# Factor Chasing and the Cross-Country Factor Momentum Anomaly*

Merlin Bartel†, Sebastian Stöckl‡

This version: May, 2022

**Abstract**

We provide evidence that factor momentum, the tendency of winning factors to outperform losing factors out-of-sample is driven by international cross-country effects. A strategy that buys a factor in winning countries and sells it in losing countries yields highly significant and economically meaningful returns and alphas. The anomaly we name "Cross-Country Factor Momentum" subsumes all national factor momentum returns, including US factor momentum.

**Keywords**: Factor Momentum, International Equity Markets

*We are grateful to all participants of the $35^{th}$ workshop of the Austrian Working Group on Banking and Finance. Also, we are grateful to Bryan Kelly for providing research data on his homepage.

†University of Liechtenstein, Institute for Finance, Fürst-Franz-Josef-Strasse, 9490 Vaduz, Liechtenstein; email: merlin.bartel@uni.li; tel: +423 265 1151 (Corresponding author).

‡University of Liechtenstein, Institute for Finance, Fürst-Franz-Josef-Strasse, 9490 Vaduz, Liechtenstein; email: sebastian.stoeckl@uni.li; tel: +423 265 1153.

# 1 Introduction

Factor momentum in US stock markets has earned high and statistically significant abnormal returns in the past. Following earlier findings of stock level momentum (see Jegadeesh and Titman, 1993), factor momentum has become an important theme in equity research. While recent findings provide evidence that factor momentum is an underlying driver of stock level momentum (Ehsani and Linnainmaa, 2022), the international evidence on factor momentum is still narrow.

Gupta and Kelly (2019) examine performance of different factor momentum strategy implementations both in US and in international markets. These factor momentum strategies are either time-series (or cross-sectional) implementations that buy winning (positive return) factors and short losing (negative return) factors within a country/region. In their intra-region setup, these strategies differ to "country momentum", another international anomaly. Country momentum strategies (e.g. Bhojraj and Swaminathan (2006)) examine the cross section of countries and buy winning, and sell losing country market factors. While prior factor momentum studies document strong patterns within countries, they miss these between-country comparisons.

In this study, we provide evidence that country momentum is expandable to a variety of factor sets and earns high and statistically significant abnormal returns. Strategies that invest into country-level factors that were gaining relatively high returns in that factor and sell countries that received relatively low returns in the same factor generally outperform strategies that focus on multiple factors in one single region. This pattern is robust to variations in the underlying country and factor sets and offers investors a new menu of international investment styles. The corresponding strategy we call "Cross-Country Factor Momentum" subsumes national factor momentum in spanning tests, and is particularly strong in times of turbulence of the underlying factor.

# 2 Cross-Country Factor Momentum

Consider the case of a factor investor, e.g. a value investor who is disappointed in her domestic factor after low return performance. Instead of switching towards other factor exposures, she sticks to her value investing strategy and seeks for value opportunities abroad, staying loyal to her style choice. She could invest her funds according to the scheme in Equation 1:

$$r_{t+1}^{CCFM} = r_{t+1}^{L} - r_{t+1}^{S} \tag{1}$$

$$with$$

$$r^L_{t+1} = \frac{1}{0.3 \cdot N} \sum_{i=1}^{N} r_{i,t+1} \; \forall \; r_{i,t} \geq Q_t(0.7)$$

$$r^S_{t+1} = \frac{1}{0.3 \cdot N} \sum_{i=1}^{N} r_{i,t+1} \; \forall \; r_{i,t} < Q_t(0.3)$$

She buys a factor in country $i$ at time $t+1$, when the factor's return at time $t$ was in the upper 30% ($r_{i,t} \geq Q_t(0.7)$). She sells a factor in country $i$ at time $t+1$, when the factor's return at time $t$ was in the lower 30% ($r_{i,t} < Q_t(0.3)$). This cross-country factor momentum (CC-FM) strategy takes equal positions in both the long leg $L$ and the short leg $S$ over all included factors. This simple implementation of the strategy follows cross-sectional intra-region factor momentum strategies (see e.g. Gupta and Kelly (2019)).

From a behavioral perspective this strategy aligns with a return chasing behavior. This behavioral perspective is especially important since both international factor returns and factor momentum are still missing a link to macro-variables (Baltussen et al., 2021). Performance chasing is one of the major behavioral biases. In practice, investors and fund managers tend to chase positive returns in assets and styles (Froot and Teo, 2008; Horst and Salganik, 2014). Return chasing is prevalent on the national level but even more pronounced in international markets (Brennan and Cao, 1997; Grinblatt and Keloharju, 2000; Froot et al., 2001). When market participants tend to chase factor returns in national markets, we would assume that this behavior is even stronger in international markets. This assumption is in alignment with prior evidence, that shows excessive trading activities by foreign investors in international markets (Tesar and Werner, 1995). This excessive trading is majorly prevalent, when past returns were high (Griffin et al., 2007). To sum up, the behavioral perspective predicts factor chasing in international markets.

Before forming strategies on cross-country factor returns, we need to assure that prior factor returns carry predictive signals. Factor momentum induces predictability into return patterns. Ehsani and Linnainmaa (2022) show that positive returns on a factor predict positive returns on all factors. This means that prior mean returns of all factors in a country predict single factors out-of-sample. Adding to this perspective we suppose that if factors exhibit spillover effects across borders, we should also observe predictability on a mean factor return level (across all countries), which forms our first research question: "Are international factor returns predictable using factor level information?"

In the remainder of the study we attempt to clarify the performance of factor chasing in international markets. Of particular interest are factors that are perceived more important (are more popular) among investors. The most important international factor funds pursue value/growth and size strategies, which will be of major interest throughout the rest of the study. To clarify the performance of factor chasing strategies, the second research question asks: "Is factor chasing a profitable strategy?". Additionally, we examine potential reversal patterns, that are predicted by the theory of Barberis and Shleifer (2003) and shown in Teo and Woo (2004). These reversal patterns emerge in strategies with holding periods of 3-5 years in Teo and Woo (2004) (in contrast to one month as in the standard setup).

Finally, if we find profitability of factor chasing, we need to disentangle the source of this performance. In many cases the long and short positions in a cross-country factor momentum strategy will coincide with the long and short position with their country level counterparts. For example, if the US value factor outperformed all other value factors in the world, this also increases the chances of this factor outperforming other factors within the US, which leads us to the third research question: "Is cross-country factor momentum driven by national factor momentum strategies?".

We use the data of Jensen et al. (2021) and restrict the sample to developed countries (Australia, Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Hong Kong, Ireland, Israel, Italy, Japan, Korea, the Netherlands, Norway, New Zealand, Poland, Portugal, Singapore, Sweden, and the United States. Additionally, we only consider the time starting from July 1998, because earlier data misses too many observations in the majority of the countries. Our data-set thus spans the time from July 1998 to December 2020.

To examine predictability of prior factor returns, we form one covariate of mean returns within each countries (the country factor return average), and one covariate of mean returns within each factors (the average of one single factor over the whole world). Subsequently, we perform the investment strategy shown in Equation 1. We test a simple version with 1 month formation and 1 month holding period, and to test for potential reversals a version of 4 years formation and 1 year holding (similar to Teo and Woo (2004)). We focus on the returns of the size-value factor chasing strategy, that is the average of two strategies that chase the two major factors size and value. Additionally, we sort the other factors into themes, following Jensen et al. (2021) and examine their short term performance. Finally, to disentangle the performance of factor chasing, we regress the returns of the size-value factor chasing strategies on all country level factor momentum (cross-sectional) strategies and vice versa.

