.3%	11.0%	0.12	-0.22	-41.0%	5.6%	12.3%	0.46	0.33	-21.0%
GRC	1.1%	14.7%	0.07	-0.13	-56.0%	5.9%	16.8%	0.35	-0.15	-53.0%
IDN	4.8%	11.0%	0.43	0.34	-22.0%	6.4%	12.2%	0.53	0.12	-25.0%
IND	4.3%	11.9%	0.37	0.25	-25.0%	10.5%	15.7%	0.67	0.56	-32.0%
KOR	0.6%	9.4%	0.06	-0.12	-42.0%	1.8%	9.7%	0.19	0.12	-31.0%
MEX	0.8%	5.9%	0.14	0.26	-21.0%	2.3%	6.1%	0.37	0.25	-12.0%
MYS	2.9%	6.5%	0.44	-0.30	-14.0%	2.8%	7.3%	0.38	-0.43	-17.0%
PAK	4.8%	8.7%	0.54	0.15	-18.0%	3.5%	8.5%	0.42	0.16	-18.0%
PER	2.6%	7.4%	0.36	-0.11	-20.0%	2.9%	6.7%	0.43	0.12	-15.0%
PHL	1.1%	7.6%	0.15	0.00	-26.0%	0.3%	7.6%	0.04	-0.05	-27.0%
POL	2.4%	8.0%	0.30	-0.12	-25.0%	5.3%	9.6%	0.55	0.12	-15.0%
QAT	-0.5%	8.8%	-0.06	-0.10	-46.0%	0.4%	8.7%	0.05	0.16	-39.0%
RUS	6.2%	17.3%	0.36	0.14	-34.0%	5.8%	14.2%	0.41	0.09	-25.0%
SAU	4.3%	7.5%	0.58	0.23	-15.0%	4.6%	7.0%	0.66	0.20	-22.0%
THA	3.5%	9.2%	0.38	0.41	-15.0%	3.1%	9.2%	0.34	-0.35	-12.0%
TUR	-0.3%	7.8%	-0.04	-0.38	-26.0%	2.0%	8.5%	0.23	-0.42	-25.0%
TWN	1.2%	7.9%	0.15	-0.15	-35.0%	2.1%	8.8%	0.24	0.09	-30.0%
ZAF	2.1%	6.8%	0.31	0.07	-16.0%	2.7%	7.2%	0.37	-0.06	-20.0%
Mean	1.9%	10.0%	0.21	-0.11	-33.0%	3.4%	10.2%	0.32	0.00	-28.0%

