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Momentum: what do we know 30 years after Jegadeesh and Titman's seminal paper?

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Abstract
For over 30 years, extensive research has found corroborating evidence that past winners continue to yield higher returns than past losers. This momentum effect is robust across various asset classes and across the globe and presents perhaps the most pervasive contradiction of the efficient market hypothesis. This article reviews three strands of literature on momentum. First, I outline the construction of momentum strategies, emphasizing improvements and alternatives such as time-series momentum, residual momentum, and risk-managed momentum. Second, I summarize the most prominent behavioral-based and risk-based explanations for the origin of momentum. Finally, I present in detail the findings on commonality in stock momentum, namely on industry and factor momentum.

Keywords Momentum · Asset pricing · Factor momentum · Industry momentum · Commonalities · Residual momentum · Behavioral finance

JEL Classification G11 · G12 · G40

1 Introduction: momentum everywhere

In their seminal paper, Jegadeesh and Titman (1993) highlight that equity trading strategies that buy past winners and sell past losers yield positive returns. The existence of momentum, a continuation of (relative) performance of the past into the future, has had a profound impact both on the investment and on the academic landscape. For investors, momentum presents a robust, variable, and profitable investment strategy that has found widespread implementation by active mutual funds, hedge funds, and passive ETFs. For financial research, momentum presents a striking contradiction to

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the weak form efficient market hypothesis of Fama (1970). As depicted in Fig. 1, the contradiction is exacerbated by a myriad of studies that find momentum in a vast number of asset classes other than stocks and in various geographical regions. Rouwenhorst (1998) applies the approach of Jegadeesh and Titman (1993) to 12 European countries and finds stock momentum in a similar magnitude as in the USA. Carhart (1997) finds persistence in relative mutual fund performance. A momentum strategy going long in funds with the best performance and short in funds with the worst performance over the previous year yields a monthly return of 0.67%. Positive momentum effects have also been found in commodity futures (Miffre and Rallis 2007), in corporate bonds (Jostova et al. 2013), and most recently in cryptocurrencies (Liu et al. 2022). Asness et al. (2013) further highlight that momentum is everywhere by constructing profitable momentum strategies for US equities, UK equities, European equities, government bonds, currencies, and commodity futures.

This literature review aims to provide a comprehensive overview of momentum by summarizing the highest quality research on the topic. Forty-seven out of the 60 cited papers have been published in the *Journal of Finance*, the *Review of Financial Studies*, or the *Journal of Financial Economics*.

First, I outline the general cross-sectional momentum strategy of Jegadeesh and Titman (1993) and highlight the potential sources of returns of such strategies using the return composition of Lewellen (2002). These include positive autocorrelation in stock returns, negative cross-correlation, and dispersion in stocks' expected returns. Further, I list several alternative construction methods that improve momentum profits. Moskowitz et al. (2012) propose a time-series momentum strategy that is a pure bet on assets' own return continuation rather than relative performance. In what they call residual momentum, Blitz et al. (2011) find that adjusting raw returns by their risk factor exposure enhances momentum profits. Novy-Marx (2012) boosts momentum profits by setting the look-back period to an intermediate horizon, and Daniel and Moskowitz (2016) do so by scaling the position in momentum by its ex ante inverse volatility.

Second, I summarize two strands of literature that examine the origin of momentum profits: behavioral-based explanations and risk-based explanations. Behavior-based explanations assume that firm-specific momentum stems from biases or irrationality in investors. Early studies propose models in which serial correlation in stock returns is driven either by a delayed overreaction to news (Daniel et al. 1998), initial underreaction (Barberis et al. 1998), or both (Hong and Stein 1999). George and Hwang (2004) and Grinblatt and Han (2005) argue that anchoring biases and a disposition effect are responsible for momentum effects. Risk-based explanations seek to unify momentum, the efficient market hypothesis, and risk-based asset pricing models. There are two ways for a momentum strategy to be risky. First, past outperformance of winners was due to higher risk exposure, which is persistent in the future. Second, winners have gotten riskier due to their past outperformance. Johnson (2002) and Sagi and Seasholes (2007) argue for the second channel by highlighting an increase in growth rate risk after a positive performance.

Lastly, I present the more recent literature studying the co-movement of momentum effects in individual assets. Models explaining momentum with uncorrelated firm-specific effects miss that due to diversification, such momentum would present a near-

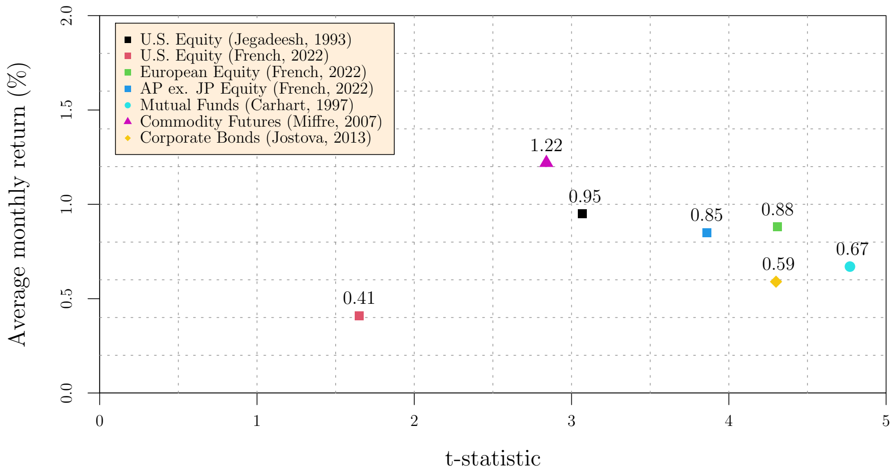

Fig. 1 Average monthly momentum profits across regions and asset classes. This figure depicts average monthly returns and t-statistics of momentum strategies reported by previous studies or calculated from data provided by Kenneth French. The studies' sample periods are as follows: Jegadeesh and Titman (1993): January 1965–December 1989, Carhart (1997): January 1963–December 1993, Miffre and Rallis (2007): March 1979–July 1985, Jostova et al. (2013): January 1973–June 2011, and Liu et al. (2022): January 2014–July 2020. The data from Kenneth French's website are obtained for the period from November 1990 to December 2021

