Does Factor Momentum Reverse?

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Abstract

This study examines whether factor returns have the tendency to reverse. Using 23 U.S. based factors, I construct time-series and cross-sectional factor momentum and reversal strategies. I find that strategies betting on the short-term continuation of factor returns yield positive results. The empirical evidence suggests that the success of this strategy is likely to be associated with investor sentiment. This finding aligns with the narrative highlighting the role of mispricing in anomaly persistence. However, short-selling environment plays no role in enhancing this phenomenon. Following strategies formed on the assumption of long-term reversal leads to losses. Equity reversal occurs independently of factor returns autocorrelation. The findings of the study remain robust after reducing the number of factors in the sample and adjustment of strategies holding periods. Lastly, the evidence from the international sample confirms the robustness of the findings.

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Contents

1 Introduction

The 2007-2009 Financial Crisis has emerged as a powerful platform for analyzing price dynamics of various assets. In the course of this period, the majority of risky assets has experienced a drop in prices. For example, the return on the U.S. Large Cap Equity was as low as -37% and international equity -43.2%. Even highly diversified assets renowned for their resilience to market crashes plummeted. One of the examples are hedge funds. The HFRI Equity Hedge Index confronted losses of 20.6%. This event has led many to question the importance of asset diversification (Ang, 2014).

The role of diversification has been subject to an extensive debate within the scientific community. Ang (2014) highlights that the discussion regarding the dynamics of asset risk premia cannot be persued without addressing the role of factor risk premia. Similarly to the author, I draw an analogy between assets and weather to illustrate the essence of factor risk premia.

In our daily lives, we frequently use the term "bad weather" to describe the unfavourable state of atmospheric conditions. Despite its comprehensiveness and wide recognition, the term merely condenses the underlying determinants of the climate. The fundamental variables which contribute to the wider term "weather" consist of the temperature, atmospheric pressure, wind, humidity, precipitation and cloudiness. Assuming the reader has conventional preferences, she would define "bad weather" as a composite of, among others, strong wind, heavy rain and low temperature. In fact, weather forecasts inform about such climate variables. Whereas certain locations, such as The Netherlands, are much more likely to be exposed to adverse conditions; others, for instance Portugal, tend to experience mild temperatures and sunshine.

This analogy translates into the relationship between assets and factors. Similarly as the rain and high atmospheric pressure drive "bad weather", factor risks determine asset risks. Furthermore, the same way certain people occupy regions with little likelihood of unfavourable weather conditions, market participants have unique preferences regarding factors exposure Ang (2014). Taken together, asset risk premium is driven by the contributing factors. Subsequently, the decision-making of an investor should be motivated by consideration of factor exposure instead of evaluation of individual assets. According to this narrative, investment strategies designed with the focus of factor exposure optimization should be generally lucrative and resilient to adverse market conditions.

The concept of returns timing has been discussed extensively in the literature. However, the majority of the studies focus on the benefits derived from timing of individual equities (Jegadeesh & Titman, 1993; Asness, 1995; De Bondt & Thaler, 1985). The notion that factors can also be timed has attracted considerably less academic research. Recent studies by Ilmanen, Israel, Moskowitz, Thapar, & Wang (2019) and Haddad, Kozak, & Santosh (2020) focus on the time-variation in factor returns and develop frameworks of factor timing.

Another strand of literature explores profitability of investment strategies formed on the prior performance of factors. For example, Arnott, Clements, Kalesnik, & Linnainmaa (2019) use the relative performance of 51 U.S. factors to construct strategies betting on the continuation in returns. They provide empirical evidence for the existence of factor momentum. Specifically, according to the authors, the strategy that buys factors with above-average returns in the formation window and sells the remaining, earns statistically significant profits. Similarly, Ehsani & Linnainmaa (2019) use a sample of 15 anomalies and conclude that timing factors solely on the basis of their own past pattern is more optimal than the procedure involving cross-sectional comparison. Additionally, they highlight that factor momentum has the ability to explain equity momentum. Following the same methodology, Gupta & Kelly (2019) confirm the observations of Ehsani & Linnainmaa (2019) and supplement them with the evidence from an international sample.

Concluding, the empirical evidence highlighted above identifies momentum in factor returns. The question naturally arises as to whether factors merely mimic equity returns patterns or report unique tendencies. Equity momentum, which bets on the continuation of stock returns, has a twin anomaly, namely reversal. This provides an optimal environment for testing the originality of factor momentum.

The purpose of this research is to examine the profitability investment strategies betting on the reversal in factor returns. Furthermore, I conduct an analysis of the relationship between equity and factor reversal strategies. I collect a sample of 23 well-established U.S. factors and construct short-term factor momentum and long-term factor reversal strategies. In order to gain a deeper understanding of what could potentially explain the anomalies, I analyze the interaction between investor sentiment and factor momentum (reversal).

The main results of this study confirm the resilience of factor momentum against the reversal effect. Short-term factor momentum, which bets on the continuation of returns, earns positive returns. On the contrary, long-term factor reversal yields negative returns, suggesting that factor returns do not mirror equity returns patterns. The observation that factor momentum and reversal exhibit no explanatory power of equity reversal attests the validity of this statement. Lastly, I find that the factor momentum anomaly is linked to investor sentiment. Contrary to the expectations, this mispricing seems to be independent of short-selling restrictions.

This paper has been organized in the following way. It begins with the introduction of the relevant literature in Section II, which lays out the theoretical foundations of the hypotheses examined in this study. Section III describes the data. Section IV is concerned with the methodology. Section V summarizes and explains the results. Section VI deals with the robustness check of the results. Lastly, the study is concluded in Section VII.

2 Literature overview

This section reviews the literature related to momentum and reversal anomalies. Specifically, it summarises the empirical evidence and the theoretical explanations for the profitability of investment strategies based on these phenomena. Furthermore, it presents recent studies on factor momentum and describes how it relates to equity momentum. Lastly, I identify studies aimed at explaining the causes of the persistence of such anomalies. The outlined theoretical and empirical findings lay out foundation for the hypotheses stated in this section.

2.1 Momentum and contrarian strategies

2.1.1 Equity-level perspective

There exists a considerable body of literature aimed at explaining the time-series and cross-sectional equity returns. A particularly well-documented and robust finding in this field is the equity market momentum. This is a phenomenon which is most commonly described as the tendency of stock returns to predict its subsequent performance (Subrahmanyam, 2018). This topic attracts a significant amount of academic effort because it directly violates the notion of the efficient market hypothesis in its weakest form, which states that future returns cannot be predicted by their historical patterns (Subrahmanyam, 2018; Ehsani & Linnainmaa, 2019).

The research in the field of returns momentum was initiated by the study of Jegadeesh & Titman (1993). They recognize that stocks with relatively outperforming returns over the past three to twelve month have the tendency to continue to earn superior returns in the next three to twelve months. They arrive at this finding by examining the profitability of 16 trading strategies constructed on the basis of stocks' prior returns. Each strategy is obtained using the following methodology. Each month, they rank stocks based on their performance over the predefined number of months. The ranking procedure allows the authors to determine which stocks have exhibited outperformance (underperformance) and should be assigned long (short) positions in the following months of the holding period. The study of Asness (1995) confirms the results of Jegadeesh & Titman (1993) and supplies evidence that past returns have explanatory power for stock returns even when the effect of size and book-to-market is accounted for. It is further explored by Fama & French (1996) who identify the momentum anomaly as the sole factor which fails to be explained by the three-factor model.

Additionally, the persistence of the phenomenon is documented across various countries (Rouwenhorst, 1998; Liew & Vassalou, 2000; Griffin, Ji, & Martin, 2003). Furthermore, a number of authors recognize that next to stocks, currencies, commodities and bonds also exhibit the momentum anomaly (Shleifer & Summers, 1990; Erb & Harvey, 2006; Asness, Moskowitz, & Pedersen, 2013). Until the study of Moskowitz, Ooi, & Pedersen (2012) the cross-sectional definition was applied most commonly by the researchers in the field. However, the authors proposed an alternative definition. Specifically, they provide evidence that securities' own prior returns (independent of peers) are capable of predicting future returns.

On the other hand, several studies suggest that in the long-run momentum anomaly reverses. Specifically, they point to the tendency of stocks with high prior three to five years returns (winners) to earn inferior returns relative to their underperforming peers (losers). The anomaly was firstly documented by De Bondt & Thaler (1985). The authors develop an overreaction hypothesis which states that people have the tendency to overreact to negative news. In line with this notion, they provide evidence that 36 months after the portfolio formation, winners earn significantly lower returns (by approximately 25%) than losers. The subsequent study of De Bondt & Thaler (1987) adds that such excess returns cannot be explained by the changes in risk, tax effects or the size effect. Additionally, studies by Jegadeesh (1990) and Lehmann (1990) document that the reversal effect is observable also when a short-term is considered. Specifically, their research highlights that stocks with relatively weak performance over the immediate prior one month earn significant positive returns in the following month. Contrarily to the long-term reversal, the success of the short-term reversal anomaly cannot be attributed to the overreaction hypothesis, but rather to short-term price pressure and limited liquidity. Specifically, the short-term reversal is likely to be linked to bid-ask prices determined by dealers given their deficits in inventory (Jegadeesh & Titman, 1995).

In short, there is a large volume of studies exploring the issue of auto-predictive qualities of securities. It is now well established that momentum and reversal are persistent anomalies which cannot be explained by other conventional factors.

2.1.2 Factor-level perspective

Although there are many studies confirming the robustness of equity momentum and reversal, other authors question whether they should earn the status of independent factors.

Particularly, a series of studies has indicated that stock momentum merely aggregates the autocorrelations of the underlying risk factors (Ehsani & Linnainmaa, 2019).

The original study which explores this notion was conducted by Moskowitz & Grinblatt (1999). The authors demonstrate that a large proportion of the momentum excess returns disappear when controlled for the industry effect. Moreover, they find that the industry momentum is more profitable than the equity cross-sectional momentum strategy. Arnott et al. (2019) investigate this discovery further and show that a similar pattern can be found among the cross-section of factors. Each month, they sort a set of 51 factors according to their return during the formation period. Following the cross-sectional methodology of Jegadeesh & Titman (1993), they determine the position in factors depending on their rank. Precisely, each month they form a portfolio long top eight and short bottom eight performers. Such a strategy, with one-month look-back window and monthly rebalancing, earns an annualized average return of 10.5% which is statistically significant even after controlling for the Fama & French (2015) five factors (referred to as FF5 in the study). Furthermore, by creating industry-neutral factors, the authors argue that the industry momentum is driven by and can be fully subsumed by factor momentum.

A study by Ehsani & Linnainmaa (2019) complements the findings of Arnott et al. (2019) by examining an alternative portfolio formation method. Namely, they adopt the time-series approach initially introduced by Moskowitz et al. (2012). Instead of ranking the factors on their relative performance, the positions are assigned on the basis of individual prior returns. According to their results, the time-series strategy earns an annualized mean return of 4.2% and the cross-sectional strategy 2.8%. A confirmation of superiority of time-series over the cross-sectional factor momentum is supplied by Gupta & Kelly (2019). They demonstrate that despite the strategies sharing a correlation of 0.9 and earning similar Sharpe ratios, the alphas of cross-sectional strategy are negative after controlling for the time-series strategy. Contrarily, the alphas of time-series factor momentum remain positive and significant, even after controlling for the cross-sectional alternative.

In addition, factor momentum is not limited to the factor constructed using the U.S. data. It is proven that an international sample of factors earns significantly positive returns regardless of the selected formation period, with the time-series strategy performing notably better than the cross-sectional one (Gupta & Kelly, 2019).

Concluding, research has provided empirical evidence documenting the persistence of the factor momentum. An interesting observation highlighted by Gupta & Kelly (2019) regards the variation in performance of factor momentum formed using alternative formation periods. Namely, they notice that the one-month look-back window strategy earns higher average returns than the strategies with formation windows of intermediate (6 to 12 months) and long (5 years) term. Furthermore, one-month factor momentum and equity short-term reversal share a highly negative correlation of -0.8. A similar effect is observed by Arnott et al. (2019), who find that both industries and factors positively predict returns in the short-term. Moreover, by performing spanning regressions, they show that the alphas of the short-term equity reversal factor are significantly higher when controlled for factor momentum. The evidence shows that factor momentum exhibits unique return patterns not found in equity momentum. However, the existing literature demonstrating the dissimilarities in reversal patterns is limited to short-term horizon. The purpose of this study is to evaluate whether the factor momentum remains resilient to the reversal effect and examines both the short- and long-term. Consequently, the main purpose of this study is to critically examine the view that:

Hypothesis 1. *Factor momentum is resilient to the reversal effect, irrespective of the time horizon considered.*

Building on the methodology of Arnott et al. (2019) and Gupta & Kelly (2019), I test the susceptibility of factor momentum to the short-term reversal effect by examining the profitability of the factor momentum using an immediate one-month look-back window. Additionally, unlike the previous studies, I construct a long-term factor reversal strategy which is long factors with underperforming returns in the formation period and short factors with outperforming returns. By examining the profitability of this strategy, I am able to directly assess whether factor-based strategies exhibit the reversal effect. To summarize, I expect that the factor reversal would manifest itself through positive returns of short-term factor momentum and negative returns of long-term factor reversal.

