# Firm-specific versus systematic momentum

Frank Graef [#]

*FHNW School of Business; University of St. Gallen*

Daniel Hoechle

*FHNW School of Business*

Markus Schmid

*University of St. Gallen*

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**Abstract**

This paper revisits prior findings that the returns to standard equity momentum strategies stem from industry or factor momentum and presents evidence to the contrary. We decompose stock returns into an idiosyncratic and a systematic component and show that persistence in the former, firm-specific part drives momentum. We obtain qualitatively identical results when using several prominent factor models for return decomposition. Further, momentum profits are largely unaffected by restricting the investment universe to stocks with inconspicuous factor loadings. Industry-neutral momentum strategies deliver similar outperformance. Our findings suggest that stock-level and portfolio-level momentum are largely independent and thus warrant separate explanations.

**Keywords:** Factor momentum, industry momentum, idiosyncratic momentum, factor timing

**JEL classification:** G14

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[#] Corresponding author: Tel.: +41-61-279-1835; E-mail: frank.graef@fhnw.ch.
Address: Institute for Finance, FHNW School of Business, Peter Merian-Strasse 86, CH-4002 Basel, Switzerland.
E-mail addresses: daniel.hoechle@fhnw.ch (D. Hoechle), markus.schmid@unisg.ch (M. Schmid).

## 1. Introduction

An extensive literature documents the profitability of stock price momentum. In a seminal paper, Jegadeesh and Titman (1993) rank stocks based on past returns over a three- to 12-month period (the formation period), and show substantial profits to buying winners and selling losers over the subsequent three to 12 months (the holding period). More recent studies document momentum at the equity portfolio level, in particular, for industry, equity style, or factor portfolios.[1] These portfolio-level momentum strategies also deliver positive returns over a prior-month formation period, which contrasts with the short-term reversal found in individual stocks (Jegadeesh, 1990; Lehmann, 1990).[2]

Is there a common explanation for momentum at both a single-stock and stock portfolio level? Prominent behavioral models explain stock momentum with biased reactions to firm-specific news.[3] However, these models arguably cannot explain momentum at the level of large, well-diversified stock portfolios (Lewellen, 2002). Alternatively, stock momentum might derive from a "top-down" transmission of portfolio-level momentum. Moskowitz and Grinblatt (1999) provide evidence that persistence in industry-specific returns is responsible for stock momentum. In a recent study, Ehsani and Linnainmaa (2021) show that equity risk factors exhibit momentum, which causes persistence in stocks' expected returns. Cross-sectional variation in stocks' factor loadings then determines the extent to which factor momentum translates into momentum in individual stocks. However, these explanations for momentum fail to account for the coexistence of short-term *reversal* in stocks and short-term *momentum* in stock portfolios. If industry or factor momentum drives stock momentum, wouldn't we also expect short-term momentum in individual stocks?

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[1] Asness, Moskowitz, and Pedersen (2013) show that momentum effects are prevalent in many asset markets. Industry momentum is studied by Moskowitz and Grinblatt (1999); Asness, Porter, and Stevens (2000); Grundy and Martin (2001); Nijman, Swinkels, and Verbeek (2004); Hoberg and Phillips (2018); Grobys and Kolari (2020). Style momentum is studied by Lewellen (2002); Barberis and Shleifer (2003); Chen and De Bondt (2004); Chou, Ko, and Yang (2019). Recent contributions by Gupta and Kelly (2019); Arnott, Clements, Kalesnik, and Linnainmaa (2021); Ehsani and Linnainmaa (2021) document momentum in long-short factor portfolios.

[2] Note that starting with Jegadeesh and Titman (1993), the last month before portfolio formation is often excluded to avoid the negative performance effect of short-term reversal.

[3] For example, Barberis, Shleifer, and Vishny (1998) argue that momentum stems from a conservatism bias and underreaction to company news. Hong and Stein (1999), attribute momentum to overreaction, caused by sequential information arrival and a failure to condition on market prices. Grinblatt and Han (2005) claim that a disposition effect may drive equilibrium prices away from fundamentals, causing momentum.

The results we present in this paper are difficult to reconcile with momentum in individual stocks originating from industry or factor momentum. Accounting for exposures against several prominent factor models, we consistently find that stock momentum is primarily driven by persistence in firm-specific returns, that is, returns unexplained by stocks' factor loadings. We show that the performance of stock momentum strategies does not hinge upon the timing of autocorrelated factors, or incidental industry bets that might induce a transmission of industry momentum. Taken together, our findings suggest that stock-level and portfolio-level momentum are largely independent of each other and possibly have different economic origins.

We first confirm the robust performance of stock- and portfolio-level investment strategies based on past returns in month $t-1$ or months $t-12$ to $t-2$. Henceforth, we refer to a formation period of month $t-1$ as "short-term" and months $t-12$ to $t-2$ as "medium-term". Throughout the paper, we focus on a holding period of one month. Our sample consists of monthly U.S. stock returns from CRSP and annual accounting information from Compustat over the period of July 1963 to December 2019. Industry and style momentum are constructed similar to Moskowitz and Grinblatt (1999) and Lewellen (2002), respectively. We construct cross-sectional factor momentum strategies using a set of 133 anomalies, which Hou, Xue, and Zhang (2020) show to outperform common benchmarks in a comprehensive replication study.[4]

We then show that large equity portfolios, which are not sorted by meaningful firm characteristics, but instead constructed in a purely random fashion, do not exhibit momentum. We run simulations, in which we randomly assign each stock to one of $N \in [10, 50, \ldots, 20{,}376]$ portfolios, compute value-weighted portfolio returns, and apply momentum and short-term reversal strategies to these portfolios. The performance of both momentum and short-term reversal strategies increases in the number of portfolios, while the explanatory power of the Fama and French (2015) factors in the cross-section of portfolio returns declines. Hence, we find significant momentum and short-term reversal only in portfolios that are sufficiently small, so that they resemble the performance of individual stocks. Our

[4] In spanning tests, these strategies behave very similar, when using a medium-term formation period. No strategy maintains a significant intercept, controlling for both the other strategies and the exposures to the Fama and French (2015) factors. However, all short-term strategies, with the exception of style momentum, possess a statistically significant alpha.

finding that large, randomly constructed portfolios do not exhibit significant momentum rules out any naïve explanation of stock momentum simply aggregating to the portfolio level.

Next, we investigate the performance of portfolios sorted by systematic and idiosyncratic stock returns. We estimate loadings against the Fama and French (2015) factors on a rolling basis, using five years of past returns and compute systematic (that is, expected) stock returns, given the firm's current betas. Idiosyncratic returns are then defined as the difference between total (excess) returns and systematic returns and represent firm-specific returns, unexplained by risk exposures. The rationale for this test is as follows: If stock momentum is caused by autocorrelation in factor premia, past systematic returns should be a better predictor for future stock performance than either past total or idiosyncratic returns. However, results from portfolio sorts point to the opposite: Over a medium-term formation period, systematic returns are not informative about future stock performance, while idiosyncratic returns are. For a short-term formation period, consistent with Da, Liu, and Schaumburg (2011, 2014), we find that the short-term reversal effect is entirely driven by mean-reversion in idiosyncratic returns. In contrast, when sorting stocks by their prior-month systematic returns, we observe short-term momentum. Following Asness et al. (2000), we repeat these portfolio sorts using industry-demeaned returns, where we subtract the value-weighted industry mean to rule out any bias from across-industry differences. We find mostly the same patterns. However, short-term momentum in systematic returns becomes statistically insignificant, suggesting that at least part of this effect stems from a transmission of short-term industry momentum. In summary, our results contradict the conclusions drawn in prior research that stock momentum stems from factor momentum (Ehsani and Linnainmaa, 2021).

We conduct a number of robustness tests on these results. First, we check whether our findings are dependent on the choice of the factor model and replace the Fama and French (2015) model by a number of other widely-used factor models, such as the Fama and French (1993) three-factor model, the augmented Q-factor model of Hou, Mo, Xue, and Zhang (2021), and the Stambaugh and Yuan (2017) mispricing factor model. Regardless of the factor model employed to compute systematic and idiosyncratic returns, we obtain qualitatively similar results. Second, we use an alternative rolling window period for the beta estimation, ranging from months $t-73$ to $t-13$, and again find the same pattern. Third, we run cross-sectional Fama and MacBeth (1973) regressions, which deliver similar

results. Fourth, we split our sample into two subsamples, one that includes stock-month observations with very large (> 80$^{th}$ percentile) or very small (< 20$^{th}$ percentile) loadings against at least one of the Fama and French (2015) factors, and one that consists of all remaining stock-month observations. We then re-estimate our analysis within the two subsamples. If stock momentum proxies for factor momentum, implementing momentum in a subsample of stocks characterized by a large dispersion in factor exposures would be expected to maximize the amount of implicit factor timing and thus momentum profits. In contrast, in the subsample including stocks with modest betas, the ability of momentum strategies to time factors is expected to be limited. We find that the net factor loadings of a momentum strategy restricted to the first, "extreme-beta" subsample exhibit much stronger time variation. However, the actual momentum performance is very similar across the two subsamples.

Our final set of tests analyzes the relationship between industry and stock momentum. We show that sorting stocks into portfolios by industry-demeaned returns as in Asness et al. (2000) still implies substantial time variation in the industry composition of the top and bottom momentum portfolios. Hence, industry-specific returns may potentially contribute to the profitability of such strategies. To address this issue, we adjust stocks' investment weights at the time of portfolio formation to ensure that an *equal amount* is invested into every industry. This approach ensures that the resulting high-low strategy is industry-neutral in a strict sense. The fact that we still obtain statistically significant momentum in this setting conflicts with the hypothesis that stock momentum originates from industry momentum. Moreover, we find that an industry-neutral short-term reversal strategy substantially outperforms a conventional short-term reversal strategy. This is because, for the latter, persistence in industry-specific returns counteracts mean-reversion in firm-specific returns.

This paper is primarily related to three strands of the literature: First, it relates to the literature on factor momentum pioneered by Gupta and Kelly (2019), who document the profitability of factor momentum strategies, Arnott et al. (2021), who show that industry momentum proxies for factor momentum and Ehsani and Linnainmaa (2021), who find that stock momentum stems from factor momentum. Our robust finding that stock momentum is driven by firm-specific returns stands at odds with Ehsani and Linnainmaa (2021), as this component is, by definition, unaffected by factor return continuation. We also investigate their hypothesis of idiosyncratic momentum being caused by

momentum in other factors that have been omitted from the (misspecified) model used for return decomposition. We show that this is unlikely, since we obtain qualitatively identical results for multiple prominent factor models. Second, this paper adds to the literature on industry momentum (Moskowitz and Grinblatt, 1999; Asness et al., 2000; Grundy and Martin, 2001; Nijman et al., 2004). Consistent with Asness et al. (2000), our results suggest no causal link between industry and stock momentum. However, we show that applying their technique of sorting stocks into portfolios by industry-demeaned past returns does not preclude incidental industry bets, that is, we document substantial variation in the industry composition of the resulting top and bottom momentum portfolios. We therefore analyze momentum strategies with equal industry weights and show that these strategies, too, exhibit statistically significant outperformance. Third, our paper relates to studies, which explore the time-varying factor loadings of momentum strategies (Grundy and Martin, 2001; Wang and Wu, 2011; Daniel and Moskowitz, 2016) and the profitability of idiosyncratic (or "residual") momentum and short-term reversal strategies (Gutierrez and Prinsky, 2007; Blitz, Huij, and Martens, 2011; Da et al., 2011, 2014). We contribute to this literature by investigating the relationship between variation in factor betas and momentum performance. We find that momentum performance is not significantly affected by the capacity for implicit factor timing. Further, we are the first to conduct a detailed analysis of the predictive power of expected stock returns.

## 2. Data and factor construction

We construct our database by merging monthly U.S. stock returns from CRSP with annual accounting information from Compustat. Databases are matched using CRSP's PERMNO identifier. We collect data for all NYSE, AMEX, and Nasdaq securities listed as ordinary common stock over the sample period of July 1963 to December 2019. Following Hou et al. (2020), we exclude financial firms (SIC code starting with "6") and firms with negative book equity. To avoid a look-ahead bias, we lag Compustat accounting information by six months, such that year-end figures become available at the end of June of next year (Fama and French, 1992). We use CSRP delisting returns. If delisting returns are missing and the delisting is performance-related, we set them to -30% (Shumway, 1997; Beaver, McNichols, and Price, 2007). We retrieve factor returns of the Fama and French (1993, 2015) three- and

five-factor models from Ken French's webpage.[5] Factor returns of the Stambaugh and Yuan (2017) mispricing factors are obtained from Robert Stambaugh's webpage.[6] Factor returns of the Hou et al. (2021) augmented q-model factors are taken from the global-q data library.[7] From the latter source, we also collect 186 anomaly returns over a sample period of January 1967 to December 2019. Hou et al. (2020) show that these 186 anomalies outperform common benchmarks in a comprehensive replication study.[8] The authors provide value-weighted returns of 3-by-5 double-sorted portfolios by size (lagged market equity) and the respective anomaly variable. They use independent sorts and NYSE breakpoints in both dimensions. Size splits separate microcaps (< 20$^{th}$ size percentile) from small caps (>20$^{th}$ and < 50$^{th}$ size percentile) and large caps (> 50$^{th}$ size percentile). We exclude 53 anomalies that are based on past returns, which might bias our results, leaving a total of 133 anomalies.[9] Next, we construct factors from these anomaly portfolios by taking the average return of the two small and large cap portfolios, which rank "high" (> 80$^{th}$ percentile) in the anomaly variable and deducting it from the average return of the two small and large cap portfolios, which rank "low" (< 20$^{th}$ percentile) in the anomaly variable.[10]

## 3. Momentum and short-term reversal in stocks and momentum in stock portfolios

### *3.1. Baseline results*

To implement stock-level momentum and short-term reversal strategies, at the beginning of each month, we rank all stocks in our sample according to their past returns. In the baseline momentum strategy, we use stocks' returns over the last year, skipping the last month before the ranking ($r_{t-12,t-2}$). In the short-term reversal strategy, we rank stocks according to their last month returns ($r_{t-1}$). Stocks are then sorted into quintile portfolios based on their ranks. We analyze both value- and equal-weighted portfolios. In the value-weighted specification, we use NYSE past-return breakpoints and compute stocks' value-weighted average returns for each quintile, using stocks' lagged market equity. In the

[5] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[6] http://finance.wharton.upenn.edu/~stambaug/
[7] http://global-q.org/index.html
[8] The set of anomaly portfolios we use in our study was released in April 2021.
[9] We exclude 41 anomalies listed in the "momentum" category, eight seasonality measures (Heston and Sadka, 2008; Keloharju, Linnainmaa, and Nyberg, 2016), three measures related to long-term reversal (De Bondt and Thaler, 1985) and one measure related to short-term reversal (Jegadeesh, 1990; Lehmann, 1990).
[10] We exclude microcaps to ensure that factor performance is not driven by very small firms, in which institutional investors can hardly invest in. Note that Hou et al. (2020) show that microcaps account for only 3.21% of total U.S. equity market capitalization.

equal-weighted specification, we use unconditional breakpoints and compute quintile returns as the average return of composite stocks. To compute strategy returns, we go long (short) the top (bottom) quintile portfolio for the current month, with monthly rebalancing.[11]

Panel A of Table 1 reports the results. The value-weighted momentum (short-term reversal) strategy achieves a statistically significant monthly return of 0.66% (-0.34%). After adjusting for exposure to the Fama and French (2015) factors, short-term reversal returns become smaller and statistically insignificant, whereas momentum returns increase. In the equal-weighted setup, momentum (short-term reversal) performance amounts to 0.85%. (-1.55%) per month.[12] The alpha terms of both strategies are statistically significant, albeit slightly smaller than the raw returns.