arbitrage opportunity and would likely not have persisted over decades. Moskowitz and Grinblatt (1999) construct a profitable industry momentum strategy that is not only profitable both in the short and intermediate term but largely explains stock momentum. They also document that the serial correlation in monthly industry returns is strongest in the first order. More recently, Grobys and Kolari (2020) argue for multiple independent forms of industry momentum after finding that strategies with a 1-month and 6-month formation period are only weakly correlated. Finally, Ehsani and Linnainmaa (2022a), Gupta and Kelly (2019), and Arnott et al. (2021) provide consistent evidence that factor portfolios exhibit momentum. Ehsani and Linnainmaa (2022a) find that stock momentum is fully spanned by factor momentum, especially by momentum found in the factors' highest eigenvalue principal components. Further, by constructing momentum-neutral factors, the authors show that factor momentum drives stock momentum and not vice versa. Arnott et al. (2021) highlights that industry momentum is driven by factor momentum.

2 Outlining momentum

2.1 General approach

Return continuation documented by Jegadeesh and Titman (1993) contrasts with earlier research of De Bondt and Thaler (1985) and Jegadeesh (1990). De Bondt and Thaler (1985) find that stocks that have performed poorly over the last 3–5 years achieve better returns than stocks that performed well over the next 3–5 years. They argue that this results from an overreaction of investors to new information, and the subsequent returns are due to a reversal to the true firm value. Jegadeesh (1990) highlights short-term reversals in stock returns and proposes that this is due to corrections after periods of low liquidity and price pressures in which stock price movements tend to be exacerbated.

Jegadeesh and Titman (1993) construct a cross-sectional momentum strategy whose underlying approach has been used and adapted by a myriad of follow-up papers on momentum. First, for each month, they calculate cumulative stock returns over a so-called look-back or formation period, which is usually between 3 and 12 months. Second, they use these returns to sort stocks into decile portfolios and calculate equal-weighted portfolio returns over the holding period. Finally, the cross-sectional momentum strategy return is the return of the highest past return portfolio minus lowest past return portfolio. It is common to skip 1 month between the formation and holding period to isolate momentum from the short-term reversal effect (e.g., Jegadeesh and Titman (1993), Carhart (1997) or Asness et al. (2013)). Jegadeesh and Titman (1993) find that momentum yields significant and positive returns across all combinations of 3-, 6-, 9-, and 12-month formation and holding periods.

To illustrate the potential sources of momentum, Lewellen (2002) decomposes the expected return of a cross-sectional momentum strategy with a 1-month formation and a 1-month holding period. The weight of each of N stocks is given by:

$$w_{i,t} = \frac{1}{N}(r_{i,t-1} - r_{m.t-1}) \tag{1}$$

where $r_{m,t-1}$ is the return of a equal-weighted market portfolio in month $t-1$. The zero-cost strategy is thus long in past winners and short past losers. The expected profit can be written as:

$$E[\pi_{i,t}^{mom}] = \frac{N-1}{N^2}tr(\Omega) - \frac{1}{N^2}[\iota'\Omega\iota - tr(\Omega)] + \sigma_{\mu}^2 \tag{2}$$

where Ω is the 1-month autocovariance matrix of returns and σ_{μ}^2 is the cross-sectional variance of expected returns. The decomposition reveals three different sources of momentum. First, momentum arises when stocks are positively autocorrelated: a high return today predicts a high return tomorrow. Second, negative cross-serial correlations also contribute to momentum profits. In that case, a stock's high past return predicts other stocks' low future returns. Third, momentum can be profitable because stocks have different expected returns that are persistent over time. A stock with high (low) return expectations will likely have higher (lower) realized returns in the future. In such a case, there is no need for time-series predictability to profit from momentum.

2.2 Alternatives and improvements

Moskowitz et al. (2012) defer from the standard cross-sectional momentum approach and instead test for time-series momentum. After scaling returns of various developed market equity indices, commodities, currencies, and government bond futures by an ex ante volatility estimate, they find that from 1965 to 2009, past 12-month returns positively predict next month's returns. Within a pooled panel regression, the β on past returns is positive and statistically significant with a t-statistic of over 5. A trading strategy that goes long (short) when past returns are positive (negative) produces statistically positive mean returns at the 5% level for 52 of the 58 assets. The equal-weighted time-series momentum returns over all assets are robust to various risk adjustments and to the returns of a cross-sectional stock momentum strategy. The profits are not only higher than cross-sectional momentum profits but also able to fully explain them. Moskowitz et al. (2012) show that this is due to positive cross-asset serial correlation, therefore reducing cross-sectional momentum profits, as shown in Eq. 2.

However, more recent studies question the results of Moskowitz et al. (2012). Goyal and Jegadeesh (2018) argue that the better performance of time-series momentum is due to higher leverage. Cross-sectional momentum is a zero-cost strategy, whereas time-series momentum is usually net long as past returns are more often positive than negative. After scaling the cross-sectional strategy by adding an investment into a market portfolio equal to the net position of the time-series momentum strategy, both strategies perform similarly for individual stocks. The leveraged cross-sectional strategy outperforms for international asset class portfolios. The underperformance of the time-series strategy is largely due to the volatility scaling, leading to a huge position in bonds that usually exhibit low volatility and low excess returns. Huang et al. (2020) criticize the pooled regression approach in Moskowitz et al. (2012) to determine autocovariance because it ignores differences in mean returns across asset classes. After regressing each asset separately on its past 12-month returns, only 8 out of 55 slope coefficients are significant on the 10% level. Further, they show that a strategy that goes long if the unconditional mean of past returns is positive produces similar profits as the strategy based on past 12-month returns. This suggests that profits are not due to the predictability of returns but due to differences in expected returns.

