ERASMUS UNIVERSITEIT ROTTERDAM

Exploring and Explaining Factor Momentum

ERASMUS UNIVERSITY ROTTERDAM

Master thesis Financial Economics, Erasmus School of Economics

Student name:	Jan Willem Voorwinden
Student number:	432146
Supervisor:	A. Soebhag
Second assessor:	Dr. J.J.G. Lemmen
Date final version:	15th December 2020

Abstract

Sorting factors instead of stocks based on their past returns generate economically and statistically significant profits. This so-called factor momentum rose to attention in the last years. However, it is unknown what the best way is to construct factor momentum or how factor momentum profits relate to the macroeconomic picture. This paper examines both issues and shows that there is no single best way to construct factor momentum. Trading more factors generate higher returns but also make strategies more volatile. This inverse return-volatility relation is almost perfect, resulting in a near-identical Sharpe ratio of 0.6 for all strategies. Factor momentum profits are unrelated to macroeconomic variables; I show that past returns drive factor momentum profits and not macroeconomic predicted returns. My results strengthen Ehsani and Linnainmaa's (2020) findings, who show that factor momentum profits arise because of positive factor autocorrelations.

Keywords: Momentum; factor investing; factor timing; asset pricing anomalies

I thank my supervisor, A. Soebhag, for his excellent help and support.

Contents

List of Figures

List of Tables

1 Introduction

The momentum anomaly (Jegadeesh & Titman, 1993) is one of the most robust and well-known asset pricing anomalies. A significant number of articles in the last 25 years found evidence that this anomaly is not only subject to the United States or equities. However, almost all articles study the momentum anomaly in single asset classes or portfolios. Less is known about momentum in anomalies themselves; although factor timing is subject to some articles, it primarily examines factor timing for a few anomalies. However, recent years saw a rise in articles that explore factor timing with a broad set of factors, the so-called factor momentum strategy. Strategies that sort factors on their prior return earn abnormally high returns as high as 10% per annum and Sharpe ratios close to one. Less is known about the robustness of factor momentum. All papers about factor momentum construct factor momentum differently, but is one way better than the other? Some papers use a time-series strategy (Gupta & Kelly, 2019; Ehsani & Linnainmaa, 2020), while others use a cross-sectional strategy (Avramov et al., 2017; Arnott et al., 2019). But is a cross-sectional strategy better than a time-series strategy? And delivers one cross-sectional strategy higher returns than other cross-sectional strategies? And does one strategy deliver a higher risk-return reward than the other? These questions are not answered in the literature.

Furthermore, explanations of factor momentum profits are scarce. Ehsani and Linnainmaa (2020) report that time-series factor momentum stems from positive autocorrelation in factors themselves, while Avramov et al. (2017) report that their cross-sectional factor momentum strategy is related to investor sentiment. Nothing is known about the relationship between factor momentum profits and the state of the economy or the macroeconomic environment. There is, however, some evidence that macroeconomic variables are related to stock momentum profits. Chordia and Shivakumar (2002) show that lagged macroeconomic variables can explain stock momentum profits. Furthermore, they show that momentum profits become statistically indistinguishable from zero after controlling for macroeconomic predicted returns. Griffin et al. (2003), on the other hand, find no evidence that momentum profits can be explained by macroeconomic risk variables. Thirdly, Cooper et al. (2004) show that momentum profits are related to the state of the market; they show that momentum profits are positive following positive market returns and negative following negative market returns. Lastly, Antoniou et al. (2013) show that momentum profits are related to investor sentiment; they show that momentum strategies are mainly profitable when market sentiment is optimistic. It is interesting to examine whether factor momentum profits are driven by the these stock momentum explanations.

This paper tries to fill those gaps in the literature by answering the following research question:

"Which factor momentum strategy delivers the highest risk-adjusted return, and can factor momentum profits be explained by macroeconomic cycles?"

I show in this paper that factor momentum is not subject to the way it is constructed. Factor momentum profits are large and significant for both the cross-sectional and time-series momentum strategy. I also show that cross-sectional factor momentum still earns positive profits, no matter the number of factors in the long and short leg. The Sharpe ratio of a strategy that only invests in the prior-month winner and loser is approximately as high as strategies that invest in multiple factors. Factor momentum profits are also significant for different formation and holding periods, although a one-month formation and holding period deliver the best performance. However, both time-series and cross-sectional factor momentum do not earn profits with look-back periods of more than a year. This result is contradictory with Gupta and Kelly (2019), who show that their time-series factor momentum strategy still earns positive profits with look-back periods of more than a year.

Consistent with Arnott et al. (2019), I show that the cross-sectional factor momentum strategy in this paper explains both industry momentum (Moskowitz & Grinblatt, 1999) and residual momentum (Blitz et al., 2011), but not other forms of stock momentum. Furthermore, no single stock momentum strategy (nor a combination of stock momentum strategies) can explain cross-sectional factor momentum profits. In contrast to Ehsani and Linnainmaa (2020), I find no evidence that factor momentum can explain other stock momentum strategies. Neither my cross-sectional factor momentum strategy nor my time-series momentum strategy can explain the intermediate momentum (Novy-Marx, 2012), standard momentum (Jegadeesh & Titman, 1993), and momentum reversals (De Bondt & Thaler, 1985) anomaly.

Factor momentum cannot be explained by macroeconomic variables or the state of the economy. Factor momentum profits are high during both good and bad economic cycles, and differences between good and bad economic conditions are not significant. Macroeconomic variables that can explain stock momentum profits (Chordia & Shivakumar, 2002) cannot explain factor momentum profits. A two-way sort on raw and predicted returns (using a regression model with lagged macroeconomic variables) also highlights the non-existing relationship between factor momentum profits and macroeconomic variables; factor momentum profits arise from sorting factors based on past returns, no matter the level of predicted return. This finding strengthens the results in Ehsani and Linnainmaa (2020) that factor momentum profits arise from positive autocorrelation in factors themselves.

Factor momentum profits primarily come from the long leg, even though the short leg earns on average a negative return. However, the average return from the long leg is more than three times as large as the average return from the short side. However, short selling the worst-performing factors is more profitable in months of low investor sentiment and less profitable in months of high investor sentiment. This result is contradictory with Stambaugh et al. (2012), who show that short side returns are more profitable in months of high investor sentiment. However, this result is in line with my observation that factor momentum strategies deliver higher returns in contractionary periods. Factor momentum profits are also not specific to the January effect, unlike some anomalies. Factor momentum generates profits in January that are not statistically different from returns in all other months.

This paper also shows that factor momentum strategies are implementable in practice. Excluding illiquid, low-priced micro-cap stocks makes sure that transaction costs are manageable. I show that factor momentum strategies are also profitable after transaction costs, especially for strategies that invest in a few factors. An investor with my set of 69 factors would realize the highest net Sharpe ratio if he/she bought (sold) the six factors with the highest (lowest) prior-month return and held them for the next month. The rest of this paper is organized as follows. Section 2 provides an overview of the related literature, while section 3 describes the data and factor construction. Section 4 present the results, and section 5 concludes.

2 Literature review

Jegadeesh and Titman (1993) first document that stocks with a good performance in the past year tend to continue performing well in the next year. This so-called momentum anomaly is one of the strongest arguments against Fama's (1970) Efficient Market Hypothesis (EMH). After all, the EMH argues that past prices should not contain information about future prices. All new information should directly be incorporated into a firm's stock price. Momentum is also problematic for well-known asset pricing models. Neither the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) nor the Fama and French three- and five-factor models can explain momentum (Fama & French, 2008, 2016). Momentum's high return and asset pricing model alpha makes momentum strategies a favorite strategy of mutual funds; Grinblatt et al. (1995) report that 77 percent of US mutual funds use some sort of momentum strategy.

Momentum strategies are mostly constructed in the cross-section. Assets with a high prior-year return *relative* to other assets are bought, while assets with low prior-year returns *relative* to other assets are sold. Sorting stocks in the cross-section based on prior-year returns can deliver returns as high as 1% per month (Jegadeesh & Titman, 1993). The momentum anomaly is the subject of many studies during the past three decades, and Jegadeesh and Titman's (1993) article is one of the most cited articles in the finance literature. Follow-up research found that momentum is not only subject to stocks in the United States, but momentum is also found in European equity markets (Rouwenhorst, 1998), emerging market stock returns (Rouwenhorst, 1999), some Asian stock markets (Chui et al., 2000), size and book-to-market sorted portfolios (Lewellen, 2002), country index futures, currencies, commodities (Asness et al., 2013), mutual funds (Carhart, 1997), industries (Moskowitz & Grinblatt, 1999), corporate bonds (Jostova et al., 2013), and in many more asset classes around the world. Other studies also found ways to improve momentum, such as scaling past returns by their volatility (Rachev et al., 2007) or by sorting stocks based on their residual return (Blitz et al., 2011).

Moskowitz et al. (2012) are the first to construct momentum as a time-series strategy. Using 58 futures contracts, they find that a factor that is long (short) futures with positive (negative) prior k-month excess returns earn profits of more than 1% per month. Furthermore, these time-series moment profits are positive for all 58 future contracts they examine, and not just positive on average across their 58 future contracts. Moskowitz et al. (2012) also show that cross-sectional and time-series momentum are related but different. They also show that time-series momentum entirely subsumes cross-sectional momentum, but not vice versa. Time-series momentum still earns a positive and statistically significant alpha after controlling for cross-section momentum. However, cross-sectional momentum does not earn a significant or positive alpha after controlling for time-series momentum. Babu et al. (2019) confirm the findings of Moskowitz et al. (2012) using an extended out-of-sample dataset.

There is a wide range of explanations for the momentum anomaly. Most explanations can be divided into rational and irrational explanations. Rational explanations argue that momentum profits exist because of some risk-based explanation or because of frictions. Conrad and Kaul (1998) argue that the cross-sectional variation in mean stock returns determines (a part of) the profitability of momentum strategies. Berk et al. (1999) and Sagi and Seasholes (2007) argue that changes in firm-specific risks drive momentum profits. Johnson (2002) argues that time-varying expected dividend growth rates drive momentum profits. Other studies argue that momentum profits arise because of trading frictions (Korajczyk & Sadka, 2004; Lesmond et al., 2004). Other studies use macroeconomic risks to explain momentum profits. Chordia and Shivakumar (2002) show that their set of macroeconomic variables can explain momentum profits and argue that time-varying expected returns could explain momentum profits. Liu and Zhang (2008) show that momentum profits depend on the growth rate of industrial production and thus argue that momentum profits are a reward for loading on this macroeconomic risk factor.

Irrational explanations of momentum include theories of under- and overreaction, and behavioral biases. Daniel et al. (1998) argue that overconfident investors with biased self-attribution lead to momentum profits. Zhang (2006) argues that information uncertainty, combined with behavioral biases, has a role in explaining momentum profits. Hong and Stein (1999) argue that prices underreact in the short run because information slowly diffuses across the public, which in turn causes momentum profits to arise. Furthermore, they show that momentum profits increase when the average risk aversion of momentum traders decreases. Hong et al. (2000) built on this and argue that momentum profits arise because firm-specific information slowly diffuses across investors, especially when this firm-specific news is negative. Antoniou et al. (2013) show that momentum profits mainly arise during periods of investor optimism and argue that this is the case because of short-selling constraints and cognitive dissonance among smaller, naive investors. Cooper et al. (2004) argue that momentum profits arise because of overreaction and show that momentum profits depend on the state of the market. Hirshleifer (2001) gives an excellent overview of other cognitive biases that could drive momentum profits.

Related to time-series momentum are research papers that study factor timing. Is it possible to time factors in such a way that you only harvest their highs and not their downs? Greenwood and Hanson (2012) show that characteristics of firms that issue new shares can forecast the performance of portfolios sorted on size or value. Hodges et al. (2017) investigate the strength of factor timing strategies using five *smart beta*[1] factors (value, quality, momentum, size, and low volatility). They find that a relative strength strategy that overweights (underweights) factors with high (low) prior returns earns a high and positive Sharpe ratio. However, Asness (2016) is less positive about factor timing and argues that there

[1] These smart beta factors are indices computed by MSCI and are long only indices. These indices can be traded by any individual using exchange-traded funds (ETFs).

is very weak historical evidence that it is possible to time factors. Furthermore, Bender et al. (2018) report mixed conclusions of factor timing possibilities. Papers that study factor momentum, however, appeared only recently. To date, there are only four published (working) papers that have studied factor momentum: Avramov et al. (2017), Arnott et al. (2019), Gupta and Kelly (2019), and Ehsani and Linnainmaa (2020).

Avramov et al. (2017) use 15 factors to construct their cross-sectional factor momentum strategy. First, they show that the Value at Risk (VaR) is much higher for single anomalies than for a strategy that invests an equal amount in all factors. Second, they show that their factor momentum strategy earns a positive and statistically significant return in the post- and pre-2000 periods. However, the returns in the post-2000 are lower than in the pre-2000 period. Third, they show that the investor sentiment index (Baker & Wurgler, 2006) is a strong predictor of future anomaly returns. Factor momentum returns are higher in high-sentiment markets than in low-sentiment markets. Fourth, they find that a factor momentum strategy that sorts on predicted (investor sentiment adjusted) anomaly returns generates a higher risk-adjusted return than a strategy that sorts anomalies on prior-month returns.

Arnott et al. (2019) use 51 factors to examine the relationship between cross-sectional factor momentum and industry momentum (Moskowitz & Grinblatt, 1999). First, they show that industry momentum stems from factor momentum and not vice versa. Industry momentum earns a significant Fama and French five-factor alpha of 8.7% per annum but does not earn a statistically significant profit after controlling for industry-adjusted factor momentum. Second, they show that factor momentum is not due to the (arbitrary) choice of factors. They show that almost every random set of factors exhibit factor momentum; factor momentum still earns profits when the universe of factors is restricted to, for example, the five factors of the Fama and French five-factor model. Third, they show that the short-term reversal anomaly of Jegadeesh (1990) a negative relation has with both industry and factor momentum. The FF5 alpha of the short-term reversal factor more than doubles when controlling for industry and factor momentum. Fourth, they show that their cross-sectional factor momentum strategy can explain all forms of industry momentum but none of the stock momentum strategies.

Ehsani and Linnainmaa (2020) use 20 publicly available factors to construct a time-series momentum strategy. First, they show that factor returns are positively autocorrelated; factors earn, on average, a higher return following a year of profits than following a year of losses. Second, they show that stock momentum is fully subsumed by factor momentum. All forms of stock momentum do not earn a profit after controlling for factor momentum, but not vice versa. Third, they show that time-series momentum is superior to its cross-sectional counterpart. They show that a high return on any factor predicts that all factors will deliver high returns, while cross-sectional factor momentum bets that a high return on some factors predicts a low return on other factors. Fourth, they show that stock momentum is not an independent risk factor; stock momentum merely aggregates the autocorrelation found in factor returns.

Gupta and Kelly (2019) use 65 factors to construct a time-series and a cross-sectional factor momentum strategy. First, they confirm the conclusion in Ehsani and Linnainmaa (2020) and show that factors themselves exhibit time-series momentum; a strategy that scales factor exposure based on their prior-month return earns a positive and significant return. Second, they show that factor momentum profits are not due to a specific look-back period, in contrast to stock momentum profits. Their time-series factor momentum strategy with look-back periods up to five years still earn profits, whereas stock momentum profits usually reverse over longer look-back periods (Jegadeesh & Titman, 2001). Third, they show that time-series factor momentum is superior to its cross-sectional counterpart, even though they share a correlation of 90 percent: Time-series factor momentum yields positive alphas when controlling for cross-sectional factor momentum, but cross-sectional factor momentum yields a negative alpha when controlling for time-series factor momentum. They further show that factor momentum profits are robust to transaction costs; factor momentum still has a high Sharpe ratio net of transaction costs. Lastly, they find that factor momentum a global phenomenon is, with worldwide profits as high as in the United States.