Next, we analyze portfolio-level momentum. To this end, we first construct industry, style, and factor momentum portfolios. We define industries via 2-digit SIC codes, following Moskowitz and Grinblatt (1999). We exclude the financial industry (SIC codes staring with "6"). Overall, our sample covers 19 distinct 2-digit SIC industries. Second, we construct size and book-to-market double-sorted ($Size\text{-}B/M$) portfolios from the intersection of independent quintile sorts in both directions. These 25 portfolios are formed once a year at the end of June, using NYSE breakpoints and book and market equity figures from the end of the previous fiscal year (Fama and French, 1992). Third, we use 133 long-short factors, constructed from Hou et al. (2020) anomaly portfolios (see Section 2 for details).[13]

Each month, we rank portfolios according to their past short-term ($r_{t-1}$), or medium-term ($r_{t-12,t-2}$) performance. We apply the same investment rule for all portfolio-level strategies. In particular, we make an equal-weighted long (short) investment into the $N_t^L = N_t^S = round(N_t/5)$ portfolios with the best (worst) past performance, where $N_t$ is the number of portfolios in the investment opportunity set in month $t$. The long and short sides are then rescaled to unit leverage and rebalanced on a monthly basis.[14]

[11] Throughout the paper, we focus on an investment period of one month to keep the amount of strategies tractable and to ensure that investment strategies are always based on the latest set of past-return information.
[12] We report the returns to short-term reversal with a negative sign for analytical reasons. Of course, by switching the long and short positions, we get an equivalent positive return.
[13] Due to the availability of Hou et al. (2020) anomaly data, the sample period for factor momentum starts in Jan. 1968. The number of factors increases over the sample period, as more anomalies become available.
[14] For instance, the industry momentum strategy is always long / short $4 = round(19/5)$ industries.

Results are reported in Panel B of Table 1. Using a short-term (medium-term) formation period, industry momentum yields a statistically significant return of 0.53% (0.39%) per month. Short-term (medium-term) style momentum amounts to 0.63% (0.40%). Cross-sectional short-term (medium-term) factor momentum delivers 1.09% (0.65%). In each case, the Fama and French (2015) alphas exceed the raw returns. Evidently, industry, style and factor momentum exhibit positive returns over both formation periods, with the short-term strategies consistently being more profitable than the medium-term strategies.[15]

Summarizing these baseline results, there are four major take-aways: First, there is robust medium-term momentum in individual stocks and industry, style and factor portfolios. Second, there is short-term reversal (momentum) on a single-stock (stock portfolio) level. Third, short-term reversal is strongest, when defined as an equal-weighted strategy. Fourth, the performance of all of these strategies is generally not well explained by static risk exposures, as the alpha terms tend to be quite close to the raw returns.[16]

[Table 1 about here]

*3.2. Robustness tests*

Table A1 in the appendix summarizes results from various robustness tests. In Panel A, we alter the construction of stock-level strategies by sorting stocks into decile portfolios. The outcomes are very similar to a recent study by Hou et al. (2020). For the value-weighted momentum (short-term reversal) specification, we obtain returns of 1.15% (-0.31%) per month, compared to 1.16% (-0.27%) in Hou et al. (2020), with similar statistical significance.[17] Panel B addresses the robustness of industry, style, and factor momentum. First, we implement industry momentum using the Fama and French 30 industry classification provided on Ken French's webpage.[18] After dropping financial services firms, we end up

[15] Figure A1 in the appendix tracks the cumulative performance of a volatility-adjusted $1 investment into each of the strategies analyzed above from Jan. 1968 to Dec. 2019. While medium-term stock momentum, and, to a lesser extent, industry momentum, experiences a dramatic "momentum crash" (Daniel and Moskowitz, 2016) around the year 2009, this downturn is less pronounced for factor and style momentum.
[16] The result that many common factor models poorly explain momentum returns is known. See, for example, Fama and French (1996, 2016), Grundy and Martin (2001), and Wang and Wu (2011).
[17] The performance of the equal-weighted strategies is also very similar. Note that, compared to the sample period in Hou et al. (2020), our sample period starts six months earlier and ends three years later.
[18] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_30_ind_port.html

with 29 industries. Compared to our baseline results, industry momentum is even stronger for 29 Fama and French industries. Second, we implement style momentum on 25 portfolios double-sorted by operating profitability and asset growth ($OPAT$-$\Delta AT$). The outcomes illustrate that style momentum is not confined to the 25 $Size$-$B/M$ portfolios analyzed by Lewellen (2002), but also exists for other characteristics-sorted portfolios.[19] Third, we analyze momentum in the Fama and French (2015) size (SMB), value (HML), profitability (RMW), and investment (CMA) factors, where we make an equal-weighted long (short) investment into the two factors with above-(below-)median past performance. Results show that factor momentum also yields statistically significant outperformance for a small set of only four factors.

### *3.3. Correlations and spanning tests*

The covariance in strategies' returns is analyzed in Table A2 in the appendix. Panel A shows that pairwise correlations between the different versions of short- and medium-term strategies are large (> 0.5) and strictly positive. For example, this means that short-term reversal in individual stocks is less pronounced, whenever short-term industry, style, or factor momentum perform well. Panel B shows spanning tests, where we regress the returns of each short- and medium-term strategy on its "peer" strategies, formed over the same time horizon, and the Fama and French (2015) factors. All short-term strategies, with the exception of style momentum, retain a statistically significant alpha. However, the alphas of medium-term momentum strategies all turn insignificant.[20]

## 4. Momentum in randomly-sorted portfolios

### *4.1. Simulation approach*

To inform the question *why* momentum shows up in both individual stocks and stock portfolios, we analyze momentum strategies using randomly-sorted stock portfolios. A simple and straightforward explanation for the existence of momentum at the portfolio level is that it approximately represents the

[19] In a recent study, Chou et al. (2019) also document significant style momentum in portfolios double-sorted by firm size and asset growth.

[20] Ehsani and Linnainmaa (2021), using a full one-year formation period ($r_{t-12,t-1}$), find that factor momentum spans stock momentum, but not vice versa. In contrast, Falck, Rej, and Thesmar (2020) show that factor momentum does not span stock momentum, when skipping the last month ($r_{t-12,t-2}$). Our own unreported results show that choices made in strategy construction (e.g., whether to include microcaps in factor construction) can severely impact the outcomes. Hence, we caution against placing too much emphasis on spanning tests.

(weighted) average momentum of stocks in the portfolio.[21] Thus, a natural question to ask is whether momentum is then a *general* feature of stock portfolios or whether it is confined to portfolios sorted by meaningful firm characteristics. To test this hypothesis, we conduct Monte-Carlo simulations, which are set up as follows:

First, a uniformly distributed random identifier is assigned to every stock in the sample. This "random PERMNO" stays constant over the entire sample period. Stocks are then ranked on this random variable and assigned to one of $N \in [10, 50, \ldots, 20{,}376]$ portfolios. Choosing this approach, we allow the number – instead of the identity – of stocks in each portfolio to change over time, as stocks enter and leave the sample. Consequently, when the number of portfolios becomes large, there is a chance that some portfolios will be empty. Portfolio returns are computed as the value-weighted average return of composite stocks, using stocks' lagged market equity. We then rank portfolios each month by their short- or medium-term returns and make an equal-weighted long (short) investment into all non-empty portfolios with past returns above (below) the 80$^{th}$ (20$^{th}$) percentile. As before, the strategy is rebalanced monthly.

### *4.2. Performance of randomly sorted portfolios*

Panel A of Table 2 shows average raw returns and Fama and French (2015) alphas of strategies based on past short- ($r_{t-1}$), or medium-term ($r_{t-12,t-2}$) portfolio returns from 1,000 simulations. The last column shows the single-stock case, where we set the number of portfolios $N = 20{,}376$ (the number of unique stocks in our sample). The outcomes for this special case are thus identical to the equal-weighted strategy in Panel A of Table 1.

The returns of both strategies increase monotonically in the number of portfolios $N$. Raw returns of short-term reversal strategies turn statistically significant as of $N = 400$ portfolios, yielding returns of -0.21% per month. However, Fama and French (2015) alphas turn significant only in the single-stock specification. Medium-term momentum starts to deliver a statistically significant alpha of 0.25% per

[21] The word "approximately" accounts for the fact that stocks may enter or leave portfolios. This divergence between portfolio-level and average stock-level momentum is more pronounced for $Size\text{-}B/M$ portfolios, which can change substantially at the time of rebalancing, compared to industry portfolios, which remain fairly stable, as industry classifications rarely change. In addition, this difference is, of course, larger for medium-term ($r_{t-12,t-2}$), compared to short-term ($r_{t-1}$) returns.

month as of $N = 50$ portfolios, increasing to 0.68% per month for $N = 800$ portfolios. Most important, both the short-term reversal and medium-term momentum strategies are most profitable in the single-stock case with $N = 20{,}376$.

*4.3. Characteristics of randomly-sorted portfolios*

Next, we analyze the properties of randomly-sorted portfolios. The first two rows of Table 2, Panel B, report the time-series averages of the number of non-empty portfolios and the number of stocks per portfolio. For $N < 400$, all portfolios are populated by at least one stock at any given point in time. For $N = 800$, an average of 789.6 portfolios are populated. When sorting stocks into $N = 5$ ($N = 800$) portfolios, each portfolio contains, on average, 789.4 (5.0) stocks. The third row shows the median R-squared of a regression of excess portfolio returns on the Fama and French (2015) factors. The explanatory power of the model is quite large for $N = 5$ portfolios (median R-squared of 0.95) and decreases in the number of portfolios $N$.[22] The last six rows report the average cross-sectional standard deviation in portfolios' returns and Fama and French (2015) factor loadings.[23]

The most important insight from this section is that momentum is *not* a general feature of stock portfolios. If portfolios are constructed randomly, a small cross-section of $N < 50$ portfolios will not exhibit momentum, on average. Only as the number of portfolios $N$ increases and the number of stocks per portfolio thus declines, so that portfolio returns become more similar to individual stock returns, we observe statistically significant momentum effects. These results clearly rule out any naïve explanation of individual stock momentum simply aggregating to the portfolio level.

[Table 2 about here]

[22] The R-squared is computed via a full-sample regression, requiring at least 36 past-return observations. When $N$ is small, portfolio returns are mostly explained by the market factor. This is not surprising, as we would expect five or ten well-diversified and *randomly* sorted portfolios to behave more or less like the market itself.
[23] We calculate portfolios' current betas as the value-weighted average of constituent stocks, estimated over a five-year rolling period from month $t-60$ to $t-1$, requiring at least 36 return observations.

## 5. Does stock momentum stem from industry or factor momentum?

### *5.1. Return decomposition into idiosyncratic and systematic returns*

The absence of momentum in a small number of random portfolios that include a large number of stocks, as documented in the previous section, can be reconciled with multiple results found in prior literature. First, in a survey of the equity momentum literature, Jegadeesh and Titman (2011) conclude that momentum most likely is a firm-specific effect. Hence, momentum may be diversified away in large portfolios that contain hundreds of stocks. Second, random portfolios are well-diversified in terms of industries. This may prevent a transmission of industry momentum, as documented by Moskowitz and Grinblatt (1999), into the cross-section of portfolio returns. Third, as random portfolios have similar risk exposures, the amount of factor momentum that can translate into the cross-section of portfolio returns is expected to be limited. Arnott et al. (2021) show this mechanism to be responsible for industry momentum. Ehsani and Linnainmaa (2021) similarly identify a transmission of factor momentum into the cross-section of *stock* returns as the root cause of stock momentum.

To empirically test these explanations, we decompose stock returns into a systematic and an idiosyncratic component, where the former represents the expected return, given stocks' current factor loadings, and the latter represents the unexplained, firm-specific return. Sorting by systematic (idiosyncratic) returns should then isolate (mitigate) the impact of momentum present in the Fama and French (2015) factors.[24] Similar to Ehsani and Linnainmaa (2021), we estimate firms' loadings $\hat{\beta}_{i,t}^{f}$ against the $F = 5$ factors of Fama and French (2015), using a five-year rolling period from month $t-60$ to $t-1$.[25] Each beta estimate is based on at least 36 past-return observations. Systematic and idiosyncratic stock returns are computed as follows:

Short-term systematic returns:

$$\hat{r}_{i,t-1} = \sum_{f=1}^{F} \hat{\beta}_{i,t}^{f} r_{t-1}^{f} \qquad (1)$$

[24] We demonstrate the existence of significant factor momentum in the Fama and French (2015) size, value, profitability and investment factors in Table A1 in the appendix.

[25] Ehsani and Linnainmaa (2021) estimate factor loadings from month $t-73$ until month $t-13$ and also require a minimum of 36 past-return observations. They perform a double sort by firm size and past returns and construct residual (i.e., idiosyncratic) momentum strategies as UMD-style factors. In Section 5.4, we show that using this alternative rolling period does not affect our results.

Short-term idiosyncratic returns: $$\hat{\varepsilon}_{i,t-1} = r^{e}_{i,t-1} - \hat{r}_{i,t-1} \quad (2)$$

Medium-term systematic returns: $$\hat{r}_{i,t-12,t-2} = \sum_{j=-12}^{-2} \hat{r}_{i,t-j} \quad (3)$$

Medium-term idiosyncratic returns: $$\hat{\varepsilon}_{i,t-12,t-2} = \sum_{j=-12}^{-2} r^{e}_{i,t-j} - \hat{r}_{i,t-j} \ , \quad (4)$$

where $r^{e}_{i,t}$ are monthly stock returns in excess of the risk-free rate and $r^{f}_{t}$ denotes monthly factor premia. Availability of Fama and French (2015) factor data and a minimum rolling period of three years limit the sample period in this analysis to July 1966 to Dec. 2019.