2.1.3 Relationship between equity and factor momentum

Ehsani & Linnainmaa (2019) provide empirical evidence that equity momentum arises as a consequence of autocorrelations in underlying factors. They lay out a theoretical framework which explains the relationship between the equity and factor momentum. Similarly to Ang (2014), they assume that individual stock returns r_i can be attributed to a set of factors F. This translates into the following relationship:

$$r_i = \sum_{f=1}^{F} \beta_i^f r_i^f + \varepsilon_{i,t}, \tag{1}$$

where r^f is the factor return, β_i^f is the stock's slope on factor return and ε_i corresponds to stock-specific return. Consequently, they derive the expected return on the cross-sectional factor momentum as:

$$E[R_t^{mom}] = \sum_{f=1}^{F}[\text{cov}(r_{-t}^f, r_t^f)\sigma_{\beta_f}^2] + \sum_{f=1}^{F}\sum_{k=1}^{F}[\text{cov}(r_{-t}^f, r_t^k)\text{cov}(\beta^f, \beta^k)] \\ + \frac{1}{N}\sum_{s=1}^{N}[\text{cov}(\varepsilon_{i,t}, \varepsilon_{i,-t}] + \sigma_\eta^2, \tag{2}$$

where f is different than k, N is the number of stock, σ_η represents the variation in the stock's unconditional expected return and $\sigma_{\beta_f}^2$ is the cross-sectional variance of the portfolio loadings. The first term of the equation suggests that stock momentum is likely to arise as a consequence of autocorrelation in factor returns. Based on this dependency, Ehsani & Linnainmaa (2019) examine the extent to which the factor momentum explains equity momentum. They report that the FF5 model augmented with the time-series factor momentum is capable of pricing the equity momentum returns. Importantly, it performs more efficiently than the model incorporating the Carhart (1997) UMD factor. Similar observations are found in Gupta & Kelly (2019) who present that UMD average annual return of 6% drops below 1% after controlling for the time-series factor momentum.

The theory proposed by Ehsani & Linnainmaa (2019) highlights that the success of equity momentum lays in the factor returns autocorrelation. Subsequently, factor-level strategies are likely to explain the corresponding cross-sectional stock-level strategies as long as they are characterized by an equivalent autocorrelation pattern. Building on the assumption that factor-level strategies do not exhibit the reversal tendencies, the objective of this study is to evaluate the following notion:

Hypothesis 2. *Equity reversal occurs independently of factor returns autocorrelation.*

Ehsani & Linnainmaa (2019) and Gupta & Kelly (2019) focus on the role of factor autocorrelation in explaining stock momentum. This study employs similar statistical methods, yet, it aims to explore the dynamics of factor reversal and its role in explaining the stock reversal.

2.2 Explaining the factor strategies

The persistence of stock momentum returns has motivated a number of authors to examine what could potentially explain it (Subrahmanyam, 2018). Most commonly, the literature points to market frictions and investors behavioural biases. For example, some studies suggest that momentum can be linked to investor sentiment.

Antoniou, Doukas, & Subrahmanyam (2013), hypothesize that investors receiving news which contradict their beliefs experience cognitive dissonance, which leads to underreaction. For example, when the sentiment is pessimistic, they underreact to good news among winners, slowing down the diffusion of information. Consequently, they assume that in pessimistic sentiment periods momentum is driven by winners. Additionally, they point to the fact that momentum might be noticeable only during periods characterised by optimistic (high) sentiment. The phenomenon is magnified by the costs associated with short-selling necessary for arbitraging the loser assets. In accordance with their expectation, Antoniou et al. (2013) provide empirical evidence that momentum profits are only observable during optimistic sentiment periods. This has also been examined in the prior study by Stambaugh, Yu, & Yuan (2012) which adds that the sentiment has no effect on the long legs of momentum strategies.

Similarly, Ehsani & Linnainmaa (2019) explore the impact of investor sentiment on factor momentum. In line with the equity momentum, factor momentum earns higher returns in high-sentiment periods. It is mainly driven by the loser leg of the strategy earning significantly higher returns following high sentiment. This study further explores this notion and tests the following hypothesis:

Hypothesis 3. *Investor sentiment impacts the profitability of factor momentum and reversal.*

A number of studies have examined efficient methods for capturing investor sentiment. Baker & Wurgler (2006) have establish a widely employed proxy. It captures most of the historical fluctuations in sentiment taking into consideration the effect of macroeconomic variables. The empirical evidence of Stambaugh et al. (2012) and Ehsani & Linnainmaa (2019), pointing to differences in factor momentum profitability depending on the level of the Baker & Wurgler (2006) index confirms the accuracy of this measure. Alternative measure of investor sentiment is proposed by Chung, Hung, & Yeh (2012) who suggest that the NBER business cycle indicator efficiently segregates states of the economy characterized by high predictive power of investor sentiment. Lastly, Bandopadhyaya & Jones (2011) and Sarwar & Khan (2017) recommend the Volatility Index (VIX) computed by the The Chicago Board Option Exchange (CBOE) as a suitable variable for measuring market uncertainty. They motive the eligibility of this measure by highlighting that it is readily accessible and widely used by market participants.

3 Data

To study the factor strategies and their qualities, I combine an extensive sample of factor returns with equity data and proxies of investor sentiment. The dataset is retrieved from multiple sources and it can be generalised into two subsets. The first set consists of monthly factor returns used for the formation of various investment strategies. The second set comprises of data used for building the market sentiment indicators.

3.1 Universe of factors

I collect the monthly factor returns data from Kenneth French, AQR's, and Robert Stambaugh's data libraries.[1] For six out of 23 selected anomalies, namely accruals, net share issue, residual variance, cashflow/price, earnings/price and dividend yield, the factor returns were not provided. Instead, I use the anomaly sorted portfolio data and compute the factor returns as the difference between the average of the top and bottom three deciles. The ranking of deciles follows the methodology of original factor studies summarized in Table 1 (Ehsani & Linnainmaa, 2019). Additionally, the table lists the factor abbreviations used in the study, returns starting dates, annualized means, standard deviations and t-statistics associated with the average returns. The considered factors are among the ones analyzed by Ehsani & Linnainmaa (2019), Gupta & Kelly (2019), Arnott et al. (2019) and Stambaugh, Yu, & Yuan (2015).

The starting dates of the 23 factors listed in Table 1 vary significantly. For the majority of anomalies, the return data starts in 1963. In contrast, the returns for such factors as betting against beta, dividend yield, long-term reversal, momentum, size and value begins considerably earlier (between 1926 and 1931), whereas those for return on assets and distress start only in 1971 and 1973, respectively. On the other hand, there is less discrepancy between the returns ending dates. Namely, for seven anomalies the data continues until December 2016, while the remainder ends in October 2020.

As reported, all factors have positive average annual returns and five of them are statistically indistinguishable from zero. Similarly to Ehsani & Linnainmaa (2019) and Gupta & Kelly (2019), betting against beta and stock momentum earn the highest average returns of 9.0% and 8.6%, respectively. Moreover, there is a notable variation in the volatility of factors. In line with Ehsani & Linnainmaa (2019), accruals factor is characterized by the lowest standard deviation. In contrast, the volatility of the distress factor is as high as 23.9%.

[1] Factor returns data retrieved from the data libraries available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html; http://finance.wharton.upenn.edu/~stambaug/; https://www.aqr.com/Insights/Datasets.

Table 1: **Descriptive statistics of factor returns.** This table presents summary statistics of the anomalies included in the factor universe dataset. It reports the abbrevations used in the paper, original study that analysed each factor, the start date, the mean annualized returns (%), volatility (denoted as SD) and t-values for the factors constructed using the U.S. data.

Abbr.	Factor	Original factor research	Start date	Mean	SD	t-value
ACCR	Accruals	Sloan (1996)	Jul 1963	2.52	7.40	2.82
BAB	Betting against beta	Frazzini & Pedersen (2014)	Dec 1930	8.97	16.02	6.93
CEI	Composite equity issues	Daniel & Titman (2006)	Jan 1963	6.11	13.75	3.64
CFR	Cashflow/price	Rosenberg, Reid, & Lanstein (1985)	Jul 1951	3.36	11.74	2.63
DIS	Distress	Campbell, Hilscher, & Szilagyi (2008)	Oct 1973	5.73	23.87	1.70
DY	Dividend yield	Litzenberger & Ramaswamy (1982)	Jul 1927	1.48	13.90	0.97
EP	Earnings/price	Basu (1983)	Jul 1951	4.50	13.06	3.50
GP	Gross profitability	Novy-Marx (2013)	Jan 1963	3.24	14.58	1.78
INV	Investment	Titman, Tompaidis, & Tsyplakov (2004)	Jul 1963	3.32	10.00	3.37
LIQ	Liquidity	Pástor & Stambaugh (2003)	Jan 1968	4.71	13.50	2.77
LTR	Long-term reversal	De Bondt & Thaler (1985)	Jan 1931	3.45	14.30	2.53
MOM	Momentum	Jegadeesh & Titman (1993)	Jan 1927	8.55	15.20	5.17
NOA	Net operating assets	Hirshleifer, Hou, Teoh, & Zhang (2004)	May 1963	6.78	12.17	4.61
NSI	Net stock issue	Ritter (1991)	Jul 1963	2.64	10.67	2.18
OP	Operating profitability	Novy-Marx (2013)	Jul 1963	3.14	8.31	3.11
OSC	O-score	Ohlson (1980)	Jan 1963	0.85	15.10	0.31
PPE	Change in PP&E	Lyandres, Sun, & Zhang (2008)	Jan 1963	6.95	12.63	4.71
QMJ	Quality minus junk	Asness, Frazzini, & Pedersen (2019)	Jul 1957	4.48	9.35	4.56
ROA	Return on assets	Wang & Yu (2013)	Nov 1971	6.97	18.47	3.02
RVAR	Residual Variance	Ang, Hodrick, Xing, & Zhang (2006)	Jul 1963	1.54	19.17	0.49
SIZE	Size	Banz (1981)	Jul 1926	2.81	12.48	2.42
STR	Short-term reversal	Jegadeesh (1990)	Feb 1926	9.03	16.95	6.78
VAL	Value	Rosenberg et al. (1985)	Jul 1926	3.33	12.63	2.59

Table 1 lists factors which use U.S. data. Additionally, I collect factor returns for 23 other countries. Each country is assigned five factors, namely betting against beta, momentum, quality minus junk, size and value. The only exception is Japan which has a more extensive sample, including investment and profitability anomalies. Lastly, I gather a number of global, emerging countries, European, North American and Asia-Pacific factors. Table A.1 in Appendix A summaries the geographical factor coverage. Lastly, the factors included in the original factors sample are characterized by distinct return behavior. Table A.2 in Appendix A reports that, similarly to the factor universe of Gupta & Kelly (2019), 60% of the factor pairs have absolute correlation below 0.25.

3.2 Market sentiment indicators

To examine the effect of market sentiment, I use the Baker & Wurgler (2006) investor sentiment index and short interest index.

The Baker & Wurgler (2006) investor sentiment index spans from July 1965 to December 2018.[2] The authors construct the index using the common variation in six underlying factors capturing sentiment: the dividend premium, the number and the average first-day returns on initial public offerings, NYSE share turnover, the closed-end fund discount and the equity share in new issues. Panel A of Figure 1 represents the index across time along with its sample median value.

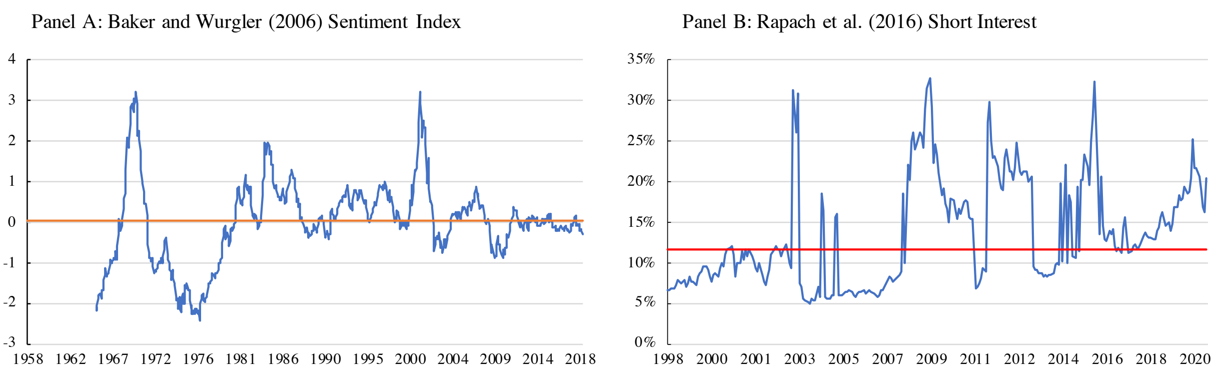


Figure 1: **Sentiment indicators across time.** Panel A of this figure plots the Baker & Wurgler (2006) sentiment index between July 1965 and December 2018. Panel B represents the Rapach et al. (2016) short interest between April 1998 and October 2020. The red horizontal lines indicate the median values of the sample.

The sentiment index represents significant shifts in market sentiment. For example, it accurately reflects the increases in sentiment associated with the biotech bubble in the early 1980s and internet bubble in the 2000s (Stambaugh et al., 2012).

Secondly, following the methodology of Rapach et al. (2016), I use the firm-level short interest data from Compustat to construct the short interest index. Each month, the U.S. exchanges release the number of shares held short in a given company as the short interest. I retrieve the data starting from the earliest release (January 1973) until October 2020. Given the raw format of the data, I normalize it by diving the short interest by the number of each firm's shares outstanding in a given month obtained from the Center for Research in Security Prices (CRSP). I exclude assets with stock prices below $5 per share and market

[2]Data retrieved from the Jeffrey Wurgler website http://people.stern.nyu.edu/jwurgler/.

capitalization below the fifth percentile breakpoint of NYSE market capitalization as defined on Kenneth French's website. To arrive at the aggregated short interest, I calculate the equal-weighted mean of all normalized short interest levels. Finally, I derive the short interest index by allocating 1 to monthly mean values above the time-series median of observations to construct an indicator variable and zero, otherwise.

