Factor momentum*

Robert D. Arnott   Mark Clements   Vitali Kalesnik   Juhani T. Linnainmaa†

This version: March 2021

First version: November 2017

Abstract

Past industry returns predict future industry returns, and this predictability is at its strongest at the one-month horizon. We show that the cross section of factor returns shares this property and that industry momentum stems from factor momentum. Factor momentum transmits into the cross section of industry returns through variation in industries' factor loadings. We show that momentum in "systematic industries," mimicking portfolios built from factors, subsumes industry momentum as does momentum in industry-neutral factors. Industry momentum is therefore a byproduct of factor momentum, not vice versa. Momentum concentrates in its entirety in the first few highest-eigenvalue factors.

*Arnott and Kalesnik are with Research Affiliates LLC. Clements is with LA Capital. Linnainmaa is with the Dartmouth College and NBER, a researcher at Kepos Capital LP, and a shareholder at Research Affiliates. We thank Mark Carhart, Sina Ehsani, Mark Grinblatt, Cam Harvey, Gerard Hoberg, Owen Lamont, Yan Liu (discussant), Lars Lochstoer (discussant), Tobias Moskowitz (discussant), Stefan Nagel, Jeff Pontiff, Josie Smith (discussant), and the seminar and conference participants at University of St. Gallen, University of Mannheim, University of Zurich, the 2017 Rodney L. White Center Conference on Financial Decisions and Asset Markets, Society of Financial Studies 2018 Cavalcade, and Western Finance Association 2018 Meetings for insightful comments.

†Corresponding author. Mailing address: Dartmouth College Tuck School of Business, 100 Tuck Hall, Hanover, NH 03755, United States. E-mail address: Juhani.T.Linnainmaa@tuck.dartmouth.edu. Telephone number: +1 (603) 646-3160.

1 Introduction

Industries exhibit momentum similar to that found in stock returns. Moskowitz and Grinblatt (1999) show that this effect is at its strongest at the one-month horizon.[1] In this paper we show that industry momentum is not about industries, but rather about the factors against which the industries load. Factor momentum transmits into the cross section of industry returns through the differences in industries' factor loadings. We show there is little to no industry momentum net of factor momentum.

Factor momentum strategies, similar to stock momentum strategies, select stocks based on their prior returns. Ehsani and Linnainmaa (2021) show that one-year factor momentum subsumes all forms of individual stock momentum. It does not, however, subsume short-term industry momentum, which is distinct from stock momentum; at the one-month horizon stocks display reversals rather than persistence (Jegadeesh 1990). We show that, similar to industries, factors also display short-term momentum and that this momentum explains industry momentum.

The challenge in testing the hypothesis that industry momentum stems from factor momentum is in demonstrating the direction of this effect: does factor momentum give rise to industry momentum, or vice versa? If factors have incidental industry exposures, industry return shocks impact factor returns via factors' industry bets (Asness, Frazzini, and Pedersen 2014). Factor momentum could thus be an expression of industry momentum. We can, however, resolve this identification problem by using industry-neutral factors. We show that industry-neutral factors display at least as much momentum as the standard factors and that they, too, subsume industry momentum. This result is consistent with industry momentum being incidental to factor momentum.

Our explanation for industry momentum builds on variation in betas. If factors display momentum and industries have different factor exposures, factor momentum transmits into the cross

[1] Asness, Porter, and Stevens (2000), Grundy and Martin (2001), Lewellen (2002), and Hoberg and Phillips (2018), among others, also study industry momentum.

section of industry returns. We illustrate this mechanism using simulations in which only factors display momentum. The more the factor exposures vary across industries, the stronger the industry momentum in these simulations. However, because all momentum stems from factors, factor momentum always subsumes industry momentum.

This explanation for why factor momentum subsumes industry momentum relies on the assumption that industries' factor loadings differ. We show that the data strongly support this assumption. The Fama and French (2015) five-factor model, for example, explains just 2% of the variation in market-adjusted industry returns when we assume that all industries have the same fixed factor loadings. The model's explanatory power, however, increases to 17% when the loadings vary across industries and to 35% when they also vary from quarter to quarter. Put differently, different industries have very different factor exposures, and these factor exposures vary over time.

We develop a concept of "systematic industries" to show that the variation in factor loadings alone generates all of industry momentum. We use three-month windows of historical daily data to estimate industries' factor loadings. We then define systematic industries as the combinations of the factors implied by these factor loadings. These systematic industries—which are mimicking portfolios for each industry, built from a small set of factors—retain only *factor-level* variation in returns; that is, they discard any industry-specific shocks. We show that these systematic industries exhibit more and more momentum as we increase the number of factors from which we build them. At the same time, the amount of industry momentum that survives net of this momentum falls to zero. That is, no industry-specific information is required to capture industry momentum—a strategy based on the factor-level replications of the industries does even better.

Our explanation for industry momentum, up this point, is lacking in economic substance. Although it is indisputable that factor momentum in the data subsumes industry momentum, what are "factors"? Factors, just as industries, are combinations of individual assets. Why should factors exhibit momentum, and what are the economic implications of this finding? If factors have no more or less economic weight than industries, moving momentum from industries to factors would represent but a small step in our understanding of momentum.[2]

We address this issue by following the footsteps of Kozak, Nagel, and Santosh (2018, 2020), Haddad, Kozak, and Santosh (2020), and Ehsani and Linnainmaa (2021). These studies note that the absence of near-arbitrage opportunities alone identifies which factors *should* be important for pricing: they should be those that explain the most variation in returns. This argument does not depend on whether factors reflect risks or mispricing. Even if all variation in expected returns stems from mispricing, only those mispricings that align with systematic risk (even just by luck!) can survive the onslaught of arbitrageurs in equilibrium (Kozak, Nagel, and Santosh 2018). The sentiment-based mispricing model of Kozak, Nagel, and Santosh (2018) predicts the existence of factor momentum when sentiment is sufficiently persistent (Ehsani and Linnainmaa 2021).

We extract principal-component (PC) factors from a set of 43 industry-neutral factors and show that momentum dramatically concentrates in the high-eigenvalue PC factors. Factor momentum found among the first five highest-eigenvalue PC factors has the highest Sharpe ratio and, controlling for momentum found within this subset of PC factors, there is neither economically nor statistically significant momentum in any of the other subsets. Moreover, high-eigenvalue PC factor momentum, and this form of momentum alone, explains industry momentum.

Our results are consistent with what we expect to find *if* momentum resides in systematic factors. It resides exactly in those factors Kozak, Nagel, and Santosh (2018) and others argue are the economically important factors. In a world absent of near-arbitrage opportunities, non-systematic returns cannot display momentum because arbitrageurs could profit from such mispricings without

[2]Moskowitz and Grinblatt (1999, p. 1287), for example, note that "[T]he results beg the question: Why industries? This paper presents a great deal of evidence documenting a strong and robust industry momentum phenomenon, but we do not state why such an effect might or should exist." No clear industry-specific explanations for momentum have been advanced; rather, the same set of explanations that have been proposed for individual stock momentum have been repurposed for industries (Moskowitz and Grinblatt 1999): overconfidence and self-attribution bias (Daniel, Hirshleifer, and Subrahmanyam 1998), slow information diffusion (Hong and Stein 1999), or a rational explanation based on productivity shocks (Berk, Green, and Naik 1999).

assuming any risk. This conclusion precludes the existence of momentum not only in idiosyncratic returns (that is, in returns generated by firm-specific news) but also in the low-eigenvalue PC factors and those components of industry returns orthogonal to factor returns—which is what we find.

The finding that industries do not display momentum net of factor momentum is perhaps not surprising, as suggested by the prior in Moskowitz and Grinblatt (1999, p. 1251):

> "Industry momentum profits may also be indicative of an important role for industries in understanding financial markets. Previous literature has shown relatively little impact of industries on asset prices, either domestically or in international markets."

Our results are consistent with this prior and with the Moskowitz and Grinblatt (1999) argument. The factors that display momentum are the factors that can impact asset prices because arbitrageurs would assume risk by trading them. Conversely, industries do not display momentum because, as Moskowitz and Grinblatt (1999) explain, they do not seem to have an impact on prices independent of their factor exposures.

The factor momentum we study in this paper is a *cross-sectional* strategy: it selects factors based on their relative performance. A companion paper, Ehsani and Linnainmaa (2021), shows that a *time-series* factor momentum strategy is distinct from the strategy that we examine here, and that this form of factor momentum, in turn, explains individual stock momentum. Our results relate to Grundy and Martin (2001), who note that momentum strategies, by the virtue of choosing stocks based on their past returns, have time-varying risk exposures.

Our results also relate to, for example, Lewellen (2002), McLean and Pontiff (2016), and Avramov, Cheng, Schreiber, and Shemer (2017) who show that momentum also works for combinations of many well-diversified portfolios or predictors. We view these results as precursors for the finding that factors display momentum. Our results draw a connection between factor momentum and industry momentum, and explain that momentum exists only where it can exist: among the highest-eigenvalue factors.

2 Data

We use monthly and daily return data on stocks listed on the NYSE, AMEX, and Nasdaq from the Center for Research in Securities Prices (CRSP). We include ordinary common shares (share codes 10 and 11) and use CRSP delisting returns. If a stock's delisting return is missing and the delisting is performance-related, we impute a return of -30% for NYSE and AMEX stocks (Shumway 1997) and -55% for Nasdaq stocks (Shumway and Warther 1999).

We obtain accounting data from annual Compustat files. We follow the standard convention and lag accounting information by six months (Fama and French 1993). For example, if a firm's fiscal year ends in December in year t, we assume that this information is available to investors at the end of June in year $t+1$.

We compute returns on our factors from July 1963 through December 2020. Some of the predictors that we use to form the factors—such as idiosyncratic volatility and market beta—use some pre-1963 return data. The factor returns themselves, however, begin in July 1963.

We construct 43 factors using information that combine information about prices, returns, volumes, and accounting information. We list these factors in Table 1 along with their monthly Fama and French (1993) three-factor model alphas and $t(\hat{\alpha})$s. We divide these factors into eight groups: common factors, non-fundamental, profitability, earnings quality, investment and growth, financing, distress, and composite. The set of factors we include comes from Linnainmaa and Roberts (2018) with two modifications. First, because we measure the relationship between industry and factor momentum, we do not include factors that relate to stock returns over the prior month or year, that is, we exclude all versions of short-term reversals or momentum. Second, because we study industry effects, we exclude the industry concentration factor of Hou and Robinson (2006).

Table 1: List of factors

This table reports monthly Fama and French (1993) three-factor model alphas for 43 factors. We construct the SMB factor using the same procedure as Fama and French (1993); all other factors are similar to their HML factor, constructed by sorting stocks into six portfolios by firm size and the return predictor. We use NYSE breakpoints—median for size and the 30th and 70th percentiles for the return predictor—and independent sorts in the two dimensions. The exceptions to this rule are the factors based on discrete signals. The high and low portfolios of the debt issuance factor, for example, include firms that did not issue (high portfolio) or did issue (low portfolio) debt during the prior fiscal year. A factor's return is the value-weighted average return on the two high portfolios minus that on the two low portfolios. We sign the return predictors so that the high portfolios contain those stocks that the original study identifies as earning higher average returns. We construct two versions of each factor: the standard factor sorts stocks into portfolios by the raw return predictors and the industry-neutral factor sorts them by the industry-adjusted predictors. An industry-adjusted predictor subtracts the its cross-sectional industry average. Each factor's sample begins in the month indicated in the start date column and ends in December 2020.