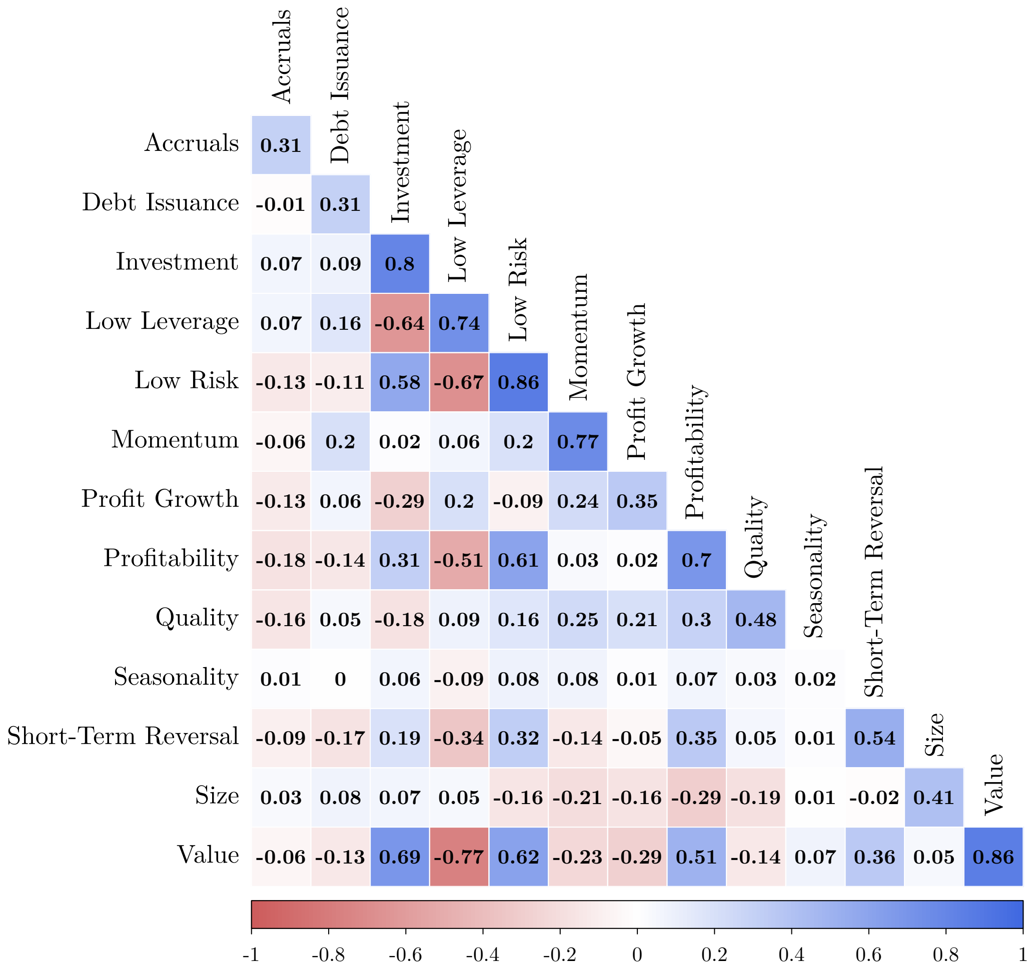
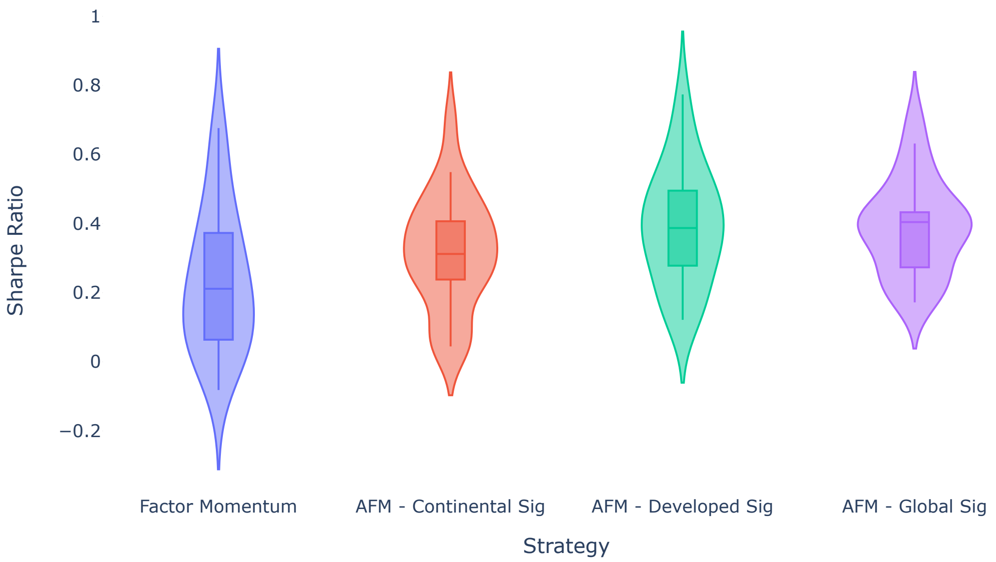
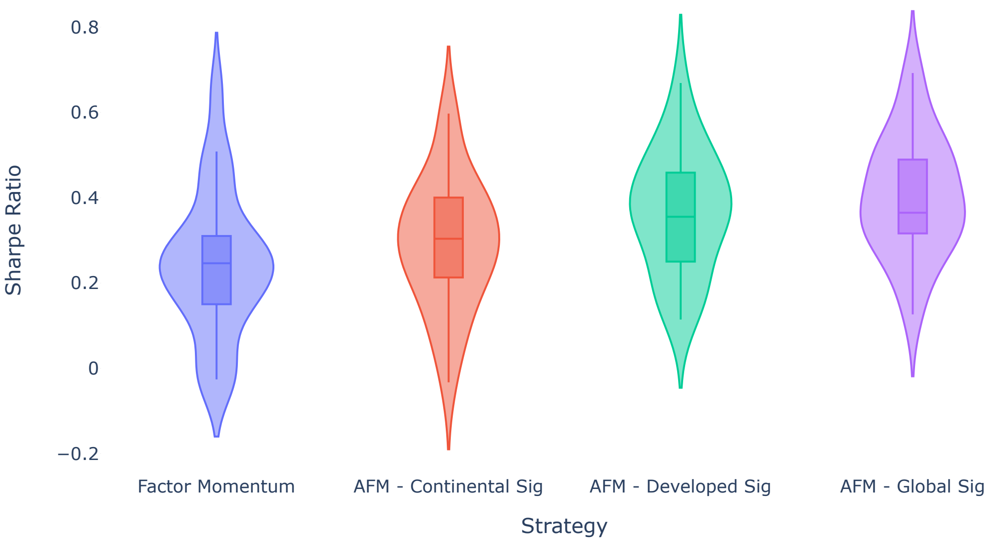