To examine the robustness of the results, I use alternative indicators of investor sentiment, namely, NBER Index and VIX Index.

The recession indicator National Bureau of Economic Research (NBER), is readily available in the organization's data library.[3] It is a time-series of monthly frequency, indicating periods of economic activity expansion and recession. The variable takes value 1 for recessionary periods and 0, otherwise. I collect the indicator data for the period between February 1926 and October 2020 to match the factor universe sample.

Next, I use The Chicago Board Option Exchange (CBOE) Volatility Index data.[4] The index captures market's view on the 30-day expected volatility. It is based on the prices of S&P 500 options. To construct of the VIX Indicator, I assign 1 to observations exceeding the sample median value of the index. I use the daily closing values of VIX from the CBOE website and modify the frequency of the time-series to monthly by selecting the value of the index on the last trading day of every month. The data starts in February 1990 and ends in October 2020.[5]

4 Methodology

4.1 Predictive power of past returns

Ehsani & Linnainmaa (2019) document that factor returns have strong explanatory power of their own future returns. By regressing factor's return in month t on the factor's returns over the prior year, they find that on average factors earn a monthly return of 1 basis point given the returns in the prior year were negative. In case the factor returns in the period $t-12$ to $t-1$ were positive, the average increases to 52 basis points. Following the approach of the authors, I investigate the serial correlation of factor returns. Namely, I evaluate whether factors can be predicted by their own past returns. First, I examine the existence of momentum using 1-month and 12-month prior performance. Second, I test the reversal using prior 3- and 5-year returns. Similarly to Ehsani & Linnainmaa (2019), I

[3]Retrieved from FRED; https://fred.stlouisfed.org/series/USRECNBER

[4]Available at https://ww2.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data

[5]Figure B.1 and B.2 in Appendix B exhibits the NBER and VIX indices plotted across time.

estimate time-series regressions for every factor in the sample. To test for the momentum in individual factor, I regress factor's returns on an indicator variable assigned 0 given prior one- or twelve-month returns were negative. Analogically, testing for reversal involves the same dependent variable; however, the independent indicator variable equals 1 if the prior returns were negative. The test procedure is formulated as following:

$$r_{t,j} = \hat{\alpha} + \hat{\beta} d_{t-1,j} \tag{3}$$

where $\hat{\alpha}$ indicates the average estimated factor returns earned following the formation period with positive or negative returns, considering momentum and reversal, respectively. $\hat{\beta}$ shows the difference between factor returns arising after outperforming and underperforming formation window returns. Additionally, I estimate pooled regressions using the whole factor universe. An indicator variable specification is selected because it resembles the procedure used for assigning signs to prior returns in long-short strategy building (Ehsani & Linnainmaa, 2019).

4.2 Construction of strategies

The evidence provided by Ehsani & Linnainmaa (2019), Gupta & Kelly (2019) and Arnott et al. (2019) suggests that momentum in equity returns is largely linked to momentum in factor returns. To further evaluate the attractiveness of factor timing strategies, I examine the profitability of time-series and cross-sectional factor momentum and reversal strategies. In both cases, I apply monthly rebalancing of portfolios.

4.2.1 Time-Series Strategy

The time-series strategy aggregates individually timed factors (Gupta & Kelly, 2019). Specifically, it assigns certain positions to factors conditional on their own prior returns. The construction of the time-series strategy involves a number of steps which can be broadly categorized into individual factor scaling and scaled factor returns aggregation. Firstly, based on the performance of a factor i over the prior j months, I scale its returns in month t as the following:

$$f_{i,j,t}^{TS} = s_{i,j,t-1} \times f_{i,j} \tag{4}$$

where the scaling term $s_{i,j,t-1}$is determined according to the following rule:

$$s_{i,j,t} = \min\left(\max\left(\frac{1}{\sigma_{i,j,t}}\sum_{\tau=1}^{j} f_{i,t-\tau+1}, -2\right), 2\right) \tag{5}$$

The scaling term allows for timing the position in individual factors according to their return over the month $t-j$ which is defined as the formation window (Gupta & Kelly, 2019). Term $\sigma_{i,j,t}$ transforms returns into z-scores and introduces annualized factor volatility, over the previous three years or ten years, in case of formation windows shorter or longer than 12 months, respectively. Additionally, I cap the z-scores at ± 2 to remove outliers by ensuring that the observations with standard deviations outside of the $(-2, 2)$ bound are accounted for. To determine the profitability of individual factor timing, I regress the scaled factor on its non-scaled returns:

$$f_{i,j,t}^{TS} = \alpha_{i,j} + \beta_{i,j} f_{i,j} + e_{i,j,t} \tag{6}$$

where $\alpha_{i,j}$ indicates the benefits derived from timing the factor and $\beta_{i,j}$ points to the proportion of scaled factor returns that occur due to autocorrelation.
I combine all scaled factors to form a time-series factor reversal strategy. Specifically, I aggregate the $f_{i,j,t}^{TS}$ as following:

$$TSR_{j,i} = TS_{j,i}^{Long} - TS_{j,i}^{Short} \tag{7}$$

where

$$TS_{j,i}^{Long} = \frac{\sum_i 1_{\{s_{i,j,t}<0\}} f_{i,j,t+1}^{TS}}{\sum_i 1_{\{s_{i,j,t}<0\}} s_{i,j,t}} \tag{8}$$

and

$$TS_{j,i}^{Short} = \frac{\sum_i 1_{\{s_{i,j,t}\geq 0\}} f_{i,j,t+1}^{TS}}{\sum_i 1_{\{s_{i,j,t}\geq 0\}} s_{i,j,t}} \tag{9}$$

By following this approach, I ensure that the time-series factor portfolio is rescaled to unit leverage (Gupta & Kelly, 2019). Forming the time-series factor momentum (labeled as TSM throughout the study) requires adjustment of long (winners) and long (losers) legs of portfolios. Specifically, they are formulated according to the following rule:

$$TS_{j,i}^{Long} = \frac{\sum_i 1_{\{s_{i,j,t}>0\}} f_{i,j,t+1}^{TS}}{\sum_i 1_{\{s_{i,j,t}>0\}} s_{i,j,t}} \tag{10}$$

and

$$TS_{j,i}^{Short} = \frac{\sum_i 1_{\{s_{i,j,t}\leq 0\}} f_{i,j,t+1}^{TS}}{\sum_i 1_{\{s_{i,j,t}\leq 0\}} s_{i,j,t}} \tag{11}$$

4.2.2 Cross-Sectional Factor Reversal

As an alternative approach to strategy formation, I use the cross-sectional factor reversal (CFR) and momentum portfolio (CFM) construction method. Following Jegadeesh & Titman (1993), Moskowitz & Grinblatt (1999) and Arnott et al. (2019), to form the CFR, I assign long positions to factors which have earned below-median returns as compared to the remaining factors over the formation period. The opposite procedure is followed in the case of CSM. Analogically, the CSM strategy long factors with above-median prior performance. Consequently, each month short and long legs of the portfolio are assigned an equal number of factors.

Following Ehsani & Linnainmaa (2019) and Arnott et al. (2019), I restructure the data in cases when the holding period is longer than a month using the overlapping approach of Jegadeesh & Titman (1993). Specifically, in each month t of the m-month holding period, I derive the factor strategy. I obtain the holding period strategy return in month k as the average of returns between k and $k - m$. For example, assuming a 3-month holding period strategy in May 2020, I obtain returns scaled using the strategies formulated in February 2020, March 2020 and April 2020. The return on the 3-month holding window strategy is the mean of these three returns. This approach ensures correcting data in a way to mitigate the impact of the overlapping observations.

4.3 Examining the relationship between the equity reversal and factor reversal

Gupta & Kelly (2019) examine the co-movements of factor momentum strategies with equity-level strategies such as cross-sectional equity momentum and reversal of various formation and holding windows. Specifically, they analyse the correlations between the strategies. Importantly, they observe that factor momentum based on the one-month formation window exhibits sharply different pattern than the short-term equity reversal (correlation between the two strategies equals -0.80). This points to the fact that the factor momentum displays characteristics distinct from the ones observed at the stock-level. Building on this methodology, I examine whether the predictive qualities of equity returns link to factor reversal strategy. Namely, I derive the correlations between equity-level strategies and factor momentum as well as reversal.

Additionally, following the approach of Gupta & Kelly (2019), I adjust the returns of factor momentum and reversal by accounting for a variety of equity-level strategies, including FF5, short-term equity reversal factor (STR), long-term equity reversal factor (LTR) and intermediate term momentum factor (UMD). This allows me to analyze whether equity-level strategies are efficient in explaining factor-level strategies.

Ehsani & Linnainmaa (2019) find that factor momentum largely contributes to the returns of cross-sectional momentum strategies. I focus on examining whether this connection holds when considering equity reversal. Specifically, I examine the performance of various asset pricing models based on FF5 in pricing portfolios sorted on the prior returns.

I begin by regressing the returns of portfolios sorted on the prior one-month returns. Next to the baseline model consisting of FF5, I specify three additional models which are complemented with STR, UMD and TSM.

Next, I follow the same procedure, whereas the dependent variable is replaced by returns of portfolios sorted on returns from the prior 60 month (skipping immediate prior 13 months). The starting model consists of FF5 and the subsequent ones are augmented with LTR, UMD and TSR.

Tables 7 and 8 show the estimates from spanning regressions. A statistically significant intercept suggests that the independent variables fail to fully explain the information contained in the dependent variable. Consequently, an investor whose portfolio is constructed using the right-hand side factors can achieve an additional return from increasing the exposure to the left-hand side factors.

In order to assess the statistical significance of the various model specification, I follow the procedure introduced by Gibbons, Ross, & Shanken (1989), known as a GRS-test. It uses 10 portfolios sorted on prior returns and tests the null hypothesis of alphas being jointly zero (Ehsani & Linnainmaa, 2019).

4.4 Analysis of anomalies drivers

Stambaugh et al. (2012) and Ehsani & Linnainmaa (2019) document that the profitability of anomalies returns is linked to the levels of investor sentiment. Specifically, they find that factor returns, including the factor momentum returns, are stronger during pessimistic periods. I perform a similar analysis for the strategies examined in this study. To distinguish between high and low sentiment periods, I use the Baker & Wurgler (2006) sentiment indicator. Each month, I classify the strategy returns into either low or high-sentiment month. A low-sentiment month is characterized by an below sample median value of the indicator. Contrarily, the high-sentiment months have the above-median values Stambaugh et al. (2012). Additionally, as a robustness check, I replace the Baker & Wurgler (2006) indicator with the NBER and VIX indices. To evaluate the importance of the short-interest restrictions, I compare the average strategy returns obtained following the periods with above and below median values of the previously defined short interest index. Using the two-sample t-test, I am able to identify whether the difference between the mean sample returns is significant.

5 Results

5.1 Examination of the reversal effect

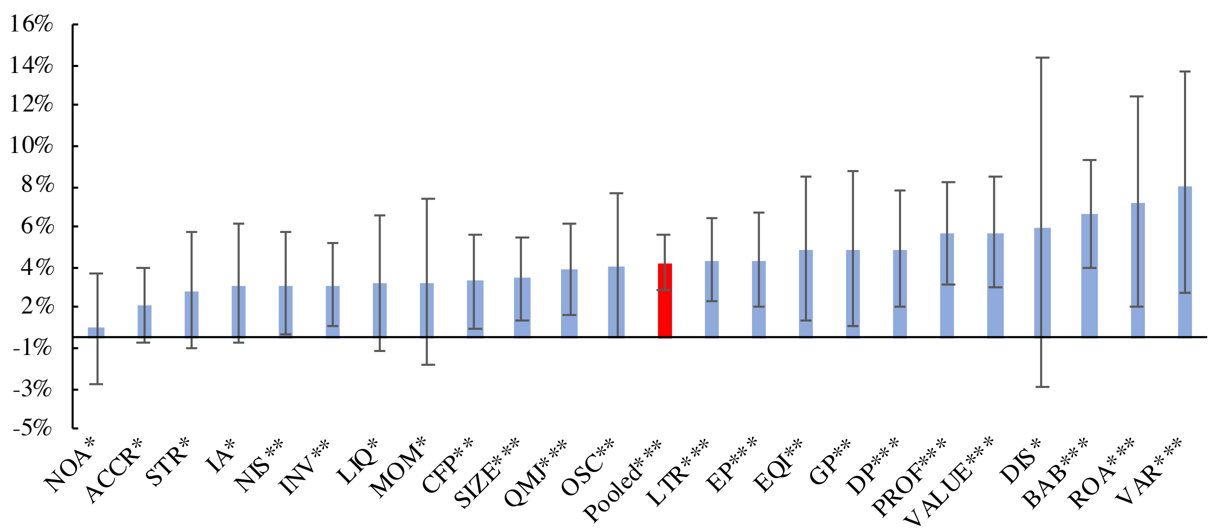
To assess the auto-predictive qualities of factors, each month, I regress their returns on a dummy variable indicating the factor's prior performance. Table 2 reports the estimates from those regressions using three different model specifications which vary in terms of the indicator variable definition and formation window. The first one uses one- and twelve-month factor returns and assigns the indicator value 1 if the formation window return is positive. This model specification allows for direct assessment of the extent to which performance of factors can predict their own returns in the short- and intermediate-term. In this case, the intercept shows the average factor returns following a period of negative returns and the slope indicates the difference between outperforming and underperforming years (Ehsani & Linnainmaa, 2019).

Table 2: **The predictability of individual factor returns.** The table shows the intercepts (%) and slopes from univariate time-series regression. Dependent variable is the monthly factor return in t. If the formation window returns were negative, the independent variable equals 1 in the first model specification and 0 in the second. To report the statistical significance of individual factors' coefficients, I use the one-sample Student t-values (in parenthesis). It tests the null hypothesis that the coefficients are different from zero. The estimates from the pooled regression (with standard errors clustered by month) indicate the average predictability of factor returns. *, ** and *** show the significance at the 10%, 5% and 1% levels.