# 3 Results

Let us first focus on factor predictability. Ehsani and Linnainmaa (2022) state that mean factor returns in a country predict single factor returns out-of-sample. As it is shown in Table 1, we find diverging evidence. Instead of countries, it is the mean factor level return (across all countries) that predicts single factor returns. This is robust to different time horizons and emerging markets.

| | VW Returns | EW Returns |
|---|---|---|
| Mean Prior Country Returns | 0.0067 | -0.0051 |
| | (0.0082) | (0.0074) |
| Mean Prior Factor Returns | 0.1418*** | 0.2150*** |
| | (0.0037) | (0.0044) |
| const | 0.0005*** | 0.0006*** |
| | (0.0000) | (0.0000) |
| Observations | 1,271,150 | 1,271,150 |
| $R^2$ | 0.0040 | 0.0114 |
| Adjusted $R^2$ | 0.0040 | 0.0114 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

**Table 1:** International factor predictability using past factor returns as well as past country returns. The table shows regression results of factor returns on lagged aggregated factor returns. The aggregation is performed on the country-, and on the factor level. Mean prior factor returns across all countries seem to be more important than mean prior factor returns across all factors in one country. The data comes from Jensen et al. (2021), we use the factor set of Ehsani and Linnainmaa (2022).

In both value weighted and equally weighted returns, we find mean prior factor returns (e.g. the mean of the value factor across all developed markets in $t$) to be positive and significant predictors of single factor returns in $t + 1$. Mean prior country returns (e.g. the mean of all factors in the US in $t$) are not significant predictors of all single factor returns in $t + 1$. In the equal weighting setup, the coefficient for mean prior country return is even negative.

As a next step, we examine the performance of the value- and size factor chasing strategies. In Figure 1 we see that both value and size factor chasing achieve considerable wealth levels, despite being zero investment strategies. The long-term strategy that has a formation period of 4 years and a holding period of one year exhibits reversal patterns in alignment with the predictions of Barberis and Shleifer (2003) and the empirical findings of Teo and Woo (2004).

Both strategies are highly correlated in different formation period setups, which is a first hint of a common driving economic mechanism. When we sort all factors into themes we find in Figure 2 that the performance substantially differs, depending on the chosen style. As such, investment and value factors tend to outperform factors

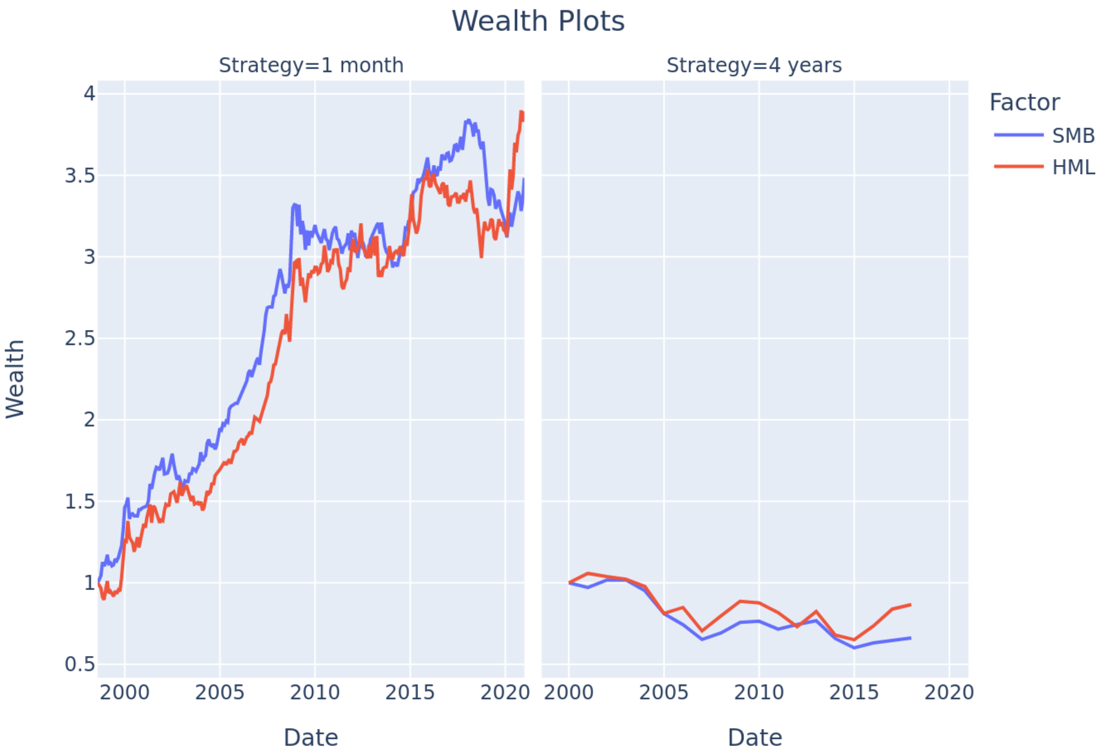


**Figure 1:** Cross country factor momentum and reversal depicted for international value as well as size using factors derived from Gupta and Kelly (2019). The investor buys the top 30% of country factor portfolios where a certain factor (e.g. size) performed well in the past and sells the bottom 30% of country factor portfolios that performed poorly in the past (cross-sectional strategy). On the left side (momentum strategy) the momentum signal is taken from the past month and factor portfolios are held for another month (similar to (Gupta and Kelly, 2019)). On the right hand side (the reversal strategy) the signal is taken from the prior four years and investments are held for another year (similar to Teo and Woo (2004)). The plots depict cumulative returns.

like skewness or momentum. Even though the mean returns of the strategies differ, the returns tend to be highly correlated.