Figure A.1: Within theme correlation of international factor returns: This figure depicts the average pairwise Pearson correlation between factor returns from different themes (off-diagonal elements) or between factors in the same theme(diagonal elements). The themes 13 themes are defined by Jensen et al. (2023). Each factor return is the average value weighted return for that factor of all countries in our sample. Our sample spans the time period from January 1998 to December 2022. Only correlations that are significant at 5% confidence are displayed.



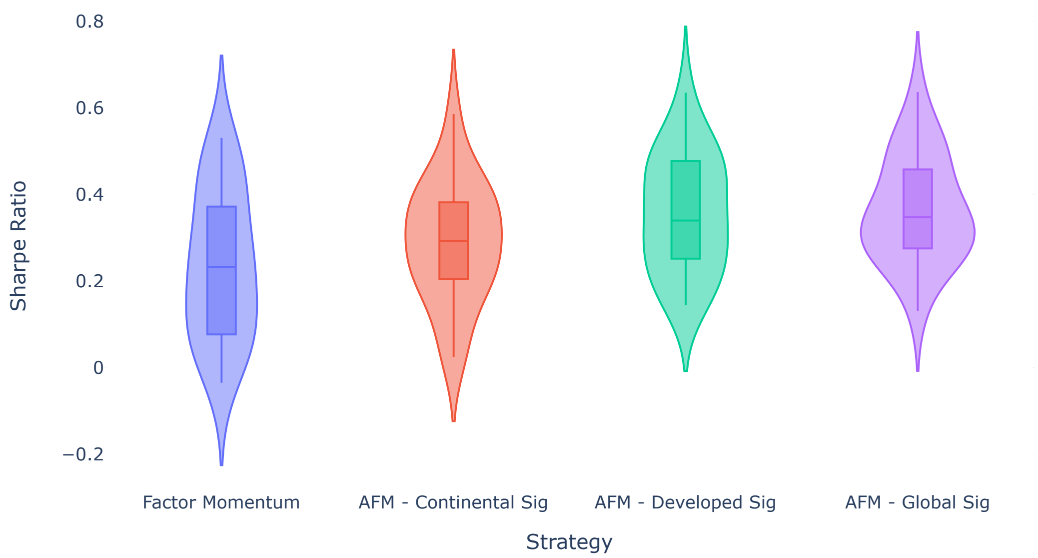
Annualized Sharpe ratios	Mean	Std	Min	Q25	Median	Q75	Max
Factor Momentum	0.23	0.20	-0.08	0.07	0.21	0.36	0.68
AFM - Continental Sig	0.32***	0.17	0.04	0.24	0.31	0.41	0.70
AFM - Developed Sig	0.39***	0.17	0.12	0.29	0.39	0.49	0.77
AFM - Global Sig	0.39***	0.14	0.17	0.28	0.40	0.43	0.71

Figure A.2: Violin plots for Sharpe ratios of different (advanced) factor momentum strategies - 3 months formation period: This figure depicts violin plots for 23 Sharpe ratios corresponding to the performance of country-level factor momentum strategies that are formed based on four different signals. All strategies are based on cross-sectional 3-month historical factor performance sorts and formed based on a median breakpoint that leading to a strategy that invests in 50% of a country's factors and shorts the other 50%.