Specification	(1) Momentum				(2) Reversal			
Formation window	1-month		12-months		36-months		60-months	
Anomaly	$\hat{\alpha}_{(1-1)}$	$\hat{\beta}_{(1-1)}$	$\hat{\alpha}_{(1-12)}$	$\hat{\beta}_{(1-12)}$	$\hat{\alpha}_{(1-36)}$	$\hat{\beta}_{(1-36)}$	$\hat{\alpha}_{(1-60)}$	$\hat{\beta}_{(1-60)}$
Pooled	0.05	0.57***	0.02	0.52***	0.43***	-0.23**	0.40***	-0.13
	(0.72)	(6.04)	(0.32)	(5.63)	(8.72)	(-2.51)	(8.45)	(-1.48)
ACCR	0.19**	7.78**	0.18**	0.07	0.22**	-0.71	0.21**	-0.32
	(2.55)	(2.04)	(2.41)	(0.07)	(2.45)	(-0.97)	(2.11)	(-0.52)
BAB	0.59***	13.40***	0.40***	3.68***	0.62***	0.42	0.60***	0.22
	(5.92)	(4.44)	(3.66)	(5.76)	(4.74)	(1.22)	(3.82)	(0.79)
CEI	0.42***	14.20***	0.43***	1.00	0.48***	0.16	0.73***	-0.61
	(3.12)	(3.63)	(2.93)	(1.01)	(2.70)	(0.27)	(3.40)	(-1.19)
CFP	0.23**	6.94**	0.17*	2.12**	0.12	1.22**	0.05	0.88**
	(2.40)	(2.00)	(1.72)	(2.43)	(1.08)	(2.41)	(0.41)	(2.26)
DIS	0.42	9.62**	0.38	1.01	0.69**	-0.77	1.09***	-1.34*
	(1.50)	(2.20)	(1.34)	(0.82)	(2.15)	(-1.00)	(2.84)	(-1.89)
DY	0.09	18.30***	0.07	1.86**	0.15	-0.05	0.37***	-1.82***
	(0.83)	(6.22)	(0.69)	(2.33)	(1.27)	(-0.10)	(3.02)	(-3.80)
EP	0.29***	12.80***	0.23**	2.36***	0.25**	0.64	0.17	0.58
	(3.05)	(3.70)	(2.27)	(2.84)	(2.12)	(1.32)	(1.23)	(1.46)
GP	0.23	10.80***	0.21	1.01	0.30*	-0.46	0.20	0.01
	(1.60)	(2.75)	(1.46)	(0.92)	(1.81)	(-0.69)	(1.12)	(0.02)
INV	0.23***	12.00***	0.18**	2.15**	0.21**	0.60	0.31***	-0.09
	(2.98)	(3.16)	(2.26)	(2.30)	(2.24)	(1.17)	(2.75)	(-0.20)
LIQ	0.35**	7.73*	0.34**	0.74	0.26	0.83	0.22	0.70
	(2.57)	(1.93)	(2.36)	(0.64)	(1.58)	(1.30)	(1.23)	(1.57)
LTR	0.20*	24.20***	0.15	3.37***	0.12	0.65*	0.10	0.36
	(1.96)	(8.16)	(1.47)	(4.66)	(1.26)	(1.86)	(1.10)	(1.35)
MOM	0.64***	7.64**	0.76***	-0.98	0.87***	-0.89	1.05***	-1.09**
	(4.71)	(2.57)	(4.95)	(-1.09)	(4.28)	(-1.45)	(4.31)	(-2.16)
NOA	0.55***	-2.32	0.34**	3.18***	0.30**	1.37***	0.36**	0.71**
	(4.56)	(-0.59)	(2.58)	(3.19)	(2.02)	(3.10)	(2.30)	(2.29)
NSI	0.18*	11.00***	0.11	3.05***	0.14	0.85*	0.21*	0.21
	(1.95)	(2.90)	(1.19)	(3.39)	(1.32)	(1.78)	(1.85)	(0.54)
OSC	0.04	5.54	0.02	2.05**	0.04	0.83	0.08***	0.34
	(0.28)	(1.41)	(0.17)	(2.06)	(0.25)	(1.52)	(0.54)	(0.85)
PPE	0.49***	9.62**	0.38***	2.14**	0.39	0.67	0.54***	0.00
	(4.14)	(2.46)	(2.90)	(2.11)	(2.50)	(1.30)	(3.01)	(0.01)
PROF.	0.22***	14.60***	0.20**	1.78*	0.34***	-0.76	0.33***	-0.36
	(2.65)	(3.87)	(2.35)	(1.89)	(3.28)	(-1.23)	(2.66)	(-0.66)
QMJ	0.30***	16.30***	0.27***	2.14**	0.36***	-0.01	0.36***	0.03
	(3.80)	(4.54)	(3.06)	(2.39)	(3.22)	(-0.02)	(2.75)	(0.07)
ROA	0.45**	16.30***	0.37*	2.42**	0.78***	-1.09	1.09***	-1.46**
	(2.56)	(3.84)	(1.95)	(2.23)	(3.36)	(-1.58)	(3.43)	(-2.02)
RVAR	0.08	10.50***	0.06	1.67*	0.16	-0.30	0.25***	-0.44
	(0.43)	(2.76)	(0.33)	(1.66)	(0.78)	(-0.49)	(1.20)	(-0.85)
SIZE	0.20**	6.67**	0.15	2.70***	0.14	1.11***	0.21**	0.30
	(2.27)	(2.25)	(1.64)	(3.50)	(1.50)	(2.97)	(2.05)	(1.08)
STR	0.69***	1.26	0.48***	2.64***	0.53***	0.84**	0.52***	0.53*
	(6.58)	(0.42)	(4.00)	(3.52)	(3.75)	(2.31)	(3.23)	(1.93)
VALUE	0.21**	20.50***	0.18*	2.16***	0.28**	-0.03	0.25**	0.13
	(2.13)	(7.02)	(1.73)	(2.90)	(2.38)	(-0.07)	(1.98)	(0.32)

The majority of the factors exhibit both positive intercepts and slopes (except NOA in the short-term and MOM in the intermediate-term) and many of them are statistically significant. As the pooled regression coefficients report, on average, factors earn 0.05% after a month and 0.02% after twelve months of negative returns. However, given a period of positive returns, the average factor return increases to 0.57% in the short-term and 0.52% in the intermediate-term. The remaining two specifications extend the formation window to 36 and 60 months and assign a value 0 to positive formation window returns. In both cases, the individual intercepts are positive and the pooled regressions intercepts equal 0.43% and 0.40% for the 36- and 60-month formation window, respectively. On average, when the formation window is extended, the statistical significance of alphas increases. Concluding, prior factor performance can significantly predict its own future returns in the short-term horizon. In the long run, a large proportion of the returns remains unexplained, pointing to a weakening autocorrelation in factor returns over time.

To complement the observations from Table 2, I analyze the profitability of the time-series strategy on the factor level, as summarized by Equation 6. Figure 2 reports the annualized alphas from regressing the one-month formation window time-series scaled returns (as defined in Equations 4 and 5) on the raw returns. All the values are positive and the majority of them



*Note: *, ** and *** indicate the statistical significance at 1%, 5% and 10%, respectively.*

Figure 2: **Annualized alphas (%) of individual factors.** This table reports the annualized average alphas from regressing individual factor one-month time-series strategy returns in month t on the raw returns in the same month. Scaling procedure follows Equation 5. The vertical bars indicate 95% confidence intervals. Clustering of standard errors by month is applied in case of the pooled regression.

highly significant, suggesting that the time-series momentum is persistent across the factor universe. On average, as reported by the pooled regression intercept, the time-series timing strategy earns an alpha of 3.8% (t-value = 5.42). The profitability of the time-series strategy decreases when the formation window is extended. As reported in Figure C.1 in Appendix C, the majority of the annualized alphas are statistically insignificant. Additionally, Table C.1 in Appendix C exhibits the slopes from the regressions. Extending the formation window results in a sharp increase in betas, suggesting that in the long-run the role of factor returns autocorrelation diminishes.

In order to examine whether the time-series and cross-sectional factor strategies experience reversal, I evaluate the profitability of factor momentum and reversal strategies. Table 3 reports the annualized average returns, standard deviations, t-values and Sharpe ratios from factor timing strategies. Additionally, I report the average returns from following an equal-weighted factor strategy which is long all factors and assigns them the same weights (Ehsani & Linnainmaa, 2019). The average annualized return of this strategy is 4.64% (t-value = 9.04). As shown in Panel B of Table 3, both the time-series and cross-sectional short-term factor momentum strategies generate positive and statistically significant returns. The success of the strategies is driven by the portfolio of factors which experienced outperforming returns in the formation window (winners). Consistent with Ehsani & Linnainmaa (2019) and Gupta & Kelly (2019), the time-series strategy outperforms both the cross-sectional (average return of 2.69%) and the equal-weighted portfolio (4.64%).

According to Panel C of Table 3, the long-term factor reversal strategies earn negative average returns. The only exception is the cross-sectional factor reversal strategy constructed using the formation window of 5 years. Although statistically insignificant, it earns a positive average return. The factor reversal strategies bet on the negative autocorrelation in long-term returns and labels factors with underperforming returns in the formation window as winners. However, in three out of four factor reversal specifications, the losers strategies earn average returns higher than the winners.

Concluding, based on the observations from Table 3, there is no evidence of a reversal effect. The short-term factor momentum strategies earn positive average returns. Contrarily, the long-term factor reversal strategies fail and result in negative or statistically insignificant returns. Therefore, hypothesis 1 is not rejected.

Table 3: **Average returns (%) of time-series and cross-sectional factor reversal strategies.** This table reports the annualized average returns, standard deviations, t-values and Sharpe ratios for different combinations of the factors included in the factor universe. The equal-weighted portfolio invests in all factors with the same weights. The time-series factor (momentum) reversal strategy is long (short) factors with negative returns over the formation window and short (long) factors with positive returns. The cross-sectional factor momentum (reversal) strategy is short (long) factors that earned below-median returns relative to other factors over the formation window and short (long) factors with above-median returns. Rebalancing occurs at a monthly frequency.

	Annualized return			
Strategy	Mean (%)	SD (%)	t-value	Sharpe ratio
Panel A: Benchmark portfolio				
Equal-weighted portfolio	4.64	1.41	9.04	3.21
Panel B: Factor momentum (1-1)				
Time-series strategy	8.65	3.88	5.94	4.77
Winners	8.59	2.33	9.75	3.69
Losers	-0.10	2.39	-0.12	-0.04
Cross-sectional strategy	2.69	1.60	4.68	1.68
Winners	3.38	1.01	10.04	2.37
Losers	-0.94	1.12	-2.36	-0.84
Panel C: Factor reversal (1-36)				
Time-series strategy	-2.11	3.72	-1.57	-0.57
Winners	3.95	2.78	3.70	1.42
Losers	5.96	2.00	7.91	2.98
Cross-sectional strategy	-1.57	1.48	-3.04	-1.06
Winners	3.11	1.14	7.58	2.73
Losers	1.55	0.90	4.70	1.72
Panel D: Factor reversal (1-60)				
Time-series strategy	-1.05	3.76	-0.76	-0.28
Winners	1.45	3.13	3.68	0.46
Losers	5.13	1.92	7.11	2.67
Cross-sectional strategy	0.65	1.31	1.39	0.50
Winners	1.97	1.02	5.38	1.93
Losers	2.78	0.92	8.07	3.02

Table 4: **Relative performance of time-series and cross-sectional strategies.** The table shows the average annualized returns (%) and t-values of the time-series (cross-sectional) strategy after controlling for the cross-sectional (time-series) alternative.

	Relative performance			
	TS vs. CS		CS vs. TS	
Strategy	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\alpha}$	$t(\hat{\alpha})$
Factor momentum (1-1)	2.54	3.94	-0.38	-1.44
Factor reversal (1-36)	-0.38	-0.64	-0.53	-2.09
Factor reversal (1-60)	-2.03	-3.06	-0.53	-0.56

Table 5: **Correlations between factor reversal and momentum strategies.** The table shows the correlations between time-series and cross-sectional strategies based on the one-month, 36-month and 60-month formation windows.

		Time-series strategy		
Formation window	Cross-sectional strategies	(1)	(2)	(3)
(1-1)	(1) Factor momentum	0.89	-0.21	-0.17
(1-36)	(2) Factor reversal	0.30	0.78	0.60
(1-60)	(3) Factor reversal	-0.07	-0.57	-0.64

Table 4 shows the relative performance of time-series and cross-sectional strategies. Despite high correlations between the strategies based on the one-month formation window (reported in Table 5), the cross-sectional strategy fails to explain the returns of the time-series portfolio. On the other hand, the returns of the cross-sectional strategy after controlling for time-series strategy are statistically insignificant. Contrary to the factor reversal strategies based on a 60-month formation, the performance of 36-month factor reversal portfolios improves after controlling for alternative strategies. Yet, neither of the reversal strategies earn positive returns.

Figure 3 depicts the cumulative returns from strategies summarized in Table 3 benchmarked against the excess return on the market (Rm-Rf). At the end of the sample period, the only strategy which exceeds passive strategies is the short-term factor momentum. Contrarily, the 1-60 cross-sectional factor reversal strategy generates returns close to zero, whereas following the remaining strategies results in losses. Taken together, the evidence indicates that factor momentum and factor reversal strategies do not exhibit the reversal pattern found in equity. Strategies betting on the continuity of factor returns succeed, whereas the ones betting on the reversal effect fail.

