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Investor Sentiment and Risk-Managed Factor Momentum

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ABSTRACT:

This thesis studies how investor sentiment affects the performance of factor momentum. The purpose is to understand whether factor and factor momentum returns are driven by mispricing. Additionally, this thesis tests whether a target volatility—a measure of risk management—increases the performance of factor momentum portfolios. Testing the target volatility approach on factor momentum portfolios is motived by earlier studies that find benefits of risk management on price and industry momentum portfolios.

Factor momentum portfolios are constructed using a dataset of 11 U.S. equity factors. The portfolio weights for the risk-managed factor momentum are calculated using option-implied market volatility (VIX) as a proxy for the expected volatility. The overall sample period spans from July 1965 to December 2019, and from February 1990 through December 2019 for the risk-managed factor momentum portfolios. The performance of factor momentum portfolios is tested against multifactor and mispricing models.

Factor momentum portfolios that are formed with one-month lagged factor returns have statistically significant alpha against all considered asset pricing models. In contrast to previous studies, factor momentum returns are higher with a relative strength strategy than they are with a trend-following strategy. Furthermore, the results suggest that both winner- and loser-factor portfolios capture mispricing—the returns of recent winner factors are driven by positive earnings surprises while the returns of recent loser factors are driven by negative earnings surprises. Contrary to expectations, the long-minus-short factor momentum returns are not significantly affected by the contemporaneous investor sentiment. The returns of winner-factor portfolios are positively correlated with investor sentiment and significant in all sentiment stats. The returns of loser-factor portfolios are significantly positive following high investor sentiment and generally indistinguishable from zero following periods of low investor sentiment. Risk-managed factor momentum portfolios have statistically significant alpha against the unscaled portfolios.

The findings of this thesis suggest that factor and factor momentum returns are driven by mispricing that is more pronounced during periods of high investor sentiment. Betting against the recent loser factors increases the performance of factor momentum following periods of low investor sentiment but decreases the performance after periods of high investor sentiment. Buying recent winner factors is a profitable investment strategy regardless of the investor sentiment. Although factor momentum portfolios do not exhibit momentum crashes or optionality during bear market states, the performance of factor momentum portfolios can be increased using the target volatility approach and measure of option-implied market volatility.

KEYWORDS: factor momentum, investor sentiment, behavioral finance, VIX, mispricing

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Abbreviations

ETF	Exchange-traded fund
IPO	Initial public offering
NBER	The National Bureau of Economic Research
NYSE	The New York Stock Exchange
R&D	Research and development
ROE	Return on equity

1 Introduction

Price momentum is one of the most robust market anomalies, and it has generated statistically significant returns in U.S. equity markets for over 200 years (Geczy & Samonov, 2016). Momentum is also persistent in international equity markets, both in developed and emerging markets, and across all major asset classes, including currency markets and commodity futures (Asness, Moskowitz & Pedersen, 2013). Recent studies show that risk or mispricing factors exhibit momentum (e.g., Gupta & Kelly, 2019), and these factor momentum returns cannot be explained with common asset pricing models. Instead, a cross-sectional factor momentum explains industry momentum returns (Arnott, Clements, Kalesnik, & Linnainmaa, 2018), and a time-series factor momentum explains price momentum returns (Ehsani & Linnainmaa, 2019).

Factor momentum can be described as a strategy that bets on factor return continuation when a factor has high prior returns and against a factor when it has low or negative prior returns. These factors or anomalies are commonly used to capture either mispricing or risk in asset pricing models—depending on whether market efficiency is regarded as a theory or a fact. To the extent that factor returns stem from mispricing between different stock types, like value and growth or quality and junk stocks, the direction of mispricing is not relevant for a factor momentum investor in the same sense as it is for a factor investor. A factor momentum investor can capture the mispricing spread regardless of its direction if the mispricing continues in the short-term (Ehsani & Linnainmaa, 2019). The key is a positive short-term autocorrelation of long-short factor returns.

To the extent that factor returns are driven by mispricing, it is important to understand how investor sentiment affects mispricing and, fundamentally, the profitability of factor momentum. Because measures of risk management have proven to be effective for other momentum strategies (e.g., Barroso & Santa-Clara, 2015), this thesis tests whether option-implied market volatility, instead of realized volatility, increases the performance of factor momentum. The dataset consists of 11 factors that are widely studied in the academic literature and for which the return data is easily accessible. For these reasons, the empirical findings are comparable with studies that use the same data, and the results can be replicated with publicly available data. The included factors are asset growth, betting against beta, two measures of book-to-market, cash flow-to-price, dividend-to-price, earnings-to-price, momentum, operating profitability, quality minus junk and short-term reversals.

1.1 Previous research

The first academic research on the price momentum by Jegadeesh and Titman (1993) finds that the past 3- to 12-month stock returns can be used to achieve significantly positive returns on the following 3- to 12-month periods. In addition to past stock returns, cross-sectional momentum can be implemented using the information of earnings surprises (Chan, Jegadeesh, & Lakonishok, 1996), industry returns (Moskowitz & Grinblatt, 1999) and a measure of 52-week high price (George & Hwang, 2004). Factor momentum is studied in a recently published paper of Gupta and Kelly (2019) and in working papers of Arnott et al. (2018) and Ehsani and Linnainmaa (2019). These studies find that factor momentum outperforms and subsumes both the traditional momentum strategy of Jegadeesh and Titman (1993) and the industry momentum of Moskowitz and Grinblatt (1999).

Barroso and Santa-Clara (2015) find that the volatility of momentum portfolios is predictable and propose a strategy that keeps the volatility of a long-short momentum portfolio constant by scaling the portfolio with its past six-month realized trading volatility. Barroso and Santa-Clara show that the risk-managed momentum performs considerably better than the unscaled momentum strategy by avoiding momentum crashes. Moreira and Muir (2017) present a volatility managed strategy that scales the monthly portfolio returns with the inverse of previous month's realized portfolio variance. They find that the volatility-managed strategy increases the risk-adjusted performance of multiple factors, including momentum, by decreasing leverage during periods of high volatility and increasing leverage during periods of low volatility. Grobys, Ruotsalainen and Äijö (2018) show that the target volatility approach of Barroso and Santa-Clara (2015) increases the performance of industry momentum.

Stambaugh, Yu and Yuan (2012) find that long-short mispricing anomalies are more profitable after periods of high investor sentiment and that the profitability is driven by low short-side returns. Furthermore, Stambaugh et al. show that the long-side portfolio returns are not affected by investor sentiment, and they suggest that high investor sentiment leads to stronger overpricing of shorted assets and that this mispricing is not corrected due to short-sale restrictions.

Ehsani and Linnainmaa (2019) find that the high profitability of long-short anomalies in high sentiment causes factor momentum to be more profitable during periods of low investor sentiment. Factors with negative earnings on preceding year earn, on average, 0.35% per month during high investor sentiment and -0.22% per month during low investor sentiment. Because investor sentiment does not have a similar effect on factors with positive returns over the prior year, the monthly spread between winner and loser factors increases from 0.18 in high sentiment to 0.71 in low sentiment. However, Ehsani and Linnainmaa do not test how investor sentiment affects the cross-sectional factor momentum, but instead, they only consider the relation between 12-month lagged time-series factor momentum and investor sentiment.

1.2 Purpose of the study

This thesis studies how investor sentiment affects the performance of factor momentum with the purpose of understanding whether factor and factor momentum returns are driven by mispricing. Additionally, this thesis tests whether the target volatility approach together with option-implied market volatility increases the performance of factor momentum portfolios.

Ehsani and Linnainmaa (2019) suggest that factor momentum returns could be driven by mispricing because the performance of factor momentum is affected by investor sentiment. However, Ehsani and Linnainmaa do not test how investor sentiment affects cross-sectional factor momentum, but instead, they only consider the relation between 12-month lagged time-series factor momentum and investor sentiment. Arnott et al. (2018) suggest similarly that the returns could stem from mispricing, but Arnott et al. or Gupta and Kelly (2019) do not specifically address the source of factor momentum in their tests.

Since prior studies find some evidence of mispricing, further research is motivated to better understand the relation between factor momentum and mispricing in different investor sentiment states. This thesis aims to answer whether factor momentum returns stem from mispricing by first, testing how investor sentiment affects cross-sectional and time-series factor momentum returns, and second, whether the mispricing factors of Daniel and Hirshleifer (2019) can explain factor momentum returns. This thesis contributes to the studies on behavioral finance by extending the research on factor momentum and investor sentiment.

Testing the target volatility approach on factor momentum portfolios is motived by earlier studies that find benefits of risk management on price momentum (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016) and industry momentum (Grobys et al., 2018) portfolios. Additionally, Moreira and Muir (2017) show that different measures of expected volatility can be used to increase the performance of seven long-minus-short factor portfolios. So far, measures of risk management, such as target volatility or volatility timing, have not yet been tested on factor momentum portfolios. This thesis provides a novel contribution to momentum literature by testing whether option-implied market volatility can be used to increase the performance of factor momentum. Testing the benefits of target volatility with factor momentum portfolios also contributes to the literature of risk management which currently finds positive results with momentum portfolios but no benefits with the market portfolio (Liu, Tang, & Zhou, 2019).

I expect that the factor and factor momentum returns are dependent on investor sentiment. Based on the findings of previous studies, I expect that long-short factors are more profitable following periods of high investor sentiment and that factor momentum is inversely more profitable following periods of low investor sentiment. I also expect that the risk-managed factor momentum generates abnormal returns and increases the performance over unscaled factor momentum.

1.3 Structure of the thesis

The first chapter introduces the topic, research question and motivation for the study. Chapter two lays out the theoretical framework for a more detailed review of previous literature and empirical analysis, covering the theory of efficient markets, different asset pricing models, behavioral finance and the factors that are used in this study. Chapter three reviews previous studies on momentum investing and covers momentum crashes, risk-managed momentum strategies and possible explanations for the returns of momentum strategies. Chapter four concentrates on factor momentum and reviews the findings of recent studies. Chapter five describes the included data and the empirical methodology of this study. Furthermore, chapter five tests the performance of factor portfolios in detail to better understand the factor momentum strategy. Chapter six tests how the investor sentiment affects the performance of factor momentum and whether the risk-managed factor momentum increases performance over the unscaled factor momentum strategy. Chapter seven concludes the findings of this thesis.

2 Theoretical framework

In order to assess the relation between investor sentiment and factor momentum, and the performance of factors and factor momentum in general, it is necessary to start by reviewing the theoretical framework of financial markets. The theory provides the foundation for asset pricing models and helps to understand the possible limitations of this study. Furthermore, it is important to understand how behavioral biases can affect decision making and cause market prices to deviate from fundamental values.

2.1 Efficient market hypothesis

The purpose of financial markets is to allow efficient allocation of assets, which requires that the market prices reflect the information of both current and expected future performance (Bodie, Kane, & Marcus, 2012, pp. 6–11). This assumption of efficient price formation is also essential in financial theories, and it is formalized as the efficient market hypothesis (EMH). The EMH states that stock prices always fully reflect all available information (Fama, 1970). Another common assumption in financial theories is that the stock prices follow a random walk. The random walk model states that the consecutive price changes are independent and identically distributed (Fama, 1970). The randomness of consecutive price changes is an intuitive interpretation given that the stock prices react to new information that should be unpredictable and random to market participants (see, e.g., Bodie et al., 2012, p. 235).

The early studies on stock returns provide support for market efficiency and randomness of price changes. Fama (1970) divides the studies on market efficiency into three categories: weak form tests, semi-strong form tests, and strong form tests. Weak form tests consider whether the information of past stock prices can be used to forecast future returns. Semi-strong form tests study the adjustment of stock prices to all publicly available information, and strong form tests consider if stock prices adjust to monopolistic or private information. Fama concludes that weak form tests find only a little evidence against market efficiency, and tests of semi-strong form efficiency suggest that new information is incorporated to stock prices efficiently. The strong form category is intended to be only a benchmark for market efficiency, and Fama specifies that it is not realistic to expect stock prices to adjust to private information.

A later study on market efficiency by Fama (1991) uses the following categories: tests for return predictability, event studies and tests for private information. While these categories describe better the contents of studies on market efficiency, the categories of the 1970 study are still commonly regarded as the three forms of market efficiency. For example, Bodie et al. (2012, pp. 238–239) define that the efficient market hypotheses can be categorized as weak, semi-strong and strong form hypotheses. Fama (1991) notes that the efficient market hypothesis itself is not testable as studies on market efficiency require an asset pricing model. Testing the market efficiency jointly with an asset pricing model leads to a joint-hypothesis problem because abnormal returns can be a result of market inefficiency or bad modeling of market equilibrium. Therefore, it is not possible to conduct direct tests of the EMH and to prove markets efficient or inefficient.

Fama (1991) concludes that event studies provide the most reliable support for market efficiency as event studies on daily data are free of the joint-hypothesis problem and because the results of event studies mostly support market efficiency. Tests for return predictability are a more controversial problem, partly because cross-sectional studies are not direct tests of market efficiency, but also because more recent studies find evidence of return predictability. These studies are discussed in more detail in the following chapter. More recent tests for private information include, for example, Aboody and Lev (2000) for insider trading and R&D activities. Aboody and Lev find that insiders in firms with high R&D investments achieve higher returns than insiders in firms that do not have R&D activities. The authors suggest that R&D activities represent information asymmetry between insiders and external investors, and therefore insider information can be exploited to achieve higher returns.

2.2 Stock return predictability and stock market anomalies

The weak form of the EMH states that past returns cannot be used to predict future performance, and this hypothesis is supported by the earliest studies on stock returns. Although some studies find evidence of positive autocorrelations in individual stock returns, the autocorrelations are weak in terms of statistical significance and absolute values (Fama, 1970). The more recent and significant findings that contradict the weak form of market efficiency include contrarian and momentum strategies. De Bondt and Thaler (1985, 1987) find that a contrarian strategy consisting of a long position in prior long-term loser stocks and short position in prior long-term winner stocks generates positive returns on three- to five-year holding periods. Jegadeesh and Titman (1993) find that momentum portfolios, which short recent loser stocks and buy recent winner stocks, achieve positive returns on holding periods from 3 to 12 months.

Evidence against the semi-strong form of market efficiency is even more extensive, and academic studies have found hundreds of stock market anomalies that seem to predict abnormal returns, and which cannot be explained by prevailing theory. There is, however, some doubt that some or even a majority of these anomalies are a result of selection bias or data mining (e.g., Harvey, Liu, & Zhu, 2016). Hou, Xue and Zhang (2018) replicate 452 anomalies controlling for micro-cap stocks and find that 65% of all the anomalies fail to achieve statistically significant returns. Hou et al. suggest that the originally reported anomalies are driven by overweighting micro-cap stocks in the use of equal-weighted returns and are not in reality anomalies.

Even if an anomaly is not a result of data mining or selection bias, proving that it generates risk-adjusted returns is ambiguous. Anomalies can either be a result of market inefficiency, such as mispricing or alternatively an asset pricing model's incapability to measure the risk correctly (Fama, 1991). If the asset pricing model is incapable of measuring the risk correctly and the returns of anomalies are a result of a higher risk, then the returns of anomalies are consistent with the EMH. The alternative explanation is that stock prices do not correctly adjust to all information.

McLean and Pontiff (2016) find that anomaly returns tend to get weaker after being published in academic journals. They suggest that anomalies are a result of mispricing and that the mispricing becomes less pronounced or disappears after investors learn and exploit the inefficiency. McLean and Pontiff report that the anomaly returns are, on average, 58% lower after publication and 26% lower out-of-sample. The decline in post-publication returns is more substantial for anomalies that have high returns and high statistical significance in the sample period and for anomalies that are based on return and trading data only.

Perhaps the three best known and widely recognized stock market anomalies are size, value and momentum. The size effect refers to small firms' tendency to outperform large firms (Banz, 1981). Value anomaly means that value stocks have higher average returns than growth or glamour stocks (Lakonishok, Shleifer, & Robert, 1994). Empirically successful measures of value include a high book-to-market (B/M) ratio (Rosenberg, Reid, & Lanstein, 1985), high earnings-to-price (E/P) ratio (Basu, 1983) and high cash flow-to-price (CF/P) ratio (Chan, Hamao, & Lakonishok, 1991). The first study to find that small firms generate higher risk-adjusted returns than large firms is by Banz (1981). Covering the period of 1936–1977, Banz finds that the CAPM cannot explain the returns of the smallest stocks. Banz documents that the size effect appears to be strongest among the smallest firms, but unstable over a long investing period.

Rosenberg et al. (1985) find that a strategy that buys stocks with a high B/M ratio and sells stocks with a low B/M outperforms the S&P 500 index by 0.36% per month during January 1973–September 1984. Rosenberg et al. also find strong seasonality in the returns of B/M portfolios—the average returns are remarkably high in January, and indistinguishable from zero in December. Litzenberger and Ramaswamy (1979) find that the dividend yield (D/P) is a strong predictor of before tax expected returns. Kothari and Shanken (1997) find that both B/M and D/P ratios have a strong relation to expected returns over the sample period of 1926-1991.

Basu (1977, 1983) finds that portfolios consisting of high E/P stocks generate higher average returns with less systematic risk than portfolios of low E/P stocks. Basu uses sample periods of 1957–1971 and 1963–1979, and CAPM to measure the systematic risk. The differences in returns between high E/P and low E/P stocks are statistically significant for all NYSE-listed firms except for those with the largest market capitalizations (Basu, 1983). As an interpretation of the results, Basu suggested that either the CAPM is not a valid measure of risk or that the NYSE is not entirely efficient.

Chan et al. (1991) study how B/M, E/P, CF/P and size can predict stock returns in the Japanese stock market. Covering the period of 1971–1988, Chan et al. find that the B/M ratio is statistically the most significant return predictor out of the three ratios. While cash flow yield has significant predictive power on expected stock returns, the size is significant only in some of the models used. E/P is the least significant variable, and when combined with the B/M ratio, the explanatory power of earnings yield is statistically indistinguishable from zero.

Lakonishok et al. (1994) provide further evidence on the return predictability of B/M, E/P and CF/P ratios using U.S. market data with the sample period of 1963–1990. The results of Lakonishok et al. are similar to the results of Chan et al. (1991) in the Japanese market. All three ratios have a statistically significant explanatory power on the average returns, with cash flow yield having the highest explanatory power (Lakonishok et al., 1994). Their analysis of long-minus-short portfolios formed on B/M, E/P and CF/P show that value stocks outperform glamour stocks on holding periods of one to five years.

B/M, E/P and CF/P anomalies survive the out-of-sample replication of Hou et al. (2018). The monthly average returns to long-minus-short strategies are, however, smaller in the out-of-sample period from 1967 to 2016 than they are in the original samples. Dividend yield fails to generate statistically significant average returns in the same replication test. These findings of Hou et al. (2018) are consistent with the results of McLean and Pontiff (2016), who find that easy-to-replicate mispricing anomalies have lower returns after being published in academic journals.

2.3 Asset pricing models

As noted earlier, many of the early return predictors, such as earnings-to-price, were considered to be anomalies because the CAPM could not explain the returns. The CAPM is developed by Sharpe (1964) and Lintner (1965) to measure the relationship between risk and expected return. The CAPM of Sharpe (1964) and Lintner (1965) is expressed by Fama and French (2004) in the following form:[1]

$$E(R_i) = R_f + \left[E(R_m) - R_f\right]\beta_{iM}, \qquad (1)$$

where $E(R_i)$ is the expected rate of return for asset *i*, R_f is the risk-free interest rate and β_{iM} is the systematic risk (market beta) of asset *i*. The systematic market risk is measured as the correlation between the return of an asset *i* and the return of the overall market (Sharpe, 1964). Unsystematic risk can be diversified, and therefore investors require premium only for the stock-specific risk (Lintner, 1965).

The efficient market response to the abnormal risk-adjusted returns described earlier is that the beta of the CAPM is not a sufficient measure of risk. Fama and French (2004) provide support for this argument by studying the average returns and betas of portfolios sorted by the B/M ratio. Covering the period of 1963–2003, they find that there is no positive relationship between the annual average returns and the market betas as the CAPM fails to explain the average returns of portfolios with the highest B/M ratios. These findings of Fama and French (2004) are consistent with the findings of Basu (1977, 1983)—stocks with high B/M ratios and stocks with low P/E ratios generate higher returns than the CAPM predicts. Fama and French (2004) argue that the unrealistic assumptions of the CAPM are not a reason to reject the model as every model makes unrealistic assumptions, but the incapability of CAPM to measure the risk correctly invalidates it.

[1] The CAPM is expressed using the notation of Fama and French (2004) for consistency with the other asset pricing models.

Fama and French (1992) find that the CAPM beta alone is not a sufficient measure of risk, but measures of size, leverage, E/P and B/M can better explain the average stock returns. Furthermore, the combination of size and B/M absorbs the explanatory power of leverage and E/P. Fama and French suggest that stock risks are multidimensional, and when asset pricing is expected to be rational, size and B/M are proxies for risk. Based on the results of their 1992 study, Fama and French (1993) identify three stock market risk factors that can explain the average stock returns: size, value (B/M) and market factor. The value factor is motivated by the relationship between profitability and B/M ratio: firms with a high B/M ratio continuously have lower earnings on assets than firms with a low B/M ratio. Correspondingly, small firms generally have lower earnings on assets than big firms.

The three-factor model of Fama and French (1993) is based on their finding that size, value and market factors are able to explain the average stock returns. To mimic the return-related risk in size and value factors, Fama and French form value-weighted portfolios of stocks that are sorted independently into two size groups and three B/M groups. Fama and French use the NYSE median market cap as the size breakpoint, and the 30th and 70th percentiles of the NYSE B/M ratios as the B/M breakpoints. The size factor (SMB) captures the return spread between small-cap and big-cap stocks by being long on a portfolio of small stocks and short on a portfolio of big stocks (small-minus-big). Correspondingly, the value factor (HML) captures the return spread between high and low B/M portfolios (high-minus-low). The market factor $\left(R_M - R_f\right)$ measures the market portfolio's (R_m) excess return over the risk-free rate (R_f), similar to the CAPM. The three-factor model can then be expressed in the following form:

$$R_i - R_f = \alpha_i + b_i\left(R_M - R_f\right) + s_i SMB + h_i HML + \varepsilon_i, \qquad (2)$$

where the coefficients b_i, s_i and h_i measure the asset's sensitiveness to market, size and value factors (Fama & French, 1996). Fama and French show that the three-factor model explains the average returns of portfolios formed on E/P, CF/P and sales growth ratios.

Carhart (1997) expands the three-factor model with a one-year momentum factor because Fama and French (1996) find that the three-factor model is unable to explain momentum returns. Carhart (1997) defines the momentum factor as the spread between an equal-weighted winner portfolio and an equal-weighted loser portfolio. The winner portfolio includes the highest 30% and loser portfolio the lowest 30% of stocks sorted by their prior 11-month returns. Carhart uses the four-factor model to explain the performance of mutual funds and finds that the four-factor model reduces pricing errors of the CAPM and the three-factor model.

A five-factor model of Fama and French (2015) extends the three-factor model with profitability and investment factors. Robust minus weak (RMW) measures the return spread between high and low profitability firms, and conservative minus aggressive (CMA) measures the return spread between low and high investment firms. The five-factor model is expressed as an extension of the three-factor model in the following form:

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it}, \quad (3)$$

where r_i and c_i measure the asset's sensitiveness to factors RMW and CMA (Fama & French, 2015). Fama and French show that the five-factor model captures the average returns of portfolios formed on size, B/M, profitability and investment better than the three-factor model. However, the five-factor model fails to capture the low average returns of small stocks with high investment rates and low profitability. They also note that the value factor (HML) turns out to be redundant for describing the average returns because the other four factors capture the value premium. Fama and French (2016) provide further evidence that the five-factor model can explain some of the anomalies that the three-factor model cannot explain. When the test assets include portfolios sorted on size together with a market beta, net share issues or volatility, the five-factor model intercepts are on average smaller than they are for the three-factor model. However, the five-factor model does not increase explanatory power over the three-factor model when portfolios are formed on size and accruals or size and momentum.