			Standard factors		Industry-neutral factors	
Category	Factor	Start date	$\hat{\alpha}_{\text{ff3}}$	$t(\hat{\alpha}_{\text{ff3}})$	$\hat{\alpha}_{\text{ff3}}$	$t(\hat{\alpha}_{\text{ff3}})$
Common factors	Size, SMB	7/63			−0.02	−0.58
	Book to market, HML	7/63			0.13	2.51
	Operating profitability, RMW	7/63	0.31	4.01	0.26	5.49
	Asset growth, CMA	7/63	0.16	3.02	0.10	2.10
	Long-term reversals, LTREV	7/63	−0.01	−0.06	−0.04	−0.75
	Residual variance, RVAR	7/63	0.50	4.90	0.58	7.97
	Quality minus junk, QMJ	7/63	0.26	4.77	0.24	5.38
	Low beta, BAB	7/63	0.35	3.63	0.30	4.23
Non-fundamental	Amihud's illiquidity	7/63	0.36	2.04	0.01	0.10
	Firm age	7/63	−0.11	−1.63	−0.09	−1.47
	Nominal price	7/63	−0.44	−3.79	−0.26	−3.71
	High-volume premium	7/63	0.45	7.51	0.25	5.14
Profitability	Gross profitability	7/63	0.38	5.58	0.36	7.54
	Return on equity	7/63	0.24	3.33	0.09	1.50
	Return on assets	7/63	0.32	4.62	0.39	7.21
	Profit margin	7/63	0.10	1.52	0.15	2.26
	Change in asset turnover	7/63	0.20	3.92	0.16	3.76

(continued)

Earnings quality	Accruals	7/63	0.17	2.94	0.22	5.16
	Net operating assets	7/63	0.27	4.67	0.11	2.34
	Net working capital changes	7/63	0.21	3.97	0.21	4.80
	Cash-flow to price	7/63	0.30	4.54	0.20	3.42
	Earnings to price	7/63	0.20	3.00	0.28	4.53
	Enterprise multiple	7/63	0.18	3.08	0.14	2.68
	Sales to price	7/63	0.11	1.52	0.15	2.49
Investment and growth	Growth in inventory	7/63	0.18	3.17	0.20	5.16
	Sales growth	7/63	−0.03	−0.50	0.04	0.89
	Sustainable growth	7/63	0.08	1.52	0.07	1.38
	Growth in sales − inventory	7/63	0.22	4.37	0.11	2.03
	Investment growth rate	7/63	0.16	3.37	0.11	2.43
	Abnormal investment	7/63	0.10	2.02	0.13	2.92
	CAPX growth rate	7/63	0.17	3.88	0.18	4.02
	Investment to capital	7/63	0.07	1.12	0.12	2.32
	Investment to assets	7/63	0.13	2.30	0.06	1.31
Financing	Debt issuance	7/72	0.20	3.50	0.20	3.52
	Leverage	7/63	−0.18	−3.32	−0.02	−0.36
	One-year share issuance	7/63	0.23	5.00	0.23	5.01
	Five-year share issuance	7/63	0.21	4.57	0.21	4.58
	Total external financing	7/72	0.39	6.42	0.40	7.90
Distress	Ohlson's O-score	7/63	0.16	2.75	0.10	1.90
	Altman's Z-score	7/63	0.17	2.52	0.09	1.44
	Distress risk	7/63	0.56	6.52	0.46	7.53
Composite	Piotroski's F-score	7/63	0.30	4.93	0.29	6.02
	M/B and accruals	7/63	0.16	2.51	0.20	3.68

We construct the SMB factor using the same procedure as Fama and French (1993); all other factors are similar to their HML factor, constructed by sorting stocks into six portfolios by firm size and the return predictor. We use NYSE breakpoints—median for size and the 30th and 70th percentiles for the return predictor—independent sorts in the two dimensions.[3] A factor's return is the value-weighted average return for the two high portfolios minus the average for the two low portfolios. We rebalance the factors either monthly or annually, depending on the choices made in the original studies. Most of the factors that use accounting information rebalance annually at

[3]The exceptions to this rule are factors that use discrete signals. The high and low portfolios of the debt issuance factor, for example, include firms that did not issue (high portfolio) or did issue (low portfolio) debt during the prior fiscal year. Because the industry-adjustment, which subtracts the industry mean from each firm's predictor, breaks much of the discreteness, we use the standard 30-70 rule for all industry-neutral factors.

the end of June while those that use only CRSP information rebalance monthly. We construct standard and industry-neutral versions of each factor. These factors differ only in the values of the predictors used to construct the underlying portfolios. The standard factors in Table 1 sort stocks by the unadjusted return predictors. The standard value factor, for example, assigns stocks into portfolios by their raw book-to-markets. In constructing the industry-neutral factors, we demean the predictors each month by subtracting the predictor's cross-sectional industry average using the 49 Fama-French industry classification (Novy-Marx 2013). The industry-neutral value factor, for example, assigns stocks into portfolios based on how high or low their book-to-markets are relative to their industry peers. This demeaning step ensures that each factor's long and short legs are approximately evenly diversified across industries, or "industry-neutral."

We sign the return predictors so that the long portfolios contain those stocks that the original study identifies as earning higher average returns.[4] This signing convention, however, is inconsequential from a momentum investor's viewpoint. For example, if big stocks significantly outperformed small stocks over the momentum strategy's formation period, the factor momentum strategy takes long positions in big stocks and shorts small stocks. It does not matter whether we express the size factor as being long small and short big, or vice versa, as long as we are consistent over the sample period in the signing convention. Factors' signs would matter for the purposes of earning the *unconditional* premiums associated with each factor, but not for strategies that condition on past returns.

Table 2: Industry momentum

This table reports average monthly returns and five- and six-factor model alphas for four industry momentum strategies. These strategies trade the twenty Moskowitz and Grinblatt (1999) industries. The six-factor model augments the Fama and French (2015) model with the stock momentum factor (UMD) of Carhart (1997). The strategies use one-, six-, or 12-month formation periods and rebalance either monthly or biannually. The strategies first sort industries by their returns over the formation period and then take long and short positions in the above- and below-median industries. When the holding period is six months, we use the Jegadeesh and Titman (1993) methodology to resolve overlapping observations. The sample begins in August 1963 for the strategy with the one-month formation period and ends in December 2020. The samples for the strategies with six- and 12-month formation periods begin in January 1964 and July 1964.

Formation period, months	Holding period, months	$\bar{r}$	Asset pricing model: FF5 $\hat{\alpha}_{\text{ff5}}$	Asset pricing model: FF5 + UMD $\hat{\alpha}_{\text{ff5+umd}}$	Asset pricing model: FF5 + UMD $\hat{b}_{\text{umd}}$
1	1	0.38	0.45	0.38	0.11
		(4.54)	(5.27)	(4.42)	(5.24)
6	1	0.15	0.17	−0.09	0.36
		(1.66)	(1.79)	(−1.18)	(20.96)
12	1	0.28	0.35	0.05	0.44
		(2.96)	(3.71)	(0.76)	(29.76)
6	6	0.14	0.17	−0.08	0.36
		(1.81)	(2.11)	(−1.56)	(28.83)

3 Industry versus factor momentum

3.1 Short- and long-term industry momentum

Table 2 reports average monthly returns and Fama and French (2015) five- and six-factor model alphas for four industry momentum strategies. These strategies have one- or six-month holding periods and choose positions based on industry returns over the prior month, the prior six months, or the prior year. Each strategy is long the industries with above-median returns and short the

[4] This signing rule does not ensure that all factors' three-factor models should be positive in Table 1; the sign may flip because of the additional data that have accrued since the original study's sample period, because the original study did not adjust for the three-factor model, or because of corrections made to the CRSP and Compustat data since the original study.

below-median industries.[5] We follow Moskowitz and Grinblatt (1999) as closely as possible and report the main results for their 20-industry classification scheme. In addition, as a continuous robustness check, we also always report the key results for an alternative industry momentum strategy that trades the 49 industries of Fama and French (1997). The four strategies we study are also the same as those examined by Moskowitz and Grinblatt (1999), constructed here for a longer sample period. Industry returns are value-weighted returns of the stocks that belong to the industry.

All four versions of industry momentum earn positive average returns and five-factor model alphas. However, only the short-term strategy, which selects industries based on their prior one-month returns and rebalances monthly, earns a statistically significant six-factor model alpha; this six-factor model controls also for individual stock momentum by adding the UMD factor of Carhart (1997). This strategy's six-factor model alpha is 38 basis points per month (t-value = 4.42), while that of the strategy that selects industries based on their prior-year returns is just 5 basis points (t-value = 0.76). Individual stock momentum therefore subsumes everything but short-term industry momentum; the remaining industry momentum is neither statistically significant nor economically meaningful.

Table A1 in the appendix shows that these results are not specific to the Moskowitz and Grinblatt (1999) industry classification scheme. A short-term industry momentum strategy that trades the 49 industries of Fama and French (1997)—which is the preferred definition in Asness, Porter, and Stevens (2000)—earns a five-factor model alpha of 38 basis points (t-value = 4.79) and a six-factor

[5] Moskowitz and Grinblatt (1999) consider strategies that are long the top-three and short the bottom-three industries. Table A1 in the Appendix replicates Table 2 using this alternative definition. Because the top-three/bottom-three strategies are less diversified than the above-median/below-median strategies, their average returns and alphas associate with lower t-values; because t-values are proportional to information ratios, this difference implies that investors would benefit less, from the perspective of expanding the investment opportunity set, by trading these less-diversified versions. The t-value associated with the short-term industry momentum's six-factor model alpha, for example, falls from 4.42 to 3.92 when we move from the 10/10 portfolio rule in Table 2 to the 3/3 rule in Table A1. We examine the well-diversified industry momentum strategies throughout this study because they set a higher bar for industry momentum.

model alpha of 32 basis points (t-value = 3.98). This alternative strategy is therefore slightly less profitable in the 1963–2020 sample than the comparable Moskowitz and Grinblatt (1999) strategy. Similar to the findings in Table 2, only the short-term industry momentum strategy earns significant profits.[6]

The result that individual stock momentum subsumes all forms of industry momentum except for its short-term version is known. Asness, Porter, and Stevens (2000) and Grundy and Martin (2001) replicate the key parts of the Moskowitz and Grinblatt (1999) study and reach the same conclusion: individual stock momentum is almost entirely independent of industry momentum and *industry-adjusted momentum* is more profitable than standard momentum.[7] This result is not due to differences in sample periods. Table A1 in the Appendix shows that the long-term industry momentum strategy, based on six month formation and holding periods, has a five-factor model alpha of 31 basis points (t-value = 1.67) in the Moskowitz and Grinblatt (1999) sample. This alpha falls to −31 basis points (t-value = −2.47) when we add to the model the individual stock momentum factor.

We henceforth use the term *industry momentum* to refer to the strategy with one-month formation and holding periods. It is this part of industry momentum, and only this part of industry momentum, that is distinct from individual stock momentum and represents an independent puzzle.

3.2 Factor momentum

In Table 3 we report average monthly returns and five-, six-, and seven-factor model alphas for a cross-sectional factor momentum strategy. This strategy is identical to the industry momentum

[6]In Panel C of Table A1 the strategy that selects industries based on their prior one-year returns and rebalances monthly retains a statistically significant six-factor model alpha of 13 basis points (t-value = 2.21). This remaining statistical significance is due to this strategy's overlap with the short-term industry momentum. In the same table, when we construct the prior-one-year strategy but skip over the most recent month (that is, month $t-1$), the six-factor model alpha is 4 basis points (t-value = 0.64).