Ilmanen et al. (2019) study the performance of four factors across six asset classes over the last century. They find contrary out-of-sample results and show that timing factors based on their prior-year return do not produce significantly positive profits in the out-of-sample period. However, it is possible that this finding is not representative of the beforementioned papers since Ilmanen et al. (2019) use four factors in multiple asset classes. In contrast, the beforementioned papers use many more factors and only study equities.

3 Data and factor construction

Monthly and daily return data is from the Center for Research in Security Prices (CRSP). I include all US firms listed on NYSE, AMEX, and Nasdaq with ordinary common shares (CRSP share codes 10 and 11), excluding American Depositary Receipts (ADRs), Real Estate Investment Trusts (REITs), closed-end funds, and units of beneficial interest. Prices are closing prices unless specified otherwise. Delisting returns are from CRSP. If a delisting return is missing and performance-related, adjustments are made following Shumway (1997) and Shumway and Warther (1999). This means that a delisting return of -30% is inserted for NYSE and AMEX stocks and a delisting return of -55% for NASDAQ stocks. All accounting data is from the quarterly and annual Compustat files. Additional data sources are Kenneth French's data library[2] for daily and monthly returns of the Fama and French (1993, 2015) three- and five-factor models, the market excess returns, and the risk-free rate and Robert F. Stambaugh's website[3] for data on the aggregate liquidity innovation.

Factors are constructed following Fama and French (1993). To ensure that accounting data is publicly available at the time of factor construction, I match the accounting data (in any month) in year $t-1$ with the returns of July of year t to June of year $t+1$. I construct the factors in the same way as the HML factor in Fama and French (1993): All firms are independently sorted on size and the variable of interest. I use NYSE breakpoints to sort firms. Size (price times shares outstanding) is below and above

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[3] http://finance.wharton.upenn.edu/stambaug/

the median NYSE size, while firms above (below) the 70$^{\text{th}}$ (30$^{\text{th}}$) NYSE percentile are classified as high (low) firms. Firms below the 70$^{\text{th}}$ NYSE percentile but above the 30$^{\text{th}}$ NYSE percentile are classified as neutral stocks. These stocks are not traded. This sort results in six different portfolios.[4] Returns within the portfolios are value-weighted. The factor return is the average return on the two high portfolios minus the average return on the two low portfolios. Factors that use binary signals are an exception. *Piotroski's F-Score*, for example, is long firms with an F-Score above six and short firms with an F-Score below three. The factors are constructed so that the high portfolios contain the firms that should outperform the firms in the low portfolios (according to the original studies).[5]

Furthermore, I exclude firms with a share price below \$5 at formation date and firms that do not have data on book value of equity.[6] This exclusion makes sure that the results are not driven by penny stocks or by microstructure effects associated with low-priced stocks. This exclusion also makes the factor momentum strategies more practically implementable since low-priced stocks are usually illiquid and expensive to trade. The factors used in this paper are amongst the well-known and robust factors in the finance literature (for an overview, see Harvey et al., 2016; McLean & Pontiff, 2016; Linnainmaa & Roberts, 2018). An overview of all factors used in this paper and the articles they are initially from can be found in Table A1 in the Appendix.

Factors are divided into accounting-based and return-based factors. Accounting-based factors use accounting data from Compustat, and return-based factors use return, price, or volume data from CRSP.[7] Accounting-based factors are constructed at the end of June, return-based factors are constructed at the end of each month. Accounting-based factors are also rebalanced at the end of the month to maintain value weighting. Factor return data start in July 1964 and end in December 2019. Compustat data availability determines the start date of factor returns since book value of equity is generally not available before 1963. Exceptions are Advertising Expenses, R&D-to-Market Value, R&D-to-Sales, R&D-to-Assets (which all start in July 1968), Total External Financing (which starts in July 1972), and Pástor-Stambaugh Liquidity (which starts in January 1968).

Standard stock momentum sort stocks based on their cumulative return in the past J months and hold them for the next K months. A stock momentum strategy can thus be described as a J-month/K-month strategy. Factor momentum is based on the same principle, except it sorts factors instead of stocks

[4] An exception for this is the *Betting Against Beta* factor (Frazzini & Pedersen, 2014). This factor *ranks* stocks on their market beta and it is thus not possible to use an unconditional sort on size and beta. I therefore use a conditional sort; I first sort all stocks on size and then compute the *Betting Against Beta* return within the small and big portfolio separately. The final factor return is then the average return of the big and small *Betting Against Beta* portfolio return.

[5] This does, however, not mean that the average factor return is always positive. Differences might occur, for example, because the original study used equal weighting, while I use value weighting. It is also possible that the average factor return is positive until the anomaly was first documented but returns became negative after publication.

[6] Book value of equity is constructed as in Davis et al. (2000). I report annual Compustat items in parentheses. Book value of equity is equal to the sum of stockholders' equity and balance sheet deferred taxes and investment tax credit (if available), minus preferred stock. Stockholders' equity is either as given in Compustat (item SEQ) or as reported by Moody's (available on Kenneth French's data library), or else common equity (item CEQ) plus the carrying value of preferred stock (item PSTK). If all three are unavailable, it is measured as total assets (item AT) minus total liabilities (item LT). Deferred taxes is either deferred taxes and investment tax credits (item TXDITC), or else deferred taxes (item TXDB) plus investment tax credit (item ITCB). Preferred stock is either redemption (item PSTKRV), liquidation (item PSTKL) or carrying value (item PSTK), in that order.

[7] I follow Arnott et al. (2019) and classify the *Size* factor as an accounting-based factor, because I construct it as the SMB factor in Fama and French (1992).

on their cumulative return in the past J months. The primary strategy in this paper is the $J = 1$, $K = 1$ strategy, since Avramov et al. (2017), Arnott et al. (2019), Gupta and Kelly (2019), and Ehsani and Linnainmaa (2020) all show that this strategy yields the highest return and Sharpe ratio. The primary strategy uses quintiles to sort factors — factor momentum is long (short) factors with prior-month returns above (below) the 80^{th} (20^{th}) percentile and hold those factors for one month. With the full set of 69 factors, factor momentum is long (short) the 14 factors with the highest (lowest) prior-month return. Although this breakpoint may seem arbitrary, it makes sure that both the long and short sides trade enough factors. Section 4.2 further deals with this issue and examines factor momentum strategies with different breakpoints and different formation and holding periods. Factor returns are equal-weighted within the long and short leg of the factor momentum strategy.

4 Results

This section reports research results. Section 4.1 gives an overview of the constructed factors and their descriptive statistics. It also reports the performance of factor momentum during different (sub)samples. Section 4.2 compares different factor momentum strategies by using different formation and holding periods or by using different breakpoints. Section 4.3 tries to explain factor momentum profits by using stock momentum strategies or macroeconomic variables.

4.1 Overview

Table 1 reports the descriptive statistics of the factors. It reports average returns, standard deviations, Sharpe ratios, average CAPM alphas, and average Fama and French three- and five-factor alphas. The standard deviations and Sharpe ratios are annualized percentages; the returns and alphas are monthly percentages. Four out of 69 factors yield negative average returns, although not significant. 37 (26) factors have a significantly positive average return at the 5% (1%) significance level. The *Betting Against Beta* factor (Frazzini & Pedersen, 2014) has the highest average monthly return and annual Sharpe ratio, with 0.75% and 0.80, respectively. Other factors with high average monthly returns are the well-known factors that sort on past returns (*Intermediate Momentum*, *Momentum*, and *Short-Term Reversal)*, factors that sort on valuation ratios (*Earnings-to-Price*, *Cash flow-to-Price*, and *Sales-to-Price*), and some lesser-known factors such as *Growth in Long-Term Net Operating Assets*, the two *Share Issuance* factors, and *Net Operating Assets*.

Accounting-based factors are, on average, less volatile than return-based factors. Accounting-based factors with annualized volatilities above 10% are rare, but, at the same time, return-based factors with annualized volatilities below 10% are rare. A reason for this might be that return-based factors are constructed at the end of each month, while accounting-based factors are constructed only once per year at the end of June. This might stabilize the accounting-based factor returns. An exception to this is *Piotroski's F-Score*. This accounting-based factor has the highest annualized volatility of 17.07%, making his relatively high average return of 39 basis points per month statistically indistinguishable from zero (t-statistic is 1.84).

Table 1: Descriptive factor statistics

This table shows average returns, volatilities, Sharpe ratios, average CAPM alphas, and average Fama-French (1993, 2015) three- and five-factor alphas for all factors. Associated t-statistics are presented in parenthesis and are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) standard errors. The average returns and alphas are in monthly percentages; the standard deviation and Sharpe ratios are annualized percentages. Panel A reports accounting-based factors; panel B reports return-based factors. Accounting-based factors use annual report data (from Compustat), return-based factors use stock data such as price, dollar trading volume, or holding period return (from CRSP). Accounting-based factors are constructed at the end of June, return-based factors are constructed at the end of each month. Accounting-based factors are also rebalanced at the end of the month to maintain value weighting. Factor returns start in July 1964 and end in December 2019, except for Advertising Expenses, R&D-to-Market Value, R&D-to-Sales, R&D-to-Assets (which all start in July 1968), Total External Financing (which starts in July 1972), and Pástor-Stambaugh Liquidity (which starts in January 1968). Table A1 in the appendix gives an overview of all factors and the papers they are initially from.

		Raw returns				CAPM alpha		FF3 alpha		FF5 alpha	
No.	Factor	$\bar{r}$	$t(\bar{r})$	Std Dev	Sharpe	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\alpha}$	$t(\hat{\alpha})$
	Panel A: Accounting-based factors										
(1)	*Abnormal Capital Investment*	0.11	(2.23)	4.56	0.29	0.10	(1.88)	0.12	(2.64)	0.18	(3.40)
(2)	*Accruals*	0.20	(2.62)	6.17	0.38	0.23	(3.00)	0.21	(2.91)	0.25	(3.55)
(3)	*Advertising Expenses*	0.14	(1.21)	9.40	0.18	0.18	(1.51)	0.01	(0.06)	-0.12	(-1.16)
(4)	*Altman's Z-Score*	0.01	(0.06)	8.13	0.01	-0.05	(-0.44)	0.15	(2.02)	0.24	(2.98)
(5)	*Asset Growth*	0.20	(2.49)	6.40	0.38	0.29	(3.86)	0.14	(2.44)		
(6)	*Asset Turnover*	0.17	(1.24)	11.18	0.18	0.29	(2.22)	0.09	(0.96)	-0.11	(-1.20)
(7)	*Book-to-Market*	0.27	(2.00)	10.06	0.32	0.37	(2.71)				
(8)	*Cash-Based Profitability*	0.24	(3.08)	6.56	0.44	0.25	(3.05)	0.43	(6.99)	0.36	(5.58)
(9)	*Cashflow-to-Price*	0.30	(2.51)	9.24	0.39	0.40	(3.36)	0.10	(1.98)	0.03	(0.51)
(10)	*Capital Turnover*	0.20	(2.32)	7.23	0.33	0.17	(1.90)	0.21	(2.51)	0.00	(0.03)
(11)	*Change in Asset Turnover*	0.08	(1.22)	5.10	0.19	0.09	(1.32)	0.09	(1.43)	0.06	(0.88)
(12)	*Change in NCO*	0.28	(4.58)	4.87	0.68	0.32	(5.15)	0.24	(4.18)	0.14	(2.86)
(13)	*Change in NFIN*	0.20	(4.41)	3.79	0.63	0.21	(4.52)	0.25	(5.57)	0.29	(6.12)
(14)	*Composite Equity Issuance*	0.27	(3.66)	6.19	0.53	0.36	(5.43)	0.32	(5.30)	0.13	(2.14)
(15)	*Debt Capacity*	0.08	(0.50)	12.44	0.07	0.06	(0.40)	0.19	(1.30)	0.41	(2.71)
(16)	*Debt Issuance*	0.13	(3.33)	3.58	0.44	0.11	(2.66)	0.16	(4.18)	0.20	(4.84)
(17)	*Earnings-to-Price*	0.27	(2.28)	8.93	0.36	0.36	(3.04)	0.08	(1.37)	0.05	(1.00)
(18)	*Enterprise Component B/P*	0.22	(1.58)	9.96	0.26	0.29	(2.00)	-0.08	(-1.71)	-0.15	(-3.41)

(continued)

Table 1 — *Continued*

(19)	*Enterprise Multiple*	0.30	(2.62)	8.49	0.42	0.39	(3.56)	0.16	(2.32)	0.03	(0.51)
(20)	*Five-Year Share Issuance*	0.27	(3.54)	6.55	0.49	0.37	(5.41)	0.33	(5.14)	0.12	(2.00)
(21)	*Gross Profitability*	0.22	(2.37)	7.86	0.34	0.18	(1.87)	0.36	(4.96)	0.23	(3.38)
(22)	*Growth in Long-Term NOA*	0.30	(3.89)	6.09	0.59	0.36	(4.73)	0.28	(3.96)	0.17	(2.53)
(23)	*Industry-Adjusted CAPEX Growth*	0.15	(2.91)	4.53	0.39	0.17	(3.29)	0.14	(2.81)	0.09	(1.79)
(24)	*Industry Concentration*	0.03	(0.35)	8.44	0.04	0.05	(0.62)	-0.02	(-0.22)	-0.03	(-0.38)
(25)	*Inventory Growth*	0.20	(3.08)	5.61	0.42	0.26	(4.26)	0.20	(3.48)	0.17	(3.46)
(26)	*Investment Growth Rate*	0.17	(3.07)	4.73	0.44	0.23	(4.02)	0.16	(2.92)	0.06	(1.44)
(27)	*Investment-to-Assets*	0.21	(3.08)	5.57	0.45	0.26	(3.75)	0.16	(2.55)	0.09	(1.74)
(28)	*Investment-to-Capital*	0.12	(1.09)	9.31	0.15	0.28	(2.96)	0.08	(1.27)	-0.08	(-1.17)
(29)	*Leverage*	0.14	(1.04)	10.38	0.16	0.21	(1.46)	-0.13	(-1.88)	-0.20	(-2.96)
(30)	*Leverage Component B/P*	0.19	(1.79)	8.54	0.27	0.17	(1.44)	0.22	(1.99)	0.49	(4.96)
(31)	*Net Operating Assets*	0.29	(4.90)	5.01	0.69	0.31	(5.28)	0.31	(5.05)	0.33	(5.20)
(32)	*Net Working Capital Changes*	0.20	(3.25)	5.24	0.47	0.27	(4.46)	0.25	(4.39)	0.24	(4.29)
(33)	*Ohlson's O-Score*	0.08	(1.16)	6.20	0.16	0.11	(1.45)	0.20	(2.97)	0.12	(1.88)
(34)	*One-Year Share Issuance*	0.30	(3.59)	6.70	0.54	0.40	(5.13)	0.30	(4.57)	0.07	(1.50)
(35)	*Operating Leverage*	0.21	(2.71)	6.56	0.39	0.21	(2.58)	0.19	(2.43)	0.05	(0.70)
(36)	*Operating Profitability*	0.25	(2.80)	7.17	0.42	0.29	(3.11)	0.31	(3.48)		
(37)	*Piotroski's F-Score*	0.39	(1.84)	17.07	0.27	0.56	(2.77)	0.54	(2.57)	0.12	(0.69)
(38)	*Profit Margin*	-0.11	(-1.37)	6.22	-0.21	-0.04	(-0.50)	0.02	(0.35)	0.06	(0.85)
(39)	*R&D-to-Market Value*	0.39	(3.20)	10.45	0.45	0.29	(2.39)	0.26	(2.32)	0.33	(2.96)
(40)	*R&D-to-Sales*	0.10	(0.59)	12.90	0.09	-0.03	(-0.18)	0.23	(1.54)	0.49	(3.63)
(41)	*R&D-to-Total Assets*	0.17	(1.06)	12.28	0.17	0.06	(0.35)	0.31	(2.18)	0.52	(3.76)
(42)	*Return on Assets*	0.11	(1.49)	6.58	0.21	0.14	(1.72)	0.29	(4.33)	0.10	(1.94)
(43)	*Return on Equity*	0.15	(1.78)	6.86	0.27	0.19	(2.12)	0.26	(3.05)	0.04	(1.06)
(44)	*Sales Growth*	0.06	(0.68)	7.05	0.10	0.16	(1.97)	0.02	(0.35)	-0.10	(-1.49)
(45)	*Sales Minus Inventory Growth*	0.13	(2.77)	4.11	0.38	0.14	(2.95)	0.14	(2.86)	0.13	(2.58)
(46)	*Sales-to-Price*	0.39	(3.25)	8.69	0.54	0.39	(3.14)	0.13	(1.57)	-0.07	(-0.93)
(47)	*Size*	0.20	(1.78)	10.04	0.24	0.10	(0.92)				
(48)	*Sustainable Growth*	0.11	(1.34)	6.73	0.20	0.20	(2.54)	0.06	(0.88)	-0.02	(-0.48)
(49)	*Total External Financing*	0.26	(3.19)	6.39	0.49	0.39	(5.54)	0.36	(5.64)	0.15	(3.34)