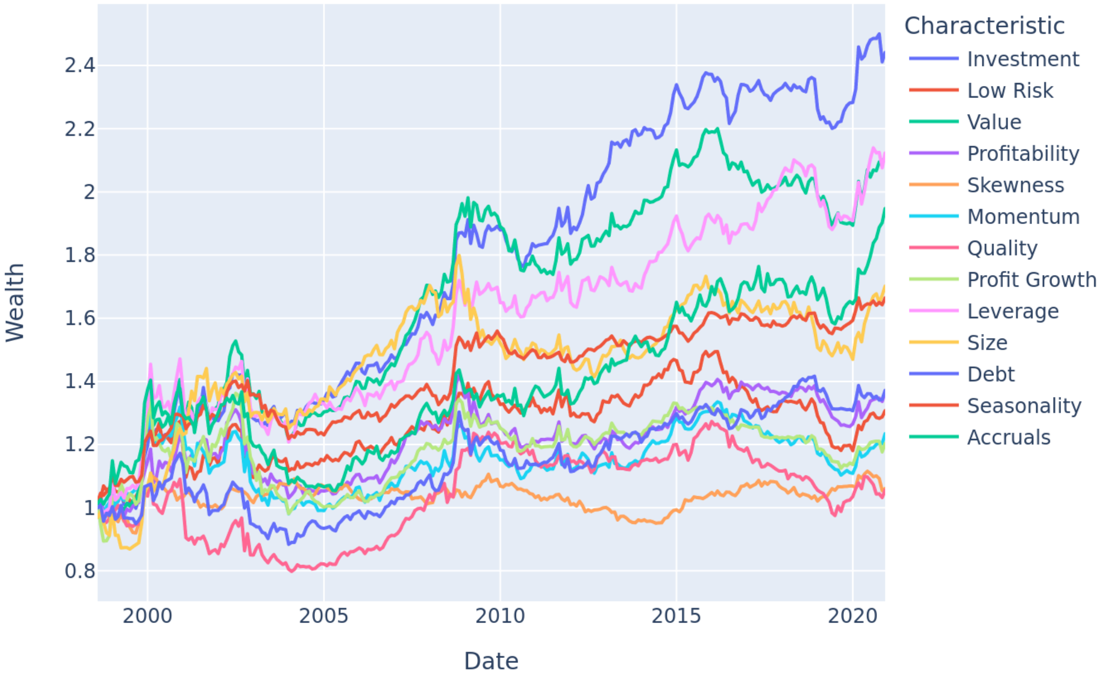


**Figure 2:** Wealth Plots of Factor Themes. The investor buys the top 30% of country factor portfolios where a certain factor (e.g. size) performed well in the past and sells the bottom 30% of country factor portfolios that performed poorly in the past (cross-sectional strategy). We sort the factors into themes following Jensen et al. (2021). We extract the within-theme average returns of all factor chasing strategies (with a formation perdiod of one month and a holding periof of one month) and invest \$1 in $t = 0$.

| | Mean | Std. Dev. | Annualized Sharpe Ratio | Maximum Drawdown | 5 Factor Alpha | 3 Factor Alpha | CAPM Alpha |
|---|---|---|---|---|---|---|---|
| Investment | 0.35*** | 1.98 | 0.61 | -0.12 | 0.32** | 0.41*** | 0.40*** |
| Low Risk | 0.12 | 2.04 | 0.20 | -0.21 | 0.09 | 0.16 | 0.14 |
| Value | 0.30** | 2.28 | 0.46 | -0.21 | 0.33** | 0.36*** | 0.35*** |
| Profitability | 0.14 | 1.96 | 0.24 | -0.21 | 0.13 | 0.17 | 0.18 |
| Skewness | 0.03 | 1.17 | 0.08 | -0.14 | 0.07 | 0.03 | 0.03 |
| Momentum | 0.04 | 2.18 | 0.07 | -0.27 | 0.09 | 0.08 | 0.06 |
| Quality | 0.10 | 2.20 | 0.16 | -0.26 | 0.13 | 0.15 | 0.14 |
| Profit Growth | 0.10 | 2.36 | 0.14 | -0.28 | 0.10 | 0.15 | 0.14 |
| Leverage | 0.31** | 2.44 | 0.44 | -0.18 | 0.32** | 0.37*** | 0.35** |
| Size | 0.22* | 2.21 | 0.35 | -0.21 | 0.25* | 0.27** | 0.26** |
| Debt | 0.14 | 1.98 | 0.24 | -0.25 | 0.17 | 0.19 | 0.18 |
| Seasonality | 0.20** | 1.34 | 0.51 | -0.13 | 0.23** | 0.24*** | 0.23*** |
| Accruals | 0.27** | 2.23 | 0.42 | -0.25 | 0.28* | 0.33** | 0.31** |

**Table 2:** Portfolio Metrics of Factor Themes. The investor buys the top 30% of country factor portfolios where a certain factor (e.g. size) performed well in the past and sells the bottom 30% of country factor portfolios that performed poorly in the past (cross-sectional strategy). We sort the factors into themes following Jensen et al. (2021). We extract the within-theme average returns of all factor chasing strategies (with a formation period of one month and a holding period of one month) and calculate portfolio metrics.

### 3.1 Factor Momentum and Cross-Country Factor Momentum

Although the CC-FM strategy works, its performance can potentially be attributed to national factor momentum. When those factors that outperform their peer factors in other countries coincide with the factors that outperform other factors in one country, one could potentially falsely derive that factor chasing works, even though it is just a more complicated bet on national factor momentum. For example, if the US value factor outperformed all other value factors in the world, this also increases the chances of this factor outperforming other factors within the US. Table 3 shows the results of three different strategy time-series spanning tests. We investigate the significance of strategy's alpha by controlling for the performance of the respective other strategies, including controls of the Fama-French 2015 5 factors model (augmented by WML). The strategies are CC-FM, cross-sectional factor momentum (CS-FM), and time-series factor momentum (TS-FM). The latter two are the strategies proposed by Ehsani and Linnainmaa (2022), CC-FM is our factor chasing strategy. The CS-FM strategy is similar to our CC-FM strategy and shown in equation 2.

$$r_{t+1}^{CSFM} = r_{t+1}^{L} - r_{t+1}^{S} \tag{2}$$

$$with$$

$$r_{t+1}^{L} = \frac{1}{0.3 \cdot N} \sum_{i=1}^{N} r_{i_{USA},t+1} \ \forall \ r_{i_{USA},t} \geq Q_t(0.7)$$

$$r_{t+1}^{S} = \frac{1}{0.3 \cdot N} \sum_{i=1}^{N} r_{i_{USA},t+1} \ \forall \ r_{i_{USA},t} < Q_t(0.3)$$

The investor buys a US factor $i_{USA}$ at time $t+1$, when the factor's return at time $t$ was in the upper 30% ($r_{i_{USA},t} \geq Q_t(0.7)$). She sells a factor $i_{USA}$ at time $t+1$, when the factor's return at time $t$ was in the lower 30% ($r_{i_{USA},t} < Q_t(0.3)$). This strategy takes equal positions in both the long leg $L$ and the short leg $S$ over all included factors.

The TS-FM strategy implementation is different to the other two strategies, and is shown in equation 3.

$$r_{t+1}^{TSFM} = r_{t+1} \cdot sgn\Big(\frac{1}{12} \sum_{\tau=-11}^{t} r_{\tau}\Big) \tag{3}$$

The TS-FM does not attempt to harvest differentials between factors. The investor buys a US factor $i_{USA}$ at time $t+1$, when the factor's return in the previous year ($t$ to $t-11$ was positive. She sells the factor when the factor's return in the previous year ($t$ to $t-11$) was negative.