[7]Asness, Porter, and Stevens (2000, p. 14), for example, write: "Moskowitz and Grinblatt (1999) find that once adjusted for industry effects, momentum profits from individual equities are significantly weaker and for the most part are statistically insignificant. We disagree and find significant profits to within-industry momentum."

Table 3: Factor momentum

This table reports estimates from time-series regressions in which the dependent variable is the monthly return on a cross-sectional factor momentum strategy. This strategy trades the 43 factors listed in Table 1; it is long the factors with above-median returns in month $t-1$ and short those with below-median returns. The strategy rebalances monthly. Column (1) reports the strategy's average monthly return; column (2) its monthly five-factor model alpha; and column (3) its monthly six-factor model alpha, in which the sixth factor is the stock momentum factor (UMD) of Carhart (1997). The model in column (4) also includes the monthly return on the time-series factor momentum strategy of Ehsani and Linnainmaa (2021). This strategy, which trades the same 43 factors as the cross-sectional strategy, is long the factors with positive returns from month $t-12$ to $t-1$ and short those with negative returns. The samples in columns (1) through (3) begin in August 1963 and end in December 2020; the sample in column (4) begins in July 1964, because of the one-year formation period.

	Regression			
	(1)	(2)	(3)	(4)
$\hat{\alpha}$	0.64	0.70	0.66	0.52
	(6.11)	(6.60)	(6.12)	(5.01)
UMD			0.06	−0.14
			(2.57)	(−4.13)
Time-series factor momentum				0.83
				(8.73)
FF5 factors	N	Y	Y	Y
N	677	677	677	666
Adjusted R^2		5.5%	6.3%	16.0%

strategy except that it takes positions in factors rather than industries. It is a monthly rebalanced strategy, long the factors with above-median returns in month $t-1$ and short those with below-median returns. This strategy trades the 43 factors listed in Table 1; we later consider strategies that trade smaller subsets of, or principal components extracted from, these factors.[8]

The six-factor model in Table 3 controls for individual stock momentum, and the seven-factor model also controls for the *time-series* factor momentum of Ehsani and Linnainmaa (2021). This

[8]In Table A2 in the Appendix we examine factor momentum strategies that use longer formation and holding periods. Although all of these alternative cross-sectional factor momentum strategies earn statistically significant five-factor model alphas, all of them, except for the short-term strategy analyzed in more detail in Table 3, are almost completely subsumed by individual stock momentum. The cross-sectional factor momentum strategies therefore behave similar to the the industry momentum strategies: it is the short-term strategy with one-month formation and holding periods that is distinct from individual stock momentum.

strategy, which trades the same 43 factors as the left-hand side factor momentum strategy, is long the factors with positive returns over the prior year and short those with negative returns.

The short-term factor momentum strategy earns an average monthly return of 64 basis points (t-value = 6.11). The five-factor model explains none of its profits: the strategy's monthly alpha, net of the five-factor model, is 70 basis points and its t-value is 6.60. Individual stock momentum does not explain the profitability of the short-term factor momentum strategy. This strategy's monthly six-factor model alpha is 66 basis points (t-value = 6.12). It is also largely unrelated to time-series factor momentum. The seven-factor model alpha associates with a t-value of 5.01. Short-term cross-sectional factor momentum therefore represents a puzzle from the viewpoint of the five-factor model, individual stock momentum, and "long-term" time-series factor momentum.

A comparison of Tables 2 and 3 indicates that industry and factor momentum strategies appear similar. Both are short-term effects that grow *stronger* when we control for the five-factor model. The t-values associated with industry momentum's average return and its five-factor model alpha are 4.44 and 5.23; those of factor momentum are 6.05 and 6.71. Our argument and hypothesis, which we test in this paper, is that this similarity in the strategies' behaviors is not a mere accident: industry momentum stems from factor momentum.

3.3 Industry momentum, factor momentum, and momentum in industry-neutral factors

Table 4 reports estimates from spanning regressions that represent horse races between industry momentum, factor momentum, and momentum in *industry-neutral* factors. We use these regressions to show that there is a significant connection between factor and industry momentums. They set the stage for our later tests that propose and show *why* they are connected. The momentum strategy that trades industry-neutral factors is identical to the one that trades standard factors. The only difference is that it selects and allocates to industry-neutral factors based on their past

Table 4: Industry momentum, factor momentum, and momentum in industry-neutral factors

This table reports monthly alphas and selected factor loadings from time-series regressions in which the dependent variable is the monthly return on one of three momentum strategies: momentum in standard factors, momentum in industry-neutral factors, and industry momentum. The model is either the Fama-French five-factor model or a six-factor model that adds one of the other momentum strategies to the right-hand side. We report factor loadings for factor momentum ($\hat{b}_{\text{fmom}}$), industry-neutral factor momentum ($\hat{b}_{\text{in-fmom}}$), and industry momentum ($\hat{b}_{\text{imom}}$). The two factor momentum strategies trade the 43 factors listed in Table 1. Industry momentum trades the twenty industries of Moskowitz and Grinblatt (1999). All strategies are short-term cross-sectional strategies that rebalance monthly. They take long positions in factors (or industries) with above-median returns in month $t-1$ and short those with below-median returns. The sample begins in August 1963 and ends in December 2020.

Dependent		Coefficients				
variable	$\hat{\alpha}$	$\hat{b}_{\text{fmom}}$	$\hat{b}_{\text{in-fmom}}$	$\hat{b}_{\text{imom}}$	FF5	R^2
Factor momentum	0.70				Y	5.5%
in standard factors	(6.60)					
	0.09		0.99		Y	71.8%
	(1.48)		(39.71)			
	0.35			0.78	Y	44.4%
	(4.21)			(21.68)		
Factor momentum	0.62				Y	4.3%
in industry-neutral factors	(6.88)					
	0.12	0.71			Y	71.4%
	(2.39)	(39.71)				
	0.33			0.65	Y	42.1%
	(4.58)			(20.95)		
Industry momentum	0.45				Y	2.6%
	(5.15)					
	0.08	0.53			Y	42.6%
	(1.16)	(21.68)				
	0.07		0.61		Y	41.0%
	(1.03)		(20.95)			

returns.

Industry-neutral factors display as much momentum as standard factors. Although the industry-neutral strategy has a lower monthly alpha—62 versus 70 basis points—it is also less volatile because the factors it trades remove industry-level variation in returns (Asness, Porter, and Stevens 2000).

This decrease in volatility more than makes up for the decrease in alpha; the two strategies' five-factor model alphas associate with t-values of 6.60 (standard factors) and 6.88 (industry-neutral factors). When controlling for each other, the momentum in standard factors does not reach conventional levels of statistical significance (t-value = 1.48), but that in industry-neutral factors has a t-value of 2.39. Industry momentum subsumes neither version of factor momentum. The two factor momentum strategies' alphas in a six-factor model that adds industry momentum are significant with t-values of 4.21 and 4.58.

Factor momentum, by contrast, subsumes industry momentum. Industry momentum's alpha falls from 45 basis points (t-value = 5.15) in the five-factor model to seven or eight basis points, net of the effects of momentum in either the standard or industry-neutral factors. Neither estimate is statistically significantly different from zero. These regressions demonstrate that, whatever the source of industry momentum's profits, factor momentum strategies derive their profits from the same source. Industry momentum's loadings against the two factor momentum strategies are significant with t-values of 21.7 and 21.0, and the model's explanatory power rises by an order of magnitude, from under 3% to 41%–43%, when we augment the five-factor model with one of the factor momentum strategies.[9]

Table 4 indicates, first, that factor momentum subsumes industry momentum and, second, that industry momentum cannot be responsible for factor momentum. If factor momentum stemmed from industry momentum, we would not expect to see meaningful momentum in industry-neutral factors; we would expect industry momentum to subsume factor momentum; and we would expect standard factor momentum to outperform the industry-neutral version. The data, however, run counter to all of these predictions.

[9]Panel A of Table A3 in the appendix shows that the result is the same for the industry momentum strategy that trades the 49 Fama-French industries; this alternative strategy's alphas are both 4 basis points—with t-values of 0.63 and 0.67—in models that control for momentum in the standard or industry-neutral factors.

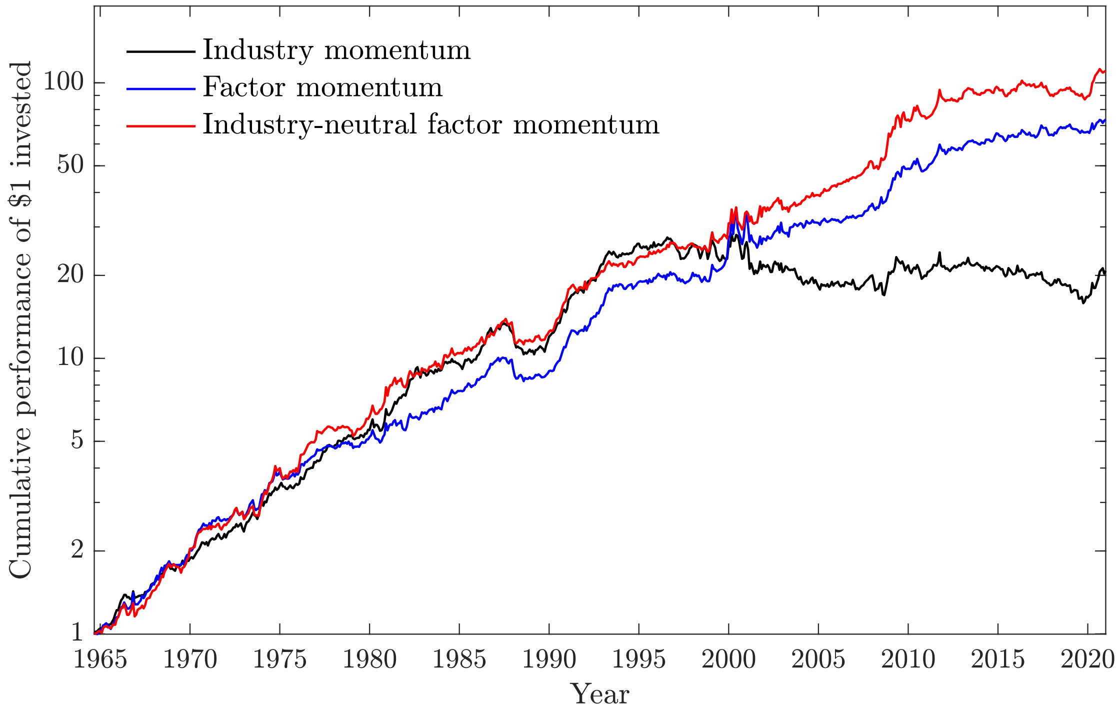

Figure 1: **Performance of factor and industry momentum strategies, July 1964–December 2020.** This figure plots cumulative returns on strategies that capture momentum in industry, factor, and industry-neutral factor returns. The factor momentum strategies trade the 43 factors listed in Table 1. The industry momentum strategy trades the twenty industry portfolios of Moskowitz and Grinblatt (1999). All strategies use one-month formation and holding periods. Each strategy is long industries (or factors) with above-median past returns and short those with below-median past returns. We lever each strategy to an annualized volatility of 10%.

3.4 Factor and industry momentum over time

Figure 1 reports cumulative returns for strategies that trade momentum in factor, industry, and industry-neutral factor returns from August 1963 through December 2020. We lever each factor to an annualized volatility of 10%.