To illustrate the relationship between factor momentum and momentum in systematic returns, consider the following decomposition of the expected returns of a momentum strategy, which chooses investment weights in proportion to stocks' past returns relative to the cross-sectional mean (Lo and MacKinlay, 1990). Ehsani and Linnainmaa (2021) derive this decomposition under the assumption that stocks' expected excess returns are generated by some $F$-factor model. The expected profits to this strategy, implemented in a cross-section of $N$ stocks then corresponds to:

$$E[\pi^{mom}_{t}] = \sum_{f=1}^{F} [cov(r^{f}_{-t}, r^{f}_{t})\, \sigma^{2}_{\beta_f}] + \sum_{f=1}^{F} \sum_{g \neq f}^{F} [cov(r^{f}_{-t}, r^{g}_{t})\, cov(\beta^{f}, \beta^{g})] + \frac{1}{N} \sum_{i=1}^{N} [\, cov(\varepsilon_{i,-t}, \varepsilon_{i,t})] + \sigma^{2}_{\eta} \ , \quad (5)$$

where $r^{f}_{t}$ is the return of factor $f$ in month $t$, $\beta^{f}$ are stocks' loadings towards factor $f$, $\varepsilon_{i,t}$ are stocks' idiosyncratic returns, $\eta$ represents stocks' unconditional expected returns and $-t$ refers to the formation period (e.g., month $t-12$ to $t-2$). The same relationship holds for the expected profits to an otherwise identical short-term reversal strategy $E[\pi^{rev}_{t}]$, when setting the formation period $-t$ to month $t-1$. The expected return $E[\pi^{mom}_{t}]$ may thus stem from any combination of:

- Factor autocorrelations $cov(r^{f}_{t-1}, r^{f}_{t})$ times the cross-sectional variance in betas $\sigma^{2}_{\beta_f}$
- Cross-serial covariances between factors $cov(r^{f}_{t-1}, r^{g}_{t})$ times the cross-sectional covariances in exposures towards different factors $cov(\beta^{f}, \beta^{g})$
- Autocorrelation in firm-specific returns $cov(\varepsilon_{i,t-1}, \varepsilon_{i,t})$

– Variation in stocks' unconditional expected returns $\sigma_\eta^2$

Importantly, factor autocorrelations translate into stock momentum via the first channel. If factor momentum was the main driver of stock momentum, we would thus be able to isolate this spill-over effect by sorting on stocks' expected, that is, systematic returns.

### *5.2. Portfolio sorts by idiosyncratic and systematic returns*

We rank stocks at the beginning of each month by one of the short- or medium-term return measures, defined in Equations (1) to (4), and sort them into value-weighted quintiles, using NYSE breakpoints. We invest long (short) in the top (bottom) quintile portfolio for the subsequent month. Table 3, Panel A, reports the raw returns of all quintile portfolios and the raw returns and Fama and French (2015) alphas of the high-low quintile strategies. For comparison, the first two columns report results from a sort on stocks' total returns. The next two columns report results from a sort on stocks' idiosyncratic returns and the last two columns on stocks' systematic returns.

Results show that sorting by short-term idiosyncratic returns ($\hat{\varepsilon}_{i,t-1}$) delivers returns that are, at a statistically significant return of -0.78% per month, more than twice as large as those resulting from a conventional short-term reversal strategy.[26] When sorting by short-term systematic returns ($\hat{r}_{i,t-1}$), the strategy yields a statistically significant positive return of 0.38%, that is, *short-term momentum*. Turning to medium-term momentum, we find that sorting by idiosyncratic returns ($\hat{\varepsilon}_{i,t-12,t-2}$) results in statistically significant positive returns of 0.57% per month, which are only slightly smaller than the 0.66% delivered by the standard momentum strategy. In contrast, when sorting by medium-term systematic returns ($\hat{r}_{i,t-12,t-2}$), we find statistically insignificant returns of 0.20% per month. The momentum strategy based on idiosyncratic returns also performs much better in terms of Fama and French (2015) alphas, compared to its systematic return counterpart.[27]

[26] This particular result is consistent with the findings of Da et al. (2011, 2014), who conduct a similar analysis.
[27] For all strategies with a statistically significant outperformance, portfolio returns increase or decrease fairly monotonously from Q1 to Q5, making it less likely that the outcomes are spurious (Patton and Timmermann, 2010). Figure A2 in the appendix plots the cumulative strategy performance of a volatility-adjusted $1 investment into each strategy from July 1966 to Dec. 2019. For short-term strategies, we observe a large divergence in performance between sorts based on idiosyncratic and sorts based on systematic returns. The cumulative performance of the medium-term strategies shows that idiosyncratic momentum outperforms total return momentum, largely due to a lower drawdown around 2009.

[Table 3 about here]

The fact that we obtain statistically insignificant strategy returns and alphas when sorting by medium-term systematic returns ($\hat{r}_{i,t-12,t-2}$) is noteworthy: If stock momentum results from momentum in equity risk factors, we would expect substantial positive predictability precisely for this measure. Yet, this is not what we find. To the contrary, medium-term idiosyncratic momentum largely captures the performance of a conventional stock momentum strategy. This suggests that stock momentum is driven by firm-specific return patterns and, therefore, unrelated to factor momentum. More precisely, the results in Table 3 suggest that, if there is a "spill-over" of factor momentum to stock momentum, this spill-over is confined to a one-month timeframe, where it is thwarted by strong reversal in idiosyncratic returns.

*5.3. Industry-demeaned predictors*

To control for incidental industry bets, we next repeat the analysis in the previous section using industry-demeaned predictors.[28] To gain an understanding of why industry effects may affect our strategy returns, consider the following scenario: Idiosyncratic returns may still include an industry-specific component which is not explained by factor exposures, even after expected returns have been subtracted.[29] If these across-industry differences in mean idiosyncratic returns are large, stocks belonging to particular industries will have a higher chance of ending up in the top or bottom momentum portfolios. In turn, this might lead to a transmission of industry momentum into stock momentum (Moskowitz and Grinblatt, 1999).

To empirically test the effect of industry-specific returns on stock momentum, we follow Asness et al. (2000) and compute each month the value-weighted means of stocks' past returns for each of the 19 Moskowitz and Grinblatt (1999) industries, which are defined by 2-digit SIC codes. We then deduct the industry mean returns from the original past-return measures. Finally, we use these industry-demeaned

[28] Several studies employ a similar industry demeaning for stock-level characteristics to account for differences in characteristics across industries. See, for example, Asness et al. (2000), Da et al. (2011, 2014), Hameed and Mian (2015), Asness, Frazzini, and Pedersen (2014), and Novy-Marx (2013).

[29] This assumption seems reasonable. Lewellen, Nagel, and Shanken (2010) use common factor models to explain the returns of 55 test assets, which include the 30 Fama-French industry portfolios, and find a lower median R-squared, compared to a test which only uses 25 $Size\text{-}B/M$ portfolios. Moreover, Fama and French (1997) document imprecise cost of equity estimates for 48 industry portfolios.

predictors to implement high-low quintile strategies. As in Panel A of Table 3, we run these strategies based on total, idiosyncratic, and systematic returns. Results are reported in Panel B of Table 3.

Consistent with Da et al. (2011, 2014), we find that the magnitude and statistical significance of the total and idiosyncratic short-term reversal strategies increases substantially when we use industry-demeaned predictors. For instance, an industry-demeaned short-term reversal strategy earns -0.70% per month, compared to -0.34% for the standard strategy. In contrast, short-term systematic momentum becomes statistically insignificant after subtracting the industry mean from the original predictor, indicating that its predictive power may at least partly be driven by an across-industry component. Looking at medium-term momentum, we find that the performance of strategies using total or idiosyncratic returns remains largely unaffected. For instance, the raw return of the idiosyncratic momentum strategy decreases from 0.57% to 0.56% per month, while the Fama and French (2015) alpha decreases from 0.94% to 0.86%, with all strategy returns significant at the 1% level. In summary, the results in this section suggest that industry momentum contributes little to stock momentum.

### *5.4. Alternative factor models*

The quality of the decomposition of total returns into systematic and idiosyncratic returns hinges on the choice of factor model. For instance, Ehsani and Linnainmaa (2021) argue that idiosyncratic momentum strategies may exhibit statistically significant outperformance if idiosyncratic returns are computed against a misspecified factor model. Momentum in the omitted factors may then lead to momentum in idiosyncratic returns, even if firm-specific returns are not serially correlated. If the omitted factors are more strongly autocorrelated than the factors included in the model, idiosyncratic returns might even display stronger momentum than total returns. Still, we would expect systematic returns to possess positive predictability in such a scenario, as they reflect compensation for stocks' exposure against other autocorrelated factors that are included in the model.[30]

To test the robustness of our results against the choice of factor model, we re-estimate our analysis using alternative factor models for return decomposition. The models we use are the CAPM, the Fama

[30] Table A1 in the appendix shows that momentum in the Fama and French (2015) size, value, profitability, and investment factors already captures a sizeable portion of the returns of a more complex factor momentum strategy.

and French (1993) three-factor model, the augmented Q-factor model of Hou et al. (2021), and the Stambaugh and Yuan (2017) mispricing factor model. For each model, we estimate factor loadings using a five-year rolling period (month $t-60$ to month $t-1$), requiring at least 36 return observations. We then compute systematic and idiosyncratic returns according to Equations (1) to (4). Finally, we implement high-low quintile strategies similar to those reported in Table 3.

Results are reported in Panel A of Table 4. Most important, the table shows that our results are insensitive to the choice of factor model used for return decomposition. Medium-term systematic returns ($\hat{r}_{i,t-12,t-2}$) consistently lack any return predictability, while idiosyncratic short-term reversal ($\hat{\varepsilon}_{t-1}$) and medium-term momentum ($\hat{\varepsilon}_{t-12,t-2}$) prevail across all factor models. Moreover, as before, short-term systematic returns ($\hat{r}_{t-1}$) exhibit positive predictability. Panel B of Table 4 shows that industry-demeaning past returns leaves results qualitatively unchanged compared to Panel B of Table 3, with the exception that, when using the CAPM, Fama and French (1993) and Stambaugh and Yuan (2017) models, short-term systematic momentum alphas remain statistically significant.

A concern related to the choice of factor model is the choice of estimation window to estimate factor exposures. To test the sensitivity of our results to the estimation window, we re-estimate the analysis in Table 3, which uses rolling windows of month $t-60$ to month $t-1$, using rolling windows of month $t-73$ to month $t-13$, instead. This alternative five-year rolling period, which does not include returns from month $t-12$ to month $t-1$, is also used by Ehsani and Linnainmaa (2021). As in our baseline analysis in Table 3, we require at least 36 monthly return observations. Results, reported in Table A3 in the appendix, are qualitatively identical to those in Table 3.

In short, results in this section show that, for multiple prominent factor models, short-term reversal and medium-term momentum are consistently driven by idiosyncratic returns, whereas medium-term systematic returns do not predict future stock performance. These findings are difficult to reconcile with idiosyncratic momentum being profitable exclusively by picking up momentum in omitted factors.[31]

[31] Still, absent knowledge of the "true" factor model and a perfect method to extract stocks' risk exposures, we cannot definitively rule out such an explanation. Indeed, in a recent study, Fama and French (2018) summarize the state of the "factor zoo" (Cochrane, 2011) debate as follows: "Given the plethora of factors that might be included in a model, choosing among competing models is an open challenge" (p. 234).

[Table 4 about here]

*5.5. Cross-sectional regressions*

In a final robustness test, we estimate Fama and MacBeth (1973) regressions. Specifically, for each month in our sample period, we estimate cross-sectional regressions, where we regress stocks returns $r_{i,t}$ on past idiosyncratic and systematic returns, controlling for additional firm-level characteristics:

$$r_{i,t} = \alpha_t + \boldsymbol{\beta_t'} \boldsymbol{X_{i,t}} + \boldsymbol{\gamma_t'} \boldsymbol{C_{i,t}} + \varepsilon_{i,t} \,, \tag{6}$$

where stocks' past systematic and idiosyncratic returns enter vector $\boldsymbol{X}$. Vector $\boldsymbol{C}$ includes a set of control variables. These include the logarithms of both market equity $log(Size)$ and the book-to-market ratio $log(B/M)$, as well as operating profitability ($OPAT$), and asset growth ($\Delta AT$).

Including multiple past-return measures in Fama and MacBeth (1973) regressions allows us to analyze their net predictive power in the cross-section. We test multiple specifications. First, we include short- ($\hat{\varepsilon}_{t-1}$) and medium-term ($\hat{\varepsilon}_{t-12,t-2}$) idiosyncratic returns and analyze whether both measures possess independent predictive power. Next, we repeat the analysis for short- ($\hat{r}_{t-1}$) and medium-term ($\hat{r}_{t-12,t-2}$) systematic returns. Lastly, we conduct a joint analysis of all four measures.

In keeping with the value-weighted approach used in portfolio sorts and to account for a potential bias from microcaps stocks, we estimate these regressions as weighted least squares (WLS), where observation weights in each cross-section are proportional to firms' lagged market equity. Columns (1) to (3) of Table A4 in the appendix report the time-series average coefficient estimates for the standard predictors, analyzed in Panel A of Table 3. Columns (4) to (6) of the same table show coefficient estimates for the industry-demeaned versions, analyzed in Panel B of Table 3.

Slope coefficients for short-term idiosyncratic returns ($\hat{\varepsilon}_{t-1}$) are consistently negative and highly significant. Effect sizes are larger for the industry-demeaned predictors in columns (4) and (6). Medium-term idiosyncratic returns ($\hat{\varepsilon}_{t-12,t-2}$), on the other hand, exhibit positive predictability that is slightly stronger, but less significant, for the standard predictors in columns (1) and (3). In contrast to the portfolio analysis in Table 3, short-term systematic returns ($\hat{r}_{t-1}$) do not exhibit any predictability in

Fama and MacBeth (1973) regressions. However, in line with the evidence from portfolio sorts, medium-term systematic returns ($\hat{r}_{t-12,t-2}$) again have no predictive power.

In general, these results are consistent with those of the portfolio analysis in Table 3. Importantly, the outcomes show that short- and medium-term idiosyncratic returns possess independent predictive power, with or without industry demeaning. None of the systematic return measures significantly predict future performance in Fama and MacBeth (1973) regressions.

### *5.6. Does cross-sectional dispersion in betas affect momentum performance?*

Prior literature shows that momentum strategies are characterized by dynamic factor loadings (Grundy and Martin, 2001; Wang and Wu, 2011; Daniel and Moskowitz, 2016). Assuming that stocks' expected returns are determined by a multifactor model, the high (low) momentum portfolio will, by construction, include stocks with large loadings to factors which have performed well (poorly) in the recent past. The composition of momentum portfolios changes at each formation date which may cause large fluctuations in factor exposures. If factors are then positively autocorrelated, momentum strategies might profit from implicit factor timing.[32]

To gauge how large the contribution of factor timing to momentum returns really is and whether stock momentum might even be *reduced* to factor timing, we next explore the relationship between the cross-sectional dispersion in stocks' factor loadings and momentum profits. Looking at Equation (5) in Section 5.1, Ehsani and Linnainmaa (2021) propose a transmission of factor momentum into stock momentum via the first term, that is, autocorrelation in factor returns, amplified by the cross-sectional variance in factor betas. Following this line of reasoning, if the stocks in our investment universe were characterized by very similar (widely varying) factor exposures, we would expect to observe lower (higher) momentum returns.

