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Factor Timing and Factor Structure: Quantitative strategies in the U.S. Equity market

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PREFACE AND ACKNOWLEDGEMENTS

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Abstract

In this research I document a new phenomenon in the U.S. equity market that I refer to as factor and cross-factor time series momentum, which departs from existing academic literature in the last decades. Using data from 156 existing equity anomalies, I show that past equity factor returns are on average positive predictors of their own future returns and simultaneously positive predictors of future returns in the sample of factors used. I use this predictability to construct a diversified factor time series momentum and a cross-factor time series momentum portfolios that yield a Sharpe ratio approximately 4 and 6 times higher than a standard long positioning in a representative index, respectively. Two approaches have been pursued in case of negative past predictive signals: investing in the risk-free asset or going short in the factor. The (cross-) factor time series momentum strategy described here is robust to both specifications. A diversified portfolio of (cross-)factor time series momentum strategies delivers substantial abnormal returns compared to a more passive indexed approach with little exposure to standard asset pricing factors and can overcome periods of extreme volatility in the markets as well as large economic downsides.

Keywords: Asset pricing; Factor premia; Predictability; Investment strategies; Equity framework; Factor time-series momentum; Cross-correlation.

JEL Classification: C31, C33, G11, G12, G14

1 Introduction

Identifying the underlying factors that have explanatory power on the cross-sectional returns in stock prices is a challenge which researchers and practitioners have been facing in asset pricing for decades. Do it in a time series framework can be even less intuitive. After Sharpe's (1964) development of the Capital Asset Pricing Model – initiated earlier by Markowitz (1952) by means of Modern Portfolio Theory – hundreds of papers have criticized and built upon the model. A common critique of the CAPM is that the market premium does not drive individual stock returns. Harvey, Liu, and Zhu (2016) for instance adopt different significance criteria for newly discovered factors, such as an earnings-to-price ratio, liquidity, size, idiosyncratic volatility, and a default risk factor. Contemporary research in the asset pricing field aims to improve the predictive power for the cross-section of returns in equities and other asset classes across markets.

Widely respected improvements over the CAPM include the Fama-French three- and five-factor models; but these models still assume a positive, linear relationship exists between the market premium and returns. However, the principle that a stock with a higher risk should provide higher returns has been refuted repeatedly. This is empirically proven in papers written by, but not limited to, Ang, Hodrick, Xing and Zhang (2006), Blitz and van Vliet (2007), and Baker and Haugen (2012). The so-called low-volatility, for example, effect predicts that assets with low historical volatility outperform stocks with a higher volatility. This low-risk anomaly has been found to persist across time and markets, and with that, appears to contradict the foundations of modern portfolio theory, where return is the compensation for the investor's risk exposure.

In a similar vein, as another instance, the momentum strategy of buying past winners and selling past losers is effective in capturing the difference in firms' performances, particularly from twelve to six months prior to portfolio formation. Jegadeesh and Titman (1993) thoroughly document that the profitability of these strategies are not due to their systematic risk or given by delayed stock price reactions to common factors. Though the first-year generated alpha does seem to disappear over time, as these abnormal returns do not hold in two subsequent years. These developments in recent research suggest the presence of tons anomalies in financial markets. These anomalies may appear only once, be consistent, or disappear over time. Whichever is the case, they garner interest in constructing long-term investment strategies to harness a significant return.

In recent years, the growing awareness regarding the benefits of strategic allocation to a number of well-rewarded factors has led increasing numbers of investors to consider this option. Flows in the sector have especially shifted from single factor to multifactor funds on the premise they enable investors to access several different factors at once, which supposedly yields better results, dilutes total risk and smooths the ride for investors. This adoption of multifactor funds has tripled in the last four years, according to a survey by FTSE Russell. One relevant reason for this is that single factors have become commoditized, especially in the passive investment space. By the numbers, there is no doubt that investment firms and retail investors are more keen on buying multi-factor ETFs and stock universe. The latest annual ESG & Smart Beta survey from FTSE Russell found that the number of asset owners adopting multi-factor fund strategies grew from 49 percent in 2018 to 71 percent in 2019. Furthermore, according to Kenneth Lamont, senior research analyst at Morningstar, the market has become saturated with single-factor ETFs tracking the five core factors that are considered robust, tried and tested. As a consequence, turnover within single portfolios can significantly change, and the way multi-factor portfolios are implemented can also mean that the total cost of ownership of a fund can increase. At the same time, investors do want to minimize overall transaction costs while reaching a superior alpha performance. According to a report published by Bloomberg from April 2019, multi-factor stock products saw an average fee of $4.70 for every $1,000 invested, compared to the 20 cents in fees for the cheapest overall U.S. ETF and smart-beta ETFs overall.

Likewise, an increasing number of researchers has been attracted by new possibilities as of trying to explain stock (and bond) returns via new components beyond traditional expected market sources, and whether or not the alpha remains after controlling for those sources of superior performance over time. But while single factor-tilted portfolios have proven they can significantly outperform the market over the long term, they can also experience periods of disappointing performance relative to other single-factor portfolios and even to classic market-cap weighted benchmarks. On the other hand, in the case of multi-factor strategies, performance is arguably more difficult to forecast hence tactical factor timing is deemed to be rather less accurate, especially from a practical perspective. At the same time, whether it is an investor firm or retail investor, one should be aware of factor mining phenomenon as many of them could simply be documented as significant in the currently existing literature as a result of lucky findings – i.e. the "factor zoo" as a result of 316 discoveries. Indeed, given that the low-hanging fruit has already been picked, meaning that the discovery rate of a true factor has likely decreased (Campbell Harvey, Liu & Zhu, 2015), I carefully assessed the existing literature and harvested the data specifically to the returns of the "good beasts in the factor zoo" (Chen and Zimmermann, 2020).

Recent academic evidence shows that multiple character-based equity factor exhibit momentum-like behavior, indicating that factors may in principle be timed (Gupta & Kelly, 2019). In fact, as stated in their paper, factor momentum earns an economically large and statistically significant alpha after controlling for traditional stock momentum, even it cannot displace the latter. The common finding with regards to factor momentum is that factors in itself exhibit momentum-like behaviour and that returns are persistent over longer time horizons. Given that positive autocorrelation is a persuasive feature of factor returns, it has been documented that momentum in individual stock returns emanates from momentum in factor returns (Ehsani and Linnainmaa, 2019). In their research paper, they report that on average a single factor earns a monthly return of 1 basis point following a year of losses and 53 basis points following a positive year. This systematically leads to a couple of conclusions. Firstly, factor momentum effect is able to explain all forms of individual stock momentum – i.e. industry momentum, industry-adjusted momentum, cross-sectional momentum, intermediate momentum and Sharpe ratio momentum; on the other hand, the opposite is not proven to be valid, meaning that factor momentum is not explained by these forms of momentum. In second instance, equity momentum strategies indirectly time factors, meaning that they obtain a profit when factor stay autocorrelated and crash when these autocorrelations cease. A slightly different view on the effectiveness of factor momentum persistency is offered by Arnott et. al. (2019). Here, the authors prove the factor momentum strategies – they focus on existing differences across industries, the so-called "industry momentum" - to be particularly strong, but only at the one-month time horizon, unlike the one documented in equity returns.

