

The Anatomy of Industry Momentum^{*}

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Abstract

Individual stocks exhibit strong one-month reversal, whereas industry, characteristic, and factor portfolios display short-term momentum. We reconcile these patterns by showing that short-horizon momentum strategies share substantial exposure to short-term reversal. This shared reversal exposure matters for inference: when it is omitted from spanning regressions, factor momentum can appear to subsume industry momentum even when industry momentum reflects distinct economic forces. Controlling for reversal exposure using either the standard stock-level short-term reversal factor or a decomposition-based residual-to-systematic reversal measure restores economically large and statistically significant industry momentum alphas. We further decompose industry returns into systematic and residual components and show that the payoff to industry momentum is not concentrated in the estimated systematic component. Instead, industry momentum is primarily associated with residual industry returns and intra-industry lead-lag effects. Taken together, the evidence suggests that one-month industry momentum is distinct from factor momentum and primarily reflects industry-specific return dynamics.

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1. Introduction

Momentum and reversal are among the most pervasive return patterns in asset pricing.¹ Since the early 1990s, Jegadeesh (1990) and Lehmann (1990) have documented strong one-month reversal in individual stock returns. By contrast, portfolios formed on industries (Moskowitz and Grinblatt, 1999), firm characteristics (Lewellen, 2002), or factors (Gupta and Kelly, 2019; Arnott, Kalesnik, and Linnainmaa, 2023) display momentum even over the same short horizon.² How can these seemingly opposing return patterns coexist? Resolving this question is important not only for interpreting industry momentum, but also for understanding the recent debate over whether industry momentum reflects industry-specific dynamics or is simply a manifestation of factor momentum.

We address this question by first asking whether forming well-diversified portfolios can eliminate the short-term reversal embedded in individual stock returns. The answer is NO. To explain this, we decompose returns into a systematic component driven by common risk factors and a residual component that captures variation unexplained by those factors. We implement this decomposition using a broad factor structure constructed from firm characteristics and returns, while deliberately excluding industry momentum from the inputs. This design prevents the decomposition from mechanically incorporating the phenomenon we seek to explain and allows us to test whether systematic exposures unrelated to industry momentum can account for industry momentum. Using this decomposition, we document a residual-to-systematic reversal (RSR) effect: a negative predictive relation between past idiosyncratic (residual) returns and future systematic returns. We interpret RSR as a decomposition-based measure of the broader reversal exposure embedded in short-horizon return-sorted portfolios. Thus, when return sorts select assets partly because of extreme past residual returns, the resulting portfolios tend to inherit a reversal drag. More broadly, this mechanism arises whenever

¹Han, He, Rapach, and Zhou (2024) show that momentum and reversal are the two most important anomalies among more than 200 documented factors.

²Arnott, Kalesnik, and Linnainmaa (2023) find that industry momentum is a short-term effect, with its strongest predictability concentrated at the one-month horizon. This short-term industry momentum is largely distinct from conventional individual stock momentum, which typically skips the most recent month between the formation and holding periods (Asness et al., 2000; Grundy and Martin, 2001).

returns reflect a combination of idiosyncratic shocks and systematic exposures, and is therefore not specific to industry momentum.

Empirically, we find that short-term momentum portfolios (e.g., industry, characteristic-based, and factor momentum portfolios) exhibit substantial negative exposure to this RSR effect, which appears to depress their observed performance. This evidence shows that short-term reversal is not eliminated by portfolio formation; rather, it remains embedded in the very portfolios that display short-horizon momentum. Thus, for any return-sorted portfolio to actually exhibit momentum, its inherent momentum-driving forces must be sufficiently powerful to overcome this embedded reversal drag. Accounting for reversal exposure therefore helps clarify both the risks embedded in momentum strategies and the economic forces shaping their returns.

These findings provide an important confounding channel in the ongoing debate over the origins of industry momentum. A large literature attributes industry momentum to industry-specific information and the gradual diffusion of news across firms (e.g., Asness, Porter, and Stevens, 2000; Grundy and Martin, 2001; Hou, 2007; Hoberg and Phillips, 2018). In contrast, Arnott, Kalesnik, and Linnainmaa (2023) (AKL) argue that industry momentum is simply factor momentum in disguise. We show that this conclusion is potentially driven by omitted-variable bias. Because both industry momentum and factor momentum heavily and negatively load on short-term reversal, unconditional spanning regressions that exclude this shared reversal exposure can overstate the comovement between the two strategies, making factor momentum appear to subsume industry momentum. Once exposure to the reversal component is properly accounted for, factor momentum no longer fully explains industry momentum. Our results do not contradict the existence of factor momentum; rather, they show that its apparent ability to subsume industry momentum is sensitive to the omission of the residual-to-systematic reversal component.

We begin by showing that short-term reversal is detectable even in diversified return-sorted portfolios. Existing studies primarily examine reversal at the individual-stock level and often

attribute it to investor overreaction or liquidity provision. However, reversal effects are observed even in the absence of firm-specific news and among large, liquid stocks (e.g., Chan, 2003; Tetlock, 2011; Da, Liu, and Schaumburg, 2014; Hameed and Mian, 2015; Du, Huang, Liu, Shi, Subrahmanyam, and Zhang, 2026; Barardehi, Bogousslavsky, and Muravyev, 2026). Moreover, short-term reversal is closely linked to industry momentum (e.g., Da, Liu, and Schaumburg, 2014; Hameed and Mian, 2015; Novy-Marx and Velikov, 2016), suggesting that it may reflect forces that extend beyond firm-level frictions. To provide a simple benchmark, we construct “random industries” by repeatedly partitioning the universe of stocks into 50 arbitrary groups, computing value-weighted returns for each group, and forming a monthly long-short strategy based on last-month returns. These random portfolios exhibit a reliable one-month reversal despite containing no industry structure. The reversal becomes substantially stronger when portfolios are sorted on past residual returns. This nonparametric placebo test shows that the benchmark return for a short-horizon return-sorted portfolio need not be zero; it can be negative when the sort aggregates past idiosyncratic shocks. In other words, short-term reversal can survive diversification even in portfolios deliberately constructed to contain no industry structure.

The same reversal force is not limited to random portfolios. It is embedded in a wide range of short-term momentum strategies, including industry, characteristic, and factor momentum. Because these strategies load negatively on the reversal factor, their raw performance is dampened, while their unconditional alphas increase once this exposure is hedged. From a practical perspective, dynamically removing reversal exposure substantially improves Sharpe ratios and increases the precision of estimated momentum premia. We begin with the well-studied stock-level short-term reversal factor (STREV), which provides a transparent and directly tradable benchmark for this reversal exposure. Moreover, because individual stock returns are largely driven by residual components, STREV serves as a standard traded proxy for the broader reversal exposure captured by RSR.

Augmenting the Fama and French (2015) model (FF5) with STREV substantially improves

its ability to explain short-term momentum portfolios. Both industry and factor momentum load strongly and negatively on STREV, and controlling for this exposure sharply increases model fit and raises their estimated alphas. For industry momentum, the R^2 rises from 4.95% to 51.73%, while its FF5 alpha increases from 0.40% to 0.56% per month. Factor momentum displays a similar pattern: its R^2 rises from 6.94% to 44.02%, and its alpha increases from 0.40% to 0.52% per month. These results indicate that negative exposure to STREV accounts for a substantial share of the time-series variation and the weaker unconditional performance of short-term momentum strategies. Hedging this exposure materially improves profitability, consistent with earlier evidence that removing adverse factor exposures enhances momentum performance (Grundy and Martin, 2001).

These findings highlight the importance of separating the momentum component of short-horizon strategies from their exposure to short-term reversal. Short-term momentum portfolios inherit negative exposure to STREV, which reduces their unconditional performance and can obscure their underlying return sources. Hedging STREV removes this adverse exposure and improves performance. This insight is related to the broader idea that characteristic-sorted portfolios may contain unpriced return variation that masks their economic content (Daniel, Mota, Rottke, and Santos, 2020; Kozak and Nagel, 2023). In our setting, the relevant unpriced component is short-term reversal, and controlling for it is essential for uncovering whether industry momentum reflects industry-specific dynamics or factor momentum.

We therefore ask whether factor momentum continues to explain industry momentum once short-term reversal is controlled for. It does not. The industry momentum alpha remains economically large and statistically significant after controlling for both STREV and factor momentum, at 0.39% per month (t -statistic = 6.11). This result contrasts with the conclusion of AKL, who argue that industry momentum is fully subsumed by factor momentum. The conclusion is similar when we dynamically hedge reversal exposure: the hedged industry momentum portfolio no longer loads on STREV, yet it cannot be explained by either raw or hedged factor momentum. Similar performance gains arise for characteristic and factor

momentum portfolios after hedging their reversal exposure.

These spanning results raise a natural question: does the same conclusion emerge in cross-sectional tests that directly compare past total and systematic industry returns? We re-examine the relation between factor and industry momentum using the Fama-MacBeth (1973) cross-sectional regression framework. If industry momentum were entirely driven by momentum in systematic returns arising from exposure to other factors, then past systematic returns should subsume past total returns in predicting future industry returns. Conversely, if past total returns retain predictive power after controlling for past systematic returns, industry momentum is distinct from factor momentum and reflects momentum in industry-specific returns. Contrary to AKL’s conclusion, we find that past-month industry returns continue to significantly predict future industry returns even after controlling for past-month systematic industry returns. At the same time, we reproduce AKL’s spanning-regression result: momentum in systematic returns can render the industry-momentum alpha insignificant in unconditional spanning regressions.

We next take a closer look at the components embedded in industry momentum. Doing so requires a framework that can separate industry returns into systematic and residual components.³ To this end, we use the Instrumented Principal Component Analysis (IPCA) model of Kelly, Pruitt, and Su (2019) as a flexible diagnostic tool. IPCA estimates latent factors with characteristic-based, time-varying loadings and is closely related to covariate-assisted latent factor methods in high-dimensional panels (Fan, Liao, and Wang, 2016; Lettau and Pelger, 2020; Fan, Ke, and Liao, 2021). We use IPCA to examine whether the predictive relation between past industry returns and future returns operates primarily through systematic or residual components. The IPCA decomposition reveals a robust pattern: industries with high past residual returns subsequently exhibit lower exposure to systematic factors. This pattern helps explain why factor momentum has limited ability to account for industry momentum once reversal exposure is controlled for.

³Total industry returns can be decomposed into a systematic component related to common risk factors and a residual component reflecting industry-specific information. Industry momentum therefore aggregates multiple effects arising from interactions between past and future systematic and residual returns.

This pattern is consistent with a residual-to-systematic reversal mechanism. Past systematic returns predict higher future systematic returns, but past residual returns predict lower future systematic returns. As a result, past total returns have limited ability to forecast future systematic returns, and the systematic component contributes little to the profitability of industry momentum. If industry momentum were driven solely by factor momentum, its payoff should be concentrated in this component. Instead, the future systematic component of the momentum portfolio is close to zero, whereas the residual component is large, statistically significant, and comparable in magnitude to total industry momentum. Correspondingly, the Sharpe ratio of industry momentum is 0.56, with -0.04 for the systematic component and 0.89 for the residual component, indicating that past industry returns primarily forecast future residual rather than systematic returns.

These decomposition results help explain why Fama-MacBeth and spanning tests appear to reach different conclusions. To bring the spanning tests closer to the mechanism identified above, we incorporate the industry-level RSR effect directly into the spanning regressions. We define “systematic industries” as the systematic component of industry returns explained by common factors and construct the RSR factor by going long systematic industries with below-median past residual returns and short those with above-median residual returns.⁴ Augmenting the FF5 model with factor momentum and RSR yields a statistically significant industry-momentum alpha of 0.34% (t -statistic = 4.60). Thus, after accounting for the shared reversal exposure highlighted by our framework, factor momentum fails to explain industry momentum, consistent with the evidence from both Fama-MacBeth regressions and the IPCA decomposition.

Having shown that industry momentum is not explained by factor momentum, we next ask what drives the remaining residual industry momentum. This analysis shifts the focus from factor-level predictability to industry-specific return dynamics. We first use the Lo and MacKinlay (1990) decomposition to show that residual industry momentum is primarily

⁴The RSR factor is designed specifically to capture the negative relation between past residual and future systematic returns and is not intended to serve as a general pricing factor.

associated with positive autocorrelation in residual industry returns. We then adapt the pairwise lead-lag decomposition of Yan and Yu (2023) to examine whether this residual autocorrelation is linked to information transmission across firms within the same industry. Within industries, stocks with larger size, longer histories, greater analyst coverage, lower idiosyncratic volatility, and lower forecast dispersion tend to lead their peers.

Our study contributes to the literature on short-term return reversals and momentum by shifting the focus from individual stocks to the role of reversal embedded within momentum portfolios (see, e.g., Avramov, Chordia, and Goyal, 2006; Nagel, 2012; Da, Liu, and Schaumburg, 2014; Hameed and Mian, 2015; Cheng, Hameed, Subrahmanyam, and Titman, 2017; Jegadeesh, Luo, Subrahmanyam, and Titman, 2025). Da, Liu, and Schaumburg (2014) show that the short-term reversal effect persists even among large stocks but becomes harder to detect in the presence of industry momentum, while Hameed and Mian (2015) document strong intra-industry reversals across subgroups of stocks. Relatedly, Yan and Yu (2023) develop a pairwise cross-stock lead-lag decomposition that is useful for studying how return predictability propagates across stocks. We demonstrate that short-term reversal is a pervasive force that persists even in short-term momentum portfolios.⁵ As a result, short-term momentum strategies based on industries, firm characteristics, and factors all load negatively on the short-term reversal factor; controlling for this exposure raises their alphas and substantially improves their performance. These findings highlight the central role of reversal exposure in shaping short-horizon momentum strategies and in understanding the economic drivers of industry momentum. Our distinct contribution is to show that shared reversal exposure can cause AKL-style spanning regressions to overstate the extent to which factor momentum subsumes industry momentum.

Our paper also contributes to the literature on characteristic-sorted portfolios (e.g., Gu, Kelly, and Xiu, 2020; Freyberger, Neuhierl, and Weber, 2020; Kozak, Nagel, and Santosh, 2020; Feng, He, Polson, and Xu, 2024; Li, Rossi, Yan, and Zheng, 2025). In particular, Daniel,

⁵Lewellen (2002) argues that size and B/M portfolios, which are highly diversified and thus primarily reflect systematic risks, exhibit strong momentum, implying a macroeconomic origin.

Mota, Rottke, and Santos (2020) show that characteristic-sorted portfolios can contain return components unrelated to the characteristic premium itself, and that removing such components improves portfolio performance and clarifies the underlying source of returns. Consistent with these insights, we show that short-term reversal is an important source of common variation embedded in short-term momentum portfolios. This common negative exposure raises alphas and substantially improves performance once it is controlled for. Our results therefore provide a new perspective on the economic drivers of industry momentum by showing that controlling for reversal exposure helps isolate the distinct sources of momentum profits.

There are two commonly used asset pricing tests: the spanning regression and the Fama and MacBeth (1973, FM) regression, which differ in how they assess whether a factor explains return predictability across assets. FM regressions estimate risk premia using cross-sectional variation in returns, whereas spanning regressions test whether a proposed factor subsumes existing return anomalies.⁶ Giglio and Xiu (2021) highlight that omitted variable bias can arise in standard risk premium estimators when the estimated model fails to capture all priced sources of risk in the economy, particularly nontradable risks that are not represented by portfolios. We show that omitted-variable bias can also arise in spanning tests when assets share substantial common variation driven by a confounding component. In our setting, shared reversal exposure generates strong common variation between industry momentum and factor momentum, causing spanning regressions to overstate the extent to which factor momentum subsumes industry momentum. Our findings therefore highlight the importance of interpreting spanning tests with caution when common confounding forces are present.⁷

Moreover, the literature often studies anomalies in isolation, overlooking the significant comovement among certain factors.⁸ Our paper highlights the importance of accounting for

⁶See, for example, Hou and Loh (2016), Bali, Brown, Murray, and Tang (2017), and Goyal, Jegadeesh, and Subrahmanyam (2025) for applications of FM regressions, and Stambaugh and Yuan (2017), Hou, Mo, Xue, and Zhang (2018), Daniel, Hirshleifer, and Sun (2019), Ehsani and Linnainmaa (2022), and Arnott, Kalesnik, and Linnainmaa (2023) for spanning tests of anomalies.

⁷Relatedly, the factor-zoo literature emphasizes that testing whether a candidate factor adds incremental explanatory power requires accounting for a high-dimensional set of existing factors and the risk of model-selection errors (Feng, Giglio, and Xiu, 2020).

⁸Several studies highlight that factor comovement can materially affect inference. For instance, Huang, Liu, Rhee, and Zhang (2009) show that omitting short-term reversal biases the estimated relation between

such comovement when evaluating momentum strategies. To do so, we employ the IPCA model of Kelly, Pruitt, and Su (2019), which provides a flexible framework for estimating time-varying exposures. Using IPCA, we decompose industry returns into systematic and residual components and show that the predictability of industry momentum primarily originates from residual industry returns rather than from momentum in common factors. These results provide new evidence that momentum in industries reflects economic forces specific to industries *per se*, rather than being driven by factor trends.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 documents the pervasive nature of short-term reversal and its confounding impact on short-term momentum strategies, along with a re-examination of the drivers of industry momentum. Section 4 provides evidence that industry momentum primarily reflects residual industry-specific momentum rather than factor momentum. Section 5 concludes. The Appendix includes extensions and robustness checks.

2. Data

Our stock returns and characteristics data are collected from Jensen, Kelly, and Pedersen (2023). We keep stocks listed on the NYSE, AMEX and Nasdaq, restricting the sample to ordinary common shares (share codes 10 and 11). Additionally, we exclude stocks with prices below \$1. For each firm, we consider 65 characteristics, as detailed in Table A.1 of the Appendix. Our final sample spans from January 1965 to December 2022, including 3,083,211 stock-month observations for 25,209 unique stocks. For further details and summary statistics, see Jensen, Kelly, and Pedersen (2023). We obtain the Fama and French five factors and the stock-level short-term reversal factor from Kenneth French’s online data library.