(*continued*)

Table 1 — *Continued*

					Panel B: Return-based factors						
(50)	*52-Week High*	0.10	(0.67)	12.90	0.09	0.34	(3.00)	0.35	(3.27)	0.16	(1.08)
(51)	*Amihud's Illiquidity*	0.34	(2.14)	16.62	0.25	0.30	(1.90)	0.12	(0.87)	0.03	(0.20)
(52)	*Betting Against Beta*	0.75	(4.82)	11.27	0.80	0.83	(5.04)	0.67	(4.60)	0.36	(2.66)
(53)	*Firm Age*	-0.05	(-0.46)	9.25	-0.06	-0.20	(-2.10)	-0.05	(-0.80)	0.20	(3.99)
(54)	*Five-Year Return Seasonality*	0.12	(1.73)	6.30	0.24	0.15	(2.02)	0.08	(1.18)	0.01	(0.15)
(55)	*Idiosyncratic Risk*	0.23	(1.35)	14.95	0.18	0.58	(4.46)	0.52	(4.72)	0.23	(2.52)
(56)	*Industry Momentum*	0.32	(1.66)	16.58	0.23	0.40	(2.08)	0.42	(2.28)	0.35	(1.53)
(57)	*Intermediate Momentum*	0.58	(4.30)	10.32	0.67	0.57	(4.15)	0.69	(5.58)	0.67	(4.78)
(58)	*Low Volatility*	0.16	(0.76)	16.99	0.11	0.55	(3.64)	0.48	(3.86)	0.18	(1.70)
(59)	*Market Beta*	-0.02	(-0.08)	15.99	-0.01	-0.40	(-2.69)	-0.35	(-3.18)	-0.10	(-0.95)
(60)	*Maximum Daily Return*	0.31	(2.14)	12.56	0.30	0.59	(5.17)	0.52	(5.44)	0.26	(3.34)
(61)	*Momentum*	0.61	(3.97)	13.47	0.54	0.65	(4.51)	0.78	(5.59)	0.69	(3.60)
(62)	*Long-Term Momentum Reversals*	0.19	(1.75)	8.25	0.27	0.21	(1.98)	0.02	(0.24)	-0.00	(-0.00)
(63)	*Nominal Price*	-0.02	(-0.14)	11.57	-0.02	-0.16	(-1.36)	-0.38	(-4.04)	-0.24	(-1.78)
(64)	*Pástor-Stambaugh Liquidity*	0.07	(0.87)	6.29	0.13	0.05	(0.64)	0.06	(0.74)	0.09	(1.10)
(65)	*Residual Momentum*	0.19	(2.02)	8.61	0.27	0.27	(2.97)	0.30	(3.19)	0.22	(2.08)
(66)	*Residual Variance*	0.24	(1.52)	13.25	0.22	0.54	(4.34)	0.47	(5.08)	0.21	(2.79)
(67)	*Share Turnover*	0.07	(0.49)	11.86	0.07	0.31	(2.61)	0.31	(2.95)	0.26	(2.28)
(68)	*Short-Term Reversals*	0.51	(4.81)	10.00	0.61	0.41	(4.02)	0.36	(3.35)	0.39	(3.06)
(69)	*Volume Variance*	0.35	(2.35)	12.62	0.33	0.61	(4.69)	0.43	(4.26)	0.16	(1.62)

Most factors' Fama and French five-factor alpha is lower than their average return, but some factors perform significantly better when controlling for the Fama and French five-factor model. The *Leverage Component Book-to-Price* factor, for example, has an insignificant average monthly return of 19 basis points (t-statistic is 1.79) but a significant five-factor alpha of 49 basis points per month (t-statistic is 4.96). Meanwhile, his counterpart (*Enterprise Component Book-to-Price*) also has an insignificant average monthly return of 22 basis points (t-statistic is 1.58) but a statistically significant negative five-factor alpha of -15 basis points per month (t-statistic is -3.41). Another example is the *R&D-to-Sales* factor, which average monthly return of 10 basis points per month (t-statistic is 0.59) is almost five times lower than its FF5 alpha of 49 basis points per month (t-statistic is 3.63).

Table A2 in the Appendix reports verification of my data. Correlations between my six-factor model returns and the six-factor model returns posted on Kenneth French's website are above 97%. The average returns, standard deviations, skewness, and kurtosis are also comparable to those on Kenneth French's website, although the posted asset growth factor (CMA) slightly differs from my own asset growth factor.[8] Table A3 in the Appendix reports the transition matrix of my factors. Factors in portfolio X usually transition into the same portfolio (as seen by the diagonals). For example, 30% of factors in the lowest prior-month return portfolio will, on average, stay in this portfolio. Remarkable is the number of factors that transition from portfolio one to portfolio five, and vice versa. Factors in the lowest prior-month(s) returns quantile transition relatively often to the highest prior-month(s) returns quantile; these percentages are always the second highest.

Table 2 reports the cross-sectional factor momentum strategy's performance for the whole sample, the half samples, and the quarter samples. This factor momentum strategy is long (short) factors with prior-month returns above (below) the 80^{th} (20^{th}) percentile. The holding period is one month. In the full data sample, factor momentum earns a significant annualized return of 8.55% (t-statistic is 5.26) with a standard deviation of 14% — yielding an annual Sharpe ratio of 0.61. Factor momentum's Fama and French five-factor model alpha is even higher at 9.52% per annum (t-statistic is 4.44). Factor momentum also earns a significantly high return of 10.58% and 6.53% per annum in the two half samples (with a t-statistic of 5.54 and 2.51, respectively). However, the return is higher and less volatile in the first half sample, resulting in a Sharpe ratio almost 2.5 times higher in the first half sample than in the last half sample. Once again, the Fama and French five-factor alpha is significantly positive in both half samples and higher than the average return.

There is quite a difference in performance between the four different quarter samples. The first two quarter samples are almost identical with returns slightly above 10%, standard deviations around 11%, and Sharpe ratios around 1.00. However, the last two quarter samples show a decline in profits. Factor momentum still earns a return of 7.44% per annum in the third quarter sample, but its high volatility of 20.47% makes its average raw return statistically indistinguishable from zero. This insignificance is

[8] The factor mean returns differ from those in Table 1. This difference is caused by the way the factors are constructed; factors in Table A3 use all stocks whereas factors in Table 1 exclude stocks with prices below $5 or stocks without data on book value of equity.

Table 2: Factor momentum performance

This table shows annualized raw returns, volatilities, Sharpe ratios, and Fama-French (2015) five-factor alphas of cross-sectional factor momentum during the full sample and six different subsamples. The full sample begins in 1965 and ends in 2019. Factor momentum is long (short) factors with prior-month returns above (below) the 80^{th} (20^{th}) percentile and hold those factors for one month. t-statistics are reported in parenthesis and are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) standard errors.

	Raw returns				FF5 alpha	
Breakpoints	$\bar{r}$	$t(\bar{r})$	Std Dev	Sharpe	$\hat{\alpha}$	$t(\hat{\alpha})$
Full sample:						
01/1965 – 12/2019	8.55	(5.26)	14.01	0.61	9.52	(4.44)
Half samples:						
01/1965 – 06/1992	10.58	(5.54)	10.95	0.97	10.95	(5.11)
07/1992 – 12/2019	6.53	(2.51)	16.50	0.40	8.22	(2.54)
Quarter samples:						
01/1965 – 09/1978	10.99	(4.70)	10.57	1.04	10.29	(3.95)
10/1978 – 06/1992	10.18	(3.36)	11.35	0.90	11.24	(3.66)
07/1992 – 03/2006	7.44	(1.66)	20.47	0.36	10.95	(1.93)
04/2006 – 12/2019	5.62	(2.10)	11.27	0.50	5.20	(2.32)

mainly attributable to the dot-com bubble; factor momentum returns were highly volatile in the first two years of the 21^{st} century. Months with negative 20% returns followed shortly after months with positive 20% returns, making the factor momentum strategy highly volatile. This return volatility also causes the Fama-French five-factor alpha to be statistically indistinguishable from zero. The last quarter sample's return is the lowest with 5.62%, but approximately as volatile as the first two quarter sample. This lower volatility leads to a significant average return (t-statistic is 2.10) and a higher Sharpe ratio than the third quarter sample.

Figure 1 dives deeper into Table 2 and plots the cumulative log-returns of factor momentum, standard stock momentum, the market, and the risk-free asset. The return on the CRSP value-weighted index is used as a proxy for the market. The return on the one-month T-Bill is used as a proxy for the risk-free asset. The returns of factor momentum and stock momentum are approximately equal during the first three quarters of the full sample. Both performed well before the dot-com bubble, but both also suffered significant losses after the bubble burst. However, stock momentum crashed following the 2008 financial crisis (Daniel & Moskowitz, 2016), whereas factor momentum performed well after the 2008 financial crisis. Factor momentum had a slowdown between the dot-com bubble and the 2008 financial crisis. Factor momentum earned moderate profits during this period, while the market skyrocketed. This return slowdown is also seen in the 2010s decade, although factor momentum still generated profits during this decade. This slowdown could be related to the disappearance and low returns of most of the well-known anomalies during the last ten years (Chordia et al., 2014), and caused factor momentum to be less profitable than the market in the 2010s decade.

Panel B and C of Figure 1 highlight two periods: The dot-com bubble and the 2008 financial crisis. Factor momentum was highly profitable in the years before the dot-com bubble. An investor who invested 1$ dollar in factor momentum at the start of 1999 would have almost doubled his investment value in 1.5 years. However, this return would be temporary: the investor would lose almost all his profits in the two and a half years after the dot-com bubble. This return peak also caused factor momentum to be highly volatile and becomes even more evident when looking at the realized (instead of cumulative) monthly profits of factor momentum. Nine (seven) out of the ten largest monthly profits (losses) occurred during the plotted period in panel B. Factor momentum was also highly profitable in the years following the 2008 financial crisis. An investor that invested 1$ dollar in factor momentum at the end of the 2008 financial crisis would have realized a profit of more than 50% in less than a year. More importantly, this investment would hold its value instead of losing it all, as happened after the dot-com bubble. On the

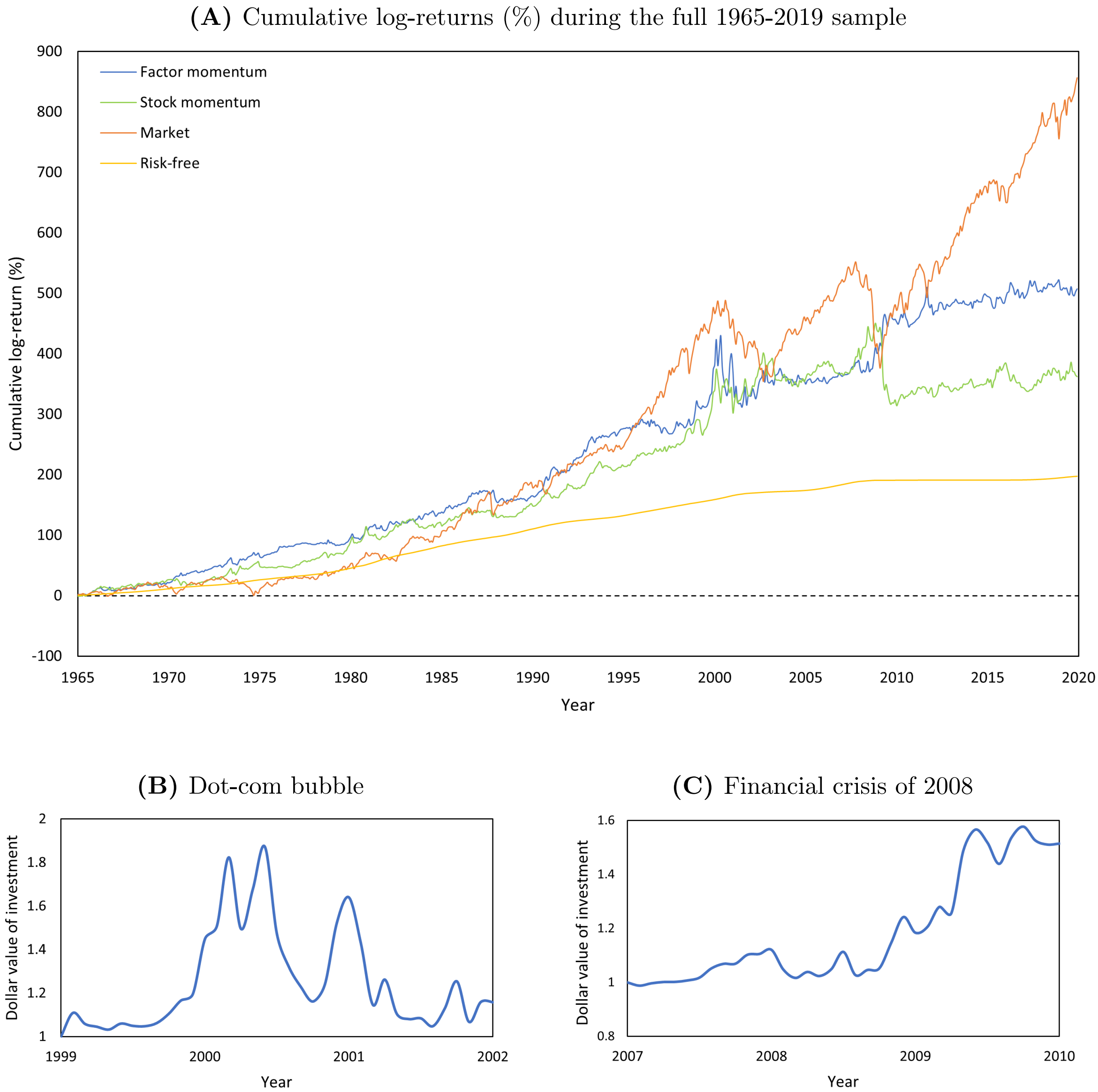


Figure 1: Factor momentum performance

Panel A of this figure plots the cumulative log-return of factor momentum, the CRSP value-weighted index (market), the stock momentum factor, and the one-month T-Bill (risk-free asset) during the full 1965-2019 sample. Panel B and C plot the cumulative factor momentum return during the dot-com bubble (panel B) and the 2008 financial crisis (panel C). Factor momentum is the cross-sectional strategy that is long factors with prior-month returns above the 80$^{\text{th}}$ percentile and short factors with prior-month returns below the 20$^{\text{th}}$ percentile. The holding period is one month.

other hand, stock momentum realized a loss of more than 50% in the same period. The high profitability of factor momentum in this period is mainly attributable to short-selling the worst-performing factors. The short leg earned an astonishing average of -1.67% per month in 2009, whereas the long side earned only a modest 0.57% per month in this year.