All three momentum strategies are profitable over the full sample period. The behaviors of the three series, however, diverge sharple from the mid- to late-1990s onward. From this point on until the end of the sample the cumulative return on the industry momentum, perhaps even *because* of its discovery, is slightly negative; this factor has been in a drawdown for twenty years by the end of the sample period.[10] The profits of the factor momentum strategies, by contrast, do not display economically meaningful breaks, and both strategies reach their all-time highs in 2020, the last year of the sample period.

4 Transmission of factor momentum into the cross section of industries: Simulations and empirical evidence

Momentum in factors transmits to the cross section of industries if industries' factor loadings differ. Even if industry-specific returns—that is, returns unrelated to industries' factor exposures—are serially uncorrelated, past industry returns positively predict future industry returns as long as past *factor* returns predict future factor returns. Why? A winning industry will, on average, load positively against winning factors and negatively against losing factors. If we sort industries by their past returns, we therefore indirectly sort on the past factor returns. The extent to which factor momentum generates industry momentum depends on how strongly factor loadings vary across industries.

We first use simulations to illustrate this transmission mechanism. We then measure the amount variation in industry loadings in the actual data to assess the economic plausibility of this transmission mechanism.

4.1 Simulations

Table 5 reports average t-values associated with the average returns and alphas for factor and industry momentum strategies. We estimate the underlying regressions using simulated data. In these simulations stock returns are driven by their factor exposures, industry return shocks, and firm-specific return shocks. Factors display momentum through the persistence in their risk

[10] This turn coincides roughly with the publication of Moskowitz and Grinblatt (1999). McLean and Pontiff (2016) suggest that informed traders learn from academic discoveries and, because of the resulting increase in the arbitrage activity, the discovery of a new anomaly significantly weakens it going forward.

premiums; industry and firm-specific shocks, on the other hand, are uncorrelated and independent of each other and of the shocks to factor returns. Stocks' factor loadings vary systematically across industries, and we vary in the simulations the size of the industry component from 0% to 50%. We repeat these simulations 100,000 times for each specification. Each run of the simulation generates a panel of monthly stock returns that approximates the dimensions and return properties of the actual data: 678 months of data for 2,000 stocks. We detail these simulations in Appendix A.

We construct tradeable industry portfolios and factors from the simulated stock returns. An industry's return is the average return on the stocks that belong to it, and a factor's return is the return on the portfolio that, based on the stocks' factor betas, most closely tracks that factor.[11] The estimates in Table 5 measure how profitable the industry and factor momentum strategies are, and how much of these profits remain when we control for the other. We construct the factor and industry momentum strategies using the same rules as in the actual data: sort by the prior-month's return, buy and sell above- and below-median industries (or factors), and rebalance monthly.

Table 5 shows that a factor momentum strategy in these simulations is profitable given the persistence in risk premiums. This strategy is significant with a t-value that ranges from 6.1 to 7.1 depending on how much of the variation in stocks' betas is industry-specific. The more of the variation is industry specific, the noisier the factors recovered from stock returns.

Industry momentum is profitable *if* factor betas vary systematically across industries. When the betas are void of an industry component, each industry's betas against all factors are approximately zero, and none of the momentum in factor returns carries over to industry returns. However, when betas vary systematically across industries, an industry's past return is informative about the performance of the factors against which it loads: an industry's return is, on average, high if it

[11] We recover factors' month-t returns by estimating a cross-sectional regression of month-t stock returns on the matrix of stock betas. The resulting slope estimates represent returns on self-financing portfolios that track each factor as closely as possible by minimizing the mean-squared error—that is, these are the returns on the factor-mimicking portfolios. This procedure is analogous to the second stage of the Fama and MacBeth (1973) procedure, which is used to recover factor risk premiums.

Table 5: Industry and factor momentum—Simulations

We run simulations in which factor premiums are persistent; individual stocks belong to industries; and stocks' factor loadings have stock- and industry-specific components. All shocks in the model are uncorrelated. The persistence in factor premiums generates factor momentum and when factor loadings vary across industries, this momentum transmits to the cross section of industry returns. The first column shows the fraction of variation in betas that we set to be attributable to the industry-specific component. We construct factor and industry momentum strategies as in the data: sort by month $t-1$ returns, buy and sell above- and below-median factors or industries, and rebalance monthly. We report t-values associated with the average returns for the factor and industry momentum strategies and with the alphas from regressions of one strategy against the other. Appendix A details these simulations. We repeat these simulations 100,000 times for each of the six specifications and report the average t-values.

Industry share of the variation in factor loadings	Factor momentum	Industry momentum	Factor momentum controlling for industry momentum	Industry momentum controlling for factor momentum
0%	7.06	0.09	7.06	−0.07
10%	6.67	2.40	6.20	−0.05
20%	6.43	3.40	5.41	0.21
30%	6.28	3.94	4.85	0.49
40%	6.16	4.28	4.44	0.77
50%	6.07	4.51	4.14	1.02

loads positively on the factors with high returns and negatively on the factors with low returns. To the extent that factor betas persist, past industry performance predicts future performance because of factor momentum. That is, a strategy that trades momentum in industry returns *indirectly* trades momentum in factor returns.

The last two columns in Table 5 show that factor momentum subsumes industry momentum but not vice versa. As the amount of industry-level variation in betas increases, factor momentum loses some of its alpha in these head-to-head regressions. This pattern stems from the fact that both industry and factor returns are linear combinations of stock returns. As the amount of industry-level variation in betas increases, factors reflect more of the industry-level return shocks. The factor and industry momentum strategies become more similar even though all momentum still ultimately resides in the unobserved factor returns. That is, by construction in these simulations, no industry momentum exists separately from factor momentum.

4.2 Empirical evidence on the transmission mechanism

The simulations underneath Table 5 illustrate the intuition for the transmission of factor momentum into the cross section of industry returns. The only assumption necessary for creating the link is the heterogeneity in industry factor loadings. In Table 6 we measure the extent to which factor exposures vary across industries.

We estimate panel regressions in which the dependent variable is the daily market-adjusted industry return. We continue to use the twenty Moskowitz and Grinblatt (1999) industries. The explanatory variables are the daily factor returns from five asset pricing models, starting with the CAPM and ending with a nine-factor model that includes four popular factors in addition to the Fama and French (2015) model: long-term reversals, residual variance, quality-minus-junk, and betting-against-beta—these together are the "popular factors" listed in Table 1. We first estimate static regressions which constrain industries' factor loadings to be equal across industries and over time. We then introduce twenty dummy variables for the industries and 228 dummy variables for all quarters starting from the third quarter of 1963 and ending in the fourth quarter of 2020. By interacting these dummy variables, or the products of the two sets of dummy variables, with the right-hand-side factors, we let the regressions capture variation in factor loadings across industries, over time, or in both dimensions.

Table 6 reports adjusted R^2s from these panel regressions. Because the dependent variable is market-adjusted, the static CAPM is the benchmark model. When the model permits market betas to vary across industries, CAPM explains 4.0% of the variation in returns; when the model permits for the variation across industries and over time, it explains 15.4% of the variation in

Table 6: Cross-sectional and time-series variation in industries' factor loadings

This table reports adjusted R^2s from panel regressions in which the dependent variable is the daily market-adjusted industry return and the explanatory variables are the factors from different asset pricing models. The bottom part of the table indicates which factors are included in each model. We estimate four specifications for each asset pricing model to capture cross-sectional and time-series variation in factor loadings: (a) factor loadings are identical across industries and over time; (b) factor loadings vary from quarter to quarter; (c) factor loadings vary across industries; and (d) factor loadings vary in both dimensions. We capture these variations by interacting the right-hand-side factors with twenty dummy variables for the Moskowitz and Grinblatt (1999) industries, with 228 dummy variables that represent quarters, or with the product of these dummy variables. The sample begins in July 1963 and ends in December 2020.

	Asset pricing model R^2s				
Specification	(1)	(2)	(3)	(4)	(5)
(a) Static	.	1.4%	2.2%	2.5%	2.8%
(b) Variation across time	1.5%	3.6%	4.0%	4.3%	4.6%
(c) Variation across industries	4.0%	12.7%	16.7%	18.5%	21.9%
(d) Variation across time and industries	15.4%	28.8%	35.1%	40.3%	44.7%
Factors included in the model:					
MKTRF	×	×	×	×	×
SMB		×	×	×	×
HML		×	×	×	×
RMW			×	×	×
CMA			×	×	×
LTREV				×	×
RVAR				×	×
QMJ					×
BAB					×

daily returns.[12] That is, exposures to market risk differ significantly across industries, and each industry's market exposure also varies over time. Because industry momentum is a short-term effect, this observation about time-series variation in exposures is important; for factor momentum to transmit to the cross section of industry returns, industries' factor loadings do not have to be fixed over the entire 57-year sample; this transmission occurs as long as industry loadings persist

[12]Because we compute *adjusted* R^2s, the model's explanatory power does not increase mechanically in the number of regressors. That is, if we generate an equal number of random indicator variables that have no rhyme or reason, the adjusted R^2 is close to zero because the adjusted-R^2 formula accounts for the degrees of freedom lost; see, for example, Foerster, Linnainmaa, Melzer, and Previtero (2017, pp. 1458–1460), for details and references.

from one month to the next.[13]

The explanatory powers of the model increase as we add more factors. A three-factor model explains up to 28.8% of the variation in daily industry, a five-factor model up 35.1%, and the explanatory power of a model that relies on nine common factors rises to 44.7%. The ordering of the models and factors is somewhat arbitrary—we address this point later by ordering principal components extracted from a large set of factors. But this arbitrariness is beside the point. What the results in Table 6 show is that, at each point in time, industries have significantly different loadings against many common factors. This result guarantees, as the simulations in Table 5 illustrate, that any momentum found in the factors will transmit to industry returns.

5 Momentum in systematic industries

5.1 Defining industry-mimicking portfolios

An industry at every point in time is exposed to multiple factors which, in turn, display momentum. Table 6 shows that the five-factor model, for example, explains one-third of the variation in daily industry returns, while the nine-factor model explains nearly half of the variation. In this section we examine the extent to which a parsimonious combination of factors, tailored for each industry, can account for a meaningful proportion of industry momentum. That is, instead of explaining industry momentum with the momentum found in a large set of factors, we test whether the posited transmission mechanism of momentum from factors to industries indeed works.

If an industry has loadings $\beta_1, \beta_2, \ldots, \beta_K$ on factors $1, 2, \ldots, K$, we can use these betas together with the factors to construct a mimicking portfolio for the industry. What we call a *systematic industry* is a linear combination of the K factors; the portfolio that best mimics industry j's

[13] The results in Table 6 are consistent with the conclusions of Fama and French (1997), who measure cross-sectional and time-series variation in industries' three-factor model loadings. They estimate, for example, that "the variation through time in the true HML slopes of many industries is almost as large as the cross-sectional standard deviation of the long-term average HML slopes of the 48 industries" (Fama and French 1997, p. 160).

return earns a return of $r^s_{j,t} = \beta_{j,1}F_{1,t} + \cdots + \beta_{j,K}F_{K,t}$ in month t, where the F_ts are the factor returns. This systematic industry captures the factor returns for the industry and strips out any industry-specific information. Based on the estimates in Table 6, a systematic industry based on the five-factor model, for example, would miss approximately two-thirds of the variation in daily industry returns, either because of omitted factors or because this remaining variation represents industry-specific return shocks.