Following AKL, all the momentum strategies in our article are cross-sectional strategies that rebalance monthly and are long factors or industries with above-median returns in the prior

idiosyncratic volatility and expected returns, while Asness, Moskowitz, and Pedersen (2013) document strong global comovement between value and momentum strategies across asset classes.

month and short those with below-median returns. In particular, AKL document that factor momentum tends to concentrate in the high-eigenvalue factors. As in AKL, we construct factor momentum strategies using the PC factors extracted from the 65 characteristics listed in Table A.1.⁹ For characteristic momentum strategies, we first sort stocks into decile portfolios based on their characteristic values from the prior month. We then construct a long-short portfolio by going long on portfolios with above-median past returns and shorting those with below-median past returns. For industry momentum strategies, we compute value-weighted returns for the Fama-French 49 industries and form a long-short portfolio by going long on industries with above-median past-month returns and shorting those with below-median past-month returns. Additionally, to assess the presence of momentum in random portfolios, we randomly assign all stocks to 50 groups at inception, treating them as hypothetical industries. We compute value-weighted group returns and repeat this process 1,000 times to generate 1,000 sets of simulated industry returns.

3. Short-Term Reversal and Its Confounding Effect

In this section, we demonstrate that short-term reversal acts as a pervasive, systematic drag on short-horizon momentum strategies. First, using randomly constructed “industries,” we show that statistically reliable reversal persists even in portfolios devoid of industry structure.

Second, we examine the implications of this reversal force for short-term momentum strategies. Because momentum portfolios naturally take positions opposite to reversal portfolios, they inherit substantial negative exposure to the reversal factor. As a result, reversal suppresses the observed profitability of momentum strategies. Once this exposure is accounted for, either through asset pricing regressions or dynamic hedging, the performance of momentum strategies improves substantially, and factor momentum no longer fully explains industry momentum.

Third, we revisit the relation between factor momentum and industry momentum using two commonly employed asset pricing tests. While spanning regressions reproduce the conclusion

⁹The details of the factor momentum construction are provided in Section A.1 of the Appendix.

of AKL that factor momentum subsumes industry momentum, Fama-MacBeth regressions yield a different conclusion. These contrasting results suggest that short-term reversal acts as a confounding force in spanning regressions, a mechanism we formalize in a simple framework presented in the Appendix.

3.1. Pervasive Short-Term Reversal

The short-term reversal effect is pronounced in individual stocks, which are the building blocks of all portfolios. In contrast, portfolios at this horizon often display momentum, such as industries, portfolios sorted by size and book-to-market ratio, and factors. How can these opposing patterns coexist? AKL emphasize one channel: past systematic components negatively predict future idiosyncratic components, suggesting that individual-stock reversal may be diversified away in portfolio-level momentum strategies.

We show that this conclusion is incomplete. If past idiosyncratic (residual) returns negatively predict future systematic returns,¹⁰ return-sorted portfolios can inherit a reversal drag even after diversification. The reason is that total past returns contain a large residual component, so sorting on past returns often selects assets with extreme past residual returns. When these residual shocks predict subsequent systematic returns with the opposite sign, the resulting portfolio embeds a systematic reversal component. Therefore, for any such return-sorted portfolio to actually exhibit a momentum pattern, its inherent momentum forces must be sufficiently powerful to overcome this embedded reversal drag.

To isolate this reversal force, we employ a nonparametric experiment using “random industries.” By randomly partitioning the universe of stocks into 50 groups, we create diversified portfolios that lack any structural industry information or significant dispersion in factor loadings. Since these portfolios possess no momentum signal, they serve as a clean

¹⁰This negative predictability is visible even in AKL’s decomposition: Panel B of their Table 12 reports a highly significant relation from past idiosyncratic components to future systematic components, with a t -statistic of -29.75 . AKL do not examine its implications for return-sorted portfolios. Our analysis shows that this channel creates reversal exposure embedded in short-horizon momentum strategies and can confound spanning tests of industry and factor momentum.

laboratory for testing whether reversal survives diversification. Importantly, the goal of this exercise is not to identify an economically large trading strategy in random portfolios. By construction, random industries are highly diversified and should have limited exposure to idiosyncratic shocks. The exercise instead provides a conservative placebo test: if reversal is still detectable in portfolios deliberately designed to contain no industry structure, then diversification alone does not mechanically eliminate short-term reversal. Specifically, we randomly assign all stocks into 50 groups, treating them as hypothetical industries, and compute value-weighted group returns to assess the presence of short-term reversal. This procedure is repeated 1,000 times to generate 1,000 simulated sets of hypothetical industry returns. For each set, we construct a strategy that rebalances monthly and is long hypothetical industries with above-median returns in month $t-1$ and short those with below-median returns.

As shown in Panel A of Figure 1, these random-industry portfolios exhibit statistically reliable short-term reversal. Across the 1,000 simulations, the mean of average long-short returns is -0.08%, with a corresponding 95% confidence interval of [-0.11%, -0.04%]. The average t -statistic for these long-short portfolio returns is -3.73. The economic magnitude is modest, as expected, because random portfolios diversify away much of the idiosyncratic variation that gives rise to reversal. This reversal effect becomes even more pronounced when portfolios are sorted based on past residual returns.¹¹ The mean of average long-short returns is -0.12% with a corresponding 95% confidence interval of [-0.15%, -0.08%]. The increase in magnitude when sorting on residual returns supports the interpretation that reversal is tied to residual shocks rather than to industry structure itself.

This nonparametric placebo test shows that the benchmark return for a short-horizon return-sorted portfolio need not be zero; it can be negative when the sort aggregates past idiosyncratic shocks. The persistence of this reversal in portfolios constructed to lack any industry structure provides evidence that short-term reversal can survive diversification and

¹¹We compute industry systematic and residual returns using the $K = 10$ IPCA model described in Section 4. The systematic return of industry j in month t is $Sys_{j,t} = \beta'_{j,t} F_t$, where F_t contains the 10 latent factors and $\beta_{j,t}$ is the value-weighted average of stock-level loadings in industry j . Residual returns are defined as $Res_{j,t} = Ret_{j,t} - Sys_{j,t}$.

is not eliminated simply by forming portfolios without industry structure. Thus, we view the random-industry result as diagnostic rather than economic: its role is to show that even diversified return-sorted portfolios can retain measurable reversal exposure. The modest magnitude is also informative, because random portfolios are deliberately constructed to have weak residual-shock exposure. The larger economic implications of this mechanism arise when the same reversal exposure is embedded in portfolios with stronger return-predictive signals.

This perspective also helps explain why many characteristic-sorted portfolios display momentum rather than reversal. They are not immune to reversal; rather, their characteristic-based signals generate sufficiently strong systematic or factor momentum to overcome the embedded reversal drag. Characteristic-managed portfolios have large spreads in factor loadings. This dispersion creates a strong systematic or factor momentum effect that masks the underlying reversal. For each of the 65 characteristics listed in Table A.1, we form decile portfolios by sorting stocks based on their characteristic values from the prior month and construct characteristic momentum strategies that rebalance monthly and are long portfolios with above-median returns and short portfolios with below-median returns. Panel B of Figure 1 presents the distribution of average returns across the 65 characteristic-managed portfolios. Consistent with AKL, we find strong momentum in these portfolios, although the statistical significance varies across characteristics. In Section 3.2, we demonstrate that characteristic portfolios exhibit momentum while simultaneously embedding the reversal effect.¹²

3.2. The Impact of Short-Term Reversal on Momentum Portfolios

Having established that short-term reversal can operate systematically across diversified portfolios, we now examine its impact on standard short-term momentum strategies. Since momentum portfolios (long winners, short losers) naturally take positions opposite to the reversal effect (long losers, short winners), they inherit a significant negative loading on

¹²Blitz, Huij, Lansdorp, and Verbeek (2013) show that reversal strategies based on residual returns orthogonal to the Fama and French (1993) factors earn substantially higher profits than standard reversal strategies. Da, Liu, and Schaumburg (2014) likewise find that residual-return-based reversals deliver alphas roughly four times larger than conventional implementations.

the systematic reversal component. We hypothesize that this “reversal drag” suppresses the observed profitability of momentum strategies and obscures their distinctness. If this conjecture holds, the embedded reversal should dampen the profits of these momentum portfolios, while controlling for the reversal effect should enhance their unconditional alphas. From a practical perspective, investors may improve the performance of short-term momentum strategies by dynamically hedging their exposures to the short-term reversal factor.¹³

3.2.1. *Unmasking Momentum Alpha in Pricing Models*

Panel A of Table 1 reports the alphas of momentum portfolios after controlling for the short-term reversal factor (STREV), obtained from Kenneth French’s online data library. For characteristic momentum, we consider the 65 characteristics listed in Table A.1 and report average results across characteristics. Panel A.1 presents alphas relative to the Fama and French five-factor model (FF5) and to the five-factor model augmented with the short-term reversal factor for industry, characteristic, and factor momentum strategies.¹⁴ The FF5 alphas are 0.40% (t -statistic=4.31), 0.22% (t -statistic=2.48), and 0.40% (t -statistic=4.76) for industry, characteristic, and factor momentum, respectively. The results uncover a substantial “suppression” effect. All three short-term momentum strategies exhibit highly significant negative loadings on STREV. Incorporating STREV (FF5+STREV) materially increases both the unconditional alphas and their statistical significance, with the values rising to 0.56% (t -statistic=7.96), 0.34% (t -statistic=4.65), and 0.52% (t -statistic=7.58), respectively.

In particular, including STREV substantially enhances the model’s explanatory power for the time-series variation in momentum portfolio returns. For the industry momentum portfolio, R^2 rises from 4.95% to 51.73% when STREV is added to the pricing model. For characteristic momentum portfolios, the average R^2 increases from 4.55% to 34.99%, and for the factor momentum portfolio, from 6.94% to 44.02%. Thus, exposure to STREV explains a

¹³Daniel, Mota, Rottke, and Santos (2020) show that characteristic portfolios are generally not mean-variance efficient and can be improved by removing unpriced common variation. In our case, short-term momentum portfolios load negatively on STREV, which increases volatility and offsets returns.

¹⁴Blitz, van der Grient, and Honarvar (2024) show that STREV strategies earn higher alphas after accounting for industry and factor momentum, highlighting the benefit of mitigating adverse exposures.

substantial share of the variation in both industry and factor momentum, thereby weakening their performance. Hedging out this exposure substantially improves the profitability of those momentum portfolios. This shared exposure helps explain why these strategies can appear difficult to distinguish in spanning regressions that omit short-term reversal.

This leads to a direct reassessment of the AKL hypothesis. Panel A.2 of Table 1 examines whether factor momentum (FMOM) can explain industry and characteristic momentum, as suggested by AKL. Consistent with their findings, FMOM fully explains both industry and characteristic momentum when STREV is not included as a control. However, once STREV is controlled for, FMOM fails to explain these effects. For example, the FF5+STREV alpha of industry momentum is 0.56% (t -statistic=7.96) and declines only to 0.39% (t -statistic=6.11) after adding FMOM (FF5+STREV+FMOM), leaving a sizable unexplained component. This finding contrasts with AKL’s conclusion that industry momentum fully emanates from factor momentum. We observe a similar pattern for characteristic momentum: adding FMOM to FF5+STREV does not eliminate its alpha, which remains at 0.16% (t -statistic=2.37). Thus, characteristic momentum also reflects sources beyond those captured by factor momentum.

These results suggest that the conclusion reached by AKL, that industry momentum is merely factor momentum, is likely driven by omitted variable bias. Both strategies load heavily on the reversal factor; omitting it from the spanning regression can induce a spurious correlation that masks the independent explanatory power of industry momentum. Daniel, Mota, Rottke, and Santos (2020) emphasize that identifying the economic sources of the premiums associated with characteristics requires constructing portfolios that capture factor premiums with the lowest possible return variance.¹⁵ Accordingly, to investigate the underlying drivers of momentum portfolios, it is important to control for their exposure to short-term reversal.

¹⁵Daniel, Mota, Rottke, and Santos (2020) point out that characteristic portfolios inherently load on unpriced sources of common variation, and this correlation can lead to incorrect inferences about the adequacy of a proposed asset pricing model.

3.2.2. Improving Momentum Performance via Dynamic Hedging

While the regression results above are ex-post, we next demonstrate that investors can exploit this insight ex-ante. Investors can dynamically hedge their exposure to short-term reversal to improve the performance of short-term momentum strategies. For each momentum portfolio, we estimate its exposure to STREV using a 60-month rolling window and then construct a hedged portfolio. The realized return of the hedged momentum strategy in month $t + 1$ is $MOM_{t+1} - \beta_t \cdot STREV_{t+1}$, where β_t is obtained by regressing the momentum portfolio return on the short-term reversal factor return over the past 60 months of data up to time t .¹⁶ We compare the performance of short-term momentum strategies before and after hedging, and report the results in Panel B of Table 1. The sample begins in January 1975, as the first five years of data are used to initialize the rolling beta estimates.

Panel B.1 of Table 1 shows that hedged momentum portfolios substantially outperform their unhedged counterparts. Raw industry momentum has a Sharpe ratio of 0.48 and an FF5 alpha of 0.34% (t -statistic=3.60). After dynamically hedging its exposure to STREV, the hedged industry momentum achieves a Sharpe ratio of 1.11, representing a 131% improvement, and an FF5 alpha of 0.47% (t -statistic=7.09). Similar improvements are observed for the other momentum portfolios; Sharpe ratios increase by 109% for characteristic momentum and by 82% for factor momentum. These results suggest that investors can enhance performance by recognizing that short-term reversals are embedded within and weaken conventional short-term momentum strategies.

Panel B.2 of Table 1 examines whether the hedged industry and characteristic momentum portfolios can be explained by raw or hedged factor momentum. The results show that factor momentum does not fully explain either of these momentum strategies. Controlling for hedged factor momentum reduces the FF5 alpha of hedged industry momentum only modestly, from 0.47% (t -statistic=7.09) to 0.34% (t -statistic=5.25), and that of hedged characteristic momen-

¹⁶In a similar vein, Novy-Marx and Velikov (2022) and Barroso, Detzel, and Maio (2025) construct BAB by hedging the low-minus-high beta portfolio against market exposure: $BAB_{t+1} = R_{t+1}^{L-H} - \beta_{MKT,t} \cdot MKT_{t+1}$. Without hedging, BAB would exhibit an insignificant mean return but a significantly positive alpha.

tum from 0.31% (t -statistic=4.11) to 0.15% (t -statistic=2.38). Although factor momentum demonstrates relatively greater explanatory power for characteristic momentum, the latter remains statistically significant after controlling for factor momentum.

Collectively, these findings help reconcile the evidence. Industry momentum and factor momentum appear closely related in spanning tests that omit short-term reversal because they share a large common component: systematic reversal. Once this component is accounted for, either by including it in pricing models or through dynamic hedging, industry momentum emerges as a distinct, economically significant strategy driven by forces separate from factor trends.

3.3. Fama-MacBeth versus Spanning Regressions

Table 1 reveals that factor momentum cannot fully explain industry momentum once short-term reversal is controlled for in the spanning regression or dynamically hedged from the industry momentum portfolio. This finding indicates that omitting short-term reversal may lead to biased conclusions about the relation between industry and factor momentum, motivating us to re-examine the underlying drivers of industry momentum. In this section, we adopt an alternative approach, the Fama-MacBeth (FM) regression, to examine whether factor momentum can fully subsume industry momentum.

In the context of this paper, the FM regression offers the advantage of testing incremental predictability directly in the cross-section. Rather than asking whether the time-series return of one constructed momentum portfolio spans another, the FM regression asks whether past industry returns continue to predict future industry returns after past systematic industry returns are included as a competing predictor. This distinction is important because spanning regressions can mistake shared omitted reversal exposure for explanatory power: if both industry momentum and factor momentum load negatively on reversal, the omitted reversal component creates common time-series variation between the two portfolios. By contrast, the FM regression conditions directly on past systematic returns and tests whether past

total industry returns retain independent predictive content. We formalize this intuition in Appendix Section A.2. If factor momentum fully explains industry momentum, the coefficient on past-month industry returns should become insignificant once past systematic returns are included. If industry momentum reflects distinct return dynamics, both predictors can remain statistically significant.

To perform the FM regression, we first calculate “systematic industries,” or the systematic component of industry returns, as a linear combination of the factors on which the actual industries load: $Sys_{j,t} = \beta_{j,1}F_{1,t} + \dots + \beta_{j,K}F_{K,t}$ in month t , where the F_t s are the factor returns. Following AKL, we first consider four pricing models with pre-specified factors to construct Sys , including (1) the Fama-French (FF) three-factor model, (2) the FF five-factor model, (3) the FF five-factor model augmented with long-term reversal and residual variance, and (4) the FF model further augmented with long-term reversal, residual variance, quality-minus-junk, and betting-against-beta factors. In addition, we consider a latent factor model, the Instrumented Principal Component Analysis (IPCA) model introduced by Kelly, Pruitt, and Su (2019).¹⁷ Given any of the five pricing models, we first estimate factor loadings for individual stocks using the method of Kelly, Pruitt, and Su (2019).¹⁸ Subsequently, we compute the factor loadings for each portfolio as the value-weighted average of the constituent stocks’ estimated loadings.

Next, we assess the relative predictive power of past industry returns and their systematic components for future industry returns by estimating the following FM regression:

$$Ret_{j,t} = \alpha_t + \beta_{imom,t} \cdot Ret_{j,t-1} + \beta_{smom,t} \cdot Sys_{j,t-1} + \varepsilon_{j,t}, \quad (1)$$

where $Ret_{j,t}$ denotes the return of industry j in month t , and $Sys_{j,t-1}$ represents its corresponding systematic return in month $t-1$. Panel A of Table 2 reports the results. Both past-month industry returns and their systematic components significantly and positively predict future

¹⁷We present the details of the IPCA model and its implementation in Section 4.1.