A six-factor model of Fama and French (2018) extends the five-factor model with a momentum factor (UMD), similar to the Carhart (1997) four-factor model. Fama and French (2018) define the six-factor model in the following form:

$$R_{it} - R_{ft} = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t \\ + r_i RMW_t + c_i CMA_t + m_i UMD_t + \varepsilon_{it}, \tag{4}$$

where MKT is the excess market return and m_i measures the sensitiveness to the UMD factor. The resulting six-factor model increases explanatory power over the five-factor model (Fama & French, 2018). However, Fama and French note that they have been, and still are, reluctant to include factors such as momentum that lack theoretical motivation but have robust performance.

Daniel and Hirshleifer (2019) propose a three-factor asset pricing model that is intended to capture both short- and long-term mispricing. Their model includes a market factor, similar to the CAPM, financing factor (FIN) to capture long-term mispricing and post-earnings announcement drift (PEAD) factor to capture short-term mispricing. The financing factor captures the return spread between firms that issue new shares and firms that purchase their own shares. Daniel and Hirshleifer explain that the financing factor is motivated by firms' incentives to exploit long-term mispricing by either issuing new shares or by repurchasing their own shares. The PEAD factor captures the return spread between firms that have positive earnings surprises and firms that have negative earnings surprises. Including the PEAD factor is motivated by previous studies that find market underreactions to earnings announcements.

Daniel and Hirshleifer (2019) find that their three-factor model explains well both short- and long-term anomalies. They test the model with 34 anomalies, of which three have statistically significant alphas on their three-factor model, whereas 18 anomalies have statistically significant alphas on the five-factor model of Fama and French (2015).

2.4 Behavioral finance

The theory of efficient markets assumes that market prices reflect all available information and adjust efficiently to new information. Numerous studies on behavioral finance have questioned this theory of market efficiency—large market price deviations from fundamental values or the previously discussed anomalies, among others, are difficult to reconcile with the efficient market theory or rationally behaving investors. While the modern finance theories are built on market efficiency and rational investors, behavioral finance seeks to explain how psychological biases affect the decision making and behavior of market participants (De Bondt, Muradoglu, Shefrin, & Staikouras, 2008).

Much of the early research on behavioral finance is motivated by anomalies that seem to predict future performance using the information of past returns (e.g., De Bondt & Thaler, 1985) or ratios of accounting information to the market price (e.g., Lakonishok et al., 1994). Market reactions to earnings-related announcements have also been studied extensively, and the evidence suggests that stock prices do not adjust efficiently to new information. Ball and Brown (1968) find that stock returns exhibit positive drifts after positive earnings announcements and negative drifts after negative earnings announcements. Sloan (1996) finds that stock prices do not adjust efficiently to information about future earnings because investors fail to distinguish the difference between accrual and cash flow components of the reported earnings. As a result, firms with low levels of accruals earn abnormally high returns, and firms with high accruals earn abnormally low returns around subsequent earnings announcements.

Hirshleifer, Lim and Teoh (2011) suggest that investors pay limited attention to earnings-related news—some investors are likely to neglect the information of the latest earnings surprise, and some are likely to neglect the information of accruals and cash flows. Their model of misreactions states that stock prices underreact to earnings surprises and overreact to accruals relative to cash flows. Hirshleifer et al. suggest that the underreaction to earnings surprises explains post-earnings announcement drifts, and overreaction to accruals relative to cash flows explains cash flow and accruals anomalies.

Studies by Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) attempt to model both long-term return reversals and short-term return continuation by explaining how investors under- and overreact to new information. Barberis et al. (1998) use conservatism and representativeness heuristics to explain how investors interpret earnings announcements. They suggest that investors underreact to earnings announcements and overreact to both positive and negative series of recurring events. Conservatism causes investors to neglect the importance of new information, and therefore, investors are likely to underreact to new information. Representativeness, on the other hand, can cause investors to interpret a series of past events as a representative of a future trend and thus overreact to a seeming trend.

Daniel et al. (1998) explain investors' misreactions using overconfidence and self-attribution biases. They suggest that overly confident investors overestimate the value of their private information, such as an analysis of a financial statement, and underestimate their forecast errors. The biased self-attribution further strengthens the overconfidence if public information confirms the earlier private information. Because public information that contradicts the private information does not decrease investors' confidence as much as confirming information rises it, the overconfidence is generally increased after new information releases. Daniel et al. conclude that investors are likely to overreact to private information and underreact to public information.

The model of Barberis et al. (1998) assumes that the earnings follow a random walk, but investors are not aware of it. If investors expect a future announcement to be positive after a series of positive announcements, a positive announcement does not significantly impact the market price as the outcome is as predicted. However, a negative announcement would have a significantly negative impact on the market price as the outcome would surprise investors. The opposite is true when investors expect a negative announcement. Barberis et al. explain that the overreaction can, therefore, be observed either as a negative average return after a series of positive announcements or as a positive average return after a series of negative announcements.

While the models of Daniel et al. (1998) and Barberis et al. (1998) focus on the behavior of individual investors, Hong and Stein (1999) attempt to model the interaction of two groups of investors: the first group of investors tends to underreact to new information, and the second group of investors seeks to exploit the underreaction by arbitrage. Hong and Stein assume that the new information is private—or at least requires private information to be analyzed—and that the information spreads gradually among the first group of investors. Another condition of the model is that the arbitrageurs are limited to use the information about past prices only. Hong and Stein explain that together the conditions imply that the first arbitrageurs can exploit the initial underreaction and continue to profit in the "momentum cycle", but without complete information of the current fundamental value, the later arbitrageurs cause overreaction as the market price of a stock exceeds its fundamental value (1999, p. 2145).

In addition to behavioral biases, an important aspect of behavioral finance is limits to arbitrage. The limits to arbitrage describe the barriers that prevent arbitrageurs from eliminating inefficiencies in market prices. De Long, Shleifer, Summers and Waldmann (1990) argue that "noise traders" cause market prices to deviate from their fundamental values and that arbitrageurs cannot eliminate the mispricing because noise traders are unpredictable. Because market prices can deviate even further from their fundamental values, eliminating the mispricing is both risky and costly in the short-term.

In a similar vein, Shleifer and Vishny (1997, p. 35) argue that realistic arbitrage opportunities are risky and require capital, unlike the "textbook" definition of arbitrage, which describes arbitrage as a risk-free opportunity to exploit mispricing. Shleifer and Vishny suggest that individual investors have generally limited resources and knowledge to exploit mispricing, and fund managers are likely to avoid the most profitable but volatile arbitrage opportunities in a fear of short-run price risk. If the mispricing deepens in the short-run, portfolio managers might not have enough liquidity to hold the position due to increasing capital requirements and fear of capital withdraws. The mispricing is further increased if the investors are required to liquidate their positions.

2.5 Investor sentiment

Investor sentiment describes how investors perceive the prevailing market state or how investors are expecting the market to develop in the near future. Barberis et al. (1998) and Daniel et al. (1998) model how behavioral biases, such as representativeness and overconfidence, cause mispricing and affect the investor sentiment. Baker and Wurgler (2006) find that the expected investor sentiment affects the cross-section of stock returns. When the investor sentiment is expected to be low, the returns are on average higher for high volatility stocks, unprofitable stocks, stocks that do not pay dividends and for recently listed companies, than they are for low volatility stocks, profitable stocks, stocks that pay dividends or more mature stocks. These patterns reverse when the sentiment is expected to be high. The returns to small stocks are notably higher than for large stocks during a low investor sentiment, but the size effect does not exist during high sentiment.

Baker and Wurgler (2006) measure the investor sentiment with six proxies: the NYSE total turnover, discount on closed-end funds, dividend premium, equity share in new equity issues, the number and average first-day returns on IPOs. The investor sentiment index is obtained by regressing each proxy on growth in industrial production, growth in consumer durables, nondurables and services, and on an NBER recession dummy, and then taking the first principal components of the regression residual series. The orthogonalization is done to capture only the variation in investor sentiment that is not due to normal business cycle variation.

As the findings of Baker and Wurgler (2006) show, companies that are the most affected by the investor sentiment are those that are difficult to value. Baker and Wurgler (2006, p. 1648) suggest that if investor sentiment is defined as “the propensity to speculate,” then high investor sentiment increases the demand for speculative stocks, and low investor sentiment decreases it. Higher demand for speculative stocks lowers their expected returns in high investor sentiment, and correspondingly lower demand in low sentiment increases the expected returns. Speculative stocks are also harder to arbitrage due to the limitations pointed by De Long et al. (1990) and Shleifer and Vishny (1997). In contrast, Baker and Wurgler (2007, p. 132) suggest that “bond-like” stocks that are easy to value—i.e., stocks that have tangible assets and long earnings history—and easy to arbitrage are not similarly subject to investor sentiment. By studying the average returns following months of high and low investor sentiment states, Baker and Wurgler (2007) show that speculative stocks have higher average returns than bond-like stocks following months of low investor sentiment and lower average returns following months of high investor sentiment. This suggests finding that speculative stocks become overvalued in high sentiment and earn lower average returns subsequently in the following month.

2.6 Additional factors

So far, this chapter has presented B/M, E/P, CF/P and D/P anomalies in addition to momentum and short-term reversal anomalies. Technically, if B/M, E/P, CF/P and D/P ratios are proxies for risk—rather than for mispricing—as suggested by Fama and French (1993, 2004), then these ratios are not anomalies, but instead risk factors. For consistency, the remaining of this thesis refers to all long-minus-short strategies as factors regardless of whether they capture mispricing or risk. The remaining of this chapter reviews asset growth, operating profitability, betting against beta, quality minus junk and a refined value factor.

Cooper, Gulen and Schill (2008) find that asset growth rates, measured as the annual changes in total assets, have a strong predictive power on future stock returns. The correlation between a firm’s asset growth and its subsequent market return is negative and statistically significant. Firms with the lowest asset growth rates earn abnormally high returns, and firms with the highest asset growth rates earn abnormally low returns. Cooper et al. rank stocks annually to ten decile portfolios based on their asset growth rates from the end of year *t*-2 to the end of year *t*-1. The monthly average return to buying the bottom decile and selling the top decile, rebalancing the portfolio annually, is 1.73% using equal-weighted portfolios and 1.05% using value-weighted portfolios.

Novy-Marx (2013) finds that profitable firms have significantly higher average returns than unprofitable firms. Novy-Marx measures the profitability using a ratio of gross profits-to-assets, where gross profits are defined as the total revenue minus cost of goods sold. The gross profitability has a similar explanatory power on the cross-section of average returns as the B/M ratio. The portfolios that are formed on gross profits-to-assets have both value and growth characteristics because profitable firms have low B/M ratios, and unprofitable firms have high B/M ratios. Novy-Marx suggests that the measure of gross profitability is best combined with value strategies because value and gross profitability are negatively correlated. Sorting stocks on both value and gross profitability results in a strategy that buys profitable value firms and sells unprofitable growth firms. The volatility of the combined value and gross profitability strategy is lower than for standalone strategies.

Fama and French (2015) adapt profitability in their five-factor model using operating profitability (OP), which is defined as the revenue minus cost of goods sold, minus selling, general and administrative expenses, minus interest expense and divided by book equity. The investment factor in the five-factor model is identical to the asset growth of Cooper et al. (2008) as both factors measure the change in total assets from the end of year t-2 to the end of year t-1.

Frazzini and Pedersen (2014) introduce a betting against beta (BAB) strategy that buys low beta stocks and sells high beta stocks. Because both individual and institutional investors are commonly subject to leverage and margin constraints, Frazzini and Pedersen suggest that investors overweight high-beta stocks, which in turn lowers their expected returns in comparison to low-beta stocks. The BAB strategy is constructed by buying low-beta stocks and then leveraging the total beta of the long position to one and selling high-beta stocks and then de-levering the total beta of the short position to one. The resulting strategy is a zero-cost strategy and has a beta of zero.

Asness and Frazzini (2013) suggest that a monthly rebalanced HML factor (HML_D), which uses the current market value of equity, is a better proxy for value than the one proposed by Fama and French (1992). Fama and French construct and rebalance the HML factor annually at the end of June and use six months lagged information of book equity and market value to ensure that the accounting information for a fiscal year preceding the portfolio construction would have been publicly available at the time. The HML factor is therefore based on information that is always at least six months old, and just before the next rebalancing, the information is 18 months old. Asness and Frazzini (2013) find that rebalancing the HML factor monthly and using the contemporaneous market value of equity yields a better proxy for the actual ex-post B/M ratio. The monthly updated measure of value also outperforms the annually updated factor when used together with momentum.

Asness, Frazzini and Pedersen (2019) find that high-quality stocks, defined in terms of high profitability, high prior growth and safety, generate on average higher risk-adjusted returns than low-quality stocks with the opposite characteristics. The authors measure quality using a composite score of profitability, growth and safety. Asness et al. follow the methodology of Asness and Frazzini (2013), and sort stocks first on size and then on quality. The quality minus junk (QMJ) factor return is obtained by subtracting the average return of two low-quality portfolios from the average return of two high-quality portfolios.

Asness et al. (2019) do not find any evidence of quality stocks bearing higher risk than junk stocks. The quality stocks have low market betas, and they tend to perform well in market downturns when investors prefer quality over uncertainty. The authors find that analysts' target prices are higher for high-quality stocks than they are for low-quality stocks, but the analysts tend to underestimate the return potential of high-quality stocks. Asness et al. conclude that quality stocks outperform junk stocks either because quality stocks are underpriced and junk stocks overpriced, or because quality stocks are exposed to an unknown risk factor.

3 Momentum strategies

The first research on momentum strategy by Jegadeesh and Titman (1993) finds that the past 3- to 12-month stock returns predict return continuation for the following 3- to 12-month period—recent winners keep winning and recent losers keep losing more. Earlier studies on stock return predictability had found evidence of return reversals on periods of one week (Lehmann, 1990) to one month (Jegadeesh, 1990), and on periods of 3 to 5 years (De Bondt & Thaler, 1985, 1987). Together the findings suggest that extreme past returns are positively correlated with future returns on 3- to 12-month periods but negatively correlated on periods shorter than a month and longer than a year.

Jegadeesh and Titman (1993) construct their winner and loser portfolios by ranking stocks monthly in ascending order based on their past 3-, 6-, 9- or 12-month returns and then dividing the stocks into ten equally weighted decile portfolios. Their strategy takes a short position in the loser portfolio (top decile) and a long position in the winner portfolio, resulting in a zero-cost momentum strategy. Jegadeesh and Titman consider both a strategy that forms portfolios immediately at the end of the formation period and an alternative strategy which forms portfolios one week after the past returns have been measured. Skipping a week between the formation and holding periods is motivated by the findings of Jegadeesh (1990) and Lehmann (1990)—bid-ask bounce and illiquidity might cause negative autocorrelation on a short-term.

The monthly average returns to winner-minus-loser (WML) portfolios on 3-, 6-, 9- and 12-month holding periods are positive for all combinations during the sample period of 1965-1989 (Jegadeesh & Titman, 1993). The returns are statistically significant for all combinations except for a strategy that is formed on 3-month lagged returns and then held for three months without skipping a week in-between. The returns are, on average, slightly higher for portfolios that are formed one week after the holding period. The highest monthly average return of 1.49% (with t-statistic of 4.28) is achieved with 12-month lagged returns and 3-month holding period, and by skipping a week between the formation and holding periods.

Jegadeesh and Titman (1993) also note that the average returns to their relative strength strategy turn negative one year after the portfolio formation and continue to be negative for the whole second year. The negative returns are not statistically significant, but the cumulative returns to a 6-month-6-month WML strategy decrease from 9.51% at the end of the first year to 5.56% at the end of the second year. Since Jegadeesh and Titman find robust returns to a zero-cost strategy that uses the information of past returns only, much of the early research on momentum focus on explaining the reason for momentum returns and testing the strategy out-of-sample to account for the possibility of data mining. The strategy is tested out-of-sample also by Jegadeesh and Titman (2001) with similar results to their 1993 study. Covering the period of 1965–1998, Jegadeesh and Titman find statistically significant momentum premia of about one percent per month.

The continuation of past extreme returns is not specific to the United States and equity markets only as momentum returns appear to be robust internationally and across asset classes. Rouwenhorst (1998) finds statistically significant momentum premia in individual stocks of 12 European countries during 1980–1995. Asness et al. (2013) find similarly significant momentum premia in individual European stocks during 1974-2011 and in U.K. stocks during 1972–2011. The results are similar, although weaker in terms of average returns, for 20 emerging countries as one universe (Rouwenhorst, 1999). A remarkable exception is Japan, where momentum has not been found to generate statistically significant returns (Asness et al., 2013; Fama & French, 2012).

Asness, Liew and Stevens (1997) find that international country equity indices generate momentum returns that are similar to the momentum returns of U.S. stocks. Similarly, Chan, Hameed and Tong (2000) find significant momentum in international country equity indices on periods of 1 to 26 weeks. The evidence of momentum returns outside equity markets includes Asness et al. (2013) for commodities, Menkhoff, Sarno, Schmeling and Schrimpf (2012) for currencies and Liu and Tsyvinski (2018) for cryptocurrencies.

In addition to past returns, academic studies have found multiple other measures that can be used to predict short-term return continuation and to explain the momentum returns. Chan et al. (1996) find that significant earnings surprises predict stock return continuation—a positive surprise predicts positive abnormal returns, and a negative surprise predicts negative abnormal returns for the subsequent six months after the portfolio formation. Moskowitz and Grinblatt (1999) suggest that industry components can explain the excess returns of price momentum. George and Hwang (2004) propose that the information of a 52-week high price explains the returns of price momentum portfolios.

Chan et al. (1996) find three measures of earnings surprises that can be used to capture earnings momentum: standardized unexpected earnings, cumulative abnormal stock returns around the previous earnings announcement day and changes in analysts' earnings forecasts. When momentum portfolios are formed using any of these three measures, the spreads between winner and loser portfolios are positive for 6- and 12-month holding periods. The average 6-month earnings momentum returns vary between 5.9% and 7.7%, and 12-month returns between 7.5% and 9.7%. In contrast, Chan et al. report the average price momentum returns to be 8.8% and 15.4%, respectively. Although earnings momentum portfolios have lower average returns than price momentum portfolios, each of the momentum strategies has predictive power that cannot be explained by the other strategies. The findings of Chan et al. suggest that each of these strategies is, at least partly, driven by different market inefficiency or risk factor.

Moskowitz and Grinblatt (1999) form industry momentum portfolios by allocating individual stocks to 20 value-weighted portfolios based on their industry. They sort the portfolios monthly on past 1- to 6-month industry returns to form a zero-cost strategy that buys the top three industries and sells the bottom three industries. Moskowitz and Grinblatt report the monthly industry momentum returns for 1- to 36-month holding periods, and find that the performance of industry momentum differs from the performance of stock price momentum.

First, Moskowitz and Grinblatt (1999) note that the industry momentum achieves its highest monthly average return of 1.05% (with t-statistic of 5.63) when the portfolios are formed using one-month lagged returns and held for one month. The monthly average return decreases to 0.43% (with t-statistic of 4.24) when the formation and holding periods are extended to six months. The decrease in long-short returns is mainly driven by the decreasing profitability of winner portfolios. Moskowitz and Grinblatt find that the profitability of winner portfolios decreases when the holding periods are extended, but the loser portfolios become more profitable on longer holding periods. In comparison, the profitability of individual stock momentum is mainly explained by selling loser stocks.

Second, Moskowitz and Grinblatt (1999) find that industry momentum can explain price momentum almost entirely. When the 6-6 price momentum strategy is adjusted for industry returns, its monthly average returns decrease from 0.43% to 0.13%, and the significance level drops from 4.65 to 2.04. Cross-sectional regression analysis provides similar results—Moskowitz and Grinblatt find that industry momentum subsumes individual stock momentum when the formation period is six months and holding period one or six months. However, industry momentum does not completely explain stock price momentum when the portfolios are formed on 12-month lagged returns and held for one month.

The 52-week high momentum of George and Hwang (2004) is based on the information of individual stocks' nearness to 52-week high price, and the authors find that their strategy provides superior returns in comparison to momentum strategies that are formed on past returns. At the beginning of each month, George and Hwang sort all included stocks on a ratio of current price to 52-week high price. The 30% of stocks with the highest ratio are assigned to the winner portfolio and the bottom 30% to the loser portfolio. George and Hwang also form portfolios on past stock returns and past industry returns to test the explanatory power of their 52-week high price against other momentum strategies.

The zero-cost portfolio returns of George and Hwang (2004) are similar to the ones obtained by Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999). The monthly average returns on a 12-month holding period are 1.07% when the portfolios are formed on past 6-month stock returns and 0.50% when formed on industry returns. The corresponding return for 52-week high momentum is 1.23%. George and Hwang (2004) compare the three strategies simultaneously by regressing the returns of individual stocks on dummy variables for each momentum strategy, and on control variables for size and possible bid-ask bounce effects. The regressions results suggest that the 52-week high momentum strategy yields over twice as large returns as price or industry momentum strategies after controlling for size and bid-ask spread.

The momentum strategies reviewed above are cross-sectional strategies that measure the relative performance of an asset against other assets. An alternative, trend-following, or time-series momentum strategy was first proposed by Moskowitz, Ooi and Pedersen (2012). The time-series momentum is built on a finding that the past 12-month abnormal return of a security will predict a positive trend that lasts up to a year. The difference between cross-sectional and time-series momentum strategies is in how the past performance is measured. Cross-sectional strategies measure the relative performance of an asset against other assets. In contrast, time-series strategies measure the absolute performance of an asset, meaning the asset's own trend (Moskowitz et al., 2012).

Moskowitz et al. (2012) find positive time-series momentum in bond, commodity, currency and equity index futures across international and U.S. markets. Georgopoulou and Wang (2017) find that the time-series momentum generates robust and positive abnormal returns across asset classes in both developed and emerging markets. The trend-following momentum returns are higher in emerging markets but more robust to different formation and holding periods in developed markets. Hurst, Ooi and Pedersen (2017) find results that are similar to Moskowitz et al. (2012) by studying the performance of time-series momentum from 1880 to 2016 on global futures contracts.

3.1 Momentum crashes

Notwithstanding the superior performance of momentum, the cross-sectional long-minus-short strategy suffers extreme negative returns, momentum crashes, after sharp market downturns. Following the financial crisis of 2008, the momentum strategy lost 73.42% of its value within three months in 2009, when the stock market started to recover (Barroso & Santa-Clara, 2015). Daniel and Moskowitz (2016) find that the extreme drawdowns of zero-cost momentum portfolios are clustered, and these momentum crashes occur after a long market decline when market prices have reached the bottom and start to recover. The market recovery is mainly driven by stocks with the worst recent returns, and as momentum strategies short these same stocks, the strong market recovery results in a momentum crash. After long periods of highly volatile and declining equity markets, the largest negative monthly returns of momentum portfolios exceed the cumulative prior two-year losses of the overall stock market. For example, in April 2009, the cumulative prior two-year stock market return was -40.62%, and the stock market was recovering with a monthly return of 10.20%, but the long-short momentum experienced a loss of -45.52% (Daniel & Moskowitz, 2016).

The long-run performance of the momentum factor is remarkably different from value, size and market factors. Barroso and Santa-Clara (2015) find that during the period 1927–2011, momentum has the worst one-month drawdown (-78.96%), highest annualized mean excess return (14.46%), highest annualized standard deviation (27.53%) and highest Sharpe ratio (0.53) in comparison to the other factors. Momentum is the only factor that has a negatively skewed (-2.47) return distribution, and together with a high kurtosis (18.24) the return distribution clearly shows the left tail risk of momentum strategy. The value factor, for example, has a skewness of 1.84 with kurtosis of 15.63, but it also has a significantly lower annualized mean excess return (4.50%). The value factor has a far less negative worst 1-month return (-13.45%), lower standard deviation (18.96%) and lower Sharpe ratio (0.36) than the momentum factor. After controlling for market, size and value factors, momentum has significantly negative loadings on all three factors and a monthly alpha of 1.75% (Barroso & Santa-Clara, 2015).

Instead of focusing on absolute returns, an alternative approach to assess momentum crashes is to study how the betas of momentum portfolios vary over time. Grundy and Martin (2001) find that momentum portfolios have negative betas when the portfolio formation period includes bear markets. The winner-minus-loser strategy is long low-beta stocks and short high-beta stocks, thus resulting in negative portfolio betas. The opposite is true when the formation period includes bull markets, and the WML strategy is long high-beta stocks and short low-beta stocks. Daniel and Moskowitz (2016) estimate the WML betas during a bear market to be -0.74 when the contemporaneous market return is negative, and -1.79 when the market return is positive.[2] The corresponding bear market beta estimates for the loser portfolio are 1.56 during the up-market and 2.16 during the down-market.

