Cross-Country Factor Momentum

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Abstract

We study a new class of the momentum effect: cross-country factor momentum. We document a persistent international pattern: factors in winning countries consistently outperform those in losing countries. The effect holds across most anomalies and is robust to many considerations.

Keywords: factor momentum, equity anomalies, return predictability, factor timing, international stock markets.

JEL codes: G11, G12, G17

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1. Introduction

A phenomenon known as "factor momentum" suggests that anomalies with strong past returns persistently outperform those with weak past returns (Avramov et al., 2017; Ehsani & Linnainmaa, 2022). While existing literature primarily centers on factor momentum within countries, our inquiry shifts focus to its existence across countries. Specifically, we aim to ascertain whether factor returns exhibit a predictable cross-sectional variation across markets in line with their historical performance. For instance, should the value factor in Germany recently outpace Brazil's, will this trend continue? Can we anticipate the German value strategy's continued dominance over its Brazilian counterpart? We term this phenomenon "cross-country factor momentum."

To investigate the factor momentum across countries, we examine data from up to 145 prominent factors from 51 countries spanning over three decades. Employing both cross-sectional and time-series strategies, we analyze countries based on past factor returns. We aim to verify whether factors in high-performing countries maintain their lead over their underperforming counterparts.

The results reveal a compelling cross-country factor momentum effect: factors in countries with high returns consistently beat those with weaker performance. The pattern prevails across most anomalies. For example, the time-series cross-country factor momentum strategy earns positive returns for 140 out of 145 anomalies considered, with 96 of these cases achieving significance at the 5% level. On average, monthly returns amount to 0.16% with an annualized Sharpe ratio of 0.47. Furthermore, certain factors like firm size, age, and value anomalies display a particularly powerful performance persistence. With a Sharpe ratio exceeding 0.9, they beat even a highly diversified benchmark that equally weights all anomalies in the sample. Finally, the cross-country factor momentum effect remains robust to alternative factor momentum definitions, as well as to different portfolio weighting schemes and both long-short and long-only anomaly designs. In sum, momentum influence seems more pervasive than previously thought, driving factor returns both within and across countries.

Our study contributes to the rapidly growing literature on the factor momentum effect, first identified by Avramov et al. (2017) and extensively investigated in the U.S. market (Ehsani & Linnainmaa, 2022; Arnott et al., 2023). Subsequent research extended the evidence to international markets (Gupta & Kelly, 2019; Fan et al., 2021). All of these studies analyzed the performance persistence in individual markets or regions. Contrasting this, we focus on the factor momentum across rather than within countries.

The remainder of the paper proceeds as follows. Section 2 presents the data and methods. Section 3 reports the findings. Finally, Section 4 concludes.

2. Data and Methods

Our sample contains 51 stock markets from around the world and the study period runs from December 1986 to December 2021. Table A1 in the Online Appendix overviews the composition of our sample. Market data for the United States is from CRSP, and the market data for other markets, as well as all accounting data, is from Compustat. All factors are computed using publicly available code from Jensen et al. (2023).[1] We use monthly returns expressed in USD, and the risk-free rate is proxied by the U.S. one-month Treasury bill rate.

The building blocks of all factor momentum strategies are long-short strategies based on cross-sectional anomalies. To avoid arbitrary selection, we replicate a comprehensive set of 145 non-momentum stock characteristics from Jensen et al. (2023), comprising the most prominent anomalies from finance literature.[2] We represent all factor strategies by long-short value-weighted portfolios that buy (sell) a tercile of stocks with the highest (lowest) expected return implied by the anomaly signal. Notably, we require at least five firms per long and short leg. If fewer than five companies are available on any side in a given month, we set the return to missing.

To explore the cross-country factor momentum, we build upon the standard factor momentum strategy of Ehsani and Linnainmaa (2022), following their choice of sorting period. Every month, we sort all countries in the sample according to the average return of factor i over the past 12 months (t-12 to t-1). We then divide the countries into two groups to compute cross-sectional and time-series strategies.