However, the ultimate takeaway from the existing factor momentum literature is that autocorrelation in factor returns does add value to the cross-sectional momentum profits, under the assumption that stock returns follow a factor structure. In other words, a past high factor return signals future high returns. This is true not only for a specific anomaly, but is also the case for several different factors, given that a "momentum factor" is the summation of the autocorrelations found in the other factors (Ehsani and Linnainmaa, 2019). What is more, another evidence worth mentioning to reinforce this argument is produced by Lewellen (2002), who finds that lead-lag effects[1] in equity portfolio returns appear to be the most significant contributor to cross-sectional momentum effects. On the other hand, Moskowitz et al. (2011) empirically show that time-series and cross-sectional momentum effects are mostly driven by positive auto-covariance in returns, after decomposing futures returns across 4 different asset classes: commodities, equity indices, bonds and currencies.

A challenge for academia lies in the estimation and conceptualization of dynamic linkages and correlations between different quantitative strategies over time. A question that arises is how several existing factors applied to a properly liquid and accessible financial market as the U.S. equity one are related to each other based on past monthly return data and to what extent they help to mutually predict future factor premia. Deciding whether to tactically monitor and adjust exposures to different factors and, if so, how to invest in them

[1] A lead-leg effect is referred to as the cross-correlation relationship between one (leading) variable and the values of another (lagging) variable at later points in time. Here, the 2 variables are a combination of pairs of different factors at disposal.

according to two-sided predictability, has been recently raised as a major concern by both academics and practitioners. Likewise, another insightful point of inspection and further analysis is situated in the capability to time factors according to ongoing market conditions. Indeed, a major reason of attraction for many academics has recently been to investigate to what extent factor returns – hence cross-factor correlations – change as the overall level of volatility in the market remarkably increases.

Therefore, the aim of this paper is to test whether specific proven anomalies taken from a large dataset within the U.S. equity framework are effective in their own time series component in first place, based on their historical returns. As a matter of fact, momentum is not intended to be a distinct risk factor as it describes average returns of portfolios sorted by prior one-year returns and aggregates the autocorrelations found in all other factors (Ehsani and Linnainmaa, 2019). In second instance, verify whether these can systematically predict future performance of other factors over the researched time horizon, whilst trying to reduce the risk of data mining to the largest extent possible.

To this end, I utilize 156 factors that have been thoroughly documented within the existing factor investing literature, 77 of which have been hand collected from the original publications by Chen & Zimmermann (2020). The Equity factors from the initial dataset have been accurately selected in order to reflect already tested long-short investment strategies following various criteria, aimed to reduce the risk of data mining to the largest extent possible. As later explained in the Data and Methodology sections, I aim to exclude those factors which provide meaningless information in explaining equity returns in the cross section. To test for cross-factor predictability, I first examine autocorrelation patterns across different anomalies. Remarkably, autocorrelations go hand-in-hand with time-series momentum strategies: although time series momentum effect is complementary to cross-sectional momentum, the former is dominant in explaining excess returns (Moskowitz et al., 2011). Combining these two could be proven to be very effective in seeking meaningful future gains, not only on the individual stock level but also on the equity factor level. Out of this research, it can be inferred that positive cross-correlation mutual effects do exist in the spectrum of equity anomalies.

However, I do not limit my research to predict the sign of cross-factor correlation, rather I target to extend the analysis by implementing potential long-short cross-factor investment strategies that can reasonably lead to outperform the market, based on the signal received during several past periods. Although it is reasonable to think of factor investing strategies being able to beat the market returns, it is rather challenging to do so consistently over time, given that market conditions change from one month to another. This evidence is consistent with initial under-reaction to stock news but may also be coherent with delayed over-reaction theories of sentiment as the time series momentum effect partially reverses after one year and gravitate back toward fundamentals. (Moskowitz et al., 2011). Therefore, I will refer to these approaches later on as cross-factor time series momentum strategies.

The key takeaways of this research project reveal that the patterns of cross-factor predictability can be used to construct cross-factor time series momentum strategies that generate significant, positive monthly alphas even after controlling for factor time series momentum strategies with the same lookback and holding periods, cross-sectional momentum under different versions, passive exposures to equity market, and standard asset pricing factors. Assuming no uncertainty in exogenous elements affecting factors' behavior and focusing primarily on the time-varying correlation as the feed of their underlying relationship, I prove that factor timing phenomenon is definitely a possibility to consider when having a diversified factor portfolio in the context of equities. What is more, the documented investment strategies turn out to be almost unaffected by volatility trends hence providing stable streams of income, also in times when external economic events have been influenced stock returns globally. Consistency in strategy excess returns has also been verified against the most widely used economic variables, ranging from monetary policy to more macro indicators.

This paper outline is structured as follows: Section II discusses the theoretical framework with respect to the factor analysis examined and tested in this paper. In Sections III and IV, I touch upon the data sample that was used and several econometric research techniques respectively, to allow me to come up with sound systematic investment strategies. Section V displays the results of the research and further evaluates and compares the corresponding economic implications. Section VI is pivoted around robustness checks and acknowledges the possibility to expand the analysis. Lastly, Section VII presents conclusions and provides room for further discussion on the studied topic.

2 Literature overview

This chapter addresses the causes and consequences of the presence of such anomalies indicating what is the status quo of time-series momentum strategies, how they can be applied in the cross section of equity returns and to shed a light on the possibility of timing different factors based on existing measures of dynamic dependence between factor returns.

The Efficient Market Hypothesis (EMH) states that markets and investors are rational, with prices reflecting all available information. Following this line of reasoning, one can conclude that stocks should always trade at their fair value, making it impossible for investors to consistently beat the market without taking on additional units of risk. Recent literature, however, has found that markets do not always follow the rules of EMH, thereby finding certain anomalies that cannot be explained in the traditional financial framework.

In this research I will focus on a range of published market anomalies, and empirically test their cross-factor influence within the U.S. equity market.