Daniel and Moskowitz (2016) note that the asymmetry of up-market and down-market betas following bear markets cause the WML momentum portfolios to behave like a short call option on the market. After a bear market, the payoffs for both cross-sectional momentum and written call option on the market are small and positive when the market keeps declining, but large and negative when the market starts to recover. This option-like behavior of momentum is only present after bear markets.

3.2 Risk-managed momentum

The disastrously large negative returns of momentum crashes have motivated researches to invent and test different measures for hedging momentum portfolios against the market risk. Based on their finding that momentum has a time-varying factor exposure, Grundy and Martin (2001) argue that this market risk can be hedged by removing momentum's exposure to market and size factors. Grundy and Martin estimate the factor exposures using realized returns, meaning that their strategy is not implementable ex-ante. The benefits of this strategy are still unambiguous, as hedging

[2] Daniel and Moskowitz (2016, p. 226) define a bear market as a period when the cumulative prior two-year market return is negative.

the exposure to size and market factors removes 78.6% of the monthly return variance while still increasing the average monthly return from 0.44% (with t-statistic of 1.83) to 1.34% (with t-statistic of 12.11) (Grundy & Martin, 2001). Grundy and Martin find that the better performance of the hedged momentum strategy is mainly due to removing the strategy's bet against size effect in January. Momentum's weak performance in January is also documented by Jegadeesh and Titman (2001), who find that the average return in January is -1.55% and 1.48% in other months.

Barroso and Santa-Clara (2015) find that the volatility of momentum portfolios is predictable, and propose a momentum strategy that keeps the volatility of a long-short momentum portfolio constant by scaling the portfolio with its past six-month realized trading volatility. Because the strategy uses only ex-ante realized volatility, it is implementable, unlike the strategy proposed by Grundy and Martin (2001). Barroso and Santa-Clara (2015, p. 115) estimate the monthly variance forecast from past six-month returns using the following model:

$$\hat{\sigma}^2_{WML,t} = \frac{21\sum_{j=0}^{125} r^2_{WML,d_{t-1}-j}}{126}, \tag{5}$$

where $\hat{\sigma}^2_t$ denotes the estimated variance of the WML portfolio for the next month, $\{r_{WML,d}\}_{d=1}^{D}$ indicates the daily momentum returns and $\{d_t\}_{t=1}^{T}$ the time series of each month's last trading dates. The scaled WML return, $r_{WML^*,t}$, in month *t* is then obtained by scaling the WML return with the forecasted variance:

$$r_{WML^*,t} = \frac{12\%}{\hat{\sigma}_t} r_{WML,t}, \tag{6}$$

where $r_{WML,t}$ denotes the unscaled momentum return of the WML portfolio in month t, and 12% is the targeted annualized volatility (Barroso & Santa-Clara, 2015, p. 115). The resulting strategy is a zero-cost portfolio that allows the weights on winner and loser portfolios to be different from one.

Similarly to Barroso and Santa-Clara (2015), also Daniel and Moskowitz (2016) suggest that the volatility of momentum portfolios can be forecasted to avoid momentum crashes. Daniel and Moskowitz propose a dynamic momentum strategy that uses the forecasted return and variance of the WML portfolio to estimate a dynamic weight for scaling the momentum portfolio. Daniel and Moskowitz (2016, p. 233) estimate the dynamic weight w* on the WML portfolio at time t-1 using the following equation:

$$w_{t-1}^{*} = \left(\frac{1}{2\lambda}\right)\frac{\mu_{t-1}}{\sigma_{t-1}^{2}}, \tag{7}$$

where μ_{t-1} and σ_{t-1}^{2} are the conditional expected return and the conditional variance, respectively, of the WML portfolio for the next month and λ is a time-invariant scaling factor for the unconditional risk and return of the dynamic momentum portfolio. Daniel and Moskowitz (2016) regress the WML returns on a bear market indicator variable and on the preceding 6-month market variance, and use the interaction between the explanatory variables of the fitted regression as a proxy for the conditional expected mean return of the WML portfolio. The estimate for conditional variance is obtained from a generalized autoregressive conditional heteroskedasticity (GARCH) model.

Both Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) show that the risk-managed momentum portfolios perform considerably better than the plain momentum portfolios. Daniel and Moskowitz also show that the dynamic momentum strategy performs well in international markets and across different asset classes. While the model of Barroso and Santa-Clara (2015) keeps the volatility of the WML portfolio constant by scaling the portfolio leverage, Daniel and Moskowitz (2016) allow the volatility to vary and scale the leverage based on the forecasted volatility and the mean return of the WML portfolio. Both models decrease leverage when the volatility is forecasted to be high and increase leverage when the volatility is forecasted to be low. The two models result in notably different strategies in terms of leverage and trading costs. As Daniel and Moskowitz (2016) note, the dynamic strategy requires significantly higher leverage but also negative portfolio weights at the times when the WML return is expected to be negative. Barroso and Santa-Clara (2015) disclose that the scaling factor for their strategy varies between 0.13 and 2.00 during 1927–2011, while Daniel and Moskowitz (2016) report that the weights for their strategy vary between -0.60 and 5.37 during 1927–2013. Barroso and Santa-Clara (2015) estimate the transaction costs to be similar for both constant volatility momentum and unscaled WML momentum, but Daniel and Moskowitz (2016) note that the transaction costs for their dynamic momentum strategy are higher than for the two other strategies.

Geczy and Samonov (2016) confirm that during 1926–2012, the constant volatility of Barroso and Santa-Clara (2015) and the dynamic weights of Daniel and Moskowitz (2016) yield higher monthly returns than equally-weighted cross-sectional momentum. However, Geczy and Samonov (2016) find that these risk-managed momentum strategies perform worse than non-managed strategy in the out-of-sample period of 1802–1926. The results are not directly comparable as Geczy and Samonov need to estimate the standard deviation using 10-month rolling returns due to a lack of daily returns for the out-of-sample period.

Moreira and Muir (2017) suggest a volatility-managed strategy that scales the monthly portfolio return by the inverse of the portfolio's realized variance in the previous month. The volatility-managed strategy is not targeted to increase the performance of momentum only, but instead, Moreira and Muir test the strategy's performance on multiple factors, including momentum, value and market portfolios. Moreira and Muir (2017, p. 1616) express the volatility-managed portfolio (f_{t+1}^{σ}) in the following form:

$$f_{t+1}^{\sigma} = \frac{c}{\hat{\sigma}_t^2(f)} f_{t+1}, \tag{8}$$

where f_{t+1} is the excess return for factor f, $\hat{\sigma}_t^2(f)$ is the proxy for the factor's conditional variance, and c is a constant for controlling the factor's exposure. Moreira and Muir set the constant so that both the volatility-managed and the non-managed factor have the same unconditional standard deviation. To simplify the construction of the volatility-managed portfolio, Moreira and Muir (2017, p. 1616) use the preceding month's realized variance (RV_t^2) as a proxy for the factor's conditional variance:

$$\hat{\sigma}_t^2(f) = RV_t^2(f) = \sum_{d=1/22}^{1} \left(f_{t+d} - \frac{\sum_{d=1/22}^{1} f_{t+d}}{22} \right)^2. \tag{9}$$

Moreira and Muir (2017) regress the volatility-managed factors on the original factors to test if volatility timing increases Sharpe ratios. The regression alphas are positive and statistically significant for market, momentum, profitability, ROE, investment and BAB factors. The annualized alpha of the volatility-managed momentum factor, 12.51%, shows the superiority of risk-managed momentum over the non-managed factor and supports the findings of both Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).

The advantages of volatility-management apply to the market factor as well. Moreira and Muir (2017) note that the positive alpha on the market factor implies that the volatility-managed strategy expands the mean-variance frontier and offers a higher return on the same level of risk than the unmanaged market portfolio. To test the performance of volatility managed factors during recession periods, Moreira and Muir regress the scaled factor returns on the original factor returns and NBER recession dummies. The regression results show that the volatility-managed factors have a lower risk-exposure and therefore lower betas during recession periods. Moreira and Muir also consider using realized volatility and expected variance instead of the realized variance to scale the factor returns. The results are similar for both realized volatility and expected variance, but the advantage of these two strategies is a lower variation in the portfolio weights and reduced trading costs.

Grobys et al. (2018) show that the volatility-scaling approach of Barroso and Santa-Clara (2015) increases the performance of industry momentum. Furthermore, Grobys et al. (2018) show that industry momentum portfolios do not exhibit optionality during bear markets like stock momentum portfolios do (Daniel & Moskowitz, 2016).

Although the findings of Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016) and Moreira and Muir (2017) provide strong support for the benefits of risk management, Harvey et al. (2018) find somewhat mixed results, and Liu, Tang and Zhou (2019) find oppositely that volatility timing does not increase the performance of a market portfolio. Harvey et al. (2018) show that volatility scaling improves the performance of equity portfolios in terms of higher Sharpe ratios, but they also find that the benefits do not apply to currencies, commodities or portfolios that do not hold stocks. Harvey et al. note that while the volatility-managed market portfolio has a lower left tail risk, also the highest positive returns are reduced by volatility scaling.

Liu et al. (2019) show that the volatility-timing strategy of Moreira and Muir (2017) suffers from look-ahead bias as the strategy uses the unconditional volatility of the whole sample period to scale the portfolio weights. Liu et al. (2019) find that even before correcting the look-ahead bias, the volatility-managed market portfolio outperforms the market index only during 2001–2017. After correcting the look-ahead bias of the volatility-timing strategy, they find that the strategy suffers drawdowns of 68%–93% in different specifications, making the strategy difficult to implement for the market portfolio. Furthermore, Liu et al. show that the volatility-target approach of Barroso and Santa-Clara (2015) does not outperform the market index during August 1936–December 2017. Liu et al. (2019) also find that the approach is sensitive to different specifications of target volatility—increasing the target volatility from 12% to 20% does not significantly improve the Sharpe ratio, but it increases the maximum drawdown from 52% to 76%.

After having shown that the measures of risk management seem to increase the performance of momentum and factor portfolios but can negatively affect the performance of the market portfolio, it is motivated to test the performance of risk-managed factor momentum.

3.3 Behavioral and risk-based explanations for momentum returns

The momentum strategies discussed earlier seem to contradict the weak form of market efficiency—information of past returns and earnings can be used to predict future performance. The competing explanations for momentum returns are a higher systematic risk of momentum portfolios and behavioral biases that create short-term price continuation. Jegadeesh and Titman (1993) suggest that the profitability of cross-sectional momentum portfolios is not driven by their systematic risk, but instead investor behavior, namely underreaction on a short-term to new information. This theory is also supported by the behavioral models of Barberis et al. (1998) and Hong and Stein (1999). Barberis et al. (1998) suggest that investors' underreaction to new information causes stock returns to be positively autocorrelated in the short-term as the initially neglected information is incorporated slowly to market prices.

Hong and Stein (1999) build their model of investors' behavior on a theory of gradually spreading private information that initially causes investors to underreact to new information. Likewise, Chan et al. (1996) suggest that new information is incorporated into stock prices only gradually. They find that approximately 41% of 6-month price momentum returns take place around earnings announcement dates and that large earnings surprises are, on average, followed by subsequent surprises in the same direction. The slow response to new information is not limited to investors only, as Chan et al. discover that also analysts are slow to update their forecasts, especially for the worst-performing companies.

Hong et al. (2000) find that firms with low analyst coverage experience higher momentum returns than firms with high analyst coverage, and the effect is stronger among past losers than past winners. Hong et al. interpret that the asymmetry in momentum returns means that stocks with low analyst coverage react slower to bad news than to good news. Similarly to Hong et al., also Chan (2003) finds market prices adjust slowly to bad news. Bad public news cause negative stock price drifts that last up to 12 months, suggesting that investors underreact to negative public information.

While Barberis et al. (1998) and Hong and Stein (1999) attempt to explain momentum returns with underreaction, Daniel et al. (1998) suggest that momentum is initially caused when investors overestimate the value of their private information and overreact to new information. Furthermore, the overreaction and momentum effect are later strengthened by self-attribution bias if new public information confirms the earlier private information.

The relation between momentum and investor sentiment is studied by Antoniou, Doukas and Subrahmanyam (2013) and Hao, Chou, Ko and Yang (2018). Based on the model of Hong and Stein (1999), Antoniou et al. (2013) expect that investors’ underreaction to new information is more pronounced when the new information contradicts the prevailing investor sentiment. The findings of Antoniou et al. support their hypothesis that momentum returns are affected by investor sentiment—momentum returns are high and statistically significant during an optimistic investor sentiment, and insignificantly low during a pessimistic investor sentiment. Hao et al. (2018) find that the profitability of the 52-week high momentum is significantly higher following periods of high investor sentiment, and that the profitability is mainly driven by the 52-week high winner stocks that have positive earnings surprises and correspondingly by 52-week loser stocks that have negative earnings surprises. Hao et al. conclude that their findings support the hypothesis of George et al. (2004)—investors tend to anchor on the 52-week high price and underreact to extreme earnings announcements.

The competing explanation for the profitability of momentum is that the returns to momentum portfolios are compensation for a higher risk, but commonly used asset pricing models without momentum factor cannot explain momentum returns. Fama and French (1996, 2016) find that momentum portfolios have significant alpha on three- and five-factor model regressions. Chan et al. (1996) show that the three-factor model of Fama and French (1993) is unable to explain the returns to portfolios that are formed on a combination of past returns and analyst forecast revisions.

Unlike the three- and five-factor models of Fama and French (1993, 2016), Daniel and Hirshleifer (2019) find that their three-factor model captures well the average returns of earnings, price and industry momentum portfolios. The returns of momentum portfolios are captured predominantly by the PEAD factor, which is intended to capture short-horizon mispricing that stems from underreaction to earnings announcements. Furthermore, the short sides of momentum portfolios have negative and statistically significant loadings on the PEAD factor, while the long sides of momentum portfolios have significantly positive loadings on the PEAD factor. The loadings on short-side portfolios are higher in absolute terms than on long-side portfolios (i.e., asymmetric), suggesting that the mispricing is more pronounced for assets that are more difficult to arbitrage. Together the findings of Daniel and Hirshleifer suggest that momentum returns, like other robust factor returns, are driven by systematic mispricing.

Because momentum returns cannot be explained by the commonly used market, size, value, investment or profitability proxies for risk, the risk-based explanations suggest that momentum portfolios have a time-varying risk exposure to either macroeconomic, stock-specific or industry-based risk-factors**.** Chordia and Shivakumar (2002) show that the profitability of momentum strategies in the United States can be explained with a conditional model that uses lagged macroeconomic variables. The authors interpret that momentum returns are driven by cross-sectional variation in conditionally expected returns. Opposite to the results of Chordia and Shivakumar (2002), Griffin, Ji and Martin (2003) do not find any evidence that macroeconomic variables would explain international momentum returns. Griffin et al. (2003) use the conditional model of Chordia and Shivakumar (2002) and the unconditional model of Chen, Roll and Ross (1986) to explain momentum returns of 17 countries, but do not find a statistically significant relation between country-specific factors and momentum returns.

Conrad and Kaul (1998) suggest that cross-sectional variation in individual stocks' unconditional mean returns explains the profitability of momentum strategies. Their explanation is based on the assumption that the mean returns of individual stocks are stationary, and therefore the profitability of momentum strategies is not dependent on return predictability. Because momentum strategies buy stocks with high mean returns and sell stocks with low mean returns, the strategy is profitable on average when stock prices are expected to follow random walks. Jegadeesh and Titman (2001) argue that the negative post-holding period returns contradict the Conrad and Kaul (1998) hypothesis because it states that high mean return stocks should constantly outperform low mean return stocks. Berk, Green and Naik (1999) suggest that the positive autocorrelation of expected stock returns explains the profitability of momentum strategies, and that momentum returns are compensation for the predictable changes in firms' systematic risk. Moskowitz and Grinblatt (1999) find that momentum strategies are mainly driven by industry momentum, and because both winner and loser portfolios tend to hold stocks from the same industry, they suggest that momentum portfolios are not well diversified. According to Moskowitz and Grinblatt, the lack of diversification in momentum portfolios can explain why arbitrageurs are not able to eliminate momentum premium.

The research evidence presented in this section suggests that momentum returns are driven by mispricing stemming from behavioral biases and that the mispricing is more pronounced during periods of high investor sentiment (Hao et al., 2018). The evidence suggests that behavioral biases cause underreaction, especially to earnings-related information (e.g., Chan, 2003), and limits to arbitrage can explain why momentum returns are persistent in the short-term but tend to reverse in the long-term.

Even though the evidence on behavioral biases is compelling, momentum returns are likely, at least to some degree, compensation for a higher risk. Momentum returns cannot be explained by traditional asset pricing models, but instead, the mispricing factors of Daniel and Hirshleifer (2019) can explain momentum returns well. Chordia and Shivakumar (2002) show that U.S. momentum returns can be explained with macroeconomic risk factors, while international momentum returns cannot be explained with similar country-specific risk factors (Griffin et al., 2003).

4 Factor momentum

Factor momentum is built on a finding that individual factors are positively autocorrelated. Instead of individual stocks, equities, indices or currencies, the strategy times investments in factors based on the factors' recent performance. Arnott et al. (2018) implement cross-sectional factor momentum with 51 U.S. equity factors, while Gupta and Kelly (2019) and Ehsani and Linnainmaa (2019) study the performances of both cross-sectional and time-series factor momentum strategies with 65 and 20 factors, respectively. The study of Ehsani and Linnainmaa combines 14 U.S. equity factors and six global equity factors. Gupta and Kelly use U.S. equity factors, but they also show that their results are similar when implemented with 62 global equity factors.

Analogously to other momentum strategies, time-series factor momentum buys factors with a positive trend and sells factors with a negative trend, whereas the cross-sectional strategy invests in factors based on the factors' relative performance. Both Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019) suggest that the time-series strategy works better for timing factors than the cross-sectional strategy. Gupta and Kelly show that individual factors are strongly autocorrelated, and for that reason, they suggest that the time-series strategy is a better measure of expected returns. They find that 49 factors have statistically significant and positive monthly first-order autocorrelation coefficients and that the average coefficient for all 65 factors is 0.11. In a similar vein, Ehsani and Linnainmaa (2019) suggest that the time-series strategy performs better because it only bets on positive autocorrelation in factor returns. In contrast, the cross-sectional strategy also bets that the factors have negative cross-covariances.

Both Gupta and Kelly (2019) and Ehsani and Linnainmaa (2019) construct the time-series factor momentum portfolios similarly by taking a long position in factors with positive formation period returns and short position in factors with negative formation period returns. Furthermore, Gupta and Kelly (2019) construct the aggregate time-series factor momentum portfolio by scaling each factor by its annualized three-year volatility. Gupta and Kelly also scale the strategy's total position in long and short sides so that the strategy always has a unit leverage. Ehsani and Linnainmaa (2019) do not scale the positions in individual factors or the leverage in long and short sides. Their strategy is still a zero-investment strategy because the individual factors are long-short portfolios, but their strategy allows the leverage to be different between long and short sides.

The construction of the cross-sectional factor momentum strategies also differs among the three studies. Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019) both construct the cross-sectional strategies so that their strategies are long factors with above-median formation period returns and short factors with below-median formation period returns. Arnott et al. (2018) select an approach that is similar to other cross-sectional momentum strategies, and take long and short positions in the best- and worst-performing factors instead of trading all the included factors. Arnott et al. follow the methodology of Moskowitz and Grinblatt (1999), who buy and sell the top and bottom three industries out of 20 industries. With 51 factors in total, Arnott et al. (2018) sort the factors by formation period returns and take a long position in the top eight factors and short position in the bottom eight factors.

Although Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019) find that the time-series factor momentum performs better than cross-sectional factor momentum, this finding might be driven by the construction of cross-sectional strategies which is different from Arnott et al. (2018) and other momentum strategies (e.g., Jegadeesh & Titman, 1993). By constructing the cross-sectional strategy so that it is short factors with below the median returns, the strategy is likely to short factors that have positive prior returns. Both Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019) show that factors with positive prior returns are likely to continue having positive future returns. In contrast, Arnott et al. (2018) construct the strategy so that it is short only the bottom 15% of all factors, and therefore, their strategy is less likely to short factors that continue to have positive returns. Studies on factor momentum have not yet compared the cross-sectional strategy, as proposed by Arnott et al. (2018), against time-series factor momentum, and thus further research is warranted.

Ehsani and Linnainmaa (2019) use spanning regressions to show that the five-factor model of Fama and French (2015), together with time-series factor momentum as an explanatory variable, fully subsumes the UMD factor and the industry momentum of Moskowitz and Grinblatt (1999) among other momentum strategies. While factor momentum subsumes both industry momentum and price momentum, these strategies, together with the five-factor model, do not span factor momentum. Arnott et al. (2018) find similarly that cross-sectional factor momentum subsumes all specifications of industry momentum. Gupta and Kelly (2019) find that industry momentum or stock price momentum alone cannot explain the returns of factor momentum strategies that are formed using 1-month lagged returns. However, industry momentum and price momentum explain the returns to cross-sectional factor momentum strategies with a formation period longer than six months.

The factor momentum strategy does not need a vast number of factors to be profitable. Arnott et al. (2018) find that randomly selected ten factors out of their study's 51 factors are enough to generate almost identical profits as the complete set of factors. Furthermore, they show that even market, size, value, investment and profitability factors of Fama and French (2015) are enough to implement the factor momentum strategy with an annualized return of 8.0%. Similarly, Gupta and Kelly (2019) point out that six factors are enough to replicate the factor momentum strategy of 65 factors.

Arnott et al. (2018) find that none of the 51 factors decreases the performance of factor momentum. This finding can explain why even a small number of factors is enough for implementing a profitable momentum strategy. However, the factors’ relative contribution towards momentum profits varies significantly, and Arnott et al. note that the factors with the highest contribution do not have the highest average returns. Arnott et al. rank 51 factors based on their contribution to momentum profits, and form factor momentum strategies using the quintile ranks. The difference in annualized returns between the portfolios of ten best and ten worst factors is 9.3% and statistically significant.

Arnott et al. (2018) find cross-sectional factor momentum to have the most robust performance when both formation and holding periods are set as one month. This strategy generates an average annualized return of 10.49% with a t-statistic of 5.01. When the same strategy is adjusted for past industry returns, thus making it industry-neutral, the annualized return drops to 6.41% with a t-statistic of 5.55. Gupta and Kelly (2019) find similarly that both time-series and cross-sectional factor momentum strategies generate the highest returns with one-month formation and holding periods. Ehsani and Linnainmaa (2019) show that the time-series strategy is more robust to longer holding periods than the cross-sectional factor momentum. Returns to the cross-sectional strategy are statistically significant up to 6-month holding periods, while the time-series strategies generate statistically significant returns on formation and holding periods up to 24 months. In line with the results of the other two studies, Ehsani and Linnainmaa find that the cross-sectional factor momentum achieves the highest average returns with 1-month lagged returns. The time-series strategy generates slightly higher returns when the formation period is 1, 6 or 12 months and the holding period 1-month.

Ehsani and Linnainmaa (2019) suggest that the autocorrelation of individual factors explains all momentum strategies—factor momentum times factors directly and other momentum strategies indirectly—and momentum strategies are on average profitable as long as the aggregate autocorrelation of individual factors is positive. Ehsani and Linnainmaa find that the returns to stock momentum strategies are correlated with factor autocorrelations and that the stock momentum crashes are concentrated to periods of negative factor autocorrelations. However, the studies on factor momentum do not explain unambiguously what ultimately drives the factor momentum returns. Ehsani and Linnainmaa (2019) find that factor momentum returns are affected by investor sentiment and suggest that factor momentum could be driven by mispricing. Arnott et al. (2018) suggest similarly that factor momentum and autocorrelation of factor returns might stem from mispricing. Gupta and Kelly (2019) do not consider the source of factor momentum returns.