The cross-sectional cross-country factor momentum strategy (XC-FMOM$_{CS}$) for factor i involves taking a long position in factor i in countries where it yielded above-median returns in the previous year and a short position in those with below-median performance. Conversely, the cross-country time-series factor momentum strategy (XC-FMOM$_{TS}$) assumes a long position in countries with positive factor i returns over the past 12 months and a short position in those with negative performance. Given the 145 factors in the

[1] We are thankful to the authors for making their code available at https://github.com/bkelly-lab/ReplicationCrisis.

[2] The original dataset of Jensen et al. (2022) contains 153 anomalies. Nonetheless, as in Ehsani and Linnainmaa (2022), we discard those directly linked to the stock momentum effect. These encompass eight factors: prc_highprc_252d, resff3_12_1, resff3_6_1, ret_12_1, ret_3_1, ret_6_1, ret_9_1, and seas_1_1na. Furthermore, several anomalies based on long-run data are unavailable in younger emerging markets. The detailed list from Table A2 in the Online Appendix overviews the anomalies covered in our paper. While most anomalies are available in all markets, a small percentage of those relying on long-run data is missing in younger emerging markets. Table A1 in the Online Appendix sheds light on the factor availability across countries.

sample, our methodological framework generates 145 XC-FMOM$_{CS}$ and XC-FMOM$_{TS}$ strategies—for each factor separately.

3. Findings

We start by examining the general performance of all 145 factors. Figure 1 displays the overall distribution of mean returns, corresponding *t*-statistics, and Sharpe ratios for the sets of 145 single-anomaly strategies. Most anomalies appear to exhibit noticeable performance persistence. The mean returns are typically positive for both cross-sectional and time-series factor momentum strategies, and many of them have *t*-statistics exceeding common significance thresholds. A distribution of annualized Sharpe ratios reveals a similar pattern, with the values for most factors ranging between 0.3 and 0.6.

[Insert Figure 1 here]

Table 1, Panel A, provides more formal insights. While we assess the performance from a bird's-eye view, detailed results for each portfolio can be found in Table A3 of the Online Appendix. First, consider the XC-FMOM$_{CS}$ portfolios (Table 1, Panel A.1). In 136 out of 145 cases (94%), the tercile of countries with high past factor returns continued to outperform the tercile of countries with low past factor returns. Moreover, for 64 factors (44% of all cases), the difference was significant at the 5% level. The average return on a typical factor momentum strategy is 0.10% per month, with a corresponding annualized Sharpe ratio of 0.33. In short, our data presents strong evidence of a novel cross-country momentum pattern in factor returns, where winner-country factors outperform and loser-country factors underperform.

[Insert Table 1 here]

Interestingly, as revealed by Table 1, Panel A.2, the evidence for the time-series version of cross-country factor momentum is even more compelling. The mean monthly return on the average XC-FMOM$_{TS}$ portfolio is 0.16%, with a typical Sharpe ratio of 0.47. Additionally, as clearly visible in Figure 1, Panel B.1, almost all strategies yielded historically positive profits, with most being significant at the 5% level. More specifically, 140 (97% of all) XC-FMOM$_{TS}$ strategies generated mean returns exceeding zero, with 96 cases (66% of all) being significant at the 5% level.

Table 1, Panel B, zooms onto the top 20 anomalies regarding their Sharpe ratios for XC-FMOM$_{TS}$ portfolios. The best-performing strategy is based on the *market_equity* anomaly, generating an annualized Sharpe ratio of 0.93 (1.13) in the cross-sectional (time-series framework), with mean returns associated with impressive *t*-statistics of 5.53 (6.67). The effect is comparably strong for the *age* anomaly, followed by factors based on various

valuation ratios, such as *fcf_me*, *ni_me*, and *sale_me*. In none of these cases do the XC-FMOM$_{TS}$ Sharpe ratios fall below 0.9. For all 20 strategies, the annualized Sharpe ratios typically exceed 0.7, and in most cases, they are higher than the Sharpe ratios for a highly diversified portfolio that equally weights a given factor strategy across all countries in our sample.

Finally, we supplement our findings with several additional insights and robustness checks. First, we revisit our findings using alternative anomaly weighting schemes, specifically equal-weighted and capped value-weighted anomaly portfolios (see Tables A4 and A5 in the Online Appendix).[3] The outcomes are consistent, confirming a reliable cross-country pattern in factor returns.