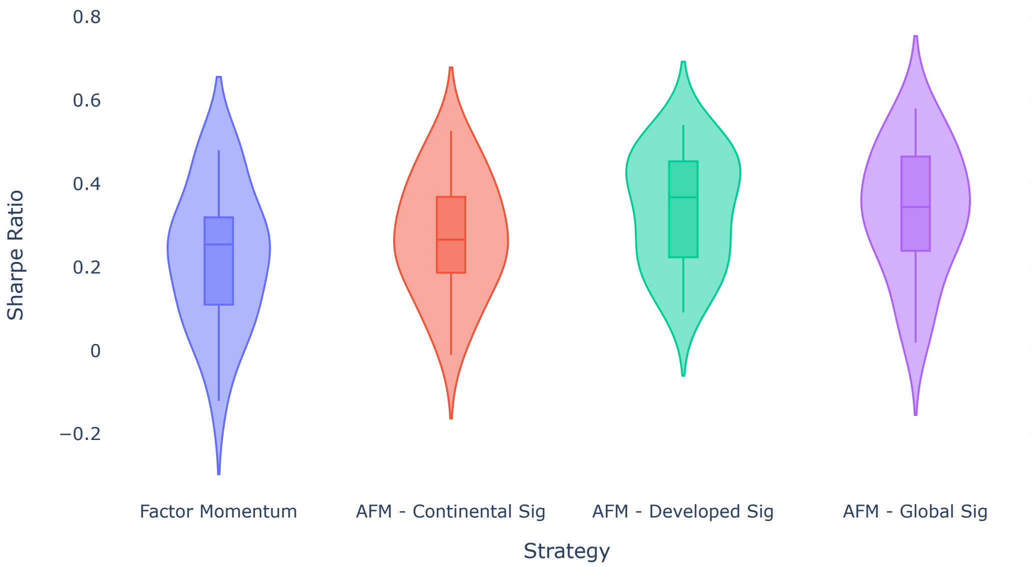
Annualized Sharpe ratios	Mean	Std	Min	Q25	Median	Q75	Max
Factor Momentum	0.24	0.17	-0.03	0.16	0.25	0.30	0.65
AFM - Continental Sig	0.29**	0.15	-0.03	0.22	0.30	0.39	0.60
AFM - Developed Sig	0.37***	0.14	0.11	0.27	0.36	0.46	0.67
AFM - Global Sig	0.40***	0.14	0.13	0.32	0.36	0.49	0.69

Figure A.3: Violin plots for Sharpe ratios of different (advanced) factor momentum strategies - 6 months formation period: This figure depicts violin plots for 23 Sharpe ratios corresponding to the performance of country-level factor momentum strategies that are formed based on four different signals. All strategies are based on cross-sectional 6-month historical factor performance sorts and formed based on a median breakpoint that leading to a strategy that invests in 50% of a country's factors and shorts the other 50%.