5 Data and methodology

The data used in this thesis consists of publicly available U.S. market data. AQR's[3] data library provides monthly return data for the BAB factor from December 1930 to December 2019 and for the QMJ factor from July 1957 to December 2019. Monthly return data for the HML_D factor spans from July 1926 to December 2019. Kenneth French's[4] data library provides monthly portfolio returns for asset growth, B/M, CF/P, D/P, E/P, momentum, operating profitability and short-term reversals from July 1963 to December 2019. The risk-free rate and market return data are also obtained from French's data library. The overall sample period for all 11 factors is July 1963–December 2019. Both AQR and French form the portfolios using all stocks traded in the NYSE and Nasdaq.

Table 1 lists the 11 factors that are used to form the factor momentum strategies. The table also provides an abbreviation for each factor together with the initial study in academic literature.

Table 1. Included equity factors and their first appearance in academic literature.

Factor	Abbreviation	Original Study
Asset growth	ASSETG	Cooper, Gulen and Schill (2008)
Betting against beta	BAB	Frazzini and Pedersen (2014)
Book-to-market	BM	Rosenberg, Reid and Lanstein (1985)
Cash flow-to-price	CFP	Lakonishok, Shleifer and Vishny (1994)
Dividend yield	DP	Litzenberger and Ramaswamy (1979)
Earnings-to-price	EP	Basu (1983)
High minus low (devil)	HML_D	Asness and Frazzini (2013)
Operating profitability	OP	Novy-Marx (2013)
Quality minus junk	QMJ	Asness, Frazzini and Pedersen (2019)
Short-term reversals	STR	Jegadeesh (1990)
Momentum	UMD	Jegadeesh and Titman (1993)

[3] https://www.aqr.com/insights/datasets
[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

Asset growth, operating profitability and quality minus junk factors are based on accounting information only, and the betting against beta is based on stock market information only. Book-to-market, cashflow-to-price, dividend yield, earnings-to-price and high-minus-low devil are based on a ratio of accounting information to market price. The momentum factor is based on prior returns from month t-12 to month t-2, skipping one month before the holding period, and short-term reversal factor is based on the returns of month t-1.

I use the orthogonalized investor sentiment index of Baker and Wurgler (2006) as a proxy for investor sentiment. The complete data for investor sentiment index is available from July 1965 to December 2018 from Wurgler's website.[5] The investor sentiment index is based on five sentiment proxies, and unlike in Baker and Wurgler (2006), the most recent dataset does not include the NYSE turnover as a proxy for investor sentiment. The five proxies are discount on closed-end funds, dividend premium, equity share in new equity issues, number of IPOs and the average first-day returns on IPOs. The orthogonalized investor sentiment index is obtained by regressing each proxy on growth in industrial production, growth in consumer durables, nondurables and services, and on NBER recession dummy variable.

Figure 1 plots the month-end values of the investor sentiment index from July 1965 to December 2018. The shaded areas represent the NBER recession periods, and the dashed lines mark the 30th and 70th quantiles. Due to the construction of the index, it has a zero mean and unit variance (Baker & Wurgler, 2006). Aligning the investor sentiment index with recession periods shows that sharp peaks in the investor sentiment index are followed by recession periods and sharply declining investor sentiment. The index reaches the maximum value of 3.20 twice; in December 1969 just before the recession period, and at the end of February 2001, a month before the recession period. The investor sentiment index from 2012 onwards has been less volatile than in the past, ranging between -0.28 and 0.18.

[5] http://people.stern.nyu.edu/jwurgler/

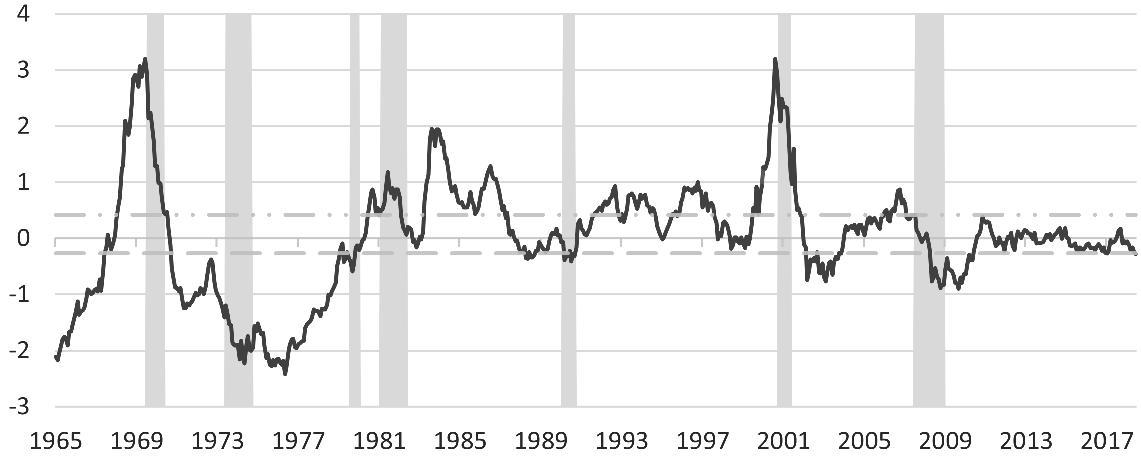

Figure 1. Investor sentiment index from July 1965 to December 2018.

The data for the volatility index (VIX) is available from January 1990 to December 2019 from the CBOE.[6] VIX measures the 30-day option implied volatility of the S&P 500 Index, and the expected volatility is quoted in annualized percentage form (Cboe, 2019). Figure 2 plots the month-end values of VIX from January 1990 to December 2019 along with the NBER recession periods, as reported in Wurgler's investor sentiment dataset. The average value of VIX is 19.14 using daily closing values, and 19.18 using month-end values. The maximum and minimum values of VIX for the period are 81.84 and 8.56, and with month-end values 59.89 and 9.51, respectively.

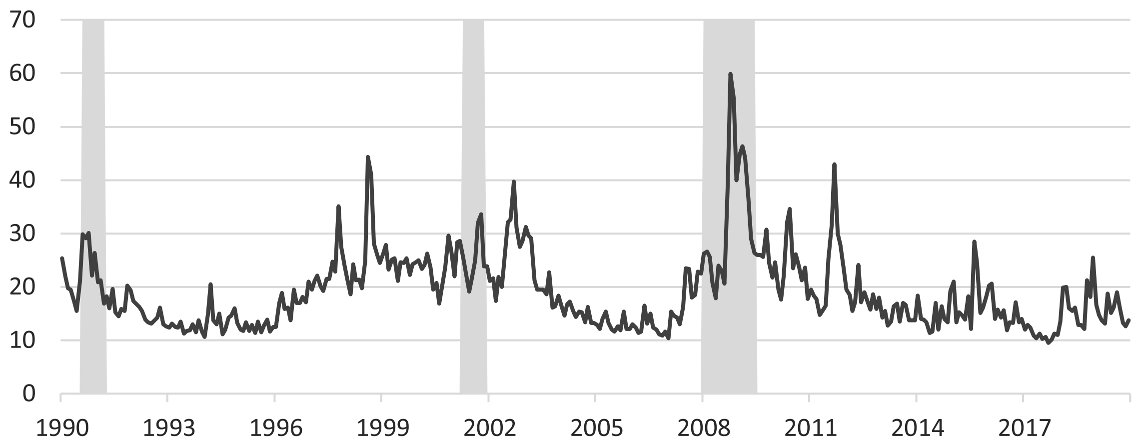

Figure 2. Month-end values of VIX from January 1990 to December 2019.

[6] http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data

5.1 Methodology

I use the five-factor model of Fama and French (2015, FF5) to assess the performance of each factor portfolio and factor momentum strategy. The return series to factor or strategy R_i are regressed on the market, size, value, profitability and investment factors in the following form:

$$R_i = \alpha_i + b_i MKT + s_i SMB + h_i HML + r_i RMW + c_i CMA + \varepsilon_i. \quad (10)$$

I also test whether the six-factor model of Fama and French (2018, FF6) increases explanatory power on factor momentum returns over the five-factor model. The factor momentum returns are regressed on the FF6 factors in the following form:

$$R_i = \alpha_i + b_i MKT + s_i SMB + h_i HML + r_i RMW + c_i CMA + m_i UMD + \varepsilon_i, \quad (11)$$

where UMD is the same momentum factor that is used to construct the factor momentum portfolios. Because Arnott et al. (2018) show that the FF6 model is not able to completely explain factor momentum returns in their tests, I also regress the factor momentum returns against the three-factor model of Daniel and Hirshleifer (2019, DH3). The model uses market, financing and post-earnings announcement drift factors to explain mispricing anomalies. The monthly return data for FIN and PEAD factors is obtained from Daniel's web site[7] and spans from July 1972 to December 2018. I repeat the FF5 and FF6 model regressions for the shorter sample period to allow comparability between the models. I follow the methodology of Daniel and Hirshleifer (2019) and use the same MKT factor as in the FF5 and FF6 models. The factor momentum returns are regressed on the DH3 model in the following form:

$$R_i = \alpha_i + b_i MKT + c_i FIN + d_i PEAD + \varepsilon_i. \quad (12)$$

[7] http://www.kentdaniel.net/data.php

Using the DH3 model to assess the performance of factor momentum strategies helps to understand whether the factor momentum returns are driven by mispricing as suggested by Ehsani and Linnainmaa (2019). Based on the asset pricing tests of Daniel and Hirshleifer (2019), I expect to find that the DH3 model increases explanatory power on factor momentum returns over the FF5 and FF6 models. To the extent that factor momentum returns stem from mispricing, a significant exposure on the PEAD factor suggest that investors underreact to earnings-related information. Following the interpretation of Daniel and Hirshleifer (2019), overpriced portfolios should have negative loadings on the FIN and PEAD factors, and underpriced portfolios should have positive loadings. I use the ordinary least squares (OLS) regression method to compute the regression estimates throughout this study. Since the individual factor returns are autocorrelated, I use the Newey and West (1987) standard errors to calculate the t-statistics.

To test whether the factor and factor momentum returns are affected by the prevailing investor sentiment, I follow the methodologies of Hao et al. (2018) and Antoniou et al. (2013) and regress the return series on investor sentiment dummy variables. Dummy variable $HIGH_t$ (LOW_t) equals to one when the value of investor sentiment index at the end of month t-1 belongs to the top (bottom) 30% of all observations, and zero otherwise. Dummy variable $MILD_t$ is equal to one when the investor sentiment index is above the bottom 30% but below the top 30%, and zero otherwise. The value of investor sentiment index at month t measures the investor sentiment at the end of the month, and therefore using the lagged value of investor sentiment gives the contemporaneous value of investor sentiment at the beginning of month t. Hao et al. (2018) and Antoniou et al. (2013) use a weighted three-month rolling average of investor sentiment index to assess the level of investor sentiment at the end of the formation period. Because the three-month average can level off sharp changes in the investor sentiment index, I use the raw month-end values of investor sentiment index. The results are similar (not reported) using the three-month rolling average.

To test whether the average factor returns are significantly different from zero in the month following high, mild and low investor sentiment, the factor returns are regressed on sentiment dummy variables without a constant in the following form:

$$R_{i,t} = \alpha_1 \mathrm{HIGH}_t + \alpha_2 MILD_t + \alpha_3 LOW_t + \varepsilon_t, \tag{13}$$

where $R_{i,t}$ denotes the return to factor *i* in month t, and α_1, α_2 and α_3 are the coefficient estimates on dummy variables HIGH_t, MILD_t and LOW_t (Hao et al., 2018). The coefficient estimates capture the average factor returns following each investor sentiment. To test whether the average factor returns in high sentiment periods are statistically different from returns in low sentiment periods, the monthly factor returns are regressed on dummy variables HIGH_t and MILD_t with a constant (α_0) in the following form:

$$R_{i,t} = \alpha_0 + \alpha_1 \mathrm{HIGH}_t + \alpha_2 MILD_t + \varepsilon_t, \tag{14}$$

where the estimate of α_1 measures the difference in average returns between periods of high and low investor sentiment (Hao et al., 2018). As a robustness check, I use the above and below median values of the investor sentiment index as in Ehsani and Linnainmaa (2019) and Stambaugh et al. (2012). Dummy variable ABOVE_t (BELOW_t) equals one when the investor sentiment is above (below) the median at the end of month t-1, and zero otherwise. The methodology is otherwise the same as above, and the corresponding regression for testing whether the factor momentum returns are significantly different from zero is defined as:

$$R_{i,t} = \alpha_1 \mathrm{ABOVE}_t + \alpha_2 BELOW_t + \varepsilon_t. \tag{15}$$

To test whether the difference in average returns between above and below the median investor sentiment states is statistically significant, the returns are regressed in the following model:

$$R_{i,t} = \alpha_0 + \alpha_1 \mathrm{ABOVE}_t + \varepsilon_t. \tag{16}$$

To test the performance of risk-managed factor momentum, I adapt the methodology of Barroso and Santa-Clara (2015) to scale the factor momentum returns. Instead of forecasting the next-month variance from past returns, I use the option-implied volatility of the S&P 500 index as a proxy for the expected market volatility. Using VIX instead of realized volatility is justified for both practical and statistical purposes. As Grobys (2019) notes, the information of VIX is easily available to an investor, unlike the measure of realized volatility. Since factor momentum portfolios are frequently rebalanced and trade factors that have low pairwise correlations, the strategy is likely to trade stocks with completely opposite characteristics over time. Realized portfolio volatility is likely to generate a more arbitrary estimate of expected volatility while option-implied market volatility is likely to provide a more uniform measure of expected volatility.

I use the one-month lagged month-end values of VIX to get the measure of expected market volatility at the time of the portfolio formation. By revising the model of Barroso and Santa-Clara (2015, p. 115), the return for risk-managed factor momentum portfolio (WML*) is obtained by scaling the WML portfolio return with the ratio of targeted market volatility to lagged month-end value of VIX in the following form:

$$r_{WML^*,t} = \frac{20\%}{VIX_{t-1}} r_{WML,t}. \tag{17}$$

Instead of using an annualized target volatility of 12% like Barroso and Santa-Clara (2015) do, I choose the target volatility so that it corresponds to the long-term average value of VIX. The average value of VIX using month-end values is 19.18, and I set the target volatility to 20%. The scaling does not result in portfolios that would have the target volatility, but instead, the risk-managed portfolios have a constant exposure to the market portfolio in relation to the expected market volatility. The purpose of using varying portfolio weights is to have a lower exposure to the market risk when the market volatility is expected to be high and a higher exposure to the market risk when the expected market volatility is low. This methodology is also closely related to the methodology of Moreira and Muir (2017).

5.2 Factor construction and factor returns

The factor construction follows the methodology of Fama and French (1996) for constructing SMB and HML factors. I calculate the monthly return for each factor from four value-weighted portfolios that are sorted on size and factor variable. AQR constructs the portfolios by sorting all included stocks first on size and then on the factor, while French sorts simultaneously on size and factor. Both AQR and French use the median NYSE market capitalization as a size breakpoint. Similarly, the high and low portfolio breakpoints are the 30th and 70th NYSE percentiles corresponding to the factor. The size and factor breakpoints are updated when the portfolios are constructed or rebalanced. The return for factor *i* in month *t* is the average return of two portfolios consisting of stocks ranked above the 70th percentile minus the average return of two portfolios consisting of stocks ranked below the 30th percentile. The factors are constructed so that the expected sign of the monthly return is positive. For example, the return for ASSETG is obtained by subtracting the average return of small and big firms with high asset growth from the average return of small and big firms with low asset growth:

$$ASSETG_t = \frac{1}{2}\left(r_t^{Small\,\&\,LowInv} + r_t^{Big\,\&\,LowInv}\right) - \frac{1}{2}\left(r_t^{Small\,\&\,HighInv} + r_t^{Big\,\&\,HighInv}\right). \quad (18)$$

I use the BAB and HML_D factor returns as reported by AQR and calculate the monthly returns for the remaining nine factors using the portfolio data of AQR and French. The construction of the BAB factor differs from the other factors as it does not control for size. A more detailed description of the factor construction is available in Appendix 1.

Table 2 reports the summary statistics for the 11 factors. The overall sample period spans from July 1963 to December 2019, and each factor has 678 observations. Reported are the average returns ($\bar{r}$), standard deviations of the monthly returns (SD), the highest (Max) and lowest (Min) monthly returns, the skewness and the kurtosis of the return series. The reported t-statistic, $t(\bar{r})$, tests whether the factor's average return is statistically different from zero.

Table 2. Summary statistics for long-short factors.

Factor	$\bar{r}$	SD	$t(\bar{r})$	Max	Min	Skewness	Kurtosis
EW Average	**0.37 %**	1.45 %	(6.57)	10.6 %	-8.5 %	0.33	9.96
ASSETG	**0.27 %**	1.99 %	(3.58)	9.6 %	-6.9 %	0.31	4.62
BAB	**0.82 %**	3.25 %	(6.55)	15.4 %	-15.6 %	-0.48	7.48
BM	**0.31 %**	2.81 %	(2.83)	12.9 %	-11.2 %	0.10	5.02
CFP	**0.28 %**	2.50 %	(2.95)	11.4 %	-12.0 %	-0.11	5.57
DP	0.01 %	2.81 %	(0.07)	10.6 %	-11.5 %	-0.05	4.33
EP	**0.29 %**	2.57 %	(2.96)	9.6 %	-13.0 %	-0.04	5.37
HML_D	**0.26 %**	3.40 %	(2.02)	27.0 %	-18.0 %	0.89	11.63
OP	**0.26 %**	2.16 %	(3.13)	13.3 %	-18.3 %	-0.31	15.44
QMJ	**0.38 %**	2.23 %	(4.47)	12.4 %	-9.1 %	0.22	5.89
STR	**0.49 %**	3.07 %	(4.20)	16.2 %	-14.6 %	0.38	8.72
UMD	**0.65 %**	4.19 %	(4.01)	18.4 %	-34.4 %	-1.30	13.35

Ten of the factors generate highly significant average returns that are similar in magnitude as in earlier studies. The dividend yield is the only factor that fails to generate statistically or economically significant returns, and this finding is consistent with the out-of-sample replication study of Hou et al. (2018). Including the dividend yield is still justified, as Arnott et al. (2018) find that an individual factor does not decrease the performance of the factor momentum portfolio. The first row of Table 2 reports the summary statistics for a portfolio that invests equally in all 11 factors. The equal-weighted portfolio has a significant monthly average return of 0.37% and notably lower standard deviation than any of the 11 factors, indicating that the factor returns have low or negative correlations. Annualized return and volatility for the equal-weighted portfolio are 4.53% and 5.02%, respectively. In comparison, the market portfolio has an annualized average return of 6.69%, with a standard deviation of 15.18% after subtracting the risk-free return from the market return.

BAB has the highest monthly average return (0.82%) and UMD the second highest (0.65%). The annualized returns for BAB and UMD factors are 10.25% and 8.02%, respectively. Both UMD and HML_D exhibit strong variation in average returns, momentum having highly negative skewness of -1.30, and HML_D having a positive skewness of 0.89. The standard deviations of monthly factor returns vary from 1.99% to

4.19%, and from 6.89% to 14.51% in annualized terms. The returns of the BAB may be driven by small-capitalization stocks like Novy-Marx and Velikov (2019) suggest. The other ten factors control for size bias by grouping stocks into two portfolios using the median NYSE market equity as a breakpoint, and by using value-weighted portfolio returns instead of equal-weighted. To control for possible micro-cap bias arising from the BAB factor, I test the robustness of factor momentum returns separately for small and large universes and without the BAB and HML_D factors in Appendix 2.

Table 3 presents the pairwise correlations for the 11 factors. Over half of all factor pairs have a correlation lower than 0.25, which is consistent with Gupta and Kelly (2019), who find similar results with 65 factors. This finding suggests that even a relatively low number of factors allow capturing different return patterns, even though five out of eleven factors are based on measures of value. The pairwise correlations among value factors are high, but interestingly the BM factor shows a higher correlation with CFP and EP than with HML_D. Even though both BM and HML_D are based on a ratio of book-to-market, the differences in rebalancing frequency and in how the market value is being measured result in different types of return behavior. Table 2 shows that the BM factor has higher average returns with lower volatility than the HML_D factor.

Table 3. Factor return correlations.

	ASSETG	BAB	BM	CFP	DP	EP	HML_D	OP	QMJ	STR	UMD
ASSETG	1.00										
BAB	0.32	1.00									
BM	0.69	0.33	1.00								
CFP	0.62	0.37	0.85	1.00							
DP	0.61	0.22	0.66	0.65	1.00						
EP	0.57	0.36	0.87	0.91	0.69	1.00					
HML_D	0.53	0.13	0.78	0.69	0.62	0.70	1.00				
OP	-0.03	0.31	0.06	0.20	0.05	0.20	-0.07	1.00			
QMJ	0.07	0.21	-0.05	0.06	0.18	0.08	-0.25	0.72	1.00		
STR	-0.11	-0.05	0.01	-0.04	-0.09	0.00	0.23	-0.09	-0.27	1.00	
UMD	-0.03	0.18	-0.20	-0.13	-0.20	-0.17	-0.65	0.11	0.28	-0.30	1.00

The correlation between UMD and HML_D is highly negative (-0.65). Similarly, the correlation coefficients between momentum and other measures of value are also negative but less so. These findings are consistent with Asness et al. (2013), who find that the correlation between momentum and value is more negative when the value is measured using contemporaneous market prices instead of 6 to 18 months lagged prices. The negative correlation between momentum and value can also be observed by examining the highest and lowest monthly returns. The highest monthly return for HML_D and the lowest return for UMD both occurred at the same time in April 2009. The opposite is true in February 2000, when UMD generates the highest monthly return of 18.36% and HML_D the lowest monthly return of 17.98%. STR is the least correlated with other factors, having only a slightly positive correlation with HML_D, and a slightly negative correlation with QMJ and UMD.

To test whether the past factor returns have predictive power on future returns, I regress the monthly factor returns conditional on their past 1- and 12-month return. I follow the methodology of Ehsani and Linnainmaa (2019) and use the following time-series regressions:

$$R_{i,t} = \alpha + \beta D_{12}, \quad R_{i,t} = \alpha + \beta D_{1}, \qquad \text{(19a, 19b)}$$

where $R_{i,t}$ denotes the return to factor i in month t, and D_{12} is a dummy variable that equals to one when the factor's average return from month t-12 to t-1 is positive, and zero otherwise. The dummy variable D_1 equals one when the return in the prior month is positive and zero otherwise. The intercept term α in (19a) captures the average returns after the prior 12-month return is negative, and the slope coefficient β measures the difference in average returns after positive and negative prior 12-month returns (Ehsani & Linnainmaa, 2019). The interpretations are similar for (19b), where the intercept term captures the average return following a month with a negative return, and the slope coefficient captures the difference in average returns following a positive and negative month.

Table 4 presents the OLS regression estimates for each factor conditional on the factor's prior 12- and 1-month returns. On average, the factors earn positive returns after 12 months of underperformance. The average return to the UMD is significantly positive following periods of negative 12-month returns (0.72%), and higher than the average return after a positive 12-month performance (0.62%). The equal-weighted portfolio that invests in all factors earns an average return of 0.10 % in the month following a negative 12-month period and 0.43% after a positive 12-month period.

Table 4. Factor returns conditional on prior 12- and 1-month returns.

	Conditional on prior 12-month return (19a)				Conditional on prior 1-month return (19b)			
	Intercept		Slope		Intercept		Slope	
Factor	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\beta}$	$t(\hat{\beta})$	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\beta}$	$t(\hat{\beta})$
Average	0.10	(0.75)	**0.33**	(2.26)	0.17	(1.92)	**0.32**	(2.83
ASSETG	0.12	(0.99)	0.25	(1.56)	-0.01	(-0.10)	**0.55**	(3.60)
BAB	-0.22	(-0.63)	**1.32**	(3.53)	0.14	(0.67)	**1.03**	(3.95)
BM	0.05	(0.27)	0.39	(1.70)	-0.10	(-0.61)	**0.75**	(3.48)
CFP	0.13	(0.78)	0.24	(1.17)	-0.03	(-0.21)	**0.57**	(2.96)
DP	0.00	(-0.05)	0.00	(0.11)	**-0.44**	**(-2.95)**	**0.91**	(4.27)
EP	0.10	(0.63)	0.30	(1.45)	-0.08	(-0.55)	**0.68**	(3.48)
HML_D	-0.17	(-0.68)	**0.73**	(2.53)	-0.25	(-1.36)	**1.01**	(3.92)
OP	0.03	(0.19)	0.35	(1.71)	-0.09	(-0.69)	**0.62**	(3.74)
QMJ	0.09	(0.65)	**0.43**	(2.51)	0.01	(0.05)	**0.68**	(3.95)
STR	0.49	(1.43)	0.01	(0.03)	**0.56**	(3.10)	-0.11	(-0.45)
UMD	**0.72**	(2.70)	-0.10	(-0.29)	0.38	(1.44)	0.43	(1.28)

Following a month of underperformance, the average returns are positive for four factors and negative for seven factors. The returns following a month of underperformance are significantly positive for STR and significantly negative for DP. The average return to the STR is higher after a negative month (0.56%) than it is after a positive month (0.45%). For every strategy, except for the STR, the average returns after a positive month are higher than the unconditional average returns (Table 2). The equal-weighted portfolio earns an average return of 0.17% after a negative month and 0.49% after a positive month.