Second, we investigate the composition of long and short factors in momentum strategies. We are interested in the stability of cross-factor momentum portfolios: do they actively reallocate funds across countries, or, alternatively, do they derive profitability from systematically emphasizing specific markets? Figure A1 in the online appendix shows the average country composition across all 145 anomalies (panel A) and the top five anomalies from Table 1 (panel B).[4] In both cases, countries are almost equally represented in the long and short legs, and there is no significant bias towards either position. On the one hand, this implies that cross-country factor momentum strategies are unlikely to generate profits simply by harvesting a risk premium associated with certain markets. On the other hand, the need to actively rotate countries may entail sizeable transaction costs, which may pose challenges to practical implementation.

Third, while our baseline analysis focuses on long-short portfolios, we now replicate the results from Table 1 using their long-only versions. As shown in Table A6 in the Online Appendix, the results for the long-only portfolios are comparably strong, and the significant gains are even more prevalent, with 65% (83%) of the XC-FMOM$_{CS}$ (XC-FMOM$_{TS}$) strategies recording t-statistics greater than 1.96.

Fourth, we examine the relationship between the cross-country factor momentum and the corresponding within-country factor momentum for the US market. Table A7 in the Online Appendix presents the corresponding Pearson's correlation coefficients. Interestingly, both strategies show substantial comovement, with the average correlation coefficient for the time-series and cross-sectional versions being 0.34 and 0.38,

[3] The capped value-weighted anomaly portfolios are formed as in Jensen et al. (2023): we winsorize equity values at their 80th percentile to obtain more balanced yet tradeable portfolios.

[4] In this exercise, we focus on the cross-sectional factor momentum. This is because the time-series version has a built-in long bias by design, which makes the interpretation of its composition less straightforward and intuitive.

respectively. This suggests a potential common component in their returns, which could be explored in future research.

4. Conclusion

The study offers evidence of the cross-country factor momentum effect. We identify a compelling cross-country factor momentum effect: anomalies in winning countries consistently beat those in losing countries. The effect is prevalent for most factors and particularly pronounced for size, age, and value anomalies. Future studies should explore the origins, reliability, and practical applications of the cross-country factor momentum effect, considering, in particular, their implementation costs.

Declarations of Interest

None. The authors declare no conflicts of interest.

Acknowledgments

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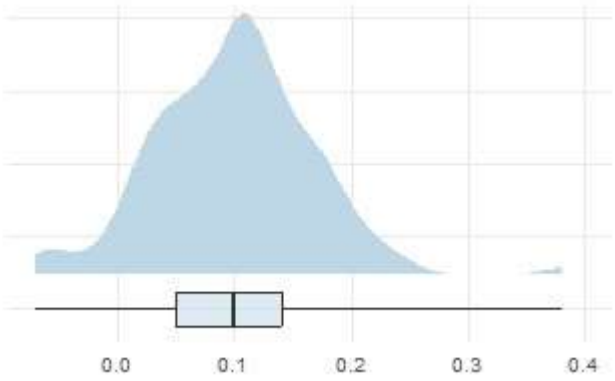
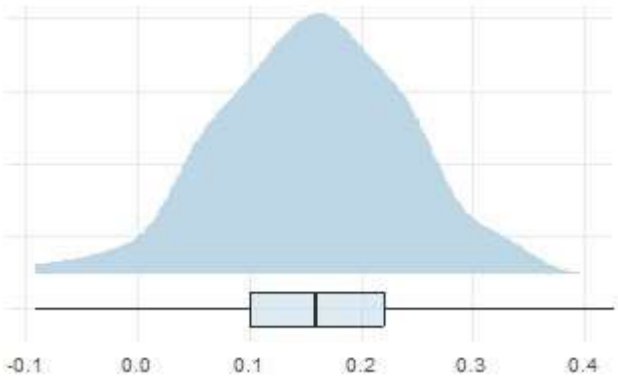
Figure 1. Performance Distributions for the Cross-Country Factor Momentum Strategies

The figure presents the density plots for the mean monthly returns (Panels A.1, B.1), their corresponding Newey-West (1987) adjusted *t*-statistics (A.2, B.2), and annualized Sharpe ratios (A.3, B.2) for the cross-sectional (XC-FMOM$_{CS}$) and time-series (XC-FMOM$_{TS}$) cross-country momentum strategies. The boxplots below the density plots indicate the quartiles and median, and the whiskers denote the maximum and minimum values.