Table 3 reports the performance of factor momentum in the 36 months after portfolio formation. Table 3 shows that most of the factor momentum returns come from the first month. The average return in the first month is a significant 71 basis points (t-statistic is 5.26), while the returns in month $t+2$ through $t+12$ are all insignificant positive, except for month $t+11$. Just as with standard stock momentum, most monthly returns are negative after the first 12 months (Jegadeesh & Titman, 1993), and all of them are statistically insignificant, except for month $t+20$. Overall, there seems to be no clear return pattern after the first 12 months. Furthermore, the cumulative return is statistically significantly different from zero up to and including month $t+25$.

Table 3: Relative performance of factor momentum

This table shows the relative performance of factor momentum in the 36 months after formation. The monthly return is the result of buying (selling) factors with prior-month returns above (below) the 80^{th} (20^{th}) percentile. t is the month after portfolio formation. Monthly and cumulative returns are in monthly percentages. Associated t-statistics are reported in parenthesis below and are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) standard errors.

t	Monthly return	Cumulative return	t	Monthly return	Cumulative return	t	Monthly return	Cumulative return
1	0.71	0.71	13	-0.09	2.43	25	-0.18	1.67
	(5.26)	(5.26)		(-0.59)	(4.01)		(-1.61)	(2.04)
2	0.17	0.89	14	-0.08	2.38	26	-0.03	1.66
	(1.27)	(3.97)		(-0.59)	(3.47)		(-0.24)	(1.95)
3	0.05	0.95	15	-0.04	2.36	27	-0.10	1.52
	(0.31)	(2.99)		(-0.30)	(3.16)		(-0.80)	(1.75)
4	0.10	1.02	16	-0.03	2.29	28	-0.08	1.43
	(0.85)	(3.04)		(-0.25)	(3.24)		(-0.82)	(1.65)
5	0.09	1.16	17	0.08	2.39	29	0.13	1.52
	(0.71)	(3.11)		(0.70)	(3.24)		(1.04)	(1.73)
6	0.15	1.31	18	-0.13	2.26	30	0.02	1.45
	(1.04)	(3.26)		(-1.05)	(3.09)		(0.15)	(1.71)
7	0.09	1.38	19	-0.05	2.20	31	0.12	1.57
	(0.71)	(3.55)		(-0.40)	(2.85)		(1.27)	(1.85)
8	0.11	1.56	20	-0.22	1.94	32	-0.24	1.32
	(0.90)	(3.72)		(-1.97)	(2.53)		(-1.77)	(1.47)
9	0.17	1.74	21	-0.11	1.90	33	0.05	1.30
	(1.38)	(4.13)		(-0.99)	(2.32)		(0.45)	(1.43)
10	0.14	1.91	22	0.02	1.91	34	-0.18	1.03
	(1.06)	(4.16)		(0.16)	(2.35)		(-1.55)	(1.13)
11	0.30	2.24	23	-0.09	1.83	35	0.18	1.14
	(2.13)	(4.44)		(-0.69)	(2.25)		(1.48)	(1.25)
12	0.16	2.48	24	-0.01	1.82	36	0.14	1.23
	(1.20)	(4.54)		(-0.10)	(2.22)		(1.04)	(1.37)

4.2 Comparing different factor momentum strategies

What is the "right" number of stocks (factors) to trade? There seems to be no correct answer to this question in the literature. Some studies sort stocks in deciles, some studies sort stocks in quantiles, while other studies use the 30^{th} and 70^{th} percentile as breakpoints. There are also differences between papers that study factor momentum. Arnott et al. (2019) form a strategy that is long the best eight and short the worst eight performing factors.[9] Ehsani and Linnainmaa (2020) use two different strategies: Their time-series factor momentum is long (short) factors with positive (negative) prior-month returns, while their cross-sectional factor momentum is long (short) factors with above (below) median prior-month returns. Gupta and Kelly (2019) also construct a time-series factor momentum but do not equal weight the factors within the factor momentum portfolios. Instead, they give higher weights to factors with higher prior-month returns and vice versa.

Table 4 reports annualized returns, standard deviations, Sharpe ratios, and turnover ratios[10] for different strategies. Cross-sectional factor momentum 50/50 is constructed the same way as the cross-sectional factor momentum in Ehsani and Linnainmaa (2020). This strategy is long factors with above-median prior-month returns and short factors with below-median prior-month returns. Cross-sectional factor momentum 70/30, cross-sectional factor momentum 80/20, and cross-sectional factor momentum 90/10 are constructed the same as in Arnott et al. (2019) but use the standard breakpoints used in the stock momentum literature. Time-series factor momentum is long factors with positive prior-month returns and short factors with negative prior-month returns. Time-series factor momentum is on average long 37 factors and short 31 factors. There is a clear trade-off visible between average return and volatility. The annualized average returns and standard deviations monotonically increase with the number of long and short factors. Cross-sectional factor momentum 90/10, for example, has a return (volatility) of 10.84% (17.85%) per year, while these numbers are 4.76% and 8.16% for the cross-sectional factor momentum 50/50. This inverse relation results in an almost identical gross Sharpe ratio of 0.6 for all strategies.

The turnover ratio shows a flat line. All strategies have approximately an equal turnover ratio of 250 basis points. The reason for this flat line is straightforward: Turnover is at its lowest when factors in the short/long side stay in the same portfolio, turnover is modest when factors move from the long or short portfolio to the middle portfolio (factors that are not traded), and turnover is at its highest when factors move from the long to the short side or vice versa. This results in a trade-off: Strategies that invest in all factors have a high chance that factors change from the short (long) to the long (short) side, but also a high chance that factors in the long (short) side stay in the long (short) side. The opposite is true for strategies that trade a few factors: They have a low chance that factors change from the short (long) to the long (short) portfolio **and** a low chance that factors in the long (short) portfolio stay in the

[9] They take long and short positions in $n = \text{round}\left(\frac{3}{20} \times N\right)$ factors.

[10] I follow Gupta and Kelly (2019) and define turnover as the sum of absolute changes in portfolio weights each month. The average of all months is multiplied by 12 to obtain the average annualized turnover. Transaction costs are estimated using the assumption that one unit of turnover equals trading costs of 10 basis points, based on the estimates in Frazzini et al. (2015).

Table 4: Applying different breakpoints for factor momentum

This table shows annualized raw returns, volatilities, (net) Sharpe ratios, and turnover ratios for factor momentum strategies applying different breakpoints. Factors are ranked based on their return in the month before ranking and are held for the next month. Cross-sectional factor momentum (FMOM) 50/50 is long (short) factors with above (below) median prior-month returns. Cross-sectional FMOM 70/30 is long (short) factors with above (below) 70^{th} (30^{th}) percentile prior-month returns. Cross-sectional FMOM 80/20 buys (sells) factors that have a prior-month return above (below) the 80^{th} (20^{th}) percentile. Cross-sectional FMOM 90/10 is long (short) factors with above (below) 90^{th} (10^{th}) percentile prior-month returns. Time-series factor momentum is long (short) factors with positive (negative) prior-month returns. Time-series factor momentum is on average long 37 factors and short 31 factors.

	Raw returns				Turnover	
Breakpoints	$\bar{r}$	$t(\bar{r})$	Std Dev	Sharpe	Turnover	Net Sharpe
Cross-sectional FMOM 50/50	4.76	(4.81)	8.16	0.58	25.37	0.27
Cross-sectional FMOM 70/30	6.91	(5.04)	11.59	0.60	24.26	0.39
Cross-sectional FMOM 80/20	8.55	(5.26)	14.01	0.61	24.05	0.44
Cross-sectional FMOM 90/10	10.84	(5.24)	17.85	0.61	24.03	0.46
Time-series FMOM	4.88	(4.78)	8.36	0.58	25.42	0.28

long (short) portfolio.[11] This trade-off causes the 90/10 factor momentum strategy to have the highest net Sharpe ratio of 0.39, even though transaction costs are approximately the same for all strategies. The reason for this is its high average return; the relative transaction costs (as a percentage of average return) are around 22% of its annual return, while the relative transaction costs exceed the 50% for the 50/50 factor momentum strategy.

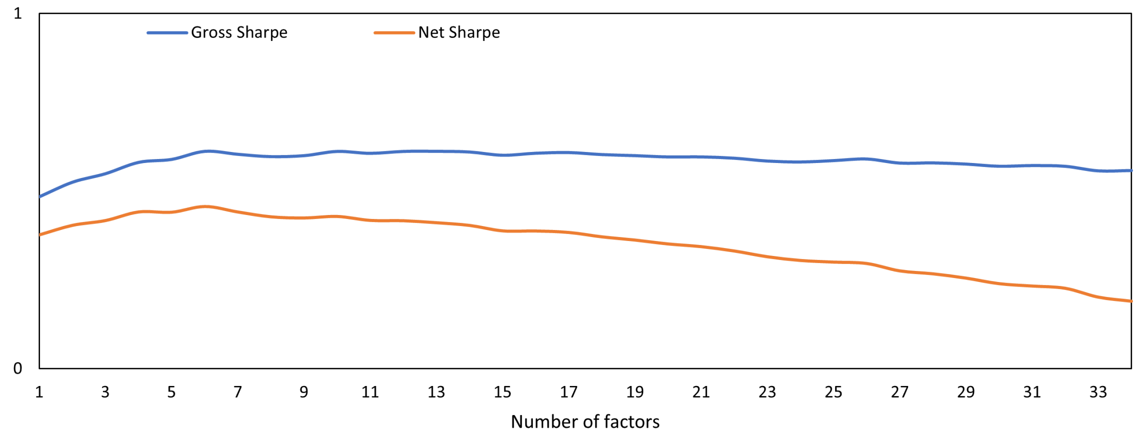
Figure 2 further investigates the relationship between the number of factors traded and the gross and net Sharpe ratios. Panel A reports the gross and net Sharpe ratios, panel B their t-statistics. Sharpe ratio standard errors (and thus t-statistics) are calculated following Opdyke (2007):

$$SE(SR) = \sqrt{\left[1 + \frac{SR^2}{4}\left(\frac{\mu_4}{\sigma^4} - 1\right) - SR\frac{\mu_3}{\sigma^3}\right] / (T-1)}, \tag{1}$$

where SR is the Sharpe ratio, $\frac{\mu_4}{\sigma^4}$ is the kurtosis of returns, $\frac{\mu_3}{\sigma^3}$ is the skewness of returns, and T is the number of observations. The number of factors is the same in the long and short side. The formation and holding period is one month. Factor momentum that trades one factor in the long and short side earns the highest average return (1.08% per month) but also has the highest volatility (an annualized volatility of 26.75%). The opposite is true for the factor momentum strategy that trades 34 factors in both the long and short side (return of 0.38% per month and annualized volatility of 8.27%, respectively). This inverse return-volatility relation causes the gross Sharpe ratio to be roughly the same for all strategies. However, this inverse relation is mostly true for strategies that trade six or more factors in each side; strategies that invest in less than six factors are too volatile and therefore have a lower gross Sharpe ratio. The net Sharpe ratio shows a different pattern. Transaction costs are roughly the same for all strategies (as also seen in Table 4), but the relative transaction costs decrease with the number of factors in each side.

[11] Take, for example, the strategy that trades one factor in the long and short side. The factor in the long and short side (at time t) are most likely to move to the middle portfolio (at time $t+1$) because this strategy invests in only 2 of all 69 factors.

(A) Gross and net Sharpe ratios



(B) Gross and net Sharpe ratio t-statistics

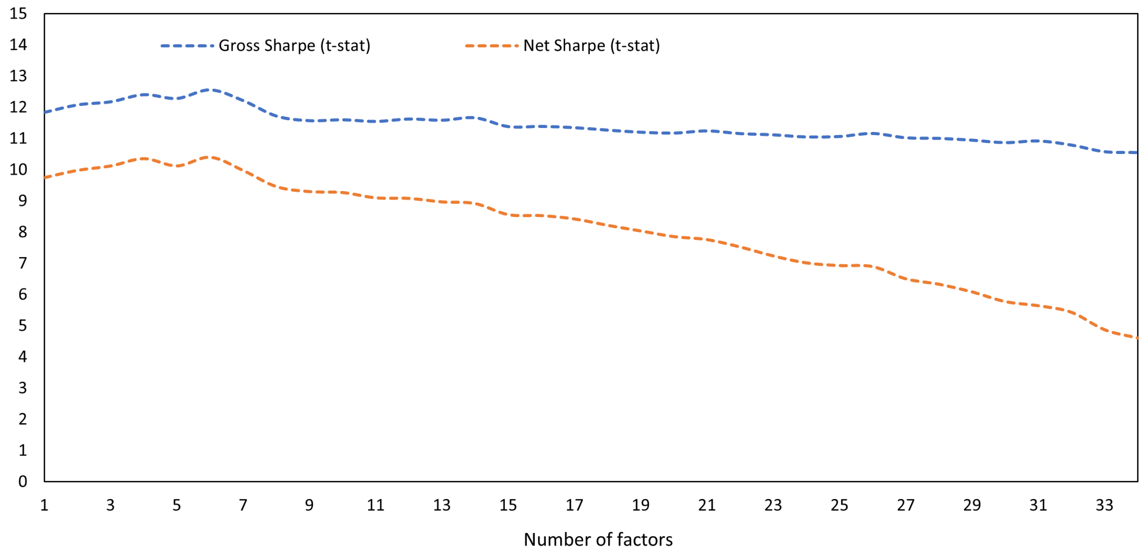


Figure 2: Using different numbers of factors

This figure plots the annualized gross and net Sharpe ratios (panel A) and their t-statistics (panel B) for different factor momentum strategies. The formation and holding period is one month. The factor momentum strategies are long (short) the best (worst) performing N factors, where N differs between 1 and 34. Sharpe ratio standard errors are calculated following Opdyke (2007).

This decrease in relative transaction costs leads to a decline in net Sharpe ratio for factor momentum strategies that trade more than six factors in each side. The highest net Sharpe ratio an investor with my set of 69 factors could realize is thus 0.46, equal to the net Sharpe of the 90/10 factor momentum strategy. It is also the most statistically significant strategy, with an associated t-statistic of 10.41.

Table 5 reports average returns, volatilities, Sharpe ratios, turnover ratios, and average Fama and French five-factor alphas for different formation and holding periods. Panel A reports these statistics for the cross-sectional factor momentum strategy; panel B reports these statistics for the time-series strategy. The cross-sectional strategy with the best performance is the strategy with a one-month formation and holding period, consistent with the other factor momentum papers. This strategy earns the highest return (8.55% per annum), the highest gross Sharpe ratio (0.61), the highest Fama and French five-factor

Table 5: Different formation and holding periods for factor momentum

This table shows annualized raw returns, volatilities, Sharpe ratios, Fama-French (2015) five-factor alphas, and Sharpe ratios net of turnover (TO) for factor momentum strategies with different holding and formation periods. Panel A reports these results for the cross-sectional factor momentum strategy; panel B for the time-series strategy. The factors are ranked based on their cumulative return in the formation period and are held for the holding period. The 20^{th} and 80^{th} percentile are used as breakpoints for the cross-sectional factor momentum strategy; factors with formation period returns above (below) the 80^{th} (20^{th}) percentile are bought (sold). Time-series factor momentum is long (short) factors with formation period returns above (below) zero. The 12-2 formation period is based on standard stock momentum (Carhart, 1997) and skips the last month before formation to account for possible bid-ask bounces. The 12-7 formation period is based on intermediate momentum (Novy-Marx, 2012), which ranks factors based on their cumulative return from month $t-12$ through $t-7$. The 60-13 formation period is based on long-term momentum reversals (Jegadeesh & Titman, 2001), which ranks factors based on their cumulative return from month $t-60$ through $t-13$. The Jegadeesh and Titman (1993) approach is used when monthly holding periods overlap. The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) standard errors.