The regression results suggest that factor returns are highly persistent, and on average higher following periods of positive returns than they are after negative-return periods. To further examine the predictive power of past factor returns, I estimate the first-order autocorrelation coefficients for each factor using the Q-test of Ljung and Box (1978). Table 5 reports the AC (1) estimates together with the Q-statistics and corresponding probabilities. The first-order autocorrelation coefficients are highly positive and statistically significant at a 1% level for nine factors. The results support the earlier finding that past factor returns can be used to predict future performance.

Table 5. First-order autocorrelation coefficients for factor returns.

	ASSETG	BAB	BM	CFP	DP	EP	HML_D	OP	QMJ	STR	UMD
AC (1)	**0.12**	**0.13**	**0.16**	**0.11**	**0.15**	**0.14**	**0.16**	**0.17**	**0.17**	-0.03	0.05
Q-stat	9.53	11.29	17.47	8.04	15.73	13.09	16.90	18.72	20.60	0.50	1.52
Prob.	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.48	0.22

Table 6 reports the five-factor model regression results with the corresponding t-statistics for seven factors. Excluded are ASSETG, BM, HML_D and OP factors as these factors are included in the five-factor model. The alphas are statistically significant for BAB, QMJ, STR and UMD. The five-factor alphas on CFP, DP and EP are indistinguishable from zero as the HML factor captures the average returns of these factors.

Table 6. FF5 model regressions for seven long-short factors.

	BAB	CFP	DP	EP	QMJ	STR	UMD
Alpha	**0.424**	0.038	0.027	0.069	**0.379**	**0.383**	**0.713**
	(2.82)	(0.75)	(0.35)	(1.38)	(7.13)	(2.76)	(3.45)
MKT-RF	0.072	**-0.041**	**-0.235**	**-0.044**	**-0.181**	**0.178**	**-0.143**
	(1.36)	(-2.95)	(-11.44)	(-3.07)	(-11.27)	(4.06)	(-2.02)
SMB	**0.129**	-0.009	**-0.178**	-0.039	**-0.133**	0.083	0.059
	(2.28)	(-0.41)	(-5.58)	(-1.69)	(-6.30)	(1.36)	(0.55)
HML	0.166	**0.704**	**0.494**	**0.814**	**-0.213**	**0.182**	**-0.534**
	(1.55)	(15.65)	(7.67)	(20.17)	(-5.80)	(1.97)	(-3.30)
RMW	**0.562**	**0.156**	**-0.162**	**0.128**	**0.619**	-0.028	0.231
	(5.71)	(4.46)	(-2.91)	(3.71)	(13.06)	(-0.18)	(1.05)
CMA	**0.468**	0.050	0.146	-0.095	**0.136**	-0.190	0.362
	(3.12)	(1.06)	(1.88)	(-1.88)	(2.96)	(-1.47)	(1.50)

Stambaugh et al. (2012) find that the average long-short factor returns are higher after periods of high investor sentiment and that the factors' short-side returns are significantly lower following periods of high investor sentiment. They also find that the long-side returns are not significantly affected by the investor sentiment. Stambaugh et al. hypothesize that investor sentiment is asymmetrically related to mispricing—high investor sentiment causes more overpricing than low investor sentiment causes underpricing due to short-sale limitations. Baker and Wurgler (2007) hypothesize that speculative stocks should be overvalued in high sentiment and undervalued in low sentiment. They find that the returns to speculative stocks are lower following months of high sentiment and higher following periods of low sentiment, thus supporting their hypothesis. They also hypothesize that the valuation of bond-like stocks is less affected by the investor sentiment, and the correlation between investor sentiment and valuation of bond-like stocks could also be negative if investors prefer quality in low sentiment.

I expect to find a positive relation between long-short factor returns and investor sentiment, and a negative relation between short-side returns and investor sentiment, similarly to Stambaugh et al. (2012). To the extent that the factors reflect mispricing, overpricing should be more pronounced following periods of high investor sentiment, and underpricing should be more pronounced following periods of low investor sentiment. If the investor sentiment affects the returns symmetrically, unlike what Stambaugh et al. (2012) find, then both long- and short-side returns should be higher following periods of low investor sentiment than they are following periods of high investor sentiment. Drawing on the hypothesis of Baker and Wurgler (2007), I also expect that the short-side returns are more affected by the investor sentiment than long-side returns in both high and low sentiment states. To test how the factor returns are affected by the prevailing investor sentiment, I regress the long-short factor returns on dummy variables HIGH, MILD and LOW that measure the investor sentiment at the beginning of the investment period. I repeat the same regressions separately for long- and short-side portfolios to test the hypothesis that short-side portfolios have lower average returns after periods of high investor sentiment.

Table 7 presents the OLS regression estimates $\widehat{\alpha}_1$, $\widehat{\alpha}_2$ and $\widehat{\alpha}_3$ for dummy variables HIGH, MILD and LOW as in (13) with the corresponding t-statistics in parentheses. Panel A reports the estimates for long-short portfolios, Panel B for long portfolios and Panel C for short portfolios. Factors HML_D and BAB do not have data separately for long and short portfolios, and therefore these factors are excluded from Panels B and C. The difference in average returns between high and low investor sentiments, the estimate of α_1 in (13), is reported at the bottom of each panel with the corresponding t-statistic. The t-statistics are calculated using the robust standard errors of Newey and West (1987). Because the data for the investor sentiment index is available from August 1965 to December 2018, the sample period is shorter than the full sample period. Dummy variables HIGH and LOW have both 192 observations, and dummy variable MILD has 257 observations.

Panel A of Table 7 shows that the average long-short factor returns are higher following periods of high investor sentiment than they are following periods of low investor sentiment. The difference in average returns is positive for 9 out of 11 factors and statistically significant at 5% level for five factors. Furthermore, the factor returns following high investor sentiment exceed the unconditional average returns. In contrast, the long-short factor returns following low investor sentiment are generally below the unconditional average returns, suggesting that mispricing is less pronounced after periods of low investor sentiment. This finding that long-short factors are, on average, more profitable after high investor sentiment is in line with expected results and the results of Stambaugh et al. (2012).

The long- and short-side returns of all factors, except DP, are higher following periods of low investor sentiment than they are following high investor sentiment. The differences between high and low sentiment states are generally smaller for long-side portfolios than they are for short-side portfolios. However, the differences in long-side returns are not statistically significant, and only three of the short-side portfolios have significantly different returns between high and low sentiment. All factors, except QMJ, have statistically significant long-side returns in all investor sentiment states. These results show that the performance of long-short factors is mainly driven by the short-side portfolios that are more affected by the prevailing investor sentiment. All factors have negative relation between short-side returns and investor sentiment as expected. The long-side returns are not significantly affected by investor sentiment. These findings are also consistent with the results of Stambaugh et al. (2012).

Table 7. Factor returns conditional on investor sentiment.

Panel A – Factor returns (Long - Short)

	ASSETG	BAB	BM	CFP	DP	EP	HML_D	OP	QMJ	STR	UMD
HIGH	**0.651**	**1.408**	**0.818**	**0.586**	**0.494**	**0.832**	**0.666**	**0.707**	**0.830**	**0.637**	**0.681**
	(3.33)	(4.29)	(3.33)	(2.65)	(2.35)	(3.37)	(2.66)	(3.55)	(5.03)	(3.30)	(2.90)
MILD	0.045	**0.716**	-0.043	0.034	-0.166	-0.014	-0.379	0.174	**0.508**	-0.045	**0.933**
	(0.40)	(2.53)	(-0.23)	(0.22)	(-0.93)	(-0.09)	(-1.73)	(1.28)	(3.22)	(-0.27)	(3.79)
LOW	0.247	**0.475**	0.285	0.318	-0.215	0.176	**0.763**	-0.047	-0.151	**1.001**	0.302
	(1.53)	(2.36)	(1.39)	(1.72)	(-0.93)	(0.97)	(2.74)	(-0.35)	(-0.96)	(5.00)	(0.74)
HIGH - LOW	0.404	**0.933**	0.533	0.267	**0.710**	**0.656**	-0.097	**0.754**	**0.981**	-0.364	0.378
	(1.59)	(2.38)	(1.67)	(0.93)	(2.27)	(2.13)	(-0.26)	(3.12)	(4.28)	(-1.30)	(0.80)

Panel B – Long-side returns

	ASSETG	BM	CFP	DP	EP	OP	QMJ	STR	UMD
HIGH	**0.992**	**1.197**	**1.156**	**1.327**	**1.343**	**0.992**	0.435	**0.922**	**0.996**
	(3.25)	(3.77)	(3.77)	(4.84)	(4.16)	(2.97)	(1.34)	(2.34)	(2.72)
MILD	**0.985**	**0.941**	**1.000**	**0.792**	**0.952**	**1.008**	**0.782**	**0.845**	**1.333**
	(3.07)	(2.85)	(3.21)	(3.22)	(3.06)	(3.31)	(2.83)	(2.13)	(3.88)
LOW	**1.566**	**1.564**	**1.589**	**1.154**	**1.506**	**1.389**	**0.930**	**1.991**	**1.677**
	(3.92)	(3.75)	(4.09)	(3.47)	(3.64)	(3.35)	(2.39)	(4.48)	(4.13)
HIGH - LOW	-0.574	-0.368	-0.433	0.173	-0.163	-0.397	-0.496	-1.069	-0.680
	(-1.13)	(-0.70)	(-0.87)	(0.40)	(-0.31)	(-0.74)	(-0.97)	(-1.78)	(-1.24)

Panel C – Short-side returns

	ASSETG	BM	CFP	DP	EP	OP	QMJ	STR	UMD
HIGH	0.341	0.378	0.570	**0.832**	0.511	0.284	-0.395	0.285	0.316
	(0.85)	(0.98)	(1.55)	(2.37)	(1.40)	(0.73)	(-0.94)	(0.82)	(0.83)
MILD	**0.940**	**0.983**	**0.966**	**0.957**	**0.966**	**0.834**	0.273	**0.890**	0.400
	(2.73)	(2.95)	(3.02)	(2.92)	(2.98)	(2.26)	(0.68)	(2.82)	(1.01)
LOW	**1.318**	**1.279**	**1.271**	**1.369**	**1.330**	**1.436**	**1.081**	**0.990**	**1.374**
	(2.94)	(2.98)	(2.93)	(3.18)	(3.08)	(3.39)	(2.21)	(2.35)	(2.39)
HIGH - LOW	-0.977	**-0.901**	-0.701	-0.537	-0.819	**-1.151**	**-1.476**	-0.705	-1.059
	(-1.61)	(-1.55)	(-1.22)	(-0.96)	(-1.44)	(-1.97)	(-2.27)	(-1.28)	(-1.52)

5.3 Factor momentum portfolios

The factor momentum portfolios are formed using L-month lagged factor returns and held for H months, and each factor momentum portfolio is denoted with an L-H pair. I test the performance of cross-sectional (CS) 1-1, 6-1, 6-6, 11-1 and 12-1 strategies and time-series (TS) 1-1, 6-1 and 12-1 strategies. Both CS and TS strategies are rebalanced monthly at the end of the formation period. The cross-sectional factor momentum portfolios are long two factors with the highest formation period returns and short two factors with the lowest formation period returns. Taking a long (short) position in two factors follows the allocation ratio of Arnott et al. (2018) when the total number of included factors is 11.[8] In contrast, the cross-sectional factor momentum strategies of Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019) are long factors with above-median returns and short factors with below-median returns. I follow the approach of Arnott et al. (2018) because previous studies have not compared the cross-sectional factor momentum against the time-series strategy in the form that momentum strategies are commonly constructed.

The 12-1 strategy is formed using the factor returns from month *t*-12 to *t*-1. The 11-1 is formed using the average returns from *t*-12 to *t*-2 and skipping the month *t*-1 before the holding month *t*. The 11-1 strategy is included to test how the performance is affected by skipping a month before the holding period. The returns to cross-sectional strategies are calculated as the spreads between long and short portfolios. The return to each long (short) portfolio in month *t* is calculated as the equal-weighted average return of the two factors with the highest (lowest) formation period returns. Since the 6-6 strategy includes overlapping holding periods, I follow the methodology of Jegadeesh and Titman (1993) and calculate the strategy's long and short returns with 1/6 weight in each portfolio formed at times *t*-6 to *t*-1.

[8] The number of long and short factors is calculated as a ratio from the total number of factors by: $max\left\{round\left(\frac{3}{20}\ X\ 11\right), 1\right\} = 2$, as in Arnott et al. (2018).

The time-series factor momentum strategies are long factors with positive formation period returns and short factors with negative formation period returns. The return to each long (short) portfolio in month *t* is calculated as the equal-weighted average return of factors with positive (negative) formation period returns. Because the number of factors in long and short portfolios varies from month to month, using equal-weighted average returns is equivalent to a zero-investment strategy that always has an equally large position in long and short portfolios. For example, if the time-series factor momentum strategy is long ten factors and short one factor, the weight on each long factor corresponds to 1/10 of the weight on the short position.

Both cross-sectional and time-series factor momentum strategies are zero-cost portfolios. The cross-sectional strategies are always long two factors and short two factors, while the time-series strategies have either a long or short position in each factor. The fact that each of the 11 factors is a long-short portfolio has two important implications. First, a factor momentum investor earns momentum premium regardless of which side of the factor earns on average higher returns—as long as the monthly returns are positively autocorrelated. This feature of factor momentum is emphasized by Ehsani and Linnainmaa (2019). For example, a long position in the QMJ factor denotes a long position in quality stocks, which is financed by a short position in junk stocks. Oppositely, a short position in the QMJ factor means taking a long position in the junk stocks and financing the purchase with a short position in quality stocks. Factor momentum strategy can, therefore, be interpreted as a strategy that bets on (against) the factors when they have relatively high (low) or positive (negative) prior returns.

Second, the long and short sides of the factor momentum strategy are not pure long and short portfolios, but instead zero-cost portfolios. Both long- and short-side portfolios have equal long and short positions in the underlying factors, and therefore, both long- and short-side portfolios are zero-cost portfolios. For consistency, I refer to long (short)-side portfolios as the winner (loser)-factor portfolios and report the WML factor momentum returns as the spreads between the winner- and loser-factor portfolios.

6 Results

Table 8 presents the summary statistics for cross-sectional (CS) and time-series (TS) factor momentum strategies that are formed on past 1-, 6- and 12-month factor returns, and rebalanced monthly. The cross-sectional strategies are long two factors with the highest formation period returns and short two factors with the lowest formation period returns. The time-series strategies are long factors with positive formation period returns and short factors with negative formation period returns. The CS 11-1 strategy is formed using factor returns from *t*-12 to *t*-2, skipping the month *t*-1 before portfolio formation. The CS 6-6 strategy includes overlapping holding periods, and the return for month *t* is calculated as the equal-weighted average return of six portfolios that are formed before the holding period at times *t*-6 to *t*-1 following the methodology of Jegadeesh and Titman (1993).

All factor momentum strategies have positive and statistically significant average returns. The CS 1-1 strategy has the highest monthly average return of 1.00%, which is higher than for any of the 11 individual factors. It is also the only strategy that has negative, although not statistically significant, short-side returns. Consistent with the results of previous studies on factor momentum, both cross-sectional and time-series strategies have the best performance with the 1-month formation and holding periods. Contrary to the findings of Gupta and Kelly (2019) and Ehsani and Linnainmaa (2019), the cross-sectional strategies have higher average returns than time-series strategies on equal formation periods. This difference is likely explained by the fact that the cross-sectional portfolios of Gupta and Kelly (2019) and Ehsani and Linnainmaa (2019) are long factors with above-median returns and short factors with below-median returns. I find that the average returns to all cross-sectional strategies are lower if the portfolios are long and short three factors instead of two factors. In comparison to the UMD factor, only cross-sectional 1-1 and 6-1 strategies have higher average returns. The CS 6-6 strategy and UMD factor have equal average returns, but the returns to the UMD factor are less volatile.

Table 8. Summary statistics for factor momentum portfolios.

Panel A – Monthly average factor momentum returns

	Winner - Loser			Winner			Loser		
(L-H)	$\bar{r}$	SD	$t(\bar{r})$	$\bar{r}$	SD	$t(\bar{r})$	$\bar{r}$	SD	$t(\bar{r})$
CS 1-1	**1.00 %**	4.42 %	5.89	**0.90 %**	2.63 %	8.95	-0.09 %	2.75 %	-0.89
CS 6-1	**0.68 %**	4.02 %	4.40	**0.77 %**	2.50 %	8.01	0.09 %	2.48 %	0.95
CS 6-6	**0.65 %**	6.32 %	2.67	**1.19 %**	4.25 %	7.23	**0.53 %**	4.18 %	3.31
CS 11-1	**0.50 %**	3.98 %	3.25	**0.69 %**	2.41 %	7.40	0.19 %	2.53 %	1.95
CS 12-1	**0.59 %**	4.06 %	3.72	**0.75 %**	2.45 %	7.89	0.16 %	2.59 %	1.63
TS 1-1	**0.61 %**	3.20 %	4.98	**0.67 %**	1.84 %	9.52	0.06 %	2.17 %	0.71
TS 6-1	**0.34 %**	3.09 %	2.83	**0.51 %**	1.89 %	6.93	**0.17 %**	2.11 %	2.06
TS 12-1	**0.33 %**	2.93 %	2.93	**0.50 %**	1.71 %	7.48	**0.16 %**	2.14 %	1.98

Values in bold are statistically significant at a 5%-level

Panel B – Lowest and highest monthly factor momentum returns

	Winner - Loser		Winner		Loser	
(L-H)	Min	Max	Min	Max	Min	Max
CS 1-1	-26.5 %	36.9 %	-12.1 %	16.3 %	-20.6 %	14.4 %
CS 6-1	-17.7 %	21.0 %	-12.6 %	11.8 %	-15.7 %	12.4 %
CS 6-6	-40.9 %	33.2 %	-29.6 %	20.3 %	-23.6 %	24.4 %
CS 11-1	-21.0 %	18.6 %	-15.2 %	11.3 %	-12.1 %	10.1 %
CS 12-1	-21.1 %	24.8 %	-15.2 %	11.3 %	-15.9 %	12.4 %
TS 1-1	-22.5 %	15.6 %	-8.0 %	10.4 %	-12.2 %	14.4 %
TS 6-1	-22.0 %	29.5 %	-13.7 %	18.4 %	-11.2 %	16.2 %
TS 12-1	-22.0 %	21.3 %	-13.7 %	10.2 %	-12.4 %	16.2 %

Panel C – Return distributions

	Winner - Loser		Winner		Loser	
(L-H)	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
CS 1-1	0.52	13.40	0.03	7.75	-0.60	11.45
CS 6-1	-0.03	7.04	-0.21	6.37	-0.14	7.96
CS 6-6	-0.71	8.60	-0.75	9.50	0.23	7.97
CS 11-1	-0.36	6.87	-0.38	7.62	-0.03	6.59
CS 12-1	-0.02	8.38	-0.38	7.46	-0.15	8.10
TS 1-1	-0.32	10.45	0.03	7.00	0.26	10.19
TS 6-1	0.22	21.29	0.43	21.16	0.72	11.78
TS 12-1	-0.78	14.74	-0.70	14.18	0.86	11.70

The time-series strategies have lower volatilities because the portfolios are more diversified than the cross-sectional portfolios. The time-series 1-1, 6-1 and 12-1 portfolios are, on average, long 6.1, 6.9 and 7.3 factors and short 4.9, 4.1 and 3.7 factors, respectively. The cross-sectional portfolios are by construction always long and short two factors. The annualized standard deviations of factor momentum strategies vary between 10.15% and 21.89%, and annualized returns between 4.03% and 12.67%.

Performance of the CS 11-1 strategy is similar to the CS 12-1, but the summary statistics show that skipping a month before the holding period does not increase the performance of factor momentum. The results of Table 4 show that the conditional average returns after a positive 1- or 12-month return are higher than the unconditional average returns. Because the aggregate factor returns do not show evidence of short-term reversals like individual stock returns do, skipping a month between the formation and holding periods does not increase the performance of factor momentum.

Panel C of Table 8 shows that the CS 1-1 and TS 6-1 strategies have positively skewed return distributions while all other strategies have negatively skewed return distributions. None of the factor momentum strategies has a higher left tail risk than the UMD factor, which has a skewness of -1.3, and only the CS 6-6 strategy has a worse one-month return than the UMD factor. These findings suggest that factor momentum strategies do not suffer as severe crashes as the individual stock momentum strategy.

Both cross-sectional strategies that are formed on 6-month lagged returns have similar long-short returns, but the returns of winner and loser portfolios show notable differences. While the CS 6-6 winner portfolio has the highest average returns, the strategy’s long-short returns are decreased by the returns of the loser factor portfolio. This finding suggests that it is costly to bet against the loser portfolio on longer holding periods because the returns of loser factors reverse towards their mean. The cross-sectional 1-1 strategy is the only strategy that benefits from betting against the loser factors—the other strategies would be more profitable trading only the winner factors.

Panel A of Table 9 reports the pairwise correlation coefficients between the returns of factor momentum strategies. The CS 11-1 strategy is omitted from here on because its performance is similar to the CS 12-1 strategy in all tests. The returns to time-series and cross-sectional strategies with equal formation periods are highly correlated even though the time-series portfolios are more diversified than the cross-sectional portfolios. Panel B reports the return correlations between factor momentum strategies and the UMD factor and factor momentum strategies and the STR factor. All factor momentum strategies are negatively correlated with the STR factor, and strategies with shorter formation periods are more negatively correlated with STR than strategies with longer formation periods. The correlations between UMD factor and factor momentum strategies are positive and linearly increasing with the length of the formation period.

Table 9. Correlations of factor momentum returns.

Panel A – Correlations between factor momentum strategies

	CS 1-1	TS 1-1	CS 6-1	CS 6-6	TS 6-1	CS 12-1	TS 12-1
CS 1-1	1.00						
TS 1-1	0.90	1.00					
CS 6-1	0.41	0.38	1.00				
CS 6-6	0.15	0.10	0.76	1.00			
TS 6-1	0.30	0.34	0.79	0.65	1.00		
CS 12-1	0.28	0.25	0.72	0.82	0.70	1.00	
TS 12-1	0.27	0.29	0.62	0.71	0.84	0.84	1.00

Panel B – Correlations between factor momentum strategies and UMD and STR factors

	CS 1-1	TS 1-1	CS 6-1	CS 6-6	TS 6-1	CS 12-1	TS 12-1
UMD	0.10	0.12	0.46	0.58	0.53	0.68	0.66
STR	-0.69	-0.67	-0.42	-0.19	-0.40	-0.32	-0.32

To better understand the correlations of factor momentum strategies, Table 10 presents the relative factor weights for 1-1 and 6-1 portfolios. The weights are calculated by dividing the frequency a factor is included in the winner (loser) portfolio by the total number of factors each strategy holds in its winner (loser) portfolio over the whole sample period.

Table 10. Factor weights in winner and loser portfolios.