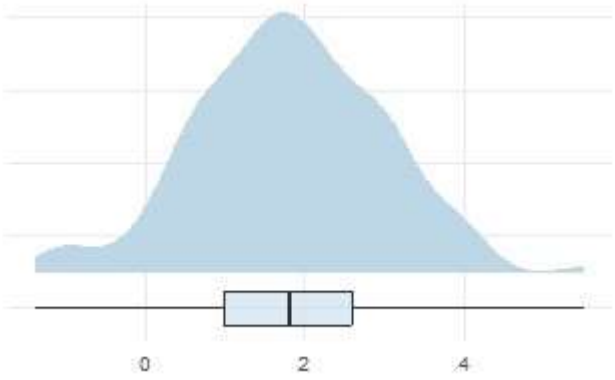
Panel A.1: XC-FMOM$_{CS}$ mean returns



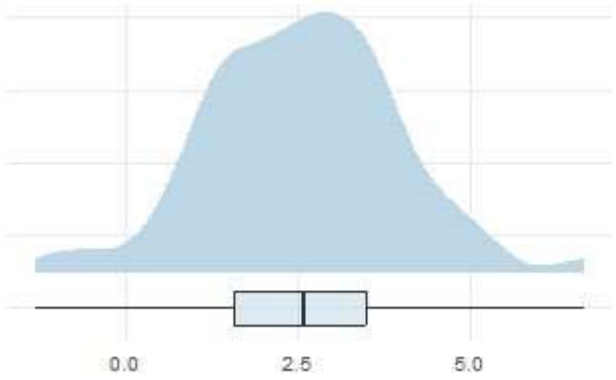
Panel B.1: XC-FMOM$_{TS}$ mean returns



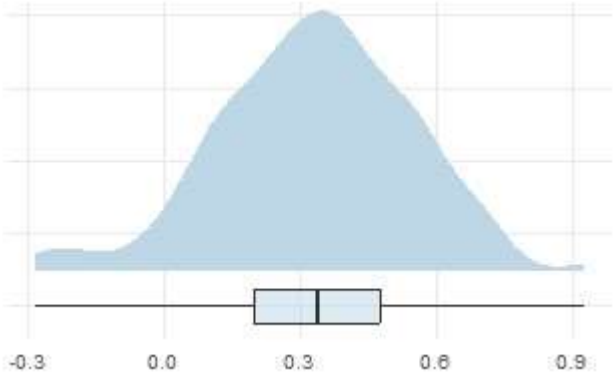
Panel A.2: XC-FMOM$_{CS}$ *t*-statistics



Panel B.2: XC-FMOM$_{TS}$ *t*-statistics



Panel A.3: XC-FMOM$_{CS}$ Sharpe ratios



Panel B.3: XC-FMOM$_{TS}$ Sharpe ratios

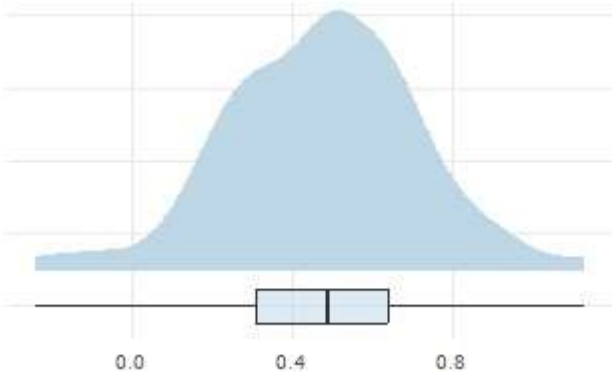


Table 1. Cross-Country Factor Momentum Portfolios

The table reports the performance of cross-sectional (XC-FMOM$_{CS}$) and time-series (XC-FMOM$_{TS}$) cross-country momentum strategies. PORT$_{EW}$ is the equal-weighted portfolio assuming a long position in a given factor in all 51 markets. *R* is the mean monthly return, and *t*-stat is the corresponding Newey-West (1987) adjusted *t*-statistic. *SR* denotes the annualized Sharpe ratio. *#Obs.* indicates the number of monthly observations. Panel A reports the summary statistics for all 145 strategies, and Panel B zooms onto the 20 strategies with the highest Sharpe ratio on the XC-FMOM$_{TS}$ portfolio (sorted accordingly).