Formation	Holding	Raw returns				FF5 alpha		Net returns	
period	period	$\bar{r}$	$t(\bar{r})$	Std Dev	Sharpe	$\hat{\alpha}$	$t(\hat{\alpha})$	TO	Sharpe
Panel A: Cross-sectional factor momentum									
1	1	8.55	(5.26)	14.01	0.61	9.52	(4.44)	24.05	0.44
6	1	5.73	(3.42)	13.89	0.41	6.12	(2.38)	14.42	0.31
6	6	3.68	(2.77)	11.57	0.32	4.07	(2.02)	2.44	0.30
12	1	6.22	(3.44)	14.21	0.44	7.52	(2.97)	12.11	0.35
12	12	1.55	(0.90)	11.87	0.13	4.14	(2.08)	1.06	0.12
12-2	1	4.91	(2.67)	14.32	0.34	6.01	(2.40)	12.36	0.26
12-7	1	4.19	(2.51)	12.00	0.35	5.06	(2.71)	14.39	0.23
60-13	1	1.12	(0.87)	8.02	0.14	-1.22	(-0.82)	10.22	0.01
Panel B: Time-series factor momentum									
1	1	4.88	(4.78)	8.36	0.58	5.43	(3.92)	25.42	0.28
6	1	3.35	(3.49)	8.17	0.41	3.49	(2.31)	12.92	0.25
6	6	2.05	(2.70)	6.57	0.31	2.13	(1.93)	2.19	0.28
12	1	3.77	(3.52)	8.38	0.45	4.16	(2.79)	10.64	0.32
12	12	0.98	(0.97)	6.89	0.14	2.21	(1.88)	0.94	0.13
12-2	1	3.13	(2.84)	8.38	0.37	3.41	(2.30)	10.93	0.24
12-7	1	2.28	(2.30)	6.98	0.33	2.55	(2.35)	12.88	0.14
60-13	1	0.55	(0.66)	5.37	0.10	-0.95	(-0.95)	8.32	-0.05

alpha (9.52% annually), and the highest net Sharpe ratio (0.44). Changing the formation period from one month to 6 or 12 months slightly lowers the profitability. Those cross-sectional strategies earn 5.73% and 6.22% per annum, respectively. Cross-sectional factor momentum strategies with a holding period of more than one month are not profitable. The $J = 6$, $K = 6$ cross-sectional strategy earns 3.68% per year, whereas its counterpart with a holding period of one month earns 5.73% per year. The volatility of the $J = 6$, $K = 6$ strategy is also only slightly lower than its counterpart with a one-month holding period, resulting in a lower Sharpe ratio (0.32 versus 0.41). The $J = 12$, $K = 12$ cross-sectional strategy is far worse than its counterpart with a 12-month holding period and does not earn a statistically significant return (1.55% per annum with a t-statistic of 0.90). This observation is consistent with the results in Table 3 that factor momentum profits primarily come from the first month.

The time-series strategy exhibit the same pattern as the cross-sectional strategy, but the time-series factor momentum returns are always lower than their cross-sectional counterparts. The time-series strategy with a one-month formation and holding period earns 4.88% per annum with a Sharpe ratio of 0.58, compared to 8.55% and 0.61 for the cross-sectional strategy. Remarkable is the difference in gross Sharpe ratio between the cross-sectional and time-series strategy. The cross-sectional strategies earn a higher return than the time-series strategies, but the cross-sectional strategies are also more volatile. This relationship results in almost identical gross Sharpe ratios for the different cross-sectional strategies and their respective time-series counterparts. The Sharpe ratio of the $J = 6$, $K = 1$ strategy, for example, is 0.41 for both the cross-sectional and the time-series strategy.

Factor momentum strategies with a gap between the formation and holding period do not perform well. Intermediate time-series factor momentum, for example, generates a profit of 2.28% per year, which is lower than the same strategy that does not skip the last six months before formation (which earns 3.77% per year). The net Sharpe ratio does not show any surprises. The net Sharpe ratio of the $J = 1$, $K = 1$ cross-sectional factor momentum strategy is the highest net Sharpe ratio (0.44), followed by the $J = 12$, $K = 12$ cross-sectional strategy (0.35). However, the $J = 12$, $K = 1$ strategy has a lower turnover ratio, which makes the gap between the net Sharpe ratios smaller compared to the gap between the gross Sharpe ratios. However, this is not the case for the time-series strategy. The highest net Sharpe ratio of the time-series strategy is the $J = 12$, $K = 1$ strategy. Meanwhile, the relatively high turnover ratio of the $J = 1$, $K = 1$ time-series strategy makes this strategy less favorable in terms of net Sharpe ratio (0.32 versus 0.28).

Consistent with Gupta and Kelly (2019), I find that both the cross-sectional and time-series factor momentum does not exhibit the same reversal effect as stock momentum (De Bondt & Thaler, 1985). The Fama and French five-factor alphas show the same pattern as the returns; the alphas are always slightly higher than the returns, which indicates that factor momentum is hardly related to the five-factor variables. The only exception is factor momentum reversals: this strategy's alpha is negative. This could indicate that momentum reversals are negatively related to the five-factor variables. (Table 1 also shows that the five-factor model is fully capable of explaining momentum reversals.)

Arnott et al. (2019) find that Moskowitz and Grinblatt's (1999) industry momentum stems from cross-sectional factor momentum. Their factor momentum strategy subsumes industry momentum, but not vice versa. Ehsani and Linnainmaa (2020) conclude that momentum strategies are not distinct (risk) factors but that momentum strategies stem from the autocorrelations found in the factor returns. Gupta and Kelly (2019) find that time-series factor momentum still earns a significant profit after controlling for stock momentum. However, they argue that their factor momentum does not replace stock momentum but that combining their factor momentum and stock momentum yields significant benefits. Table 6 examines this issue.

Table 6 reports regression results of five different stock momentum strategies and my factor momentum strategy. Factor momentum is either the dependent variable (panel A) or the independent variable (panel B). The first five models try to explain factor momentum using one of the five different stock momentum strategies. Regression model (6) uses all five stock momentum strategies together. Panel A shows that none of the five different stock momentum strategies can fully explain factor momentum profits. Two stock momentum strategies, industry momentum and residual momentum, can explain a part of the factor momentum profits (their t-statistics are 3.02 and 3.47, respectively). However, the factor momentum alpha is still positive and significant (0.65% and 0.64% per month with t-statistics of 4.53 and 4.72, respectively). Factor momentum still earns a positive and significant 0.64% per month when all five different stock momentum strategies are included in the regression (t-statistic is 4.87).

Factor momentum is the independent variable in panel B. Factor momentum is unable to explain intermediate momentum returns since its coefficient is statistically insignificant (t-statistic is 1.34), while the intermediate momentum alpha is still positive and significant (t-statistic is 4.66). The same is true for standard stock momentum; its coefficient is insignificant, while the momentum alpha is still a positive and significant 0.62% per month (the t-statistics are 3.50 and 0.95, respectively). Factor momentum can explain both industry momentum and residual momentum. Their alphas are statistically indistinguishable from zero (the t-statistics are 0.80 and 1.27, respectively), and the factor momentum coefficient is positive and statistically significant (the t-statistics are 2.28 and 2.31, respectively). Momentum reversals and factor momentum seem to be unrelated; the Fama and French five-factor model can completely explain the momentum reversals profits (as shown in Table 1). Factor momentum has no additional power to explain them.

Some of the results in panel B of Table 6 are quite surprising compared to the beforementioned papers. The regression results with industry momentum as either independent or dependent variable are comparable to the results in Arnott et al. (2019, Table 3). However, Ehsani and Linnainmaa (2020, Table 6) show that their time-series factor momentum can explain both standard stock momentum and intermediate momentum. However, my results in Table 6 say that my cross-sectional strategy cannot explain those stock momentum strategies. This difference might be caused by the way factor momentum is constructed; Ehsani and Linnainmaa (2020) construct a $J = 12$, $K = 1$ time-series factor momentum strategy, while I use quantiles to construct a $J = 1$, $K = 1$ cross-sectional factor momentum strategy. I estimate regressions (1) and (3) in panel B again with my $J = 12$, $K = 1$ time-series factor momentum strategy. I can report[12] that these regression results are quite comparable to the results in Ehsani and Linnainmaa (2020, Table 6): The factor momentum coefficient is 0.80 and significant (t-statistic is 11.23), but the intermediate momentum alpha is still positive and significant (alpha is 0.41% with a t-statistic of 4.31). The same is true for standard stock momentum. The factor momentum coefficient is 1.28 and significant (t-statistic is 18.78), and the alpha is also positive and significant (alpha is 0.27% with a t-statistic of 2.46). This result means that my $J = 12$, $K = 1$ time-series factor momentum strategy can only explain a part of the intermediate momentum and standard momentum returns.

[12] I do not tabulate these results for the sake of brevity, but the results are available upon request.

Table 6: Factor momentum and stock momentum strategies

This table shows time-series regression results from regressing returns of five different stock momentum strategies on cross-sectional factor momentum returns and vice versa. Factor momentum is long (short) factors with above (below) $80^{\text{th}}(20^{\text{th}})$ percentile prior-month returns. Panel A reports the results with factor momentum as the dependent variable and a stock momentum strategy as the independent variable. Model (6) uses all the stock momentum strategies as independent variables. Panel B reports time-series regression results with one of the stock momentum strategies as the independent variable and factor momentum, augmented with the Fama and French five-factor model, as independent variables. $\text{MOM}_{\text{n,m}}$ refers to the stock momentum strategy that sort stocks based on their cumulative return in month $t-n$ through month $t-m$. INDMOM is the industry momentum factor (Moskowitz & Grinblatt, 1999), RESMOM is the residual momentum factor (Blitz et al., 2011). t-statistics are reported in parenthesis and are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) standard errors.

Panel A: Factor momentum as dependent variable

	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
Regressor	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	0.63	(4.71)	0.65	(4.92)	0.64	(4.53)	0.70	(5.26)	0.64	(4.72)	0.64	(4.87)
Intermediate momentum	0.14	(1.11)									0.30	(2.19)
Industry momentum			0.20	(3.02)							0.24	(3.90)
Momentum					0.12	(1.14)					-0.44	(-2.54)
Momentum reversals							0.09	(0.82)			0.04	(0.34)
Residual momentum									0.37	(3.47)	0.41	(2.71)
Adjusted R^2	0.01		0.06		0.01		0.00		0.05		0.09	

Panel B: Factor momentum as independent variable

	(1) y = $\text{MOM}_{12,7}$		(2) y = INDMOM		(3) y = $\text{MOM}_{12,2}$		(4) y = $\text{MOM}_{60,13}$		(5) y = RESMOM	
Regressor	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	0.61	(4.66)	0.16	(0.80)	0.62	(3.50)	0.01	(0.11)	0.14	(1.27)
Mkt-RF	-0.02	(-0.35)	-0.09	(-1.33)	-0.10	(-1.49)	-0.00	(-0.06)	-0.10	(-2.48)
SMB	0.04	(0.65)	0.04	(0.37)	0.08	(0.76)	0.20	(4.96)	-0.02	(-0.48)
HML	-0.34	(-3.76)	-0.23	(-1.80)	-0.48	(-3.38)	0.22	(3.96)	-0.14	(-1.90)
CMA	0.02	(0.14)	0.35	(1.35)	0.25	(1.14)	0.43	(4.85)	0.19	(1.59)
RMW	0.06	(0.45)	0.01	(0.03)	0.13	(0.63)	-0.16	(-2.44)	0.12	(1.32)
Factor momentum	0.08	(1.34)	0.25	(2.28)	0.10	(0.95)	-0.00	(-0.16)	0.11	(2.31)
Adjusted R^2	0.10		0.07		0.09		0.40		0.12	

4.3 Explaining factor momentum

Even though stock momentum documentation started more than 25 years ago, there is still no widely accepted explanation for it. Fama and French (1996, 2016) show that neither their unconditional three- or five-factor model can explain momentum profits. Some studies find evidence that lagged macroeconomic variables can explain momentum (Chordia & Shivakumar, 2002). However, other studies find no proof that lagged macroeconomic variables can explain momentum profits (Griffin et al., 2003). Other studies try to explain momentum using investor irrationalities, such as overreaction and underreaction to firm-specific news (Jegadeesh & Titman, 1993), or cognitive biases (for an overview, see Hirshleifer, 2001). Furthermore, Ehsani and Linnainmaa (2020) show that momentum aggregates the autocorrelations found in all the individual factors.

I follow Chordia and Shivakumar's (2002; hereafter CS) methods and investigate if lagged macroeconomic variables can explain factor momentum profits. CS first look at the difference in momentum profits during expansionary and contractionary periods and investigate whether momentum profits depend on the overall state of the economy. Secondly, CS directly investigate the relation between momentum profits and a set of lagged macroeconomic variables by regressing momentum profits directly on their set of lagged macroeconomic variables. Table 7 reports average factor momentum returns during expansionary and contractionary periods. The start and end dates are determined by the National Bureau of Economic Research (NBER).[13] There are 575 expansionary months and 85 contractionary months during the full sample. Factor momentum earns on average 0.64% per month during expansionary periods (t-statistic is 4.01) and 1.19% per month during contractionary periods (t-statistic is 2.10). This result suggests that factor momentum profits are not linked to either expansionary or contractionary periods. The opposite is true for stock momentum; stock momentum earns positive returns during expansionary periods and negative returns during contractionary periods (Chordia & Shivakumar, 2002, Table II). The average factor momentum profits during the contractionary periods are even higher than the average factor momentum profits during the expansionary periods. However, the average factor momentum profits during the contractionary periods lack strong statistical significance, possibly caused by their short duration. Furthermore, all factor momentum profits are positive during the expansionary periods, but not during the contractionary periods. Factor momentum yielded negative returns during the first months of 1980 and a part of the dot-com bubble burst. Overall, this table does not suggest that business cycles are related to factor momentum profits.

Cooper et al. (2004; hereafter CGH) investigate whether investor overreaction is attributable to momentum profits by examining whether momentum profits are different during different market states. They find that momentum profits are positive (negative) in months following positive (negative) market returns. I follow CGH and test if their finding is also the case for factor momentum profits. CGH define two market states: The market is "UP" if the market return is positive in the past three years, and the market is "DOWN" if the market return is negative in the past three years. The value-weighted CRSP

[13] `https://www-nber-org.eur.idm.oclc.org/research/data/us-business-cycle-expansions-and-contractions`

Table 7: Factor momentum profits during expansionary and contractionary periods

This table shows the cross-sectional factor momentum profits during either an expansionary period (left side) or a contractionary period (right side). Factor momentum is long (short) factors with above (below) 80^{th} (20^{th}) percentile prior-month returns. The expansionary and contractionary periods are determined by the National Bureau of Economic Research (NBER) and are available on `https://www-nber-org.eur.idm.oclc.org/research/data/us-business-cycle-expansions-and-contractions`. Associated t-statistics are reported in parenthesis and are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) standard errors.

Expansionary periods			Contractionary periods		
Period	$\bar{r}$	$t(\bar{r})$	Period	$\bar{r}$	$t(\bar{r})$
01/1965 – 12/1969	0.81	(2.01)	01/1970 – 11/1970	2.20	(1.74)
12/1970 – 11/1973	1.00	(1.75)	12/1973 – 03/1975	1.83	(0.85)
04/1975 – 01/1980	0.76	(2.59)	02/1980 – 07/1980	-0.86	(-0.56)
08/1980 – 07/1981	1.95	(1.29)	08/1981 – 11/1982	0.80	(0.85)
12/1982 – 07/1990	0.56	(1.99)	08/1990 – 05/1991	2.77	(1.96)
06/1991 – 03/2001	0.91	(1.62)	04/2001 – 11/2001	-0.64	(-0.19)
12/2001 – 12/2007	0.46	(1.16)	01/2008 – 06/2009	1.88	(1.25)
07/2009 – 12/2019	0.19	(0.79)			
Mean:	0.64	(4.01)	Mean:	1.19	(2.10)

index (VWRETD) is used as a proxy for the market. There are 571 "UP" months and 89 "DOWN" months in the full 1965-2019 sample.