	CS 1-1		CS 6-1		TS 1-1		TS 6-1	
	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser
ASSETG	4.7 %	6.1 %	3.9 %	7.4 %	8.6 %	9.7 %	8.70 %	9.8 %
BAB	16.4 %	7.2 %	21.0 %	7.2 %	10.8 %	7.0 %	10.61 %	6.5 %
BM	6.7 %	6.1 %	6.3 %	6.3 %	8.8 %	9.4 %	8.68 %	9.8 %
CFP	4.8 %	4.9 %	4.6 %	4.1 %	9.0 %	9.2 %	8.68 %	9.8 %
DP	6.3 %	11.7 %	3.7 %	16.9 %	8.0 %	10.5 %	7.00 %	12.6 %
EP	4.7 %	5.5 %	3.7 %	5.1 %	8.9 %	9.4 %	8.57 %	10.0 %
HML_D	8.3 %	12.7 %	9.5 %	12.5 %	8.3 %	10.0 %	8.14 %	10.7 %
STR	12.1 %	11.2 %	12.4 %	7.6 %	9.2 %	8.9 %	10.29 %	7.1 %
OP	7.6 %	10.7 %	5.9 %	10.3 %	9.1 %	9.1 %	9.30 %	8.7 %
QMJ	10.1 %	10.9 %	8.9 %	11.2 %	9.1 %	9.1 %	9.49 %	8.4 %
UMD	18.2 %	12.9 %	20.0 %	11.4 %	10.2 %	7.7 %	10.55 %	6.6 %

The winner portfolio of the CS 1-1 strategy overweighs BAB, STR, QMJ and UMD factors and underweights the remaining factors. The winner portfolio of the CS 6-1 strategy overweighs BAB, STR and UMD factors and underweights the remaining factors. Both time-series strategies trade BAB and UMD factors similarly more often in the winner portfolios, but these strategies have lower weights on the traded factors.

To understand how the factor momentum strategies have performed over time and against the UMD factor, Figures 3 and 4 plot the cumulative returns of $1 invested. Figure 3 plots the cumulative raw returns, and Figure 4 the cumulative returns of portfolios that are scaled to have monthly volatility of the UMD factor. The y-axis in both figures is in logarithmic form. The cumulative returns of the CS 1-1 strategy are superior to any other strategy. When the monthly volatilities are scaled to match the volatility of the UMD factor, CS 1-1, TS 1-1 and CS 6-1 outperform the UMD factor. The cumulative returns show that factor momentum strategies are not similarly prone to crashes like the UMD factor. For example, the UMD factor lost 49.09% of its cumulative value from the end of March 2009 to the end of May 2009, while the CS 1-1 and TS 1-1 strategies gained 26.39% and 11.35%, respectively. Nevertheless, the summary statistics of Table 8 show that factor momentum portfolios have still experienced significant drawdowns, and therefore, testing the impact of volatility scaling on factor momentum portfolios is justified.

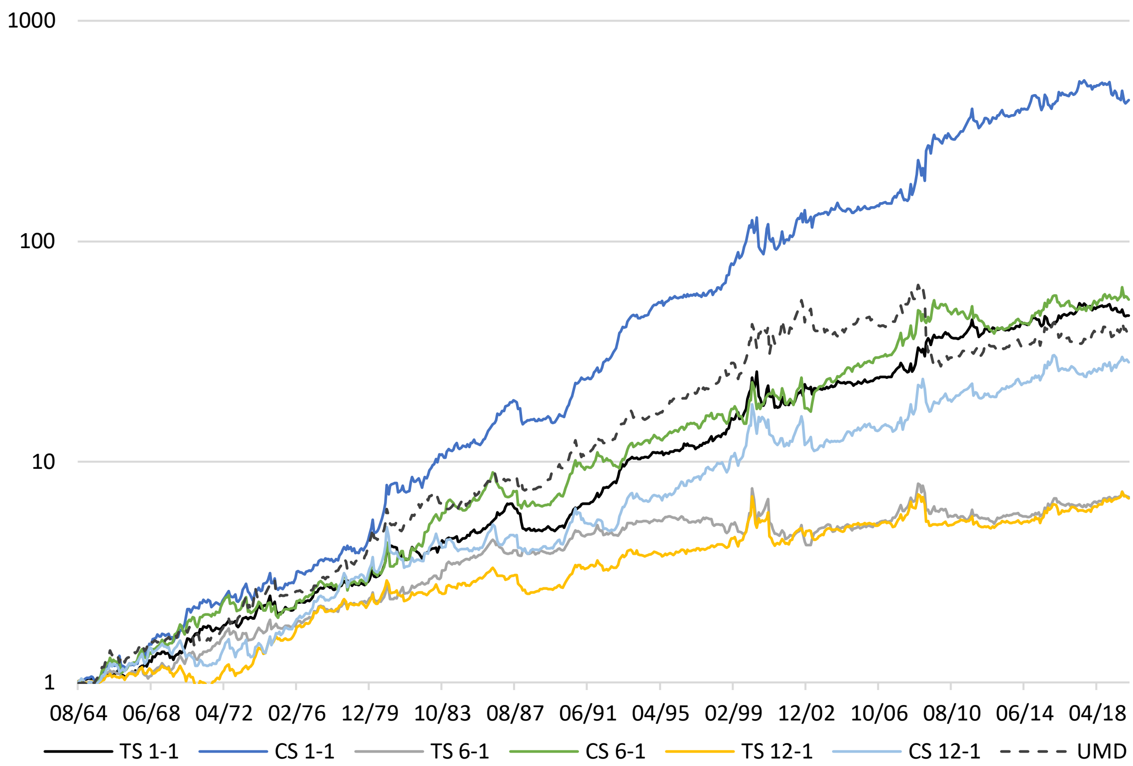

Figure 3. Cumulative factor momentum returns, July 1964–December 2019.

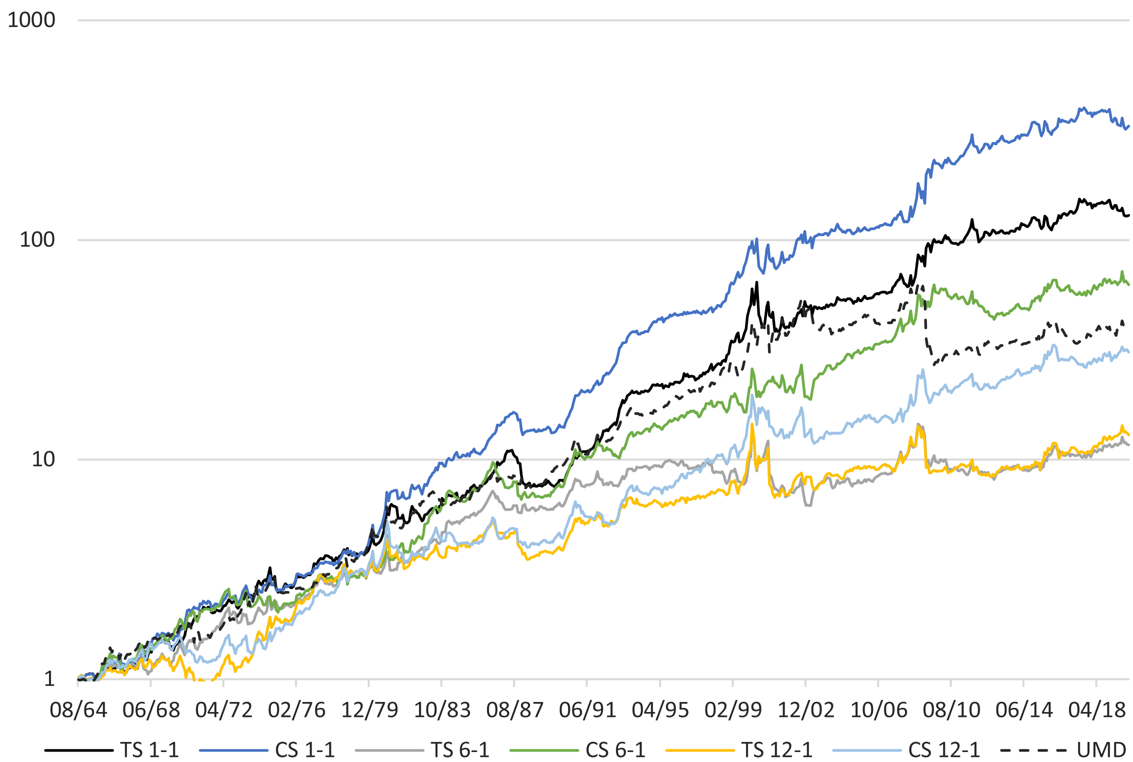

Figure 4. Cumulative factor momentum returns, July 1964–December 2019 (scaled).

Table 11 reports the performance of long-short factor momentum strategies against the five-factor and six-factor models of Fama and French (2015, 2018). Reported are the coefficient estimates with the corresponding t-statistics and the adjusted R-squared for the regression model. Panel A reports the regression estimates for the FF5 model and Panel B for the FF6 model.

Table 11. FF5 and FF6 model regressions for factor momentum portfolios.

	CS 1-1	TS 1-1	CS 6-1	TS 6-1	CS 12-1	TS 12-1	CS 6-6
Panel A – FF5 model							
Alpha	**0.874**	**0.550**	**0.760**	**0.434**	**0.645**	**0.361**	**0.736**
	(4.96)	(3.69)	(4.74)	(2.73)	(3.51)	(2.42)	(2.79)
MKT-RF	-0.044	-0.070	-0.069	-0.101	-0.062	-0.053	-0.071
	(-0.70)	(-1.53)	(-0.91)	(-1.76)	(-0.82)	(-0.97)	(-0.57)
SMB	0.027	0.036	0.149	0.117	**0.259**	**0.157**	**0.398**
	(0.34)	(0.58)	(1.79)	(1.42)	(2.85)	(2.19)	(2.94)
HML	-0.168	-0.130	-0.219	-0.227	**-0.394**	**-0.303**	-0.351
	(-1.22)	(-1.23)	(-1.44)	(-1.66)	(-2.36)	(-2.45)	(-1.40)
RMW	0.166	0.044	-0.105	-0.207	0.000	-0.055	0.043
	(1.01)	(0.32)	(-0.56)	(-0.99)	(0.00)	(-0.33)	(0.16)
CMA	**0.550**	**0.441**	0.059	0.191	0.097	0.235	-0.162
	(3.58)	(3.78)	(0.30)	(1.04)	(0.46)	(1.49)	(-0.45)
Adjusted R^2	0.041	0.060	0.029	0.067	0.085	0.070	0.063
Panel B – FF6 model							
Alpha	**0.815**	**0.493**	**0.436**	0.150	0.176	0.038	0.094
	(4.33)	(3.40)	(2.68)	(1.23)	(1.42)	(0.41)	(0.38)
MKT-RF	-0.033	-0.058	-0.003	-0.043	0.035	0.015	0.060
	(-0.55)	(-1.35)	(-0.05)	(-1.09)	(0.76)	(0.45)	(0.72)
SMB	0.022	0.031	**0.121**	0.092	**0.217**	**0.129**	**0.343**
	(0.28)	(0.52)	(2.03)	(1.45)	(3.90)	(2.52)	(4.11)
HML	-0.124	-0.087	0.028	-0.011	-0.031	-0.052	0.138
	(-1.16)	(-1.02)	(0.25)	(-0.13)	(-0.30)	(-0.71)	(0.74)
RMW	0.147	0.025	-0.209	**-0.299**	-0.154	-0.161	-0.164
	(0.88)	(0.19)	(-1.70)	(-1.96)	(-1.75)	(-1.77)	(-0.96)
CMA	**0.520**	**0.412**	-0.110	0.043	-0.151	0.064	**-0.498**
	(3.48)	(3.70)	(-0.75)	(0.35)	(-1.45)	(0.78)	(-2.04)
UMD	0.082	0.080	**0.458**	**0.402**	**0.672**	**0.463**	**0.908**
	(0.59)	(0.94)	(5.23)	(7.56)	(12.01)	(13.88)	(7.42)
Adjusted R^2	0.045	0.069	0.236	0.336	0.526	0.473	0.392

The results of Table 11 show that all factor momentum strategies have statistically significant FF5 model alphas. The alphas of the CS 1-1 and TS 1-1 strategies are slightly lower than their unconditional average returns, but their statistical significance is higher after controlling for the FF5 factors. The alphas of the remaining three CS and two TS strategies exceed their unconditional average returns. The adjusted coefficient of determination (R^2) is below 10% for every regression model. These findings are in line with the results of Gupta and Kelly (2019) and Arnott et al. (2018) and show that the FF5 model is unable to explain factor momentum returns regardless of the formation period.

Regressing the factor momentum returns on the FF6 model lowers the alphas of all factor momentum strategies, and four of the strategies lose statistical significance. The six-factor model does little to explain the returns of 1-1 strategies, but it captures well the average returns of 12-1, CS 6-6 and TS 6-1 strategies. The returns to these strategies are explained almost completely by the UMD factor. The annualized alphas for the CS 1-1 and TS 1-1 strategies are 10.23% and 6.08%, respectively. Arnott et al. (2018) find similarly that CS 1-1 and CS 6-6 strategies have significant alphas against the FF6 model. Gupta and Kelly (2019) find that time-series portfolios that are formed on 1-, 6- and 12-month lagged returns have significantly positive alpha against the UMD factor, but the results of Table 11 show that only the TS 1-1 strategy has significantly positive alpha against the FF6 model.

The CS 1-1 and TS 1-1 strategies have significantly positive exposure to the CMA factor in both FF5 and FF6 model regression. However, Table 10 shows that both of these strategies trade the ASSETG factor less than almost any other factor. Instead, the investment factor in five- and six-factor model specifications is likely to capture both value and investment characteristics, similar to what Fama and French (2015) find in their five-factor model tests. All cross-sectional and time-series strategies with matching formation periods have similar factor loadings, but the coefficients across different formation periods show substantial variation. This finding suggests that each formation period captures different types of mispricing by trading different factors.

To test whether the three-factor model of Daniel and Hirshleifer (2019) can explain the factor momentum returns better than the FF5 and FF6 models, I regress the factor momentum returns on MKT, FIN and PEAD factors. Panel A of Table 12 presents the regression estimates for the DH3 model and Panel B for the FF6 model. Reported in parentheses are the Newey and West (1987) corrected t-statistics and the adjusted coefficients of determination (R^2) for the regression models. The sample period spans from July 1972 to December 2018. Because the sample period is shorter than previously, the first row reports the unconditional average returns for the sub-sample.

Table 12. DH3 and FF6 model regressions for factor momentum portfolios.

	CS 1-1	TS 1-1	CS 6-1	TS 6-1	CS 12-1	TS 12-1	CS 6-6
Mean	1.064	0.653	0.653	0.303	0.613	0.358	0.619
Panel A – DH3 model							
Alpha	**0.712**	**0.437**	0.245	0.021	0.167	0.009	-0.026
	(2.56)	(2.23)	(1.18)	(0.13)	(0.73)	(0.06)	(-0.08)
MKT-RF	-0.037	-0.081	0.006	-0.070	0.026	-0.008	0.080
	(-0.52)	(-1.44)	(0.07)	(-1.16)	(0.31)	(-0.13)	(0.61)
FIN	0.187	0.096	-0.041	-0.087	-0.047	-0.032	-0.041
	(1.71)	(0.92)	(-0.39)	(-0.62)	(-0.33)	(-0.27)	(-0.23)
PEAD	0.375	**0.303**	**0.704**	**0.619**	**0.754**	**0.609**	**1.021**
	(1.61)	(2.15)	(4.68)	(3.67)	(4.99)	(4.87)	(5.50)
Adjusted R^2	0.049	0.062	0.098	0.142	0.109	0.139	0.082
Panel B – FF6 model							
Alpha	**0.847**	**0.510**	**0.388**	0.100	0.203	0.049	0.076
	(3.96)	(3.12)	(2.06)	(0.73)	(1.40)	(0.49)	(0.26)
MKT-RF	-0.028	-0.063	0.006	-0.046	0.031	0.012	0.055
	(-0.43)	(-1.33)	(0.09)	(-1.09)	(0.60)	(0.34)	(0.61)
SMB	0.011	0.021	0.123	0.102	**0.208**	**0.132**	**0.326**
	(0.12)	(0.31)	(1.82)	(1.43)	(3.33)	(2.30)	(3.19)
HML	-0.152	-0.103	0.056	0.011	-0.011	-0.027	0.173
	(-1.34)	(-1.15)	(0.45)	(0.12)	(-0.09)	(-0.35)	(0.83)
RMW	0.170	0.032	-0.208	**-0.315**	-0.179	**-0.190**	-0.227
	(0.99)	(0.23)	(-1.57)	(-2.04)	(-1.92)	(-2.11)	(-1.16)
CMA	**0.600**	**0.457**	-0.119	0.045	-0.138	0.081	-0.466
	(3.85)	(3.92)	(-0.69)	(0.33)	(-1.15)	(0.93)	(-1.55)
UMD	0.071	0.086	**0.487**	**0.428**	**0.700**	**0.486**	**0.934**
	(0.46)	(0.90)	(4.98)	(7.67)	(11.45)	(14.10)	(6.64)
Adjusted R^2	0.052	0.077	0.261	0.372	0.543	0.513	0.392

Panel A of Table 12 shows that the DH3 model explains the factor momentum returns better than the FF6 model. Both CS 1-1 and TS 1-1 strategies still have statistically significant alphas, but the alphas and their statistical significance are lower than in the FF6 model regressions. All factor momentum strategies, except CS 1-1, have significantly high loadings on the PEAD factor. Panel B shows that the FF6 model alphas are similar as in Table 11, but their t-statistics are slightly lower here due to the shorter sample period. The factor loadings are also similar in the sub-sample as in the full sample period. The regression estimates for the FF5 model (not reported) are similar as in Table 11.

To test whether the winner- and loser-factor portfolios have different exposures to the DH3 model, Table 13 repeats the DH3 model regression separately for the winner- and loser-factor portfolios.

Table 13. DH3 model regressions for winner- and loser-factor portfolios

Panel A – Winner-factor portfolios (long)

	CS 1-1	TS 1-1	CS 6-1	TS 6-1	CS 12-1	TS 12-1	CS 6-6
Alpha	**0.610**	**0.499**	**0.410**	**0.238**	**0.446**	**0.265**	**0.512**
	(4.38)	(5.70)	(3.31)	(2.60)	(3.46)	(2.89)	(2.33)
MKT-RF	-0.026	-0.041	-0.032	-0.052	-0.002	-0.041	-0.024
	(-0.72)	(-1.39)	(-0.74)	(-1.47)	(-0.04)	(-1.26)	(-0.35)
FIN	**0.354**	**0.241**	**0.213**	0.135	**0.214**	**0.164**	**0.478**
	(7.04)	(3.99)	(2.76)	(1.29)	(2.46)	(2.04)	(4.12)
PEAD	0.177	**0.113**	**0.401**	**0.337**	**0.346**	**0.274**	**0.602**
	(1.58)	(1.98)	(5.30)	(2.58)	(4.05)	(3.04)	(4.79)
Adjusted R^2	0.277	0.299	0.191	0.207	0.155	0.242	0.227

Panel B – Loser-factor portfolios (short)

	CS 1-1	TS 1-1	CS 6-1	TS 6-1	CS 12-1	TS 12-1	CS 6-6
Alpha	-0.102	0.062	0.165	0.217	**0.279**	**0.256**	**0.538**
	(-0.62)	(0.45)	(1.31)	(1.75)	(2.20)	(2.17)	(2.81)
MKT-RF	0.011	0.039	-0.038	0.018	-0.028	-0.034	-0.104
	(0.27)	(1.12)	(-0.93)	(0.47)	(-0.66)	(-0.89)	(-1.42)
FIN	**0.167**	**0.145**	**0.254**	**0.222**	**0.261**	**0.196**	**0.519**
	(2.27)	(2.64)	(5.41)	(4.90)	(4.27)	(4.51)	(6.01)
PEAD	-0.197	**-0.190**	**-0.303**	**-0.283**	**-0.408**	**-0.335**	**-0.419**
	(-1.50)	(-2.08)	(-3.50)	(-4.70)	(-5.26)	(-6.16)	(-3.45)
Adjusted R^2	0.061	0.074	0.229	0.203	0.255	0.235	0.313

The estimates of Table 13 show that winner-factor portfolios have significantly positive exposure to the PEAD factor and loser-factor portfolios have significantly negative exposure to the PEAD factor. These findings suggest that the returns of prior winner-factor portfolios stem from positive earnings surprises and the returns of loser-factor portfolios from negative earnings surprises. To the extent that the PEAD factor captures mispricing, winner factors profit by being long in underpriced stocks and short in overpriced stocks. Oppositely, loser factors' negative exposure to the PEAD factor suggests that loser factors capture mispricing by being long in overpriced stocks and short in underpriced stocks.

These findings and interpretations are consistent with the expectation that, on average, individual long-short factors capture mispricing by being long in underpriced stocks and short in overpriced stocks. When the long-short factor returns turn negative, previously overpriced stocks have become underpriced, and previously underpriced stocks have become overpriced. If the mispricing continues in the short-term, factor momentum portfolios profit by trading the factor oppositely to its long-term average. This means shorting the stocks that are now overpriced and buying the stocks that are now relatively underpriced. The summary statistics of Table 8 and the results of Table 13 show that only the cross-sectional 1-1 loser-factor portfolio captures negative average returns. The returns of the loser-factor portfolios increase with the length of the formation period, suggesting that the short-term contrary mispricing is not as persistent as long-term mispricing. This interpretation is also supported by the results of Table 4.

6.1 Investor sentiment and factor momentum

Having shown that the individual factor returns are significantly affected by the prevailing investor sentiment, I now test whether the factor momentum returns are dependent on investor sentiment. Because individual factor returns are affected by the contemporaneous investor sentiment and factor momentum returns are, at least partly, driven by mispricing, I expect the long-short factor momentum returns to be dependent on investor sentiment but with the opposite effect. This hypothesis is motivated by the previous results and the findings of Stambaugh et al. (2012)—a long-short factor is, on average, more profitable in high investor sentiment because increased overpricing causes the short-side returns to be lower (i.e., more profitable) in high sentiment. The factor momentum returns should, therefore, be lower in high investor sentiment, like Ehsani and Linnainmaa (2019) find, because betting against loser factors becomes more expensive when the long-short factors have higher average returns. I also expect that the returns of loser factor portfolios are more affected by the contemporaneous investor sentiment than the returns of winner-factor portfolios because the loser factor portfolios exhibit returns that are contrary to long-term factor returns, and thus more likely to be affected by the investor sentiment.

To test these hypotheses, I regress the factor momentum returns on investor sentiment dummy variables. I use the one-month lagged value of Baker and Wurgler's (2006) investor sentiment index as a proxy for investor sentiment at the time of the portfolio formation. Table 14, Panel A reports the regression estimates for factor momentum portfolios conditional on high, mild, and low investor sentiment. As a robustness test, Panel B reports the estimates conditional on investor sentiment that is either above or below the median value. The investor sentiment index has a zero-mean, and median close to zero (0.024). Reported are the regression estimates for the long-short factor portfolio, and separately for the winner and loser portfolios. The t-statistics are calculated using the robust standard errors of Newey and West (1987) and reported in parentheses below the regression estimates. The sample period is August 1965–December 2018. Estimates reported in bold are statistically significant at a 5%-level.

Table 14. Factor momentum returns conditional on investor sentiment.