To empirically test this conjecture, we first rank stocks by their loadings against each Fama and French (2015) factor (i.e., every stock receives five different ranks; one for each factor). We then construct an "extreme-beta" subsample for each month by selecting all stocks, which rank above the

[32] Grundy and Martin (2001) recognize this issue and state: "A momentum strategy may spuriously appear to earn abnormal returns if it tends to load heavily on a factor when exposure to that factor requires a high return (…) [This] could explain momentum profits provided the factors themselves displayed positive momentum" (p. 49).

80th or below the 20th percentiles in terms of their exposures against *at least one* factor. The remaining stocks are included in the "modest-beta" subsample.[33] We then implement high-low quintile short- and medium-term strategies, with stocks sorted according to their past total, idiosyncratic, or systematic returns, within each of these two subsamples.

Panel A of Table 5 reports the outcomes from sorts on total returns, Panel B from sorts on idiosyncratic returns, and Panel C from sorts on systematic returns. Results in Panel A show that medium-term momentum returns are only marginally higher in the "extreme-beta" subsample (0.58% per month), compared to the "modest-beta" subsample (0.54%). The same holds true for the Fama and French (2015) alphas which are 0.68% per month in the "extreme-beta" subsample and 0.64% per month in the "modest-beta" subsample. In contrast, the performance of short-term reversal strategies differs substantially across the two subsamples, in that the performance is much stronger in the "modest-beta" subsample. Sorting by stocks' short-term (medium-term) idiosyncratic returns in Panel B, raw returns and alphas are more (less) similar across the two subsamples, compared to the outcomes for standard short-term reversal (momentum) strategies. Lastly, results reported in Panel C demonstrate that medium-term systematic returns do not predict future stock performance in either subsample, while short-term systematic momentum only emerges in the "extreme-beta" subsample. Taken together, these results indicate that positive factor timing counteracts mean-reversion in firm-specific returns at a *one-month* horizon. The impact of the factor timing channel is bound to be limited in the "modest-beta" subsample, since we restrict the investment universe to stocks with similar betas. Hence, short-term reversal becomes more pronounced. The opposite holds in the "extreme-beta" subsample, where sorting on short-term systematic returns allows us to fully exploit short-term factor autocorrelations.

To complement the analysis in Panel A of Table 5, we plot the evolution of the total return strategies' net loadings against the Fama and French (2015) factors over the entire sample period in Figure A3 in the appendix. Factor loadings of the top and bottom past-return quintiles are computed as

[33] Table A5 in the appendix shows the number of observations and distributional characteristics of total, excess, idiosyncratic and systematic stock returns, as well as firm size and factor loadings for the full sample with non-missing factor loadings and both subsamples. Average firm size and return measures are similar in both subsamples. Unsurprisingly, the standard deviation in factor betas is larger in the "extreme-beta", compared to the "modest-beta" subsample.

the value-weighted average loadings of composite stocks. The blue (red) lines depict dynamic factor loadings for strategies implemented within the "extreme-beta" ("modest-beta") subsamples. Panel A reports results on medium-term momentum strategies, Panel B on short-term reversal strategies. Results in both panels show that strategies implemented in the "extreme-beta" subsample indeed exhibit much greater time series variation in net factor loadings and thus a larger capacity to benefit from factor timing. However, as Table 5 shows, this is not reflected in a superior performance of medium-term momentum strategies, suggesting that the lion's share of stock momentum does not stem from factor timing.

In summary, the results in this section do not support the conjecture that stock momentum profits are to a significant extent affected by the cross-sectional variation in stocks' betas.

[Table 5 about here]

## 6. Strategies with equal industry weights

Demeaning past returns with their industry averages, as proposed by Asness et al. (2000), does not ensure that the industry composition of momentum portfolios remains stable over time. Certain industries might then be more heavily represented in the top and bottom momentum portfolios and, assuming that the relative share of each industry reflects past industry performance, industry momentum may potentially still contribute to the profitability of stock momentum.

To address this concern, we construct medium-term momentum and short-term reversal strategies with equal industry weights. To this end, each month, we first rank stocks by their past total, idiosyncratic, or systematic returns (defined as in Table 3) and sort them into quintile portfolios, using NYSE breakpoints. Within each past-return quintile, that contains $N_t$ stocks, we then compute a scaling factor $k_{j,t}$ for every Moskowitz and Grinblatt (1999) industry $j \in M_t$ represented by at least one stock, based on the sum of included stocks' lagged market equity $ME_{i,j,t-1}$.

$$k_{j,t} = \frac{\sum_{i=1}^{N_t} ME_{i,j,t-1}}{\sum_{i=1}^{N_t} ME_{i,j,t-1} * \theta_{i,j,t}} \quad , \tag{7}$$

where $\theta_{i,j,t}$ is a dummy variable which equals one if stock $i$ belongs to industry $j$ at time $t$, and zero otherwise. We then scale stocks' market equity with $k_{j,t}$ and compute portfolio weights $\widetilde{w}_{i,j,t}$ for each stock as follows:

$$\widetilde{ME}_{i,j,t-1} = k_{j,t} * ME_{i,j,t-1} \tag{8}$$

$$\widetilde{w}_{i,j,t} = \frac{\widetilde{ME}_{i,j,t-1}}{\sum_{i=1}^{N_t} \widetilde{ME}_{i,j,t-1}} \quad , with \sum_{i=1}^{N_t} \widetilde{w}_{i,j,t} = 1 \tag{9}$$

Finally, we compute quintile portfolio returns as the weighted average, using weights $\widetilde{w}_{i,j,t}$, and implement high-low quintile strategies. Adjusting portfolio weights in this manner ensures that stocks within each industry are value-weighted, while industries $j \in M_t$ within the portfolio are equal-weighted. This allows us to rule out the possibility that investment performance is driven by either static or dynamic industry exposures.[34] The relative share of each industry in the portfolio only changes, whenever $M_t \neq M_{t-1}$.[35]

Table 6 reports portfolio returns and returns of high-low quintile strategies. The outcomes suggest that stock momentum exists largely separate from industry momentum. Compared to the results for industry-demeaned returns, reported in Panel B of Table 3, raw returns for short-term reversal strategies based on total (idiosyncratic) returns increase in magnitude from -0.70% (-0.98%) per month to -1.07% (-1.15%) per month, respectively. In contrast, average returns for medium-term momentum strategies based on total (idiosyncratic) decrease from 0.65% (0.56%) to 0.49% (0.34%), yet remain statistically significant. Fama and French (2015) alphas increase or decrease in line with the corresponding changes in raw returns. Finally, consistent with results in Table 3, none of the strategies based on stocks' systematic returns achieve statistically significant outperformance.

[Table 6 about here]

In Figure A4 in the appendix we graphically compare the industry composition of portfolios that results from either industry-demeaning past returns (see Table 3) or adjusting portfolio weights (see

[34] Of course, this conclusion rests on the assumption that our industry definitions are appropriate. Unreported results show that the outcomes are robust to using 29 Fama-French industries, instead.
[35] In some months, certain industries are not represented in the top or bottom past-return portfolios.

Table 6). Panel A displays the amount invested into each industry for the industry-demeaned total return strategies. Looking at the industry composition of the top (Q5) and bottom (Q1) momentum portfolios, it becomes evident that there is substantial time variation. For example, around the year 2000, a sizeable portion of the Q1 portfolio consists of electrical equipment stocks. Panel B shows that this variation is almost completely eliminated for strategies with equal industry weights, which renders them industry-neutral in a strict sense.[36]

In summary, the results in this section show that stock momentum is unlikely to be driven by industry momentum. Even when adjusting portfolio weights in a way that ensures that the industry composition of each past-return quintile remains largely constant over time, the performance of the resulting momentum strategies remains comparable to that of momentum strategies which either (1) do not account for industry effects at all, or (2) use a more coarse control for industry effects by demeaning past returns with industry averages.

## 7. Conclusion

Prior research shows that individual stocks, as well as industry, equity style, and long-short factor portfolios exhibit price momentum, that is, a tendency of assets, which outperformed (underperformed) in the past to outperform (underperform) into the future. These empirical findings pose a challenge for behavioral models, which focus on psychological biases in how the investment community processes firm-specific information (Lewellen, 2002). For instance, why should patterns of under-, or overreaction to news about specific companies induce return continuation at the level of well-diversified portfolios? Other studies provide evidence that equity momentum is a systematic phenomenon, which originates at the portfolio level. In particular, momentum in industries (Moskowitz and Grinblatt, 1999), or equity risk factors (Ehsani and Linnainmaa, 2021) might transmit "top-down" into the cross-section of stock returns, as long as stocks differ in terms of their industry affiliations or factor exposures.

[36] The industry composition of the top and bottom past-return portfolios remains constant, except when industries disappear (due to not being represented by at least one stock) or re-appear. Investment weights for the remaining industries are then scaled up or down accordingly.

We revisit the findings of prior literature and present evidence that momentum in individual U.S. stocks exists separate from momentum in industries or factors. To this end, we decompose stocks' past returns into systematic (i.e., expected) and idiosyncratic (i.e., firm-specific) returns and show that, consistently, positive predictability only resides in the latter, firm-specific component. Specifically, a momentum strategy based on idiosyncratic (systematic) returns, measured over the last year and skipping the month before portfolio formation, does (does not) deliver statistically significant outperformance – the opposite of what we would expect if factor momentum were responsible for momentum in individual stocks. This central finding is robust to demeaning stocks' past returns with the average past returns of their respective industries, following Asness et al. (2000), and survives additional robustness tests. Most important, we compute idiosyncratic returns according to multiple factor models and obtain qualitatively identical outcomes. Restricting the investment universe to stocks with similar factor exposures leaves momentum performance largely unaffected, which stands at odds with the hypothesis that stock momentum stems from implicit timing of autocorrelated factors. Finally, we adjust stocks' investment weights within momentum-sorted portfolios, such that each industry is weighted equally. This industry-neutral momentum strategy performs similar to a conventional momentum strategy, demonstrating that implicit industry bets, too, do not meaningfully contribute to stock momentum profits.

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**Table 1: Equity momentum and reversal**

Panel A shows mean returns and Fama and French (2015) alphas of short-term reversal ($r_{t-1}$) and medium-term momentum ($r_{t-12,t-2}$) strategies using individual stocks. At the beginning of each month, stocks are ranked on their past returns and sorted into five value-weighted (NYSE breakpoints) or equal-weighted (unconditional breakpoints) portfolios. The strategies then go long (short) the top (bottom) quintile for the current month, with monthly rebalancing. Panel B shows the performance of short- ($r_{t-1}$) and medium-term ($r_{t-12,t-2}$) momentum in industry, style and factor portfolios. We rank portfolios each month, going long / short $N_t^L = N_t^S = round(N_t/5)$ portfolios, where $N_t$ is the number of portfolios in the investment opportunity set in month $t$. The long and short sides are rescaled to unit leverage and rebalanced monthly. Industry portfolios are formed every month, following Moskowitz and Grinblatt (1999). We exclude financial firms (SIC codes starting with 6), resulting in a total of 19 industries. Style momentum is implemented using 25 portfolios double-sorted by firm size ($Size$) and book-to-market ratios ($B/M$). Portfolios are formed once a year at the end of June, using Compustat book and market equity figures for the end of the previous fiscal year and NYSE breakpoints. We construct cross-sectional factor momentum, using a set of 133 anomaly portfolios provided by Hou, Xue, and Zhang (2020). See Section 1 for a detailed description of factor construction. The sample period is July 1966 to Dec. 2019. The starting date for factor momentum is Jan. 1968. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Panel A: Stock momentum and short-term reversal

| Q5-Q1 | Short-term stock returns ($r_{t-1}$) | | Medium-term stock returns ($r_{t-12,t-2}$) | |
|---|---|---|---|---|
| | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| Value-weighted | **-0.337** | -0.190 | **0.660** | **0.755** |
| | (-2.19) | (-1.06) | (3.05) | (2.83) |
| Equal-weighted | **-1.548** | **-1.518** | **0.846** | **0.765** |
| | (-7.87) | (-5.21) | (3.52) | (2.45) |

Panel B: Industry, style and factor momentum

| Q5-Q1 | Short-term portfolio returns ($r_{t-1}$) | | Medium-term portfolio returns ($r_{t-12,t-2}$) | |
|---|---|---|---|---|
| | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| 19 Moskowitz-Grinblatt industries | **0.532** | **0.591** | **0.395** | **0.535** |
| | (3.62) | (3.57) | (2.22) | (2.70) |
| 25 $Size$-$B/M$ portfolios | **0.632** | **0.648** | **0.397** | **0.459** |
| | (4.54) | (3.50) | (2.62) | (2.49) |
| 133 Hou-Xue-Zhang factors | **1.085** | **1.161** | **0.652** | **0.733** |
| | (6.52) | (5.86) | (3.57) | (3.33) |

**Table 2: Momentum and reversal strategies on random portfolios**

Panel A shows mean returns and Fama and French (2015) alphas of short-term reversal ($r_{t-1}$) and medium-term momentum ($r_{t-12,t-2}$) strategies, implemented using value-weighted randomized stock portfolios. We assign a random variable to each stock once it enters the sample. Stocks are ranked on this random identifier and permanently assigned to one of $N \in [10, 50, \ldots, 20{,}376]$ portfolios. The number of stocks in each portfolio changes over time, as stocks enter and leave the sample. Portfolio returns are computed as the value-weighted average return of composite stocks. In the second step, we rank portfolios each month by their past returns and make an equal-weighted long (short) investment into the portfolios with the largest (smallest) past returns, using the 80% (20%) past-return percentiles. We report the average performance of these strategies from 1,000 random sampling exercises. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher. Panel B reports the time-series averages of the number of non-empty portfolios, the number of stocks included in these portfolios, the cross-sectional standard deviation in portfolio returns and Fama and French (2015) factor loadings, as well as the median R-squared from a full-sample regression of excess portfolio returns on the Fama and French (2015) model, requiring at least 36 return observations. The sample period is July 1966 to Dec. 2019.