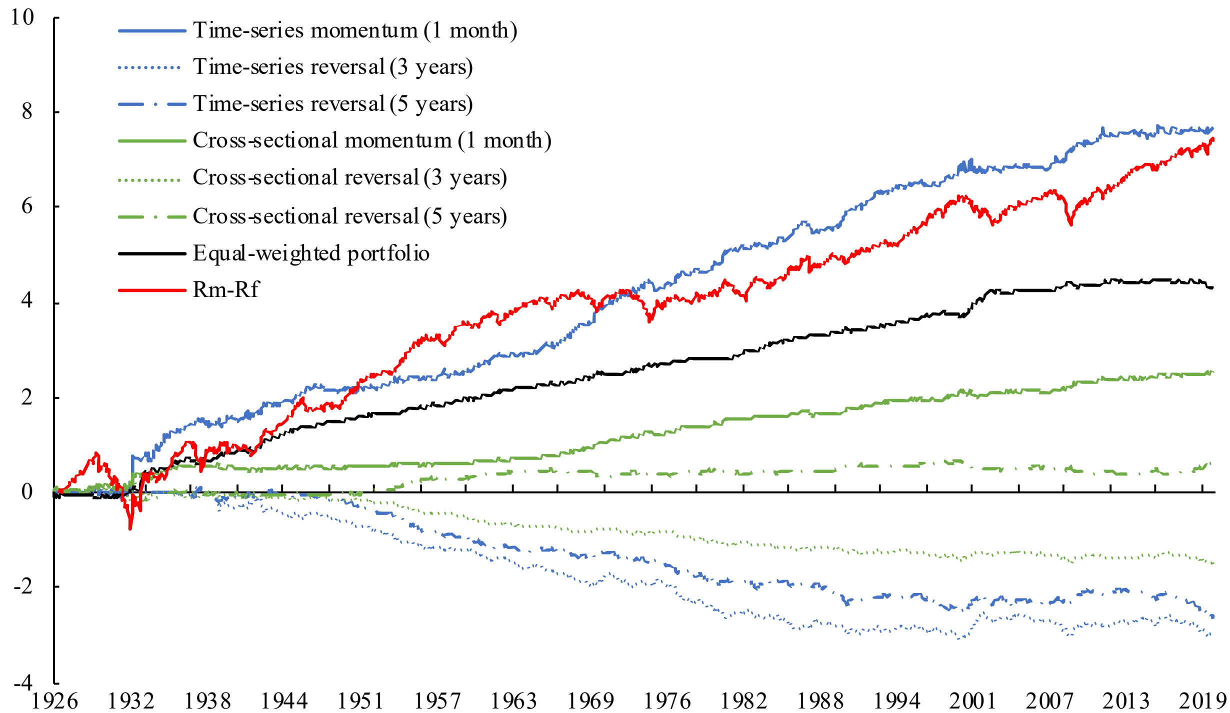


Figure 3: **Cumulative total returns (%).** The figure exhibits the cumulative total returns of time-series and cross-sectional factor reversal and momentum strategies from February 1926 to October 2020. Equal-weighted portfolio invests in the whole factors universe. Market excess return includes all stocks from NYSE, Nasdaq and AMEX. Rebalancing of the strategies takes place at a monthly frequency.

5.2 Explaining equity reversal

In this section, I examine the role of factor momentum and reversal in explaining the equity reversal. Table 6 shows the momentum and reversal correlations. It summarizes important insights about the co-movement tendencies between stock and factor strategies. The strategies built using an immediate one-month formation window exhibit a high negative correlation which is in line with the observations by Gupta & Kelly (2019). This suggests that, in contrast to the equity momentum, the short-term factor momentum is resilient to the reversal effect. Considering the long-term time-series and cross-sectional factor strategies, their correlations with the UMD differ depending on the length of their formation windows. For strategies formed on the 3-year long window the correlations are negative and 5-year long positive. The correlations of the remaining strategies are relatively lower, pointing to dissimilarities in return tendencies.

To gain a more thorough understanding of the strategies' time-series dynamics, I regress the factor momentum and reversal against a set of equity-based factors. Panel A of Figure 4 reports the annualized alphas of the short-term factor momentum after controlling for FF5, STR and UMD. Whereas the FF5 and UMD seem to have relatively little explanatory power, the STR notably improves the performance of the factor momentum strategies which aligns with the observed high negative correlation.

Analogically, Panel B of Figure 4 reports the annualized average returns from factor reversal obtained after regressing them against the same set of factors with the exception of the short-term reversal factor. In this case, it is replaced by the LTR to more closely match the formation window. Based on the evidence from the figure, several interesting observations can be made. Firstly, the 5-year cross-sectional factor reversal exhibits behavior which is distinct from the remaining strategies. Its performance improves after controlling for the FF5 and LTR, whereas, it falls below 0 when complemented by the UMD. The rest of the strategies react negatively to the addition of FF5 and LTR and show slight improvement after controlling for the UMD. If factor reversal was merely mimicking the equity returns dynamic, it should by largely explained by the long-term reversal factor. As shown in the figure, the response of the factor reversal to equity factors is inconsistent which leads to the conclusion that they do not share any similarities in terms of returns persistence.

Ehsani & Linnainmaa (2019) find that factor momentum significantly contributes to equity momentum. According to the authors, equity momentum occurs partly due to positive autocorrelation in factor returns. The purpose of this section is to determine whether equity reversal is driven by negative autocorrelation in factor returns. Thus far, it is evident that in the short-term, equity reversal and factor momentum strategies exhibit sharply opposite trends. In the long-run, there is no evidence pointing to any common patterns between

Table 6: **Correlations between factor and equity-level factors.** The table represents the correlations between factor (reversal) momentum and individual factors determined on the basis of the equity prior returns. Short-term reversal factor (STR) captures the average returns obtained from the difference between two low and two high prior (1-1) returns. Cross-sectional momentum factor (UMD) is derived by subtracting the average two low from two high prior (2-12) returns. The long-term reversal factor (LTR) is determined in the same way as STR, however, the prior returns are formed using a 13-60 formation window. The table additionally reports the formation windows of factor reversal and momentum.

	Factor momentum		Factor reversal		Factor momentum	
Formation window	(1-1)		(1-36)		(1-60)	
Equity-level factors						
STR	-0.66	-0.65	0.15	0.03	0.15	-0.01
UMD	0.06	0.06	-0.50	-0.53	0.29	0.52
LTR	0.04	-0.02	-0.48	0.10	0.30	-0.37

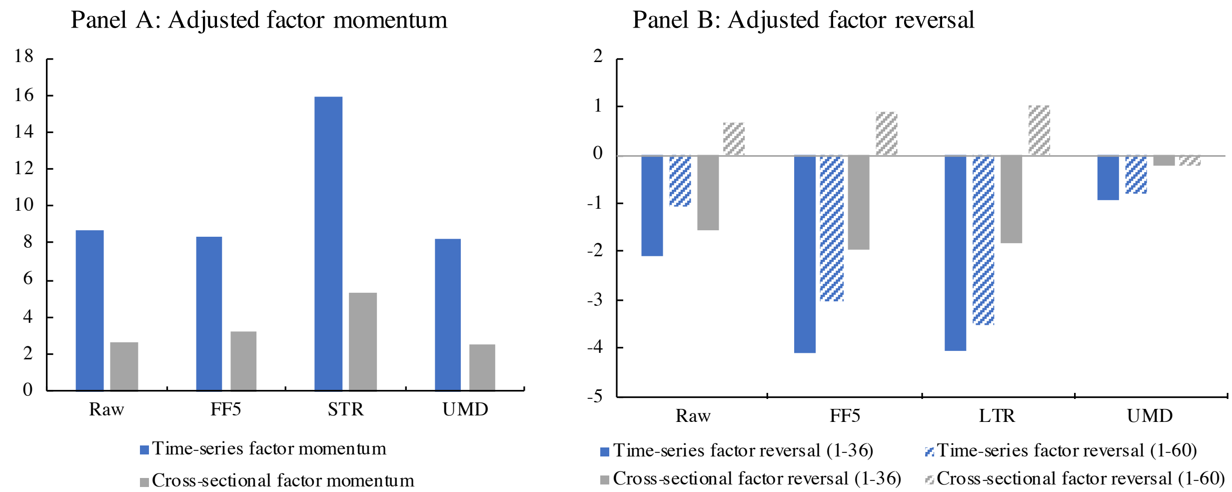


Figure 4: **Adjusted factor momentum and factor reversal returns (%).** Panel A of this figure exhibits the average annualized factor momentum returns after adjusting for the FF5, short-term reversal factor (STR) and cross-sectional momentum (UMD). Panel B represents the annualized 36- and 60-month factor reversal controlled for FF5 factors, long-term reversal factor (LTR) and cross-sectional momentum (UMD).

equity and factor reversal. This suggests that, contrarily to equity, factor returns too are resilient to the reversal effect. Consequently, factor-level strategies are expected to perform poorly in explaining equity reversal.

As the final step of examining the connection between equity and factor-based strategies, I reverse the analysis summarized in Figure 4. Table 7 reports the results from regressing returns of portfolios sorted on the prior one-month against asset pricing models built on the FF5. According to the first model specification, alpha for the decile portfolio constructed on the prior low returns is higher than the one for high prior returns portfolio. This observation, together with the excess return from the Low-minus-High (LmH) portfolio being positive, points to the existence of short-term equity reversal. The average of absolute values of deciles excess returns is 36 basis points. From all of the model specifications, the one limited solely to the FF5 is the most effective in explaining the short term equity reversal. In this case, the return of the Low-minus-High portfolio is observably higher than the deciles return, yet it is statistically insignificant with a t-value of 0.57.

Augmenting the original model with the additional factors increases the statistical significance of Low-minus-High portfolios excess returns. The alpha of the LmH portfolio is negative after accounting for the short-term reversal factor and positive after including the UMD. On the other hand, the performance of the model augmented with factor momentum is the weakest. Specifically, it is characterized by the highest alpha of LmH portfolios.

Additionally, the average alpha and GRS test statistic are notably higher than in other models.

Additionally, UMD and the TSM augmented models are distinct from each other. Although both of the strategies bet on the positive autocorrelation in returns, they relate differently to equity reversal. Taken together, factor momentum fails to capture equity reversal. This result seems to be consistent with the prior observations. Portfolio deciles formed on the prior one-month returns bet on negative autocorrelation in stock returns. Contrarily, short-term factor momentum is constructed in a way to benefit from positive autocorrelations in factor momentum. Therefore, the results reported in Table 8 are in line with the expectations.

The results summarized in Table 7 examine the relationship between the equity and factor returns autocorrelation indirectly. The analysis reported in Table 8 directly assesses whether long-term equity reversal can be explained by factor reversal. According to the prior evidence, the factors show no tendencies to reverse. Moreover, time-series and cross-sectional factor strategies betting on reversal fails. Table 8 reports the coefficients from regressing returns of portfolios sorted using the 13-60 months returns on a variety of asset pricing models. The fact that the bottom decile alpha (t-value = 2.46) of the FF5 model is below the top one (t-value = 6.01) contradicts the equity long-term reversal. Augmenting the model by the LTR and UMD, results in a reduction of the absolute alpha of the LmH portfolio from 1.75% to 0.12% and 0.03%, respectively. Given that the LTR is constructed on the same assumptions as the decile portfolios, it is striking that the UMD augmented model is superior to its LTR counterpart.

Despite the minor discrepancies in average alpha values across various model specifications, the remaining observations provide several important insights. Firstly, the model with the addition of the (1-36) factor reversal results in the highest absolute LmH alpha. Secondly, looking at the absolute alphas of the LmH portfolios, the (1-60) factor reversal augmented model performs as well as the one with UMD, and slightly better considering the GRS statistics.

Concluding, there is sufficient evidence to conclude that factor-based strategies fail to explain short-term equity reversal. The asset pricing model which includes factor momentum performs weakly in accounting for the excess returns of decile portfolios. Evidently, the short-term autocorrelation in factor returns is not the predominant driver of the equity short-term reversal. A possible explanation for this might be that the equity short-term reversal effect

Table 7: **Explaining the returns of equity short-term reversal.** This table summarizes the results from regressing the returns of portfolios sorted on the prior one-month returns on four alternative asset pricing models. First of the models, uses the FF5. Second, adds the equity short-term reversal factor (STR). Similarly, the third model builds on the FF5, but it is augmented with the equity momentum factor (UMD). The last model uses the time-series short-term (1-1) factor momentum (TSM). The table exhibits the intercepts and slopes associated with STR, UMD and TSM. T-values are reported in parentheses. The bottom section of the table reports the average of absolute values of intercepts, as well as the results of the Gibbons et al. (1989) test. *, ** and *** show the significance at the 10%, 5% and 1% levels, respectively.