Panel A

	CS 1-1			CS 6-1			CS 6-6		
	WML	Winner	Loser	WML	Winner	Loser	WML	Winner	Loser
HIGH	**0.814**	**1.223**	0.409	**0.566**	**1.045**	**0.479**	-0.060	**1.525**	**1.585**
	(2.60)	(5.26)	(1.85)	(2.23)	(4.92)	(2.74)	(-0.13)	(3.86)	(5.03)
MILD	**1.444**	**0.959**	**-0.485**	**1.095**	**0.870**	-0.225	**1.396**	**1.275**	-0.120
	(5.05)	(7.22)	(-2.51)	(4.44)	(5.55)	(-1.59)	(3.46)	(4.61)	(-0.45)
LOW	**0.853**	**0.677**	-0.175	0.370	**0.476**	0.106	0.480	**0.868**	0.388
	(3.43)	(4.17)	(-1.15)	(1.28)	(2.77)	(0.59)	(0.99)	(2.60)	(1.37)
HIGH -	-0.039	0.545	**0.584**	0.196	**0.569**	0.373	-0.540	0.656	**1.197**
LOW	(-0.10)	(1.91)	(2.18)	(0.50)	(2.04)	(1.48)	(-0.80)	(1.26)	(2.83)

	TS 1-1			TS 6-1			TS 12-1		
	WML	Winner	Loser	WML	Winner	Loser	WML	Winner	Loser
HIGH	0.435	**0.891**	**0.457**	0.223	**0.821**	**0.598**	0.026	**0.686**	**0.660**
	(1.78)	(5.81)	(2.09)	(1.04)	(5.67)	(2.65)	(0.13)	(4.46)	(2.79)
MILD	**0.945**	**0.718**	-0.228	**0.606**	**0.431**	-0.176	**0.523**	**0.478**	-0.045
	(4.52)	(7.60)	(-1.62)	(3.64)	(4.46)	(-1.39)	(2.96)	(5.75)	(-0.33)
LOW	**0.547**	**0.526**	-0.021	0.143	**0.343**	0.200	0.433	**0.389**	-0.045
	(3.65)	(4.37)	(-0.17)	(0.63)	(2.08)	(1.46)	(1.92)	(2.38)	(-0.40)
HIGH -	-0.112	0.366	0.478	0.080	**0.478**	0.398	-0.407	0.297	**0.705**
LOW	(-0.39)	(1.87)	(1.90)	(0.25)	(2.17)	(1.51)	(-1.33)	(1.32)	(2.69)

Panel B

	CS 1-1			CS 6-1			CS 6-6		
	WML	Winner	Loser	WML	Winner	Loser	WML	Winner	Loser
ABOVE	**0.945**	**1.091**	0.146	**0.779**	**1.042**	0.263	0.422	**1.515**	**1.092**
	(4.48)	(6.95)	(0.91)	(3.99)	(7.36)	(1.87)	(1.29)	(5.76)	(4.29)
BELOW	**1.202**	**0.815**	**-0.387**	**0.663**	**0.570**	-0.093	**0.943**	**0.943**	0.000
	(5.72)	(6.69)	(-2.92)	(3.25)	(4.62)	(-0.71)	(2.71)	(4.03)	(0.00)
ABOVE -	-0.257	0.276	**0.533**	0.117	**0.472**	0.355	-0.520	0.572	**1.092**
BELOW	(-0.93)	(1.42)	(2.83)	(0.42)	(2.54)	(1.92)	(-1.09)	(1.68)	(3.39)

	TS 1-1			TS 6-1			TS 12-1		
	WML	Winner	Loser	WML	Winner	Loser	WML	Winner	Loser
ABOVE	**0.632**	**0.833**	0.201	**0.374**	**0.702**	**0.327**	0.142	**0.616**	**0.474**
	(3.63)	(7.71)	(1.34)	(2.32)	(6.96)	(2.06)	(0.92)	(6.05)	(2.82)
BELOW	**0.699**	**0.591**	-0.108	**0.331**	**0.344**	0.013	**0.546**	**0.412**	-0.134
	(5.23)	(7.21)	(-1.00)	(2.15)	(3.11)	(0.12)	(3.44)	(3.80)	(-1.41)
ABOVE -	-0.067	0.242	0.309	0.043	**0.357**	0.315	-0.405	0.203	**0.608**
BELOW	(-0.34)	(1.81)	(1.77)	(0.19)	(2.39)	(1.68)	(-1.88)	(1.37)	(3.26)

The regression estimates for the TS 12-1 strategy in Panel B of Table 14 are, expectedly, similar to the results of Ehsani and Linnainmaa (2019) as the construction of factor momentum portfolios and the measurement of investor sentiment are identical. However, Ehsani and Linnainmaa (2019) only consider the relation between TS 12-1 factor momentum and investor sentiment. The results here suggest that the relation between investor sentiment and the performance of factor momentum is dependent on the look-back period and how the factor momentum portfolios are constructed. The results of Table 14 show two important findings that contradict the findings of Ehsani and Linnainmaa (2019).

First, while Ehsani and Linnainmaa (2019) find that the winner-factor portfolios have similar performance in high and low investor sentiment, the results here show that winner factor portfolios that are formed using six-month lagged returns (CS 6-1 and TS 6-1) have significantly higher returns following periods of high investor sentiment. Furthermore, the returns of all winner-factor portfolios are positively correlated with the investor sentiment. The returns of loser-factor portfolios exhibit larger variation between investor sentiment states and are always, similarly to the returns of winner-factor portfolios, highest following periods of high investor sentiment state. This finding is consistent with the results of Ehsani and Linnainmaa (2019). However, the returns of loser-factor portfolios are not significantly negative following periods of low investor sentiment like Ehsani and Linnainmaa find. Only the CS 1-1 loser-factor portfolio in Panel B has significantly negative average returns after low investor sentiment state.

Second, the returns of WML factor momentum portfolios are not significantly different between high and low or above and below the median investor sentiment states. While the differences in average WML portfolio returns between high and low sentiment are negative for four out of six strategies, none of the differences is statistically significant. The TS 12-1 WML strategy in Panel B replicates the findings of Ehsani and Linnainmaa (2019), but the long-short returns of the five other factor momentum portfolios are less affected by investor sentiment. In Panel A, the CS 1-1 strategy has statistically significant average returns in all investor sentiment states, while the other WML portfolios lose statistical significance either in high or low (or both) sentiment states. In Panel B, four of the long-short factor momentum portfolios have significantly positive returns in both investor sentiment states. Contrary to the expected results, the average returns to all long-short strategies are highest following mild investor sentiment and exceed the unconditional average returns. The results of Table 7 explain this finding—the variation in long-short factor returns is at the highest following mild investor sentiment.

Although the performance of long-short factor momentum is not significantly affected by the prevailing investor sentiment, the results suggest that factor momentum is driven by mispricing. Winner factor portfolios capture mispricing in all sentiment states. The fact that winner factors have higher average returns following periods of high investor sentiment and loser factors have significant average returns *only* following high investor sentiment suggest that mispricing is more pronounced when investor sentiment is high. Furthermore, the fact that mispricing is affected by investor sentiment like Stambaugh et al. (2012) suggest has still an important implication on factor momentum strategies. Following periods of high investor sentiment, betting against the loser factors, while the mispricing is at its strongest, decreases the performance of long-short factor momentum. This effect is more pronounced when the formation or holding period is longer than a month. When the investor sentiment is low and the mispricing is less pronounced, the returns of loser factors tend to reverse, and betting against the loser factors increases the profitability of factor momentum.

To test whether a factor momentum investor can benefit from mispricing that varies with investor sentiment, I construct three cross-sectional and time-series factor momentum strategies that consider the prevailing investor sentiment state. For brevity, I only consider strategies with the one-month formation and holding periods. The first CS 1-1 and TS 1-1 WML strategies are constructed as previously (i.e., the prevailing investor sentiment does not affect portfolio formation). The second set of factor momentum strategies (WML**) are always long winner factors, but short loser factors only following periods of mild or low investor sentiment. As a robustness test, the third set of factor momentum strategies are always long winner factors, but short loser factors only following periods of investor sentiment that is below the median. Fundamentally, the strategies bet against the loser factor portfolio only when the contemporaneous value of dummy variable LOW_t or $MILD_t$ ($BELOW_t$) equals one. The drawback of this approach is that it is not implementable ex-ante as it uses the information of the whole sample period.

Table 15 reports the summary statistics for factor momentum portfolios that use the information of investor sentiment to time short positions in loser factor portfolios. Panel A reports the statistics for WML portfolios that do not account for the investor sentiment (i.e., the WML portfolios are constructed as previously). The portfolios in Panel B are always long winner factors, but short loser factors only when the investor sentiment is categorized as mild or low at the time of the portfolio formation. Panel C reports the statistics for WML portfolios that are always long winner factors and short loser factors only when investor sentiment is below the median. Periods of high, mild and low (above and below the median) investor sentiment are defined as previously.

Table 15. Results for timing short positions in loser-factor portfolios.

Panel A – Always long winner factors and always short loser factors

	$\bar{r}$	$t(\bar{r})$	Max	Min	SD	Skewness	Kurtosis
CS 1-1 WML	**1.08 %**	(6.13)	36.9 %	-26.5 %	4.45 %	0.54	13.52
TS 1-1 WML	**0.67 %**	(5.24)	15.6 %	-22.5 %	3.25 %	-0.35	10.36

Panel B - Short loser-factor portfolio when dummy variable MILD=1 or LOW=1

	$\bar{r}$	$t(\bar{r})$	Max	Min	SD	Skewness	Kurtosis
CS 1-1 WML**	**1.20 %**	(7.47)	36.9 %	-13.2 %	4.07 %	1.13	14.26
TS 1-1 WML**	**0.81 %**	(7.30)	15.6 %	-10.9 %	2.81 %	0.42	7.24

Panel C - Short loser-factor portfolio when dummy variable BELOW=1

	$\bar{r}$	$t(\bar{r})$	Max	Min	SD	Skewness	Kurtosis
CS 1-1 WML**	**1.13 %**	(7.45)	36.9 %	-13.2 %	3.84 %	1.36	17.33
TS 1-1 WML**	**0.76 %**	(7.34)	15.6 %	-10.9 %	2.61 %	0.41	8.44

The result of Panels B and C suggest that the performance of CS 1-1 and TS 1-1 factor momentum strategies can be increased by timing short position on loser factors using the measure of investor sentiment. The portfolios in Panels B and C have higher average returns and lower standard deviations than the portfolios that are always long (short) winner (loser) factors. Even though the strategy is not implementable ex-ante, this test serves the purpose to show that investor sentiment could be used to increase the profitability of factor momentum investing.

6.2 Risk-managed factor momentum

Motivated by the performance of risk-managed momentum strategies, I test whether the option-implied stock market volatility can be used to increase the performance of factor momentum. I follow the methodology of Barroso and Santa-Clara (2015), but instead of using realized volatility, I use the 1-month lagged month-end value of VIX as a proxy for the expected market volatility. Because I use the month-end values of VIX, the 1-month lagged value is the most accurate proxy for the option-implied market volatility at the time of the portfolio construction.

Although factor momentum does not suffer crashes like price momentum portfolios, the strategy is still subject to significant drawdowns. Furthermore, testing the impact of target volatility on factor momentum portfolios contributes to the literature of risk management as currently, studies offer mixed results regarding the benefits of risk management (see, e.g., Liu et al., 2019). I expect that the scaled average returns exceed the unscaled returns with equal risk-level. This expectation is motivated by the findings of Moreira and Muir (2017)—volatility-managed factor portfolios have higher alphas and Sharpe ratios than portfolios that do not scale the portfolio weights. Because factor momentum times investments in individual factors, I expect that increasing (decreasing) portfolio weights when the market volatility is expected to be low (high) increases the overall performance of factor momentum.

I use a target annualized volatility of 20%, which is close to the long-term average of VIX, to calculate the portfolio weights for each month. Figure 5 plots the monthly WML* portfolio weights (scaling factor) from February 1990 to December 2019 with a target volatility of 20%. The scaling factor varies between 0.33 and 2.10, with an average of 1.17. These portfolio weights are similar to the risk-managed momentum strategy of Barroso and Santa-Clara (2015), who report that in their approach the portfolio weights vary between 0.13 and 2.00, with an average of 0.90.

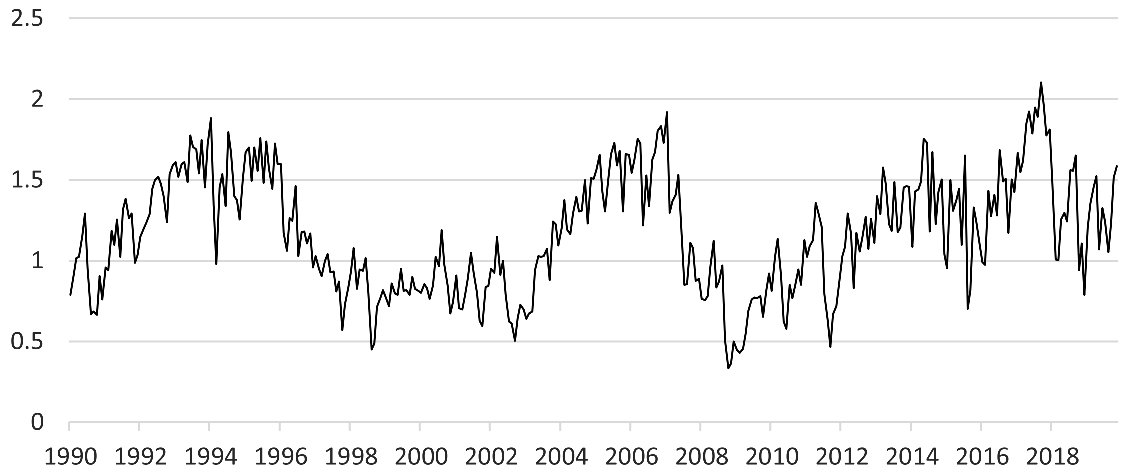

Figure 5. WML* portfolio weights, February 1990–December 2019.

Panel A of Table 16 reports the summary statistics for the unscaled (WML) and Panel B for the scaled (WML*) factor momentum portfolios. The data for VIX is available from January 1990 onwards, and therefore, the sample period spans from February 1990 to December 2019. The CS 1-1 and TS 1-1 strategies have slightly higher average returns in the sub-sample than in the full sample, but CS 6-6, TS 6-1 and TS 12-1 strategies have lower average returns that are not statistically significant in the sub-sample. The lowest and highest one-month returns are the same in the sub-sample as in the full sample. All strategies, except the CS 6-6, are more volatile in the sub-sample. Panel B of Table 16 shows that all risk-managed factor momentum portfolios have higher average returns and lower monthly volatility than the unscaled WML portfolios. Furthermore, the average returns of scaled factor momentum portfolios are statistically significant with higher t-statistics than the unscaled portfolios.

Table 16. Summary statistics for risk-managed factor momentum portfolios.

Panel A – Unscaled WML factor momentum

	CS 1-1	CS 6-1	CS 6-6	CS 12-1	TS 1-1	TS 6-1	TS 12-1
Mean	**1.05 %**	**0.66 %**	0.60 %	**0.62 %**	**0.68 %**	0.22 %	0.31 %
	(3.96)	(2.98)	(1.74)	(2.74)	(3.60)	(1.15)	(1.83)
Maximum	36.91 %	20.92 %	33.17 %	24.82 %	15.56 %	29.52 %	21.28 %
Minimum	-26.51 %	-17.75 %	-40.90 %	-21.06 %	-22.46 %	-21.98 %	-21.98 %
Volatility	5.01 %	4.18 %	6.57 %	4.30 %	3.58 %	3.56 %	3.24 %
Skewness	0.64	0.25	-0.43	0.10	-0.42	0.48	-0.84
Kurtosis	13.61	6.63	9.91	8.71	10.73	21.78	17.03

Panel B – Scaled WML factor momentum, annualized target volatility 20%

	CS 1-1*	CS 6-1*	CS 6-6*	CS 12-1*	TS 1-1*	TS 6-1*	TS 12-1*
Mean	**1.17 %**	**0.78 %**	**0.75 %**	**0.78 %**	**0.76 %**	**0.33 %**	**0.41 %**
	(4.92)	(3.75)	(2.22)	(3.68)	(4.38)	(2.01)	(2.63)
Maximum	18.32 %	16.77 %	28.05 %	19.90 %	12.41 %	23.67 %	17.06 %
Minimum	-22.42 %	-11.40 %	-26.27 %	-13.53 %	-18.99 %	-16.38 %	-16.38 %
Volatility	4.50 %	3.93 %	6.42 %	4.03 %	3.30 %	3.07 %	2.97 %
Skewness	-0.04	0.28	-0.04	0.24	-0.33	0.70	-0.18
Kurtosis	6.32	4.22	5.55	5.11	7.51	14.91	9.60

The risk-managed factor momentum portfolios have less negative worst 1-month returns than unscaled portfolios. However, also the highest 1-month returns are lower for risk-managed portfolios. Volatility scaling lowers the kurtosis and generally shifts the return distributions towards the right tale. However, the CS 1-1 strategy has a slightly negative (-0.04) skewness after volatility scaling whereas the unscaled portfolio has a positively skewed (0.64) return distribution. These findings suggest that the performance of factor momentum is increased after volatility scaling, but the benefits are not as remarkable as they are for price momentum portfolios (e.g., Daniel & Moskowitz, 2016).

Figure 6 plots the cumulative returns to $1 invested in the unscaled and scaled CS 1-1 and TS 1-1 WML portfolios. The y-axis is in logarithmic form. Figure 6 shows that the cumulative returns of both risk-managed portfolios exceed the unscaled returns. The cumulative returns are at the highest in August 2017 and continue to decrease until the end of 2019. Both CS 1-1 and TS 1-1 strategies have negative average returns in 2019 and a weak performance in 2018. The low performance of these factor momentum portfolios stems from low factor returns—eight of the long-short factors have negative average returns in 2019, and in 2018 eight of the factors have average returns that are below their long-term averages. However, the CS 12-1 and TS 12-1 strategies both have a monthly average return of over 1% in 2019, suggesting that strategies with longer formation periods occasionally perform better.

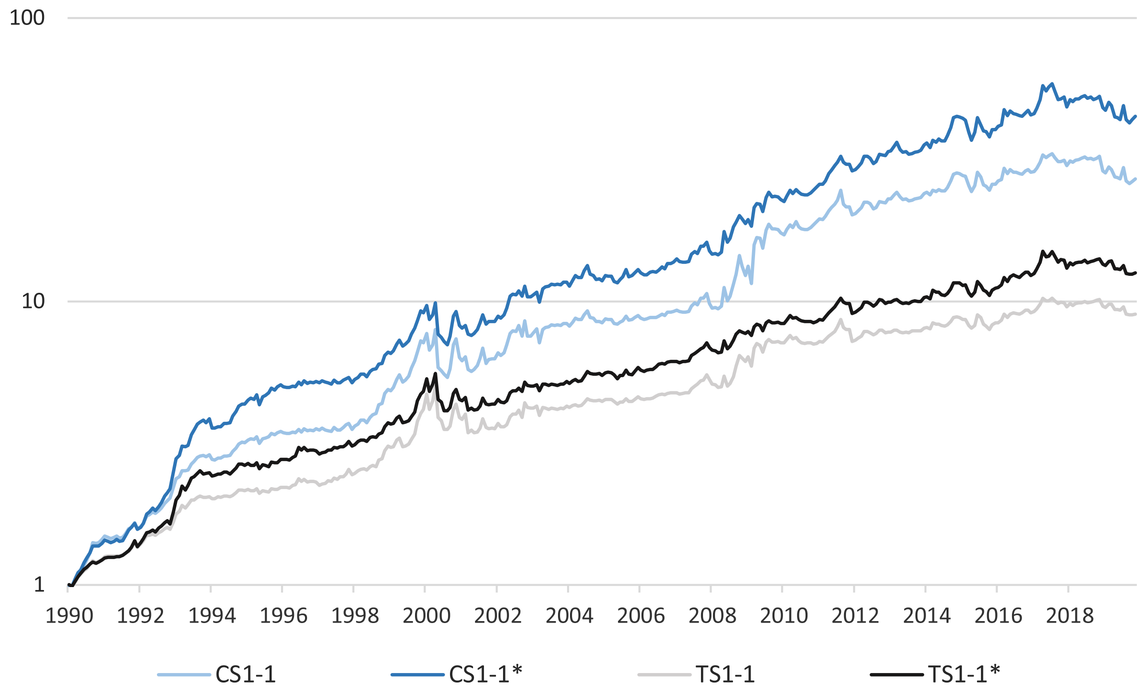

Figure 6. Cumulative returns of scaled 1-1 factor momentum portfolios.

To test whether the risk-managed factor momentum portfolios perform significantly better than the plain factor momentum portfolios, I regress the scaled WML* return series on the unscaled WML returns. Panel A of Table 17 presents the alphas for each risk-managed factor momentum portfolio (WML*) against the corresponding unscaled factor momentum portfolio (i.e., the portfolio with equal formation and holding periods). As a robustness test, I regress the risk-managed factor momentum returns on the FF5 model that is augmented with the corresponding factor momentum portfolio (Panel B) and on the FF6 model (Panel C). The sample period is February 1990–December 2019.

All risk-managed factor momentum portfolios, except the CS 6-6 strategy, have statistically significant alphas against the plain factor momentum portfolios. The alphas against FF5 factors and unscaled factor momentum portfolios (Panel B) are higher, but not statistically significant for TS 1-1, TS 12-1 and CS 6-6 strategies. Panel C of Table 17 shows that the FF6 factors have similar explanatory power on the risk-managed factor momentum returns as the unscaled factor momentum portfolios (Panel A).

Table 17. Performance of risk-managed factor momentum.

Panel A – Alpha against corresponding unscaled factor momentum portfolio

	CS 1-1*	CS 6-1*	CS 6-6*	CS 12-1*	TS 1-1*	TS 6-1*	TS 12-1*
Alpha	**0.299**	**0.197**	0.198	**0.238**	**0.172**	**0.149**	**0.143**
	(3.38)	(3.12)	(1.66)	(2.97)	(3.61)	(3.13)	(2.55)

Panel B – Alpha against FF5 model and corresponding factor momentum portfolio

	CS 1-1*	CS 6-1*	CS 6-6*	CS 12-1*	TS 1-1*	TS 6-1*	TS 12-1*
Alpha	**1.116**	**0.720**	0.382	**0.573**	0.744	**0.744**	0.220
	(4.50)	(3.42)	(1.07)	(2.94)	(0.76)	(3.99)	(1.70)

Panel C – Alpha against FF6 model

	CS 1-1*	CS 6-1*	CS 6-6*	CS 12-1*	TS 1-1*	TS 6-1*	TS 12-1*
Alpha	**0.324**	**0.190**	0.146	**0.197**	**0.180**	**0.147**	**0.122**
	(2.85)	(2.69)	(1.19)	(2.28)	(2.87)	(2.85)	(2.01)

While Figures 3 and 4 that plot the cumulative returns of factor momentum portfolios suggest that factor momentum does not exhibit crashes similar to the price momentum, the performance of factor momentum is nevertheless increased by volatility scaling. As noted earlier, Daniel and Moskowitz (2016) find that momentum portfolios exhibit optionality during bear market states. To further test whether the factor momentum portfolios are subject to optionality and momentum crashes, similar to price momentum, I follow the methodology of Daniel and Moskowitz (2016, p. 227) and regress factor momentum returns on the following model:

$$R_{WML,t} = (\alpha_0 + \alpha_\beta \cdot \mathrm{I}_{B,t-1}) + \left(\beta_0 + \mathrm{I}_{B,t-1}(\beta_B + \mathrm{I}_{U,t} \cdot \beta_{B,U})\right) R_{m,t} + \varepsilon_t, \tag{20}$$

where $\mathrm{I}_{B,t-1}$ is an ex-ante bear market indicator variable, $\mathrm{I}_{U,t}$ is a contemporaneous up-market indicator variable and $R_{m,t}$ is the excess market return. Following Daniel and Moskowitz (2016), the bear market indicator variable ($\mathrm{I}_{B,t-1}$) equals to one when the 24-month cumulative excess market returns is negative, and zero otherwise. The up-market indicator variable ($\mathrm{I}_{U,t}$) equals to one when the excess market returns exceeds the risk-free rate, and zero otherwise.

Table 18, Panel A reports the optionality regressions for factor momentum portfolios and Panel B for the risk-managed factor momentum portfolios. The sample period in Panel A is July 1965–December 2019 and February 1990–December 2019 in Panel B. The t-statistic for each regression estimate is reported in parentheses below the estimate. Following the interpretations of Daniel and Moskowitz (2016), $\hat{\beta}_0 + \hat{\beta}_B$ is the estimate for bear market beta when the contemporaneous market return is negative, and $\hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U}$ is the estimate for bear market beta when the contemporaneous market return is positive. Significantly negative $\hat{\beta}_{B,U}$ implies option-like behavior in bear markets (Daniel & Moskowitz, 2016).

The regression estimates of Table 18 suggest that only the CS 6-6 factor momentum portfolio exhibits optionality in bear markets, and the point estimate for $\hat{\beta}_{B,U}$ is not statistically significant for the risk-managed CS 6-6 portfolio. Furthermore, the strategy's point estimate for α_β is highly positive, although not statistically significant, whereas all other factor momentum strategies (except TS 12-1) have negative estimates for the increment of bear market alpha. Consistent with the previous findings in this study, the risk-managed factor momentum portfolios have higher alphas ($\hat{\alpha}_0$) than plain factor momentum portfolios. However, the sample period in Panel B is significantly shorter than in Panel A. The CS 6-1, 6-6 and 12-1, and TS 12-1 portfolios have significant exposure on the market risk, and all factor momentum portfolios have a negative market exposure during bear markets regardless whether the contemporaneous market return is positive or negative. This market risk is partly removed by the volatility scaling in Panel B.