Panel A: Performance of momentum and short-term reversal using random portfolios

| Q5-Q1 | | Number of portfolios | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 5 | 10 | 50 | 100 | 200 | 400 | 800 | 20,376 |
| Short-term returns ($r_{t-1}$) | $\bar{r}$ | -0.018 | -0.029 | -0.063 | -0.088 | -0.130 | **-0.210** | **-0.386** | **-1.548** |
| | | (-0.29) | (-0.46) | (-0.87) | (-1.09) | (-1.42) | (-2.01) | (-3.22) | (-7.87) |
| | $\alpha^{FF5F}$ | -0.002 | -0.008 | -0.020 | -0.032 | -0.056 | -0.119 | -0.293 | **-1.518** |
| | | (-0.04) | (-0.12) | (-0.25) | (-0.33) | (-0.50) | (-0.91) | (-1.88) | (-5.21) |
| Medium-term returns ($r_{t-12,t-2}$) | $\bar{r}$ | 0.046 | 0.074 | 0.180 | **0.235** | **0.311** | **0.429** | **0.595** | **0.846** |
| | | (0.70) | (1.06) | (1.92) | (2.16) | (2.47) | (2.97) | (3.65) | (3.52) |
| | $\alpha^{FF5F}$ | 0.064 | 0.104 | **0.246** | **0.320** | **0.413** | **0.534** | **0.676** | **0.765** |
| | | (0.87) | (1.25) | (2.13) | (2.37) | (2.64) | (2.96) | (3.30) | (2.45) |

Panel B: Characteristics of random portfolios

| Time-series average characteristics | Number of portfolios | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 5 | 10 | 50 | 100 | 200 | 400 | 800 | 20,376 |
| # non-empty port. | 5.0 | 10.0 | 50.0 | 100.0 | 200.0 | 399.8 | 789.6 | 3,830.3 |
| # stocks in port. | 789.4 | 394.7 | 78.9 | 39.5 | 19.7 | 9.9 | 5.0 | 1.0 |
| median $R^2_{FF5F}$ | 0.95 | 0.92 | 0.76 | 0.68 | 0.58 | 0.47 | 0.36 | 0.20 |
| $\sigma^{CS}(r_p)$ | 0.98 | 1.37 | 2.66 | 3.41 | 4.40 | 5.83 | 8.15 | 16.49 |
| $\sigma^{CS}(\beta_{RMRF})$ | 0.06 | 0.08 | 0.15 | 0.20 | 0.25 | 0.34 | 0.47 | 0.72 |
| $\sigma^{CS}(\beta_{SMB})$ | 0.10 | 0.14 | 0.27 | 0.35 | 0.45 | 0.59 | 0.76 | 1.14 |
| $\sigma^{CS}(\beta_{HML})$ | 0.12 | 0.16 | 0.32 | 0.40 | 0.52 | 0.68 | 0.91 | 1.46 |
| $\sigma^{CS}(\beta_{RMW})$ | 0.15 | 0.21 | 0.38 | 0.48 | 0.62 | 0.83 | 1.12 | 1.84 |
| $\sigma^{CS}(\beta_{CMA})$ | 0.18 | 0.24 | 0.45 | 0.55 | 0.69 | 0.89 | 1.20 | 1.99 |

**Table 3: Sorts by total, idiosyncratic, and systematic stock returns**

The first five rows of Panel A show mean returns of value-weighted quintile portfolios sorted on stocks' past total, idiosyncratic, or systematic returns. Below, we report raw and risk-adjusted returns of the corresponding high-low quintile strategies. Firms' loadings against the Fama and French (2015) factors are determined via five-year rolling regressions of monthly stock returns from month $t-60$ to $t-1$, requiring at least 36 monthly return observations. Factor loadings are then used to compute idiosyncratic and systematic prior-month ($\hat{\varepsilon}_{i,t-1}$, $\hat{r}_{i,t-1}$) or medium-term ($\hat{\varepsilon}_{i,t-12,t-2}$, $\hat{r}_{i,t-12,t-2}$) returns (see Equations (1)-(4)). At the beginning of each month, individual stocks are ranked on these past-return measures and sorted into value-weighted quintiles, using NYSE breakpoints. The strategies then go long (short) the top (bottom) portfolio for the current month, with monthly rebalancing. In Panel B, we subtract the value-weighted mean of each Moskowitz and Grinblatt (1999) industry from the original past-return measures, resulting in industry-demeaned predictors. The sample period is July 1966 to Dec. 2019. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Panel A: Standard predictors

| Portfolio return | Total returns | | Idiosyncratic returns | | Systematic returns | |
|---|---|---|---|---|---|---|
| | $r_{t-1}$ | $r_{t-12,t-2}$ | $\hat{\varepsilon}_{t-1}$ | $\hat{\varepsilon}_{t-12,t-2}$ | $\hat{r}_{t-1}$ | $\hat{r}_{t-12,t-2}$ |
| Q1 | 1.066 | 0.628 | 1.357 | 0.635 | 0.828 | 0.831 |
| Q2 | 1.117 | 0.851 | 1.227 | 0.985 | 0.930 | 1.001 |
| Q3 | 0.975 | 0.900 | 0.926 | 0.864 | 1.063 | 1.064 |
| Q4 | 0.856 | 0.982 | 0.789 | 0.926 | 1.083 | 1.084 |
| Q5 | 0.729 | 1.288 | 0.575 | 1.206 | 1.211 | 1.031 |
| Q5-Q1 | **-0.337** | **0.660** | **-0.783** | **0.571** | **0.383** | 0.200 |
| $\bar{r}$ | (-2.19) | (3.05) | (-6.13) | (3.24) | (2.19) | (1.00) |
| Q5-Q1 | -0.190 | **0.755** | **-0.579** | **0.937** | **0.414** | 0.040 |
| $\alpha^{FF5F}$ | (-1.06) | (2.83) | (-4.41) | (5.65) | (2.35) | (0.17) |

Panel B: Industry-demeaned predictors

| Portfolio return | Total returns | | Idiosyncratic returns | | Systematic returns | |
|---|---|---|---|---|---|---|
| | $r_{t-1}$ | $r_{t-12,t-2}$ | $\hat{\varepsilon}_{t-1}$ | $\hat{\varepsilon}_{t-12,t-2}$ | $\hat{r}_{t-1}$ | $\hat{r}_{t-12,t-2}$ |
| Q1 | 1.287 | 0.652 | 1.483 | 0.664 | 0.917 | 0.858 |
| Q2 | 1.180 | 0.847 | 1.298 | 0.983 | 0.965 | 0.958 |
| Q3 | 0.942 | 0.901 | 0.922 | 0.874 | 1.026 | 0.939 |
| Q4 | 0.793 | 0.965 | 0.763 | 0.948 | 1.031 | 1.108 |
| Q5 | 0.591 | 1.299 | 0.501 | 1.224 | 1.134 | 1.069 |
| Q5-Q1 | **-0.696** | **0.647** | **-0.982** | **0.559** | 0.216 | 0.211 |
| $\bar{r}$ | (-5.31) | (3.71) | (-9.16) | (4.02) | (1.46) | (1.33) |
| Q5-Q1 | **-0.541** | **0.724** | **-0.836** | **0.856** | 0.260 | 0.128 |
| $\alpha^{FF5F}$ | (-3.63) | (3.93) | (-7.57) | (6.20) | (1.69) | (0.75) |

**Table 4: Constructing idiosyncratic and systematic returns using different factor models**

Panel A of this table shows raw returns and Fama and French (2015) alphas for high-low quintile strategies sorted on stocks' past idiosyncratic, or systematic returns, computed using different factor models. For each factor model, firms' factor loadings are determined via five-year rolling regressions of monthly stock returns from month $t-60$ to $t-1$, requiring at least 36 monthly return observations. Factor loadings are then used to compute idiosyncratic and systematic short- ($\hat{\varepsilon}_{i,t-1}$, $\hat{r}_{i,t-1}$) or medium-term ($\hat{\varepsilon}_{i,t-12,t-2}$, $\hat{r}_{i,t-12,t-2}$) returns (see Equations (1)-(4)). At the beginning of each month, individual stocks are ranked on these past-return measures and sorted into value-weighted quintiles, using NYSE breakpoints. The strategies then go long (short) the top (bottom) portfolio for the current month, with monthly rebalancing. In Panel B, we subtract the value-weighted mean of each Moskowitz and Grinblatt (1999) industry from the original past-return measures, resulting in industry-demeaned predictors. The sample periods differ due to availability of factor returns and the requirement for a minimum rolling period of 36 months. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Panel A: Standard predictors

| Q5-Q1 | | Idiosyncratic returns | | | | Systematic returns | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\hat{\varepsilon}_{t-1}$ | | $\hat{\varepsilon}_{t-12,t-2}$ | | $\hat{r}_{t-1}$ | | $\hat{r}_{t-12,t-2}$ | |
| Factor model | Period | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| Fama & French (2015) | 07/1966 – | **-0.783** | **-0.579** | **0.571** | **0.937** | **0.383** | **0.414** | 0.200 | 0.040 |
| 5-factor model | 12/2019 | (-6.13) | (-4.41) | (3.24) | (5.65) | (2.19) | (2.35) | (1.00) | (0.17) |
| Fama & French (1993) | 07/1966 – | **-0.758** | **-0.607** | **0.537** | **0.738** | **0.539** | **0.681** | 0.191 | 0.145 |
| 3-factor model | 12/2019 | (-5.87) | (-4.55) | (3.11) | (3.82) | (2.69) | (3.12) | (0.93) | (0.66) |
| CAPM | 07/1966 – | **-0.564** | **-0.410** | **0.701** | **0.889** | **0.570** | **0.727** | -0.126 | -0.205 |
| 1-factor model | 12/2019 | (-3.87) | (-2.36) | (3.71) | (3.87) | (2.55) | (2.93) | (-0.50) | (-0.73) |
| Hou et al. (2021) | 01/1970 – | **-0.657** | **-0.471** | **0.458** | **0.701** | **0.383** | **0.550** | 0.227 | 0.198 |
| 5-factor model | 12/2019 | (-5.11) | (-3.40) | (2.76) | (4.01) | (2.16) | (3.03) | (1.23) | (0.95) |
| Stambaugh & Yuan | 07/1966 – | **-0.690** | **-0.506** | **0.496** | **0.849** | **0.476** | **0.503** | 0.047 | -0.156 |
| (2016) 4-factor model | 12/2016 | (-5.48) | (-3.49) | (2.65) | (4.10) | (2.50) | (2.50) | (0.23) | (-0.73) |

Panel B: Industry-demeaned predictors

| Q5-Q1 | | Idiosyncratic returns | | | | Systematic returns | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\hat{\varepsilon}_{t-1}$ | | $\hat{\varepsilon}_{t-12,t-2}$ | | $\hat{r}_{t-1}$ | | $\hat{r}_{t-12,t-2}$ | |
| Factor model | Period | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| Fama & French (2015) | 07/1966 – | **-0.982** | **-0.836** | **0.559** | **0.856** | 0.216 | 0.260 | 0.211 | 0.128 |
| 5-factor model | 12/2019 | (-9.16) | (-7.57) | (4.02) | (6.20) | (1.46) | (1.69) | (1.33) | (0.75) |
| Fama & French (1993) | 07/1966 – | **-0.964** | **-0.819** | **0.583** | **0.799** | **0.378** | **0.522** | 0.185 | 0.138 |
| 3-factor model | 12/2019 | (-8.72) | (-7.26) | (4.02) | (5.09) | (2.19) | (2.68) | (1.09) | (0.77) |
| CAPM | 07/1966 – | **-0.847** | **-0.700** | **0.729** | **0.952** | 0.341 | **0.432** | -0.055 | -0.136 |
| 1-factor model | 12/2019 | (-6.73) | (-4.64) | (4.64) | (5.40) | (1.91) | (2.23) | (-0.28) | (-0.63) |
| Hou et al. (2021) | 01/1970 – | **-0.930** | **-0.756** | **0.456** | **0.691** | 0.168 | 0.277 | 0.196 | 0.176 |
| 5-factor model | 12/2019 | (-8.26) | (-6.17) | (3.27) | (4.65) | (1.11) | (1.71) | (1.30) | (1.09) |
| Stambaugh & Yuan | 07/1966 – | **-0.932** | **-0.790** | **0.460** | **0.756** | **0.320** | **0.380** | 0.093 | -0.034 |
| (2016) 4-factor model | 12/2016 | (-8.30) | (-6.19) | (3.01) | (4.72) | (2.08) | (2.34) | (0.57) | (-0.21) |

**Table 5: Momentum and reversal within "modest-beta" and "extreme-beta" subsamples**

This table shows mean returns and Fama and French (2015) alphas of high-low quintile strategies, where value-weighted quintile portfolios are sorted on stocks' past total (Panel A), idiosyncratic (Panel B), or systematic returns (Panel C), using NYSE breakpoints (see Table 3 for details). We implement these strategies on two different subsamples. We define the "extreme-beta" subsample as all stocks, for which at least one of the current-month betas against the Fama and French (2015) factors ranks above the 80th or below the 20th percentile. Firms' loadings are determined via five-year rolling regressions of monthly stock returns from month $t-60$ to $t-1$, requiring at least 36 monthly return observations. All other stocks with non-missing factor loadings then form the "modest-beta" subsample. Table A5 in the appendix presents summary statistics for the full sample and the two subsamples. The sample period is July 1966 to Dec. 2019. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Panel A: Total returns

| Q5-Q1 | Short-term returns ($r_{t-1}$) | | Medium-term returns ($r_{t-12,t-2}$) | |
|---|---|---|---|---|
| | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| "Modest-beta" sample | **-0.821** | **-0.637** | **0.544** | **0.642** |
| | (-5.45) | (-3.95) | (2.83) | (2.90) |
| "Extreme-beta" sample | **-0.360** | -0.181 | **0.585** | **0.682** |
| | (-2.27) | (-1.00) | (2.61) | (2.45) |

Panel B: Idiosyncratic returns

| Q5-Q1 | Short-term returns ($\hat{\varepsilon}_{t-1}$) | | Medium-term returns ($\hat{\varepsilon}_{t-12,t-2}$) | |
|---|---|---|---|---|
| | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| "Modest-beta" sample | **-0.897** | **-0.672** | **0.536** | **0.709** |
| | (-6.17) | (-4.41) | (3.05) | (3.89) |
| "Extreme-beta" sample | **-0.748** | **-0.536** | **0.621** | **1.014** |
| | (-5.45) | (-3.84) | (3.32) | (5.73) |

Panel C: Systematic returns

| Q5-Q1 | Short-term returns ($\hat{r}_{t-1}$) | | Medium-term returns ($\hat{r}_{t-12,t-2}$) | |
|---|---|---|---|---|
| | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| "Modest-beta" sample | 0.168 | 0.287 | 0.167 | 0.212 |
| | (1.02) | (1.76) | (1.02) | (1.14) |
| "Extreme-beta" sample | **0.466** | **0.502** | 0.201 | 0.031 |
| | (2.39) | (2.48) | (0.94) | (0.12) |