Blitz et al. (2011) find that a raw return momentum strategy based on past 12-month returns, excluding the most recent month, has time-varying factor exposure. They create a residual momentum strategy by adjusting raw returns with the three risk factors of Fama and French (1993) and then sorting on residuals. Due to the reduced factor exposure, the volatility of the residual momentum strategy is almost reduced by half compared to the raw momentum strategy, boosting the annual Sharpe ratio from 0.45 to 0.90.

Instead of the usual 12-month minus the most recent month formation period, Novy-Marx (2012) sorts returns from t-12 to t-7 to create an intermediate momentum strategy. From 1927 to 2010, the intermediate momentum strategy produces monthly profits of 1.20%, much higher than a t-6 to t-2 momentum strategy that produces 0.67%. The intermediate momentum returns are robust even after controlling for the risk factors of Fama and French (1993) (size and value) Carhart (1997) (momentum).

Daniel and Moskowitz (2016) tackle the issue that momentum crashes in times of high market volatility when markets rebound after bear markets. They formulate a dynamic momentum strategy whose position is scaled proportionally to its conditional Sharpe ratio. Conditional expected returns take into account the negative effects of high

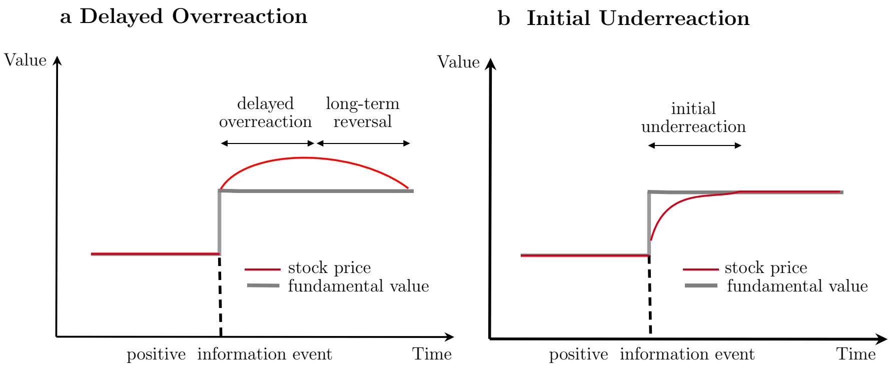

Fig. 2 This figure sketches the stock price movement (red) after a positive information event in relation to its fundamental value (grey) for **a** the delayed overreaction models and **b** the initial underreaction models

market volatility and past market declines. Conditional variance is estimated using a GJR GARCH model. From 1934 to 2013, the dynamic momentum strategy produces a Sharpe ratio of 1.20, therefore almost doubling the Sharpe ratio of 0.68 of the standard zero-cost momentum strategy. The results of Daniel and Moskowitz (2016) are consistent with those of Barroso and Santa-Clara (2015) and Moreira and Muir (2017), who show that scaling by realized volatility significantly improves momentum strategies.

3 Explanations for momentum

As shown, the literature generally agrees that momentum exists, is persistent, and spans a variety of asset classes and countries. However, the origin of this perhaps strongest contradiction to the weak form of Fama (1970)'s efficient market hypothesis is still hotly debated. The two main strands of literature trying to explain momentum differ in the rationality assumption in investors. Risk-based explanations treat investors as rational and momentum profits compensate for risks that arise from trading momentum. Behavioral explanations suggest that investors exhibit certain biases that influence their trading behavior and drive stock prices away from their fundamental value.

3.1 Behavioral explanations

Behavioral models for momentum usually assume serial correlation of individual stock returns. This serial correlation is driven by investors' biases and the inability to instantaneously and correctly price new information. Generally, studies have emphasized underreaction, overreaction, and disposition effects as drivers of momentum.

Daniel et al. (1998) argue that momentum stems from investors' biased self-attribution and overconfidence. In their model, investors first trade stocks based on signals gathered from their research. If a public signal later confirms the private signal, overconfidence increases. If a positive public information event occurs after a buy based on private information, investors attribute the success to their skill and further drive the price up. If a public signal disagrees with the buy, they discard the signal as external noise and do not readjust their price expectation. Therefore, as depicted in Fig. 1a, on average public signals will drive prices away from fundamental values in the direction of their private signal. Public information will gradually reverse stock prices to their fundamental value in the long term. The delayed overreaction model of Daniel et al. (1998) is consistent with medium-term positive autocovariance in stock returns found by Jegadeesh and Titman (1993) and long-term reversals found by De Bondt and Thaler (1985).

As depicted in Fig. 1b, initial underreaction to information can also cause momentum. New information is not fully incorporated into stock prices, driving them away from their fundamental value. Barberis et al. (1998) argue that conservatism bias—an under-weighing of new information—drives the initial underreaction. While investors update their posteriors in the right direction when faced with new evidence, they do not do so in the same magnitude as a rational Bayesian benchmark. The subsequent price adjustments to the stock's intrinsic value produce positive autocovariance and thus momentum in stock returns.

Unifying under- and overreaction theories, Hong and Stein (1999) introduce a model with two types of investors—"news-watchers" and "momentum-traders". News-watchers estimate stock prices based on news they privately observe but not based on past or current prices. Momentum-traders, on the other hand, condition their stock forecasts only on past and current prices. Private signals diffuse only gradually across the news-watchers, leading to initial underreaction. Momentum traders chase past performance, thereby accelerating the initial price reaction to the point of overreaction. Interestingly, Hong and Stein (1999) do not rely on any irrationality assumptions—both actors act rationally within the boundaries of their respective subset of available information.