¹⁸Their method instruments the estimation of factor loadings with observable characteristics, thereby improving estimation efficiency and enhancing model performance.

industry returns. The predictability of systematic industry returns for future industry returns reflects the impact of factor momentum on industry returns. The positive and significant estimates for *Sys* coefficients are consistent with the findings of AKL. Notably, we find that the coefficient on past industry returns, *Ret*, remains significantly positive across all pricing models employed to construct systematic returns. Even when using the most comprehensive latent factor model (IPCA), the estimate for the *Ret* coefficient is 0.31 with a *t*-statistic of 3.03. These findings provide evidence that momentum in factors cannot fully explain industry momentum.

Then, following AKL’s framework, we conduct spanning regressions to test whether momentum in systematic industries can subsume industry momentum. Similar to the construction of industry momentum (IMOM), we construct systematic industry momentum (SMOM) strategies by taking long positions in systematic industries with above-median past returns and short positions in systematic industries with below-median past returns. Specifically, we estimate the following spanning regression:

$$\text{IMOM}_t = \alpha + \beta_{smom} \cdot \text{SMOM}_t + \sum_k \beta_k \cdot \text{FF}_{k,t} + u_t, \quad (2)$$

where FF_k s represent the FF5 factors. As shown in Panel B of Table 2, momentum in systematic industries can largely explain and even subsume industry momentum, consistent with AKL. For example, the FF5-alpha of IMOM is 0.40% with a *t*-statistic of 4.34. After controlling for SMOM, the alpha declines markedly to 0.18% with a much smaller *t*-statistic of 2.20. Furthermore, as shown in the last column, the IPCA-based SMOM fully subsumes IMOM, rendering the alpha insignificant at 0.08% with a *t*-statistic of 1.04. Although the results presented in Panel B are consistent with those in AKL, they contrast sharply with those reported in Panel A of Table 2.

To pinpoint exactly where the predictability comes from, we decompose the forecasting relationship. AKL imply that industry momentum works because past returns predict future systematic returns. To test this, we construct industry return components using the IPCA

model, which, as evidenced in Table 2, is well suited to capturing the patterns central to our analysis. The Fama-MacBeth regression results are presented in Panel A of Table 3. Notably, past total industry return Ret_{t-1} has no predictive power for future systematic industry return Sys_t , with a coefficient of 0.02 (t -statistic = 0.27), but significantly predicts future residual industry return Res_t with a coefficient of 0.54 (t -statistic = 6.67). Moreover, controlling for past systematic industry return Sys_{t-1} renders the coefficient of Ret_{t-1} for future systematic return Sys_t significantly negative, whereas its predictive power for future residual return Res_t is strengthened. Thus, the FM regressions show that the predictive content of Ret_{t-1} remains robust even after conditioning on Sys_{t-1} , indicating that past industry returns forecast future industry returns through channels economically distinct from those captured by past systematic industry returns.

Panel B of Table 3 breaks the predictability down into four underlying effects. Effect 1 represents momentum in systematic components, corresponding to factor momentum. Effect 2 reflects the residual-to-systematic reversal effect. Effect 3 captures the predictability of past industry systematic components for future residual components, and Effect 4 captures momentum in residual industries. The results indicate that Effects 1 and 4 are positive and statistically significant, Effect 2 is negative and significant, and Effect 3 is economically negligible. Given that the majority of variation in industry returns is attributable to the residual component, Effect 1 is largely neutralized by Effect 2, and Effect 4 dominates Effect 3.¹⁹

Building on these results, we show that the residual-to-systematic reversal effect suppresses the transmission of factor momentum to industry portfolios. Industry momentum and factor momentum may therefore stem from distinct sources. However, since both industry and factor momentum portfolios exhibit negative exposures to the systematic reversal factor, factor momentum appears to subsume industry momentum in the spanning regression due to the

¹⁹The offset is about economic magnitudes, not coefficients alone. Although Effect 1 has a larger predictive coefficient (0.79), it applies to the much smaller systematic component of industry returns, which explains only 19.88% of total variation under IPCA. Effect 2 has a smaller coefficient (−0.27), but applies to the much larger residual component. As a result, the positive contribution from systematic momentum is largely offset by the negative contribution from residual-to-systematic reversal.

omission of this reversal effect.

To formalize why spanning regressions and Fama-MacBeth regressions yield conflicting results, we develop a simple descriptive framework in Section A.2 of the Appendix. We show that short-term reversal acts as an “omitted confounder” that induces substantial spurious correlation in time-series spanning tests, while leaving cross-sectional inference relatively intact. Intuitively, a confounder that jointly influences both the dependent variable (industry momentum) and the explanatory variable (factor or systematic momentum) induces spurious correlation when excluded. Spanning tests are especially vulnerable because they estimate factors in a first stage and regress the target factor on candidate factors in a second; any correlation between the omitted confounder and both momentum measures is absorbed in this second stage, overstating the extent to which factor momentum spans industry momentum. In contrast, FM regressions explicitly test for the incremental predictive power of past industry returns while controlling for past systematic returns in the cross-section, leaving the omitted confounder with limited impact on the results.

All in all, regarding the question of whether industry momentum stems from factor momentum, the FM regression results differ from those obtained through unconditional spanning regressions. Our analyses show that short-term reversal, which affects both industry momentum and factor momentum, acts as a confounding force in the spanning regressions. The results in this section motivate us to re-examine the main claim of AKL that *factors are at the root of momentum and factor momentum subsumes momentum in industries*. In this paper, we provide evidence suggesting that industry momentum is about industries *per se*, and is largely distinct from momentum in factors.

4. Sources of Industry Momentum

Having identified systematic reversal as the key confounder in the industry-versus-factor momentum debate, the remaining task is to pinpoint where industry momentum actually comes from. This requires (i) isolating the industry-level residual-to-systematic reversal

effect (RSR), (ii) separating systematic versus residual components of industry returns, and (iii) determining which component drives momentum. To accomplish this, we rely on a flexible decomposition framework, Instrumented Principal Component Analysis (IPCA), which decomposes returns into systematic and residual components using latent factors and dynamic loadings.

The goal of this section is conceptual, not implementation-oriented: we use IPCA as a flexible bottom-up diagnostic decomposition to uncover the economic mechanism behind industry momentum. In practice, as shown in Section 3.2, a simple hedge that removes reversal exposure already delivers substantial performance improvement. But understanding the source of industry momentum requires the decomposition that follows.

4.1. Methodology

We employ the IPCA model of Kelly, Pruitt, and Su (2019), which provides a flexible framework for estimating latent factors and time-varying systematic exposures for both individual stocks and managed portfolios. IPCA features latent factors and time-varying loadings, where the latter are modeled as functions of observable firm characteristics. Relative to the observable-factor models with static loadings used in AKL, IPCA delivers a more flexible and informative description of the factor structure: it incorporates information beyond returns and allows factor exposures to adjust quickly as characteristics evolve. Kelly, Pruitt, and Su (2019) show that IPCA performs well relative to other leading pricing models in explaining both systematic risks and the cross-section of average returns.²⁰ To capture time-varying factor loadings, we use an instrument set of 65 firm characteristics, as detailed in Table A.1 of the Internet Appendix.²¹

²⁰Kelly, Pruitt, and Su (2019) show that, in their specification with five factors and all stock-level intercepts restricted to zero, the IPCA model is the best-performing model they analyze for jointly explaining realized variation in stock returns and differences in average returns.

²¹Following Kelly, Pruitt, and Su (2019), we transform instruments month-by-month in the cross-section. For each characteristic, we compute cross-sectional ranks, divide by the number of non-missing observations, and subtract 0.5, mapping each characteristic to the interval $[-0.5, 0.5]$ to emphasize ordering rather than magnitude.

Specifically, the model expresses excess returns $r_{i,t}$ as:

$$r_{i,t} = z'_{i,t-1} \Gamma_{\beta} f_t + \epsilon_{i,t}. \quad (3)$$

The model spans N assets over T periods and allows for dynamic factor loadings $\beta_{i,t-1} = z'_{i,t-1} \Gamma_{\beta}$, where $\beta_{i,t-1}$ denotes the loadings on a K -dimensional vector of latent factors f_t . The $L \times 1$ instrument vector $z_{i,t-1}$, which includes a constant, collects observable firm characteristics. The matrix Γ_{β} maps this potentially high-dimensional characteristic space into a low-dimensional space of risk exposures.

This specification of $\beta_{i,t-1}$ is central to IPCA's advantage over the AKL models. Observable-factor models with pre-specified factors implicitly assume that researchers can identify the true underlying factors ex ante. By instead linking latent factor loadings to observable characteristics, IPCA uses richer cross-sectional information to shape the factor structure. This improves both the efficiency of estimation and overall model fit.

The IPCA framework nests commonly used models with observable, pre-specified factors. In that case, the functional form of betas is identical, but the factors themselves are observed, which simplifies estimation of dynamic betas. Let g_t denote a vector of observable factors. The corresponding observable-factor model with instruments is

$$r_{i,t} = z'_{i,t-1} \Gamma_{\beta} g_t + \varepsilon_{i,t} = \text{vec}(\Gamma_{\beta})' (z_{i,t-1} \otimes g_t) + \varepsilon_{i,t} \quad (4)$$

where the second equality follows from the standard vectorization identity. In this setting, instrumented betas for observable factors can be efficiently estimated by panel OLS, using interactions between instruments and factors as regressors. Observable-factor models with instruments therefore also allow for dynamic loadings and provide a more accurate representation of the factor structure than their counterparts without instruments, as shown in Kelly, Pruitt, and Su (2019).

We evaluate model performance along two dimensions. First, a successful factor model

should capture the common variation in realized returns. We measure this using the model’s total panel R^2 , which aggregates explained variation from contemporaneous factor realizations and dynamic factor exposures across all assets and time periods:

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t} \left(r_{i,t} - \hat{\beta}'_{i,t-1} \hat{f}_t \right)^2}{\sum_{i,t} r_{i,t}^2}. \quad (5)$$

Total R^2 summarizes the model’s ability to describe shared risks in asset returns.

Second, a successful asset pricing model should explain differences in average returns across assets. To assess this, we use a measure based on pricing errors. Let $\alpha_i = \frac{1}{T_i} \sum_t \left(r_{i,t} - \hat{\beta}'_{i,t-1} \hat{f}_t \right)$ be the average time-series error, or “pricing error,” for the i^{th} test asset; and let $\bar{r}_i = \frac{1}{T_i} \sum_t r_{i,t}$ be the asset’s time-series average excess return. We define the relative pricing error of a model as the sum of squared pricing errors divided by the sum of squared average returns:

$$\text{Relative Pricing Error} = \frac{\sum_i \alpha_i^2}{\sum_i \bar{r}_i^2}. \quad (6)$$

4.2. *IPCA as a Diagnostic Decomposition*

To assess whether IPCA is appropriate for our decomposition exercise, we compare competing pricing models using a diagnostic test tailored to our setting. A useful decomposition model for our purpose should be able to capture, at a minimum, characteristic momentum and random-industry reversal. Table 4 presents a comparison of five pricing models: (1) the Fama-French three-factor model; (2) the Fama-French five-factor model; (3) the five-factor model augmented with long-term reversal and residual variance; (4) the five-factor model further augmented with long-term reversal, residual variance, quality-minus-junk, and betting-against-beta factors; and (5) the $K=10$ IPCA model. Models 1 through 4 are observable factor models with instrumented dynamic loadings. We use the 65 firm characteristics listed in Table A.1 as instruments for all five models.

For each strategy, we decompose the total return into two components: (1) the systematic

component of portfolio p in month t , defined as $Sys_{p,t} = \beta_{p,1,t}F_{1,t} + \cdots + \beta_{p,K,t}F_{K,t}$, where F_t s represent the chosen factors and $\beta_{p,t}$ s are the value-weighted average of the dynamic stock-level factor loadings corresponding to the chosen factors within portfolio p , and (2) the residual component, derived by subtracting the systematic component from the total return. Table 4 presents the average monthly returns, systematic returns, and residual returns for 65 characteristic momentum strategies in Panel A, and for 1,000 random-industry reversal strategies in Panel B. The total R^2 values and relative pricing errors for all five models are also presented.

Panel A of Table 4 shows that the profits of characteristic momentum strategies are primarily reflected in the predictability of future systematic returns, rather than future residual returns. This is evidenced by the significant and positive returns for the systematic component, whereas those for the residual component are insignificant and close to zero. On average, characteristic momentum strategies generate a statistically significant positive return of 22 bps per month, with a t -statistic of 3.03. Among the models considered, the IPCA model (model (5)) demonstrates the best performance, achieving an overall R^2 of 80.62% and a pricing error as low as 6.27%. In particular, the systematic returns captured by the IPCA model are statistically significant at 20 bps with a t -statistic of 3.04, accounting for over 90% of total return. In contrast, Panel B indicates that only the IPCA model captures the systematic reversal component in random-industry portfolios, producing systematic returns averaging -5 bps (t -statistic = -5.29) compared to total returns averaging -8 bps (t -statistic = -3.73). The other factor models do not capture this reversal effect. Notably, the IPCA model achieves a total R^2 of 30.31% and a pricing error of just 12.34%, whereas other observable factor models have total R^2 values below 20% and pricing errors exceeding 100%.

All in all, there is a statistically reliable short-term reversal effect in the random-industry portfolios, which is effectively captured by the IPCA model but overlooked by other models with pre-specified factors. The IPCA model also captures characteristic momentum. These results highlight the importance of employing a flexible decomposition model to investigate

the drivers of industry momentum.

4.3. *Does Exposure to Systematic Factors Generate Industry Momentum?*

Having shown that IPCA captures both characteristic momentum and random-industry reversal, we now apply it to decompose the sources of industry momentum. The central claim of AKL is that industry momentum is merely a manifestation of factor momentum transmitted through industry factor loadings. If this were true, the profitability of industry momentum should stem primarily from its *systematic* component. However, the RSR effect may mitigate or counteract the impact of factor momentum. Therefore, exposure to systematic factors does not guarantee the transmission of factor momentum into industry momentum.

Table 5 presents the average monthly raw returns, Sharpe ratios, and alphas relative to the Fama-French five-factor model for industry momentum, alongside its systematic and residual components. The final three columns of Table 5 present estimates from the Fama-French five-factor model augmented with the Carhart (1997) UMD factor. The results indicate that industry momentum exhibits a significantly positive return, which cannot be explained by the six-factor model.

If industry momentum stems solely from factor momentum, its returns would originate entirely from the systematic component. However, the results show that the systematic component of industry momentum return is nearly zero, whereas the residual component remains significantly positive and comparable to the total industry momentum return, even after accounting for the six-factor model. Specifically, the Sharpe ratio of industry momentum return is 0.56, with its systematic component exhibiting a Sharpe ratio of -0.04, whereas its residual component achieves a Sharpe ratio of 0.89.²²

These findings suggest that exposures to systematic factors do not drive industry momentum, challenging AKL's argument that profits of industry momentum strategies arise from the

²²This finding, derived from the IPCA analysis, is also consistent with the FM regression results reported in Panel A of Table 3. Specifically, the FM regressions show no evidence that past total industry returns predict future systematic industry returns.

transmission of factor momentum to industry returns through variations in industry factor loadings.

4.4. *Understanding the Residual-to-Systematic Reversal Effect*

Why does the systematic component fail to contribute? The answer lies in the residual-to-systematic reversal. We propose that this reversal effect inhibits the transmission of factor momentum, thereby rendering the systematic component of industry momentum insignificant, as shown in Table 5. Therefore, we expect that the industry momentum strategy derives its profits from the positive autocorrelation in residual industry returns.

Figure 2 illustrates the predictive power of past residual returns over the preceding 12 months for future residual and systematic components across three sets of portfolios: the industry momentum portfolio (Panel A), 65 characteristic momentum portfolios (Panel B), and 1,000 random-industry reversal portfolios (Panel C). The results reveal a strong *positive* relationship between Res_{t-1} and Res_t in the industry momentum portfolio, whereas such a relationship is absent in the characteristic momentum and random-industry reversal portfolios. As expected, we find a strong negative relationship between Res_{t-1} and Sys_t for both the industry momentum and random-industry reversal portfolios.

Table 6 examines the explanatory power of factor momentum strategies constructed from various sets of high-eigenvalue PC factors for the residual and systematic components of the long-short momentum spreads in month t , based on portfolios sorted by Res_{t-1} . We find that momentum in factors, regardless of the underlying set of PC factors, fails to explain momentum in residual industries, which remain significantly positive. Furthermore, regressing the systematic component of residual industry momentum on factor momentum yields significantly negative alphas. For example, when factor momentum is constructed using the top 10 high-eigenvalue PC factors, the systematic component of residual industry momentum produces a significant alpha of -30 bps with a t -statistic of -7.47 relative to the AKL model.

These results confirm that there is a strong residual-to-systematic reversal effect embedded in the industry momentum portfolio. Omitting this effect can bias inference about industry momentum as shown in Section 3. In the next section, we further elaborate on the OVB issue in the AKL framework, which explains the discrepancy between their spanning regression results and our findings based on FM regressions and IPCA analysis.

4.5. *Omitted Variable Bias*

We now return to the conflict between our findings and AKL’s spanning regressions. We argue that AKL’s conclusion that factor momentum subsumes industry momentum is driven by omitted variable bias (OVB) due to the exclusion of the RSR effect. To demonstrate this empirically, we construct an industry-level RSR Factor: a strategy that goes long systematic industries with below-median past-month residual industry returns and short systematic industries with above-median past-month residual industry returns. We construct the RSR factor in this way to ensure it has a positive average return. The RSR factor is highly correlated with the stock-level short-term reversal factor, exhibiting a correlation of 61%.