5.2 Empirical estimates

We measure the amount of momentum in systematic industries and the connection between this form of momentum and industry momentum in Table 7. We use the same models and methods as in Table 6; what were columns in Table 6 are now rows in Table 7. We estimate each industry's factor loadings at the end of month t from daily industry and factor returns over the prior three months. We use these estimated loadings to compute the systematic industry's returns for months t and $t+1$ using these end-of-month-t estimated loadings. We define the systematic industry momentum strategy in the same way as we define the standard industry momentum strategy: we sort systematic industries by their month-t returns, buy and sell those with above- and below-median returns, and rebalance monthly. Because we estimate factor loadings using information only up to month t, the systematic industry momentum strategy is tradeable as well. That is, instead of investing in industry j at the end of month t, an investor could just as well invest in its mimicking portfolio, the systematic industry j.

In Table 7 we report monthly alphas for industry and systematic industry momentum strategies based on different models for systematic industries. On the FF3 row, for example, we construct systematic industries from the three factors of the Fama and French (1993) model. This systematic industry momentum strategy has a monthly five-factor model alpha of 55 basis points (t-value $= 5.86$). This strategy, by definition, only trades momentum found in the underlying model's

Table 7: Momentum in systematic and non-systematic industry returns

This table reports monthly alphas for industry and systematic industry momentum strategies. We define *systematic industries* as linear combinations of the factors against which the actual industries load. We use the three months of daily data up to the end of month t to estimate each industry's factor loadings for five asset pricing models, starting with the CAPM and ending with a nine-factor model. Systematic industry j's return in month t' is $r^s_{j,t'} = \sum_{k=1}^{K} \hat{\beta}_{j,k,t} F_{k,t'}$, where t' is either t or $t+1$. Month $t+1$ return is out-of-sample from the viewpoint of the beta estimates. Industry and systematic industry momentum strategies are long industries with above-median returns in month t and short those with below-median returns. The first set of columns reports alphas for the industry momentum strategy from the five-factor model augmented with systematic industry momentum, except for the first row, which represents the standard five-factor model. The second set of columns reports alphas for systematic industry momentum strategies either from the five-factor model (1) or from this model augmented with industry momentum (2). The sample begins in October 1963 and ends in December 2020.

	Dependent variable						
	Industry momentum			Momentum in systematic industries			
Model for systematic industries				(1)	(2)		
	$\hat{\alpha}_{\text{ff5+smom}}$	$\hat{b}_{\text{smom}}$	R^2	$\hat{\alpha}_{\text{ff5}}$	$\hat{\alpha}_{\text{ff5+imom}}$	$\hat{b}_{\text{imom}}$	R^2
None	0.45		2.5%				
	(5.16)						
CAPM	0.38	0.25	7.2%	0.25	0.16	0.20	7.2%
	(4.51)	(5.95)		(3.22)	(2.08)	(5.95)	
FF3	0.23	0.40	20.5%	0.54	0.34	0.46	24.1%
	(2.85)	(12.43)		(5.86)	(3.95)	(12.43)	
FF5	0.20	0.46	25.5%	0.53	0.31	0.51	29.6%
	(2.57)	(14.48)		(5.88)	(3.78)	(14.48)	
FF5 + LTREV + RVAR	0.14	0.52	32.0%	0.60	0.34	0.59	35.2%
	(1.83)	(17.17)		(6.52)	(4.31)	(17.17)	
FF5 + LTREV + RVAR + QMJ + BAB	0.09	0.54	38.0%	0.66	0.35	0.68	40.6%
	(1.30)	(19.70)		(6.77)	(4.49)	(19.70)	

three factors. It does so by constructing twenty different portfolios of these factors, where the portfolios are based on the estimates of how each industry loads on them. When the strategy takes a long position in the systematic industry j, it does so because the factors against which the the actual industry j has positive betas must have performed well or the factors against which it has negative betas must have performed poorly. On the same FF3 row, we report industry momentum's alpha from the five-factor model augmented with systematic industry momentum. Although industry momentum's alpha remains significant at 23 basis points (t-value = 2.88), this alpha is approximately half of its value of 45 basis points (t-value = 5.23) in the five-factor model. That is, the momentum found in the three factors of the Fama and French (1993) alone account for a meaningful amount of industry momentum.

Table 7 shows that systematic industry momentum grows stronger when we build these mimicking portfolios from a larger set of factors. From the first model to the last, systematic industry momentum's five-factor model alpha increases from 25 basis points per month (t-value = 3.22) to 66 basis points (t-value = 6.77). Controlling also for industry momentum, this last form of systematic industry momentum retains an alpha of 35 basis points (t-value = 4.49). That is, similar to the results in Table 4, this evidence indicates that there is momentum in factors not found in industry returns.

As systematic momentum becomes stronger, less and less remains of industry momentum. Momentum in the CAPM-based systematic industries remove just 14% of industry momentum's alpha; the three-factor model removes 49%; the five-factor model removes 56%; the seven-factor model removes 70%; and the nine-factor model removes 79%. By the last two models, industry momentum's alpha falls to 14 and 9 basis points, and statistical significance disappears. At the same time as industry momentum's alpha decreases, the model's explanatory power increases. This increase, which parallels the increase in the explanatory powers of the models in Table 6, again suggests that industry momentum profits derive from the same source as the factor momentum profits.

6 Industry momentum and momentum in principal component factors

6.1 Momentum in high- and low-eigenvalue PC factors

Table 6 shows that factor loadings vary systematically across industries, which is a necessary condition for factor momentum to transmit into industry returns. Table 7 takes this transmission mechanism into the data and shows that momentum in systematic industries, which we construct as mimicking portfolios that trade small sets of factors, can subsume industry momentum. The extent to which systematic industry momentum subsumes industry momentum, however, depends on the number and identity of the factors included in the model. All factors models, with the exception of the CAPM, are arbitrary collections of factors.[14] If factors are no less arbitrary combinations of individual securities than industries, explaining industry momentum with factor momentum lacks economic substance.

Economic theory, however, provides precise guidance on what factors should associate with pricing effects. Kozak, Nagel, and Santosh (2018, 2020), among others, emphasize the implications emanating from the lack of near-arbitrage opportunities. These studies, which build on the arbitrage pricing theory foundations of Ross (1976), note that the absence of near-arbitrage opportunities alone identifies the factors which *should* be important: they should be those factors that explain the most variation in returns. Whether pricing is rational or behavioral, differences in expected returns should align with covariances. In rational models the argument is that of Merton (1973); in mispricing-based explanations, it is based on the behavior of arbitrageurs. If a mispricing does not align with covariances, arbitrageurs can trade the mispricing aggressively because, by doing so, they do not assume any factor risk. In equilibrium only those mispricings that align with covariances

[14]Nagel (2013), for example, calls these reduced-form factor models "ad hoc" factor models to emphasize their arbitrariness.

remain (Kozak, Nagel, and Santosh 2018).

From this perspective of economic theory, stocks, industries, and (ad hoc) factors *all* lack substance. What matters is only the risk that arbitrageurs would have to bear if they were to seek to profit from a factor. By extension, the extent to which stocks, industries, and factors can display any pricing effects, such as momentum, depends on their exposures to undiversifiable risk. The theory therefore guides us to look for those combinations of factors that explain the most variation in returns.

Kozak, Nagel, and Santosh (2018) extract principal-component factors from a large set of factors and show that factor premiums concentrate to a small set of the highest-eigenvalue factors; their result therefore supports their conjecture regarding the lack of near-arbitrage opportunities. We use the same methods to examine factor momentum. The difference is that, instead of studying PC factors' unconditional average returns, we measure the amount of momentum in these factors' returns. We expect to find more factor momentum among the high- than low-eigenvalue factors. The existence of significant momentum profits among the low-eigenvalue PC factors would be inconsistent with the absence of near-arbitrage opportunities. Factors can display momentum without violating the absence of near-arbitrage opportunities. Ehsani and Linnainmaa (2021) note that the sentiment-based mispricing model of Kozak, Nagel, and Santosh (2018) predicts the existence of factor momentum when sentiment is highly persistent and, just as argued by Kozak et al. about the pricing effects, the momentum in the model concentrates into the high-eigenvalue factors.

We extract principal-component factors from the 43 industry-neutral factors listed in Table 1. We use an extending-sample approach similar to that in Ehsani and Linnainmaa (2021) to render the returns on the PC factors in month $t+1$ out-of-sample relative to the estimation of the eigenvectors. We use daily return data up to the end of month t, normalize all factors to 10% volatility, and then compute the first 41 eigenvectors, ordered by their eigenvalues. We stop at 41 because the

Table 8: Momentum in high- and low-eigenvalue PC factors

This table reports monthly alphas for cross-sectional momentum strategies that trade of subsets of PC factors ordered by their eigenvalues. We extract 41 principal components from the 43 industry-neutral factors listed in Table 1; we stop at 41 because the returns on two of the factors on this list begin nine years after the start of the sample. We use daily returns up to the end of month t, standardize all factors to 10% annualized volatility, compute all eigenvectors, and compute month t and $t + 1$ returns on the PC factors from these eigenvectors. We order the PC factors by their eigenvalues and assign them into groups. A PC factor momentum strategy sorts the factors by their month t returns, takes long and short positions in the factors with above- and below-median returns, and rebalances monthly. We report five-factor models alphas for the subsets of PC factors and alphas from the five-factor model augmented with the momentum found in the high-eigenvalue PC factors (factors 1–5).

	Momentum in subsets of PC factors ordered by eigenvalues							
	1–5	6–10	11–15	16–20	21–25	26–30	31–35	36–41
				Five-factor model				
$\hat{\alpha}$	0.76	0.16	0.45	0.21	0.28	0.28	0.24	0.25
	(6.11)	(1.26)	(3.61)	(1.64)	(2.25)	(2.24)	(1.88)	(1.98)
Adj. R^2	4.0%	4.4%	2.5%	1.6%	2.6%	4.9%	1.1%	0.2%
				Five-factor model augmented with momentum in high-eigenvalue factors				
$\hat{\alpha}$		−0.13	0.20	0.06	0.05	0.09	0.03	0.12
		(−1.13)	(1.60)	(0.45)	(0.43)	(0.73)	(0.23)	(0.91)
$\hat{b}_{\text{fmom1–5}}$		0.38	0.34	0.20	0.30	0.25	0.27	0.17
		(9.83)	(8.49)	(4.70)	(7.43)	(6.07)	(6.66)	(4.13)
Adj. R^2		18.3%	13.4%	5.1%	11.1%	10.6%	8.2%	2.9%

returns on two factors on the list begin in July 1972. We compute month t *and* month $t+1$ returns on the PC factors from these eigenvectors. The month $t + 1$ returns are out of sample relative to the estimation step. Because we compute both month t and $t + 1$ returns using the same set of eigenvectors, the rotation of the factors is locally the same. That is, when we sort PC factors by their month t returns to create the momentum strategy, the month $t + 1$ returns correspond to the *same* rotation of factors.

In Table 8 we examine the performance of momentum strategies that trade eight different subsets of PC factors. The first subset contains the five highest-eigenvalue PC factors; the second subset contains the five next-highest-eigenvalue factors, and so forth. The first row of Table 8 shows that the highest-eigenvalue set of PC factors has a five-factor model alpha of 76 basis points per month (t-value = 6.11). The second set has an alpha of 16 basis points (t-value = 1.26).