Table 8 reports average returns and average Fama and French three- and five-factor model alphas for three different momentum strategies: The $J = 1$, $K = 1$, $J = 6$, $K = 1$, and the $J = 6$, $K = 6$ strategy. Panel A reports average returns and average Fama and French three- and five-factor model alphas following "UP" markets. All three different factor momentum strategies earn significant returns and alphas. FF5 alphas are larger than FF3 alphas, which in turn are larger than the raw returns. Panel B reports average returns and average Fama and French three- and five-factor alphas following "DOWN" markets. There is a clear difference between the three different factor momentum strategies. The $J = 1$, $K = 1$ factor momentum strategy earns a higher return and higher FF three- and five-factor alphas when the market is in a "DOWN" state compared to a "UP" state. This strategy yields, for example, an FF3 alpha of 1.06% per month following "DOWN" markets, whereas it yields an FF3 alpha of 0.74% per month following "UP" markets. However, the opposite is true for the two other factor momentum strategies. The $J = 6$, $K = 6$ strategy, for example, earns 0.39% per month following "UP" markets but a negative return following "DOWN" markets.

Table 9 further investigates the link between factor momentum profits and macroeconomic variables and reports results from regressing factor momentum profits directly on lagged macroeconomic variables. This rolling-window regression is in the form of:

$$R_t = \alpha + \beta X_{t-1} + \theta JANDUM_t + \epsilon_t, \tag{2}$$

where R_t is the factor momentum profits in month t, β are the factor coefficients, the vector X_{t-1} represents the four lagged macroeconomic variables, $JANDUM$ is a binary dummy variable that takes

Table 8: Factor momentum returns during different states of the market

This table shows cross-sectional factor momentum profits following "UP" (panel A) and "DOWN" (panel B) market states. The market is in a "UP" ("DOWN") state if the market return is positive (negative) in the past three years. The CRSP value-weighted index is used as a market proxy. Panel C reports results for the two-sample t-test that the return is not equal in both market states. $\text{FMOM}_{\text{J,K}}$ is the factor momentum strategy with formation period J and holding period K. Factor momentum is long factors with prior-month(s) returns above the 80^{th} percentile, and short factors with prior-month(s) returns above the 20^{th} percentile. Associated t-statistics are presented in parenthesis.

	$\text{FMOM}_{1,1}$		$\text{FMOM}_{6,1}$		$\text{FMOM}_{6,6}$	
Panel A: Returns and alphas following "UP" markets						
Return	0.68	(4.01)	0.51	(3.05)	0.33	(2.34)
FF3 alpha	0.74	(4.50)	0.59	(3.59)	0.39	(2.91)
FF5 alpha	0.78	(4.71)	0.59	(3.66)	0.39	(2.96)
Panel B: Returns and alphas following "DOWN" markets						
Return	0.92	(2.12)	0.26	(0.62)	0.18	(0.50)
FF3 alpha	1.06	(2.49)	0.32	(0.76)	0.20	(0.58)
FF5 alpha	0.90	(2.12)	0.01	(0.04)	-0.02	(-0.05)
Panel C: T-test for equality ("UP" - "DOWN" = 0)						
Return	-0.24	(-0.52)	0.25	(0.54)	0.15	(0.39)
FF3 alpha	-0.31	(-0.69)	0.27	(0.60)	0.19	(0.52)
FF5 alpha	-0.12	(-0.26)	0.57	(1.31)	0.41	(1.13)

the value of one in January, zero otherwise (only included in panel B), and ϵ_t is the regression residual. The dependent variables are the same as in CS. The four lagged macroeconomic variables are the dividend yield, default spread, term spread, and the yield on the three-month T-Bill. All variables are retrieved from the Global Financial Data (GFD) database. The dividend yield is the S&P 500 monthly dividend yield. The default spread is the difference between the average credit rating of Baa rated bonds and Aaa rated bonds (the credit ratings are from Moody's). The term spread is the difference between the yield of the 10-year Treasury bond and the three-month T-Bill yield. Fama and French (1988) show that the default and term spread are related to long-term business cycles, whereas the yield on the three-month T-Bill is closely related to short-term business cycles. The unexplained factor momentum profits are the sum of the intercept and the residual. The regression parameters β_i ($i = \in 1, 2, 3, 4$) are estimated using the last 60 months of observations. At least 12 monthly observations are required to estimate the regression parameters.

Panel A of Table 9 reports the regression results without a January dummy. The intercept and the residual are positive in the half samples and the full sample. This result is the opposite of my expectation; the unexplained factor momentum profits are even larger than the raw factor momentum profits. The regression parameters have the expected sign in the half samples and the full sample, apart from the dividend yield in the first half sample. The coefficients of the term spread and the three-month T-Bill are significantly positive. The coefficients of the dividend yield and the default spread are negative, although not significant. Panel B of Table 9 reports the regression results with a January dummy. The results are almost identical to the results in panel A. The January dummy has the expected sign and is

Table 9: Explaining cross-sectional factor momentum profits with macroeconomic variables
This table shows the coefficients from regressing cross-sectional factor momentum profits on lagged macroeconomic variables that could explain factor momentum profits. Factor momentum profits are the profits from going long the 14 best-performing factors and going short the 14 worst-performing factors. The unexplained factor momentum profits are the sum of the intercept (INT) and the residual (RES) of the following regression model: $R_t = \alpha + \beta X_{t-1} + \theta JANDUM_t + \epsilon_t$, where the vector X_{t-1} represents the four explanatory variables, which are the same as in Chordia and Shivakumar (2002). The explanatory variables are dividend yield (DIV), default spread (DEF), term spread ($TERM$), and the yield on the three-month T-Bill (YLD). The dividend yield is the S&P 500 dividend yield. The default spread is the difference between the average yield of Baa rated and Aaa rated bonds (ratings are from Moody's). The term spread is the difference between the yield of the 10-year Treasury bond and the three-month T-Bill yield. $JANDUM$ is a binary dummy variable that takes the value of one in January, zero otherwise. The regression is estimated using at least one year of monthly data observations from month $t-1$ through month $t-60$. Associated t-statistics are reported below in parenthesis and are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) standard errors.

Panel A: Regression without a January dummy

Period	RES	INT	DEF	DIV	$TERM$	YLD	Adj. R^2
1966 – 1992	0.04	0.81	-0.86	0.21	0.36	0.17	-0.01
	(0.20)	(1.19)	(-0.78)	(1.01)	(1.53)	(1.65)	
1993 – 2019	0.22	2.87	-0.26	-1.76	0.53	1.38	0.01
	(0.86)	(1.21)	(-0.48)	(-2.10)	(3.54)	(2.49)	
1966 – 2019	0.13	1.84	-0.56	-0.78	0.44	0.77	0.00
	(0.81)	(1.49)	(-0.91)	(-1.75)	(3.18)	(2.68)	

Panel B: Regression with a January dummy

Period	RES	INT	DEF	DIV	$TERM$	YLD	$JANDUM$	Adj. R^2
1966 – 1992	0.04	0.96	-0.19	0.17	0.25	0.10	0.19	-0.01
	(0.23)	(1.30)	(-0.12)	(0.66)	(1.05)	(0.98)	(0.95)	
1993 – 2019	0.20	3.76	-0.24	-2.04	0.47	1.25	-1.17	0.01
	(0.77)	(1.57)	(-0.44)	(-2.38)	(3.08)	(2.29)	(-4.62)	
1966 – 2019	0.12	2.36	-0.21	-0.94	0.36	0.68	-0.49	0.00
	(0.76)	(1.87)	(-0.26)	(-2.03)	(2.53)	(2.38)	(-2.76)	

statistically different from zero. Moreover, the dividend yield coefficient becomes statistically different from zero when the January dummy is added. Table A4 in the Appendix replicates Table 9 with the use of a time-series strategy instead of a cross-sectional strategy. The results are similar to the results in Table 9. The intercept and residual are both positive and not significant. The independent variables also have the expected signs, and the dividend yield, the term spread, the yield, and the January dummy are all significant (Panel B). However, there is one concern with the results in Table 9 and Table A4. The average adjusted R-squared is approximately zero for all periods. This low R-squared means that the four independent variables cannot explain the variation in factor momentum profits. The low adjusted R-squared, combined with the positive unexplained factor momentum profits and the results in Table 7, indicate that the lagged macroeconomic variables used in CS cannot explain factor momentum profits.

CS also report a low adjusted R-squared in the first part of their article. CS argue that the low R-squared is concerning because it might be the case that "earlier results are due to the possibility that the model is simply capturing information contained in past raw returns." (p. 1000). They further investigate this concern by using a two-way sort on raw returns and predicting returns. They find that sorting on predicted returns, holding past raw returns constant still earns significant profits. However, sorting on past raw returns, keeping predicted returns constant does not earn a significant profit. Their result indicates that momentum profits do not stem from past raw returns, but instead from past predicted returns, even though their model used to predict returns has a low adjusted R-squared. CS thus conclude that their result suggests "that the predicted returns from our model are not simply capturing the effect of past returns, but in fact, the reverse is true — the ability of past raw returns to predict future returns is due to information contained in the predicted component of returns." (p. 1003). However, CGH find a different result. CGH find that the macroeconomic variables in CS are unable to explain momentum profits after some simple methodological adjustments. The methodological adjustments they make are: (1) the exclusion of stocks with prices below 1$ at the end of the formation period, and (2) implementing a one-month gap between the formation and holding period. The results in Table 9 could be caused by the way I construct factors since I also exclude stocks with prices below 5$ at the end of the formation period.

I follow CS and CGH and construct a two-way sort on raw returns and predicting returns. At the beginning of month t, I first sort factors into quantiles based on their raw return in month $t-1$ (this is how factor momentum is constructed throughout this paper). Within each quantile, factors are further sorted based on their predicted return in month $t-1$. I also use the two-way sort the other way; I also sort first on predicted returns and then on raw returns. This two-way sort is used to isolate the possible effect of raw (predicted) returns on factor momentum profits, holding predicted (raw) returns constant. This 5x5 sort results in 25 different portfolios. The predicted return of a factor is the fitted value from the following rolling-window regression:

$$R_t = \alpha + \beta_1 DEF_{t-1} + \beta_2 DIV_{t-1} + \beta_3 TERM_{t-1} + \beta_4 YLD_{t-1} + \epsilon_t, \tag{3}$$

where R_t is the factor profit in month t, β_i ($i = \in 1, 2, 3, 4$) are the factor coefficients, DEF is the default spread, DIV is the dividend yield, $TERM$ is the term spread, YLD is the yield on the three-month T-Bill, and ϵ_t is the regression residual. (Note that this is equation (2) without a January dummy.) The regression parameters β_i are estimated for each independent variable using the last 60 months of observations. At least 12 monthly observations are required to estimate the regression parameters.

Table 10 reports the results from this two-way sort. Panel A sort factors first on raw return and then on predicted return; panel B sorts factors first on predicted return and then on raw return. The High-Low row in panel A shows that a strategy that sorts on predicted return is not profitable. Factors with a high past predicted return do not outperform factors with a low past predicted return. Their High-Low t-statistic is statistically insignificant, except for the fourth quantile. However, a strategy that sorts on raw returns earns a statistical profit. A strategy that sorts on raw factor returns within the second predicted factor return quantile earns, on average, a statistically significant profit of 0.83% per month (t-statistic is 4.91). This strategy even outperforms the standard factor momentum strategy in terms of raw returns. However, there is no clear pattern in the High-Low column between the different predicted return quantiles, even though returns monotonically increase within each predicted return quantile. Panel

Table 10: Using a two-way sort on raw returns and predicted returns

At the beginning of month t, all factors from Table 1 are sorted into quantiles based on their raw return in month $t-1$ and on their predicted return in month $t-1$. The predicted return of a factor is the fitted value from the following rolling-window regression: $R_t = \alpha + \beta_1 DEF_{t-1} + \beta_2 DIV_{t-1} + \beta_3 TERM_{t-1} + \beta_4 YLD_{t-1} + \epsilon_t$, where R_t is the factor profit in month t, β_i ($i =\in 1, 2, 3, 4$) are the factor coefficients, DEF is the default spread, DIV is the dividend yield, $TERM$ is the term spread, YLD is the yield on the three-month T-Bill, and ϵ_t is the regression residual. The default spread is measured as the difference between the average credit rating of Baa and Aaa rated bonds (ratings are from Moody's). The dividend yield is the S&P 500 monthly dividend yield. The term spread is measured as the difference between the yield of the 10-year Treasury bond and the three-month T-Bill yield. The regression coefficients are estimated using a rolling window of month $t-60$ through month $t-1$ (minimum of 12 months required). Panel A first sort factors on their raw return and then on their predicted return. Panel B first sort factors on their predicted return and then on their raw return. The t-statistics of the High-Low returns are presented in parenthesis.

	Raw return						t-stat
Predicted return	1 (Low)	2	3	4	5 (High)	High-Low	(High-Low)
Panel A: First sorted on past return, then on predicted return							
1 (Low)	-0.22	0.06	0.13	0.23	0.47	0.69	(3.80)
2	-0.23	0.13	0.17	0.36	0.60	0.83	(4.91)
3	-0.14	0.11	0.19	0.27	0.53	0.68	(3.92)
4	-0.09	0.13	0.30	0.40	0.60	0.69	(3.93)
5 (High)	-0.03	0.25	0.28	0.53	0.59	0.62	(3.20)
High-Low	0.19	0.19	0.15	0.30	0.12		
t-stat (High-Low)	(1.43)	(1.40)	(1.34)	(2.52)	(0.85)		
Panel B: First sorted on predicted return, then on past return							
1 (Low)	-0.14	0.02	0.16	0.18	0.46	0.60	(3.54)
2	-0.19	0.10	0.20	0.28	0.56	0.75	(5.40)
3	-0.10	0.15	0.23	0.34	0.56	0.66	(4.84)
4	-0.02	0.10	0.32	0.35	0.56	0.58	(4.06)
5 (High)	0.00	0.30	0.26	0.53	0.73	0.73	(4.20)
High-Low	0.14	0.28	0.11	0.35	0.27		
t-stat (High-Low)	(0.90)	(1.75)	(0.65)	(2.24)	(1.65)		

B shows similar results. Sorting on past predicted returns does not earn significant profits (except for the fourth quantile, 0.35% per month with a t-statistic of 2.24), while sorting on past raw returns always earns a statistically significant profit. There is again no clear pattern in the High-Low column between the different predicted return quantiles. The combined results in Tables 7 to 10 strongly indicate that the macroeconomic variables in CS cannot explain factor momentum profits, nor that factor momentum profits are specific to a specific state of the economy.