	Model specification						
	FF5	FF5 + STR		FF5 + UMD		FF5 + TSM (1-1)	
Portfolio	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{STR}$	$\hat{\alpha}$	$\hat{\beta}_{UMD}$	$\hat{\alpha}$	$\hat{\beta}_{TSM}$
Low	0.33**	0.00	0.88***	0.54***	-0.29***	0.79***	-0.69***
	(2.38)	(0.02)	(30.27)	(4.08)	(-8.96)	(7.15)	(-20.42)
2	0.47***	0.24***	0.63***	0.57***	-0.14***	0.80***	-0.49***
	(5.02)	(4.12)	(33.37)	(6.13)	(-5.97)	(10.90)	(-21.86)
3	0.52***	0.35***	0.46***	0.55***	-0.04**	0.75***	-0.35***
	(6.50)	(5.91)	(24.04)	(6.81)	(-2.23)	(10.80)	(-16.17)
4	0.42***	0.36***	0.18***	0.43***	-0.01	0.52***	-0.15***
	(6.62)	(5.87)	(9.20)	(6.68)	(-0.94)	(8.34)	(-7.73)
5	0.41***	0.38***	0.10***	0.41***	0.00	0.47***	-0.09***
	(7.49)	(6.94)	(5.47)	(7.35)	(0.08)	(8.55)	(-5.24)
6	0.34***	0.33***	0.02	0.33***	0.00	0.33***	0.01
	(6.35)	(6.17)	(1.17)	(6.20)	(0.25)	(6.05)	(0.79)
7	0.35***	0.40***	-0.15***	0.35***	0.00	0.26***	0.13***
	(6.32)	(7.63)	(-8.64)	(6.26)	(-0.24)	(4.84)	(7.84)
8	0.37***	0.47***	-0.27***	0.36***	0.01	0.23***	0.21***
	(5.83)	(8.55)	(-15.41)	(5.59)	(0.80)	(3.85)	(11.68)
9	0.22***	0.39***	-0.46***	0.19**	0.04**	-0.03	0.38***
	(2.94)	(7.34)	(-26.65)	(2.49)	(2.28)	(-0.48)	(19.93)
High	0.21**	0.45***	-0.64***	0.14	0.10***	-0.16*	0.55***
	(1.99)	(6.03)	(-26.87)	(1.31)	(3.73)	(-1.93)	(21.73)
LmH	1.41	-5.19***	1.52***	4.90**	-0.38***	12.00***	-1.24***
	(0.57)	(-4.40)	(46.81)	(2.00)	(-7.89)	(6.72)	(28.67)
Avg. $\|\alpha\|$	0.36	0.34		0.39		0.43	
GRS F-value	1.88	6.66		1.77		15.91	
GRS p-value	0.04	0.00		0.06		0.00	

Table 8: **Explaining the returns of equity long-term reversal.** This table represents the results from regressions in which the dependent variable is the return of decile portfolios sorted on the prior one-month returns. It summarizes the explanatory power of the following model specifications by reporting the intercepts and slopes of model components. Model 1, uses the FF5. Model 2 adds the equity long-term reversal factor (LTR). Model 3 builds on FF5 but adds UMD. Models 4 and 5 use FF5 as a basis but they are augmented with the time-series long-term reversal factors (TSR) using 36- and 60-month formation windows, respectively. T-values are reported in parentheses. Additionally, the average absolute alphas and the results of the Gibbons et al. (1989) test are reported. *, ** and *** show the significance at the 10%, 5% and 1% levels, respectively.

	Model								
	FF5	FF5 + LTR		FF5 + UMD		FF5 + TSR (1-36)		FF5 + TSR (1-60)	
Portfolio	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{\beta}_{LTR}$	$\hat{\alpha}$	$\hat{\beta}_{UMD}$	$\hat{\alpha}$	$\hat{\beta}_{TSM}$	$\hat{\alpha}$	$\hat{\beta}_{TSM}$
Low	0.29**	0.31***	0.97***	0.40***	-0.14***	0.43***	0.40***	0.40***	0.42***
	(2.46)	(3.34)	(20.72)	(3.35)	(-4.93)	(3.81)	(9.07)	(3.56)	(9.33)
2	0.28***	0.30***	0.73***	0.33***	-0.07***	0.37***	0.24***	0.36***	0.30***
	(3.25)	(4.42)	(21.63)	(3.78)	(-3.13)	(4.33)	(7.29)	(4.38)	(9.27)
3	0.31***	0.32***	0.69***	0.31***	0.00	0.36***	0.15***	0.36***	0.21***
	(3.86)	(5.34)	(22.88)	(3.80)	(-0.03)	(4.57)	(4.99)	(4.66)	(6.76)
4	0.31***	0.31***	0.23***	0.33***	-0.04**	0.35***	0.12***	0.35***	0.16***
	(4.81)	(5.07)	(7.56)	(5.15)	(-2.25)	(5.49)	(4.75)	(5.56)	(6.27)
5	0.32***	0.32***	0.13***	0.32***	0.00	0.34***	0.06**	0.35***	0.10***
	(5.23)	(5.34)	(4.26)	(5.17)	(-0.11)	(5.55)	(2.54)	(5.69)	(4.13)
6	0.33***	0.33***	-0.02	0.31***	0.03*	0.34***	0.03	0.33***	0.01
	(5.43)	(5.42)	(-0.58)	(5.03)	(1.79)	(5.55)	(1.23)	(5.44)	(0.38)
7	0.37***	0.37***	-0.15***	0.33***	0.06***	0.35***	-0.07***	0.36***	-0.06**
	(6.01)	(6.07)	(-4.97)	(5.27)	(3.92)	(5.61)	(-2.75)	(5.76)	(-2.39)
8	0.40***	0.39***	-0.33***	0.39***	0.01	0.37***	-0.08***	0.38***	-0.10***
	(6.41)	(6.89)	(-11.51)	(6.16)	(0.80)	(5.94)	(-3.43)	(6.04)	(-3.99)
9	0.24***	0.23***	-0.40***	0.20***	0.05***	0.21***	-0.07***	0.20***	-0.15***
	(3.75)	(4.15)	(-14.53)	(3.16)	(3.04)	(3.36)	(-2.72)	(3.20)	(-6.11)
High	0.44***	0.43***	-0.42***	0.43***	0.01	0.41***	-0.09***	0.40***	-0.14***
	(6.01)	(6.55)	(-12.56)	(5.81)	(0.56)	(5.56)	(-3.25)	(5.57)	(-4.95)
LmH	-1.75	0.12	-1.44***	0.03	-0.15***	0.30	0.49***	-0.03	0.56***
	(-1.01)	(-1.20)	(27.15)	(-0.24)	(-4.26)	(0.18)	(9.06)	(-0.02)	(10.27)
Avg. $\lvert\alpha\rvert$	0.33	0.33		0.33		0.35		0.35	
GRS F-value	2.06	2.21		2.27		1.53		1.88	
GRS p-value	0.03	0.02		0.01		0.12		0.04	

Table 9: **Average annualized returns (%) of factor momentum depending on the level of investor sentiment.** The table summarizes the factor momentum strategies classified on the investor sentiment level in the prior month. Investor sentiment is defined as high (low) when the Baker & Wurgler (2006) sentiment index is above (below) its sample median. The HmL indicates the difference between the average portfolio returns in high and low-sentiment environments. Additionally, the two-sample t-value indicates the statistical significance of the difference in means.

	Sentiment level					
	High		Low		Difference	
Strategy	Mean	t-value	Mean	t-value	HmL	t-value
Time-series factor momentum	0.69	3.79	0.76	4.43	-0.07	-0.27
Winners	0.80	7.13	0.55	5.45	0.25	1.69
Losers	0.11	0.96	-0.21	-2.02	0.32	2.07
Cross-sectional factor momentum	0.23	3.28	0.32	4.67	-0.09	-0.90
Winners	0.38	6.93	0.23	5.16	0.15	2.10
Losers	-0.15	-3.12	0.09	1.94	-0.24	-3.61

is to linked to a variety of determinants different than autocorrelation. For example, limited liquidity due to deficits faced by dealers could be one possible explanation (Jegadeesh & Titman, 1995).

On the other hand, in spite of the relatively weak link between the long-term equity and factor reversal, the asset pricing model augmented with the (5-year) time-series factor reversal is highly efficient in explaining the equity long-term reversal. This observation contradicts the prior findings which highlight that the autocorrelation in factor returns weakens across time. Subsequently, the conclusion that the long-term factor reversal drives stock reversal is not plausible. Taken together, equity reversal seems to be distinct from the factor reversal. Thus, hypothesis 2 is not rejected.

5.3 Investor sentiment and short-selling conditions

Table 9 shows the factor momentum returns conditional on the level of investor sentiment in the prior month. Despite the fact that the time-series factor momentum returns do not differ substantially depending on the sentiment, the dynamics observed across the legs of the strategy reveal interesting observations. The time-series losers portfolio earns 0.11% following high sentiment periods and -0.21% after low sentiment periods. This difference equals 32 basis points and is significant (t-value = 2.07). It is in line with the findings of Stambaugh et al. (2012) and Ehsani & Linnainmaa (2019) as well as with the mispricing narrative developed earlier. On the contrary, the evidence from the cross-sectional strategy contradicts the expectations. Losers perform better following low sentiment periods. This result might be explained by the fact that, contrary to the time-series strategy which only bets on the autocorrelation in factor returns, the cross-sectional additionally compares the performance of peers in the formation window. The effect of investor sentiment is likely to manifest itself through the mispricing of individual assets, which could serve as a potential explanation as to the resilience of the cross-sectional factor momentum.

Table 10 explores the notion that the factor momentum anomaly mispricing is magnified by short selling restrictions. Specifically, it compares the portfolio returns classified on the basis of the short interest in the prior month. The returns of the long-short factor momentum do not differ substantially depending on the short interest level. Additionally, the returns of time-series losers and winners assigned to specific short interest groups are statistically insignificant. Concluding, the results confirm the substantial role of investor sentiment in time-series factor momentum persistence. Consequently, hypothesis 3 is not rejected. Nevertheless, given the counterintuitive observations regarding the effect of the short-selling conditions, there is insufficient evidence to confirm that it contributes to the widening of the anomaly.

Table 10: **Average annualized returns (%) of factor momentum depending on the level of short interest.** The table groups the factor returns on the short interest index. The index is determined using the short interest as defined by Rapach et al. (2016). Similarly to the investor sentiment, short interest is labeled as high if it exceeds the sample median level. The HmL is the return difference of high and low short interest samples. The statistical significance of the differences is described by the two-sample t-values.

	Short interest					
	High		Low		Difference	
Strategy	Mean	t-value	Mean	t-value	HmL	t-value
Time-series factor momentum	0.48	1.21	0.41	1.51	0.08	0.16
Winners	0.72	2.96	0.10	0.65	0.62	2.19
Losers	0.23	0.96	-0.31	-1.79	0.54	1.86
Cross-sectional factor momentum	0.18	1.13	0.25	2.31	-0.08	-0.42
Winners	0.38	3.00	0.08	1.28	0.30	2.26
Losers	-0.20	-1.96	0.17	2.10	-0.37	-2.87

6 Robustness Test

I evaluate the robustness of the results by introducing an adjustment to the factor universe. Given that the short-term reversal factor (STR), cross-sectional momentum (MOM) and long term reversal factor (LTR) are constructed on the assumption of autocorrelation in returns, they are likely to play a crucial role in the dynamics of factor momentum and factor reversal. Therefore, excluding them from the sample ensures that the mechanical correlation between the strategies and equity momentum is reduced (Ehsani & Linnainmaa, 2019). Table 11 reports the average annualized returns of the equal-weighted portfolio, factor reversal and factor momentum. Similarly to the results obtained from the complete sample, the only strategy which yields profits higher than the benchmark portfolio is the time-series factor momentum (t-value = 5.61). In line with the expectations, the time-series strategies from an alternative sample have lower average returns than the ones from the full sample. For example, after excluding the anomalies built on the prior returns, the 3-year time-series factor momentum decreases to -2.41% from the original return of -2.11%. Contrarily, annualized average returns of the cross-sectional strategies experience a moderate improvement. The most notable difference is observed in the case of the 3-year factor reversal strategy which records an increase of 63 basis points. This highlights that regardless of their presumed similarities, the time-series and cross-sectional strategies exhibit unique tendencies. As expected, the success of the time-series strategies is largely linked to autocorrelations in individual stock returns.

Table 11: **Average annualized returns (%) of factor momentum and reversal using a restricted factor universe.** This table reports the annualized average returns, standard deviations, t-values and Sharpe ratios for factor momentum and reversal. The strategies are formulated following the same methodology as in the main body of the study. The sample used for this table is based on the original factor universe but excludes LTR, STR and UMD.

	Annualized return			
Strategy	Mean (%)	SD (%)	t-value	Sharpe ratio
Panel A: Benchmark portfolio				
Equal-weighted portfolio	3.83	1.71	6.15	2.24
Panel B: Factor momentum				
Time-series	7.77	3.69	5.61	2.11
Cross-sectional	3.16	1.73	5.05	1.83
Panel C: 3-year factor reversal				
Time-series	-2.41	2.53	-2.56	-0.95
Cross-sectional	-0.94	1.33	-2.00	-0.71
Panel D: 5-year factor reversal				
Time-series	-1.94	2.38	-2.18	-0.82
Cross-sectional	0.72	1.48	1.36	0.49

Table 12: **Average annualized returns (%) of factor momentum and reversal from international factor sample.** This table shows the annualized average returns, standard deviations and t-values of time-series and cross-sectional strategies constructed following the same procedure as in Table 3. The original U.S. factor universe is extended to include the international equity market factors summarized in Table A.1 in Appendix A.

	Annualized return			
Strategy	Mean (%)	SD (%)	t-value	Sharpe ratio
Panel A: Benchmark portfolio				
Equal-weighted portfolio	5.32	1.29	11.31	1.12
Panel B: Factor momentum				
Time-series	10.16	3.66	7.45	2.78
Cross-sectional	3.03	1.49	5.64	2.03
Panel C: 3-year factor reversal				
Time-series	-5.25	2.38	-6.01	-2.21
Cross-sectional	-2.28	1.40	-4.64	-0.49
Panel D: 5-year factor reversal				
Time-series	-4.71	2.05	-6.26	-2.30
Cross-sectional	1.92	1.26	4.24	-1.52

Table 13: **Average annualized returns (%) of factor momentum and reversal using extended holding periods.** This table reports the annualized average returns and t-values (in parentheses) of time-series and cross-sectional strategies as defined in Table 3. In this table, the holding periods range from 3 to 24 months and the returns are corrected following the Jegadeesh & Titman (1993) method.