To illustrate the presence of this bias, we plot the residuals from AKL’s model against the RSR factor in Figure 3. These residuals are obtained from regressions of industry momentum on factor momentum and the Fama–French five factors, following AKL’s framework. The analysis begins in January 1970, reflecting the initial estimation window required to construct factor momentum using principal components.²³ Panel A of Figure 3 reports results using factor momentum constructed from the top 10 highest-eigenvalue PC factors, yielding a slope estimate of -0.37 with a t -statistic of -20.39 , revealing a significantly negative relation between the residuals from AKL’s model and the RSR factor. This relationship remains robust when factor momentum is instead constructed from the top 20 eigenvalue PCs, as shown in Panel B, where the slope remains significantly negative with a t -statistic of -13.05 . These findings

²³We use a binned scatter plot, a non-parametric method widely used in microeconomics, which groups observations into bins and plots mean outcomes within each bin. Light bars represent pointwise confidence intervals and shaded areas indicate uniform confidence bands.

confirm the presence of omitted-variable bias in AKL’s model.²⁴

We move on to examine whether factor momentum can subsume industry momentum when the RSR factor is accounted for. Table 7 presents estimates from four models used to price the returns of loser industries in month t (those with below-median returns in month $t-1$), winner industries (those with above-median returns in month $t-1$) and the industry momentum portfolio. The four models are as follows: (1) the Fama-French five-factor model, (2) the five-factor model augmented with momentum in the top 10 high-eigenvalue PC factors, (3) the five-factor model augmented with the RSR factor, and (4) the five-factor model augmented with both factor momentum that trades the 10 highest-eigenvalue PCs and the RSR factor.

Consistent with AKL, factor momentum appears to subsume industry momentum, yielding an insignificant monthly alpha of 9 bps with a t -statistic of 1.24. As expected, we also find that the industry momentum alpha is significantly influenced by the RSR factor. Specifically, when the RSR factor is controlled for, the monthly alpha for industry momentum increases substantially from 40 bps (t -statistic = 4.34) to 66 bps (t -statistic = 7.81). Crucially, when the RSR factor is added to AKL’s model, factor momentum no longer explains industry momentum, leaving a significant alpha of 34 bps (t -statistic = 4.60). The result in the last column is consistent with earlier FM regression and IPCA evidence, which indicate that factor momentum cannot fully explain industry momentum. The conclusion is not specific to the decomposition-based RSR factor: using the stock-level short-term reversal factor (STREV) as the control yields quantitatively similar results, as shown in Table A.3 in the Appendix.²⁵

In summary, our analysis shows that AKL overstates the explanatory power of factor momentum for industry momentum because of omitted-variable bias in their framework. Once this bias is addressed, industry momentum exhibits a distinct and economically significant alpha that cannot be explained by factor momentum. This result reconciles the spanning

²⁴The main results are based on the Fama–French 49-industry classification. Table A.7 in the Appendix shows that the results remain both qualitatively and quantitatively similar across alternative classification schemes.

²⁵Table A.2 in the Appendix examines AKL’s claim by varying the number of highest-eigenvalue principal components used to construct factor momentum. Once the RSR factor is included, factor momentum no longer prices industry momentum, while model fit improves across specifications.

regressions with our Fama–MacBeth and IPCA results: factor momentum alone does not explain industry momentum. The apparent “spanning” arises as a statistical artifact driven by the shared exposure of the two strategies to systematic reversal.

4.6. *Explaining Industry Momentum with Residual Industry Momentum*

The evidence thus far suggests that industry momentum may arise from momentum in residual industries. We define residual industry returns as the difference between actual industry returns and their systematic component following AKL.²⁶ The residual industry momentum strategy is defined analogously to the industry momentum strategy.

In Table 8, we directly examine whether residual-industry momentum (RMOM) explains industry momentum. For comparison, we first report industry momentum alphas relative to the Fama-French five-factor model augmented with the RSR and factor momentum factors. We then report alphas relative to the same model further augmented with the residual industry momentum factor. The results show that the losers (winners) significantly and negatively (positively) load on RMOM. In addition, RMOM renders the industry momentum alpha insignificant, from 34 bps (t -statistic = 4.60) to 7 bps (t -statistic = 1.40). These results suggest that residual industry momentum, which exhibits minimal exposure to systematic factors, accounts for industry momentum even after controlling for the RSR effect.²⁷ Therefore, industry momentum stems from industry-specific shocks, rather than momentum in factors.

In sum, these findings indicate that industry-specific information is the primary driver of industry momentum, and strategies that rely solely on factor-level replications of industries are unlikely to fully capture it effectively.

²⁶As in AKL, systematic industries are constructed as linear combinations of the factors onto which actual industries load. Specifically, systematic industry j earns a return of $Sys_{j,t} = \beta_{j,1,t}F_{1,t} + \dots + \beta_{j,K,t}F_{K,t}$ in month t , where the F_t s are factor returns.

²⁷Table A.6 in the Appendix further shows that factor momentum cannot explain residual industry momentum.

4.7. What Drives Residual Industry Momentum?

So far, we have demonstrated that exposure to systematic factors cannot generate industry momentum and that industry-specific momentum is the main driver. In this section, we continue to explore the source of momentum in industry-specific returns.

First, we decompose the profits of the residual industry momentum strategies using the Lo and MacKinlay (1990) method. Specifically, we decompose the expected return of the residual industry momentum into three terms,

$$\mathbb{E}(r_t^{LM}) = \underbrace{\frac{N_t - 1}{N_t^2} \text{Tr}(\Omega_t)}_{\text{autocovariance}} - \underbrace{\frac{1}{N_t^2} (1' \Omega_t 1 - \text{Tr}(\Omega_t))}_{\text{cross-serial covariance}} + \underbrace{\sigma_{\mu,t}^2}_{\text{mean effect}}, \quad (7)$$

where $\Omega_t = \mathbb{E}_t[(r_{i,t} - \mu)(r_{i,t+1} - \mu)']$ is the autocovariance matrix of asset returns at time t , $\text{Tr}(\Omega_t)$ is the trace of this matrix, and $\sigma_{\mu,t}^2$ is the cross-sectional variance of mean asset returns at time t . Therefore, the Lo-MacKinlay decomposition separates the residual industry momentum profits into three sources, namely positive autocovariances in residual industry returns, negative cross-serial covariances, and cross-sectional variation in mean returns.

Panel A of Table 9 reports the decomposition of residual industry momentum strategy returns based on Equation (7) across various industry classification schemes. The first two terms in Equation (7) are derived from the full-sample autocovariance matrix, while the final term is computed as the residual difference between the strategy returns and the sum of the first two components. We analyze the Fama and French 49-industry, 38-industry, and 30-industry classifications, as well as the 20-industry classification proposed by Moskowitz and Grinblatt (1999). Cross-sectional momentum strategies in residual industries, irrespective of the classification scheme, are primarily driven by positive autocorrelations in residual returns. Both the cross-serial covariance and the mean effect are economically small, reinforcing the conclusion that the primary driver of residual industry momentum returns is the short-term positive autocorrelation in industry returns.

A natural question arises: what are the underlying drivers of this positive autocorrelation?

Since an industry is a portfolio of stocks, a natural mechanism is gradual information diffusion across firms within the same industry. For example, positive industry-specific news might first be reflected in the leading firms, driving their stock prices up and resulting in a positive industry return. Subsequently, this good news may be incorporated by the lagging firms, further driving their stock prices up and contributing to a positive industry return. The same applies to negative news.

To examine this mechanism, we adapt the pairwise lead-lag decomposition of Yan and Yu (2023) to residual industry returns. Our objective is not to revisit their broad cross-stock momentum result, but to use their methodology as a diagnostic tool for identifying whether the residual component of industry momentum reflects within-industry information transmission. For each stock pair k and j , there are two lead-lag linkages between the two stocks: the linkage from R_{t-1}^j to R_t^k and the linkage from R_{t-1}^k to R_t^j . Following Yan and Yu (2023), we decompose the residual industry momentum according to whether stock j leads k .²⁸ Specifically, a high (low) $j \rightarrow k$ link is determined by:

$$j \rightarrow k \text{ link} = \begin{cases} \text{high} & \text{if } \text{Cor}(R_{t-1}^j, R_t^k) \geq \text{Cor}(R_{t-1}^k, R_t^j), \\ \text{low} & \text{if } \text{Cor}(R_{t-1}^j, R_t^k) < \text{Cor}(R_{t-1}^k, R_t^j). \end{cases} \quad (8)$$

We focus on the following equivalent version of the residual industry momentum:

$$\frac{1}{I} \mathbb{E} \left[\sum_{i=1}^I (R_{t-1}^i - \bar{R}_{t-1})(R_t^i - \bar{R}_t) \right]. \quad (9)$$

The average residual industry return $\bar{R}_{t-1}$ can be re-written using individual stock returns as $\bar{R}_{t-1} = \sum_j \bar{w}_{t-1}^j R_{t-1}^j$, where $\bar{w}_{t-1}^j \equiv \frac{1}{I} \sum_{i=1}^I w_{t-1}^{j,i}$ is the average weight of stock j in all

²⁸There is no need to adjust the signs of the linkages as in Yan and Yu (2023), because the weights of the two stocks within industry i are consistently positive.

industries. Therefore,

$$\begin{aligned}
(R_{t-1}^i - \bar{R}_{t-1})(R_t^i - \bar{R}_t) &= \left(\sum_j w_{t-1}^{j,i} R_{t-1}^j - \sum_j \bar{w}_{t-1}^j R_{t-1}^j \right) \left(\sum_k w_t^{k,i} R_t^k - \sum_k \bar{w}_t^k R_t^k \right) \\
&= \left(\sum_j \tilde{w}_{t-1}^{j,i} R_{t-1}^j \right) \left(\sum_k \tilde{w}_t^{k,i} R_t^k \right) \quad \text{where } \tilde{w}_t^{k,i} \equiv w_t^{k,i} - \bar{w}_t^k \\
&= \sum_{\substack{j \neq k \\ \text{high } j \rightarrow k \text{ link}}} \tilde{w}_{t-1}^{j,i} \tilde{w}_t^{k,i} R_{t-1}^j R_t^k + \sum_{\substack{j \neq k \\ \text{low } j \rightarrow k \text{ link}}} \tilde{w}_{t-1}^{j,i} \tilde{w}_t^{k,i} R_{t-1}^j R_t^k \\
&\quad + \sum_j \tilde{w}_{t-1}^{j,i} \tilde{w}_t^{j,i} R_{t-1}^j R_t^j, \tag{10}
\end{aligned}$$

Panel B of Table 9 shows the results for the residual industry momentum decomposition in Equation (10). The residual industry momentum component corresponding to high cross-stock links is significantly higher than the residual industry component corresponding to low cross-stock links. Regardless of the industry classification employed, the residual industry momentum component associated with high cross-stock links consistently surpasses that of low cross-stock links. For instance, the difference amounts to 0.14 (t -statistic = 2.68) under the Fama-French 49-industry classification and 0.79 (t -statistic = 2.55) under the Moskowitz and Grinblatt (1999) 20-industry classification.

These results indicate that residual industry momentum is concentrated in stock-pair linkages with stronger within-industry lead-lag relations. This evidence complements our earlier decomposition by showing that, after removing systematic factor exposure, the remaining industry momentum is tied to the propagation of industry-specific information across related firms. Our finding aligns with Asness, Porter, and Stevens (2000), who show that strategies based on within-industry variables outperform those relying on market-wide measures. Our finding is also consistent with Hou (2007), who demonstrates that the gradual diffusion of industry-specific information leads to the strong intra-industry lead-lag effect in stock returns.²⁹

²⁹Appendix Table A.8 examines firm-level determinants of the intra-industry lead-lag relation underlying residual industry momentum. Consistent with Hou (2007), firms with lower information uncertainty are more likely to lead within industries: lead stocks tend to be larger, older, more heavily followed by analysts, and to exhibit lower idiosyncratic volatility and forecast dispersion than lag stocks.

5. Conclusion

This paper identifies a pervasive residual-to-systematic reversal (RSR) component embedded within a broad class of short-term momentum strategies. Because momentum portfolios inherently absorb this systematic drag, hedging this reversal exposure substantially enhances their performance. More broadly, accounting for this reversal effect provides new insights into the profitability and shared risk exposures of short-term momentum anomalies. These findings are economically important given the central role of momentum strategies in both academic research and investment practice.

The presence of RSR also sheds new light on the conclusion of Arnott, Kalesnik, and Linnainmaa (2023) that industry momentum is subsumed by factor momentum. Our analysis indicates that this conclusion is influenced by omitted-variable bias: because both industry and factor momentum load negatively on RSR, unconditional spanning regressions that exclude RSR tend to misattribute industry momentum to factor momentum. Once this reversal confounder is properly controlled for, industry momentum re-emerges as a distinct and economically meaningful phenomenon driven primarily by residual industry momentum and intra-industry lead-lag dynamics rather than by the timing of systematic factors. We further find that Fama-MacBeth regressions are less sensitive to this bias. Taken together, these results reaffirm that industry momentum is distinct from factor momentum.

These results carry broader implications for empirical asset pricing. Unconditional spanning regressions are widely used to assess factor redundancy, yet our findings illustrate their sensitivity to omitted common components. In particular, RSR induces substantial common variation between industry momentum and factor momentum, and omitting this component can lead spanning regressions to overstate the extent to which one strategy subsumes the other. More generally, our analysis highlights the importance of isolating common reversal forces when evaluating return predictability and testing asset-pricing models. Once these forces are properly accounted for, industry momentum emerges as a distinct and economically meaningful source of return predictability.

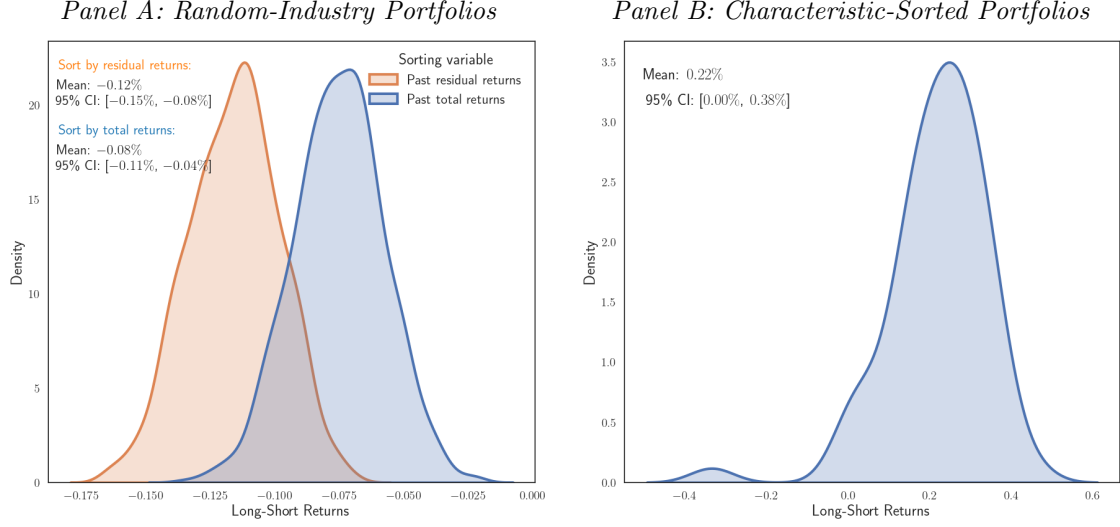


Fig. 1 Short-Term Trends in Random-Industry and Characteristic-Sorted Portfolios

Panel A reports the return distributions of short-term trend strategies constructed from 1,000 sets of random-industry portfolios. In each simulation, all stocks are randomly assigned into 50 groups treated as hypothetical industries, value-weighted group returns are computed, and a long-short strategy is formed each month by going long industries with above-median past-month returns and short industries with below-median past-month returns. We report results for both raw random-industry returns and residual random-industry returns, where residual returns are obtained by removing the systematic component estimated from the $K = 10$ IPCA model (see Section 4). Panel B reports the return distributions of 65 characteristic-sorted short-term trend strategies (characteristics listed in Table A.1). For each characteristic, stocks are sorted into decile portfolios based on the characteristic, and the strategy goes long decile portfolios with above-median past-month returns and short those with below-median past-month returns. Both panels report mean returns and 95% confidence intervals. The sample period is January 1965 to December 2022.



Fig. 2 The Anatomy of Residual Predictability for Different Portfolios.

This figure plots the t -statistics from regressions of future residual returns and future systematic returns on past residual returns measured at horizons $t - k$ over the preceding 12 months. Results are shown for three sets of strategies: the industry momentum strategy (Panel A), 65 characteristic momentum strategies (Panel B), and 1,000 random-industry reversal strategies (Panel C). Systematic and residual returns are obtained from a portfolio return decomposition described in the text. The sample period spans January 1965 through December 2022.

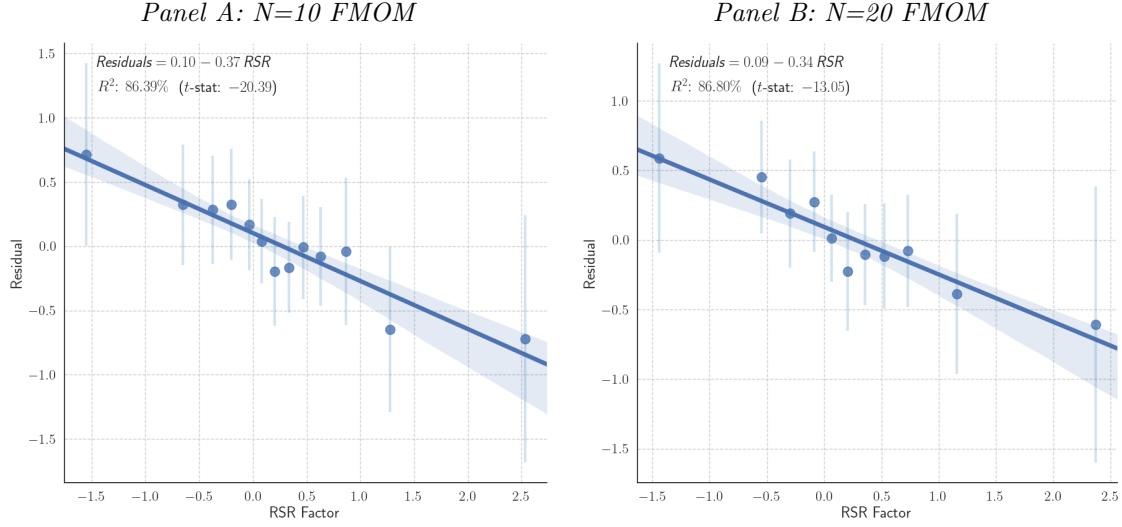


Fig. 3 Residuals from AKL's Model versus the RSR factor.