Based on the framework EMH provides, the Capital Asset Pricing Model has become a standard financial tool. Combining the two leads to a widely used decision making tool for practitioners. Fama (1965) and Malkiel and Fama (1970) introduce the EMH in three levels of efficiency: a strong level where all relevant information regarding an asset is fully reflected in its price; a semi-strong level where all publicly available information is reflected in the price; and a weak level where current prices reflect all past history of the prices. Fama and French (2004, p. 25) note that the CAPM of Sharpe (1964) and Lintner (1965) marks the birth of asset pricing theory (resulting in a Nobel Prize for Sharpe in 1990). However, Fama and French (2004) evaluate the performance of the CAPM and conclude that empirical evidence invalidates the use of CAPM in applications, after finding that passive funds invested in low-beta, small, or value stocks tend to produce positive abnormal returns relative to the CAPM's predictions. The next sub-sections treat all the investigated steps across both the cross-sectional and time-series dimensions in discovering past signals, which can turn to be persistent and useful to systematically predict future stock returns. The goal is to use past factor returns as regressors on the right-hand side in order to explain as much of specific factor's out-of-sample variation in excess returns as possible, after having verified that positive autocorrelation and cross-factor correlation effects exist on average across the sample of factors used.

2.1 Momentum factor and Factor momentum

Almost any set of equity factors exhibits momentum properties. However, a distinction needs to be made between the traditional role of the momentum factor (Jeegadesh & Titman, 1993) and the momentum feature of the returns of a quantitative investment strategy, the so-called "factor". In the former case, momentum appears to violate the efficient market hypothesis in its weakest form. Past returns should not indeed predict future returns in case asset prices promptly reacted to new market information and to the right extent - unless past returns of the same (group of) stocks correlate with changes in systematic risk. Researchers have sought to explain the profitability of momentum strategies by trying to attribute an explanation of its existence. They did so by means of time-varying risk, behavioral biases and frictions induced by trading - i.e. transaction costs.

From a behavioural perspective, people (and investors) intend to overreact to unexpected news (Kahneman & Tversky, 1982). Overreaction is said to exist in stock markets, because investors tend to overweigh the recent information in an attempt to revise their expectations about a firm; as a consequence, they undervalue previous information. Seeing a move in a stock price, either downwards or upwards, can be regarded as new information. According to this behavioral phenomenon, this can translate into the overshooting of stock prices. If the overshooting of stock prices is systematic, this would mean that the reversal should be predictable (De Bondt & Thaler, 1985). This reasoning implies that in some time frame, the past returns of a certain asset will explain the future returns of said asset. However, De Bondt and Thaler found that portfolios consisting of stocks having lower excess returns outperformed portfolios consisting of stocks with higher excess returns over the following period of three years. Jegadeesh and Titman (1993) argue that the findings of De Bondt and Thaler were not attributed to overreaction but rather to a size effect and systematic risk. They conducted similar research to De Bondt and Thaler, but found that portfolios with high one-year past returns outperformed portfolios of stocks with lower one-year past returns. This phenomenon is the momentum effect, and they attributed the effect discovered by De Bondt and Thaler to a "reversal momentum effect". This effect implies that implementing strategies involving the buying of high momentum assets and selling assets with a low momentum would be profitable. In addition to these findings, questions have been raised over the timeframes in which this momentum factor has been said to exist. In a study conducted by Novy-Marx (2012) it was found, for instance, that using intermediate past-horizon performance in constructing portfolios outperforms using recent past-horizon performance. Subsequent research has shown that momentum is also present in other asset classes and has been over long periods of time (Asness, Moskowitz & Pedersen, 2013).

On the other hand, positive autocorrelation is a pervasive feature of factor returns. Factors with positive returns over the prior year earn significant premiums; those with negative returns earn premiums that are indistinguishable from zero. Factor momentum (FMOM) is a strategy that bets on these autocorrelations in factor returns (Ehsani et al., 2019). It is shown that well-diversified industry portfolios are also proven to exhibit momentum which, unlike the one found in stock returns, is particularly strong at the one-month horizon (Moskowitz & Grinblatt, 1999). Along the lines, Arnott et al. (2019) show that different factors exhibit momentum in a similar fashion to the one found in industry portfolios, being even stronger than industry momentum. According to them, this effect remains solid even after controlling for stock price momentum, industry momentum, and the five factors of the Fama-French model. Compared to the momentum effect found in the cross section of portfolios sorted by size and book-to-market, factor momentum turns out to deliver a better performance ceteris paribus. In a similar way, Gupta et al. (2019) document robust persistence in the returns of equity factor portfolios. This persistence is exploitable with a time-series momentum trading strategy that scales factor exposures up and down in proportion to their recent performance. Factor timing in this manner produces economically and statistically large excess performance relative to untimed factors, setting the ground to become a persuasive phenomenon in financial markets.

2.2 Own factor predictability

2.2.1 Factor Time-series momentum

Hypothesis 1. *Past 1- to 12-month factor returns in the dataset are positive predictors of their own future returns within the U.S. stock market.*

In order to test for this hypothesis, some academic papers need to be taken into account. First of all, as documented by Moskowitz et al. (2012), the time series momentum effect (TSMOM) is found significant and remarkably consistent across major asset classes and derivatives over the last 25 years. However, in order to be able to estimate and decompose factor (time-series) momentum (FMOM) – as well as cross-sectional momentum effects – the auto-covariance between an asset's excess return next month and its lagged 1-year return needs to be positive. In this case, the subject of the whole analysis is represented by factor returns rather than security returns. The most intuitive and effective tool to verify the presence of time-series momentum features – as discussed in the 'Methodology' section later on - is the autocorrelation in each of the selected factor returns over some key past months, coupled with the average pairwise correlation across the "cross-section" of the different available factors.

2.2.2 Correlation analysis

Hypothesis 2. *(Cross-)factor correlations increase considerably during highly volatile periods.*

Zooming in the cross-factor momentum correlations, and thus factor mutual predictability, it certainly deserves attention and curiosity to see whether factor momentum dies out once this is controlled for high-volatility periods. To test this assumption, volatility is computed over rolling 1-year lookback windows. It would be reasonable to expect that during episodes of global crisis and contagion periods – e.g. OPEC Oil Crisis and Early 90's U.S. recession (1990), the Asian Flu (1997), the Russian crisis (1998), the Dot-com bubble (2001), the GFC (2007), and the European sovereign debt crisis (2009-10) – equity markets worldwide crash, so by definition we should obtain high persistency and high correlations, and investors should see their returns exposed to more systematic risk. However, this assumption is valid on the individual security level, if a bunch of stocks belonging to a specific sector and geographical region is taken. I instead aim at verifying whether the same holds for equity anomalies rather than single assets. The analysis is carried out within Section VI, which is centered around robustness checks. Further tests are conducted on the sentiment index and several macroeconomic variables.