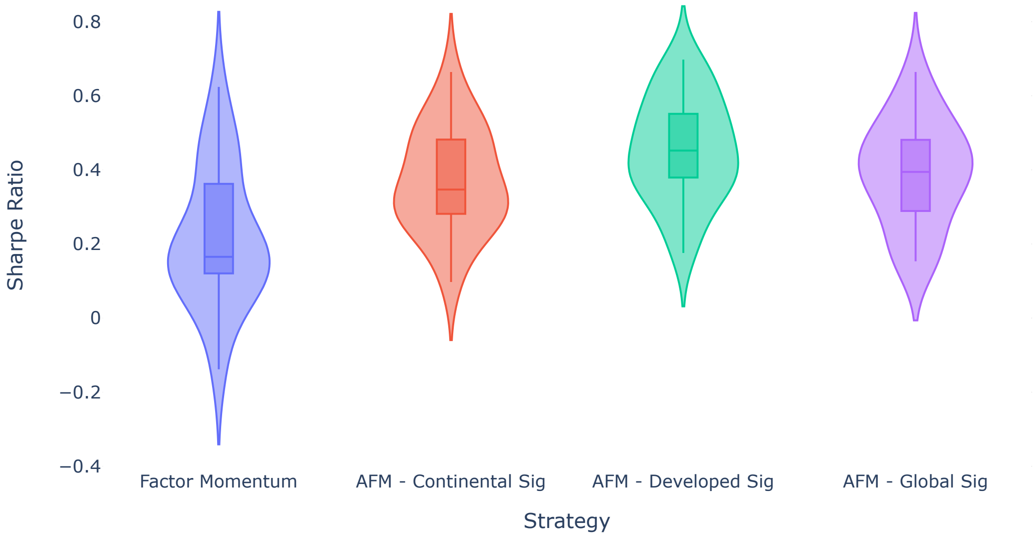
Annualized Sharpe ratios	Mean	Std	Min	Q25	Median	Q75	Max
Factor Momentum	0.23	0.17	-0.03	0.08	0.23	0.37	0.53
AFM - Continental Sig	0.29***	0.14	0.02	0.21	0.29	0.38	0.59
AFM - Developed Sig	0.36***	0.13	0.14	0.25	0.34	0.47	0.63
AFM - Global Sig	0.36***	0.12	0.13	0.28	0.35	0.45	0.64

Figure A.4: Violin plots for Sharpe ratios of different (advanced) factor momentum strategies - 9 months formation period: This figure depicts violin plots for 23 Sharpe ratios corresponding to the performance of country-level factor momentum strategies that are formed based on four different signals. All strategies are based on cross-sectional 9-month historical factor performance sorts and formed based on a median breakpoint that leading to a strategy that invests in 50% of a country's factors and shorts the other 50%.



Annualized Sharpe ratios	Mean	Std	Min	Q25	Median	Q75	Max
Factor Momentum	0.22	0.16	-0.12	0.11	0.25	0.32	0.48
AFM - Continental Sig	0.28**	0.14	-0.01	0.19	0.27	0.36	0.53
AFM - Developed Sig	0.34***	0.13	0.09	0.23	0.37	0.45	0.54
AFM - Global Sig	0.34***	0.15	0.02	0.24	0.34	0.45	0.58

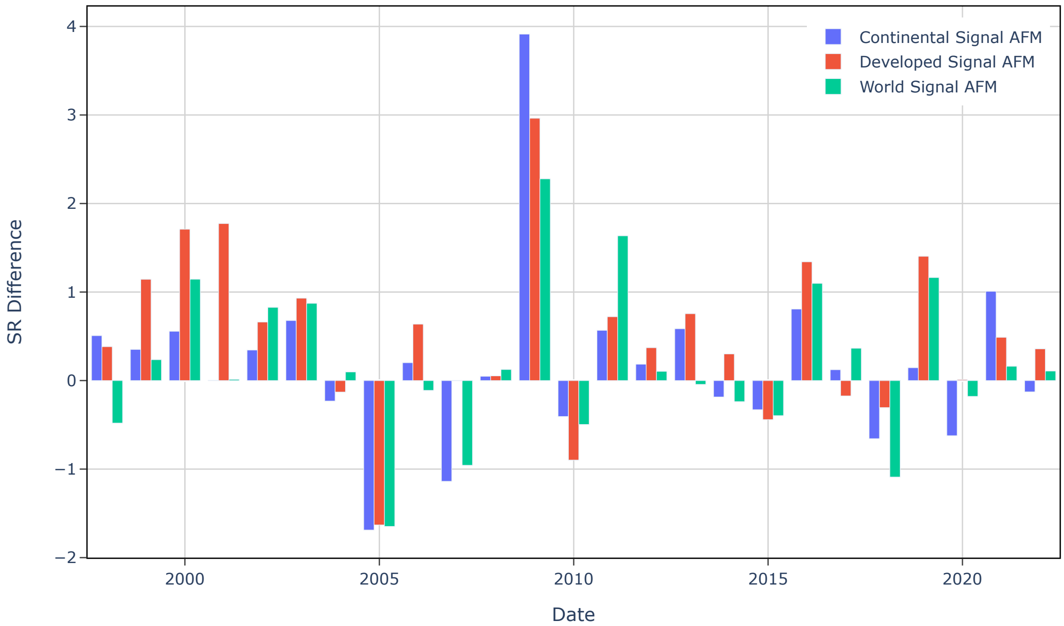
Figure A.5: Violin plots for Sharpe ratios of different (advanced) factor momentum strategies - 12 months formation period: This figure depicts violin plots for 23 Sharpe ratios corresponding to the performance of country-level factor momentum strategies that are formed based on four different signals. All strategies are based on cross-sectional 12-month historical factor performance sorts and formed based on a median breakpoint that leading to a strategy that invests in 50% of a country's factors and shorts the other 50%.