Table 18. Optionality of factor momentum portfolios.

Panel A – Optionality of factor momentum portfolios

C	Variable	CS 1-1	CS 6-1	CS 6-6	CS 12-1	TS 1-1	TS 6-1	TS 12-1
$\hat{\alpha}_0$	1	**1.092**	**0.632**	0.540	**0.562**	**0.736**	**0.412**	**0.354**
		(5.43)	(3.51)	(1.93)	(3.14)	(5.08)	(2.96)	(2.70)
$\hat{\alpha}_B$	$\mathrm{I}_{B,t-1}$	-0.736	-0.033	1.573	-0.199	-0.494	-0.062	0.272
		(-1.16)	(-0.06)	(1.78)	(-0.35)	(-1.08)	(-0.14)	(0.66)
$\hat{\beta}_0$	$R_{m,t}$	-0.046	**0.169**	**0.394**	**0.238**	-0.063	0.058	**0.108**
		(-0.93)	(3.79)	(5.69)	(5.35)	(-1.74)	(1.67)	(3.33)
$\hat{\beta}_B$	$\mathrm{I}_{B,t-1} \cdot R_{m,t}$	**-0.374**	**-0.499**	**-0.491**	**-0.563**	**-0.234**	**-0.253**	**-0.220**
		(-2.76)	(-4.12)	(-2.61)	(-4.67)	(-2.40)	(-2.70)	(-2.49)
$\hat{\beta}_{B,U}$	$\mathrm{I}_{B,t-1} \cdot \mathrm{I}_{U,t}$	0.317	0.108	**-0.595**	0.080	0.146	-0.060	-0.157
	$\cdot R_{m,t}$	(1.47)	(0.56)	(-1.99)	(0.42)	(0.94)	(-0.40)	(-1.12)
Adjusted R^2		0.025	0.051	0.076	0.074	0.037	0.041	0.046

Panel B - Optionality of risk-managed factor momentum portfolios

C	Variable	CS 1-1*	CS 6-1*	CS 6-6*	CS 12-1*	TS 1-1*	TS 6-1*	TS 12-1*
$\hat{\alpha}_0$	1	**1.380**	**0.762**	0.569	**0.810**	**1.005**	**0.429**	**0.502**
		(5.17)	(3.24)	(1.49)	(3.41)	(5.17)	(2.33)	(2.84)
$\hat{\alpha}_B$	$\mathrm{I}_{B,t-1}$	-1.199	-0.900	1.150	-0.100	-1.286	-0.506	-0.057
		(-1.16)	(-0.99)	(0.78)	(-0.11)	(-1.71)	(-0.71)	(-0.08)
$\hat{\beta}_0$	$R_{m,t}$	**-0.215**	0.067	**0.274**	0.100	**-0.168**	0.018	0.030
		(-3.05)	(1.08)	(2.72)	(1.60)	(-3.27)	(0.37)	(0.65)
$\hat{\beta}_B$	$\mathrm{I}_{B,t-1} \cdot R_{m,t}$	-0.058	**-0.373**	-0.305	-0.312	-0.081	-0.121	-0.083
		(-0.31)	(-2.28)	(-1.15)	(-1.88)	(-0.60)	(-0.95)	(-0.67)
$\hat{\beta}_{B,U}$	$\mathrm{I}_{B,t-1} \cdot \mathrm{I}_{U,t}$	0.348	0.293	-0.497	-0.184	0.244	-0.053	-0.227
	$\cdot R_{m,t}$	(1.03)	(0.98)	(-1.03)	(-0.61)	(0.99)	(-0.23)	(-1.01)
Adjusted R^2		0.022	0.009	0.022	0.035	0.037	0.007	0.016

The regression estimates in Table 18 are similar to what Grobys et al. (2018) find with industry-momentum portfolios. Similarities in return behavior between industry and factor momentum portfolios could be explained by the finding of Arnott et al. (2018) and Ehsani and Linnainmaa (2019) that factor momentum portfolios subsume industry momentum.

Table 19 presents the regression estimates of (20) separately for the winner- (Panel A) and loser-factor (Panel B) portfolios. The sample period is July 1965–December 2019. Assessing the optionality of the winner- and loser-factor portfolios separately shows that only the loser-factor portfolio of the CS 1-1 strategy exhibits optionality. However, the estimate for the up-market beta in bear markets is only slightly negative (-0.219), and the corresponding beta for the WML portfolio is -0.103. In contrast, Daniel and Moskowitz (2016) report that the up-market beta estimate in bear markets for the price momentum portfolio is -1.796.

Table 19. Optionality of winner- and loser-factor portfolios.

Panel A – Optionality of winner-factor portfolios

C	Variable	CS 1-1	CS 6-1	CS 6-6	CS 12-1	TS 1-1	TS 6-1	TS 12-1
$\hat{\alpha}_0$	1	**0.980**	**0.819**	**1.213**	**0.749**	**0.780**	**0.553**	**0.569**
		(8.59)	(7.53)	(6.58)	(7.00)	(9.83)	(6.66)	(7.66)
$\hat{\alpha}_B$	$\mathrm{I}_{B,t-1}$	0.239	0.088	1.131	-0.120	-0.049	0.179	0.229
		(0.66)	(0.26)	(1.95)	(-0.36)	(-0.19)	(0.68)	(0.98)
$\hat{\beta}_0$	$R_{m,t}$	**-0.116**	-0.029	-0.046	0.012	**-0.120**	**-0.074**	**-0.077**
		(-4.09)	(-1.08)	(-1.01)	(0.44)	(-6.12)	(-3.62)	(-4.17)
$\hat{\beta}_B$	$\mathrm{I}_{B,t-1} \cdot R_{m,t}$	**-0.161**	**-0.271**	**-0.303**	**-0.357**	-0.064	-0.092	-0.047
		(-2.10)	(-3.69)	(-2.45)	(-4.96)	(-1.20)	(-1.65)	(-0.94)
$\hat{\beta}_{B,U}$	$\mathrm{I}_{B,t-1} \cdot \mathrm{I}_{U,t} \cdot R_{m,t}$	-0.047	0.006	-0.337	0.147	-0.010	-0.048	-0.112
		(-0.38)	(0.05)	(-1.71)	(1.28)	(-0.12)	(-0.54)	(-1.42)
Adjusted R^2		0.115	0.102	0.113	0.090	0.125	0.090	0.106

Panel B - Optionality of loser-factor portfolios

C	Variable	CS 1-1	CS 6-1	CS 6-6	CS 12-1	TS 1-1	TS 6-1	TS 12-1
$\hat{\alpha}_0$	1	-0.112	0.187	**0.673**	0.187	0.044	0.141	**0.215**
		(-0.89)	(1.70)	(3.76)	(1.65)	(0.44)	(1.49)	(2.29)
$\hat{\alpha}_B$	$\mathrm{I}_{B,t-1}$	**0.974**	0.121	-0.442	0.079	0.446	0.241	-0.043
		(2.45)	(0.35)	(-0.78)	(0.22)	(1.41)	(0.81)	(-0.14)
$\hat{\beta}_0$	$R_{m,t}$	**-0.069**	**-0.198**	**-0.440**	**-0.226**	**-0.058**	**-0.132**	**-0.185**
		(-2.21)	(-7.27)	(-9.92)	(-8.04)	(-2.33)	(-5.63)	(-7.96)
$\hat{\beta}_B$	$\mathrm{I}_{B,t-1} \cdot R_{m,t}$	**0.213**	**0.229**	0.188	**0.205**	**0.170**	**0.161**	**0.173**
		(2.50)	(3.09)	(1.56)	(2.69)	(2.53)	(2.53)	(2.74)
$\hat{\beta}_{B,U}$	$\mathrm{I}_{B,t-1} \cdot \mathrm{I}_{U,t} \cdot R_{m,t}$	**-0.363**	-0.102	0.258	0.067	-0.156	0.012	0.045
		(-2.70)	(-0.87)	(1.35)	(0.55)	(-1.46)	(0.12)	(0.45)
Adjusted R^2		0.015	0.071	0.135	0.089	0.008	0.048	0.085

Daniel and Moskowitz (2016) show that the portfolio of extreme loser stocks has a strong up-market beta and high $\hat{\beta}_{B,U}$ in bear markets whereas the portfolio of extreme winner stocks has a lower estimate for the up-market beta and slightly negative estimate for $\hat{\beta}_{B,U}$. The results of Table 19 show that winner-factor portfolios have negative up-market betas in bear markets and loser-factor portfolios have either slightly negative or slightly positive up-market betas. Interestingly, the $\hat{\alpha}_0$ for the CS 1-1 winner factor portfolio is significantly positive and the estimate for the bear market alpha increment is insignificant but positive. In contrast, the $\hat{\alpha}_0$ for the CS 1-1 loser factor portfolio is insignificant while the bear market alpha increment is significantly high.

Table 20 reports the 15 worst monthly returns for the UMD factor in a similar way as Daniel and Moskowitz (2016, p. 227) and Grobys et al. (2018, p. 11) report the worst price momentum returns with the corresponding market and industry momentum returns. Along with the UMD return, Table 20 reports the contemporaneous 1-1 factor momentum returns. The results of Table 20 confirm that CS 1-1 and TS 1-1 strategies are not subject to the same momentum crashes as the UMD factor.

Table 20. Worst monthly UMD returns.

	Date	UMD	CS 1-1	TS 1-1	CS 1-1*	TS 1-1*
1	04/2009	-34.39 %	36.91 %	15.56 %	16.72 %	7.05 %
2	01/2001	-25.06 %	-14.31 %	-10.39 %	-10.66 %	-7.74 %
3	11/2002	-16.18 %	13.46 %	12.62 %	8.64 %	8.11 %
4	05/2009	-12.44 %	5.91 %	3.93 %	3.24 %	2.16 %
5	03/2009	-11.38 %	-12.83 %	-7.29 %	-5.54 %	-3.15 %
6	05/2003	-10.78 %	11.79 %	6.38 %	11.11 %	6.02 %
7	04/2003	-9.47 %	-10.71 %	-7.18 %	-7.35 %	-4.93 %
8	05/2000	-9.08 %	13.00 %	12.33 %	9.93 %	9.41 %
9	04/1999	-9.07 %	6.70 %	5.42 %	5.76 %	4.66 %
10	08/2009	-8.84 %	15.51 %	8.65 %	11.97 %	6.67 %
11	01/2019	-8.68 %	-11.51 %	-5.53 %	-9.05 %	-4.35 %
12	04/2000	-8.58 %	4.44 %	7.08 %	3.68 %	5.87 %
13	11/2001	-8.58 %	3.59 %	-1.17 %	2.14 %	-0.70 %
14	10/2001	-8.42 %	-11.67 %	-7.12 %	-7.31 %	-4.46 %
15	04/2001	-7.97 %	-9.95 %	-14.03 %	-6.95 %	-9.79 %

Table 21 reports the 15 worst monthly CS 1-1 (Panel A) and TS 1-1 (Panel B) returns along with the corresponding returns for the risk-managed portfolios. Both cross-sectional and time-series strategies have similar crashes, and the monthly drawdowns are less negative for risk-managed factor momentum portfolios.

Table 21. Worst monthly CS 1-1 and TS 1-1 returns.

Panel A – Worst monthly CS 1-1 returns

	Date	CS 1-1	UMD	TS 1-1	CS 1-1*	TS 1-1*
1	06/2000	-26.51 %	16.59 %	-22.46 %	-22.42 %	-18.99 %
2	01/2001	-14.31 %	-25.06 %	-10.39 %	-10.66 %	-7.74 %
3	03/2009	-12.83 %	-11.38 %	-7.29 %	-5.54 %	-3.15 %
4	03/2000	-12.35 %	-6.39 %	-11.62 %	-10.57 %	-9.94 %
5	12/2002	-11.96 %	9.64 %	-3.71 %	-8.70 %	-2.70 %
6	10/2001	-11.67 %	-8.42 %	-7.12 %	-7.31 %	-4.46 %
7	01/2019	-11.51 %	-8.68 %	-5.53 %	-9.05 %	-4.35 %
8	10/2011	-10.80 %	-1.42 %	-6.55 %	-5.03 %	-3.05 %
9	04/2003	-10.71 %	-9.47 %	-7.18 %	-7.35 %	-4.93 %
10	07/2008	-10.34 %	-5.14 %	-7.73 %	-8.63 %	-6.46 %
11	09/2019	-10.33 %	-6.85 %	-5.84 %	-10.88 %	-6.15 %
12	04/2001	-9.95 %	-7.97 %	-14.03 %	-6.95 %	-9.79 %
13	10/2002	-8.46 %	-5.30 %	-5.32 %	-4.26 %	-2.68 %
14	12/2008	-7.99 %	-5.08 %	-2.28 %	-2.89 %	-0.82 %
15	07/2009	-7.48 %	-5.36 %	-5.31 %	-5.68 %	-4.03 %

Panel B – Worst monthly TS 1-1 returns

	Date	TS 1-1	UMD	CS 1-1	CS 1-1*	TS 1-1*
1	06/2000	-22.46 %	16.59 %	-26.51 %	-22.42 %	-18.99 %
2	04/2001	-14.03 %	-7.97 %	-9.95 %	-6.95 %	-9.79 %
3	03/2000	-11.62 %	-6.39 %	-12.35 %	-10.57 %	-9.94 %
4	01/2001	-10.39 %	-25.06 %	-14.31 %	-10.66 %	-7.74 %
5	01/2012	-9.24 %	-7.96 %	-6.28 %	-5.37 %	-7.90 %
6	07/2008	-7.73 %	-5.14 %	-10.34 %	-8.63 %	-6.46 %
7	03/2009	-7.29 %	-11.38 %	-12.83 %	-5.54 %	-3.15 %
8	04/2003	-7.18 %	-9.47 %	-10.71 %	-7.35 %	-4.93 %
9	10/2001	-7.12 %	-8.42 %	-11.67 %	-7.31 %	-4.46 %
10	06/1999	-6.92 %	4.88 %	-6.15 %	-4.85 %	-5.45 %
11	08/2000	-6.89 %	5.71 %	-2.96 %	-2.86 %	-6.64 %
12	10/2011	-6.55 %	-1.42 %	-10.80 %	-5.03 %	-3.05 %
13	09/2019	-5.84 %	-6.85 %	-10.33 %	-10.88 %	-6.15 %
14	01/2019	-5.53 %	-8.68 %	-11.51 %	-9.05 %	-4.35 %
15	09/2015	-5.40 %	5.33 %	-6.45 %	-4.54 %	-3.80 %

7 Conclusions

The results regarding factor returns are consistent with previous studies. Factor returns are positively autocorrelated, and the correlations between factor returns are generally low, similar to what Gupta and Kelly (2019) find. Factor returns are predictable from prior 1- and 12-month returns, and negative factor returns are not long-lasting. These results have two important implications for factor momentum strategies. First, betting that prior 1- to 12-month winner factors continue to perform well is profitable, but betting against recent loser factors is only profitable with the factors that have the worst prior 1-month returns. Effectively, only the cross-sectional 1-1 strategy captures negative short-side returns. Second, because factors have generally low or even negative correlations, factor momentum strategies can be constructed with a relatively low number of factors.

Factor momentum portfolios generate robust returns that exceed the returns of individual factors. The five-factor model of Fama and French (2015) cannot explain factor momentum returns. After controlling for the six-factor model of Fama and French (2018), three out of seven factor momentum portfolios have statistically significant alphas, and two of the factor momentum portfolios have significant alphas after controlling for the three-factor model of Daniel and Hirshleifer (2019). Both cross-sectional and time-series strategies perform best with a one-month formation and holding periods. Contrary to the results of Gupta and Kelly (2019) and Ehsani and Linnainmaa (2019), I find that cross-sectional strategies have higher average returns than time-series strategies on equal formation periods. Furthermore, the cross-sectional and time-series portfolios that are formed using 1-month lagged returns have robust excess returns in all considered specifications.

Consistent with Stambaugh et al. (2012), the average long-short factor returns are generally at the highest following periods of high investor sentiment because short-side portfolios become relatively more overpriced than long-side portfolios. In contrast, the long-short factor returns are low and generally below the unconditional average returns following periods of low investor sentiment because mispricing becomes less pronounced. Because each factor is likely to capture a different type of mispricing, the contemporaneous investor sentiment affects mispricing and factor returns differently—two of the factors have the highest average returns following mild investor sentiment and one following low investor sentiment.

Against the expected results and the findings of Ehsani and Linnainmaa (2019), the differences in long-short factor momentum returns are not statistically significant between periods of high and low investor sentiment. WML factor momentum returns are highest following mild investor sentiment because the variation in long-short factor returns is at the highest. Winner-factor portfolios capture mispricing in all investor sentiment states, and loser-factor portfolios only after periods of high investor sentiment. The returns of the loser-factor portfolios increase with the length of the formation period, suggesting that the contrary short-term mispricing is not as persistent as long-term mispricing. Regressing the factor momentum returns on the three-factor model of Daniel and Hirshleifer (2019) suggest that the returns of winner-factor portfolios are driven by positive earnings surprises, and the returns of loser-factor portfolios are driven by negative earnings surprises.

Although the WML factor momentum returns are not significantly different between high and low investor sentiment, the investor sentiment and varying mispricing have an important implication on factor momentum's performance. Betting against the recent loser factors increases the performance of factor momentum following periods of low or mild investor sentiment but decreases the performance after periods of high investor sentiment. A cross-sectional 1-1 factor momentum strategy that is always long two winner factors and short two loser factors only after periods of low or mild investor sentiment achieves a monthly average return of 1.20%.

Risk-managed factor momentum portfolios have statistically significant alphas against the unscaled portfolios. Although factor momentum portfolios do no exhibit optionality in bear markets, the average returns of factor momentum portfolios can be increased while lowering the return volatility using option-implied market volatility to scale the portfolio weights. Furthermore, the optionality regressions show that factor momentum portfolios generally have significant market risk, and this risk is partly removed with volatility scaling.

An issue that was not addressed in this thesis is the trading costs of the factor momentum strategy. Since factor momentum portfolios are rebalanced monthly, the trading costs have a negative impact on the net returns. The issue of trading costs is discussed by Gupta and Kelly (2019), who find that both cross-sectional and time-series factor momentum portfolios with a one-month holding period have higher Sharpe ratios than price momentum or industry momentum strategies after controlling for trading costs. Because factor momentum strategy manages to time investments profitably in different factors, the strategy could be constructed using ETFs that aim to replicate factor returns. This idea is left for future research.

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Appendices

Appendix 1. Description of factor construction

Factor	Sorting	Long-side portfolio	Short-side portfolio	Portfolio rebalancing
ASSETG	Bivariate Independent (2 Size x 3 Investment)	0.5 x (Small & Low Growth + Big & Low Growth)	0.5 x (Small & High Growth + Big & High Growth)	Annually at the end of June
BAB	Univariate on market beta	Low-beta stocks	High-beta stocks	Monthly
BM	Bivariate Independent (2 Size x 3 B/M)	0.5 x (Small & High B/M + Big & High B/M)	0.5 x (Small & Low B/M + Big & Low B/M)	Annually at the end of June
CFP	Bivariate Independent (2 Size x 3 CFP)	0.5 x (Small & High CF/P + Big & High CF/P)	0.5 x (Small & Low CF/P + Big & Low CF/P)	Annually at the end of June
DP	Bivariate Independent (2 Size x 3 DP)	0.5 x (Small & High D/P + Big & High D/P)	0.5 x (Small & Low D/P + Big & Low D/P)	Annually at the end of June
EP	Bivariate Independent (2 Size x 3 E/P)	0.5 x (Small & High E/P + Big & High E/P)	0.5 x (Small & Low E/P + Big & Low E/P)	Annually at the end of June
HML_D	Bivariate Dependent (2 Size x 3 B/M)	0.5 x (Small & High B/M + Big & High B/M)	0.5 x (Small & Low B/M + Big & Low B/M)	Annually at the end of June
OP	Bivariate Independent (2 Size x 3 OP)	0.5 x (Small & High OP + Big & High OP)	0.5 x (Small & Low OP + Big & Small OP)	Monthly
QMJ	Bivariate Dependent (2 Size x 3 Quality)	0.5 x (Small & High quality + Big & High quality)	0.5 x (Small & Low quality + Big & Low quality)	Annually at the end of June
STR	Bivariate Independent (2 Size x 3 prior (t-1) return	0.5 x (Small & Low return + Big & Low return)	0.5 x (Small & High return + Big & High return)	Monthly
UMD	Bivariate Independent (2 Size x 3 Prior (t-12 to t-2) return)	0.5 x (Small & High return + Big & High return)	0.5 x (Small & Low return + Big & Low return)	Monthly

All factor portfolios (except BAB) use the median NYSE market equity as a size breakpoint. Factor breakpoints are the 30th and 70th NYSE percentiles corresponding to the sorting factor. BAB portfolio returns are rank-weighted, all other portfolios are value-weighted.

Appendix 2. Factor momentum portfolios with big- and small-cap factors

Panel A presents the summary statistics for factor momentum portfolios that are formed using big- and small-capitalization factors and without HML_D and BAB factors. For example, the return for $ASSETG_{Small}$ is calculated as follows:

$$ASSETG_{Small,t} = r_t^{Small\,\&\,LowInv} - r_t^{Small\,\&\,HighInv}.$$

The cross-sectional factor momentum portfolios are long (short) two factors with the highest (lowest) formation period returns, and the time-series factor momentum portfolios are long (short) factors with above (below) the median formation period returns. Panel B presents the regression estimates for the three-factor model of Daniel and Hirshleifer (2019). The sample period spans from July 1972 to December 2018.

Panel A – Summary statistics

	CS 1-1 (Big)	CS 1-1 (Small)	CS 6-1 (Big)	CS 6-1 (Small)	TS 1-1 (Big)	TS 1-1 (Small)	TS 6-1 (Big)	TS 6-1 (Small)
Mean	**0.57 %**	**0.78 %**	0.32 %	**0.55 %**	**0.54 %**	**0.50 %**	0.22 %	**0.47 %**
	(3.17)	(4.74)	(1.93)	(3.61)	(3.90)	(3.83)	(1.76)	(3.80)
Max	28.1 %	34.8 %	24.5 %	35.7 %	20.2 %	19.7 %	17.1 %	30.6 %
Min	-19.2 %	-27.1 %	-17.5 %	-20.4 %	-13.7 %	-20.7 %	-17.5 %	-29.6 %
SD	4.67 %	4.26 %	4.34 %	3.95 %	3.58 %	3.36 %	3.30 %	3.17 %
Skewness	0.46	0.12	-0.07	0.48	0.16	-0.32	-0.42	-0.17
Kurtosis	7.54	15.10	6.17	15.83	6.67	10.05	6.78	28.38

Panel B – DH3 model

	CS 1-1 (Big)	CS 1-1 (Small)	CS 6-1 (Big)	CS 6-1 (Small)	TS 1-1 (Big)	TS 1-1 (Small)	TS 6-1 (Big)	TS 6-1 (Small)
Alpha	0.096	0.525	-0.178	0.194	0.238	0.326	0.002	0.243
	(0.38)	(1.87)	(-0.85)	(0.84)	(1.24)	(1.68)	(0.01)	(1.13)
MKT-RF	-0.067	-0.074	-0.014	-0.041	-0.088	-0.061	-0.070	-0.039
	(-0.94)	(-0.93)	(-0.20)	(-0.52)	(-1.35)	(-1.02)	(-1.17)	(-0.58)
FIN	0.172	0.091	-0.040	-0.056	0.150	0.099	-0.087	-0.070
	(1.93)	(0.50)	(-0.51)	(-0.29)	(1.53)	(0.77)	(-1.03)	(-0.43)
PEAD	**0.571**	**0.550**	**0.677**	**0.710**	**0.346**	**0.353**	**0.440**	**0.492**
	(2.93)	(2.43)	(4.03)	(3.74)	(2.61)	(2.29)	(3.60)	(2.85)
Adj. R^2	0.075	0.068	0.076	0.107	0.078	0.059	0.070	0.082