2.3 Cross-factor predictability

2.3.1 Cross-factor Time-series momentum

Hypothesis 3. *Past 1- to 12-month returns of specific factors within the U.S. stock market are (positive) predictors of other factors' future returns. Long-short strategies are possible.*

Following the procedure adopted in the previous sub-section, in order to be able to test the magnitude of cross-factor time-series momentum (XFTSMOM), whilst keeping the simple nature of the measures, pair-wise time-series correlation coefficients between the factors included in the dataset can be of help in this research. According to the methodology adopted by Conlon et al. (2009) paired with the extensive contribution made by Pitkäjärvi et al. (2020),

$$R_{x,y,k} = g_k^{x,y} * \sqrt{\sigma_x \sigma_y}. \tag{1}$$

, where

$$g_k^{x,y} = \frac{1}{n} * \sum_{t=1}^{n-k} (y_t - \bar{y})(x_{t+k} - \bar{x}). \tag{2}$$

Based on the values of these time-varying correlation coefficients taken as first step, something can be inferred on the predictability of the performance of equity factors when looking at what is happening i) within the same equity anomalies on average and ii) across their peers on average. In the following section, a detailed description is given on the inputs used for this research, inclusive of extensive statistics to summarize and analyze the dataset.

3 Data

Equities were battered in March 2020 but have rebounded to levels that almost exceed where they were before coronavirus struck. This has led some investors to question whether the equity asset class now looks expensive given the extreme economic uncertainty that threatens the earnings of many companies. Timothy Woodhouse, manager of the JP Morgan Global Growth & Income trust, said that because the equity risk premium looks elevated versus history, the current situation suggests that stocks, on a long-term basis, remain cheap. Although investments across other asset classes have gained ground in the most recent years, including credits, convertibles and the apparent unstoppable advent of green bonds to a name a few, equities did not substantially lose momentum from an individual investor's perspective[2], yet being seen as instruments tracking the overall level of the global economy. Furthermore, notwithstanding the huge downward effect of the coronavirus on small and medium business and their lending schemes, corporate earnings started to rebound significantly that can potentially lead to a solid start of 2021. Although a portion of uncertainty for future return expectations is given by equity volatility, as will be explained in the following sections of this research, investors might be able to prudently time the unsystematic part of their portfolios by means of factor investing strategies that do consider the time-series dimension as key. The combination of these motivations made me concentrate on the yet open opportunities on the equity side.

Ideally, a factor dataset should in order (1) cover a comprehensive set of predictors, (2) use standardized performance measures, and (3) use statistics reported in the original publications. Achieving all three goals is far from feasible, however, as performance measures are only partially standardized across publications. The dataset employed is taken from a recent publication by Chen & Zimmermann (2020), where is documented that only about half of the predictors examined report portfolio returns, with the other half reporting regression results. Thus, they constructed standardized performance measures for 156 equally-weighted long-short portfolios by replicating 115 publications in well-known accounting, economics, and finance journals (Chen & Zimmermann, 2020). All but two portfolios are equal weighted, as most of the original publications focus on either equal-weighted portfolios or Fama-Macbeth regressions. The only two documented exceptions are idiosyncratic volatility (Ang et al. 2006) and the Gompers, Ishii, and Metrick (2003) governance index. These two predictors were value weighted by Chen & Zimmermann, as they perform far better using value weighting in both the original papers and the replications. The sample spans the period from January 1, 1985, till December 31, 2016.

Table 1 provides several top-level summary statistics comprehensive of the whole predictor list used, whereas the Appendix offers detailed definitions, extensive calculation methodology and complete references to the original literature. The possibility of extend the analysis to different versions of the long-short portfolio returns, related to both portfolio allocation schemes – e.g. value-weighted returns – and portfolio construction schemes – e.g. deciles or binaries – will be examined more accurately in Sections VI and VII.

Although perfect replication of all 156 predictors is rather hard to achieve, the reproduc-

[2]Retail investors' standpoint needs to consider broad regional and sector diversification in allocating capital in first place, so as to limit losses in the event of systematic crises.

tions have been made in such a way to produce t-statistics above 1.5 (Chen & Zimmermann, 2020), which differs from traditional thresholds such as 1.96. However, as documented in Campbell Harvey et al. (2015), a t-statistic of 2.0 is too low for producing statistically significant factors without the risk of incurring in the data mining spectrum – that is, “discovering” historical patterns that are driven by random, not real, relationships and assuming they will repeat over time. A reasonable critique to this claim made by Chen and Zimmermann (2020) lies in the fact that replicating exactly equity return predictors that are published in the main journals is rather a reliable starting point to develop from. To this aim, around 90% of employed predictors are published in the “top-3” finance journals, the “top-3” accounting journals, or the “top-5” general interest economics journals. The remaining 22 are also published in reputable journals and include important predictors like the Titman, Wei, and Xie (2004) investment anomaly and the Amihud (2002) illiquidity measure. Based on the presence of such anomalies in the major financial and econometric research and their adoption in previous literature, it can be therefore assumed the reliability of data sources used for timing such a wide dataset of equity factors.

Table 1: **Descriptive statistics of the Dataset by Category**

Reported are top-level descriptive statistics for replications of 156 cross-sectional return predictors (*retrieved from Chen & Zimmermann, 2020*). Top-3 Finance includes the Journal of Finance, the Journal of Financial Economics, and the Review of Financial Studies. Top-3 Accounting includes the Accounting Review, the Journal of Accounting Research, and the Journal of Accounting and Economics. Top-5 Econ includes the Quarterly Journal of Economics and the Journal of Political Economy (other econ journals did not have predictors that we replicated). The Appendix at the bottom of the document provides a complete list of predictors. Monthly portfolio returns can be found at `http://sites.google.com/site/chenandrewy/code-and-data` .