Annualized Sharpe ratios	Mean	Std	Min	Q25	Median	Q75	Max
Factor Momentum	0.22	0.18	-0.14	0.12	0.17	0.34	0.62
AFM - Continental Sig	0.37***	0.14	0.10	0.28	0.35	0.48	0.66
AFM - Developed Sig	0.45***	0.14	0.18	0.38	0.45	0.55	0.70
AFM - Global Sig	0.39***	0.14	0.15	0.29	0.39	0.48	0.66

Figure A.6: Violin plots for Sharpe ratios of different (advanced) factor momentum strategies - Demeaned: This figure depicts violin plots for 23 Sharpe ratios corresponding to the performance of country-level factor momentum strategies that are formed based on four different signals. All strategies are based on cross-sectional 1-month historical factor performance sorts and formed based on a median breakpoint that leading to a strategy that invests in 50% of a country's factors and shorts the other 50%. Differing from the benchmark strategy, the sorting signals are demeaned using 12-month expanding windows to account for sorting on unconditional differences in prior risk premia.

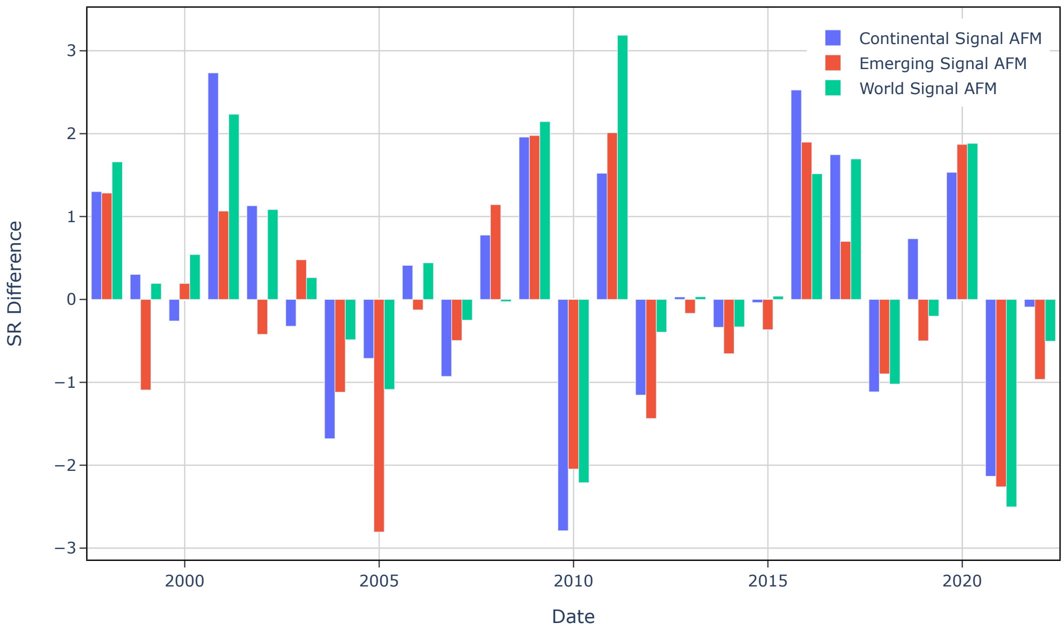
B Robustness over Time



	Continental AFM	Developed AFM	World AFM
# Outperforming FM	16	19	15
# Underperforming FM	9	6	10
# Best Strategy	3	13	5
# Worst Strategy	5	2	5
SR in Recession Years	0.84	1.20	0.56
SR in non-Recession Years	0.06	0.36	0.11

Figure B.1: This figure depicts yearly aggregated Sharpe ratios for non-local factor momentum strategies vs. a local factor momentum strategy in emerging countries over years 1998-2022. Each year we calculate excess returns of advanced factor momentum strategies by subtracting standard factor momentum strategy returns. We then calculate the Sharpe ratios of all three strategies using excess returns and then take an equal weighted average across all countries for each strategy. The bars show the Sharpe ratios of excess returns for the non-local strategies compared to the local factor momentum strategy. The table below the figure counts how often the non-local strategies out-/underperformed the local strategy (rows 1-2), how often a strategy was the best/worst performing strategy (rows 3-4), and reports the respective average Sharpe ratios in recession and non-recession years (rows 5-6).

To further investigate the temporal stability of the strategies' performance, we calculate annual Sharpe ratios for aggregated factor momentum strategies separately for developed and emerging markets. In doing so, we first calculate the return of advanced momentum strategies in each country and substract the standard factor momentum strategies returns to retrieve excess returns. We then calculate annual Sharpe ratios using these excess returns. We then aggregate the Sharpe ratios into an equally weighted average for each year so we can compare the average yearly Sharpe ratios



	Continental AFM	Emerging AFM	World AFM