This figure plots regression estimates relating industry momentum residuals from AKL's pricing model to the residual-to-systematic reversal (RSR) factor. The dependent variable is the residual from regressing industry momentum on the Fama–French five factors and factor momentum (FF5+FMOM). Panel A uses FMOM constructed from the 10 highest-eigenvalue principal-component (PC) factors, while Panel B uses FMOM constructed from the 20 highest-eigenvalue PC factors. The figure reports binned-scatter regression estimates with pointwise confidence intervals (light bars) and uniform confidence bands (shaded areas). PC factors are estimated using data from January 1965 to December 1969; accordingly, the analysis sample begins in January 1970 and ends in December 2022.

Table 1 The Impact of Short-Term Reversal on Short-Term Momentum Strategies

This table examines how short-term reversal affects industry, characteristic, and factor momentum strategies. Results are based on the Fama–French five-factor model (FF5) and the short-term reversal factor (STREV). For characteristic momentum, results are averaged across the 65 characteristics listed in Table A.1. Factor momentum is constructed from the corresponding 65 characteristic-based factors. Panel A reports alphas, factor loadings, and adjusted R^2 s from pricing models with and without STREV. Panel B evaluates dynamically STREV-hedged momentum portfolios. Panel B.1 reports annualized Sharpe ratios and FF5 alphas for raw and hedged portfolios, and Panel B.2 tests whether hedged industry and characteristic momentum are explained by raw or hedged factor momentum. The sample period for Panel A spans January 1970 to December 2022. Panel B begins in January 1975 to allow for the initialization of hedging exposures.

<i>Panel A: Short-Term Reversal and Momentum Portfolio Alphas</i>									
<i>Panel A.1: Exposures of Short-Term Momentum Strategies to the Short-Term Reversal Factor</i>									
	α	MKT	SMB	HML	RMW	CMA	STREV		$R^2(\%)$
Industry MOM	0.40	-0.08	-0.01	-0.10	-0.08	0.15			4.95
	(4.31)	(-2.94)	(-0.31)	(-1.84)	(-1.00)	(1.91)			
	0.56 (7.96)	0.02 (0.90)	0.04 (1.45)	0.00 (-0.04)	-0.09 (-2.68)	0.03 (0.40)	-0.48 (-19.74)		51.73
Characteristic MOM	0.22	-0.04	0.04	-0.08	-0.03	0.17			4.55
	(2.48)	(-1.88)	(0.78)	(-1.29)	(-0.38)	(2.07)			
	0.34 (4.65)	0.03 (1.51)	0.08 (2.24)	0.00 (0.11)	-0.04 (-0.81)	0.07 (0.99)	-0.37 (-8.54)		34.99
Factor MOM	0.40	-0.07	0.01	-0.06	-0.06	0.17			6.94
	(4.76)	(-3.21)	(0.24)	(-1.08)	(-0.64)	(2.72)			
	0.52 (7.58)	0.00 (0.01)	0.05 (1.37)	0.01 (0.24)	-0.07 (-1.25)	0.08 (1.70)	-0.34 (-10.28)		44.02
<i>Panel A.2: Explaining Industry and Characteristic Momentum via Factor Momentum, Controlling for Short-Term Reversal</i>									
	α	MKT	SMB	HML	RMW	CMA	STREV	FMOM	$R^2(\%)$
Industry MOM	0.09	-0.03	-0.02	-0.06	-0.04	0.02		0.76	38.65
	(1.21)	(-1.38)	(-0.86)	(-1.72)	(-0.96)	(0.43)		(13.74)	
	0.39 (6.11)	0.02 (0.91)	0.02 (0.97)	0.00 (-0.14)	-0.07 (-2.19)	0.00 (0.00)	-0.37 (-11.43)	0.32 (6.45)	55.35
Characteristic MOM	-0.05	0.00	0.03	-0.04	0.00	0.05		0.66	31.80
	(-0.45)	(-0.05)	(0.97)	(-0.89)	(0.04)	(0.83)		(7.62)	
	0.16 (2.37)	0.03 (1.51)	0.06 (2.04)	-0.01 (-0.02)	-0.02 (-0.44)	0.04 (0.59)	-0.25 (-6.23)	0.36 (4.92)	40.17
<i>Panel B: Dynamically Hedged Short-Term Momentum Portfolios</i>									
<i>Panel B.1: Raw versus Hedged Short-Term Momentum</i>									
		SR	α	MKT	SMB	HML	RMW	CMA	$R^2(\%)$
Industry MOM	Raw	0.48	0.34	-0.07	0.03	-0.12	-0.05	0.17	4.19
	Hedged	1.11	0.47 (7.09)	(3.60) (1.26)	(0.59) (2.66)	(-2.15) (0.10)	(-0.60) (-1.94)	(1.98) (0.04)	4.39
Characteristic MOM	Raw	0.34	0.19	-0.04	0.05	-0.10	-0.02	0.19	4.98
	Hedged	0.71	0.31 (4.11)	(2.14) (0.78)	(0.95) (2.29)	(-1.47) (-0.46)	(-0.28) (-1.14)	(2.28) (0.98)	6.20
Factor MOM	Raw	0.71	0.37	-0.06	0.03	-0.08	-0.04	0.19	6.01
	Hedged	1.29	0.48 (7.35)	(4.21) (0.25)	(0.64) (1.74)	(-1.42) (-0.14)	(-0.46) (-1.39)	(2.80) (1.10)	4.01
<i>Panel B.2: Explaining Hedged Industry and Characteristic Momentum via Factor Momentum</i>									
	Control for	α	MKT	SMB	HML	RMW	CMA	FMOM	$R^2(\%)$
Industry MOM	FMOM _{raw}	0.42	0.03	0.06	0.02	-0.06	-0.02	0.15	6.82
	FMOM _{hedged}	(6.40)	(1.79)	(2.73)	(0.39)	(-1.81)	(-0.36)	(2.98)	
Characteristic MOM		0.34	0.02	0.05	0.01	-0.05	-0.01	0.27	9.62
		(5.25)	(1.26)	(2.36)	(0.15)	(-1.47)	(-0.19)	(4.94)	
	FMOM _{raw}	0.23	0.03	0.07	-0.01	-0.05	0.03	0.23	11.18
	FMOM _{hedged}	(3.19)	(1.47)	(2.24)	(-0.11)	(-1.12)	(0.39)	(3.27)	
		0.15	0.02	0.06	-0.03	-0.04	0.05	0.34	13.07
		(2.38)	(0.71)	(1.89)	(-0.54)	(-0.83)	(0.76)	(4.50)	

Table 2 Fama-MacBeth versus Spanning Regressions

This table compares the explanatory power of momentum in systematic industries for industry momentum using Fama-MacBeth and spanning regressions. Systematic industries are constructed as the systematic components of industry returns based on alternative factor models: (1) FF3, (2) FF5, (3) FF5+LTREV+RVAR, (4) FF5+LTREV+RVAR+QMJ+BAB, and (5) the $K = 10$ IPCA model. Panel A reports Fama-MacBeth regressions of industry returns on lagged own returns and lagged systematic industry returns. To facilitate interpretation, predictive coefficients are scaled to represent the percentage change in monthly industry returns associated with a two-standard-deviation increase in each predictor. Panel B reports spanning regressions of industry momentum on systematic industry momentum (SMOM) and the FF5 factors. Industry momentum and SMOM are constructed from the Fama–French 49 industries and their systematic counterparts, respectively. The sample period is January 1970 to December 2022.

<i>Panel A: Fama-MacBeth Regressions</i>						
	Univariate	Model for Systematic Industries				
		(1)	(2)	(3)	(4)	(5)
Intercept	0.66 (3.28)	0.62 (2.67)	0.47 (2.09)	0.55 (2.55)	0.49 (2.33)	0.64 (3.02)
Ret_{t-1}	0.56 (5.26)	0.42 (4.06)	0.42 (3.97)	0.39 (3.69)	0.35 (3.37)	0.31 (3.03)
Sys_{t-1}		0.51 (2.04)	0.37 (2.17)	0.55 (3.34)	0.59 (3.72)	0.65 (5.21)
R^2 (%)	4.38	11.48	11.02	10.98	10.81	10.90
<i>Panel B: Spanning Regressions</i>						
	α_{FF5}	$\alpha_{FF5+smom}$				
		(1)	(2)	(3)	(4)	(5)
α	0.40 (4.34)	0.18 (2.20)	0.17 (2.23)	0.17 (2.13)	0.17 (2.21)	0.08 (1.04)
β_{smom}		0.59 (9.13)	0.64 (11.13)	0.65 (12.28)	0.64 (11.26)	0.67 (12.43)
R^2 (%)	4.97	29.03	33.28	37.66	37.82	41.72

Table 3 Channels of Industry Momentum

This table examines how past-month industry returns and their components forecast future systematic and residual industry returns. Industry returns are decomposed using the $K = 10$ IPCA model into systematic ($Sys_{j,t}$) and residual ($Res_{j,t}$) components. Panel A reports Fama-MacBeth regressions of future systematic and residual industry returns on lagged total industry returns ($Ret_{j,t-1}$) and lagged systematic returns ($Sys_{j,t-1}$). Panel B further decomposes industry momentum by estimating cross-sectional regressions of each future return component ($Sys_{j,t}$ or $Res_{j,t}$) on lagged systematic and residual returns ($Sys_{j,t-1}$ and $Res_{j,t-1}$), thereby isolating the four channels linking past and future systematic and residual returns. The sample spans January 1970 to December 2022.

<i>Panel A: Fama-MacBeth Predictability of Industry Return Components</i>				
	Sys_t	Sys_t	Res_t	Res_t
Intercept	0.56 (2.85)	0.43 (2.49)	0.10 (1.63)	0.21 (1.88)
Ret_{t-1}	0.02 (0.27)	-0.36 (-8.45)	0.54 (6.67)	0.66 (7.42)
Sys_{t-1}		0.94 (10.96)		-0.28 (-3.14)
<i>Panel B: Cross-Sectional Decomposition of Industry Momentum</i>				
	Effect 1	Effect 2	Effect 3	Effect 4
	Sys_t	Sys_t	Res_t	Res_t
Intercept	0.42 (2.42)	0.65 (3.16)	0.18 (1.59)	0.02 (0.70)
Sys_{t-1}	0.79 (8.97)		0.00 (0.05)	
Res_{t-1}		-0.27 (-6.42)		0.58 (7.10)

Table 4 Pricing Characteristic Momentum and Random-Industry Reversal

This table compares the performance of alternative pricing models in explaining characteristic momentum and random-industry reversal. Panel A reports results for 65 characteristic momentum portfolios, and Panel B reports results for 1,000 sets of random-industry reversal portfolios. For each portfolio, total returns are decomposed into systematic and residual components based on alternative factor models: (1) FF3, (2) FF5, (3) FF5+LTREV+RVAR, (4) FF5+LTREV+RVAR+QMJ+BAB, and (5) the $K = 10$ IPCA model. The table reports average monthly total returns and their systematic and residual components, along with corresponding t -statistics, total R^2 values, and relative pricing errors. Total R^2 and the relative pricing error are defined for total returns as in Section 4.1. The sample period is January 1970 to December 2022.

	Model for Systematic Portfolio Returns				
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Characteristic Momentum</i>					
<i>Total Return</i>	0.22 (3.03)	0.22 (3.03)	0.22 (3.03)	0.22 (3.03)	0.22 (3.03)
<i>Systematic Return</i>	0.14 (2.90)	0.16 (3.03)	0.17 (3.10)	0.18 (3.28)	0.20 (3.04)
<i>Residual Return</i>	0.07 (1.69)	0.06 (1.47)	0.05 (1.41)	0.04 (1.07)	0.02 (0.55)
Total R^2 (%)	61.64	69.15	74.37	75.52	80.62
Relative Pricing Error (%)	22.06	16.89	15.64	13.31	6.27
<i>Panel B: Random-Industry Reversal</i>					
<i>Total Return</i>	-0.08 (-3.73)	-0.08 (-3.73)	-0.08 (-3.73)	-0.08 (-3.73)	-0.08 (-3.73)
<i>Systematic Return</i>	0.00 (0.79)	0.01 (0.96)	0.01 (0.97)	0.01 (1.46)	-0.05 (-5.29)
<i>Residual Return</i>	-0.08 (-4.09)	-0.08 (-4.20)	-0.08 (-4.22)	-0.09 (-4.42)	-0.02 (-1.28)
Total R^2 (%)	12.71	14.13	15.33	15.88	30.31
Relative Pricing Error (%)	112.21	115.55	115.43	124.95	12.34

Table 5 Industry Momentum and Its Components

This table reports monthly raw returns, Sharpe ratios, and alphas relative to the Fama–French five- and six-factor models for industry momentum and its systematic and residual return components. The industry momentum strategy, along with its systematic (residual) return, takes long positions in industries (or their systematic/residual returns) with above-median past-month returns and short positions in those with below-median past-month returns. All strategies use a one-month formation period, are rebalanced monthly, and are based on the Fama–French 49-industry classification. The six-factor model augments FF5 with the momentum factor (UMD). The sample spans January 1970 to December 2022.

	Avg. Ret	SR	FF5	FF5 + UMD		
			$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{umd}$	R^2 (%)
<i>Total Return</i>	0.35 (4.14)	0.56	0.40 (4.34)	0.33 (3.88)	0.10 (2.55)	9.60
<i>Systematic Return</i>	-0.02 (-0.29)	-0.04	0.04 (0.60)	-0.01 (-0.20)	0.08 (2.04)	14.38
<i>Residual Return</i>	0.36 (5.50)	0.89	0.36 (5.39)	0.34 (4.90)	0.03 (1.26)	0.94

Table 6 The Anatomy of Residual Industry Predictability

This table examines whether past-month residual industry returns (Res_{t-1}) predict future residual industry returns (Res_t) and future systematic industry returns (Sys_t). Industry returns are decomposed into systematic ($Sys_{j,t}$) and residual ($Res_{j,t}$) components using the $K = 10$ IPCA model. We construct long–short portfolios by sorting industries on past-month residual returns: Panel A goes long (short) residual industries with above- (below-) median Res_{t-1} , while Panel B applies the same sort to systematic industries. Monthly alphas are computed relative to the Fama–French five-factor model augmented with a factor momentum strategy constructed from subsets of the top N high-eigenvalue principal components derived from our 65 factors, where N ranges from 5 to 40. For each portfolio, we also report loadings on the corresponding factor momentum strategy. The sample period spans January 1970 to December 2022.

	Number of Top High-Eigenvalue PC Factors in FMOM Formation: N							
	5	10	15	20	25	30	35	40
<i>Panel A: Long-Short Portfolios of Res_t, sorted on Res_{t-1}</i>								
$\hat{\alpha}_{FF5+FMOM}$	0.38 (5.74)	0.34 (5.23)	0.34 (5.18)	0.33 (4.90)	0.32 (4.96)	0.33 (5.09)	0.32 (5.04)	0.31 (4.82)
$\hat{\beta}_{fmom}$	0.09 (2.65)	0.18 (4.34)	0.23 (4.62)	0.25 (4.40)	0.29 (5.28)	0.29 (5.53)	0.31 (5.07)	0.34 (4.99)
$R^2(\%)$	1.92	4.67	6.14	6.05	7.34	6.81	7.41	8.04
<i>Panel B: Long-Short Portfolios of Sys_t, Sorted on Res_{t-1}</i>								
$\hat{\alpha}_{FF5+FMOM}$	-0.27 (-6.98)	-0.30 (-7.47)	-0.30 (-7.52)	-0.32 (-7.91)	-0.32 (-7.93)	-0.31 (-7.72)	-0.32 (-8.03)	-0.32 (-8.18)
$\hat{\beta}_{fmom}$	0.15 (6.75)	0.21 (7.05)	0.25 (7.61)	0.29 (7.98)	0.31 (8.40)	0.30 (7.47)	0.34 (9.91)	0.35 (9.60)
$R^2(\%)$	17.43	18.95	22.21	23.63	23.65	21.49	25.51	25.46

Table 7 Pricing Industry Momentum with Factor Momentum: Controlling for Residual-to-Systematic Reversal

This table examines whether factor momentum (FMOM) can explain industry momentum (IMOM) when the residual-to-systematic reversal (RSR) factor is controlled for. Loser (winner) industries are those with below- (above-) median past-month returns. The models considered to explain IMOM include (i) FF5, (ii) FF5+factor momentum (FMOM), (iii) FF5+residual-to-systematic reversal (RSR), and (iv) FF5+FMOM+RSR. Industry returns are decomposed using the $K = 10$ IPCA model into systematic ($Sys_{j,t}$) and residual ($Res_{j,t}$) components. FMOM trades the top 10 high-eigenvalue principal component factors extracted from the 65 factors listed in Table A.1 and, following Arnott, Kalesnik, and Linnainmaa (2023), is implemented as a cross-sectional strategy that rebalances monthly, going long factors with above-median prior-month returns and short factors with below-median returns. RSR is constructed by going long systematic industries with below-median past-month residual industry returns and short systematic industries with above-median residual returns. Monthly alphas relative to the four models and the loadings on the RSR and FMOM factors are reported. The sample period spans January 1970 to December 2022.