A. Predictor counts by journal and data category

	Accounting only	Market price	Analyst	Trading	Corporate Event	Other	Total
Top-3 finance	21	37	11	7	10	8	94
Top-3 accounting	30	4	0	2	0	0	36
Top-5 Econ	1	2	0	0	0	1	4
Other	10	5	2	3	2	0	22
Total	62	48	13	12	12	9	156

B. Statistics for long-short returns in original sample periods

	Mean return (% per month)			t-statistics	
	N	Mean	SD	Mean	SD
Journal					
Top-3 finance	94	0.75	0.47	3.85	2.20
Top-3 accounting	36	0.64	0.54	5.21	3.97
Top-5 Econ	4	0.56	0.14	2.87	1.98
Other	22	0.80	0.39	5.27	3.42
Data category					
Accounting only	62	0.65	0.43	4.99	3.33
Market price	48	0.82	0.49	3.82	2.12
Corporate event	13	0.42	0.20	2.74	0.91
Analyst forecast	12	1.02	0.52	6.82	4.07
Trading	12	0.64	0.18	2.81	1.05
Other	9	0.92	0.77	3.72	2.82
Portfolio construction					
Quintiles	130	0.74	0.47	4.42	2.96
Indicator	26	0.69	0.49	3.97	2.81

Alternatively, as the main results use replicated data, they do not measure the bias in the original reported numbers. Instead, each publication suggests a trading strategy and provides a volume of statistics in support. The relevant reader must turn the statistics into precise portfolio constructions, as done in the replications. These replicated expected returns are at risk of containing bias due to the publication process. To examine this issue, replications are supplemented with hand-collected statistics. As an additional check, raw return quintile sorts have been collected when available, but also returns that adjust for factor models and characteristics, as well as portfolios that use alternative portfolio breakpoints, when necessary. Chen & Zimmermann prove that, due to the proximity of portfolio and t-statistic figures of these 77 hand-collected anomalies to the original publications, the same correlation patterns and investment strategies are equally applicable and valid.

Slightly different from the above-shown representation, Table 2 below presents more detailed descriptive statistics of the examined equity factor excess returns. Looking at the data on the top-level side, there is undoubtedly some variation in the average monthly returns, reason for which top 5 and bottom 5 factors by excess return on average have been embedded, with Earnings quarterly forecast (EPforecast) exhibiting the lowest monthly return (-0.52%) and Profitability the highest (2.16%). A notable observation is the dispersion in the standard deviation between the top and bottom 5 factors. The best-performing group of factors during the period 1985-2016 has a larger standard deviation. This possibly could imply that these factors are more prone to contagion in different market conditions – i.e. some external economic events might directly affect the profitability of these specific factors more than done to their peers. All factors in both groups face negative skewness, implying fat left tails. The null hypothesis of normality is rejected in all cases, using the Shapiro-Wilk test. One last observation is that equity factors do exhibit on average significant autocorrelations over 12 past lags at the 95% confidence level, as indicated by the Ljung-Box test statistic. This last input can be of great relevance later on during the course of the analysis, while elaborating factor strategies, as my goal is to depart from time-varying correlations throughout the used timespan in order to construct systematic investment approaches.

Table 2: **Summary statistics (Factor excess returns)**

Displayed below are the summary statistics for the used dataset of 156 equity factors, originally validated and taken from *Chen & Zimmerman (2020)*. The upper part reports the figures for the relevant equity index, whereas the bottom part regards the factors themselves, including a useful overview of the top/bottom 5 factors in terms of average excess return. SW denotes the Shapiro-Wilk test statistic for non-normality of the excess returns. LB denotes the Ljung-Box statistic for autocorrelation patterns with 12 lags. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is Jan-1985 to Dec-2016.

Buy-and-hold LONG Index	N	Mean	SD	Min	1st Q	Median	3rd Q	Max	SW	LB(12)
MSCI U.S.A. - Total Return Index	384	0.97%	4.35%	-21.22%	-1.58%	1.31%	3.77%	13.28%	0.967***	7.79
Total dataset	N	Mean	SD	Min	1st Q	Median	3rd Q	Max	SW	LB(12)
	384	0.25%	3.43%	-67.88%	-1.37%	0.15%	1.80%	67.83%	0.83**	23.20**
Top 5 factors	*Profitability*	2.16%	4.62%	-22.34%	0.31%	2.41%	4.58%	18.68%	0.91***	16.95
	IndRetBig	1.57%	4.93%	-17.11%	-0.62%	1.19%	3.45%	39.59%	0.85**	18.67*
	FirmAgeMom	1.46%	6.01%	-31.55%	-0.96%	1.41%	3.89%	31.31%	0.88***	33.37***
	DelBreadth	1.43%	4.56%	-26.37%	-0.64%	0.88%	3.24%	29.51%	0.88***	268.47***
	ChTax	1.38%	4.93%	-9.00%	0.29%	1.58%	2.61%	16.70%	0.97***	63.07***
Bottom 5 factors	*BetaSquared*	-0.31%	5.45%	-27.39%	-3.69%	-0.57%	2.83%	35.23%	0.90***	10.89
	BPEBM	-0.31%	1.70%	-7.14%	-1.21%	-0.34%	0.63%	7.57%	0.97***	18.31
	DivInit	-0.32%	2.16%	-8.49%	-1.46%	-0.33%	1.01%	9.64%	0.97***	19.82*
	PensionFunding	-0.44%	1.86%	-10.47%	-1.48%	-0.44%	0.71%	7.71%	0.96***	31.44***
	EPforecast	-0.52%	4.75%	-23.40%	-2.12%	-0.29%	1.52%	29.38%	0.87**	47.04***

4 Methodology

I now turn to the core analysis of this research project. I first review how the single-factor strategies (FMOM also known as FTSMOM) are constructed based on their auto-correlation patterns, resulting mainly from a combination of the approaches adopted by Moskowitz et al. (2011) and Pitkäjärvi et al. (2020) in their publications, but rather centralizing on factor excess returns in place of single equity securities. Then I describe how I modify them to build the cross-factor strategies in the time-series dimension (XFTSMOM) by making use of cross-correlation patterns over several lookback periods. The aim of using (cross-)factor correlation patterns is to prove the existence of a lead-lag effect between them, where one equity anomaly can consistently predict its own and other anomalies' future returns with a certain level of confidence. Overall, I prove that the (multi-)factor investment strategies described and developed in the time-series momentum research on the security level can be ultimately replicated on the factor level itself.

Starting from this principle, the vast majority of existing literature willing to analyze in detail the developments in the (time-series) relationship between 2 or more variables typically adopt correlation, as this is the most straightforward and popular measure of dependence. In this case, it needs to be adjusted to capture the dynamic component in the time series dimension.