Much literature has since come forward to corroborate the models of Daniel et al. (1998) and Hong and Stein (1999) with empirical evidence. In support of Daniel et al. (1998), Chui et al. (2010) capture cross-country differences in self-attribution bias and overconfidence with the individualism index of Hofstede (2001), which they argue is positively related to these attributes. The authors find that profitability of momentum in a country is positively related to individualism: average monthly momentum returns are 0.60% higher in countries that rank in the top 30% based on individualism than in countries that rank in the bottom 30%. More recently, Hillert et al. (2014) corroborate the overreaction model of Daniel et al. (1998) by constructing a firm-specific measure for excess media coverage that controls for firm size, analyst coverage, and stock index memberships. Arguing that newspapers act as a source for investors' private signals, the authors show that monthly momentum profits are three times higher (1.02% vs. 0.33%) when using the subset of stocks in the highest quintile of media coverage than when using stocks in the lowest quintile. They further provide evidence for Daniel et al. (1998) and Chui et al. (2010) by demonstrating that this spread increases for stocks with higher uncertainty, which overconfident investors favor, and in highly individualistic states. Finally, in line with the overreaction models, the media momentum profits reverse in the long run.

Hong et al. (2000) show that momentum is mostly driven by small firms, and after controlling for firm size, that momentum works better when analyst coverage is low. Arguing that information travels more slowly for smaller and less covered firms, they thus provide supporting evidence for the hypothesis of Hong and Stein (1999) that the initial underreaction to news is due to the slow, gradual diffusion of information. Similarly, Zhang (2006) shows that momentum effects increase with information uncertainty. They find that the degree to which good (bad) news predicts high (low) future returns is higher for small and young firms, for firms with high cash flow volatility, for firms with low analyst coverage and high analyst forecast dispersion, and for stocks with high return volatility. More recently, Antoniou et al. (2013) find that a 6-month momentum strategy produces average monthly returns of 2.00% when investor sentiment is high but only 0.34% when investor sentiment is low. The authors argue that investors' slow diffusion of information in Hong and Stein (1999) is exacerbated by cognitive dissonance that arises from information that contradicts their level of optimism. In good times, bad news for loser stocks will diffuse more slowly than in pessimistic times, resulting in subsequent negative returns for loser stocks. Antoniou et al. (2013) show that this effect is more pronounced when severe short-selling constraints limit arbitrageurs' ability to push down loser stocks to their intrinsic value.

Finally, Cooper et al. (2004) find that the success of momentum depends on the state of the market. From 1929 to 1995, if the market was up over the last 3 years, momentum produced a mean monthly return of 0.93%, otherwise only −0.37%. They link their results to Daniel et al. (1998)'s assumption of investor overconfidence. Since investors are long in equities on aggregate and due to their self-attribution bias, an up-market state will lead to a higher increase in confidence and thus to higher overreactions and momentum. Additionally, in line with overreaction theory, Cooper et al. (2004) find reversal of momentum profits in the long term.

Novy-Marx (2012) finds evidence against the positive short-term autocorrelation predicted by underreaction and overreaction models. He shows that the predictive power of past returns is only inherent in the intermediate horizon. Sorting on past 12- to 7-month returns produces larger profits than standard momentum and generates alpha even after controlling for risk factors of Fama and French (1993) and for the momentum factor of Carhart (1997). Additionally, stocks winning in the short term but losing in the intermediate term significantly underperform stocks losing in the short term but winning in the intermediate term, providing further evidence against the short-term continuation of stock price movements predicted by Daniel et al. (1998) and Hong and Stein (1999).

Alternatively, George and Hwang (2004) explain momentum with an anchoring bias, where investors' decisions are influenced by or driven towards a certain reference point. The anchor in their study is a stock's 52-week high price, which most newspapers reporting on the stock market publish. The authors propose that for stocks near their 52-week high, new positive information is at first only partially incorporated into prices because traders are reluctant to cross the anchoring point. Similarly, bad news does not—to the extent that would be warranted—drive down prices of stocks that are already far away from their 52-week high. To create a momentum strategy, George and Hwang (2004) rank stocks based on their distance to the 52-week high price and go long (short) in the 30% stocks with the lowest (highest) distance. After controlling for size and skipping a month between ranking and holding period, returns of the 52-week strategy are about twice as large as the standard momentum strategy, indicating that not past returns but price levels are important predictors for the cross-section of future returns.

Grinblatt and Han (2005) propose that a disposition effect in investors drives momentum. Per prospect theory, because of a kink at a reference point in his utility function, an investor is risk-averse after gaining on his reference point and risk-seeking after suffering losses. The reference point in the case of the stock market is the average buying price. Thus, the model predicts that after positive news and a stock price increase, there is excess selling pressure on the stock, while after negative news, investors tend to hold on to the stock for too long. Grinblatt and Han (2005) calculate the reference point by calculating a probability-weighted average of past prices, where the probabilities are based on past turnover and measure the likelihood that a stock was purchased in the respective period. They find that returns of a momentum strategy sorting on the distance to the reference point can fully explain standard momentum based on past returns.

3.2 Risk-based explanations

Contrary to behavioral explanations, risk-based explanations test potential sources of momentum without having to leave the sphere of rational investors and Fama (1970)'s efficient market hypothesis. Instead, momentum profits are considered to be compensation for risk. Risk-based models make sense of the decade-long persistence of momentum. While there is room for rational investors to profit from near-arbitrage in the behavioral model and to neutralize any momentum effects, there are no profits without additional risk in the realm of risk-based models. In the Abritrage Pricing Theory of Ross (1976) stocks' expected excess returns are a linear combination of expected returns of priced risk factors μ_t^f multiplied by the stocks' exposures to the respective risk factors β^f:

$$\mu_i = \sum_{i=1}^{F} \beta^f \mu^f \tag{3}$$

A stock momentum strategy can be risky in two ways.