Panel A: Summary statistics for all 145 strategies

	Mean	Quintiles					#R>0	#*t*-stat >1.96
		10th	25th	50th	75th	90th		
				Panel A.1: XC-FMOM$_{CS}$				
R	0.10	0.02	0.05	0.10	0.14	0.18	136 [94%]	64 [44%]
t-stat	1.82	0.42	0.99	1.83	2.61	3.26		
SR	0.33	0.08	0.20	0.34	0.48	0.59		
				Panel A.2: XC-FMOM$_{TS}$				
R	0.16	0.06	0.10	0.16	0.22	0.26	140 [97%]	96 [66%]
t-stat	2.57	0.92	1.57	2.60	3.49	4.21		
SR	0.47	0.19	0.31	0.49	0.64	0.77		

Panel B: Top 20 strategies in terms of Sharpe ratio on the XC-FMOM$_{TS}$ portfolio

	XC-FMOM$_{CS}$			XC-FMOM$_{TS}$			PORT$_{EW}$			#Obs.
	R	*t*-stat	SR	R	*t*-stat	SR	R	*t*-stat	SR	
market_equity	0.25	*(5.53)*	0.93	0.33	*(6.67)*	1.13	0.17	*(2.48)*	0.42	420
age	0.38	*(4.24)*	0.72	0.67	*(6.55)*	1.11	-0.73	*(-5.65)*	-0.96	419
fcf_me	0.11	*(2.17)*	0.42	0.32	*(5.03)*	0.98	0.50	*(6.83)*	1.33	317
ni_me	0.18	*(3.77)*	0.67	0.30	*(5.45)*	0.97	0.42	*(4.64)*	0.83	380
sale_me	0.21	*(3.98)*	0.71	0.32	*(5.24)*	0.93	0.33	*(3.35)*	0.60	379
ebitda_mev	0.14	*(2.90)*	0.52	0.29	*(5.12)*	0.91	0.50	*(6.13)*	1.09	379
ocf_me	0.14	*(2.74)*	0.49	0.28	*(5.06)*	0.90	0.51	*(6.20)*	1.10	380
dsale_dinv	0.18	*(3.53)*	0.65	0.24	*(4.57)*	0.85	0.12	*(2.45)*	0.45	350
z_score	0.22	*(3.90)*	0.70	0.29	*(4.69)*	0.84	-0.03	*(-0.36)*	-0.06	374
ppeinv_gr1a	0.14	*(2.84)*	0.52	0.22	*(4.58)*	0.83	0.09	*(1.51)*	0.27	362
ebit_bev	0.12	*(2.43)*	0.43	0.25	*(4.64)*	0.83	0.34	*(5.23)*	0.93	379
div12m_me	0.14	*(3.08)*	0.53	0.25	*(4.70)*	0.81	0.29	*(4.05)*	0.69	409
op_at	0.20	*(3.85)*	0.69	0.26	*(4.40)*	0.78	0.24	*(2.91)*	0.52	379
aliq_mat	0.17	*(3.07)*	0.56	0.28	*(4.22)*	0.77	-0.32	*(-3.43)*	-0.62	362
cop_atl1	0.17	*(3.33)*	0.61	0.24	*(4.25)*	0.77	0.32	*(4.76)*	0.87	362
cop_at	0.18	*(3.25)*	0.59	0.26	*(4.17)*	0.76	0.37	*(5.33)*	0.97	362
gp_at	0.23	*(3.96)*	0.72	0.26	*(4.19)*	0.76	0.16	*(2.34)*	0.42	368
corr_1260d	0.23	*(4.14)*	0.73	0.26	*(4.17)*	0.74	0.05	*(0.51)*	0.09	381
seas_2_5an	0.05	*(1.22)*	0.22	0.17	*(3.98)*	0.73	0.30	*(4.97)*	0.91	360
debt_gr3	0.15	*(2.99)*	0.56	0.21	*(3.83)*	0.72	0.19	*(3.43)*	0.64	344