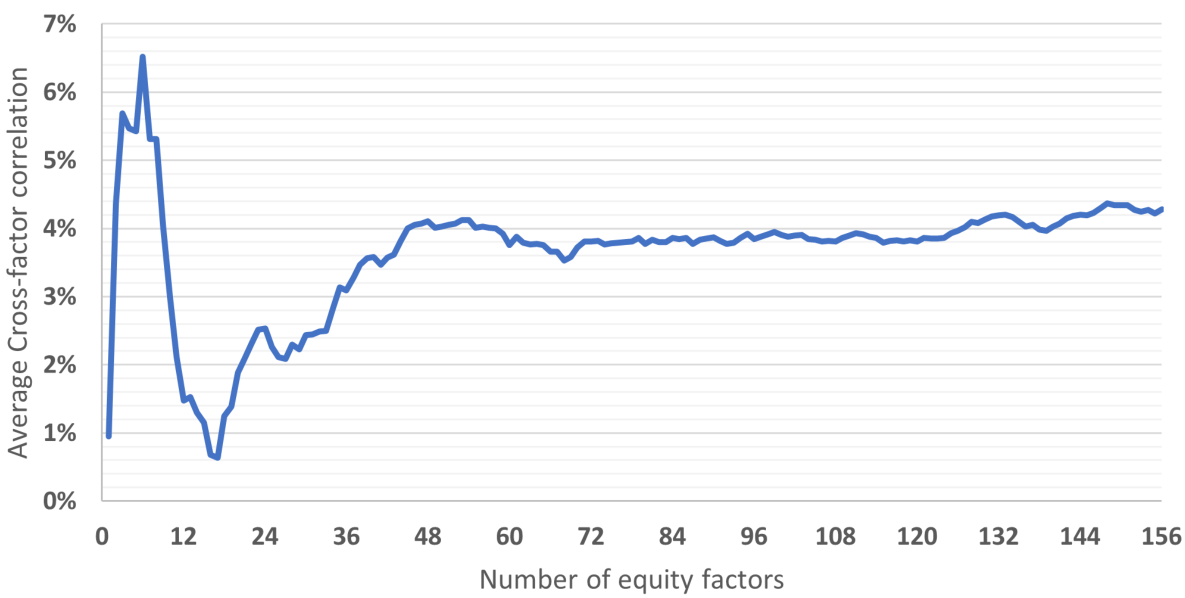

Figure 1: Average Cross-correlation per number of factors

Plotted are the average nominal values of dynamic correlation of factor excess returns per n amount of factors adopted. The used dataset includes the 156 cross-sectional return predictors (*retrieved from Chen Zimmermann, 2020*). Refer to the Appendix A for more detailed overview and complete list of predictors. The sample period is Jan-1986 to Dec-2016.

In order to give a perspective of the power of correlation across the 156 sample excess returns at disposal and its applicability in the field of systematic factor investing rather than individual securities, Figure 1 above displays the cross-correlation on average between the equity factors given a certain number of factors used, starting 12 months after the beginning date of the dataset – i.e. to be able to collect enough datapoints. It is noticeable straight away that for the first 25-30 factors, the average measure of their dependence is highly volatile with peaks up to 7% (6 factors) and troughs at almost null coefficient (17 factors). Eventually the cross-factor correlation tends to steadily rise as the amount of anomalies analyzed surpasses the 20 units and finally it stabilizes around the "long-term trend" value of about 4% which gets more reliable as the number of observed anomalies also increases after a certain threshold.

4.1 Time series predictability

4.1.1 Own single-factor time series predictability

I chose to begin my analysis of time series predictability by examining whether the signs of factors' lagged returns are predictive of their future returns in my U.S. stock exchange dataset, closely following the approach of Pitkäjärvi et al. (2020). Given that assets are represented by equity factors in this case, I focus my attention on the predictive power of the signs of the retrieved factors' as these are most closely related to the FTSMOM and XFTSMOM strategies analyzed later on – e.g. Moskowitz et al. (2012) and Baltas and Kosowski (2020).

For single anomalies first and crosswise anomalies next, all of which belonging to the equity spectrum, I perform a pooled panel regression where I pool all equity factor returns and dates and regress the excess return r_t^{sf} of the equity factor sf in month t on the sign of its own excess return lagged $k = 1, 2, \ldots, 60$ months:

$$r_t^{sf} = \alpha + \beta_h sign(r_{t-h}^{sf}) + \epsilon_t^{sf}. \tag{3}$$

In order to compute factor excess returns, the common risk-free rate of 1-month U.S. Treasury Bill return – taken from Ibbotson and Associates via Kenneth French's data library – has been adopted in this circumstance. The t-statistics of the signs of the lagged excess returns for each lag are hereby plotted in Panel A of Figure 2. Following Moskowitz et al. (2012), the t-statistics are clustered by month, as the return observations at disposal are strictly related to each other. In this plot, it can be noticed that equity factor returns on average display mostly positive significant autocorrelation patterns, and these are even significant when compared against their 1-, 6-, 12-, 24-, 36- and 48-month lagged versions. This suggests the possibility to exploit these effects to predict their own future excess returns over these timeframes.

4.1.2 Cross-factor time series predictability

Now I extend my analysis of time series predictability by examining whether the signs of a given anomaly's lagged returns are predictive of the future returns of (several) other anomalies within the U.S. equity cross section and vice versa. To start, I perform a pooled panel regression where pool all equity factor returns and dates and regress the excess return r_t^{fi} of the equity factor *fi* in month t on the sign of its own excess return lagged $h =$ 1, 2 ,..., 60 months, as well as the sign of the similarly lagged excess return of the remaining set of stock factors *fk*, with $k = 1, 2, \ldots, 155$:

$$r_t^{sf} = \alpha + \beta_h^{fi} sign(r_{t-h}^{fi}) + \beta_h^{fk} sign(r_{t-h}^{fk}) + \epsilon_t^{fi}. \tag{4}$$

The t-statistics of the signs of the lagged returns for each lag on average are plotted in Panel B of Figure 2. As done in the previous section, the t-statistics are clustered by month. This effect is further exacerbated this time by a factor k meaning that, on top of the individual time-series dimension, the "cross-section" of factor past compensations is also taken into account. Along the lines, from Panel B, we can see that the cross-factor t-statistics do show a positive and significant trend over 1-,2- and 12-month time horizons, while being negative though insignificant for several other lags. In the following paragraphs as well as sections, the 12-month lag will be principally used for developing investment strategies as it represents the key past interval during which some further analysis is academically produced.

4.2 Factor time-series investment strategies

4.2.1 Own single-factor investment strategies

By trailing the approach of Pitkäjärvi et al. (2020), it is worthwhile to especially take the perspective of a US-based investor willing to hold their investable capital in a dollar-denominated bundle of equity factors. Indeed, the main goal pursued by retail investors does not necessarily bound to the correlation stage, they rather have in scope earning a reasonably persistent return on their investments. For each factor in the adopted dataset, I aim first to take a long (short) position in a given month if the past k-month cumulative excess return of the same factor is positive (negative). As a result of that, long positions are financed by borrowing at the risk-free rate while investing proceeds from short positions at the local risk-free asset.