First, higher (lower) returns in the cross-section of past returns are due to relatively higher (lower) risk exposure, and the relative risk exposure is persistent in the future. A dispersion in risk exposures leads to dispersion in expected returns, σ_μ^2, thus producing momentum profits through the third channel of Lewellen (2002)'s momentum decomposition illustrated in Eq. 2. Conrad and Kaul (1998) find high importance of σ_μ^2 for momentum. They document that the cross-sectional dispersion of mean returns contributed to 539% of profits of a momentum strategy with a 12-month look-back period. There are three drawbacks to Conrad and Kaul (1998)'s hypothesis. First, Jegadeesh and Titman (2002) find that the findings of Conrad and Kaul (1998) are mainly due to small sample biases. Some expected returns are calculated with less than 12 months of data, resulting in unreasonable ex ante estimates for stock returns, with both negative values and values above 100%. Second, constant expected returns cannot explain long-term reversals in stock prices. Third, if higher expected returns are due to higher risk exposure, then APT risk factor models should be able to explain momentum profits. Suppose, for example, the winner portfolio outperformed the loser portfolio because of higher past market-risk exposure, and the differences in exposure are persistent. In that case, the momentum strategy should inhibit positive market betas. However, both Jegadeesh and Titman (1993) and Grundy and Martin (2001) find that momentum profits are robust to market-risk adjustments, and Fama and French (1996) find that even their three-factor model is unable to explain momentum profits. More recently, however, Kelly et al. (2021) find conditional factor exposures help to explain momentum profits. Whereas a traditional based on past t-2 to t-12 month raw returns delivers annual profits of 8.3%, a residual momentum strategy where returns are adjusted using conditional factor exposures only delivers 4.4%. Instead of using rolling-window regressions or higher-frequency data to estimate their conditional β_t^f, they estimate them as a function of time-varying and observable firm characteristics.

Second, the riskiness of stocks might increase with positive returns and drop with negative returns. In a single firm model, Johnson (2002) shows that changes in stock prices in response to growth rate changes are highly convex. Therefore, growth rate risk, which is assumed to be positively priced in the stochastic discount factor, rises with the level of growth rates. If starting levels of growth rates are similar between winner stocks and loser stocks, and if then some positive (negative) returns among the winner (loser) portfolio are due to a positive (negative) growth rate shock, then momentum is implicitly a sort on growth rates. Momentum is therefore a compensation for higher growth rate risk.

Berk et al. (1999) find a way to unify short-term negative and longer-term positive autocorrelation in stock returns within a rational model. The authors determine a firm's value as the sum of discounted cash flows of the current asset base and the value of its growth options. When firms realize an attractive investment into a low-risk project, the firm value increases sharply. However, the expected return lowers with the decrease in riskiness, thereby generating short-term return reversals. On the other hand, if project turnover is slow, the firm's asset base, systematic risk, and expected returns are persistent, generating return momentum, particularly over the horizon of its projects' life cycle.

Similarly, Sagi and Seasholes (2007) document that momentum is stronger in high book-to-market firms because these firms have better growth options. After good news on growth opportunities, both firm value and the fraction of firm value in growth options rise. Because these growth options are riskier than the steady-revenue producing existing assets, the firm on aggregate becomes riskier, and investors demand a higher expected return as compensation. Pástor and Stambaugh (2003) construct a market-wide liquidity measure as an equal-weighted average of stocks' liquidity. They measure liquidity as the order volume-induced return reversals from 1 day to the next. After sorting on stocks' sensitivity to market liquidity, they find that liquidity risk is priced in the cross-section of returns. Importantly for risk-based explanations, this liquidity risk factor explains 50% of momentum returns. Avramov et al. (2007) find that low credit rating firms largely drive momentum profits. They create momentum strategies with a 6-month holding period using equal-weighted portfolios sorted on past 7-month returns but skipping the most recent month. After excluding firms with an S&P rating below BB, momentum effects become insignificant. On the other hand, sorts including only stocks with a rating of B or lower produce statistically significant profits of 3.74% per month.

4 Commonalities in momentum

Behavior-based explanations for momentum argue that past winners outperform past losers based on individual stock mispricing due to underreactions or overreactions. However, if such firm-specific effects are uncorrelated, rational investors could profit from near-arbitrage as systematic risks would be diversified away in a broad long-short momentum portfolio (Moskowitz and Grinblatt 1999). Additionally, firm-specific mispricing does not answer the question as to why the past winner and loser stocks co-move in the future and why the momentum factor should be priced and load on the stochastic discount factor. As John Cochrane noted in his presidential address: "why should all the momentum stocks then rise and fall together the next month, just as if they are exposed to a pervasive, systematic risk?" [p.1075]Cochrane (2011). To determine whether momentum is due to mispricing or due to systematic risk, a new strand of literature analyzes momentum in portfolios that capture the factor structures underlying individual stocks. Moskowitz and Grinblatt (1999) finds positive returns for a strategy sorting on past industry returns due to positive serial autocovariances of industry factors. More recently, Gupta and Kelly (2019), Arnott et al. (2021), and Ehsani and Linnainmaa (2022b) find momentum in factor returns used to explain the cross-section of stock returns due to serial autocovariances of risk factors.

4.1 Industry momentum

Moskowitz and Grinblatt (1999) construct 20 value-weighted industry portfolios and employ a strategy that invests equally in the top three industries while shorting the bottom three industries based on their past 6 months' returns. With a holding period of 6 months, this strategy achieves an average return of 0.43% from July 1963 to July 1995. After finding negligible factor serial correlation, firm-specific serial correlation, and cross-sectional dispersion of industry mean returns—three components that could produce industry momentum profits—the authors conclude that industry momentum is due to positive serial correlation in industry returns. Further, Moskowitz and Grinblatt (1999) subtract industry returns from stock returns and then sort on the industry-adjusted 6-month returns. The resulting momentum strategy produces only 0.13% per month compared to 0.43% of a momentum strategy based on raw stock returns. These results provide evidence that stock momentum is at least partly driven by industry momentum. However, the study shows that industry momentum is most profitable with a 1-month look-back and 1-month holding period. This finding is in stark contrast to the short-term reversals in stocks found by Jegadeesh (1990). Grundy and Martin

(2001) also construct a momentum strategy based on value-weighted industry returns but include a 1-month interval between the formation and the investment period. For the same sample period as Moskowitz and Grinblatt (1999), profits decrease to an insignificant 0.16% per month. After highlighting the importance of the 1-month autocovariance in industry returns, the authors conclude that it is too early to proclaim industry momentum as the main source of stock momentum.