**Table 6: Momentum and reversal with equal industry weights**

The first five rows of this table show mean returns of quintile portfolios with equal industry weights sorted on stocks' past total, idiosyncratic, or systematic returns. Below, we report raw and risk-adjusted returns of the corresponding high-low quintile strategies. Firms' loadings against the Fama and French (2015) factors are determined via five-year rolling regressions of monthly stock returns from month $t-60$ to $t-1$, requiring at least 36 monthly return observations. Factor loadings are then used to compute idiosyncratic and systematic prior-month ($\hat{\varepsilon}_{i,t-1}$, $\hat{r}_{i,t-1}$) or medium-term ($\hat{\varepsilon}_{i,t-12,t-2}$, $\hat{r}_{i,t-12,t-2}$) returns (see Equations (1)-(4)). At the beginning of each month, individual stocks are ranked on these past-return measures and sorted into quintiles, using NYSE breakpoints. We adjust stocks' monthly investment weights, such that Moskowitz and Grinblatt (1999) industries represented by at least one stock are equal weighted. Stocks within each industry are value-weighted (see Equations (7) to (9)). The strategies then go long (short) the top (bottom) portfolio for the current month, with monthly rebalancing. The sample period is July 1966 to Dec. 2019. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

| Portfolio return | Total returns | | Idiosyncratic returns | | Systematic returns | |
|---|---|---|---|---|---|---|
| | $r_{t-1}$ | $r_{t-12,t-2}$ | $\hat{\varepsilon}_{t-1}$ | $\hat{\varepsilon}_{t-12,t-2}$ | $\hat{r}_{t-1}$ | $\hat{r}_{t-12,t-2}$ |
| Q1 | 1.584 | 0.777 | 1.640 | 0.826 | 0.988 | 0.915 |
| Q2 | 1.293 | 0.910 | 1.303 | 1.044 | 1.119 | 1.002 |
| Q3 | 1.033 | 1.052 | 1.030 | 0.947 | 1.118 | 1.111 |
| Q4 | 0.812 | 1.074 | 0.797 | 1.078 | 1.068 | 1.150 |
| Q5 | 0.512 | 1.262 | 0.486 | 1.169 | 1.027 | 1.173 |
| Q5-Q1 | **-1.072** | **0.485** | **-1.154** | **0.343** | 0.040 | 0.259 |
| $\bar{r}$ | (-8.53) | (2.49) | (-10.66) | (2.22) | (0.28) | (1.67) |
| Q5-Q1 | **-0.895** | **0.669** | **-0.963** | **0.627** | 0.121 | 0.192 |
| $\alpha^{FF5F}$ | (-6.46) | (3.43) | (-8.54) | (4.43) | (0.88) | (1.11) |

# Appendix A: Additional tables and figures

### Table A1: Equity momentum and reversal: Robustness

Panel A shows mean returns and Fama and French (2015) alphas of short-term reversal ($r_{t-1}$) and medium-term momentum ($r_{t-12,t-2}$) strategies using individual stocks. At the beginning of each month, stocks are ranked on their past returns and sorted into ten value-weighted (NYSE breakpoints) or equal-weighted (unconditional breakpoints) portfolios. The strategies then go long (short) the top (bottom) decile for the current month, with monthly rebalancing. Panels B shows the performance of short- ($r_{t-1}$) and medium-term ($r_{t-12,t-2}$) momentum in industry, style and factor portfolios. We rank industry and style portfolios each month, going long / short $N_t^L = N_t^S = round(N_t/5)$ portfolios, where $N_t$ is the number of portfolios in the investment opportunity set in month $t$. The long and short sides are rescaled to unit leverage and rebalanced monthly. Industry portfolios are formed every month, following the definitions on Ken French's webpage for 30 industries. We exclude financial firms (SIC codes starting with 6), resulting in a total of 29 industries. Style momentum is implemented using 25 portfolios double-sorted by operating profitability and asset growth. Portfolios are formed once a year at the end of June, using Compustat figures for the end of the previous fiscal year and NYSE breakpoints. $OPAT$ is operating profitability, computed by deducting selling, general, and administrative expenses (without R&D expenses) from gross profit and then dividing by the book value of total assets from year $t-1$ (Ball, Gerakos, Linnainmaa, & Nikolaeva, 2015). $\Delta AT$ is asset growth, computed as the change in total assets from year $t-2$ to year $t-1$, divided by total assets in year $t-2$. We implement factor momentum using the Fama and French (2015) size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. Factors are ranked each month and an equal-weighted long (short) investment is made into the two factors with above-(below-)median past performance. The sample period is July 1966 to Dec. 2019. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Panel A: Stock momentum and short-term reversal

| D10-D1 | Short-term stock returns ($r_{t-1}$) | | Medium-term stock returns ($r_{t-12,t-2}$) | |
|---|---|---|---|---|
| | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| Value-weighted | -0.307 | -0.134 | **1.149** | **1.283** |
| | (-1.68) | (-0.65) | (4.14) | (3.90) |
| Equal-weighted | **-2.418** | **-2.377** | **0.865** | **0.758** |
| | (-9.00) | (-6.17) | (2.85) | (1.91) |

Panel B: Industry, style and factor momentum

| Q5-Q1 | Short-term industry returns ($r_{t-1}$) | | Medium-term industry returns ($r_{t-12,t-2}$) | |
|---|---|---|---|---|
| | $\bar{r}$ | $\alpha^{FF5F}$ | $\bar{r}$ | $\alpha^{FF5F}$ |
| 29 Fama-French industries | **0.675** | **0.773** | **0.558** | **0.661** |
| | (4.69) | (4.91) | (2.93) | (2.91) |
| 25 $OPAT$-$\Delta AT$ portfolios | **0.316** | **0.325** | **0.261** | 0.266 |
| | (2.89) | (2.70) | (2.48) | (1.94) |
| Fama and French (2015) factors (w/o market) * | **0.629** | **0.675** | **0.233** | **0.328** |
| | (5.51) | (4.96) | (2.00) | (2.49) |

* two factors long / short

**Table A2: Correlations and spanning tests**

This table show pairwise correlations (Panel A) and the outcomes of spanning tests (Panel B), for short- ($r_{t-1}$) and medium-term ($r_{t-12,t-2}$) strategies. See Table 1 for details on the construction of each strategy. Stock-level strategies analyzed in this table correspond to the value-weighted Q5-Q1 specification. On the left-hand (right-hand) side of Panel B, the dependent variables are the returns of short-term (medium-term) strategies implemented using individual stocks, industries, style portfolios, or factors, which are regressed on their peer strategies, constructed over the same formation period, and the five factors of Fama and French (2015). The sample period is Jan. 1968 (starting date for factor momentum) to Dec. 2019. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Panel A: Pairwise correlations

| | Short-term strategies ($r_{t-1}$) | | | | Medium-term strategies ($r_{t-12,t-2}$) | | | |
|---|---|---|---|---|---|---|---|---|
| | Stock rev. | Industry mom. | Style mom. | Factor mom. | Stock mom. | Industry mom. | Style mom. | Factor mom. |
| Stock mom. / rev. | 1.000 | | | | 1.000 | | | |
| Industry mom. | 0.738 | 1.000 | | | 0.778 | 1.000 | | |
| Style mom. | 0.650 | 0.521 | 1.000 | | 0.587 | 0.526 | 1.000 | |
| Factor mom. | 0.737 | 0.681 | 0.700 | 1.000 | 0.730 | 0.702 | 0.732 | 1.000 |

Panel B: Spanning tests

| | Dependent variables: Short-term strategies ($r_{t-1}$) | | | | Dependent variables: Medium-term strategies ($r_{t-12,t-2}$) | | | |
|---|---|---|---|---|---|---|---|---|
| Independent variables | Stock rev. | Industry mom. | Style mom. | Factor mom. | Stock mom. | Industry mom. | Style mom. | Factor mom. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Stock mom. / rev. | | **0.507** | **0.310** | **0.307** | | **0.486** | **0.194** | **0.217** |
| | | (10.13) | (5.54) | (6.08) | | (13.17) | (3.78) | (4.72) |
| Industry mom. | **0.461** | | -0.061 | **0.304** | **0.623** | | **-0.087** | **0.281** |
| | (10.36) | | (-1.08) | (6.47) | (10.33) | | (-2.02) | (6.25) |
| Style mom. | **0.262** | -0.057 | | **0.399** | **0.263** | **-0.092** | | **0.480** |
| | (5.45) | (-1.11) | | (5.85) | (4.44) | (-1.99) | | (7.16) |
| Factor mom. | **0.268** | **0.292** | **0.412** | | **0.308** | **0.310** | **0.503** | |
| | (5.52) | (6.03) | (4.38) | | (5.01) | (5.44) | (7.31) | |
| Constant | **-0.918** | **0.355** | 0.223 | **0.803** | 0.068 | -0.009 | -0.014 | 0.200 |
| | (-6.74) | (2.79) | (1.43) | (6.12) | (0.47) | (-0.08) | (-0.11) | (1.57) |
| FF5 factor control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 624 | 624 | 624 | 624 | 624 | 624 | 624 | 624 |
| adj. $R^2$ | 0.699 | 0.593 | 0.534 | 0.665 | 0.720 | 0.660 | 0.588 | 0.703 |

**Table A3: Sorts by idiosyncratic and systematic stock returns: Alternative rolling period**

The first five rows of Panel A show mean returns of value-weighted quintile portfolios sorted on stocks' past idiosyncratic, or systematic returns. Below, we report raw and risk-adjusted returns of the corresponding high-low quintile strategies. Firms' loadings against the Fama and French (2015) factors are determined via five-year rolling regressions of monthly stock returns from month $t-72$ to $t-13$, requiring at least 36 monthly return observations. Factor loadings are then used to compute idiosyncratic and systematic prior-month ($\hat{\varepsilon}_{i,t-1}$, $\hat{r}_{i,t-1}$) or medium-term ($\hat{\varepsilon}_{i,t-12,t-2}$, $\hat{r}_{i,t-12,t-2}$) returns (see Equations (1)-(4)). At the beginning of each month, individual stocks are ranked on these past-return measures and sorted into value-weighted quintiles, using NYSE breakpoints. The strategies then go long (short) the top (bottom) portfolio for the current month, with monthly rebalancing. In Panel B, we subtract the value-weighted mean of each Moskowitz and Grinblatt (1999) industry from the original past-return measures, resulting in industry-demeaned predictors. The sample period is July 1967 to Dec. 2019. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Panel A: Standard predictors

| Portfolio return | Idiosyncratic returns | | Systematic returns | |
|---|---|---|---|---|
| | $\hat{\varepsilon}_{t-1}$ | $\hat{\varepsilon}_{t-12,t-2}$ | $\hat{r}_{t-1}$ | $\hat{r}_{t-12,t-2}$ |
| Q1 | 1.328 | 0.686 | 0.682 | 0.896 |
| Q2 | 1.189 | 0.898 | 0.850 | 0.938 |
| Q3 | 0.983 | 0.912 | 1.064 | 1.040 |
| Q4 | 0.765 | 0.980 | 1.059 | 1.041 |
| Q5 | 0.597 | 1.162 | 1.252 | 1.023 |
| Q5-Q1 | **-0.730** | **0.476** | **0.570** | 0.126 |
| $\bar{r}$ | (-5.62) | (2.74) | (3.56) | (0.74) |
| Q5-Q1 | **-0.567** | **0.744** | **0.610** | -0.056 |
| $\alpha^{FF5F}$ | (-4.14) | (3.94) | (3.72) | (-0.28) |

Panel B: Industry-demeaned predictors

| Portfolio return | Idiosyncratic returns | | Systematic returns | |
|---|---|---|---|---|
| | $\hat{\varepsilon}_{t-1}$ | $\hat{\varepsilon}_{t-12,t-2}$ | $\hat{r}_{t-1}$ | $\hat{r}_{t-12,t-2}$ |
| Q1 | 1.473 | 0.719 | 0.764 | 0.899 |
| Q2 | 1.255 | 0.946 | 0.911 | 0.970 |
| Q3 | 0.937 | 0.883 | 1.023 | 0.946 |
| Q4 | 0.756 | 0.954 | 1.021 | 1.027 |
| Q5 | 0.482 | 1.223 | 1.234 | 1.072 |
| Q5-Q1 | **-0.991** | **0.505** | **0.470** | 0.172 |
| $\bar{r}$ | (-8.98) | (3.61) | (3.65) | (1.19) |
| Q5-Q1 | **-0.851** | **0.774** | **0.525** | 0.037 |
| $\alpha^{FF5F}$ | (-6.99) | (5.10) | (4.12) | (0.23) |

**Table A4: Fama and MacBeth (1973) regressions with idiosyncratic and systematic returns**

This table presents the outcomes of Fama and MacBeth (1973) cross-sectional regressions, where stocks' monthly (total) returns are regressed on short-term ($\hat{\varepsilon}_{i,t-1}$, $\hat{r}_{i,t-1}$) and medium-term ($\hat{\varepsilon}_{i,t-12,t-2}$, $\hat{r}_{i,t-12,t-2}$) idiosyncratic and systematic returns, defined as in Table 3, plus additional stock characteristics. Columns (1) to (3) report time-series average coefficient estimates for the standard predictors, analyzed in Table 3 Panel A. Columns (4) to (6) show coefficient estimates for the industry-demeaned predictors, analyzed in Table 3 Panel B. Observations in each cross-section are value-weighted, using firms' lagged market equity. We include the logarithm of market equity ($Size$), the logarithm of the book-to-market ratio ($B/M$), operating profitability ($OPAT$), and asset growth ($\Delta AT$) as controls. Exact variable definitions are provided in Table 1 and Table A1. The sample period is July 1966 to Dec. 2019. $t$-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

| Independent variables | Dependent variable: Stock returns ($r_t$) | | | | | |
|---|---|---|---|---|---|---|
| | Standard predictors | | | Industry-demeaned predictors | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\hat{\varepsilon}_{t-1}$ | **-0.037** | | **-0.039** | **-0.045** | | **-0.046** |
| | (-7.91) | | (-8.50) | (-10.81) | | (-10.91) |
| $\hat{r}_{t-1}$ | | 0.013 | 0.006 | | -0.004 | -0.010 |
| | | (0.68) | (0.33) | | (-0.28) | (-0.72) |
| $\hat{\varepsilon}_{t-12,t-2}$ | **0.008** | | **0.008** | **0.007** | | **0.007** |
| | (4.00) | | (4.18) | (4.46) | | (4.42) |
| $\hat{r}_{t-12,t-2}$ | | 0.004 | 0.007 | | 0.003 | 0.005 |
| | | (0.86) | (1.48) | | (0.99) | (1.39) |
| $\log(Size)$ | -0.001 | -0.000 | -0.000 | -0.001 | -0.000 | -0.000 |
| | (-1.72) | (-1.29) | (-1.27) | (-1.77) | (-1.51) | (-1.51) |
| $\log(B/M)$ | **0.002** | **0.002** | **0.002** | **0.002** | **0.002** | **0.002** |
| | (2.68) | (2.24) | (2.60) | (2.59) | (2.22) | (2.47) |
| $OPAT$ | **0.016** | **0.016** | **0.015** | **0.017** | **0.017** | **0.017** |
| | (4.58) | (4.67) | (4.52) | (4.79) | (4.62) | (4.68) |
| $\Delta AT$ | **-0.002** | **-0.002** | **-0.002** | **-0.002** | **-0.002** | **-0.002** |
| | (-2.22) | (-2.24) | (-2.44) | (-2.15) | (-2.37) | (-2.58) |
| N | 1,739,193 | 1,739,193 | 1,739,193 | 1,738,716 | 1,738,716 | 1,738,716 |
| $R^2$ | 0.101 | 0.108 | 0.137 | 0.088 | 0.088 | 0.107 |

**Table A5: Summary statistics of "modest-beta" and "extreme-beta" subsamples**

This table presents distributional characteristics of total ($r_t$), excess ($r_t^e$), idiosyncratic ($\hat{\varepsilon}_t$), and systematic ($\hat{r}_t$) returns (see Equations (1) to (4)), as well as firm size and factor loadings for different stock-month samples. Panel A shows this information for the full sample of stock-months with non-missing factor loadings. In Panel B, we define the "extreme-beta" subsample as all stocks, for which at least one of the current-month betas against the Fama and French (2015) factors ranks above the 80th or below the 20th percentile (see Table 5). Firms' loadings are determined via five-year rolling regressions of monthly stock returns from month $t-60$ to $t-1$, requiring at least 36 monthly return observations. All other stocks with non-missing factor loadings then form the "modest-beta" subsample. $Size$ corresponds to Compustat market equity in June, using prior year-end figures. The sample period is July 1966 to Dec. 2019.