Only CC-FM remains with positive and significant alphas/constants, while the alpha for the time-series strategy even turns negative (and insignificant). Furthermore, CC-FM is the only strategy that loads significantly on the momentum factor.

| | CC-FM | CC-FM | CS-FM | CS-FM | TS-FM | TS-FM |
|---|---|---|---|---|---|---|
| const | 0.50*** | 0.48*** | 0.09 | 0.17 | 0.01 | 0.10 |
| | (0.17) | (0.17) | (0.23) | (0.23) | (0.13) | (0.13) |
| CC-FM | | | 0.30*** | | 0.26*** | |
| | | | (0.10) | | (0.06) | |
| CS-FM | 0.19*** | | | | | 0.20*** |
| | (0.05) | | | | | (0.06) |
| TS-FM | | 0.46*** | | 0.55*** | | |
| | | (0.09) | | (0.19) | | |
| Mkt-RF | -0.06 | -0.05 | 0.01 | 0.00 | -0.00 | -0.02 |
| | (0.05) | (0.05) | (0.08) | (0.07) | (0.04) | (0.03) |
| SMB | -0.16 | -0.11 | 0.40*** | 0.34** | 0.08 | -0.02 |
| | (0.11) | (0.11) | (0.15) | (0.14) | (0.10) | (0.10) |
| HML | -0.06 | -0.05 | -0.24 | -0.20 | -0.10 | -0.08 |
| | (0.13) | (0.12) | (0.16) | (0.15) | (0.09) | (0.10) |
| RMW | -0.03 | -0.19 | -0.19 | -0.36* | 0.28** | 0.31** |
| | (0.17) | (0.15) | (0.20) | (0.19) | (0.11) | (0.12) |
| CMA | -0.03 | -0.09 | 0.19 | 0.08 | 0.20 | 0.16 |
| | (0.20) | (0.18) | (0.23) | (0.21) | (0.13) | (0.14) |
| WML | -0.01 | 0.18*** | 0.88*** | 0.96*** | -0.09 | -0.23*** |
| | (0.07) | (0.06) | (0.10) | (0.09) | (0.07) | (0.08) |
| Observations | 269 | 269 | 269 | 269 | 269 | 269 |
| $R^2$ | 0.15 | 0.21 | 0.64 | 0.67 | 0.18 | 0.17 |
| Adjusted $R^2$ | 0.13 | 0.19 | 0.63 | 0.66 | 0.15 | 0.15 |
| Residual Std. Error | 2.67(df = 261) | 2.58(df = 261) | 3.35(df = 261) | 3.24(df = 261) | 1.96(df = 261) | 1.97(df = 261) |
| F Statistic | 4.32*** (df = 7.0; 261.0) | 6.77*** (df = 7.0; 261.0) | 25.06*** (df = 7.0; 261.0) | 42.88*** (df = 7.0; 261.0) | 4.33*** (df = 7.0; 261.0) | 6.27*** (df = 7.0; 261.0) |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 3:** Spanning Tests: Value. Ehsani and Linnainmaa (2022, JF) show that factor momentum subsumes stock momentum in the US, as regressing time series factor momentum on stock momentum leaves insignificant constants. Here we report linear regressions of three strategies on the respective other strategies, including the 5 factor model developed by Fama and French (2015). Two of the strategies are time series and cross-sectional factor momentum from Ehsani and Linnainmaa (2022, TS-FM and CS-FM), whereas (CC-FM) is our proposed factor chasing strategy. CC-FM subsumes the other two strategies and yields sizeable abnormal monthly returns. The tables handles US factors only (TS-FM and CS-FM) and the data comes from Jensen et al. (2021).

Table 4 shows the results of similar regressions, this time for all developed countries separately. We only assess the cross-sectional strategy versions. CC-FM consistently remains with positive and significant alphas, while the country level factor momentum strategies lose their significance in all but three cases. Around the half of the country level factor momentum strategies turn into carrying negative alphas. Overall both the CC-FM strategy and the national factor momentum strategies are important predictors for each other.

## 3.2 Factor Loadings and Cross-Country Factor Momentum

This section examines factor loadings of the CC-FM strategy. Since the investor holds factors in both the long- and the short leg, the strategies are should be unrelated to the factor being chased. This side-note has large implications for investors because

| | CC-FM | CC-FM | CS-FM | CS-FM | TS-FM | TS-FM |
|---|---|---|---|---|---|---|
| const | 0.50*** | 0.48*** | 0.12 | 0.17 | -0.00 | 0.10 |
| | (0.15) | (0.15) | (0.24) | (0.23) | (0.13) | (0.13) |
| CC-FM | | | 0.26** | | 0.29*** | |
| | | | (0.10) | | (0.08) | |
| CS-FM | 0.11** | | | | | 0.20*** |
| | (0.04) | | | | | (0.06) |
| TS-FM | | 0.34*** | | 0.55*** | | |
| | | (0.08) | | (0.19) | | |
| Mkt-RF | -0.03 | -0.02 | -0.00 | 0.00 | -0.01 | -0.02 |
| | (0.04) | (0.04) | (0.08) | (0.07) | (0.04) | (0.03) |
| SMB | -0.12 | -0.10 | 0.39** | 0.34** | 0.07 | -0.02 |
| | (0.10) | (0.08) | (0.15) | (0.14) | (0.10) | (0.10) |
| HML | -0.04 | -0.03 | -0.25 | -0.20 | -0.11 | -0.08 |
| | (0.10) | (0.09) | (0.17) | (0.15) | (0.09) | (0.10) |
| RMW | -0.08 | -0.20* | -0.19 | -0.36* | 0.30** | 0.31** |
| | (0.11) | (0.11) | (0.20) | (0.19) | (0.12) | (0.12) |
| CMA | -0.03 | -0.08 | 0.20 | 0.08 | 0.20 | 0.16 |
| | (0.16) | (0.15) | (0.24) | (0.21) | (0.14) | (0.14) |
| WML | -0.03 | 0.09** | 0.91*** | 0.96*** | -0.07 | -0.23*** |
| | (0.05) | (0.04) | (0.10) | (0.09) | (0.07) | (0.08) |
| Observations | 269 | 269 | 269 | 269 | 269 | 269 |
| $R^2$ | 0.07 | 0.14 | 0.63 | 0.67 | 0.16 | 0.17 |
| Adjusted $R^2$ | 0.04 | 0.11 | 0.62 | 0.66 | 0.13 | 0.15 |
| Residual Std. Error | 2.23(df = 261) | 2.14(df = 261) | 3.40(df = 261) | 3.24(df = 261) | 1.98(df = 261) | 1.97(df = 261) |
| F Statistic | 1.38 (df = 7.0; 261.0) | 2.95*** (df = 7.0; 261.0) | 26.95*** (df = 7.0; 261.0) | 42.88*** (df = 7.0; 261.0) | 3.60*** (df = 7.0; 261.0) | 6.27*** (df = 7.0; 261.0) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 4:** Spanning Tests: Size. Ehsani and Linnainmaa (2022, JF) show that factor momentum subsumes stock momentum in the US, as regressing time series factor momentum on stock momentum leaves insignificant constants. Here we report linear regressions of three strategies on the respective other strategies, including the 5 factor model developed by Fama and French (2015). Two of the strategies are time series and cross-sectional factor momentum from Ehsani and Linnainmaa (2022, TS-FM and CS-FM), whereas (CC-FM) is our proposed factor chasing strategy. CC-FM subsumes the other two strategies and yields sizeable abnormal monthly returns. The tables handles US factors only (TS-FM and CS-FM) and the data comes from Jensen et al. (2021).