Holding window	Holding period					
Strategy	3	6	8	12	18	24
Panel A: Factor momentum						
Time-series	3.20	2.84	2.55	2.05	1.49	0.99
	(3.48)	(4.43)	(4.46)	(4.47)	(3.36)	(2.33)
Cross-sectional	1.04	0.73	0.64	0.67	0.36	0.14
	(3.26)	(3.03)	(3.09)	(4.13)	(2.52)	(1.10)
Panel (B): 3-year factor reversal						
Time-series	-21.82	-17.30	-20.95	-29.32	-25.56	-26.83
	(-3.56)	(-3.76)	(-7.58)	(-2.86)	(-3.50)	(-2.85)
Cross-sectional	-1.47	-1.30	-1.24	-1.23	-1.09	-0.95
	(-4.37)	(-5.84)	(-6.62)	(-8.22)	(-9.16)	(-9.35)
Panel (C): 5-year factor momentum						
Time-series	-14.53	-18.60	-18.70	-19.29	-18.60	-18.00
	(-7.06)	(-10.93)	(-11.39)	(-14.07)	(-15.48)	(-17.38)
Cross-sectional	0.59	0.53	0.49	0.37	0.29	0.32
	(2.22)	(3.03)	(3.24)	(2.85)	(2.55)	(3.03)

In addition to the results from the restricted factor universe, I document the performance of factor momentum and factor reversal in an international market. Table 12 reports that the average annualized return of the time-series factor momentum exceeds the benchmark portfolio. Consistent with the US sample, the factor reversal strategies are unsuccessful and yield either negative or relatively low average annualized returns. The U.S. and international samples produce similar results, suggesting that the dynamics of the strategies are persistent.

In the Results section, I focus of the performance of factor momentum and factor reversal with a one-month holding period. Following the methodology of Jegadeesh & Titman (1993), I form alternative strategies with holding periods ranging from 3 to 24 moths. The results of this analysis are recorded in Table 13. Factor momentum loses profitability when the holding period is extended. Specifically, the time-series and cross-sectional strategies with 24-month

Table 14: **Factor momentum returns (%) conditional on alternative investor sentiment proxies.** This table reports the annualized average factor momentum returns depending on the level of investor sentiment in the prior month proxied by VIX in Panel A and NBER Indicator in Panel B. VIX level is classified as high when the VIX Index exceeds its sample median. NBER Indicator take values of 1 or 0 . The High-Low (HmL) is the return difference between subgroups and its statistical significance is specified by two-sample t-values.

Panel A	VIX level					
	High		Low		Difference	
Strategy	Mean	t-value	Mean	t-value	HmL	t-value
Time-series factor momentum	0.50	1.23	0.58	3.09	-0.08	-0.20
Winners	0.80	3.27	0.33	2.89	0.47	1.99
Losers	0.30	1.20	-0.25	-2.15	0.55	2.28
Cross-sectional factor momentum	0.20	1.24	0.26	3.45	-0.06	-0.40
Winners	0.41	3.29	0.17	3.53	0.25	2.24
Losers	-0.22	-2.12	0.09	1.63	-0.31	-2.89

Panel B	NBER indicator					
	1		0		Difference	
Strategy	Mean	t-value	Mean	t-value	HmL	t-value
Time-series factor momentum	0.33	0.82	0.74	6.05	-0.41	-1.08
Winners	0.62	2.51	0.70	9.49	-0.08	-0.35
Losers	0.29	1.19	-0.04	-0.59	0.33	1.43
Cross-sectional factor momentum	0.15	0.96	0.23	4.59	-0.08	-0.51
Winners	0.35	2.73	0.30	9.83	0.05	0.49
Losers	-0.20	-1.96	-0.07	-1.90	-0.13	-1.17

holding periods earn relatively low annualized average returns of 99 (t-value = 2.33) and 24 (t-value = 1.10) basis points, respectively. Considering the factor reversal, the only strategy which experiences improvement is the one based on the 3-year formation window.

Lastly, I cross-check the results regarding the impact of investor sentiment on the factor momentum. Specifically, I replace the Baker & Wurgler (2006) sentiment index with alternative measures of investors attitude. For this purpose, I use the VIX index and NBER recession indicator. Table 14 represent the annualized strategy results conditional on the value of indicator in the previous month. In line with the prior observations, the time-series losers experience higher returns in high-sentiment environment. Nevertheless, the difference seems to be statistically insignificant when considering the NBER indicator classification. On the other hand, the cross sectional losers earn lower returns following periods of high-uncertainty proxied by the indicators. Taken together, the robustness test confirms the findings on investor sentiment in the main body of the study.

7 Conclusion

Recent literature in the field of factor investing has established a novel investment strategy, namely, factor momentum. Building on the assumption of continuation in returns, it determines exposure to factors conditional on their prior performance. The purpose of this study was to assess whether factor momentum mimics return pattern found it equity, specifically the reversal tendency.

Based on the evidence from the equity-level research, returns are most likely to revert in the short- and long-term. This study has found that factor momentum, formulated using immediate prior one-month performance, yields positive and statistically significant returns. On the other hand, an investment strategy which bets on the long-term factor return reversal results in negative average annualized returns. These findings reveals that factor momentum is persistent and does not follow reversal tendency characteristic of stock returns. Importantly, numerous strategy specifications yield similar results. The same conclusions are drawn from strategies adjusted to include international factors, exclude certain equity anomalies or extend holding period.

The second aim of this study was to analyze the link between equity and factor reversal. Based on the theoretical framework developed by Ehsani & Linnainmaa (2019), I provide evidence that factor reversal fails to explain stock reversal factor. Similarly, I find that the equity-level factors are ineffective in capturing the factor momentum and reversal. Concluding, equity reversal is a distinct anomaly unrelated to autocorrelations in factor returns.

The investigation of potential causes of factor momentum has indicated that it is likely linked to investor sentiment. The strategy earns higher returns following periods of high sentiment proxied by Baker & Wurgler (2006) investor sentiment index. Additionally, alternative measures of sentiment seem to produce similar results, although weaker in terms of statistical significance. Driven by cognitive dissonance, an investor tends to underreact to news, causing a slow-down in asset pricing (Antoniou et al., 2013; Ehsani & Linnainmaa, 2019). One of the significant findings to emerge from this analysis is that short interest plays no significant role in the mispricing process.

A natural limitation of the study lies in the factors universe selection. Despite the fact that it consists of 23 well-established factors, the results of the study could potentially be affected if it was extended to include all 314 factors from top academic journals gathered by Harvey, Liu, & Zhu (2016). Additionally, as reported in Table 1, the starting dates of the factor returns differ substantially. This could potentially reduce the effectiveness of strategies in the periods when the set of available factors is limited. The final limitation regards the choice of the sentiment proxy, namely the Baker & Wurgler (2006) sentiment index. Stambaugh et al. (2012) highlight that the six macrovariables included in the index may fail to sufficiently control for the macro-related variation. Consequently, additional variables could be accounted for to improve the accuracy of the measure.

This thesis is the first comprehensive investigation of factor reversal. It contributes to the existing knowledge in the field of factor investing by providing evidence on factor momentum persistence. The undertaken analysis provides market practitioners with a deeper understanding of factor returns dynamics. It provides evidence that reversal effect typically found in equity, is not observed in factor returns. A natural progression of this work is to analyze whether other equity-level dynamics can be observed in the cross-section of factors. For instance, future research might explore the consequences of betting against factor betas as in Frazzini & Pedersen (2014). Moreover, the findings regarding equity reversal shed new light on its determinants. Given that factor reversal and momentum fail to explain stock reversal, it must originate from sources different than factor autocorrelation. Further research is required to understand drivers of equity reversal.

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Appendix

A Supplementary factors information

Table A.1: **Geographic coverage of factor returns.** The table summarizes the international factor sample by specifying anomalies assigned to the countries/regions listed.

	Anomalies						
Country/region	BAB	INV	MOM	QMJ	SIZE	VALUE	PROF
AUS	✓		✓	✓	✓	✓	
AUT	✓		✓	✓	✓	✓	
BEL	✓		✓	✓	✓	✓	
CAN	✓		✓	✓	✓	✓	
CHE	✓		✓	✓	✓	✓	
DEU	✓		✓	✓	✓	✓	
DNK	✓		✓	✓	✓	✓	
ESP	✓		✓	✓	✓	✓	
FIN	✓		✓	✓	✓	✓	
FRA	✓		✓	✓	✓	✓	
GBR	✓		✓	✓	✓	✓	
GRC	✓		✓	✓	✓	✓	
HKG	✓		✓	✓	✓	✓	
IRL	✓		✓	✓	✓	✓	
ISR	✓		✓	✓	✓	✓	
ITA	✓		✓	✓	✓	✓	
JPN	✓	✓	✓	✓	✓	✓	✓
NLD	✓		✓	✓	✓	✓	
NOR	✓		✓	✓	✓	✓	
NZL	✓		✓	✓	✓	✓	
PRT	✓		✓	✓	✓	✓	
SGP	✓		✓	✓	✓	✓	
SWE	✓		✓	✓	✓	✓	
Global	✓		✓	✓	✓	✓	
Developed		✓	✓				✓
Europe	✓	✓	✓	✓	✓	✓	✓
North America	✓	✓	✓	✓	✓	✓	✓
Emerging	✓	✓	✓	✓	✓	✓	✓
Asia-Pacific	✓	✓	✓	✓	✓	✓	✓

Table A.2: **Correlations between factor returns.** The table exhibits the correlations between factors included in the factors universe and summarized in Table 1.

Factor		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.
1.	ACCR																						
2.	BAB	-0.06																					
3.	CEI	0.16	0.27																				
4.	CFP	0.04	0.20	0.45																			
5.	DIS	0.10	0.26	0.28	-0.05																		
6.	DP	0.09	0.05	0.64	0.57	0.09																	
7.	EP	-0.03	0.23	0.47	0.87	-0.14	0.61																
8.	GP	-0.12	-0.06	0.01	-0.32	0.54	-0.26	-0.47															
9.	INV	0.13	0.32	0.58	0.47	0.13	0.60	0.43	-0.20														
10.	LIQ	-0.06	0.07	0.10	0.12	0.01	-0.04	0.06	0.05	0.03													
11.	LTR	-0.09	-0.11	0.21	0.32	-0.21	0.37	0.33	-0.26	0.47	-0.01												
12.	MOM	0.12	0.30	-0.04	-0.11	0.58	-0.37	-0.16	0.34	-0.02	-0.03	-0.23											
13.	NOA	0.09	0.02	0.19	-0.12	0.06	0.11	0.08	-0.20	0.16	-0.00	0.19	0.01										
14.	NSI	0.07	0.30	0.53	0.15	0.46	0.28	0.09	0.28	0.45	0.01	0.04	0.12	0.15									
15.	OSC	0.21	-0.13	0.27	-0.23	0.43	0.05	-0.20	0.34	-0.08	0.06	-0.23	0.04	0.23	0.37								
16.	PPE	0.19	0.10	0.33	0.16	0.03	0.39	0.25	-0.17	0.51	-0.08	0.34	0.06	0.32	0.13	-0.08							
17.	PROF	-0.14	0.31	0.25	0.04	0.44	0.04	0.04	0.40	-0.02	0.03	-0.27	0.12	-0.03	0.52	0.37	-0.20						
18.	QMJ	0.03	0.19	0.39	-0.17	0.69	0.09	-0.16	0.55	0.08	0.01	-0.29	0.30	0.15	0.60	0.65	-0.01	0.69					
19.	ROA	-0.00	0.19	0.16	-0.16	0.67	-0.04	-0.17	0.51	-0.03	-0.07	-0.33	0.34	-0.00	0.47	0.51	-0.11	0.67	0.73				
20.	RVAR	0.13	0.36	0.58	0.06	0.61	0.41	0.08	0.17	0.40	0.00	-0.12	0.23	0.21	0.66	0.54	0.17	0.52	0.73	0.56			
21.	SIZE	-0.28	0.01	-0.37	0.05	-0.41	-0.03	0.08	-0.08	-0.17	-0.02	0.37	-0.11	-0.17	-0.44	-0.65	0.01	-0.36	-0.50	-0.43	-0.75		
22.	STR	-0.09	-0.07	-0.14	0.02	-0.52	-0.05	0.08	-0.21	-0.11	0.05	0.06	-0.20	-0.09	-0.18	-0.12	-0.01	-0.09	-0.28	-0.23	-0.24	0.25	
23.	VALUE	0.04	-0.03	0.57	0.77	-0.05	0.60	0.77	-0.43	0.72	0.07	0.64	-0.39	0.13	0.30	-0.13	0.37	0.04	-0.10	-0.13	0.29	0.15	0.03

B Alternative sentiment indicators

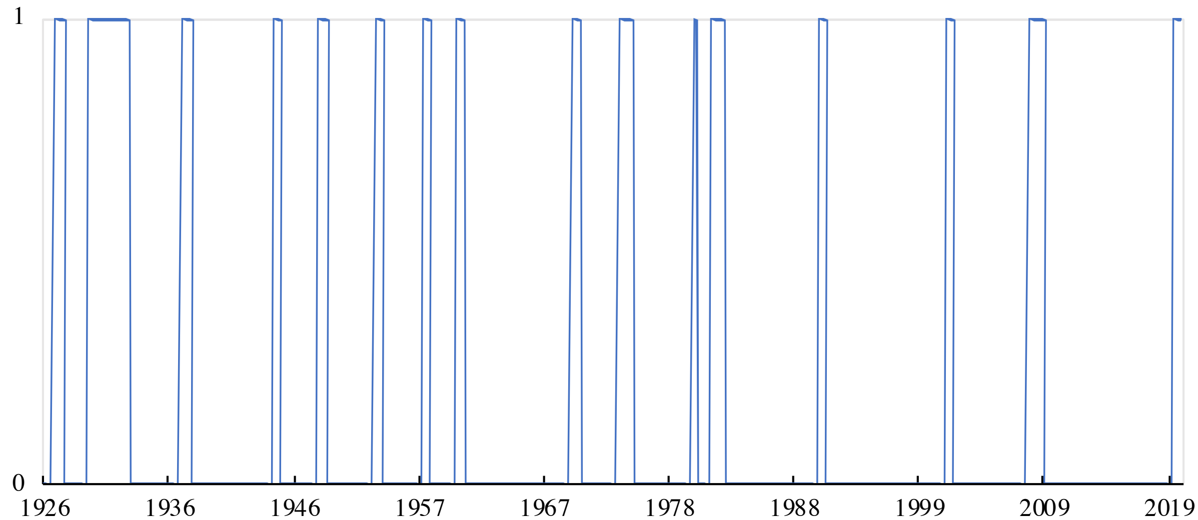


Figure B.1: **NBER recession dummy.** This figure plots the NBER recession dummy for the period between February 1926 and October 2020. The graph is a visual representation of the NBER based recession indicator time-series. The indicator takes value 1 during recessionary periods and value 0 during periods of expansion.