Hoberg and Phillips (2018) rely on text-based network industry classifications (TNIC) instead of fixed industry classifications. The authors collect public firms' product descriptions stated in 10-K reports filed with the SEC. After analyzing these texts, each firm is assigned its own set of distinct competitors based on product similarity (Hoberg and Phillips 2016). Hoberg and Phillips (2018) find that while return shocks to peers classified by public industry classifications transmit to a firm within 1–2 months, return shocks to peers classified by TNIC take up to 12 months. Additionally, they find that industry momentum profits are stronger following shocks to companies whose similarity is less visible to investors. This stronger form of industry momentum is robust to the criticism of Grundy and Martin (2001) that short-term autocovariances heavily drive momentum in industry returns. The fact that momentum is stronger and longer-lasting after shocks to less visible industry peers provides evidence for the theory of Barberis et al. (1998) and Hong and Stein (1999) that momentum stems from inattention or slow-moving information.

With a longer sample from July 1926 to February 2018 and with more granular industry classifications—48 industries instead of 20—Grobys and Kolari (2020) investigate industry momentum based on the ideas of Moskowitz and Grinblatt (1999). The authors construct three different industry momentum strategies. The first strategy (1–0–1) is long in the quintile of industries with the highest return over the previous month and short in the quintile of industries with the lowest return. The other two strategies (6–1–1) and (12–1–1) are based on compounded industry returns over the last 6 and 12 months but skipping the most recent month. The three strategies produce mean monthly returns of 0.62% (1–0–1), 0.57% (6–1–1), and 0.80% (12–1–1), respectively. The correlation of only 0.14 between the (1–0–1) and the (12–1–1) strategy is fairly low, suggesting that there are multiple independent forms of industry momentum and that not only the first-order autocorrelation in industry-returns drives industry momentum. Although returns of the (1–0–1) strategy significantly load on a market risk factor (−), on the Fama and French (1993) SMB (−) and HML (+) factors, as well as on the (6–1–1) (+) strategy, a statistically significant monthly α of 0.56% remains.

Further, Grobys and Kolari (2020) built on the studies of Barroso and Santa-Clara (2015) and Moreira and Muir (2017) to improve stock momentum strategies by scaling the (1–0–1) strategy based on its realized volatility of daily returns over the previous month. The strategy is scaled down when volatility is high and scaled up when volatility is low. Like Moreira and Muir (2017), Grobys and Kolari (2020) consider leverage-constrained volatility-managed strategies by limiting the up-scaling factor to 1 and 1.5. The unconstrained strategy achieves mean monthly returns of 1.16%, while the leveraged constrained strategies produce monthly returns of 0.64% and 0.90%. Notably, the original (1–0–1) strategy exhibited a negative skewness of −0.47, whereas the volatility-managed strategies do not exhibit skewness risk. The improved returns cannot be explained by additional exposure to the original strategy or to the Fama and French (1993) risk factors. Grobys and Kolari (2020) also test whether industry momentum exhibits the same optionality as stock momentum. As discussed in chapter 2.2, stock momentum strategies behave similarly to a short call option at the end of bear markets (Daniel and Moskowitz 2016). The authors find that all of their three industry momentum strategies do not exhibit optionality effects. The strategies' returns do not load negatively on an interaction term of an ex ante bear market indicator, an contemporaneous up-market indicator, and a value-weighted market factor. Lewellen et al. (2010) find that standard factor models such as the three-factor model of Fama and French (1993) poorly explain the cross-section of industry returns. For this reason, Grobys and Kolari (2020) include the industry momentum strategies to estimate the stochastic discount factor to price industry portfolios. They find that the inclusion of the (1–0–1) strategy into the pricing kernel reduces pricing errors on a 5% significance level, while the other two strategies are not useful for pricing industry portfolios.

In a recent study, Ali and Hirshleifer (2020) propose the number of shared analysts between firms as a refined measure to capture firm connections. For any firm, the portfolio of connected firms (CF) is constructed as a linear combination of firms that share at least one analyst with the firm. The number of pairwise shared analysts gives the weights of each connected firm. The authors find that the contemporaneous relation between a firm's and its CFs' sales growth is stronger than the relation between a firm's and its industry's sales growth, providing evidence that their shared analyst measure captures fundamental similarities between firms better than an industry classification. Stocks are sorted into quintiles based on their CFs' past month return to construct a momentum strategy. Depending on whether quintile returns are calculated with value- or equal-weighting, the momentum strategy produces monthly 4-factor alphas of 0.89% and 1.81%. In spanning tests, Ali and Hirshleifer (2020) find that after controlling for CF momentum, none of industry, geographic, customer, supplier industry, or technology momentum delivers significant 4-factor alphas. Notably, none of the other momentum strategies can explain CF momentum returns. The authors conclude that there is only one dominating spillover effect driving momentum, namely the one that arises because analysts with limited attention only slowly transmit new information from one firm that they cover to the others.