| | SMB | HML | RMW | CMA | WML |
|---|---|---|---|---|---|
| const | 0.48*** | 0.55*** | 0.31* | 0.27 | 0.27** |
| | (0.11) | (0.14) | (0.17) | (0.17) | (0.13) |
| Market-WorldF | -0.04 | -0.06 | -0.07 | -0.06 | -0.08** |
| | (0.03) | (0.04) | (0.05) | (0.04) | (0.04) |
| SMB-WorldF | -0.07 | -0.14* | -0.15* | -0.08 | -0.13 |
| | (0.06) | (0.08) | (0.08) | (0.08) | (0.08) |
| HML-WorldF | -0.24*** | -0.26** | -0.22* | -0.19 | -0.26** |
| | (0.09) | (0.11) | (0.12) | (0.15) | (0.11) |
| RMW-WorldF | -0.14 | -0.18 | -0.15 | -0.30** | -0.13 |
| | (0.10) | (0.14) | (0.15) | (0.13) | (0.12) |
| CMA-WorldF | 0.20* | 0.29** | 0.08 | 0.07 | 0.45*** |
| | (0.10) | (0.13) | (0.16) | (0.14) | (0.14) |
| WML-WorldF | -0.09* | -0.05 | -0.09 | -0.03 | -0.12* |
| | (0.05) | (0.06) | (0.08) | (0.09) | (0.07) |
| Observations | 269 | 269 | 269 | 269 | 269 |
| $R^2$ | 0.10 | 0.14 | 0.06 | 0.05 | 0.15 |
| Adjusted $R^2$ | 0.08 | 0.12 | 0.04 | 0.03 | 0.13 |
| Residual Std. Error | 1.67(df = 262) | 2.04(df = 262) | 2.36(df = 262) | 2.09(df = 262) | 2.03(df = 262) |
| F Statistic | 2.68** (df = 6.0; 262.0) | 3.58*** (df = 6.0; 262.0) | 2.47** (df = 6.0; 262.0) | 1.79 (df = 6.0; 262.0) | 4.15*** (df = 6.0; 262.0) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 5:** Risk Adjusted Returns: Cross-country factor momentum may be sourced in the performance of multiple national factor momentum strategies. This table reports univariate regressions of factor momentum strategies (per country) on the size-value cross-country factor momentum signal. It can be clearly seen, that after controlling for CC-FM the national factor momentum strategies remain with insignificant alphas/constanst. CC-FM, even though frequently loading on national factor momentum strategies remains significant for all considered countries.

different investors follow different characteristics in their factor portfolios. Even if an investor does not believe in certain stock characteristics, the factor chasing strategy will be unrelated to the risk premium of a factor. Instead it harvests the differentials between countries.

Despite the factors are hold in both long and short legs, we find the factor chasing strategy to be somehow related to the underlying factor. To account for risk we regress 5 strategies related to the 5 alternative factors in the Fama-French 2015 five factor (plus WML) on their corresponding underlying factor (results reported in Table 6). The value chasing strategy loads significantly negative on the value factor and exhibits a strong negative correlation of -0.33. This negative correlation is potentially attractive to investors, as it offers diversification opportunities. The value chasing strategy yields returns especially in times, in which the factor itself faces losses. Since we assume factor chasing to be behaviorally driven, the low performance of the corresponding factors is the potential trigger that causes the factor chasing. That the factor performance tends to be especially high in times, in which the factor itself performs poorly, is additionally in alignment with the stylized fact of excess trading in turbulent times.

| | market equity | be/me | gp/at | capex abn | ret 12-1 |
|---|---|---|---|---|---|
| const | 0.0053*** | 0.0054*** | 0.0004 | 0.0014 | 0.0026 |
| | (0.0015) | (0.0017) | (0.0020) | (0.0019) | (0.0020) |
| Mkt-RF | -0.0300 | -0.0610 | -0.0801 | -0.0352 | -0.0705 |
| | (0.0468) | (0.0492) | (0.0507) | (0.0539) | (0.0640) |
| SMB | -0.0801 | -0.0912 | -0.0776 | -0.1383 | 0.0728 |
| | (0.1032) | (0.1279) | (0.1293) | (0.1429) | (0.1513) |
| HML | -0.0742 | -0.1092 | -0.0679 | 0.1510 | -0.2080 |
| | (0.0991) | (0.1415) | (0.1627) | (0.1671) | (0.1829) |
| RMW | -0.1046 | -0.0662 | -0.1669 | 0.0297 | -0.1070 |
| | (0.1125) | (0.1829) | (0.1644) | (0.1319) | (0.1823) |
| CMA | -0.0112 | 0.0027 | 0.0988 | -0.2448 | 0.1796 |
| | (0.1665) | (0.2139) | (0.2383) | (0.2499) | (0.2552) |
| WML | 0.0722 | 0.1626** | 0.0704 | 0.0783 | 0.0257 |
| | (0.0514) | (0.0723) | (0.0802) | (0.0917) | (0.0754) |
| Observations | 269 | 269 | 269 | 269 | 269 |
| $R^2$ | 0.0416 | 0.1009 | 0.0339 | 0.0209 | 0.0359 |
| Adjusted $R^2$ | 0.0197 | 0.0803 | 0.0118 | -0.0016 | 0.0138 |
| Residual Std. Error | 0.0226(df = 262) | 0.0274(df = 262) | 0.0311(df = 262) | 0.0302(df = 262) | 0.0317(df = 262) |
| F Statistic | 0.8744 (df = 6.0; 262.0) | 2.1701** (df = 6.0; 262.0) | 1.2706 (df = 6.0; 262.0) | 0.5557 (df = 6.0; 262.0) | 1.0554 (df = 6.0; 262.0) |
| *Note:* | | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 6:** Factor loadings w.r.t. FF5. The table shows results of regressing 5 factor chasing strategies on their respective Fama-French 2015 developed markets model. In 4 of 5 cases, the factor chasing strategies correlate negatively with their corresponding factor return.

# 4 Robustness Tests

Up to now we examined the performance of long-short factors in developed markets over the time-span from 1998-2020. Since the data-set is relatively short, we skip on dividing it into time sub-samples. Instead this section examines the performance of decomposed portfolio factor chasing strategies and simple factor chasing in emerging markets instead of developed markets.

| | market equity | be/me | gp/at | capex abn | ret 12-1 |
|---|---|---|---|---|---|
| const | 0.0067*** | 0.0072*** | 0.0023 | 0.0050** | 0.0044** |
| | (0.0017) | (0.0019) | (0.0023) | (0.0024) | (0.0019) |
| Mkt-RF | -0.0431 | -0.0801 | -0.1116** | -0.0815 | -0.1270** |
| | (0.0496) | (0.0514) | (0.0559) | (0.0553) | (0.0607) |
| market equity F | -0.1270* | -0.1675 | -0.1375 | -0.1749 | -0.0877 |
| | (0.0738) | (0.1017) | (0.0966) | (0.1164) | (0.1257) |
| be/me F | -0.3157*** | -0.3344** | -0.3403** | -0.4239* | -0.3974*** |
| | (0.1134) | (0.1681) | (0.1599) | (0.2267) | (0.1526) |
| gp/at F | -0.2227 | -0.2369 | -0.2832 | -0.5735*** | -0.1900 |
| | (0.1380) | (0.1743) | (0.1863) | (0.1936) | (0.1709) |
| capex abn F | 0.2316* | 0.2942 | 0.2096 | 0.2432 | 0.5554*** |
| | (0.1354) | (0.1787) | (0.2179) | (0.2281) | (0.2140) |
| ret 12-1 F | -0.1108* | -0.0257 | -0.1247 | -0.1457 | -0.2365** |
| | (0.0583) | (0.0955) | (0.1137) | (0.1350) | (0.1091) |
| Observations | 269 | 269 | 269 | 269 | 269 |
| $R^2$ | 0.0932 | 0.1459 | 0.0660 | 0.0835 | 0.0998 |
| Adjusted $R^2$ | 0.0724 | 0.1264 | 0.0446 | 0.0625 | 0.0792 |
| Residual Std. Error | 0.0219(df = 262) | 0.0267(df = 262) | 0.0306(df = 262) | 0.0292(df = 262) | 0.0306(df = 262) |
| F Statistic | 2.0990* (df = 6.0; 262.0) | 3.5305*** (df = 6.0; 262.0) | 2.2228** (df = 6.0; 262.0) | 2.0499* (df = 6.0; 262.0) | 3.1286*** (df = 6.0; 262.0) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 7:** Factor Loadings w.r.t. Jensen et al. (2021) factors. The table shows results of regressing 5 factor chasing strategies on their respective global Jensen et al. (2021) factor return. In 4 of 5 cases, the factor chasing strategies correlate negatively with their corresponding factor return. This is similar to the Fama-French 2015 developed factors model.