Regardless of the holding period h, this will allow to take a new position every month based on the factor's past k-month excess return. In general terms, for holding periods h longer than one month, I would thus have multiple active positions in the asset each month; hence, in order not to increase the complexity of the approach and focus on monthly rebalancing strategies, I preferred to take only h equal to 1-month horizon. Once own-factor time series momentum return series for each combination of lookback period k and holding period h for each anomaly is generated, diversified time series momentum portfolios are formed, which I denote $FTSMOM^{(k,h)}$, by taking *equal-weighted averages* of the individual factor time series momentum returns for the given lookback and holding periods.

One note worthwhile to mention is that I decided to analyze monthly returns of $FTSMOM^{(k,h)}$ by taking two separate scenarios into consideration in the case in which cumulative past factor returns negatively predict their own future returns. In fact, I first assumed to short the specific factor by simply swapping the sign of the respective lagged returns. Afterwards, I took into account the possibility of investing in the risk-free rate – U.S. 1-month Treasury Bill rate – when this same condition verifies. The two scenarios here described will be denoted from now on as $FTSMOMshort_t$ and $FTSMOMrf_t$, respectively. This way, I also aim to verify whether a more proactive investment approach is worth bearing a higher amount of risk compared to making safer though more stable transactions.

4.2.2 Cross-factor investment strategies

The cross-asset time series momentum strategies build on the single-factor strategies by adding a cross-factor predictor to the strategy's trading rule – that is, average cross-correlation coefficient is a pre-requisite for these strategies to enter in action (denoted as *predictor*). Concretely, the cross-factor strategies are very similar to factor autocorrelation strategies, except long (short) position in an anomaly is taken only when both the past k-month cumulative excess return of the anomaly itself, *and* the past k-month cumulative excess return of the cross-asset predictor, indicate that a long (short) position should be taken. If the signs of excess returns of the factor and the cross-factor predictor disagree, the risk-free asset is held. Therefore, consistent signals are required from both sides before taking an active position.

Once cross-asset time series momentum return series are generated for each combination of lookback period k and holding period h for each factor, diversified portfolios are formed, which are here denoted as $XFTSMOM^{(h,k)}$, by taking *equal-weighted averages* of the individual factors' cross time series momentum returns. Because the cross-factor strategy sometimes holds the risk-free rate, the amount of capital allocated to active positions is smaller on average than the amount allocated by the single own-factor strategies. For simplicity, I am going to refer to equal weights as the main allocation scheme, which also allows for more diversified portfolios and, therefore, may carry less risk. Also in this case, the separation of the two scenarios is applied. In particular, when past excess returns of the same factor and the ones of the predictor are both negative, I first adopt the perspective of shorting the specific factor – e.g. taking the opposite sign of the return, assuming there are no Short investments restrictions - and then investing in the risk-free asset while holding the position for one month. Instead, in the event where the two signals are not concordant, the risk-free asset position is always augmented for the following month at least[3].

4.3 Alpha component: Risk-adjusted performance

For consistency with the prior time series momentum literature, I now centralize the research focus to 12-month as look-back period and 1-month as holding period. For brevity, I drop the *(k,h)* superscript and refer to FTSMOM(12,1) and XFTSMOM(12,1) as FTSMOM and XFTSMOM strategies, respectively.

Table 6 examines the results of risk-adjusted performance of a diversified XFTSMOM strategy and its factor exposures. Panel A of Table 6 regresses the excess return of the XFTSMOM strategy on the returns of the FTSMOM strategy, MSCI World stock market index and the standard Fama-French factors SMB, HML, and UMD, representing the size, value, and cross-sectional momentum premium among individual stocks.

$$XFTSMOMrf_t = \alpha + \beta_1 FTSMOMrf_t + \beta_2(MKT_t - rf) + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + \epsilon_t. \tag{5}$$

$$XFTSMOMshort_t = \alpha + \beta_1 FTSMOMshort_t + \beta_2(MKT_t - rf) + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + \epsilon_t. \tag{6}$$

Panel B of Table 6 yet repeats the regressions above, however using the Asness, Moskowitz, and Pedersen (2010) value and momentum "everywhere" factors (i.e., factors diversified across asset classes) in place of the Fama and French factors. Asness, Moskowitz, and Pedersen (2010) form long-short portfolios of value and momentum across individual equities from four international markets, namely stock index futures, bond futures, currencies,

[3]Nowadays negative real interest rates invalidate the theory of a risk-free rate as the foundation of long-term investment returns and also pose a long-term inflation risk. However, investors should not simply eliminate cash from the list of asset classes in which they invest as holding liquidity is prudent to prefund near-term expenditures. Also, given the negative correlation existing between short-term U.S. Treasury rates and U.S. inflation rates, holding riskless assets would benefit the economy in the long-term from a macro perspective, assuming monetary buying programs from Fed to continue (Research Affiliates, 2016).

and commodities. Similar to the Fama and French factors, these are cross-sectional factors. This means that studying this type of factors cannot establish an unbiased cause-and-effect relationship. Nonetheless, they allow to analyze behavior of series over a period of time, thereby proving the existence of a lead-lag effect. In this specification, I also consider controlling for a cross-country momentum factor (XSMOM) built from the equity factors in the used sample using the Asness et al. (2013) methodology. This cross-sectional momentum strategy is constructed based on the relative ranking of each factor's past 12-month returns and form portfolios that go long or short the factors in proportion to their ranks relative to the median rank.

$$\begin{aligned} XFTSMOMrf_t = \alpha + \beta_1 FTSMOMrf_t + \beta_2(MKT_t - rf) + \\ \beta_3 VALevw_t + \beta_4 MOMevw_t + \beta_5 XSMOM_t + \epsilon_t. \end{aligned} \tag{7}$$

$$\begin{aligned} XFTSMOMshort_t = \alpha + \beta_1 FTSMOMshort_t + \beta_2(MKT_t - rf) \\ + \beta_3 VALevw_t + \beta_4 MOMevw_t + \beta_5 XSMOM_t + \epsilon_t. \end{aligned} \tag{8}$$