Related to research on industry momentum is style momentum. Chou et al. (2019) construct a momentum strategy not based on industry classification but on stocks' co-movement with an investment style. They build their hypothesis on a study by Barberis and Shleifer (2003) who show in a model that investors' style chasing can lead to positive autocorrelation of style returns. The authors focus on a firm's asset growth as the investment style, because it negatively predicts future returns (Cooper et al. 2008), it is a familiar measure to investors, and it is priced in the cross-section of stock returns (Fama and French 2015). Portfolio sorts are constructed by first splitting stocks into three groups based on their 12-month past return, and then splitting each group by three based on the stocks' beta to the asset growth style returns. With a holding period of 6 months, the momentum strategy constructed from the lowest style beta stocks produces a mean monthly return of 0.14%. In contrast, the momentum strategy constructed from the highest style beta stocks produces a mean return of 0.60%. The difference of 0.46% is statistically significant at the 1% level.

Additionally, Chou et al. (2019) construct a momentum strategy from 25 value-weighted portfolios sorted by asset growth and size. The strategy goes long (short) in the seven portfolios with the highest (lowest) past 12-month return. The average monthly returns to this strategy are 0.76% for a 3-month holding period and 0.48% for a 12-month holding period. Finally, the authors find that the style momentum strategy returns are higher than those of a stock momentum strategy, they remain significant after adjusting for the Fama-French risk factors, and they are not due to higher risk exposure to the investment factor itself. Due to the absence of such risk-based explanations for the style momentum profits, Chou et al. (2019) turn to behavioral explanations. They propose that investors under-react to style performance when stocks are stable in their style because their attention is limited to stocks changing styles. They provide evidence for this hypothesis by showing that a style momentum strategy limited to stocks that change between the 25 asset growth-size portfolios within 2 years prior to portfolio formation achieves considerable lower returns than an identical strategy limited to stocks that do not change style (0.31% versus 0.60%).

4.2 Factor momentum

Several studies have recently documented momentum in a broad set of factor portfolios. Ehsani and Linnainmaa (2022a) show that if stock returns are a linear combination of factor returns as shown in Eq. 3, then a cross-sectional momentum strategy of N stocks can be decomposed as follows:

$$
\begin{aligned}
E[\pi_{i,t}^{mom}] = & \underbrace{\sum_{f=1}^{F}[cov(r_{-t}^{f}, r_{t}^{f})\sigma_{\beta^f}^{2}]}_{\text{factor autocovariances}} + \underbrace{\sum_{f=1}^{F}\sum_{g\neq f}^{F}[cov(r_{-t}^{f}, r_{t}^{g})cov(\beta^{f}, \beta^{g})]}_{\text{factor cross-serial covariances}} \\
& + \underbrace{\frac{1}{N}\sum_{i=1}^{N}[cov(\epsilon_{i,-t}, \epsilon_{i,t})]}_{\text{autocovariances in residuals}} + \underbrace{\sigma_{\eta}^{2}}_{\text{variation in mean returns}}
\end{aligned} \tag{4}
$$

where $\sigma_{\beta^f}^{2}$ and σ_{η}^{2} are the cross-sectional variances of factor exposures and unconditional expected stock returns. Four channels drive factor momentum: positive autocovariance in factor returns that is amplified by dispersion in stocks' exposures to the respective factor, cross-serial autocovariance between factors, autocovariance in returns not explained by factor exposure, and cross-sectional dispersion in stocks' mean returns.

Gupta and Kelly (2019) highlight the importance of the first channel with a sample of 65 characteristics-based factor portfolios constructed by bivariate sorts, first on size and then on the characteristic. They show that factors exhibit time-series momentum. Forty-nine of 65 have a statistically significant positive first-order autoregressive slope coefficient on the 5% level. Further, they construct a time-series momentum strategy that goes long (short) in a factor if its return over the look-back period is positive (negative). The absolute exposure is determined by the magnitude of past returns and the longer-term volatility but is limited to -2 and 2, respectively. Strategies based on 1-month past returns produce positive and significant alphas over the original factor returns for 47 factors. A time-series-factor momentum strategy that combines all 65 factors yields an annual Sharpe ratio of 0.84. Returns are robust to controls for the Fama and French (2015) risk factors, static factor returns, stock momentum, industry momentum and short-term reversals. Factor momentum also outperforms standard stock momentum in an international sample including Europe, Canada, and Pacific-Asia. Stock momentum can party explain factor momentum when the look-back period is 1 year skipping the most recent month, but not for when the look-back period is the most recent month. While stock returns reverse over 1 month, factor momentum works best with that look-back period. The authors conclude that if factor momentum was capturing stock-level momentum, one would expect it to exhibit short-term reversals.

Zhang (2022) also documents time-series factor momentum in two factors explaining the cross-section of currency returns: dollar and carry. The dollar factor is the average excess returns of foreign currencies over the US dollar. The carry factor is a long-short portfolio based on the currencies' forward discount. A strategy that combines the two time-series momentum strategies outperforms usual time-series and cross-sectional momentum strategies in currencies and fully spans them.

Ehsani and Linnainmaa (2022a) shed light on the first channel of factor momentum: positive autocovariance in factor returns. They highlight that out of 20 factors, the average monthly return after a year of positive returns is 51 bps, and after a year of negative returns, it is only 6 bps. Next, Ehsani and Linnainmaa (2022a) show that a model of sentiment investors proposed by Kozak et al. (2018) can explain autocorrelation in factors. The crux of the model is that sentiment-driven investors inhibit demand for stocks in excess of a rational investor. If sentiment is sufficiently persistent, then the excess demand produces persistence in factor returns. The autocovariance of principal components of the matrix of asset cash flows is given by:

$$cov(PC_t^k, PC_{t+1}^k) = \lambda_k^2 \beta_k^2 c_0 \sigma^2 [(1 + R_f^2)\phi - R_f - R_f \phi^2] \tag{5}$$