## 4.1 Long-Short Decomposition

Long-short portfolios have the advantage of being a pure signal of the measured quantity and of being orthogonal to the market factors, which is a desirable property regarding multicollinearity issues in linear regression tasks. Anyhow, this advantage comes at a cost. Due to short-sale constraints the performance of long-short portfolios strongly depends on the unrealistic performance of the short leg. Instead of relying on the long-short value minus growth factor (value factor), we attempt to decompose the factor chasing performance into a growth and a value component. Both of these legs then are chases independently. As depicted in figure 3, the long leg of the value minus growth factor, namely the value portfolio strongly outperforms the growth chase. For both portfolios the long leg significantly contributes to the overall performance, and as a bottom line, the factor chasing strategy attempts to be also profitably under long-only contraints.

## 4.2 Data Subsets

Developed markets attempt to be more efficient, more liquid and more stable than emerging markets. It is thus appears apparent to conclude that less efficient markets should exhibit stronger frictions and behavioral biases that lead to CC-FM. Anyhow as we find in Figure 4, the opposite holds true. Even though factor chasing also works in the emerging markets sample, the performance is slightly lower than in developed markets (Figure 2). Interestingly, in emerging markets the ranking of the themes is similar to developed markets. In emerging markets some themes lose money, which stands in stark contrast to developed markets, of which all themes at least preserve the \$1 invested in $t = 0$. In Emerging markets, the correlation between the themes is

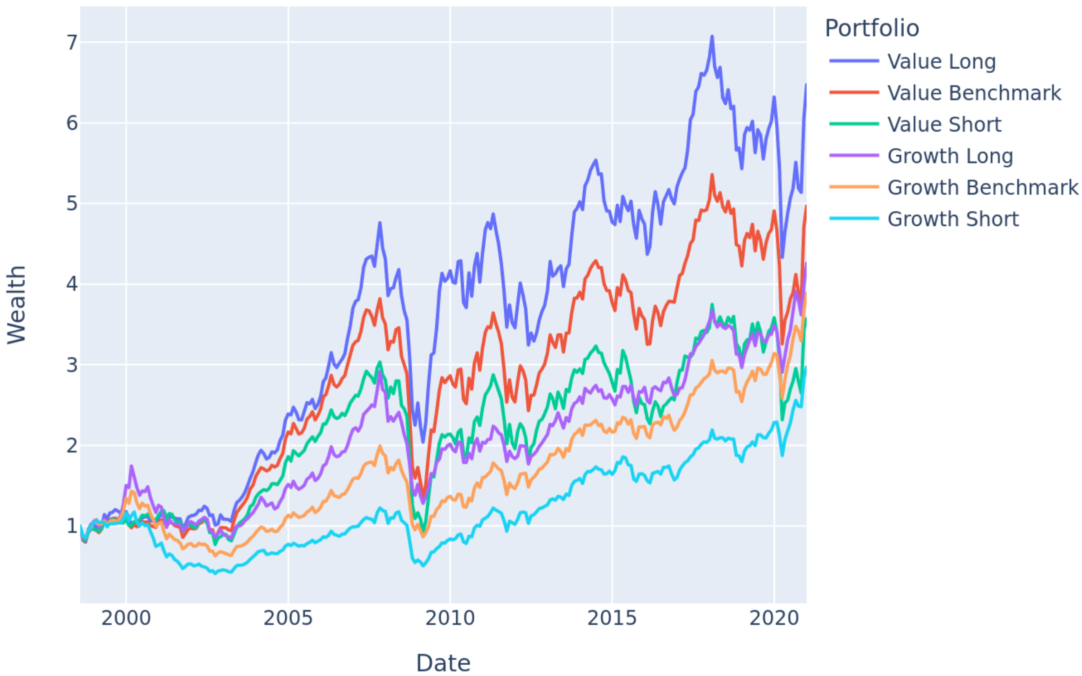


**Figure 3:** Decomposition into long and short leg. The figure depicts wealth plots of 4 different factor chasing strategies and their long-short benchmark. Instead of chasing the value factor, which is constructed by subtracting growth stocks' from value stocks' returns, the investor chases growth and value portfolios independently. The performance is stronger for value than for growth stocks, but is also profitable under long-only constraints.

overall lower than in developed markets. The second half of the sample yields lower returns and more frequent losses than the first half of the sample.