Panel A: Full sample

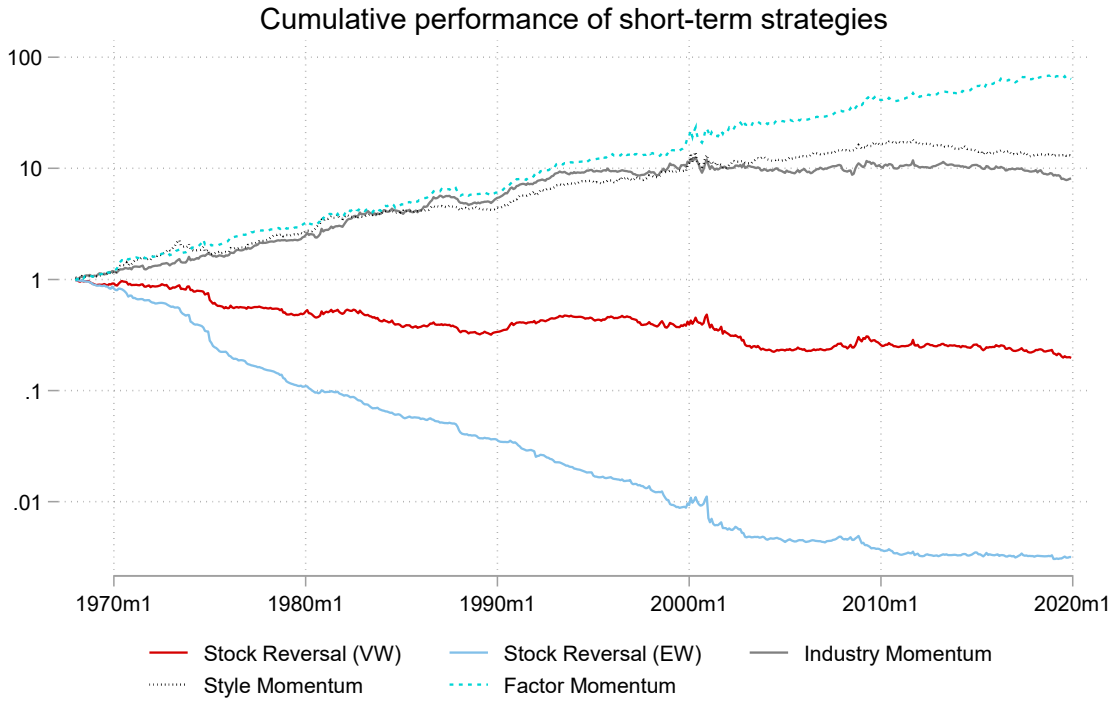
| Full sample | N | Mean | SD | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| $r_t$ | 1,841,110 | 1.33 | 17.65 | -6.45 | 0.00 | 7.36 |
| $r_t^e$ | 1,841,110 | 0.93 | 17.65 | -6.85 | -0.32 | 6.98 |
| $\hat{\varepsilon}_t$ | 1,841,110 | 0.17 | 17.42 | -7.22 | -0.63 | 6.10 |
| $\hat{r}_t$ | 1,841,110 | 0.76 | 9.04 | -3.01 | 0.88 | 4.80 |
| $Size$ | 1,838,658 | 2,102.7 | 13,950.0 | 23.6 | 109.9 | 631.8 |
| $\beta^{MKT}$ | 1,841,110 | 0.98 | 0.75 | 0.57 | 0.95 | 1.35 |
| $\beta^{SMB}$ | 1,841,110 | 0.89 | 1.20 | 0.20 | 0.77 | 1.45 |
| $\beta^{HML}$ | 1,841,110 | 0.04 | 1.50 | -0.68 | 0.07 | 0.81 |
| $\beta^{RMW}$ | 1,841,110 | -0.19 | 1.89 | -1.00 | -0.03 | 0.79 |
| $\beta^{CMA}$ | 1,841,110 | 0.00 | 2.12 | -0.98 | 0.02 | 0.98 |

Panel B: Subsamples ("modest-beta" versus "extreme-beta" stock-months)

| "modest-beta" sample | N | Mean | SD | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| $r_t$ | 269,272 | 1.33 | 11.62 | -4.59 | 0.70 | 6.52 |
| $r_t^e$ | 269,272 | 0.94 | 11.63 | -4.99 | 0.33 | 6.14 |
| $\hat{\varepsilon}_t$ | 269,272 | 0.12 | 10.70 | -5.27 | -0.37 | 4.74 |
| $\hat{r}_t$ | 269,272 | 0.82 | 5.52 | -1.97 | 1.05 | 3.89 |
| $Size$ | 269,153 | 2,340.4 | 10,493.8 | 57.1 | 251.2 | 1,160.7 |
| $\beta^{MKT}$ | 269,272 | 0.92 | 0.28 | 0.71 | 0.92 | 1.13 |
| $\beta^{SMB}$ | 269,272 | 0.71 | 0.43 | 0.36 | 0.65 | 1.01 |
| $\beta^{HML}$ | 269,272 | 0.12 | 0.51 | -0.26 | 0.13 | 0.50 |
| $\beta^{RMW}$ | 269,272 | 0.03 | 0.61 | -0.40 | 0.10 | 0.50 |
| $\beta^{CMA}$ | 269,272 | 0.05 | 0.67 | -0.43 | 0.07 | 0.54 |
| "extreme-beta" sample | N | Mean | SD | P25 | Median | P75 |
| $r_t$ | 1,571,838 | 1.33 | 18.48 | -6.83 | 0.00 | 7.55 |
| $r_t^e$ | 1,571,838 | 0.93 | 18.49 | -7.24 | -0.39 | 7.17 |
| $\hat{\varepsilon}_t$ | 1,571,838 | 0.18 | 18.33 | -7.66 | -0.69 | 6.40 |
| $\hat{r}_t$ | 1,571,838 | 0.75 | 9.52 | -3.24 | 0.84 | 5.03 |
| $Size$ | 1,569,505 | 2,062.0 | 14,459.5 | 20.5 | 93.8 | 551.5 |
| $\beta^{MKT}$ | 1,571,838 | 0.98 | 0.81 | 0.52 | 0.97 | 1.42 |
| $\beta^{SMB}$ | 1,571,838 | 0.92 | 1.28 | 0.13 | 0.81 | 1.57 |
| $\beta^{HML}$ | 1,571,838 | 0.03 | 1.61 | -0.81 | 0.05 | 0.92 |
| $\beta^{RMW}$ | 1,571,838 | -0.22 | 2.03 | -1.19 | -0.08 | 0.91 |
| $\beta^{CMA}$ | 1,571,838 | -0.01 | 2.28 | -1.15 | 0.00 | 1.13 |

**Figure A1: Cumulative performance of stock-level and portfolio-level strategies**

This figure shows the cumulative performance of a $1 investment into high-low quintile portfolios for short-term reversal in stocks and momentum in stocks, industries, style portfolios, and factors, following the descriptions in Table 1. The performance of the short-term ($r_{t-1}$) strategies is depicted above and the performance of the medium-term ($r_{t-12,t-2}$) strategies is depicted below. We show both value- and equal-weighted specifications for the two stock-level strategies. Portfolio value (y-axis) is shown in logarithmic scale. For better comparability, we adjust the leverage of each strategy to a realized annual volatility of 10%. The sample period is Jan. 1968 (starting date for factor momentum) to Dec. 2019.



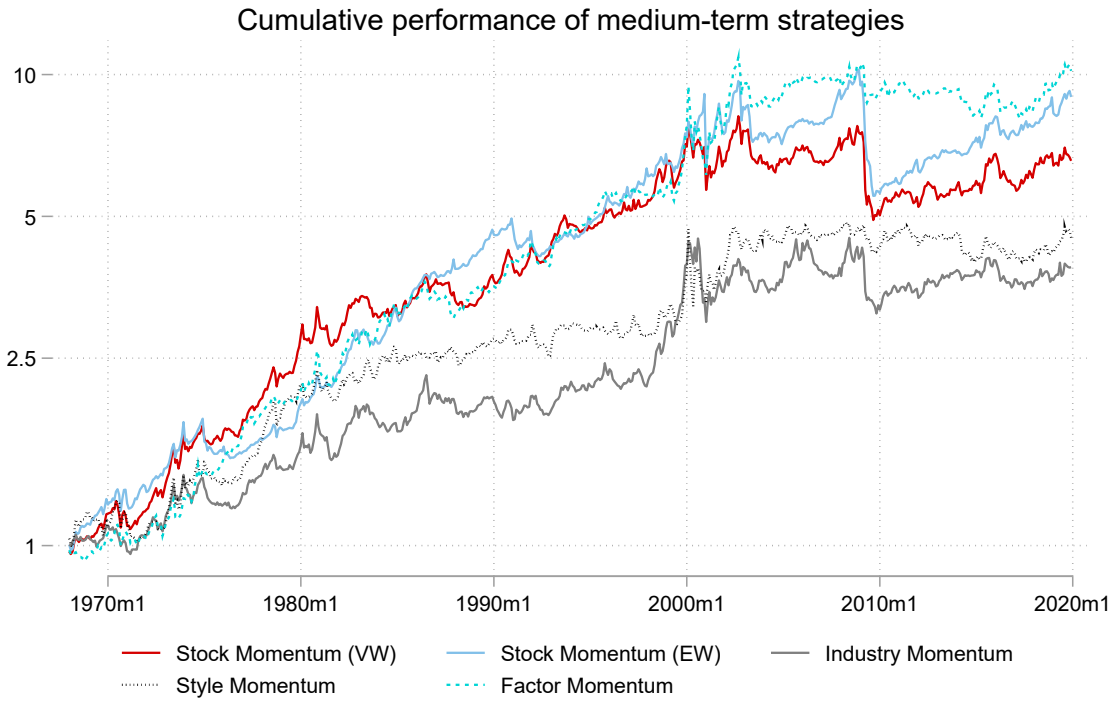
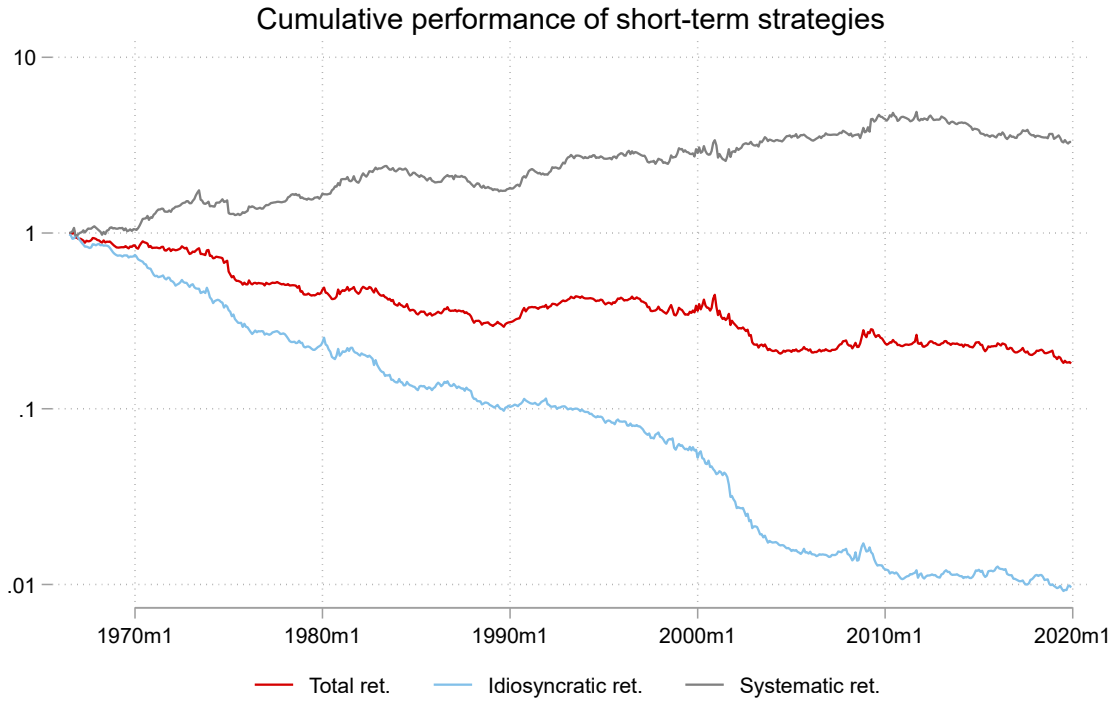



**Figure A2: Cumulative performance of sorts by total, idiosyncratic, and systematic past returns**

This figure shows the cumulative performance of a $1 investment into value-weighted high-low quintile portfolios sorted on stocks' past total, idiosyncratic, or systematic returns, following the descriptions in Table 3. Short- and medium-term systematic and idiosyncratic returns are defined according to Equations (1)-(4). The performance of the short-term ($r_{t-1}$, $\hat{\varepsilon}_{t-1}$, $\hat{r}_{t-1}$) strategies is depicted above and the performance of the medium-term ($r_{t-12,t-2}$, $\hat{\varepsilon}_{t-12,t-2}$, $\hat{r}_{t-12,t-2}$) strategies is depicted below. Portfolio value (y-axis) is shown in logarithmic scale. For better comparability, we adjust the leverage of each strategy to a realized annual volatility of 10%. The sample period is July 1966 to Dec. 2019.