	FF5	FF5+FMOM		FF5+RSR		FF5+FMOM+RSR		
	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\alpha}$	$\hat{\beta}_{rsr}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\beta}_{rsr}$
Losers	-0.33 (-4.19)	-0.15 (-2.37)	-0.45 (-7.77)	-0.51 (-6.47)	0.81 (7.07)	-0.33 (-4.83)	-0.33 (-6.12)	0.59 (5.55)
Winners	0.06 (1.16)	-0.06 (-1.05)	0.30 (4.97)	0.15 (2.65)	-0.41 (-4.60)	0.01 (0.20)	0.26 (3.86)	-0.24 (-2.48)
Winners	0.40	0.09	0.76	0.66	-1.22	0.34	0.59	-0.82
-Losers	(4.34)	(1.24)	(13.75)	(7.81)	(-9.67)	(4.60)	(10.15)	(-7.08)

Table 8 Does Residual Industry Momentum Explain Industry Momentum?

This table evaluates whether residual industry momentum (RMOM) can explain industry momentum (IMOM). The asset pricing models considered to explain IMOM include (i) FF5+residual-to-systematic reversal(RSR)+factor momentum (FMOM), and (ii) FF5+RSR+FMOM+RMOM. Industry returns are decomposed using the $K = 10$ IPCA model into systematic ($Sys_{j,t}$) and residual ($Res_{j,t}$) components. RSR is constructed by going long systematic industries with below-median past-month residual industry returns and short systematic industries with above-median residual returns. FMOM trades the top 10 high-eigenvalue principal component factors extracted from the 65 factors listed in Table A.1, going long factors with above-median prior-month returns and short those with below-median returns. RMOM is long residual industries with above-median past-month returns (winners) and short those with below-median past-month returns (losers), with monthly rebalancing. Monthly alphas for loser and winner industry momentum portfolios relative to these two models, as well as loadings on the RSR, FMOM, and RMOM factors, are reported. The sample period spans January 1970 to December 2022.

	FF5+RSR+FMOM	FF5+RSR+FMOM+RMOM				$R^2(\%)$
	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{rsr}$	$\hat{\beta}_{fmom}$	$\hat{\beta}_{rmom}$	
Losers	-0.33 (-4.83)	-0.17 (-3.00)	0.57 (6.14)	-0.26 (-4.97)	-0.43 (-10.28)	95.32
Winners	0.01 (0.20)	-0.10 (-1.88)	-0.22 (-2.43)	0.20 (3.01)	0.33 (8.62)	94.60
Winners	0.34	0.07	-0.79	0.46	0.76	72.78
–Losers	(4.60)	(1.40)	(-9.57)	(9.69)	(21.67)	

Table 9 Decomposition of Residual Industry Momentum

This table reports the components of residual industry momentum via two decomposition methods. Industry returns are decomposed using the $K = 10$ IPCA model into systematic ($Sys_{j,t}$) and residual ($Res_{j,t}$) components. Residual industry momentum is long residual industries with above-median past-month returns, and short those with below-median past-month returns. Panel A decomposes the total profits of residual industry momentum using the methodology of Lo and MacKinlay (1990) into profits due to three terms: asset autocovariances, cross-serial covariances, and the mean effect. Panel B decomposes residual industry momentum into three components as shown in Equation (10) according to Yan and Yu (2023). Cross-stock links, $Corr(R_{t-1}^i, R_t^j)$, are calculated using a five-year lookback window. The 49, 38 and 30 Fama-French industry portfolios (FF49, FF38 and FF30, respectively) and the 20 Moskowitz and Grinblatt (1999) industry portfolios (MG20) are considered. The sample period spans January 1970 to December 2022.

<i>Panel A: Lo-MacKinlay Decomposition</i>				
	Auto- Covariance	Cross-Serial Covariance	Mean Effect	Total
FF49	0.84 (3.53)	-0.07 (-0.96)	0.07	0.85 (3.73)
FF38	0.69 (3.75)	-0.05 (-0.79)	0.07	0.71 (4.26)
FF30	0.76 (3.14)	-0.03 (-0.37)	0.06	0.79 (3.63)
MG20	0.49 (3.48)	0.02 (0.31)	0.04	0.55 (4.35)
<i>Panel B: Decomposition via Cross-Stock Linkages Following Yan and Yu (2023)</i>				
	Own-Stock Lead-Lag	Cross-Stock Link		High-Low
		Low	High	
FF49	0.05 (0.90)	0.11 (2.43)	0.25 (4.36)	0.14 (2.68)
FF38	0.14 (1.54)	0.17 (1.20)	0.52 (3.04)	0.35 (2.39)
FF30	0.15 (1.42)	0.11 (0.81)	0.63 (4.19)	0.52 (3.75)
MG20	0.25 (1.58)	0.19 (0.65)	0.97 (2.71)	0.79 (2.55)

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Internet Appendix of

“The Anatomy of Industry Momentum”

This appendix describes the construction of factor momentum and reports the complete results from the robustness analyses discussed in the paper. The appendix is organized as follows. Section A.1 details the construction of factor momentum. Section A.2 presents a descriptive model to explain the discrepancies in the results of the Fama–MacBeth and spanning regressions. Section A.3 demonstrates that momentum in systematic industries cannot fully explain industry momentum once we control for the residual-to-systematic reversal (RSR) factor. Section A.4 shows that momentum in residual industries explains industry momentum even after accounting for the reversal effect. Section A.5 documents that momentum in industries originates from sources distinct from those driving momentum in firm characteristics. Section A.6 establishes that our findings remain robust across alternative industry classifications. Section A.7 examines firm-level determinants of intra-industry lead–lag relations, showing that firms with lower information uncertainty tend to lead their industry peers. A brief overview of the appendix figures and tables is provided below.

- Figure A.1: Does Characteristic Momentum Explain Residual Industry Momentum?
- Table A.1: Details of the 65 Firm Characteristics
- Table A.2: The Impact of Omitting RSR on Pricing Industry Momentum
- Table A.3: Pricing Industry Momentum Portfolios with Factor Momentum: Controlling for Stock-Level Short-Term Reversal
- Table A.4: Momentum in Residual Industries: Controlling for Stock-Level Short-Term Reversal
- Table A.5: Spanning Regressions: Controlling for Residual-to-Systematic Reversal
- Table A.6: Does Factor Momentum Explain Residual Industry Momentum?

- Table A.7: Industry Momentum versus Factor Momentum: Alternative Industry Definitions
- Table A.8: Determinants of Intra-industry Lead-lag Effect

A.1. Construction of Factor Momentum

To compute the factor PC momentum strategy’s return in month t , we first compute eigenvectors from the correlation matrix of monthly factor returns, using data from January 1965 through month $t-1$. Using these eigenvectors, we compute monthly returns for the PC factors up to month t . We then demean and rescale the leverage of all PC factors so that their average returns up to month $t-1$ are zero and their time-series variances match that of the average original factor up to month $t-1$. The PC factors are ordered by their eigenvalues, and the factor momentum strategies trade the subset of the top N PC factors. Our full sample of factor returns spans January 1965 through December 2022. The first estimation sample for PC factors covers the period from January 1965 to December 1969, so the PC factor returns begin in January 1970. This approach ensures that the eigenvectors and PC factor returns are computed recursively, using only information available up to the portfolio formation date. AKL compute eigenvectors using ten years of daily returns up to the end of month $t-1$ and normalize all factors to 10% volatility. While this approach differs slightly from ours, the differences do not materially impact the results.

A.2. Theoretical Framework: Omitted Confounder Bias

To formalize why spanning regressions and Fama-MacBeth regressions yield conflicting results, we develop a tractable return-generating framework. We show that short-term reversal acts as an “omitted confounder” that induces substantial spurious correlation in time-series spanning tests, while leaving cross-sectional inference relatively intact.

A.2.1. Return Generating Process and Proxies

For simplicity, we assume that industry returns are generated by the following process:

$$Ret_{j,t} = \gamma_{0,t} + \gamma_{M,t} \cdot M_{j,t-1} + \gamma_{S,t} \cdot S_{j,t-1} + \gamma_{R,t} \cdot R_{j,t-1} + \varepsilon_{j,t}, \quad (\text{A.1})$$

where $Ret_{j,t}$ denotes the excess return of industry j at time t . We consider two underlying drivers of return predictability: M , which captures industry momentum, and S , which captures systematic (factor) momentum. If both effects are present, we expect $E[\gamma_M] > 0$ and $E[\gamma_S] > 0$. The two signals are likely to be positively correlated, with $\text{Cov}(M, S) > 0$. In addition, we introduce a third signal, R , which potentially predicts future industry returns, $E[\gamma_R] \geq 0$, and is assumed to be orthogonal to both M and S .¹ In the context of this paper, R is intended to capture the reverse of short-term reversal, which, as shown earlier, systematically arises across portfolios.

The latent drivers M and S are not directly observable. Instead, we rely on noisy proxies for the industry-momentum and systematic-momentum signals. Both proxies are contaminated by the additional predictor R :

$$Mom_{j,t-1} = m_0 + m_1 \cdot M_{j,t-1} + m_2 \cdot R_{j,t-1} + \varepsilon_{j,t-1}^m, \quad (\text{A.2})$$

$$Sys_{j,t-1} = s_0 + s_1 \cdot S_{j,t-1} + s_2 \cdot R_{j,t-1} + \varepsilon_{j,t-1}^s, \quad (\text{A.3})$$

where $Mom_{j,t-1}$ denotes the cross-sectionally standardized lagged industry return used as the observable signal to construct industry momentum portfolios, and $Sys_{j,t-1}$ is the signal used to form systematic momentum. We suppose that $m_1, s_1 > 0$ and $m_2, s_2 < 0$. Because R positively predicts future returns but enters both observable proxies with negative loadings, it drives the true signals M and S and their empirical proxies in opposite directions. This opposite loading structure makes R a confounder and a source of omitted-variable bias.² Substituting

¹When $E[\gamma_R] = 0$, R represents an “unpriced” source of variation in a characteristic-based pricing framework, directly analogous to the unpriced factor “g” of Equation (2) in Daniel, Mota, Rottke, and Santos (2020).

²Note that the assumption of $m_2, s_2 < 0$ is intended to capture the negative correlation of short-term reversal factor with both industry and factor momentum, as indicated in Table 1. Similarly, Daniel, Mota, Rottke, and Santos (2020) assume that the characteristic of interest is cross-sectionally correlated with the loading on the unpriced factor.

Equations (A.2) and (A.3) into Equation (A.1), the true process can be rewritten as:

$$\begin{aligned}
Ret_{j,t} &= \left[\gamma_{0,t} - \frac{m_0}{m_1} \gamma_{M,t} - \frac{s_0}{s_1} \gamma_{S,t} \right] + \frac{\gamma_{M,t}}{m_1} Mom_{j,t-1} + \frac{\gamma_{S,t}}{s_1} Sys_{j,t-1} \\
&+ \left[\gamma_{R,t} - \frac{m_2}{m_1} \gamma_{M,t} - \frac{s_2}{s_1} \gamma_{S,t} \right] R_{j,t-1} + \left[\varepsilon_{j,t} - \frac{\gamma_{M,t}}{m_1} \varepsilon_{j,t-1}^m - \frac{\gamma_{S,t}}{s_1} \varepsilon_{j,t-1}^s \right] \\
&= \gamma'_{0,t} + \gamma'_{M,t} \cdot Mom_{j,t-1} + \gamma'_{S,t} \cdot Sys_{j,t-1} + \gamma'_{R,t} \cdot R_{j,t-1} + \varepsilon'_{j,t}
\end{aligned} \tag{A.4}$$

A.2.2. Bias in Spanning Regressions

We first examine the impact of omitting the confounder R on the spanning regression test. To conduct spanning regressions, we first construct factors of interest. The industry momentum factor (IMOM) is equivalent to the time series of slope coefficients from cross-sectional regressions of industry returns on the momentum signal $Mom_{j,t-1}$ (i.e., OLS slope factor):³

$$Ret_{j,t} = \alpha_t^{imom} + IMOM_t \cdot Mom_{j,t-1} + \epsilon_{j,t}^{imom}. \tag{A.5}$$

The regression is performed each month, yielding a time-series industry momentum return:

$$\begin{aligned}
\widehat{IMOM}_t &= \frac{\text{Cov}(Ret_{j,t}, Mom_{j,t-1})}{\text{Var}(Mom_{j,t-1})} \\
&= \gamma'_{M,t} + \gamma'_{S,t} \cdot \beta_{Sys|Mom,t-1} + \gamma'_{R,t} \cdot \beta_{R|Mom,t-1},
\end{aligned} \tag{A.6}$$

where $\beta_{Sys|Mom,t-1} = \frac{\text{Cov}(Sys_{j,t-1}, Mom_{j,t-1})}{\text{Var}(Mom_{j,t-1})}$ and $\beta_{R|Mom,t-1} = \frac{\text{Cov}(R_{j,t-1}, Mom_{j,t-1})}{\text{Var}(Mom_{j,t-1})}$ are the coefficients from regressing $Sys_{j,t-1}$ on $Mom_{j,t-1}$ and $R_{j,t-1}$ on $Mom_{j,t-1}$, respectively. This reflects the omitted variable bias inherent in IMOM, arising from the exclusion of $Sys_{j,t-1}$ and $R_{j,t-1}$ in its construction. Furthermore, $\beta_{R|Mom,t-1} < 0$ as we assume $m_2 < 0$ in Equation (A.2). Thus, controlling for $\gamma'_{R,t}$ increases the performance of IMOM, consistent with Table 1 that controlling for short-term reversal increases the unconditional alpha of industry momentum.

³Fama and French (2020) use the slopes of monthly cross-sectional OLS regressions of returns on characteristics as factor portfolio returns. The MSCI BARRA factor model, which goes back to Rosenberg (1974) and is widely applied in industry, is also based on OLS factors.

Similarly, we construct the systematic momentum factor by performing the following cross-sectional regression every month:

$$Ret_{j,t} = \alpha_t^{smom} + SMOM_t \cdot Sys_{j,t-1} + \epsilon_{j,t}^{smom}, \quad (A.7)$$

and we obtain the systematic momentum factor as:

$$\begin{aligned} \widehat{SMOM}_t &= \frac{\text{Cov}(Ret_{j,t}, Sys_{j,t-1})}{\text{Var}(Sys_{j,t-1})} \\ &= \gamma'_{S,t} + \gamma'_{M,t} \cdot \beta_{Mom|Sys,t-1} + \gamma'_{R,t} \cdot \beta_{R|Sys,t-1}, \end{aligned} \quad (A.8)$$

where $\beta_{Mom|Sys,t-1} = \frac{\text{Cov}(Mom_{j,t-1}, Sys_{j,t-1})}{\text{Var}(Sys_{j,t-1})}$ and $\beta_{R|Sys,t-1} = \frac{\text{Cov}(R_{j,t-1}, Sys_{j,t-1})}{\text{Var}(Sys_{j,t-1})}$ are the coefficients from regressing $Mom_{j,t-1}$ on $Sys_{j,t-1}$ and $R_{j,t-1}$ on $Sys_{j,t-1}$, respectively. This again reflects the omitted variable bias inherent in SMOM due to the exclusion of $Mom_{j,t-1}$ and $R_{j,t-1}$ in its construction. Furthermore, $\beta_{R|Sys,t-1} < 0$ as we assume $s_2 < 0$ in Equation (A.3). Therefore, controlling for $\gamma'_{R,t}$ increases the performance of SMOM. This is also consistent with our findings in Table 1 that controlling for short-term reversal increases the unconditional alpha of factor momentum.

To examine whether the success of industry momentum stems from its loading on systematic momentum ($\gamma'_{S,t} \cdot \beta_{Sys|Mom,t-1}$), as in AKL, we estimate the spanning regression:

$$\widehat{IMOM}_t = \alpha + \beta_{smom} \cdot \widehat{SMOM}_t + u_t. \quad (A.9)$$

The key question is whether IMOM's alpha remains significantly positive after controlling for systematic (factor) momentum. A major concern is that the spanning regression is mis-specified due to omitted-variable bias. In particular, SMOM is a noisy linear combination of the three true drivers and therefore absorbs the variation in $\gamma'_{M,t}$, $\gamma'_{S,t}$, and $\gamma'_{R,t}$. Since both $\widehat{IMOM}_t$ and $\widehat{SMOM}_t$ are negatively correlated with $\gamma'_{R,t}$ (with m_2 and s_2 being negative), omitting $\gamma'_{R,t}$ induces upward bias in $\hat{\beta}_{smom}$ and downward bias in $\hat{\alpha}$. We now show why.

One of the key assumptions of OLS in *time-series regression* is that the residuals are uncorrelated with the independent variables. If we omit $\gamma'_{R,t}$ in Equation (A.9), the regression will result in strong correlation between the regression model residuals, u_t , and $\widehat{SMOM}_t$. To illustrate this OVB issue, suppose the true model is

$$IMOM = \alpha^* + \beta_{smom}^* \cdot SMOM + \beta_{\gamma'_R}^* \cdot \gamma'_R + \epsilon, \quad (\text{A.10})$$

where we drop hats and time subscripts for simplicity.⁴ However, if we omit γ'_R , then

$$IMOM = \alpha + \beta_{smom} \cdot SMOM + u, \quad (\text{A.11})$$

where $u = \beta_{\gamma'_R}^* \cdot \gamma'_R + \epsilon$. This is what we have in Equation (A.9). Since IMOM and SMOM are both negatively correlated with γ'_R , the estimate of β_{smom} is biased. In fact,

$$\hat{\beta}_{smom} = \hat{\beta}_{smom}^* + \hat{\beta}_{\gamma'_R}^* \cdot \frac{\text{Cov}(SMOM, \gamma'_R)}{\text{Var}(SMOM)} = \hat{\beta}_{smom}^* + \hat{\beta}_{\gamma'_R}^* \cdot \hat{\beta}_{\gamma'_R|smom}, \quad (\text{A.12})$$

The bias in $\hat{\beta}_{smom}$ can be expressed as

$$\text{Bias}(\hat{\beta}_{smom}) = \hat{\beta}_{\gamma'_R}^* \cdot \hat{\beta}_{\gamma'_R|smom} > 0, \quad (\text{A.13})$$

since IMOM and SMOM are both negatively correlated with γ'_R , implying $\hat{\beta}_{\gamma'_R}^* < 0$ and $\hat{\beta}_{\gamma'_R|smom} < 0$. As such, $\text{Bias}(\hat{\beta}_{smom}) > 0$, indicating an overstated impact of SMOM on IMOM.⁵

⁴For exposition, we abstract from $\gamma'_{M,t}$, which primarily captures industry-specific momentum, to highlight the effect of omitting $\gamma'_{R,t}$ in the spanning regressions. In the empirical analysis, we also consider industry-specific momentum in the spanning regressions in Section A.4.