# Outperforming FM	13	10	14
# Underperforming FM	12	15	11
# Best Strategy	6	2	8
# Worst Strategy	6	5	2
SR in Recession Years	1.75	1.51	1.56
SR in non-Recession Years	-0.09	-0.42	0.08

Figure B.2: This figure depicts yearly aggregated Sharpe ratios for non-local factor momentum strategies vs. a local factor momentum strategy in emerging countries over years 1998-2022. Each year we calculate excess returns of advanced factor momentum strategies by subtracting standard factor momentum strategy returns. We then calculate the Sharpe ratios of all three strategies using excess returns and then take an equal weighted average across all countries for each strategy. The bars show the Sharpe ratios of excess returns for the non-local strategies compared to the local factor momentum strategy. The table below the figure counts how often the non-local strategies out-/underperformed the local strategy (rows 1-2), how often a strategy was the best/worst performing strategy (rows 3-4), and reports the respective average Sharpe ratios in recession and non-recession years (rows 5-6).

of each strategy. This analysis allows us to examine whether the performance of the advanced factor momentum strategies remains consistent in more recent years, addressing concerns over potential temporal effects on the discorvered regional factor predictability.

Figure B.1 and Figure B.2 depict annual Sharpe ratio differences between the local and the the 3 advanced factor momentum strategies in developed and emerging markets respectively. The figures reveal no significant drop in performance over time, indicating the persistence of factor momentum effects across different market conditions.

Strikingly in both, developed and emerging markets, the advanced factor momentum strategies deliver extraordinary Sharpe ratios in recession years and can hence be efficiently used for diversification purposes. Moreover, in developed markets we find that non-local strategies outperform local strategies roughly twice as often as they underperform, with the developed market strategy again being the clear winner. This indicates again that in developed markets, where country factor returns are more integrated, non-local factor momentum strategies can create a stronger outperformance than in regions of weaker integration.

The robustness tests lend further support to our initial findings, demonstrating the applicability and durability of advanced factor momentum strategies. The consistent performance across different temporal and geographic contexts underscores the value of incorporating broader market signals into factor momentum strategies. These findings not only validate the robustness of our methodology but also suggest that investors could benefit from a more global perspective, even in the face of market volatility and economic uncertainty.