Avramov et al. (2013) report that a large portion of factor returns are from short-selling the loser portfolio. Figure 3 examines this issue and looks at the difference in returns between the long (winners) and short (losers) leg of the factor momentum strategy. Do factor momentum profits primarily come from the long side, or primarily from short selling the loser portfolio? Factor momentum might earn a high average monthly return, but a constrained investor with short selling restrictions would not be able to generate profits when the profits primarily come from short selling the loser portfolio. This is not the case for factor momentum profits; the winner portfolio earns an average monthly return of 55

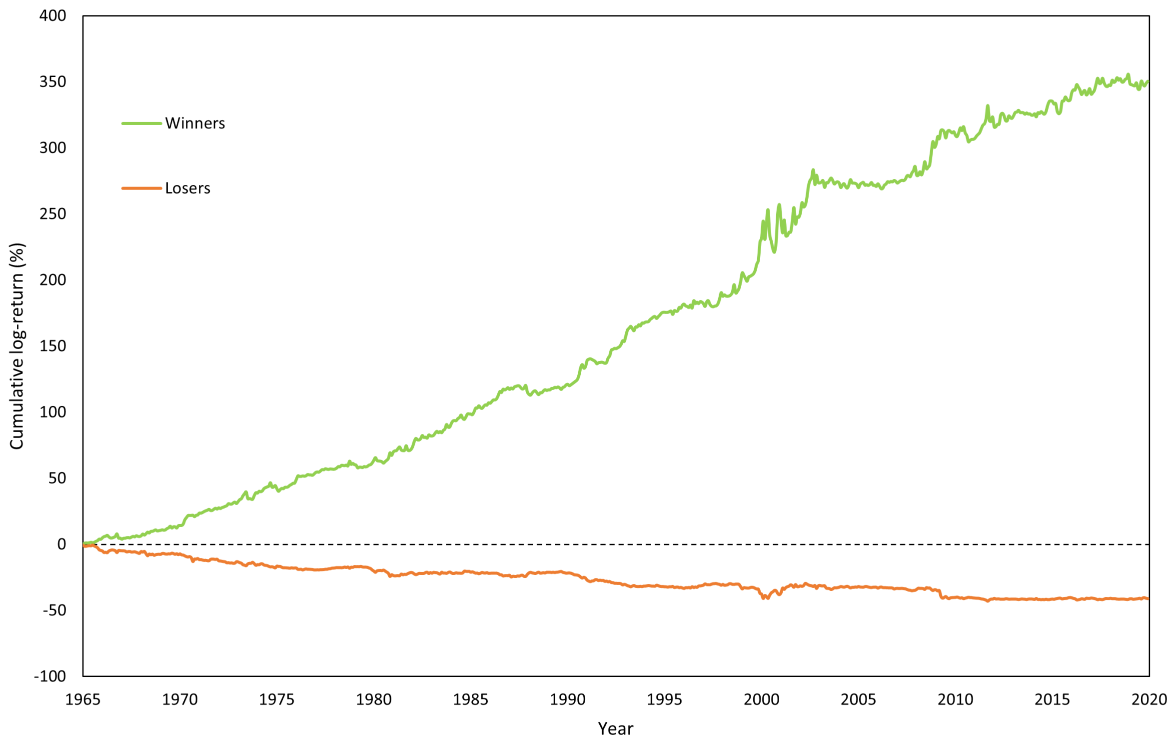


Figure 3: Decomposing factor momentum profits

This figure plots the cumulative log-returns from the long and short side of factor momentum. The cumulative log-return at time t is the total return an investor would have achieved if they invested 1$ in the portfolio at the start of January 1965. Factor momentum uses the 69 factors from Table 1 and has a one-month formation and holding period. The long side (winners) invest in factors whose prior-month return is above the 80^{th} percentile, the short side (losers) invest in factors whose prior-month return is below the 20^{th} percentile.

basis points; the loser portfolio earns an average monthly return of -16 basis points.[14] The winner and loser portfolio's volatility is also approximately the same; winners have an annualized standard deviation of 7.77%, losers 7.22%. Furthermore, the winner (loser) portfolio earns a positive return in 417 (294) months and a negative return in 243 (366) months.

Stambaugh et al. (2012) show that the result in Avramov et al. (2013) is primarily the case during periods of high investor sentiment. They show that short leg factor returns are positive following low-sentiment months and negative following high-sentiment months. I can report that investor sentiment is related to the short side returns.[15] The short leg of factor momentum earns on average 1 (-34) basis points in months following above-median (below-median) investor sentiment. This difference is statistically significant (t-statistic is 2.15). This is the opposite of Stambaugh et al. (2012) since the short side returns are positive following high-sentiment months and negative following low-sentiment months. These returns are 65 and 48 basis points for the long side, respectively (t-statistic for this difference is 0.97). Thus, I can conclude that factor momentum profits mostly come from the long side and not from the short side, although it is less true for months following below-median investor sentiment.

[14] Note that an investor without short-selling possibilities would realize the long side return (on average 55 basis points per month), because the long side is already a combination of zero-investment factor portfolios.

[15] Investor sentiment data is available on Jeffrey Wurgler's website: `http://people.stern.nyu.edu/jwurgler/`

Rozeff and Kinney (1976) first document that market returns are abnormally high in January. This January effect is mostly concentrated in small stocks with negative prior-year returns. A common explanation for this January effect is the tax-loss-selling hypothesis (Gultekin & Gultekin, 1983). There are also quite some factors that perform significantly differently in January.[16] Although the January effect no longer exists in the stock market (Patel, 2016), it is still interesting to compare factor momentum performance in January to the performance in other months. My factor momentum strategy earns an insignificant average monthly return of 0.25% in January (t-statistic is 0.44) and a significant 0.76% per month in the remaining months. This difference is also not statistically significant (t-statistic is 0.89) and indicates that factor momentum profits are not driven by the January effect.

5 Conclusion

This paper tries to answer the following research question:

"Which factor momentum strategy delivers the highest risk-adjusted return, and can factor momentum profits be explained by macroeconomic cycles?"

Firstly, I show in this paper that there is no best way to construct factor momentum strategies. Both cross-sectional and time-series momentum earn statistically and economically significant returns and Sharpe ratios. Although sorting into deciles delivers the highest return (more than 10 percent per annum), it also makes factor momentum volatile. This inverse return-volatility relation is almost perfect: Both the time-series and cross-sectional factor momentum strategies, no matter the number of factors traded, earn Sharpe ratios of approximately 0.6. I confirm the findings of Arnott et al. (2019), Avramov et al. (2017), Gupta and Kelly (2019), and Ehsani and Linnainmaa (2020) that factor momentum is the strongest with a one-month formation and holding period. This cross-sectional strategy earns a statistically and economically significant return of 8.55 percent per year with a Sharpe ratio of 0.61. This strategy's Fama and French five-factor alpha is even higher, with 9.52 percent per annum. However, formation periods should not be longer than one year, and holding periods should not be longer than six months. Future research could examine this strong performance in an out-of-sample test. (Ilmanen et al. (2019) briefly examine factor timing in an out-of-sample period but do not construct a factor momentum strategy.)

Secondly, I show that both the cross-sectional and the time-series factor momentum cannot explain most stock momentum strategies. Consistent with Arnott et al. (2019), I show that my cross-sectional factor momentum strategy can explain industry momentum (Moskowitz & Grinblatt, 1999) and

[16] My *Size* factor, for example, earns an average return of 135 basis points in January, but only 10 basis points in all other months. This absolute difference of 125 basis points is statistically significant with a t-statistic of 3.08. The opposite is true for my *Momentum* factor; this factor earns an average return of -94 basis points in January, but 75 basis points in all other months (t-statistic for this difference is 3.11). Thirteen (seventeen) of my factors perform significantly better (worse) in January than in all other months. Differences can be as big as 328 basis points.

residual momentum (Blitz et al., 2011), but not intermediate momentum (Novy-Marx, 2012), standard stock momentum, and long-term momentum reversals. This result stays unchanged even when I use a time-series factor momentum strategy or a different cross-sectional factor momentum strategy. This result is contradictory to Ehsani and Linnainmaa (2020), who find evidence that stock momentum is not a distinct (risk) factor, but that stock momentum profits arise from aggregating the autocorrelation found in factors. Future research could reveal whether this contradictory result is due to, for example, the difference in the number of factors studied.

Thirdly, I show that factor momentum profits cannot be explained by macroeconomic variables or the state of the economy. Factor momentum earns on average 68 (92) basis points per month following positive (negative) cumulative three-year market returns and 64 (119) basis points per month during expansionary (contractionary) periods. Furthermore, regression models with lagged macro-economic variables show an average R-squared of zero, indicating that lagged macroeconomic variables cannot explain factor momentum profits. Moreover, two-way sorts on past and predicted returns show that sorting on past returns is the only way to generate factor momentum profits — sorting on past returns generates statistically and economically significant profits between 58 and 83 basis points per month while sorting on predicted return delivers insignificant factor momentum profits. Future research could reveal if other macroeconomic models can explain factor momentum profits.[17]

Lastly, I show that the factor momentum strategy used in this paper is implementable in practice. Trading costs are approximately 250 basis points per year, which is manageable, especially for large funds. The cross-sectional factor momentum's net Sharpe ratio of 0.44 reflects this. Furthermore, returns from the long and short leg are both consistent, and the long leg is the primary part of factor momentum returns, even though the short leg earns on average a negative return. This paper thus shows that factor momentum a good alternative is for stock momentum. Yet, only the future will tell if factor momentum will become as popular as momentum is nowadays.

[17] The model used in Chordia and Shivakumar (2002) and this paper is a conditional model. Griffin et al. (2003), for example, use an unconditional model based on Chen et al. (1986) to explain stock momentum profits.

Appendix

Table A1: Factor overview

This table shows an overview of all the factors used in this paper, including the article that is used to construct the factors. This is, however, not always the first article that documented the anomaly. The long-term momentum reversals anomaly, for example, is first documented by De Bondt and Thaler (1985), but I construct it as in Jegadeesh and Titman (2001).

No.	Factor	Author(s)	Journal	Year
		Panel A: Accounting-based factors		
(1)	*Abnormal Capital Investment*	Titman, Wei, and Xie	JFQA	2004
(2)	*Accruals*	Sloan	AR	1996
(3)	*Advertising Expenses*	Chan, Lakonishok, and Sougiannis	JF	2001
(4)	*Altman's Z-Score*	Altman	JF	1968
(5)	*Asset Growth*	Cooper, Gulen, and Schill	JF	2008
(6)	*Asset Turnover*	Soliman	AR	2008
(7)	*Book-to-Market*	Davis, Fama, and French	JF	2000
(8)	*Cash-Based Profitability*	Ball, Gerakos, Linnainmaa, and Nikolaev	JFE	2016
(9)	*Cashflow-to-Price*	Lakonishok, Shleifer and Vishny	JF	1994
(10)	*Capital Turnover*	Haugen and Baker	JFE	1996
(11)	*Change in Asset Turnover*	Soliman	AR	2008
(12)	*Change in NCO*	Richardson, Sloan, Soliman, and Tuna	JAE	2005
(13)	*Change in NFIN*	Richardson, Sloan, Soliman, and Tuna	JAE	2005
(14)	*Composite Equity Issuance*	Daniel and Titman	JF	2006
(15)	*Debt Capacity*	Hahn and Lee	JF	2009
(16)	*Debt Issuance*	Linnainmaa and Roberts	RFS	2018
(17)	*Earnings-to-Price*	Basu	JF	1977
(18)	*Enterprise Component B/P*	Penman, Richardson, and Tuna	JAR	2007
(19)	*Enterprise Multiple*	Loughran and Wellman	JFQA	2011
(20)	*Five-Year Share Issuance*	Pontiff and Woodgate	JF	2008
(21)	*Gross Profitability*	Novy-Marx	JFE	2013
(22)	*Growth in Long-Term NOA*	Fairfield, Whisenant, and Yohn	AR	2003
(23)	*Industry-Adjusted CAPEX Growth*	Abarbanell and Bushee	AR	2002
(24)	*Industry Concentration*	Hou and Robinson	JF	2006
(25)	*Inventory Growth*	Thomas and Zhang	RAS	2002
(26)	*Investment Growth Rate*	Xing	RFS	2008
(27)	*Investment-to-Assets*	Lyandres, Sun, and Zhang	RFS	2008
(28)	*Investment-to-Capital*	Xing	RFS	2008
(29)	*Leverage*	Bhandari	JF	1988
(30)	*Leverage Component B/P*	Penman, Richardson, and Tuna	JAR	2007
(31)	*Net Operating Assets*	Hirshleifer, Hou, Teoh, and Zhang	JAE	2004
(32)	*Net Working Capital Changes*	Soliman	AR	2008
(33)	*Ohlson's O-Score*	Dichev	JF	1998
(34)	*One-Year Share Issuance*	Pontiff and Woodgate	JF	2008
(35)	*Operating Leverage*	Novy-Marx	RF	2010
(36)	*Operating Profitability*	Fama and French	JFE	2015
(37)	*Piotroski's F-Score*	Piotroski	JAR	2000
(38)	*Profit Margin*	Soliman	AR	2008
(39)	*R&D-to-Market Value*	Chan, Lakonishok, and Sougiannis	JF	2001

(*continued*)

Table A1 — *Continued*

(40)	*R&D-to-Sales*	Chan, Lakonishok, and Sougiannis	JF	2001
(41)	*R&D-to-Total Assets*	Li	RFS	2011
(42)	*Return on Assets*	Chen, Novy-Marx, and Zhang	WP	2010
(43)	*Return on Equity*	Haugen and Baker	JFE	1996
(44)	*Sales Growth*	Lakonishok, Shleifer, and Vishny	JF	1994
(45)	*Sales Minus Inventory Growth*	Abarbanell and Bushee	AR	2002
(46)	*Sales-to-Price*	Barbee, Mukherji, and Raines	FAJ	1996
(47)	*Size*	Fama and French	JF	1992
(48)	*Sustainable Growth*	Lockwood and Prombutr	JFR	2010
(49)	*Total External Financing*	Bradshaw, Richardson, and Sloan	JAE	2006
		Panel B: Return-based factors		
(50)	*52-Week High*	George and Hwang	JF	2004
(51)	*Amihud's Illiquidity*	Amihud	JFM	2002
(52)	*Betting Against Beta*	Frazzini and Pedersen	JFE	2014
(53)	*Firm Age*	Jiang, Lee, and Zhang	RAS	2005
(54)	*Five-Year Return Seasonality*	Heston and Sadka	JFE	2008
(55)	*Idiosyncratic Risk*	Avramov, Chordia, Jostova, and Philipov	JFE	2013
(56)	*Industry Momentum*	Moskowitz and Grinblatt	JF	1999
(57)	*Intermediate Momentum*	Novy-Marx	JFE	2012
(58)	*Low Volatility*	Blitz and Van Vliet	JPM	2007
(59)	*Market Beta*	Fama and MacBeth	JPE	1970
(60)	*Maximum Daily Return*	Bali, Cakici, and Whitelaw	JFE	2011
(61)	*Momentum*	Carhart	JF	1997
(62)	*Long-Term Momentum Reversals*	Jegadeesh and Titman	JF	2001
(63)	*Nominal Price*	Blume and Husic	JF	1973
(64)	*Pástor-Stambaugh Liquidity*	Pástor and Stambaugh	JPE	2003
(65)	*Residual Momentum*	Blitz, Huij, and Martens	JEF	2011
(66)	*Residual Variance*	Ang, Hodrick, Xing, and Zhang	JF	2006
(67)	*Share Turnover*	Datar, Naik, and Radcliffe	JFM	1998
(68)	*Short-Term Reversals*	Jegadeesh	JF	1990
(69)	*Volume Variance*	Chordia, Subrahmanyam, and Anshuman	JFE	2001

Note: *AR = The Accounting Review; FAJ = Financial Analyst Journal; JAE = Journal of Accounting and Research; JAR = Journal of Accounting Research; JEF = Journal of Empirical Finance; JF = The Journal of Finance; JFQA = Journal of Financial and Quantitative Analysis; JFE = Journal of Financial Economics; JFM = Journal of Financial Markets; JFR = The Journal of Financial Research; JPE = Journal of Political Economy; JPM = The Journal of Portfolio Management; RAS = Review of Accounting Studies; RF = Review of Finance; RFS = The Review of Financial Studies; WP = Working paper.*

Table A2: Data verification

This table shows correlations, means (in basis points per month), annualized standard deviations, skewness, and kurtosis for my own six-factor model returns and for the six-factor model returns on Kenneth French's website. MKT, SMB, HML, RMW, and CMA are the five Fama and French (FF) factors (Fama & French, 2015). UMD is Carhart's (1997) momentum factor.