⁵This is consistent with the findings in Table 1. For example, in Panel A.2, the loading of industry momentum on factor momentum is 0.76 (t -statistic = 13.74) in FF5+FMOM pricing model. After controlling for STREV, the coefficient on FMOM declines substantially to 0.32 (t -statistic = 6.45).

Furthermore, the alpha in the misspecified model with the omitted γ'_R is

$$\begin{aligned}
\hat{\alpha} &= \text{avg}(IMOM) - \hat{\beta}_{smom} \cdot \text{avg}(SMOM) \\
&= \hat{\alpha}^* + \hat{\beta}_{smom}^* \cdot \text{avg}(SMOM) + \hat{\beta}_{\gamma'_R}^* \cdot \text{avg}(\gamma'_R) - \hat{\beta}_{smom} \cdot \text{avg}(SMOM) \\
&= \hat{\alpha}^* + \underbrace{(\hat{\beta}_{smom}^* - \hat{\beta}_{smom}) \cdot \text{avg}(SMOM)}_{< 0} + \underbrace{\hat{\beta}_{\gamma'_R}^* \cdot \text{avg}(\gamma'_R)}_{< 0}, \tag{A.14}
\end{aligned}$$

suggesting downward bias from omitting γ'_R .

A.2.3. Bias in Fama-MacBeth Regressions

We next examine how omitted-variable bias (OVB) affects inference in cross-sectional Fama-MacBeth (FM) regressions. Each month, we estimate the following predictive regressions to assess the forecasting power of $Mom_{j,t-1}$:

$$Ret_{j,t} = \alpha'_t + \beta'_{imom,t} \cdot Mom_{j,t-1} + \epsilon'_{j,t}, \tag{A.15}$$

$$Ret_{j,t} = \alpha_t + \beta_{imom,t} \cdot Mom_{j,t-1} + \beta_{smom,t} \cdot Sys_{j,t-1} + \epsilon_{j,t}. \tag{A.16}$$

In the univariate specification Equation (A.15), both $Sys_{j,t-1}$ and $R_{j,t-1}$ are omitted. Under the return-generating process in Equation (A.4), this omission induces standard OVB in the estimated slope coefficient:

$$\hat{\beta}'_{imom,t} = \gamma'_{M,t} + \gamma'_{S,t} \cdot \beta_{Sys|Mom,t-1} + \gamma'_{R,t} \cdot \beta_{R|Mom,t-1}, \tag{A.17}$$

where $\gamma'_{M,t}$ denotes the true coefficient on $Mom_{j,t-1}$ in Equation (A.4), $\beta_{Sys|Mom,t-1}$ is the coefficient from regressing $Sys_{j,t-1}$ on $Mom_{j,t-1}$, and $\beta_{R|Mom,t-1}$ is the coefficient from regressing $R_{j,t-1}$ on $Mom_{j,t-1}$. Equation (A.17) shows that, when $Sys_{j,t-1}$ and $R_{j,t-1}$ are omitted, the estimated predictive power of Mom captured by $\hat{\beta}'_{imom,t}$ reflects not only its direct effect $\gamma'_{M,t}$ but also indirect contributions arising from its correlations with $Sys_{j,t-1}$ and $R_{j,t-1}$ through

the $\gamma'_{S,t} \cdot \beta_{Sys|Mom,t-1}$ and $\gamma'_{R,t} \cdot \beta_{R|Mom,t-1}$ terms.

Equation (A.16) augments the regression by including $Sys_{j,t-1}$ in order to examine whether the predictive content of industry momentum remains after controlling for systematic momentum. In this specification, $R_{j,t-1}$ remains omitted and therefore continues to induce OVB. By the Frisch–Waugh–Lovell theorem, the bias in $\hat{\beta}_{imom,t}$ depends on the partial projection of $R_{j,t-1}$ on $Mom_{j,t-1}$ controlling for $Sys_{j,t-1}$:

$$\hat{\beta}_{imom,t} = \gamma'_{M,t} + \gamma'_{R,t} \cdot \beta_{R|Mom+Sys,t-1}, \quad (\text{A.18})$$

where $\beta_{R|Mom+Sys,t-1}$ is the coefficient on $Mom_{j,t-1}$ from a regression of $R_{j,t-1}$ on both $Mom_{j,t-1}$ and $Sys_{j,t-1}$.

The key distinction between FM and spanning regressions lies in how the omitted component $R_{j,t-1}$ affects inference. FM regressions are cross-sectional in nature and assess whether $Mom_{j,t-1}$ has incremental predictive power for $Ret_{j,t}$ conditional on observed covariates. As a result, omitting $R_{j,t-1}$ influences $\hat{\beta}_{imom}$ only through its partial correlation with $Mom_{j,t-1}$ after conditioning on $Sys_{j,t-1}$. In contrast, spanning regressions operate on portfolio returns that directly embed exposure to R_{t-1} , causing the confounder to mechanically inflate comovement between industry momentum and factor momentum portfolios.

Consequently, while omitting $R_{j,t-1}$ introduces bias in both settings, its impact is substantially more severe in spanning regressions than in FM regressions. Within the FM framework, the key question is whether augmenting the specification with $Sys_{j,t-1}$ purges the $\gamma'_{S,t} \cdot \beta_{Sys|Mom,t-1}$ channel and renders $E[\beta_{imom}]$ insignificant. Comparing Equations (A.17) and (A.18) shows that FM can effectively achieve this: directly including $Sys_{j,t-1}$ in the regression removes that channel with minimal impact from the omission of $R_{j,t-1}$. We find that $E[\beta_{imom}]$ remains significantly positive in Equation (A.18), indicating that industry momentum is distinct from systematic (factor) momentum.⁶

⁶Including $R_{j,t-1}$ in Equation (A.16) would further increase both the magnitude and statistical significance of $\hat{\beta}_{imom}$.

A.3. Momentum in Systematic Industries

AKL construct “systematic industries” that preserve only factor-level variation in returns and exclude any industry-specific shocks. They argue that variation in factor loadings alone fully accounts for industry momentum. As in AKL, we construct systematic industries as linear combinations of the factors onto which the actual industries load; systematic industry j earns a return of $Sys_{j,t} = \beta_{j,1,t}F_{1,t} + \dots + \beta_{j,K,t}F_{K,t}$ in month t , where the F_t s are the factor returns. The systematic industry momentum strategy is defined in the same way as the industry momentum strategy, going long systematic industries with above-median past-month returns and short systematic industries with below-median past-month returns, and is rebalanced monthly.

We consider five models for the construction of systematic industries: (1) the Fama–French three-factor model, (2) the Fama–French five-factor model, (3) the five-factor model augmented with long-term reversal (LTREV) and residual variance (RVAR), (4) the five-factor model further augmented with LTREV, RVAR, quality-minus-junk (QMJ), and betting-against-beta (BAB), and (5) the $K = 10$ IPCA specification. Panel A of Table A.5 reports monthly alphas of the industry momentum strategy relative to the Fama–French five-factor model augmented with systematic industry momentum. Consistent with AKL, momentum in systematic industries appears to have explanatory power for industry momentum. When the underlying model is sufficiently rich to fully capture systematic returns, such as IPCA, systematic industry momentum appears to subsume industry momentum, with its alpha falling to 8 bps and losing statistical significance.

However, once we incorporate the RSR factor into the pricing model, we find that systematic industry momentum no longer fully explains industry momentum. As shown in Panel B of Table A.5, the industry momentum strategy produces a significant alpha of 31 bps (t -statistic = 4.15), even when systematic industry momentum is based on IPCA. These results reaffirm that industry momentum is distinct from momentum in the factors driving systematic returns.

A.4. Momentum in Residual Industries

We next examine whether residual industry momentum can be explained by factor momentum or by the reversal channel captured by the RSR factor. Table A.6 reports asset pricing tests for the residual industry momentum strategy under four models: (1) the Fama–French five-factor model (FF5), (2) FF5 augmented with factor momentum, (3) FF5 augmented with the RSR factor, and (4) FF5 augmented with both factor momentum and the RSR factor.

Consistent with our earlier findings, factor momentum fails to explain residual industry momentum. Under Model (2), residual industry momentum earns a large and statistically significant alpha of 0.34% per month (t -statistic = 5.23), indicating that momentum in systematic factor returns does not subsume momentum in residual industry returns.

Importantly, adding the RSR factor has virtually no effect on the pricing of residual industry momentum. Model (3) produces an alpha that is nearly identical to that under the baseline FF5 specification in Model (1), indicating that residual industry momentum is not related to the residual-to-systematic reversal channel captured by RSR. This contrasts sharply with the behavior of systematic industry momentum, whose apparent relation with factor momentum is shown earlier to be driven by omitted-variable bias arising from RSR.

When both factor momentum and RSR are included simultaneously in Model (4), the alpha of residual industry momentum declines only marginally, from 41 bps (t -statistic = 6.30) to 36 bps (t -statistic = 5.28), and remains highly significant. Thus, neither momentum in factor returns nor the RSR channel accounts for the profitability of residual industry momentum.

Taken together, these results show that residual industry momentum is a distinct return component, separate from both factor momentum and the systematic reversal mechanism emphasized in this paper. While RSR plays a central role in confounding tests based on systematic industry returns, it is irrelevant once industry returns are purged of systematic components, reaffirming that residual industry momentum reflects forces beyond those driving factor-level predictability.⁷

⁷Using the stock-level short-term reversal factor (STREV) in place of RSR yields the same quantitative conclusions, as shown in Table A.4 in the Appendix.

A.5. Momentum in Characteristic Portfolios and Residual Industries

We have shown that the profits of momentum strategies based on industries and factors arise from distinct sources. However, AKL claim that all of these momentum strategies significantly correlate with each other and therefore likely emanate from the same source. In this section, we further examine whether the profits of momentum strategies based on industries and other characteristics are driven by a shared underlying source.

Specifically, we examine whether residual industry momentum can be explained by momentum in each of the 65 firm characteristics. Panel A of Figure A.1 in the Appendix displays the distribution of t -statistics for RMOM alphas relative to the Fama-French five-factor model augmented with momentum in each characteristic. All alphas are statistically significant and positive, with t -statistics exceeding 3. Panel B of Figure A.1 presents the correlations between residual industry momentum and momentum in other characteristics, all of which are below 0.25. Thus, momentum in industries originates from sources distinct from those driving momentum in other firm characteristics.

A.6. Alternative Industry Classifications

To ensure the robustness of our results, we re-evaluate our findings using alternative industry classifications, including the Fama and French 38-industry and 30-industry classifications (FF38 and FF30, respectively) as well as the Moskowitz and Grinblatt (1999) 20-industry classification (MG20).⁸ For each industry classification, we calculate value-weighted returns for each industry and then construct both industry momentum strategies and residual industry momentum strategies in the same way as the standard industry momentum strategy.

Panel A of Table A.7 in the Appendix presents the results for industry momentum strategies,

⁸The Fama-French industry definitions are obtained from Ken French's website. For the 20-industry classification scheme, we follow Moskowitz and Grinblatt (1999) as closely as possible.

and Panel B reports the findings for residual industry momentum strategies. Consistent with our main results, the findings remain robust across all three alternative industry classifications. For instance, under the MG20 classification, industry momentum appears to be subsumed by factor momentum; however, once the RSR factor is included in the pricing model, the industry momentum alpha rises to 34 bps with a t -statistic of 4.11. Similarly, factor momentum fails to explain residual industry momentum, which delivers an alpha of 32 bps with a t -statistic of 4.67. Overall, these results confirm that our findings are robust to alternative industry classifications.

A.7. Determinants of Intra-industry Lead-lag Relation

Hou (2007) demonstrates that size, analyst coverage, institutional ownership, trading volume, market share, and forecast dispersion are key determinants of lead-lag patterns within industries, based on weekly returns from July 1963 to December 2001. Building on this work, we examine differences in firm characteristics between stocks predominantly identified as lead stocks and those primarily classified as lag stocks within their respective stock pairs. Specifically, we calculate the proportion of “lead” relationships across all stock pairs for each stock, defining this measure as its leading power. Stocks are then sorted into quintiles based on their leading power. Finally, we compute the differences in the equal-weighted averages of firm characteristics between stocks in the top quintile of leading power and those in the bottom quintile.

Table A.8 presents the estimation results, highlighting strong intra-industry lead-lag effects driven by firm size, firm age, idiosyncratic volatility, analyst coverage, and forecast dispersion. Firm size is measured as the natural logarithm of a firm’s market capitalization, firm age is the number of years since its inception, and idiosyncratic volatility is calculated based on the CAPM using 252 trading days of daily returns. Analyst coverage refers to the number of analysts covering the firm, and forecast dispersion is measured by EPS Forecast Dispersion. Specifically, firms with higher market capitalization, greater firm age, or higher analyst coverage tend to lead firms with lower levels of these characteristics within the same industry. Similarly,

firms with lower idiosyncratic volatility or lower forecast dispersion lead those with higher levels of these attributes. Our results suggest that firms with lower information uncertainty tend to lead those with higher information uncertainty, consistent with Hou (2007).

Taken together, our findings demonstrate that industry momentum is driven by the slow diffusion of industry-specific information within industries, which manifests as the intra-industry lead-lag effects.

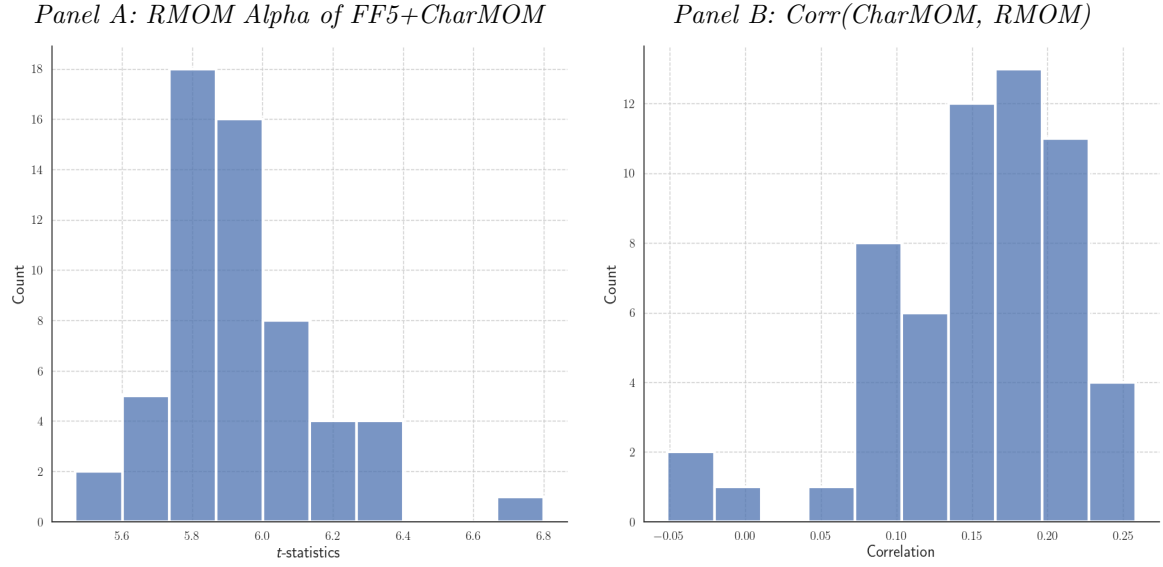


Fig. A.1 Does Characteristic Momentum Explain Residual Industry Momentum?

This figure illustrates the explanatory power of momentum in 65 firm characteristics for residual industry momentum. Panel A shows the distributions of t -statistics for residual industry momentum alphas relative to the Fama–French five-factor model augmented with each characteristic’s momentum. Panel B reports the distributions of correlations between each characteristic momentum and residual industry momentum.

Table A.1 Details of the 65 Firm Characteristics

This table reports the names, abbreviations and citations for the 65 firm characteristics used in our study. For further details and summary statistics, see Jensen, Kelly, and Pedersen (2023).