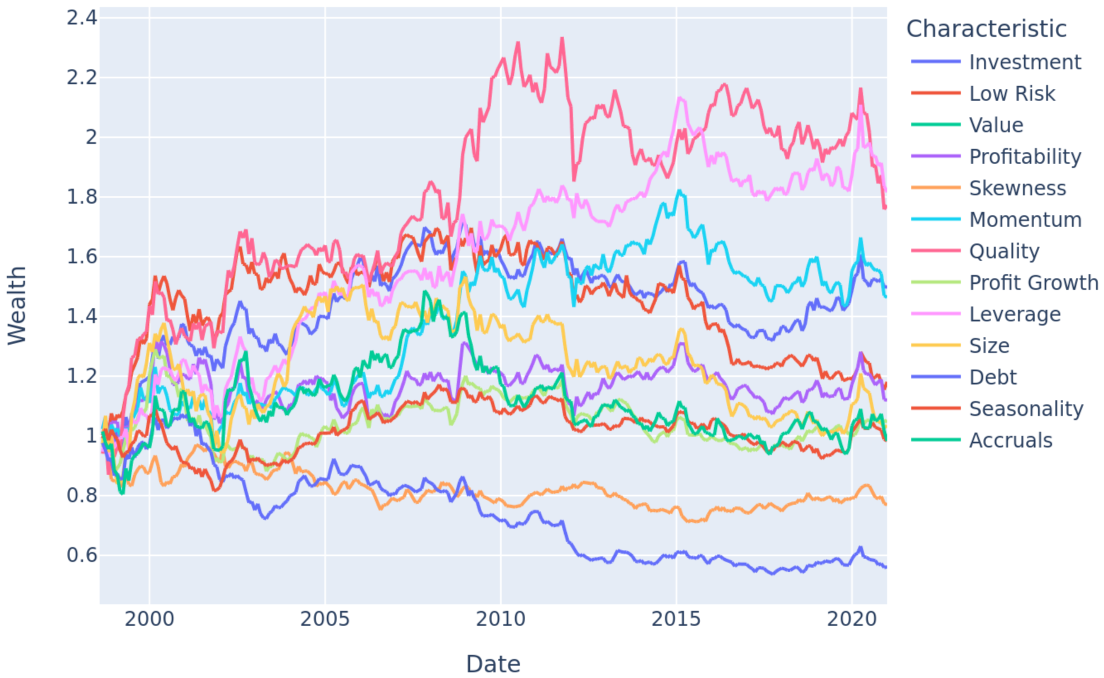


**Figure 4:** Wealth Plots of Factor Themes in Emerging Markets. Instead of restricting the data-set to developed markets, it is restricted to emerging markets. The investor buys the top 30% of country factor portfolios where a certain factor (e.g. size) performed well in the past and sells the bottom 30% of country factor portfolios that performed poorly in the past (cross-sectional strategy). We sort the factors into themes following Jensen et al. (2021). We extract the within-theme average returns of all factor chasing strategies (with a formation period of one month and a holding period of one month) and invest \$1 in $t = 0$.

## 4.3 Mining the Strategy

We found both the size- and the value chasing strategies to yield considerable performances. This subsection investigates the construction of the strategies, that applied a formation- and a holding period of one month respectively. If factor chasing is not related to a statistical fluke, we anyhow should also see performance with other strategy construction combinations. To investigate the impact of different combinations between formation- and holding periods we now investigate the single Sharpe ratios per month of holding for both the value- and size chasing strategies.

Figure 5 depicts the performance of the value chasing strategy. For the value chasing strategy, a formation period of the first 18 months is especially lucrative (with a holding period of one month). The value chasing strategy requires a formation period that is smaller than 42 months for the 1 month holding period setup. The returns for

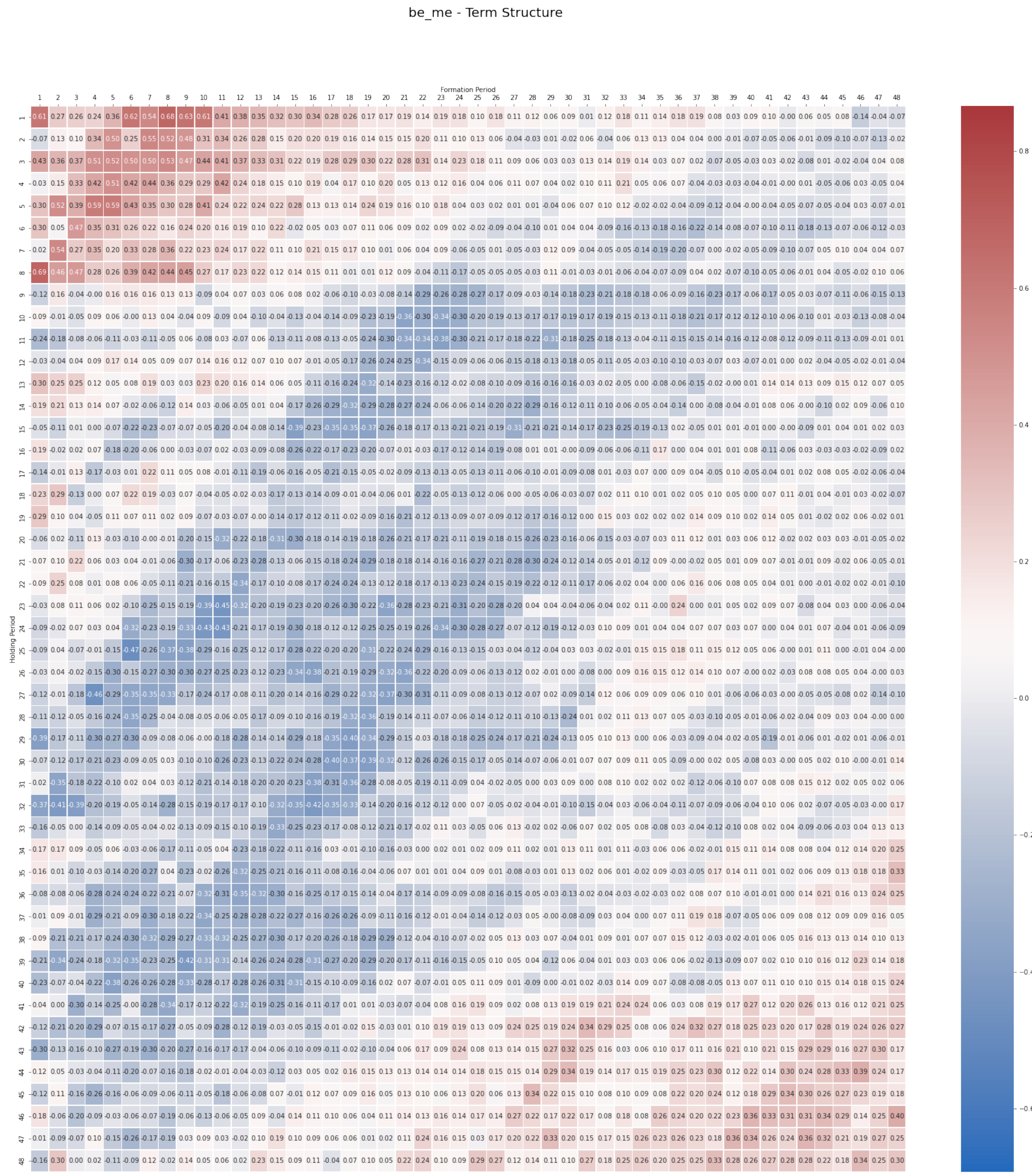


**Figure 5:** Similar to Jegadeesh and Titman (1993, JF), we extract the performance of different holding- and formation periods for all factors. The figure depicts annual Sharpe ratios for different strategy combinations of the value factor "book-to-market".

several different formation periods reverse after 8 months. The reversion of the value chasing strategy yields Sharpe ratios in the range of -0.36 to -0.47.