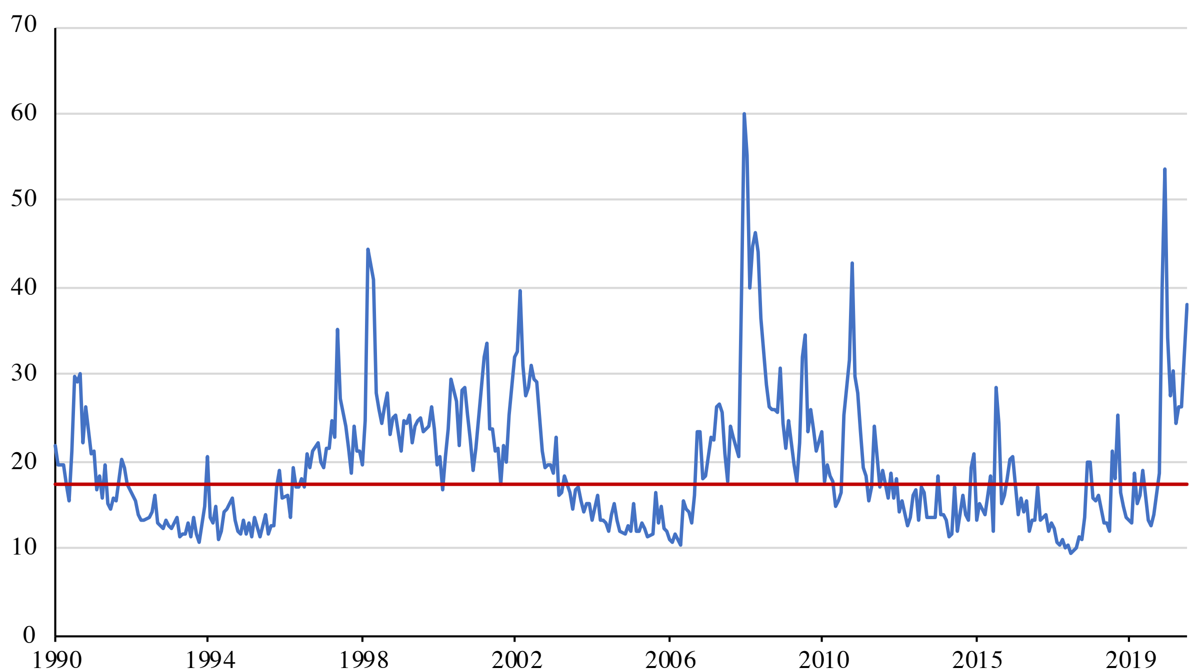
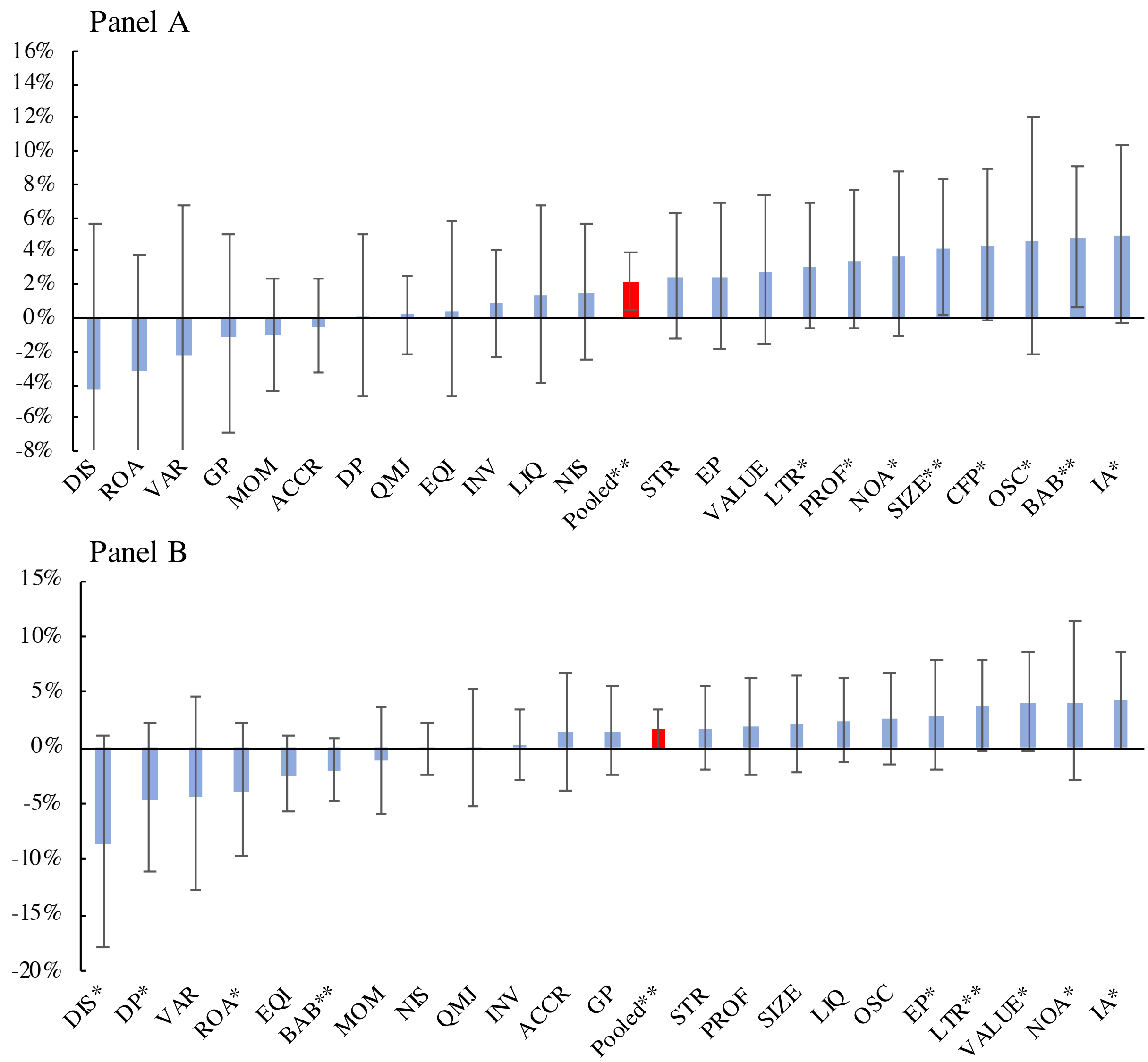


Figure B.2: **VIX index.** This figure represent the VIX index for the period between February 1990 and October 2020. The red line indicates the sample median value.

C Profitability of individual factor timing



*Note: *, ** and *** indicate the statistical significance at 1%, 5% and 10%, respectively.*

Figure C.1: **Annualized alphas (%) of individual factors.** This table reports the annualized average alphas from regressing individual factor (36-month and 60-month formation windows in Panel A and B, respectively) time-series strategy returns in month t on raw returns in the same month. Scaling procedure follows Equation 5. In pooled regressions, standard errors are clustered by month. The vertical bars indicate 95% confidence intervals.

Table C.1: **Betas of individual alphas.** This table reports the slopes and their t-values from regressing individual factor time-series strategy returns in month t on raw returns in the same month using formation windows of 1, 36 and 60 months. Scaling procedure follows Equation 5 described in the Methodology section. Additionally, I report the pooled betas for which the standard errors are clustered by month. *, ** and *** show the significance at the 10%, 5% and 1% levels.

	Formation window					
	(1-1)		(1-36)		(1-60)	
Factor	$\hat{\beta}_{(1-1)}$	t-value	$\hat{\beta}_{(1-36)}$	t-value	$\hat{\beta}_{(1-60)}$	t-value
Pooled	0.13	3.01***	0.79***	14.20	1.02***	19.54
ACCR	0.15***	3.58	0.94***	14.92	1.42***	27.74
BAB	0.12***	3.48	0.80***	14.43	1.84***	82.65
CEI	0.32***	7.77	1.11***	17.71	1.42***	26.81
CFP	0.09***	2.64	0.53***	8.00	0.72***	11.11
DIS	0.29***	5.54	1.15***	17.83	1.31***	21.50
DY	0.24***	7.53	0.04	0.67	0.01	0.25
EP	0.19***	5.60	0.51***	7.87	1.02***	17.97
GP	0.13***	3.04	0.89***	12.95	1.09***	16.52
INV	0.26***	6.13	0.85***	12.87	1.32***	24.01
LIQ	0.12***	2.98	1.05***	16.04	1.18***	18.50
LTR	0.04	1.47	0.24***	4.08	0.61***	10.64
MOM	-0.01	-0.40	1.60***	49.76	1.83***	83.06
NOA	0.17***	4.40	0.92***	13.58	1.20***	19.02
NSI	0.26***	6.15	0.74***	10.75	0.88***	13.03
OSC	-0.04	-0.95	0.42***	5.47	0.45***	5.78
PPE	0.21***	4.98	0.77***	10.63	1.12***	16.84
PROF	-0.09**	-1.98	0.28***	3.76	0.86***	13.45
QMJ	0.23***	-5.69	1.55***	35.18	1.64***	38.05
ROA	0.21***	4.22	1.06***	15.12	1.58***	31.06
RVAR	0.09**	2.04	0.27***	3.70	0.34***	4.73
SIZE	-0.08***	-2.83	0.54***	9.67	0.40***	7.45
STR	0.01	0.25	1.25***	28.41	1.52***	41.31
VALUE	0.32***	9.88	0.11**	1.97	0.17***	2.96

D Factor reversal conditional of alternative measures of investor sentiment

Table D.1: **Factor reversal returns (%) conditional on VIX Index.** This table reports the annualized average factor reversal returns (36-month and 60-month formation windows in Panel A and B, respectively) depending on the level of investor sentiment in the prior month proxied by VIX. VIX is defined as high if it exceeds its sample median and low, otherwise. The difference between portfolio returns conditional on VIX is captured by High-Low (HmL) and its two-sample t-values.

	VIX level					
	High		Low		Difference	
Strategy	Mean	t-value	Mean	t-value	HmL	t-value
Panel A: 3-year factor reversal						
Time-series factor reversal	-0.20	-0.79	0.01	0.05	-0.21	-0.72
Winners	0.55	2.22	0.13	1.20	0.42	1.79
Losers	0.72	3.97	0.12	1.23	0.60	3.12
Cross-sectional factor reversal	-0.15	-1.44	-0.06	-0.81	-0.09	-0.72
Winners	0.39	4.04	0.07	1.21	0.32	3.07
Losers	0.24	2.37	0.01	0.20	0.23	2.42
Panel B: 5-year factor reversal						.
Time-series factor reversal	-0.18	-0.75	-0.11	-0.68	-0.06	-0.21
Winners	0.47	1.95	0.02	0.12	0.45	1.73
Losers	0.60	3.43	0.13	1.42	0.47	2.63
Cross-sectional factor reversal	-0.01	-0.14	0.06	0.91	-0.07	-0.64
Winners	0.32	3.15	0.01	0.18	0.31	3.27
Losers	0.31	3.51	0.07	1.33	0.24	2.50

Table D.2: **Factor reversal returns (%) conditional on NBER Indicator.** This table shows the annualized average factor reversal returns (36-month and 60-month formation windows in Panel A and B, respectively) conditional on the level of investor sentiment in the prior month proxied by NBER Indicator. High-Low (HmL) and its two-sample t-values show the difference and its statistical significance between portfolios classified by NBER Indicator.

	NBER indicator					
	1		0		Difference	
Strategy	Mean	t-value	Mean	t-value	HmL	t-value
Panel A: 3-year factor reversal						
Time-series factor reversal	-0.06	-0.24	-0.33	-3.90	0.27	1.07
Winners	0.56	2.32	0.15	2.01	0.41	1.82
Losers	0.59	3.17	0.47	9.73	0.12	0.80
Cross-sectional factor reversal	-0.09	-0.88	-0.14	-2.95	0.05	0.33
Winners	0.32	3.17	0.25	7.01	0.07	0.59
Losers	0.22	2.32	0.12	4.13	0.11	1.23
Panel B: 5-year factor reversal						.
Time-series factor reversal	-0.07	-0.29	-0.28	-3.70	0.21	0.92
Winners	0.45	1.87	0.17	2.20	0.28	1.24
Losers	0.48	2.74	0.43	9.94	0.05	0.39
Cross-sectional factor reversal	-0.06	-0.66	0.07	1.56	-0.13	-1.00
Winners	0.30	2.97	0.15	4.71	0.15	1.54
Losers	0.24	2.65	0.23	7.62	0.01	0.13