Name	Abbreviation	Original Study
Abnormal Corporate Investment	capex_abn	Titman et al. (2004)
Altman Z-score	z_score	Dichev (1998)
Amihud measure	ami_126d	Amihud (2002)
Asset growth (1 year)	at_gr1	Cooper et al. (2008)
Assets-to-market	at_me	Fama and French (1992)
Book leverage	at_be	Fama and French (1992)
Book-to-market equity	be_me	Rosenberg et al. (1985)
CAPEX growth (1 year)	capx_gr1	Xie (2001)
Capital turnover	at_turnover	Haugen and Baker (1996)
Cash flow volatility	ocfq_saleq_std	Huang (2009)
Cash-based operating profits-to- book assets	cop_at	Ball et al. (2016)
Cash-to-assets	cash_at	Palazzo (2012)
Change in common equity	be_gr1a	Richardson et al. (2005)
Change in current operating assets	coa_gr1a	Richardson et al. (2005)
Change in current operating working capital	cowc_gr1a	Richardson et al. (2005)
Change in net noncurrent operating assets	nncoa_gr1a	Richardson et al. (2005)
Change in net operating assets	noa_gr1a	Hirshleifer et al. (2004)
Change in noncurrent operating assets	ncoa_gr1a	Richardson et al. (2005)
Change in operating cash flow to assets	ocf_at_chg1	Bouchaud et al. (2019)
Change PPE and Inventory	ppeinv_gr1a	Lyandres et al. (2008)
Change sales minus change SG&A	dsale_dsga	Abarbanell and Bushee (1998)
Coefficient of variation for dollar trading volume	dolvol_var_126d	Chordia et al. (2001)
Coefficient of variation for share turnover	turnover_var_126d	Chordia et al. (2001)
Coskewness	coskew_21d	Harvey and Siddique (2000)
Debt-to-market	debt_me	Bhandari (1988)
Earnings persistence	ni_ar1	Francis et al. (2004)
Ebitda-to-market enterprise value	ebitda_mev	Loughran and Wellman (2011)
Equity net payout	eqnpo_12m	Daniel and Titman (2006)
Firm age	age	Jiang et al. (2005)
Free cash flow-to-price	fcf_me	Lakonishok et al. (1994)
Gross profits-to-assets	gp_at	Novy-Marx (2013)
High-low bid-ask spread (1 month)	bidaskhl_21d	Corwin and Schultz (2012)
Hiring rate	emp_gr1	Belo et al. (2014)
Idiosyncratic volatility from the CAPM (252 days)	ivol_capm_252d	Ali et al. (2003)
Inventory growth	inv_gr1	Belo and Lin (2012)
Labor force efficiency	sale_emp_gr1	Abarbanell and Bushee (1998)
Liquidity scaled by lagged Assets	aliq_at	Ortiz-Molina and Phillips (2014)
Liquidity scaled by lagged Market Assets	aliq_mat	Ortiz-Molina and Phillips (2014)
Long-term reversal	ret_60_12	De Bondt and Thaler (1985)
Market Beta	beta_60m	Fama and Macbeth (1973)
Market Equity	market_equity	Banz (1981)
Net debt-to-price	netdebt_me	Penman et al. (2007)
Net equity issuance	eqnetis_at	Bradshaw et al. (2006)
Net payout yield	eqnpo_me	Boudoukh et al. (2007)
Net stock issues	chcsho_12m	Pontiff and Woodgate (2008)
Net total issuance	netis_at	Bradshaw et al. (2006)
Number of zero trades with turnover as tiebreaker (1 month)	zero_trades_21d	Liu (2006)
Ohlson O-score	o_score	Dichev (1998)
Operating cash flow to assets	ocf_at	Bouchaud et al. (2019)
Operating profits-to-book assets	op_at	Ball et al. (2016)
Percent operating accruals	oaccruals_ni	Hafzalla et al. (2011)
Pitroski F-score	f_score	Piotroski (2000)
Price momentum t-12 to t-1	ret_12_1	Jegadeesh and Titman (1993)
Price momentum t-12 to t-7	ret_12_7	Novy-Marx (2012)
Price momentum t-6 to t-1	ret_6_1	Jegadeesh and Titman (1993)
Profit margin	ebit_sale	Soliman (2008)
Quality minus Junk: Composite	qmj	C. S. Asness et al. (2019)
Quarterly return on assets	niq_at	Balakrishnan et al. (2010)
Quarterly return on equity	niq_be	Hou et al. (2015)
R&D-to-sales	rd_sale	Chan et al. (2001)
Sales Growth (1 year)	sale_gr1	Lakonishok et al. (1994)
Sales-to-market	sale_me	Barbee Jr et al. (1996)
Share turnover	turnover_126d	Datar et al. (1998)
Short-term reversal	ret_1_0	Jegadeesh (1990)
Total accruals	taccruals_at	Richardson et al. (2005)

Table A.2 The Impact of Omitting RSR on Pricing Industry Momentum

This table examines the explanatory power of factor momentum for industry momentum (IMOM), with and without controlling for the residual-to-systematic (RSR) factor. The model in Panel A is FF5 augmented with a factor momentum strategy (FMOM) that trades varying subsets of the top N high-eigenvalue PC factors extracted from the 65 factors listed in Table A.1 with N ranging from 5 to 40. The model in Panel B is FF5 augmented with both FMOM and RSR factors. RSR is constructed by going long systematic industries with below-median past-month residual industry returns and short systematic industries with above-median past-month residual industry returns. The sample period spans January 1970 to December 2022.

	Number of top PC Factors in FMOM Formation: N							
	5	10	15	20	25	30	35	40
$\hat{\alpha}_{FF5}$: 0.40 (4.34)								
<i>Panel A: Explaining IMOM with FF5+FMOM as in AKL</i>								
$\hat{\alpha}_{FF5+FMOM}$	0.20	0.09	0.11	0.06	0.06	0.08	0.07	0.04
	(2.54)	(1.24)	(1.53)	(0.82)	(0.78)	(1.08)	(0.95)	(0.55)
$\hat{\beta}_{fmom}^{AKL}$	0.54	0.76	0.85	0.95	1.03	1.04	1.13	1.17
	(13.48)	(13.75)	(11.74)	(12.05)	(12.89)	(12.60)	(12.88)	(13.74)
$R^2(\%)$	32.13	38.64	40.90	42.17	43.25	41.37	46.00	46.20
<i>Panel B: Adding RSR to the AKL Model</i>								
$\hat{\alpha}_{FF5+FMOM+RSR}$	0.45	0.34	0.34	0.29	0.29	0.32	0.28	0.26
	(5.73)	(4.60)	(4.85)	(3.99)	(3.98)	(4.34)	(3.87)	(3.52)
$\hat{\beta}_{fmom}$	0.40	0.59	0.66	0.74	0.81	0.81	0.90	0.94
	(9.02)	(10.15)	(8.80)	(8.96)	(9.51)	(9.68)	(9.72)	(10.28)
$\hat{\beta}_{rsr}$	-0.90	-0.82	-0.76	-0.73	-0.72	-0.77	-0.67	-0.67
	(-7.14)	(-7.08)	(-6.33)	(-6.11)	(-6.21)	(-6.71)	(-6.17)	(-6.11)
$R^2(\%)$	44.88	49.14	49.54	49.99	50.83	50.19	52.34	52.52

Table A.3 Pricing Industry Momentum Portfolios with Factor Momentum: Controlling for Stock-Level Short-Term Reversal

This table compares the performance of four asset pricing models in explaining the monthly excess returns of loser industries with below-median past-month returns and winner industries with above-median past-month returns. The models include (i) FF5, (ii) FF5+factor momentum (FMOM), (iii) FF5+stock-level short-term reversal (STREV), and (iv) FF5+FMOM+STREV. FMOM trades the top 10 high-eigenvalue principal component factors extracted from the 65 factors listed in Table A.1, going long factors with above-median prior-month returns and short factors with below-median returns. Monthly alphas relative to the four models and the loadings against the STREV and FMOM factors are reported. The sample period spans January 1970 to December 2022.

	FF5	FF5+FMOM		FF5+STREV		FF5+STREV+FMOM		
	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\alpha}$	$\hat{\beta}_{strev}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\beta}_{strev}$
Losers	-0.33 (-4.19)	-0.15 (-2.37)	-0.45 (-7.77)	-0.43 (-6.21)	0.28 (8.52)	-0.32 (-4.96)	-0.20 (-3.59)	0.21 (5.91)
Winners	0.06 (1.16)	-0.06 (-1.05)	0.30 (4.97)	0.13 (2.28)	-0.20 (-7.48)	0.07 (1.26)	0.12 (1.89)	-0.16 (-5.91)
Winners	0.40	0.09	0.76	0.56	-0.48	0.39	0.32	-0.37
-Losers	(4.34)	(1.24)	(13.75)	(7.92)	(-19.64)	(6.07)	(6.45)	(-11.39)

Table A.4 Momentum in Residual Industries: Controlling for Stock-Level Short-Term Reversal

This table reports monthly alphas for residual industry momentum relative to four asset pricing models. Industry returns are decomposed using the $K = 10$ IPCA model into systematic ($Sys_{j,t}$) and residual ($Res_{j,t}$) components. Residual industry momentum is long residual industries with above-median past-month returns (winners), and short those with below-median past-month returns (losers), with monthly rebalancing. The models considered include (i) FF5, (ii) FF5+factor momentum (FMOM), (iii) FF5+short-term reversal (STREV), and (iv) FF5+FMOM+STREV. FMOM trades the top 10 high-eigenvalue principal component factors extracted from the 65 factors listed in Table A.1 and, following Arnott, Kalesnik, and Linnainmaa (2023), is implemented as a cross-sectional strategy that rebalances monthly, going long factors with above-median prior-month returns and short factors with below-median returns. Monthly alphas for loser and winner residual industry portfolios relative to the four models, as well as loadings on the FMOM and STREV factors, are reported. The sample period spans January 1970 to December 2022.

	FF5	FF5 +FMOM		FF5 +STREV		FF5 +FMOM+STREV		
	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\alpha}$	$\hat{\beta}_{strev}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\beta}_{strev}$
Losers	-0.19 (-3.84)	-0.18 (-3.70)	-0.02 (-0.65)	-0.20 (-3.94)	0.03 (1.53)	-0.22 (-4.31)	0.03 (0.62)	0.04 (1.70)
Winners	0.22 (5.19)	0.16 (3.76)	0.16 (6.43)	0.24 (5.91)	-0.07 (-4.03)	0.17 (3.96)	0.13 (3.81)	-0.02 (-1.04)
Winners	0.41	0.34	0.18	0.45	-0.10	0.39	0.11	-0.06
–Losers	(6.30)	(5.23)	(4.34)	(6.92)	(-4.12)	(6.03)	(1.94)	(-1.99)

Table A.5 Spanning Regressions: Controlling for Residual-to-Systematic Reversal

This table examines the explanatory power of momentum in systematic industries for industry momentum, with and without controlling for the RSR factor, using spanning regressions. Systematic industries are constructed as the systematic components of industry returns based on alternative factor models: (1) FF3, (2) FF5, (3) FF5+LTREV+RVAR, (4) FF5+LTREV+RVAR+QMJ+BAB, and (5) the $K = 10$ IPCA model. RSR is constructed by going long systematic industries with below-median past-month residual industry returns and short systematic industries with above-median past-month residual industry returns. Panel A reports spanning regressions of industry momentum (IMOM) on systematic industry momentum (SMOM) and the FF5 factors. Panel B reports results from an extended specification that includes both SMOM and RSR factors alongside the FF5 factors. IMOM and SMOM are constructed from the Fama–French 49 industries and their systematic counterparts, respectively. The sample period is from January 1970 to December 2022.

	Model for Systematic Industries				
	(1)	(2)	(3)	(4)	(5)
FF5 $\hat{\alpha}$: 0.40 (4.34)					
<i>Panel A: Explaining IMOM with model FF5+SMOM</i>					
$\hat{\alpha}$	0.18 (2.20)	0.17 (2.23)	0.17 (2.13)	0.17 (2.21)	0.08 (1.04)
$\hat{\beta}_{smom}$	0.59 (9.13)	0.64 (11.13)	0.65 (12.28)	0.64 (11.26)	0.67 (12.43)
$R^2(\%)$	29.03	33.28	37.66	37.82	41.72
<i>Panel B: Explaining IMOM with model FF5+SMOM+RSR</i>					
$\hat{\alpha}$	0.44 (5.70)	0.42 (5.53)	0.40 (5.21)	0.41 (5.11)	0.31 (4.15)
$\hat{\beta}_{smom}$	0.46 (7.54)	0.49 (8.31)	0.51 (9.55)	0.49 (8.80)	0.52 (10.50)
$\hat{\beta}_{rsr}$	-0.97 (-8.20)	-0.91 (-7.63)	-0.86 (-7.51)	-0.83 (-7.01)	-0.75 (-6.18)
$R^2(\%)$	44.77	46.80	49.36	48.47	49.95

Table A.6 Does Factor Momentum Explain Residual Industry Momentum?

This table evaluates whether factor momentum (FMOM) can explain residual industry momentum (RMOM). The asset pricing models considered to explain RMOM include (i) FF5, (ii) FF5+FMOM, (iii) FF5+residual-to-systematic reversal (RSR), and (iv) FF5+FMOM+RSR. Industry returns are decomposed using the $K = 10$ IPCA model into systematic ($Sys_{j,t}$) and residual ($Res_{j,t}$) components. RMOM is long residual industries with above-median past-month returns (winners) and short those with below-median past-month returns (losers), with monthly rebalancing. FMOM trades the top 10 high-eigenvalue principal component factors extracted from the 65 factors listed in Table A.1, going long factors with above-median prior-month returns and short those with below-median returns. RSR is constructed by going long systematic industries with below-median past-month residual industry returns and short systematic industries with above-median residual returns. Monthly alphas for loser and winner residual industry portfolios relative to the four models, as well as loadings on the FMOM and RSR factors, are reported. The sample period spans January 1970 to December 2022.

	FF5	FF5 +FMOM		FF5 +RSR		FF5 +FMOM+RSR		
	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\alpha}$	$\hat{\beta}_{rsr}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\beta}_{rsr}$
Losers	-0.19 (-3.84)	-0.18 (-3.70)	-0.02 (-0.65)	-0.20 (-3.91)	0.05 (0.73)	-0.19 (-3.74)	-0.02 (-0.42)	0.04 (0.51)
Winners	0.22 (5.19)	0.16 (3.76)	0.16 (6.43)	0.25 (5.42)	-0.12 (-1.90)	0.16 (3.48)	0.15 (5.83)	-0.01 (-0.24)
Winners	0.41	0.34	0.18	0.45	-0.17	0.36	0.17	-0.05
–Losers	(6.30)	(5.23)	(4.34)	(6.79)	(-1.86)	(5.28)	(3.77)	(-0.52)

Table A.7 Industry Momentum versus Factor Momentum: Alternative Industry Definitions

This table reports monthly alphas and selected factor loadings from spanning regressions in which the dependent variables are the monthly returns of industry momentum strategies across alternative industry classifications, including the 38-industry and 30-industry Fama-French classifications (FF38 and FF30, respectively) and the 20-industry classification from Moskowitz and Grinblatt (1999) (MG20). Four asset pricing models are considered: i) FF5, ii) FF5+factor momentum (FMOM), iii) FF5+residual-to-systematic-reversal (RSR), and iv) FF5+FMOM+RSR. Industry returns are decomposed using the $K = 10$ IPCA model into systematic ($Sys_{j,t}$) and residual ($Res_{j,t}$) components. FMOM goes long the top 10 high-eigenvalue PC factors with above-median prior-month returns and short those with below-median returns. RSR is constructed by going long systematic industries with below-median prior-month residual industry returns and short systematic industries with above-median prior-month residual industry returns. Panel A presents results for industry momentum strategies, and Panel B reports results for residual industry momentum strategies. Industry momentum goes long industries with above-median prior-month returns, and short those with below-median prior-month returns. Residual industry momentum goes long residual industries with above-median past-month returns, and short those with below-median past-month returns. The sample begins in January 1970 and ends in December 2022.

	FF5	FF5 +FMOM	FF5 +RSR	FF5 +FMOM+RSR			
	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{fmom}$	$\hat{\beta}_{rsr}$	R^2 (%)
<i>Panel A: Industry Momentum</i>							
FF38	0.36 (3.68)	0.08 (1.02)	0.58 (6.44)	0.27 (3.48)	0.57 (7.87)	-0.62 (-6.29)	34.92
FF30	0.41 (4.62)	0.12 (1.61)	0.65 (7.77)	0.35 (4.35)	0.55 (7.67)	-0.76 (-6.96)	39.70
MG20	0.46 (4.42)	0.13 (1.72)	0.71 (7.09)	0.34 (4.11)	0.67 (10.67)	-0.69 (-5.82)	44.01
<i>Panel B: Residual Industry Momentum</i>							
FF38	0.50 (7.09)	0.42 (6.06)	0.52 (7.49)	0.41 (5.91)	0.20 (3.55)	0.05 (0.52)	3.87
FF30	0.42 (6.42)	0.34 (5.21)	0.46 (6.86)	0.36 (5.32)	0.18 (3.56)	-0.08 (-1.00)	5.13
MG20	0.42 (5.95)	0.32 (4.67)	0.50 (6.93)	0.38 (5.29)	0.23 (4.22)	-0.20 (-2.18)	9.47

Table A.8 Determinants of Intra-industry Lead-lag Effect

This table reports the difference in firm characteristics between leading stocks and lagging stocks within each industry. The 49-industry, 38-industry and 30-industry Fama-French classifications (FF49, FF38 and FF30, respectively) and the 20-industry Moskowitz and Grinblatt (1999) classification (MG20) are considered. Following Eq. (16) from Yan and Yu (2023) and utilizing residual returns derived from the decomposition of stock returns via the $K = 10$ IPCA model, we assess whether stock j leads stock i within each intra-industry stock pair. A stock's leading power is measured by the proportion of "lead" relationships it exhibits across all its intra-industry stock pairs. Each month, stocks are sorted into quintiles based on their leading power. For the lead-minus-lag portfolio, we report equal-weighted firm characteristics, including firm size ($\log(\text{market cap})$), firm age (in years), idiosyncratic volatility (IVOL, in %), analyst coverage, and forecast dispersion (DISP, in %).

	Firm Size	Firm Age	IVOL	Analyst Coverage	DISP
FF49	3.70 (6.14)	9.49 (16.72)	-1.08 (-12.33)	8.75 (19.32)	-5.57 (-3.71)
FF38	3.68 (5.42)	10.09 (14.30)	-1.07 (-11.95)	8.69 (17.28)	-6.57 (-3.86)
FF30	3.65 (4.61)	9.52 (14.43)	-1.11 (-11.87)	8.76 (16.63)	-5.93 (-3.48)
MG20	3.65 (5.52)	10.25 (13.83)	-1.09 (-11.83)	8.95 (17.32)	-6.46 (-3.52)