The significance of the alphas beyond the set of the highest-eigenvalue factors—the alpha of the third set, for example, is significant with a t-value of 3.61—does not imply that these momentums are incrementally informative about future returns. Although the PC factors are, by definition, orthogonal in the estimation period, the strategies that time these factors need not be. That is, given the properties of the PC factors, a regression of one factor against another in the estimation period would always return a slope of zero. But if the momentum profits that the PC factors earn derive from a common source, *timed* portfolios of the factors can correlate. The bottom part of Table 8 augments the five-factor model with a strategy that trades momentum in the five highest-eigenvalue PC factors. This regression shows that all PC factor momentum strategies indeed significantly correlate with each other. In the regression of the second strategy on the first strategy, for example, the slope coefficient is 0.38 (t-value = 9.83), suggesting a high degree of correlation between the two sets.

The alphas from these six-factor model regressions measure the extent to which the other momentum strategies would expand the investment opportunity set of an investor who already trades momentum in the first set of PC factors (Huberman and Kandel 1987). The economically small and statistically insignificant alpha estimates indicate that the other strategies are not incrementally informative about future returns. From an asset pricing perspective, the results imply that a model that includes only the high-eigenvalue momentum suffices to describe the cross section of average returns (Barillas and Shanken 2016).[15]

[15] In Table A4 in the Appendix we reverse the regressions shown in the bottom part of Table 8. We augment the Fama and French (2015) model with each of the PC factor momentum strategies in turn, or all of them at the

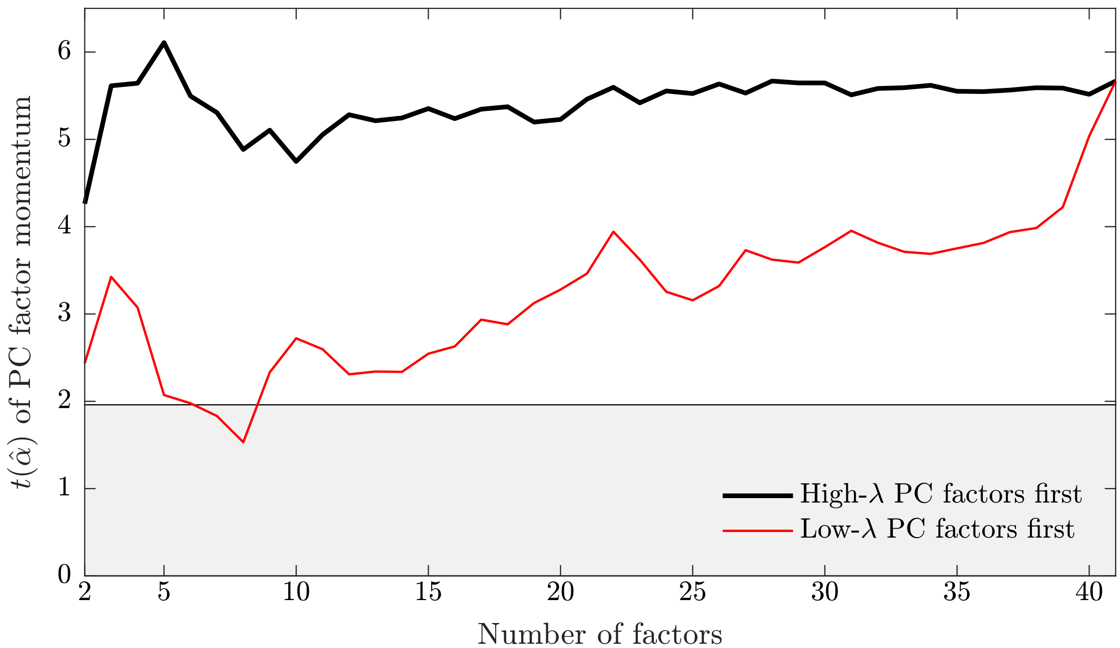

Figure 2: **Factor momentum $t(\hat{\alpha})$s as a function of the number of PC factors.** We extract 41 principal component factors from the factors listed in Table 1 using daily returns up to month t, compute monthly returns for months t and $t+1$, and order the resulting PC factors by eigenvalues. We construct strategies that trade factor momentum in an increasing number of these PC factors with the number of factors in the strategy shown on the x-axis. The black line starts from the two highest-eigenvalue factors and works down the list towards the lowest-eigenvalue factor; the red line works through the factors in the reverse order. We compute and plot in this figure the t-value associated with the Fama-French five-factor model alpha for each strategy. The sample begins in July 1973 and ends in December 2020.

Figure 2 illustrates the striking difference in the amount of momentum found in the high- and low-eigenvalue factors. In this figure we start from a strategy that trades momentum in just two PC factors; in this case the strategy is always long the better-performing factor and short the worse-performing one. We start either from the two highest-eigenvalue factors (black line) or from the two lowest-eigenvalue factors (red line). We then increase the number of factors included in these strategies, one factor at a time, until they both include all 41 factors. We compute and plot the $t(\hat{\alpha})$s from the five-factor model for each of the resulting strategies.

same time. In all of these alternative models the highest-eigenvalue PC factor momentum's alpha remains high and statistically significant. It is the lowest, at 0.53 basis points per month (t-value = 4.85), in the model that controls for all other momentum strategies at the same time.

By construction, the two lines converge at the same point when both strategies include all 41 factors. These two lines, however, start from very different levels and follow different paths before arriving at this endpoint. Consistent with the estimates in Table 8, momentum strategies that trade the highest-eigenvalue factors are more profitable than those that trade any of the low-eigenvalue factors. In fact, strategies that trade just a few of the highest-eigenvalue factors are just as (or even more) profitable than the one that trades the full set. The reason is that these additional factors, as shown in the bottom part of Table 8, are not incrementally informative about future returns.

The strategies that start from the lowest-eigenvalue PC factors, by contrast, benefit from adding more and more factors until the very end, with the final three PC factors—those with the highest eigenvalues—being decisive. The profitable of these strategies jumps up at the very end because the few highest-eigenvalue PC factors that have not yet been included contain information not found in all of the other factors that have been included.

6.2 Industry momentum vis-à-vis high-eigenvalue PC factor momentum

Table 9 and Figure 3 show that the momentum found in the high-eigenvalue PC factors fully subsumes industry momentum. In Table 9 we use the same sets of PC factors as in Table 8. We augment the the five-factor model with a momentum strategy that trades each set of PC factors and compute industry momentum's alpha from the resulting six-factor model.

Momentum found among the highest-eigenvalue PC factors explains industry momentum. Industry momentum's five-factor model alpha in this post-1973 sample is 38 basis points per month (t-value = 3.84). This alpha falls to 8 basis points (t-value = 0.86) when we add to the model the momentum in the five highest-eigenvalue PC factors. Momentum in industries and PC factors correlate significantly. The industry momentum coefficient against the first PC factor momentum strategy is 0.4 (t-value = 13.9), and this regression explains 27% of the variation in industry momentum's profits; this proportion represents a marked increase from the 3% explained by the

Table 9: Industry momentum versus momentum in high- and low-eigenvalue PC factors

This table reports monthly alphas for the industry momentum strategy from the five-factor model (first row) and from six-factor models that augment the five-factor model with different PC factor momentum strategies. The PC factor momentum strategies are the same as those described in Table 8; they trade different subsets of PC factors ordered by their eigenvalues. We report alphas, slope coefficients against the PC factor momentum strategy, the t-values associated with these alphas and slopes, and the adjusted R^2. The sample begins in July 1973 and ends in December 2020.

Control for momentum in PC factors	Alpha $\hat{\alpha}_{\text{ff5+fmom}}$	Alpha $t(\hat{\alpha})$	Factor momentum $\hat{b}_{\text{fmom}}$	Factor momentum $t(\hat{b})$	Adj. R^2
None	0.38	3.84			2.9%
1–5	0.08	0.86	0.40	13.86	27.4%
6–10	0.33	3.63	0.31	9.89	17.1%
11–15	0.22	2.47	0.35	11.76	21.9%
16–20	0.33	3.51	0.23	7.29	11.1%
21–25	0.31	3.28	0.26	8.10	12.8%
26–30	0.32	3.32	0.23	7.14	10.8%
31–35	0.32	3.41	0.25	7.99	12.6%
36–41	0.33	3.42	0.22	6.80	10.1%

five-factor model.

Although all other PC factor momentum strategies also correlate with industry momentum—all slopes against these strategies are positive and statistically significant—none of these other sets subsumes industry momentum.

The results in Table 9 are again not specific to the momentum found in the twenty Moskowitz and Grinblatt (1999) industries. Panel B in Table A3 shows the results for the alternative specification that trades momentum in the 49 Fama-French industries. This alternative strategy's five-factor model alpha is 29 basis points per month (t-value = 3.24) in the July 1973 through December 2020 sample. Momentum found in the set of the highest-eigenvalue PC factors explains this form of industry momentum as well. Industry momentum's alpha in the first six-factor model is essentially zero (−1 basis points; t-value = −0.09).

Figure 3 illustrates the connection between industry and PC factor momentum using the same

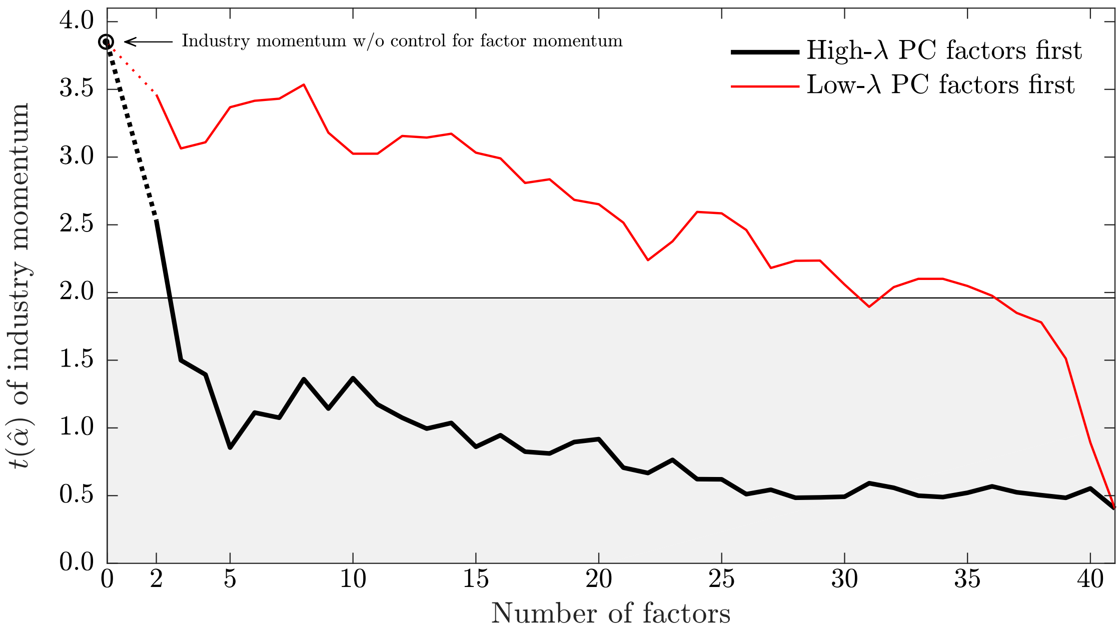

Figure 3: **Industry momentum $t(\hat{\alpha})$s when controlling for momentum in PC factors.** We extract 41 principal component factors from the factors listed in Table 1 using daily returns up to month t, compute monthly returns for months t and $t+1$, and order the resulting PC factors by eigenvalues. We construct strategies that trade factor momentum in an increasing number of these PC factors with the number of factors in the strategy shown on the x-axis. The black line starts from the two highest-eigenvalue factors and works down the list towards the lowest-eigenvalue factor; the red line works through the factors in the reverse order. We compute industry momentum's alpha from all different six-factor models that augment the five-factor model with the resulting strategies. In this figure we plot the t-values associated with these alphas. The sample begins in July 1973 and ends in December 2020.

technique as Figure 2. We construct the same high-eigenvalue-factors-first and low-eigenvalue-factors-first strategies and augment the Fama-French five-factor model with each of them in turn. We compute industry momentum's alphas from the resulting six-factor models and plot the t-values associated with these alphas as a function of the number of PC factors included in the momentum strategies. The point on top of the y-axis, corresponding the case with no factors, represents industry momentum's $t(\hat{\alpha})$ from the five-factor model, absent any factor momentum effects.