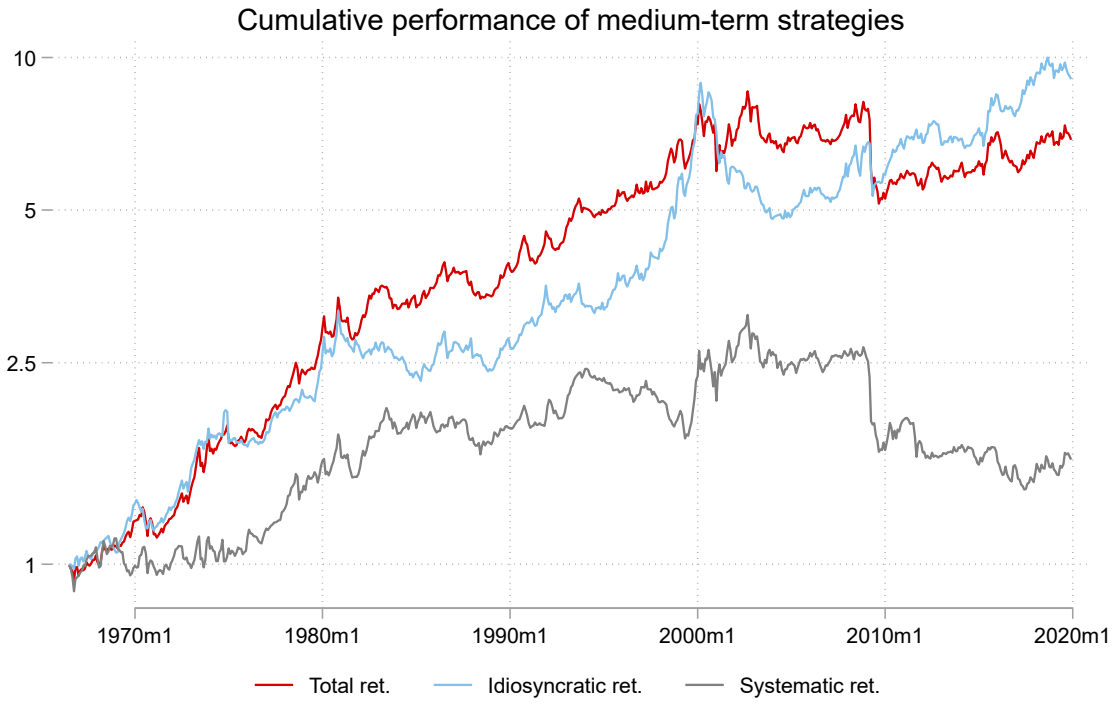



**Figure A3: Factor loadings of strategies within "modest-beta" and "extreme-beta" subsamples**

Panel A (B) of this figure shows net Fama & French (2015) factor loadings of total return momentum (short-term reversal) strategies, implemented within the "modest-beta" and "extreme-beta" subsamples, defined using a 80$^{th}$ / 20$^{th}$ percentile cut-off for stocks' betas (see Table 5 for details). For the high and low past-return quintiles, we compute the current value-weighted mean loadings of composite stocks against each factor ($\beta_H$ and $\beta_L$). The strategies' net loadings then correspond to $\beta_{H-L} = \beta_H - \beta_L$.The sample period is July 1966 to Dec. 2019.

Panel A: Momentum within "modest-beta" and "extreme-beta" subsamples

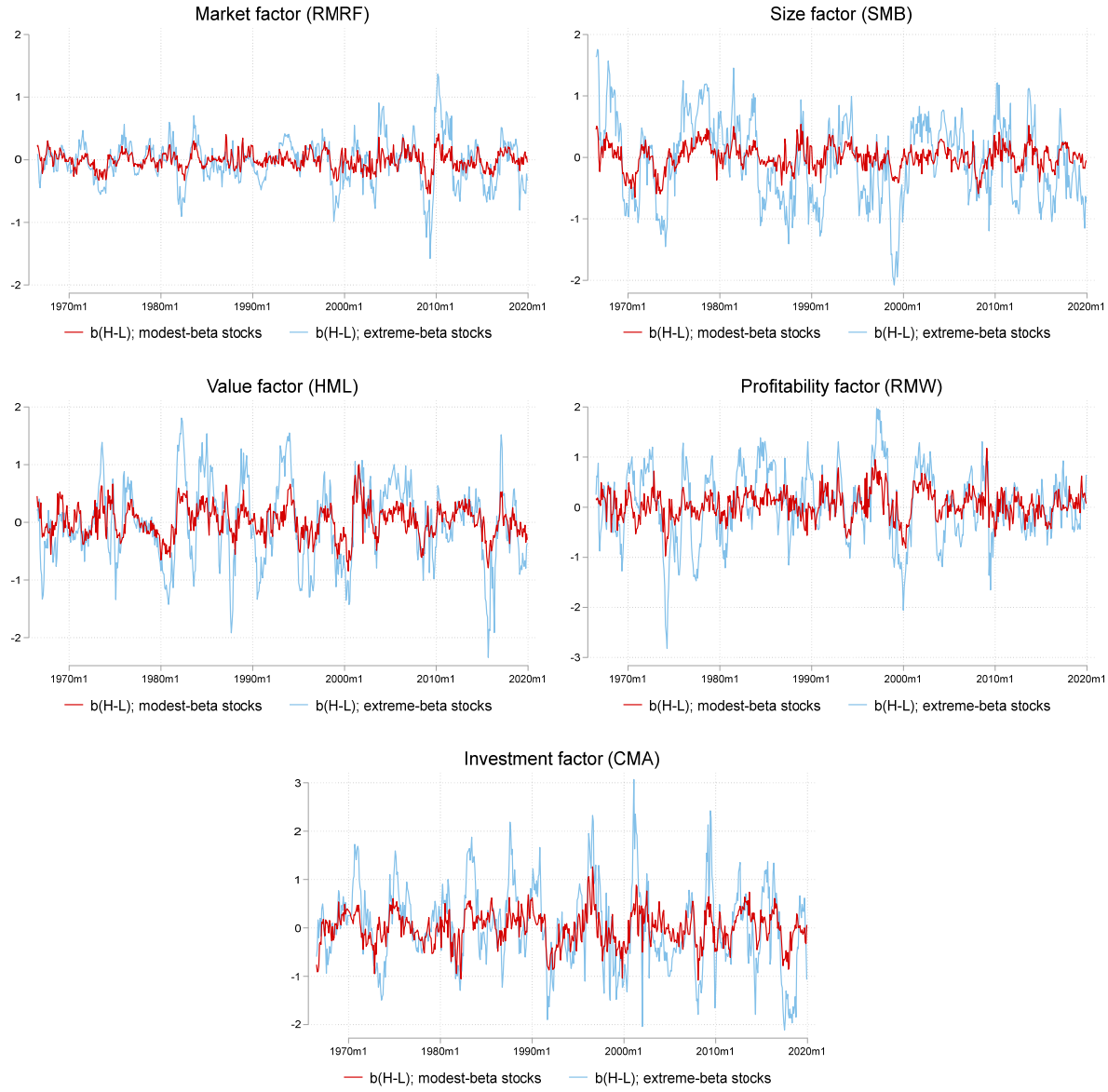


**Figure A3 (cont.)**

Panel B: Short-term reversal within "modest-beta" and "extreme-beta" subsamples

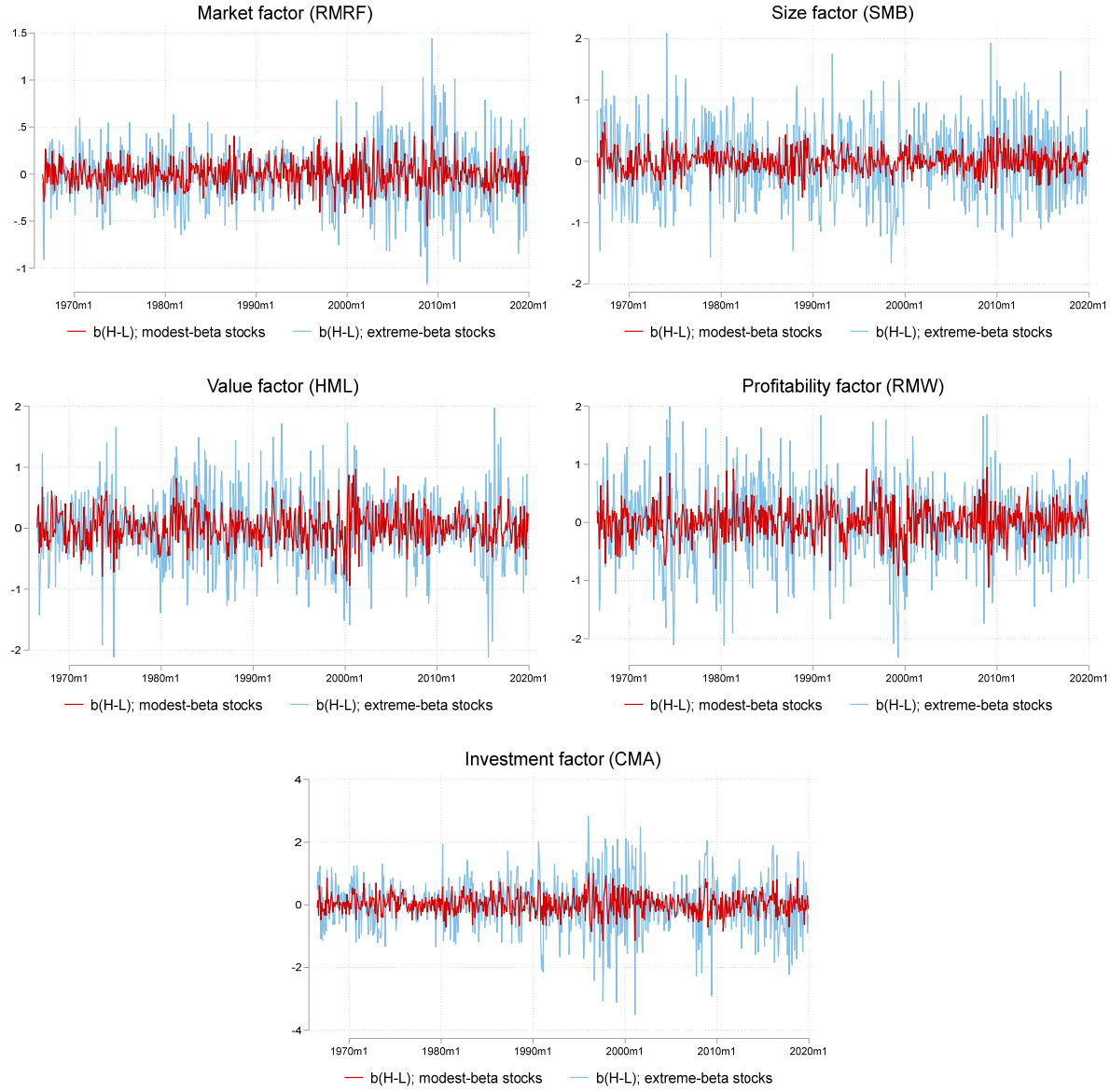


**Figure A4: Industry composition of Q5 and Q1 momentum / short-term reversal portfolios**

This figure shows the industry composition of top (Q5) and bottom (Q1) momentum / short-term reversal portfolios (19 Moskowitz and Grinblatt (1999) industries; w/o financial firms). Panel A plots industry weights for strategies, which rank stocks by their industry-demeaned total returns (see Table 3 Panel B). Panel B shows the same information for strategies with equal industry weights (see Table 6). The sample period is July 1966 to Dec. 2019.

Panel A: Quintile sorts on industry-demeaned total past returns (value-weighted)

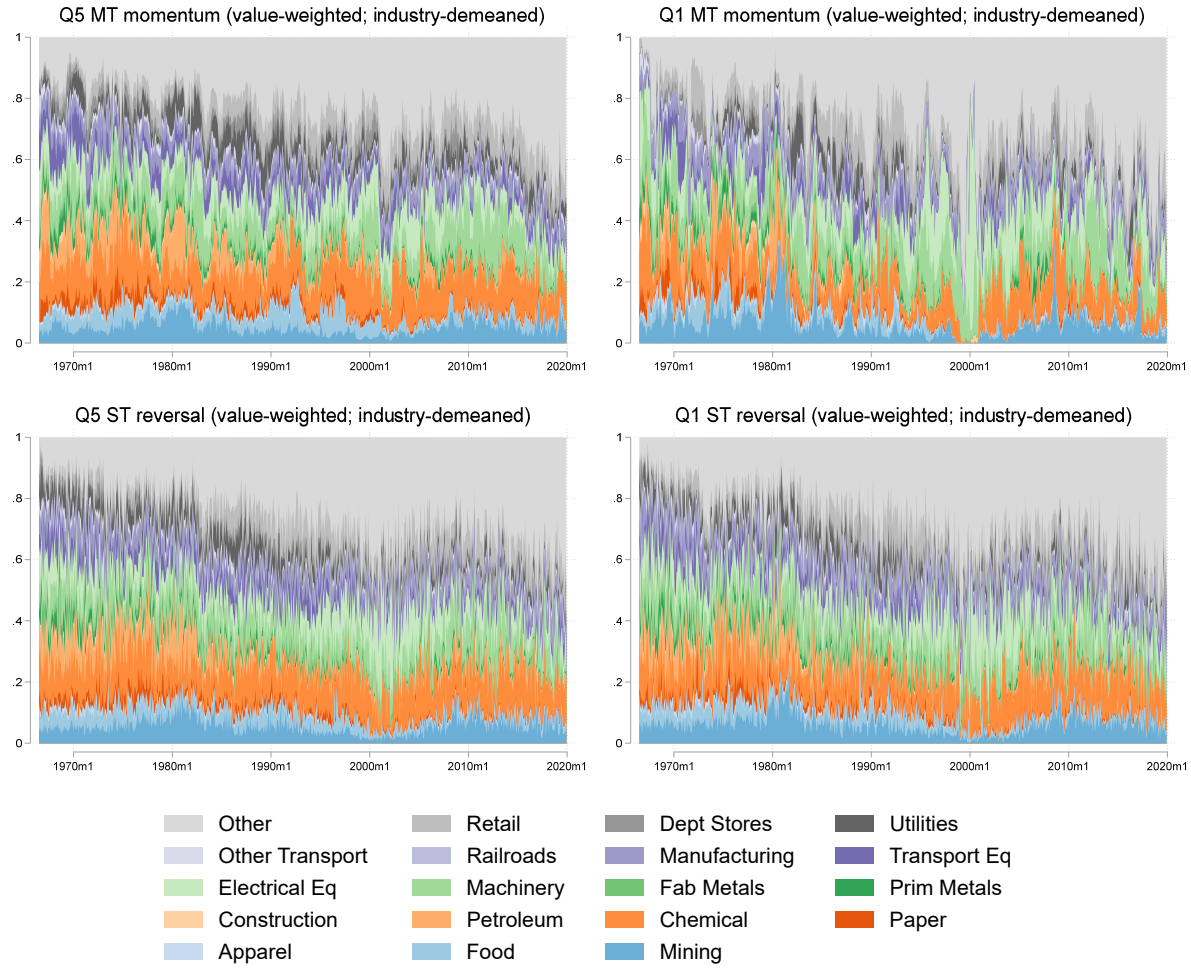


**Figure A4 (cont.)**

Panel B: Quintile sorts on total past returns (equal industry weights)