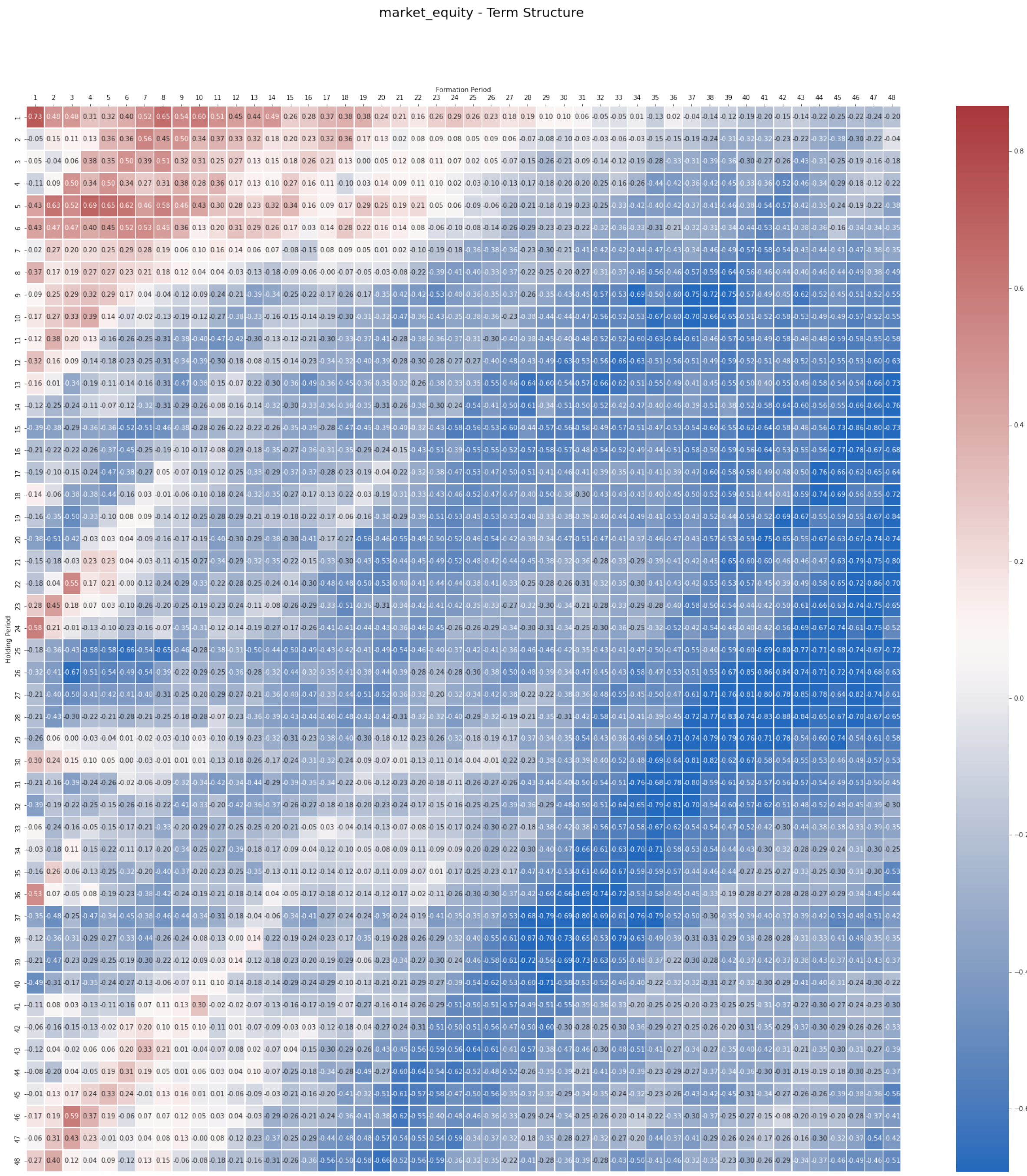


**Figure 6:** Similar to Jegadeesh and Titman (1993, JF), we extract the performance of different holding- and formation periods for all factors. The figure depicts annual Sharpe ratios for different strategy combinations of the size factor "market equity".

Figure 6 depicts the performance of the size chasing strategy. For the size chasing strategy, a formation period of the first 14 months is especially lucrative (with a holding period of one month). The size chasing strategy requires a formation period that is smaller than 32 months for the 1 month holding period setup. The longer the holding period of the portfolio, the faster the reversion occurs. If we hold a portfolio as long as 12 months, we need to form it with a formation period as small as 3 months to avoid reversion in the $12^{th}$ month. The reversion of the size chasing strategy is especially strong and yields Sharpe ratios in the range of -0.6 to -0.9.

# 5 Conclusion

Return chasing (positive feedback trading) is one of the most important behavioral biases of investors. By examining international factor momentum returns, we show that chasing factor returns through the world is a profitable trading strategy. In alignment with prior evidence of return chasing, factor chasing in domestic markets and excessive trading in international markets, prior aggregated factor level returns carry significant predictability for future single factor returns. Besides cross-country factor momentum patterns with formation periods of one month and holding periods of one month we uncover cross-country factor reversal patterns. Consistent with with earlier findings of factor level reversal effects in US markets, cross-country factor reversals occur at longer horizon formation- and holding periods.

Building a simple cross-country factor momentum strategy with size and value, two major factors, subsumes both US cross-sectional factor momentum and US time-series momentum (as proposed in Ehsani and Linnainmaa (2022)). Additionally, this strategy is able to subsume 21 out of 23 country level factor momentum strategies in spanning tests, while preserving robust positive alphas in the opposite regression exercises. Factor chasing frequently loads negative on a global version of the corresponding factor being chased. Especially in times of low average performance of the factor, factor chasing patterns appear. From a practical perspective this is particularly attractive to investors, because it offers a diversification advantage over simple factor harvesting strategies.

Overall factor chasing is a robust and highly profitable strategy, that is able to explain national level factor momentum patterns. These results provide evidence that factor momentum might be driven by international cross-country effects.

## References


Baltussen, G., Swinkels, L., and Van Vliet, P. (2021). Global Factor Premiums. *Journal of Financial Economics*, 142(3):1128–1154.

Barberis, N. and Shleifer, A. (2003). Style Investing. *Journal of Financial Economics*, 68(2):161–199.

Bhojraj, S. and Swaminathan, B. (2006). Macromomentum: Returns Predictability in International Equity Indices. *The Journal of Business*, 79(1):429–451. Publisher: The University of Chicago Press.

Brennan, M. J. and Cao, H. H. (1997). International Portfolio Investment Flows. *The Journal of Finance*, 52(5):1851–1880. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1997.tb02744.x.

Ehsani, S. and Linnainmaa, J. T. (2022). Factor Momentum and the Momentum Factor. *The Journal of Finance*, page jofi.13131.

Fama, E. F. and French, K. R. (2015). A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, 116(1):1–22.

Froot, K. and Teo, M. (2008). Style Investing and Institutional Investors. *Journal of Financial and Quantitative Analysis*, 43(4):883–906.

Froot, K. A., O'Connell, P. G. J., and Seasholes, M. S. (2001). The Portfolio Flows of International Investors. *Journal of Financial Economics*, 59(2):151–193.

Griffin, J. M., Nardari, F., and Stulz, R. M. (2007). Do Investors Trade More When Stocks Have Performed Well? Evidence from 46 Countries. *The Review of Financial Studies*, 20(3):905–951.

Grinblatt, M. and Keloharju, M. (2000). The Investment Behavior and Performance of Various Investor Types: a study of Finland's Unique Data Set. *Journal of Financial Economics*, 55(1):43–67.

Gupta, T. and Kelly, B. (2019). Factor Momentum Everywhere. *The Journal of Portfolio Management*, 45(3):13–36. Publisher: Institutional Investor Journals Umbrella.

Horst, J. t. and Salganik, G. (2014). Style Chasing by Hedge Fund Investors. *Journal of Banking & Finance*, 39:29–42.

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48(1):65–91.

Jensen, T. I., Kelly, B. T., and Pedersen, L. H. (2021). Is There a Replication Crisis in Finance? *SSRN Electronic Journal*.

Teo, M. and Woo, S.-J. (2004). Style Effects in the Cross-Section of Stock Returns. *Journal of Financial Economics*, 74(2):367–398.

Tesar, L. L. and Werner, I. M. (1995). Home bias and high turnover. *Journal of International Money and Finance*, 14(4):467–492.