Industry momentum's alpha falls quickly to statistical insignificance when we control for momentum found among the first few high-eigenvalue factors. By the time we consider a strategy with the first three PC factors, industry momentum's alpha is no longer statistically significant (t-value = 1.50). The pattern in the t-values, and the contrast between this pattern and that for the strategy that starts from the low-eigenvalue factors (red line), is perhaps even more important. As we add more and more factors, the black line keeps on declining, but it does so at a decreasing pace. The red line, which starts from the "wrong" factors, has the opposite shape. Controlling for momentum in the first few low-eigenvalue factors does very little to industry momentum's alpha; and industry momentum's alpha does not breach the 5% significance level until we consider a strategy that includes more than 30 factors. And, similar to the pattern in Figure 2, the last few factors, which are now the highest-eigenvalue PC factors, carry a disproportionate weight in explaining away industry momentum's profits.

7 Conclusions

Jegadeesh and Titman (1993) show that prior one-year returns predict the cross section of stock returns. Subsequent research has shown that momentum is also present in other asset classes, and has been over long periods of time (Asness, Moskowitz, and Pedersen 2013). Moskowitz and Grinblatt (1999) show that industry portfolios exhibit momentum as well. This momentum, unlike that found in stock returns, is particularly strong at the one-month horizon, and it is only this one-month effect that is distinct from stock momentum (Asness, Porter, and Stevens 2000).

In this paper we first show that factors exhibit short-term momentum that looks similar to industry momentum: both are fully unrelated to individual stock momentum and, if anything, these effects grow stronger when controlling for the five-factor model. This form of factor momentum is also distinct from the long-term "time-series" factor momentum studied in, for example, Ehsani and Linnainmaa (2021).

We show that the similarities in the behaviors of the industry and factor momentum strategies are not coincidental: industries exhibit momentum *because* of the momentum found in the factors. The transmission mechanism is the systematic variation in industries' factor loadings. An industry with a high past return, on average, loads positively on factors with positive past returns and negatively on those with negative returns. By buying industries with high returns and selling those with low returns, industry momentum strategy therefore implicitly bets on the continuation in factor returns.

We have two key results. The first is that factor momentum subsumes industry momentum, and it does so because of the transmission mechanism we posit. We demonstrate this connection in three different ways:

1. Momentum found in a large set of *industry-neutral* factors subsumes industry momentum. This result in itself suggests that the momentum in factors drives industry momentum and not vice versa.

2. Systematic industries—these are mimicking portfolios for the industries we build from small sets of factors, thereby excluding industry-specific returns—exhibit similar amounts of momentum as actual industries. Systematic industry momentum also subsumes industry momentum as the number of factors increases. This result suggests that an investor can capture industry momentum profits without any industry-specific information.

3. Momentum found in just the first three highest-eigenvalue PC factors subsumes industry momentum. Residual industry momentum lacks both statistical and economic significance. Momentums residing among almost any lower-eigenvalue PC factors do not. Because we extract these PC factors from industry-neutral factor returns, the principal components cannot possibly recover any industry-specific information from the factor data.

Our second key result relates to the PC factor results and, specifically, about what they imply about asset pricing. If individual stocks or industries were to display momentum because of their own idiosyncracies, such patterns would be inconsistent with the existence of rational arbitrageurs. Kozak, Nagel, and Santosh (2018) suggest that the lack of near-arbitrage opportunities alone guarantees that only "systematic factors" can have pricing effects. They note that the fact that return patterns align with covariances cannot tell us whether pricing is rational or not; expected returns must align with risks because arbitrageurs would trade away any mispricings that do not expose them to factor risks.

The fact that factors exhibit momentum, and that this factor momentum subsumes industry momentum would be void of economic content if the factors necessary for doing so were as arbitrary and economically unimportant as individual stocks or industries. The PC factor results, however, show that momentum concentrates, in its entirety, precisely where the lack of near-arbitrage opportunity argument suggests it should: among the highest-eigenvalue PC factors. Controlling for the momentum found among these, by definition the most important, the other PC factors display no momentum of their own. Although this result by itself does not explain *why* factors exhibit momentum, it shows that momentum exists only where it can exist: in places where arbitrageurs find it risky to trade it. One explanation for factor momentum, which is consistent with the empirical facts, is the sentiment-based mispricing model of Kozak, Nagel, and Santosh (2018). In the dynamic version of this model factors exhibit momentum when sentiment is sufficiently persistent, and this momentum concentrates into the high-eigenvalue factors (Ehsani and Linnainmaa 2021).

REFERENCES

Asness, C., T. J. Moskowitz, and L. H. Pedersen (2013). Value and momentum everywhere. *Journal of Finance 68*(3), 929–985.

Asness, C. S., A. Frazzini, and L. H. Pedersen (2014). Low-risk investing without industry bets. *Financial Analysts Journal 70*(4), 24–41.

Asness, C. S., R. B. Porter, and R. L. Stevens (2000). Predicting stock returns using industry-relative firm characteristics. AQR Capital Management working paper.

Avramov, D., S. Cheng, A. Schreiber, and K. Shemer (2017). Scaling up market anomalies. *Journal of Investing 26*(3), 89–105.

Barillas, F. and J. Shanken (2016). Which alpha? *Review of Financial Studies 30*(4), 1316–1338.

Berk, J. B., R. C. Green, and V. Naik (1999). Optimal investment, growth options, and security returns. *Journal of Finance 54*(5), 1553–1607.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance 52*(1), 57–82.

Daniel, K., D. A. Hirshleifer, and A. Subrahmanyam (1998). Investor psychology and security market under- and overreaction. *Journal of Finance 53*(6), 1839–1885.

Ehsani, S. and J. T. Linnainmaa (2021). Factor momentum and the momentum factor. *Journal of Finance,* forthcoming.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Fama, E. F. and K. R. French (1997). Industry costs of equity. *Journal of Financial Economics 43*(2), 153–193.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*(1), 1–22.

Fama, E. F. and J. D. MacBeth (1973). Risk, return and equilibrium: Empirical tests. *Journal of Political Economy 71*(3), 607–636.

Foerster, S., J. Linnainmaa, B. Melzer, and A. Previtero (2017). Retail financial advice: Does one size fit all? *Journal of Finance 72*(4), 1441–1482.

Grundy, B. D. and J. S. Martin (2001). Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies 14*(1), 29–78.

Haddad, V., S. Kozak, and S. Santosh (2020). Factor timing. *Review of Financial Studies 33*(5), 1980–2018.

Hoberg, G. and G. M. Phillips (2018). Text-based industry momentum. *Journal of Financial and Quantitative Analysis 53*(6), 2355–2388.

Hong, H. and J. C. Stein (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of finance 54*(6), 2143–2184.

Hou, K. and D. T. Robinson (2006). Industry concentration and average stock returns. *Journal of Finance 61*(4), 1927–1956.

Huberman, G. and S. Kandel (1987). Mean-variance spanning. *Journal of Finance 42*(4), 873–888.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance 45*(3), 881–898.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance 48*(1), 65–91.

Kozak, S., S. Nagel, and S. Santosh (2018). Interpreting factor models. *Journal of Finance 73*(3), 1183–1223.

Kozak, S., S. Nagel, and S. Santosh (2020). Shrinking the cross-section. *Journal of Financial Economics 135*(2), 271–292.

Lewellen, J. (2002). Momentum and autocorrelation in stock returns. *Review of Financial Studies 15*(2), 533–563.

Linnainmaa, J. T. and M. R. Roberts (2018). The history of the cross section of stock returns. *Review of Financial Studies 31*(7), 2606–2649.

McLean, R. D. and J. Pontiff (2016). Does academic research destroy stock return predictability? *Journal of Finance 71*(1), 5–32.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica 41*(5), 867–887.

Moskowitz, T. J. and M. Grinblatt (1999). Do industries explain momentum? *Journal of Finance 54*(4), 1249–1290.

Nagel, S. (2013). Empirical cross-sectional asset pricing. *Annual Review of Financial Economics 5*(1), 167–199.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics 108*(1), 1–28.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory 13*(3), 341–360.

Shumway, T. (1997). The delisting bias in CRSP data. *Journal of Finance 52*(1), 327–340.

Shumway, T. and V. A. Warther (1999). The delisting bias in CRSP's Nasdaq data and its implications for the size effect. *Journal of Finance 54*(6), 2361–2379.

Appendix

A Simulations: Assumptions and parameters

We set up simulations similar to those in Ehsani and Linnainmaa (2021). In these simulations only factor returns display momentum, but this momentum carries over to individual stock and industry returns through variation in stocks' betas. We extend the simulations in Ehsani and Linnainmaa (2021) by introducing industry effects. Every stock belongs to an industry, stock betas divide into stock- and industry-specific components, and industries are subject to their own return shocks. A stock's return in these simulations is determined by its factor loadings, the returns on these factors, and the stock- and industry-specific return shocks.

A.1 Assumptions

We assume the following. We simulate T months of returns for N stocks. Stock i's excess return in month t is

$$R_{i,t} = \sum_{f=1}^{F} \beta_i^f r_t^f + \varepsilon_{i,t} + \delta_{j(i),t}, \tag{A-1}$$

where F is the number of factors, β_i^f is stock i's loading against factor f, r_t^f is factor f's return, $\varepsilon_{i,t}$ is a firm-specific return shock, $\delta_{j,t}$ is the return shock to industry j, and $j(i)$ is the index of the industry into which stock i belongs. We draw firm- and industry-specific return shocks from normal distributions $N(0, \sigma_\varepsilon^2)$ and $N(0, \sigma_\delta^2)$. Firm- and industry-specific shocks are all uncorrelated with each other.

A stock's beta against a factor is the sum of industry- and stock-specific components:

$$\beta_i^f = B_{j(i)}^f + \xi_i^f, \tag{A-2}$$

where $B^f_{j(i)}$ is industry j's loading against factor f, shared by all firms that belong to the industry, and ξ^f_i is the stock-specific beta. We draw the two components from normal distributions $N(0, \sigma^2_B)$ and $N(0, \sigma^2_\xi)$. All draws of the industry- and stock-level betas are uncorrelated.

Factor f's return in month t is

$$r^f_t = \lambda^f_t + \eta_{f,t}, \tag{A-3}$$

in which λ^f_t is the factor's risk premium in month t and $\eta_{f,t}$ is a factor-specific return shock drawn from a normal distribution $N(0, \sigma^2_\eta)$. A factor's risk premium λ^f_t follows an AR(1) process with a zero mean,

$$\lambda^f_t = \kappa\lambda^f_{t-1} + \omega_{f,t}, \tag{A-4}$$

in which κ controls the persistence of the risk premium process and $\omega_{f,t}$ is the shock to the process drawn from a normal distribution $N(0, \sigma^2_\omega)$. We draw the initial value of λ^f_0 from the stationary distribution of the risk-premium process, $N\big(0, \sigma^2_\omega/(1-\kappa^2)\big)$.