	Correlation	Mean (in bp)	Standard deviation	Skewness	Kurtosis
Own MKT	100.00	52.91	15.30	-0.54	1.92
FF MKT		52.91	15.31	-0.54	1.92
Own SMB	99.64	20.16	10.54	0.46	5.29
FF SMB		20.90	10.62	0.49	5.37
Own HML	98.09	28.69	10.03	0.15	2.83
FF HML		29.11	9.79	0.11	2.01
Own RMW	98.28	25.40	7.38	-0.36	12.45
FF RMW		26.51	7.52	-0.32	12.42
Own CMA	97.93	23.26	6.32	0.17	0.66
FF CMA		27.46	6.93	0.31	1.64
Own UMD	99.93	63.61	14.58	-1.34	10.66
FF UMD		64.19	14.62	-1.29	10.24

Table A3: Transition matrix

At the beginning of month t, all factors from Table 1 are sorted into quantiles based on their cumulative return in the past J months. This procedure is repeated in month $t+K$. Portfolio 1 (5) is the portfolio of factors with the lowest (highest) past J-month returns. Table rows presents the factors in the different portfolios at time t. Table columns presents the percentage of factors that transitioned from one portfolio (at time t) to the other portfolios at time $t+K$. Panel A reports these results for the $J = 1$, $K = 1$ pair; panel B for the $J = 12$, $K = 12$ pair.

	Portfolio 1 (%)	Portfolio 2 (%)	Portfolio 3 (%)	Portfolio 4 (%)	Portfolio 5 (%)
Panel A: $J = 1$, $K = 1$					
Portfolio 1	30	19	15	16	20
Portfolio 2	19	24	22	20	15
Portfolio 3	15	23	24	23	14
Portfolio 4	16	20	23	23	18
Portfolio 5	22	15	16	19	29
Panel B: $J = 12$, $K = 12$					
Portfolio 1	28	19	16	18	20
Portfolio 2	19	23	21	21	15
Portfolio 3	16	21	24	22	14
Portfolio 4	16	21	23	22	18
Portfolio 5	23	17	16	19	29

Table A4: Explaining time-series factor momentum profits with macroeconomic variables

This table shows the coefficients from regressing time-series factor momentum profits on lagged macroeconomic variables that could explain factor momentum profits. Factor momentum profits are the profits from going long factors with positive prior-month returns and short factors with negative prior-month returns. The unexplained factor momentum profits are the sum of the intercept (INT) and the residual (RES) of the following regression model: $R_t = \alpha + \beta X_{t-1} + \theta JANDUM_t + \epsilon_t$, where the vector X_{t-1} represents the four explanatory variables, which are the same as in Chordia and Shivakumar (2002). The explanatory variables are dividend yield (DIV), default spread (DEF), term spread ($TERM$), and the yield on the three-month T-Bill (YLD). The dividend yield is the S&P 500 dividend yield. The default spread is the difference between the average yield of Baa rated and Aaa rated bonds (ratings are from Moody's). The term spread is the difference between the yield of the 10-year Treasury bond and the three-month T-Bill yield. $JANDUM$ is a binary dummy variable that takes the value of 1 in January, zero otherwise. The regression is estimated using at least one year of monthly data observations from month $t-1$ through month $t-60$. Associated t-statistics are reported below in parenthesis and are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) standard errors.

Panel A: Regression without a January dummy

Period	RES	INT	DEF	DIV	$TERM$	YLD	Adj. R^2
1966 – 1992	0.01	0.56	-0.26	0.03	0.33	0.13	-0.00
	(0.11)	(1.43)	(-0.37)	(0.28)	(1.79)	(0.82)	
1993 – 2019	0.14	1.24	-0.39	-1.00	0.46	0.81	0.01
	(0.91)	(0.89)	(-1.13)	(-2.02)	(4.99)	(2.86)	
1966 – 2019	0.08	0.90	-0.32	-0.48	0.40	0.47	0.00
	(0.80)	(1.24)	(-0.84)	(-1.85)	(3.81)	(3.11)	

Panel B: Regression with a January dummy

Period	RES	INT	DEF	DIV	$TERM$	YLD	$JANDUM$	Adj. R^2
1966 – 1992	0.01	0.54	-0.03	0.03	0.30	0.11	0.21	-0.01
	(0.12)	(1.35)	(-0.04)	(0.20)	(1.66)	(1.62)	(1.93)	
1993 – 2019	0.14	1.78	-0.39	-1.17	0.43	0.75	-0.64	0.01
	(0.86)	(1.27)	(-1.16)	(-2.29)	(4.91)	(2.67)	(-4.02)	
1966 – 2019	0.07	1.16	-0.21	-0.57	0.36	0.43	-0.21	0.01
	(0.76)	(1.59)	(-0.45)	(-2.10)	(3.60)	(2.89)	(-2.01)	

References

Abarbanell, J. S., & Bushee, B. J. (1998). Abnormal returns to a fundamental analysis strategy. *The Accounting Review, 73*(1), 19-45.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589-609.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31-56.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance, 61*(1), 259-299.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis, 48*(1), 245-275.

Arnott, R. D., Clements, M., Kalesnik, V., & Linnainmaa, J. T. (2019). Factor momentum. *Working paper, SSRN.*

Asness, C. S. (2016). The siren song of factor timing. Invited Editorial. *The Journal of Portfolio Management, 42*(5), 1-6.

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

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

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2013). Anomalies and financial distress. *Journal of Financial Economics, 108*(1), 139-159.

Babu, A., Levine, A., Ooi, Y. H., Pedersen, L. H., & Stamelos, E. (2019). Trends everywhere. *Journal of Investment Management*, forthcoming.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance, 61*(4), 1645-1680.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics, 99*(2), 427-446.

Ball, R., Gerakos, J., Linnainmaa, J. T., & Nikolaev, V. V. (2016). Accruals, cash flows, and operating profitability in the cross section of stock returns. *Journal of Financial Economics, 121*(1), 28-45.

Barbee, W. C., Jr., Mukherji, S., & Raines, G. A. (1996). Do sales-price and debt-equity explain stock returns better than book-market and firm size?. *Financial Analysts Journal, 52*(2), 56-60.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance, 32*(3), 663-682.

Bender, J., Sun, X., Thomas, R., & Zdorovtsov, V. (2018). The promises and pitfalls of factor timing. *The Journal of Portfolio Management, 44*(4), 79-92.

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

Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. *The Journal of Finance, 43*(2), 507-528.

Blitz, D., & Van Vliet, P. (2007). The volatility effect: lower risk without lower return. *The Journal of Portfolio Management, 34*(1), 102-113.

Blitz, D., Huij, J., & Martens, M. (2011). Residual momentum. *Journal of Empirical Finance, 18*(3), 506-521.

Blume, M. E., & Husic, F. (1973). Price, beta, and exchange listing. *The Journal of Finance, 28*(2), 283-299.

Bradshaw, M. T., Richardson, S. A., & Sloan, R. G. (2006). The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics, 42*(1-2), 53-85.

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

Chan, L. K. C., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance, 56*(6), 2431-2456.

Chen, L., Novy-Marx, R., & Zhang, L. (2011). An alternative three-factor model. *Working paper, SSRN.*

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business, 59*(3), 383-403.

Chordia, T., & Shivakumar, L. (2002). Momentum, business cycle, and time-varying expected returns. *The Journal of Finance, 57*(2), 985-1019.

Chordia, T., Subrahmanyam, A., & Anshuman, V. R. (2001). Trading activity and expected stock returns. *Journal of Financial Economics, 59*(1), 3-32.

Chordia, T., Subrahmanyam, A., & Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?. *Journal of Accounting and Economics, 58*(1), 41-58.

Chui, A. C., Titman, S., & Wei, K. C. (2000). Momentum, legal systems, and ownership structure: An analysis of Asian stock markets. *Working paper, University of Texas.*

Conrad, J., & Kaul, G. (1998). An anatomy of trading strategies. *The Review of Financial Studies, 11*(3), 489-519.

Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *The Journal of Finance, 63*(4), 1609-1651.

Cooper, M. J., Gutierrez, R. C., Jr., & Hameed, A. (2004). Market states and momentum. *The Journal of Finance, 59*(3), 1345-1365.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics, 122*(2), 221-247.

Daniel, K., & Titman, S. (2006). Market reactions to tangible and intangible information. *The Journal of Finance, 61*(4), 1605-1643.

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

Datar, V. T., Naik, N. Y., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets, 1*(2), 203-219.

Davis, J. L., Fama, E. F., & French, K. R. (2000). Characteristics, covariances, and average returns: 1929 to 1997. *The Journal of Finance, 55*(1), 389-406.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact?. *The Journal of Finance, 40*(3), 793-805.

Dichev, I. D. (1998). Is the risk of bankruptcy a systematic risk?. *The Journal of Finance, 53*(3), 1131-1147.

Ehsani, S., & Linnainmaa, J. T. (2020). Factor momentum and the momentum factor. *Working paper, SSRN.*

Fairfield, P. M., Whisenant, J. S., & Yohn, T. L. (2003). Accrued earnings and growth: Implications for future profitability and market mispricing. *The Accounting Review, 78*(1), 353-371.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383-417.

Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics, 22*(1), 3-25.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427-465.

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

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance, 51*(1), 55-84.

Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance, 63*(4), 1653-1678.

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

Fama, E. F., & French, K. R. (2016). Dissecting anomalies with a five-factor model. *The Review of Financial Studies, 29*(1), 69-103.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607-636.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics, 111*(1), 1-25.

Frazzini, A., Israel, R., & Moskowitz, T. J. (2015). Trading costs of asset pricing anomalies. *Working paper, Fama-Miller Center.*

George, T. J., & Hwang, C. Y. (2004). The 52-week high and momentum investing. *The Journal of Finance, 59*(5), 2145-2176.

Greenwood, R., & Hanson, S. G. (2012). Share issuance and factor timing. *The Journal of Finance, 67*(2), 761-798.

Griffin, J. M., Ji, X., & Martin, J. S. (2003). Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance, 58*(6), 2515-2547.

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American Economic Review, 85*(5), 1088-1105.

Gultekin, M. N., & Gultekin, N. B. (1983). Stock market seasonality: International evidence. *Journal of Financial Economics, 12*(4), 469-481.

Gupta, T., & Kelly, B. (2019). Factor momentum everywhere. *The Journal of Portfolio Management, 45*(3), 13-36.

Hahn, J., & Lee, H. (2009). Financial constraints, debt capacity, and the cross-section of stock returns. *The Journal of Finance, 64*(2), 891-921.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). . . . and the cross-section of expected returns. *The Review of Financial Studies, 29*(1), 5-68.

Haugen, R. A., & Baker, N. L. (1996). Commonality in the determinants of expected stock returns. *Journal of Financial Economics, 41*(3), 401-439.

Heston, S. L., & Sadka, R. (2008). Seasonality in the cross-section of stock returns. *Journal of Financial Economics, 87*(2), 418-445.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *The Journal of Finance, 56*(4), 1533-1597.

Hirshleifer, D., Hou, K., Teoh, S. H., & Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets?. *Journal of Accounting and Economics, 38*, 297-331.

Hodges, P., Hogan, K., Peterson, J. R., & Ang, A. (2017). Factor timing with cross-sectional and time-series predictors. *The Journal of Portfolio Management, 44*(1), 30-43.

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

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travel slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance, 55*(1), 265-295.

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

Ilmanen, A., Israel, R., Moskowitz, T. J., Thapar, A. K., & Wang, F. (2019). How do factor premia vary over time? A century of evidence. *Working paper, SSRN.*

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

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

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance, 56*(2), 699-720.

Jiang, G., Lee, C. M., & Zhang, Y. (2005). Information uncertainty and expected returns. *Review of Accounting Studies, 10*(2-3), 185-221.

Johnson, T. C. (2002). Rational momentum effects. *The Journal of Finance, 57*(2), 585-608.

Jostova, G., Nikolova, S., Philipov, A., & Stahel, C. W. (2013). Momentum in corporate bond returns. *The Review of Financial Studies, 26*(7), 1649-1693.

Korajczyk, R. A., & Sadka, R. (2004). Are momentum profits robust to trading costs?. *The Journal of Finance, 59*(3), 1039-1082.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance, 49*(5), 1541-1578.

Lesmond, D. A., Schill, M. J., & Zhou, C. (2004). The illusory nature of momentum profits. *Journal of Financial Economics, 71*(2), 349-380.

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

Li, D. (2011). Financial constraints, R&D investment, and stock returns. *The Review of Financial Studies, 24*(9), 2974-3007.

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

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics, 47*(1), 13-37.

Liu, L. X., & Zhang, L. (2008). Momentum profits, factor pricing, and macroeconomic risk. *The Review of Financial Studies, 21*(6), 2417-2448.

Lockwood, L., & Prombutr, W. (2010). Sustainable growth and stock returns. *The Journal of Financial Research, 33*(4), 519-538.

Loughran, T., & Wellman, J. W. (2011). New evidence on the relation between the enterprise multiple and average stock returns. *Journal of Financial and Quantitative Analysis, 46*(6), 1629-1650.

Lyandres, E., Sun, L., & Zhang, L. (2008). The new issues puzzle: Testing the investment-based explanation. *The Review of Financial Studies, 21*(6), 2825-2855.

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

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

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics, 104*(2), 228-250.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica, 55*, 703-705.

Novy-Marx, R. (2011). Operating leverage. *Review of Finance, 15*(1), 103-134.

Novy-Marx, R. (2012). Is momentum really momentum?. *Journal of Financial Economics, 103*(3), 429-453.

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

Opdyke, J. D. (2007). Comparing Sharpe ratios: so where are the p-values?. *Journal of Asset Management, 8*(5), 308-336.

Pástor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(3), 642-685.

Patel, J. B. (2016). The January effect anomaly reexamined in stock returns. *Journal of Applied Business Research, 32*(1), 317-324.

Penman, S. H., Richardson, S. A., & Tuna, I. (2007). The book-to-price effect in stock returns: accounting for leverage. *Journal of Accounting Research, 45*(2), 427-467.

Piotroski, J. D. (2000). Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research, 38*, 1-41.

Pontiff, J., & Woodgate, A. (2008). Share issuance and cross-sectional returns. *The Journal of Finance, 63*(2), 921-945.

Rachev, S., Jašic, T., Stoyanov, S., & Fabozzi, F. J. (2007). Momentum strategies based on reward-risk stock selection criteria. *Journal of Banking and Finance, 31*(8), 2325-2346.

Richardson, S. A., Sloan, R. G., Soliman, M. T., & Tuna, I. (2005). Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics, 39*(3), 437-485.

Rouwenhorst, K. G. (1998). International momentum strategies. *The Journal of Finance, 53*(1), 267-284.

Rouwenhorst, K. G. (1999). Local return factors and turnover in emerging stock markets. *The Journal of Finance, 54*(4), 1439-1464.

Rozeff, M. S., & Kinney, W. R., Jr. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics, 3*(4), 379-402.

Sagi, J. S., & Seasholes, M. S. (2007). Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics, 84*(2), 389-434.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance, 19*(3), 425-442.

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

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

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings?. *The Accounting Review, 71*(3), 289-315.

Soliman, M. T. (2008). The use of DuPont analysis by market participants. *The Accounting Review, 83*(3), 823-853.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics, 104*(2), 288-302.

Thomas, J. K., & Zhang, H. (2002). Inventory changes and future returns. *Review of Accounting Studies, 7*(2-3), 163-187.

Titman, S., Wei, K. C., & Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis, 39*(4), 677-700.

Xing, Y. (2008). Interpreting the value effect through the Q-theory: An empirical investigation. *The Review of Financial Studies, 21*(4), 1767-1795.

Zhang, X. F. (2006). Information uncertainty and stock returns. *The Journal of Finance, 61*(1), 105-137.