where R_f is the risk-free rate plus 1, c_0 is a constant that relates to the magnitude in which sentiment-investor demand drives returns, σ^2 is the variance in sentiment-investor demand, β_k captures how well investor-demand in excess of rational demand lines up with the kth eigenvector of the decomposition of the covariance matrix of returns and λ is the eigenvalue of PC^k. There are two key takeaways from this equation. First, sentiment must be extremely persistent for the autocovariance to be positive. For a risk-free monthly rate of 0.39%, the threshold is $\phi > 0.996$. Second, for significant autocovariances, irrational demand of sentiment-driven investors must line up with high eigenvalue principal components ($\lambda_k^2 \beta_k^2$). This is consistent with risk-based explanations: factor momentum still exists because arbitrageurs would have to carry high systematic risks. Further, Ehsani and Linnainmaa (2022a) hypothesize that factor momentum must be concentrated in the highest eigenvalue principal components. They find this in an expanded sample of 47 factors by constructing a time-series momentum strategy from the ten dominant principal components. The returns of this strategy explain most of the momentum in lower eigenvalue principal components in the first half of the sample period from 1973 to 2019, and all of it in the second half. Further, factor momentum subsumes cross-sectional stock momentum, industry momentum, industry-adjusted momentum and intermediate horizon momentum. The authors construct momentum-neutral factors to highlight that stock momentum stems from factor momentum and not vice versa. Stock weights to construct factor portfolios are updated by minimizing the change to the original weights while orthogonalizing the weights to past returns. When constructing momentum strategies, such factors do not benefit from stock momentum and achieve even higher alphas than the original ones. Finally, Ehsani and Linnainmaa (2022a) address the conflicting findings of, e.g., Blitz et al. (2011) that residual return momentum strategies perform better than raw return strategies. Such results suggest that firm-specific effects drive momentum, not exposures to factors with serial correlation. Ehsani and Linnainmaa (2022a) show that residual momentum strategies profit from omitted factor momentum. If omitted factors are more strongly autocorrelated than those used to adjust stock returns, residual momentum yields better performance than stock momentum.

Arnott et al. (2021) connect stock momentum, factor momentum, and industry momentum. With a sample of 43 US equity factor portfolios from 196 to 2020, they construct a cross-sectional factor momentum strategy that is long in above-median return factors and short below-median return factors over the look-back period. They highlight in two ways that factor momentum subsumes industry momentum. First, momentum found in industry-neutral factors fully explains industry momentum. The industry-neutral strategy is constructed by subtracting industry means from the stock characteristics such that the factors are roughly exposed equally to the various industries. Second, Arnott et al. (2021) construct industry-mimicking portfolios as a linear combination of factors, where the industries' factor exposures give the weights. These portfolios contain no industry-specific information but capture industries' systemic risks. Even mimicking portfolios built from a small set of factors exhibit similar momentum as industry portfolios and subsume industry momentum as the number of factors increases.

Additionally, Arnott et al. (2021) find that momentum in the three highest eigenvalue principal components of industry-neutral factors subsumes all industry momentum. They connect these results with the argumentation of Ehsani and Linnainmaa (2022a). There cannot be idiosyncratic stock or industry momentum, as it would not be consistent with the existence of rational arbitrageurs. Only systematic factors can have pricing effects; therefore, momentum concentrates in the high eigenvalue principal components where arbitrageurs find it risky to trade against it.

While Ehsani and Linnainmaa (2022a) and Arnott et al. (2021) find consistent evidence that 1-year stock momentum is largely driven by factor momentum, it remains an open question why stock returns reverse in the short-term, whereas monthly factor returns exhibit strong positive first-order autocorrelation. In a follow-up working paper, Ehsani and Linnainmaa (2022b) propose that residual momentum has additional components other than firm-specific momentum, namely omitted factor momentum and a betting-against-beta effect. The betting-against-beta effect stems from too flat security factor lines and can be illustrated with the example of CAPM residuals. If the security market line is too flat, high beta stocks earn negative alpha and low beta stocks earn positive alphas. Sorting by CAPM residuals is thus equal to a betting-against-beta sort. Ehsani and Linnainmaa (2022b) remove the betting-against beta effect by orthogonalizing the short-term stock residuals to the long-term betting against beta effect. This is done by regressing stock returns on factors over a time period over which returns display no momentum or reversals to estimate long-term alphas attributed to the betting-against-beta effect. After, they run a cross-sectional regression of short-term residuals on the long-term alphas. The residuals of this regression are the beta-neutral residuals. A momentum strategy sorting on these beta-neutral residuals yields an annual Sharpe ratio of 1.23, more than double the Sharpe ratio of 0.59 of a standard residual momentum strategy. Further, the beta-neutral strategies are less correlated to factor momentum. After analyzing autocorrelations of different order in factor returns and beta neutral residuals, the authors conclude that short-term reversal effects are purely firm-specific. In contrast, firm-specific momentum and factor momentum create the intermediate momentum effect.

5 Conclusion

Overall, there is general agreement in academia that momentum strategies yield robust and significant profits across various asset classes and around the globe. Moreover, the profits are robust to standard risk-factor adjustments and can be enhanced by various changes in the construction methodology. Improvements include isolating firm-specific returns from factor-exposure, scaling position with the inverse of ex ante volatility, or lagging the formation period to calculate past returns.

However, the origin of momentum is still debated. While both risk-based and behavioral-based models provide reasonable arguments for the existence of firm-specific momentum, new findings on the existence of industry momentum and factor momentum lack theoretical foundation.

Another open question is the extent to which momentum in stocks is driven by an exposure to systematic risk factors or to industry factors, which themselves exhibit serial correlation. Ehsani and Linnainmaa (2022a) and Arnott et al. (2021) find that factor momentum subsumes both stock momentum and industry momentum. Nonetheless, because factor returns exhibit strong first-order autocorrelation, a pure factor-driven stock momentum conflicts with short-term reversals.

To provide answers, future research faces the difficult task of isolating firm-specific returns from returns that arise from factor risk exposure. This is even more demanding in light of a vast zoo of potentially priced risk factors, and in light of time-varying factor exposures.

To summarize, momentum was one of the most prominent topics in financial research over the last three decades, and recent findings on the commonality in momentum effects present fruitful grounds for future prominence.

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