A.2 Parameter values

We use the simulations to illustrate two effects: (1) factor momentum transmits into the cross section of industries *if* betas vary systematically across industries and (2) factor momentum subsumes industry momentum. That is, industry momentum emerges even when everything in the simulations is serially uncorrelated *except* for the factor risk premiums. Because we are interested in the industry and factor momentum strategies' Sharpe and information ratios—which are proportional to the t-values associated with their average returns and alphas—we can normalize most of the variances to one and choose values for how the parameters are proportional to each other. We set the parameters values as follows:

- We simulate data for $N = 2{,}000$ stocks for $T = 678$ months. These dimensions approximate the size of the actual data.

- We set the number of both industries and factors to $F = J = 20$, and we assume that all stock-, industry-, and factor-specific parameters are the same for all stocks, industries, and factors.
- We draw stocks' industry assignments from a uniform distribution.
- We normalize the cross-sectional variance of stock betas to one and assume that proportion θ of the variation is due to the industry specific component, that is, $\frac{\sigma_B^2}{\sigma_B^2+\sigma_\xi^2} = \theta$, where we vary θ from 0 to 50% in Table 5.
- We assume that 10% of the time-series variation in factor returns is due to variation in the risk premium and the remaining 90% to factor-specific return shocks, $\eta_{f,t}$.
- We set the persistence of the risk premium processes to $\kappa = 0.8$.
- We normalize variance of stock returns to $\sigma_\varepsilon^2 = 1$ and assume that 40% of the variation in stock returns is due to factors and the remaining variation is evenly split between firm- and industry-specific return shocks; that is, $\sigma_\varepsilon^2 = \sigma_\delta^2 = 0.3$.
- The choices above determine the parameters for the risk premium and factor return processes; the shocks to the factor risk premiums have a variance of $\sigma_\omega^2 = 0.00072$ and the factor return shocks have a variance of $\sigma_\eta^2 = 0.018$.

Table A1: Industry momentum: Alternative strategies and sample periods

This table reports average monthly returns and five- and six-factor model alphas for alternative industry momentum strategies and sample periods. The six-factor model augments the Fama and French (2015) model with the stock momentum factor (UMD) of Carhart (1997). In Panels A and B the industry momentum strategies take long and short positions in the top-three and bottom-three industries using the twenty Moskowitz and Grinblatt (1999) industries. The strategies are constructed using one-, six-, or 12-month formation periods and they are rebalanced either monthly or biannually. When the holding period is six months, we use the Jegadeesh and Titman (1993) methodology to resolve overlapping observations. The sample begins in August 1963 for the strategy with the one-month formation period and ends in December 2020 in Panel A. The samples for the strategies with six- and 12-month formation periods begin in January 1964 and July 1964. In Panel B the start dates are the same but the data end in July 1995 to match the Moskowitz and Grinblatt (1999) sample. Panel C reports average returns and alphas for industry momentum strategies that trade the 49 industries of Fama and French (1997) instead of the Moskowitz-Grinblatt industries. Similar to Table 2, these strategies take long and short positions in all above- and below-median instead of just the bottom- and top-three industries. The formation period marked as $12^\dagger$ runs from month $t-12$ to $t-2$ and not to $t-1$ as all other formation periods. The sample period in Panel C is the same full sample period as in Panel A.

Panel A: Top-3 and bottom-3 industries, full sample period, July 1963–December 2020

Formation period, months	Holding period, months	$\bar{r}$	Asset pricing model: FF5 $\hat{\alpha}_{\text{ff5}}$	FF5 + UMD $\hat{\alpha}_{\text{ff5+umd}}$	$\hat{b}_{\text{umd}}$
1	1	0.74	0.82	0.68	0.20
		(4.41)	(4.73)	(3.92)	(4.98)
6	1	0.41	0.42	−0.10	0.75
		(2.24)	(2.27)	(−0.68)	(21.93)
12	1	0.65	0.76	0.10	0.96
		(3.22)	(3.72)	(0.76)	(30.13)
6	6	0.32	0.39	−0.11	0.72
		(2.08)	(2.43)	(−0.99)	(27.76)

Panel B: Top-3 and bottom-3 industries, Moskowitz and Grinblatt (1999) sample period, July 1963–July 1995

Formation period, months	Holding period, months	$\bar{r}$	Asset pricing model: FF5 $\hat{\alpha}_{\text{ff5}}$	FF5 + UMD $\hat{\alpha}_{\text{ff5+umd}}$	$\hat{b}_{\text{umd}}$
1	1	1.21	1.25	0.92	0.40
		(6.52)	(6.17)	(4.73)	(7.61)
6	1	0.47	0.42	−0.20	0.75
		(2.31)	(1.91)	(−1.16)	(15.91)
12	1	0.82	0.77	−0.07	1.00
		(3.75)	(3.19)	(−0.43)	(24.87)
6	6	0.38	0.31	−0.31	0.75
		(2.24)	(1.67)	(−2.47)	(22.33)

Panel C: Fama and French (1997) industry classification, July 1963–December 2020

Formation period, months	Holding period, months	$\bar{r}$	Asset pricing model: FF5 $\hat{\alpha}_{\text{ff5}}$	FF5 + UMD $\hat{\alpha}_{\text{ff5+umd}}$	$\hat{b}_{\text{umd}}$
1	1	0.35	0.38	0.32	0.09
		(4.44)	(4.79)	(3.98)	(4.90)
6	1	0.34	0.34	0.05	0.41
		(3.61)	(3.61)	(0.79)	(25.23)
12	1	0.47	0.49	0.14	0.52
		(4.71)	(4.87)	(2.38)	(38.93)
12[†]	1	0.38	0.39	0.04	0.52
		(3.77)	(3.87)	(0.64)	(38.00)
6	6	0.26	0.25	−0.03	0.41
		(3.23)	(3.07)	(−0.72)	(37.03)

[†] Note: This formation period skips month $t-1$ and runs from $t-12$ to $t-2$.

Table A2: Factor momentum: Alternative formation and holding periods

This table reports average monthly returns and five- and six-factor model alphas for factor momentum strategies that use one-, six-, or 12-month formation periods and that are rebalanced either monthly or biannually. The formation period marked as 12† runs from month $t-12$ to $t-2$ and not to $t-1$ as all other formation periods. Each strategy trades the 43 factors listed in Table 1; they are long the factors with above-median returns in the formation period and short those with below-median returns. When the holding period is six months, we use the Jegadeesh and Titman (1993) methodology to resolve overlapping observations. The sample begins in August 1963 for the strategy with the one-month formation period, in January 1964 for the strategy with the six-month formation period, and in July 1964 for the strategy with the one-year formation period. All samples end in December 2020.

Formation period, months	Holding period, months	$\bar{r}$	Asset pricing model: FF5 $\hat{\alpha}_{\text{ff5}}$	FF5 + UMD $\hat{\alpha}_{\text{ff5+umd}}$	FF5 + UMD $\hat{b}_{\text{umd}}$
1	1	0.64	0.70	0.66	0.06
		(6.11)	(6.60)	(6.12)	(2.57)
6	1	0.42	0.45	0.20	0.36
		(3.97)	(4.19)	(2.20)	(16.77)
12	1	0.48	0.54	0.22	0.45
		(4.45)	(5.06)	(2.85)	(25.18)
12†	1	0.37	0.43	0.10	0.47
		(3.48)	(4.06)	(1.36)	(27.24)
6	6	0.25	0.26	0.01	0.36
		(2.87)	(2.96)	(0.11)	(23.91)

† Note: This formation period skips month $t-1$ and runs from $t-12$ to $t-2$.

Table A3: Momentum in 49 Fama-French industries—Robustness checks

This table reports the key results for an alternative industry momentum strategy. The strategy in the main tests trades the twenty industries of Moskowitz and Grinblatt (1999). The strategy in this table trades the 49 Fama-French industries. Panel A corresponds to the regressions reported at the bottom of Table 4. These regressions explain industry momentum with the five-factor model and this model augmented with momentum in either the standard or industry-neutral factors. Panel B corresponds to the regressions reported in Table 9. These regressions explain industry momentum with momentum found in different subsets of PC factors ordered by eigenvalues. The sample in Panel A begins in August 1963 and that in Panel B begins in July 1973. Both samples end in December 2020.

Panel A: Industry momentum, factor momentum, and momentum in industry-neutral factors

Dependent variable	$\hat{\alpha}$	Coefficients $\hat{b}_{\text{fmom}}$	Coefficients $\hat{b}_{\text{in-fmom}}$	FF5	R^2
Momentum in FF49 industries	0.39			Y	4.8%
	(4.82)				
	0.04	0.50		Y	45.7%
	(0.63)	(22.48)			
	0.04		0.56	Y	41.5%
	(0.67)		(20.52)		

Panel B: Industry momentum versus momentum in high- and low-eigenvalue PC factors

Control for momentum in PC factors	Alpha $\hat{\alpha}_{\text{ff5+fmom}}$	Alpha $t(\hat{\alpha})$	Factor momentum $\hat{b}_{\text{fmom}}$	Factor momentum $t(\hat{b})$	Adj. R^2
None	0.29	3.24			4.9%
1–5	−0.01	−0.09	0.39	15.33	32.8%
6–10	0.24	2.98	0.28	10.18	19.5%
11–15	0.16	1.93	0.28	10.43	20.2%
16–20	0.25	2.88	0.21	7.39	13.2%
21–25	0.22	2.61	0.25	8.78	16.2%
26–30	0.22	2.64	0.23	8.11	14.7%
31–35	0.23	2.77	0.23	8.12	14.7%
36–41	0.24	2.81	0.18	6.50	11.4%

Table A4: Momentum in high-eigenvalue PC factors when controlling for momentum in lower-eigenvalue PC factors

This table uses data on the same subsets of PC factors as Table 8. We report monthly alphas and slope coefficients from time-series regressions in which the dependent variable is the high-eigenvalue PC factor momentum strategy. This strategy trades momentum in the first five PC factors. The model is the five-factor model augmented with one of the lower-eigenvalue PC factor momentum strategies or, in the case of the last column, all of these strategies. The sample begins in July 1973 and ends in December 2020.

	Regression							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{\alpha}_{\text{ff5+fmom}}$	0.70	0.61	0.72	0.68	0.69	0.70	0.72	0.53
	(6.08)	(5.13)	(5.88)	(5.67)	(5.70)	(5.79)	(5.83)	(4.85)
$\hat{b}_{\text{fmom6–10}}$	0.38							0.22
	(9.83)							(5.17)
$\hat{b}_{\text{fmom11–15}}$		0.33						0.18
		(8.49)						(4.53)
$\hat{b}_{\text{fmom16–20}}$			0.19					0.07
			(4.70)					(1.87)
$\hat{b}_{\text{fmom21–25}}$				0.30				0.12
				(7.43)				(2.87)
$\hat{b}_{\text{fmom26–30}}$					0.25			0.11
					(6.07)			(2.93)
$\hat{b}_{\text{fmom31–35}}$						0.27		0.10
						(6.66)		(2.55)
$\hat{b}_{\text{fmom36–41}}$							0.17	0.03
							(4.13)	(0.81)
FF5	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	17.9%	14.8%	7.5%	12.4%	9.8%	10.9%	6.7%	27.6%