Finally, I conclude the risk-adjusted performance section by means of testing whether XFTSMOM returns might be driven or exaggerated by illiquidity in the time series dimension, defined by the Treasury Eurodollar (TED) spread, a proxy for funding liquidity (Brunnermeier and Pedersen (2009), Asness, Moskowitz, and Pedersen (2010)). Data is hereby retrieved from AQR Capital Management website, in the research papers section. Likewise, the CBOE's Volatility Index of the S&P 500 (VIX) and the sentiment index measures used by Baker and Wurgler (2006, 2007) are used as a proxy of control variables. All variables of this econometric test are summarized in Equation (7). Regarding the former, the VIX index is a measure of implied volatility, which is the expectation of the volatility for the S&P500 over the next 30 days. Index data is obtained from Datastream. A further robustness check is carried out in Section VI by verifying the linear dependence between seasonally adjusted levels of the VIX index and 12-month average rolling correlation pattern. Positive (negative) correlation between these two variables should also reflect in the regression panel C of Table 6, if an actual significant relationship exists. Concerning the latter, data is retrieved from the website of Jeffrey Wurgler, on a monthly frequency. This composite index equals the first principal component extracted from six indirect measures of U.S. focused investor sentiment as documented in their paper: trading volume (NYSE turnover), dividend premium, closed-end fund discount, the P/E ratio, the equity share in new issues, the number of IPOs, and their first-day returns. Specifically, the orthogonalized sentiment index is deployed which is untouched by business cycle related variations, meaning that each of the six sentiment proxies used by Baker and Wurgler has been first orthogonalized with respect to a set of macroeconomic conditions. Therefore, this sentiment index is expected to be uncorrelated with macroeconomic fundamentals. Positive values of this index are associated with a high level of investor sentiment, indicating more optimism. Also in this case, Section VI illustrates a robustness test where sentiment index measures are paired with average cross-factor rolling correlations over time. Interestingly, during specific crisis periods, as investor sentiment in the market decreases the average pairwise correlation tends to rise.

$$XFTSMOMshort_t = \alpha + \beta_1 FTSMOMshort_t + \beta_2 (MKT_t - rf) + \beta_3 TEDspread_t + \beta_4 VIX_t + \beta_5 Sentiment \perp_t + \epsilon_t. \tag{9}$$

At the beginning of this part within the Results section, the risk-adjusted performance of FTSMOM and XFTSMOM is coupled with a graphical representation where the two strategies are compared against a buy-and-hold scheme, where it is assumed to passively invest Long in the MSCI USA Total return index. This will give us a first indication on which strategy is to be preferred, both in the cases where either short positions are taken or the risk-free asset position is piled up in one's portfolio.

Furthermore, Moskowitz et al. (2012) show that the quarterly returns of the (asset) time series momentum exhibit a "smile" when plotted against the quarterly returns of the equity market index, meaning time series momentum performs well in both up and down markets. In the Results section corresponding to paragraph 5.4, I show that cross-factor time series momentum exhibits a similar, although with not perfectly equal shape, smile thereby aiming to replicate what has already been done in academia.

4.4 Spanning tests

In Table 7, I report the results from spanning tests of the diversified XFTSMOM, FTSMOM, and XSMOM portfolio returns. Unlike done in Moskowitz et al. (2012), I do not perform any formal decomposition of the cross-factor time series momentum returns into the individual time-series and cross-sectional elements. The objective of the Spanning tests in this circumstance is just limited to verify whether each of the three types of Momentum has unique information about historical excess returns in the period 1985-2016. Like already described before, the XSMOM portfolio is constructed using the methodology of Asness et al. (2013). The relevant linear regression equations are hereby represented below:

$$XFTSMOMrf_t = \alpha + \beta_1 FTSMOMrf_t + \beta_2 XSMOM_t + \epsilon_t. \tag{10}$$

$$FTSMOMrf_t = \alpha + \beta_1 XFTSMOMrf_t + \beta_2 XSMOM_t + \epsilon_t. \tag{11}$$

$$XSMOM_t = \alpha + \beta_1 XFTSMOMrf_t + \beta_2 FTSMOMrf_t + \epsilon_t. \tag{12}$$

The same goes for the case in which there is the possibility of shorting individual securities belonging to a particular anomaly, yet whether both signals express a negative sign:

$$XFTSMOMshort_t = \alpha + \beta_1 FTSMOMshort_t + \beta_2 XSMOM_t + \epsilon_t. \tag{13}$$

$$FTSMOMshort_t = \alpha + \beta_1 XFTSMOMshort_t + \beta_2 XSMOM_t + \epsilon_t. \tag{14}$$

$$XSMOM_t = \alpha + \beta_1 XFTSMOMshort_t + \beta_2 FTSMOMshort_t + \epsilon_t. \tag{15}$$

While it is really appealing to see that the described strategies lead to positive trends in predicting future returns based on past performance and that this is also reflected graphically, it is even more worthwhile to explore possible root causes and sources being able to supply explanatory information of such promising predictions. On this note, an extended version of the Spanning tests documented in the literature has been run in order to incorporate also the "standard" *Time-series momentum (TSMOM)* factor, as described by Moskowitz, Ooi and Pedersen (2012). Returns for this covariate are costlessly offered by AQR Capital Management website, in a similar fashion to the liquidity control variable used in the below regression analysis – Section 5.3.1. These returns will then be used in a separate Spanning table within the robustness check passage – in Table 8 – in order to verify whether the traditional time series momentum within individual equity securities can somehow explain what documented within the equity factor dimension. The linear regression equations thus become (only the risk-free investment scenario is hereby shown, but exactly the same holds for the Long/Short case):

$$\begin{aligned} XFTSMOMshort_t = \alpha + \beta_1 FTSMOMshort_t + \beta_2 XSMOM_t \\ +\beta_3 TSMOM_t + \epsilon_t. \end{aligned} \tag{16}$$

$$\begin{aligned} FTSMOMshort_t = \alpha + \beta_1 XFTSMOMshort_t + \beta_2 XSMOM_t + \\ +\beta_3 TSMOM_t + \epsilon_t. \end{aligned} \tag{17}$$

$$\begin{aligned} XSMOM_t = \alpha + \beta_1 XFTSMOMshort_t + \beta_2 FTSMOMshort_t + \\ +\beta_3 TSMOM_t + \epsilon_t. \end{aligned} \tag{18}$$

where $TSMOM_t$ is the overall return of the strategy that diversifies across all the S_t individual U.S. stocks that are available at time t, as defined by Moskowitz et al. (2012) – in formula hereby below:

$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t} \sum_{s=1}^{S_t} sign(r_{t-12,t}^{s}) \frac{40}{\sigma_t^s} r_{t,t+1}^{s}. \tag{19}$$

5 Results

5.1 Predictability in the time series dimension

As a first step, I look at the correlation patterns existing by looking both at the single factors and across different equity anomalies. As already described in previous Sections, the aim is not to hunt for the highest correlation trend, as this would ultimately harm the benefits of the diversification in investments, but rather to find out that positive (negative) repetitive trends in correlations among a bunch of stock factors – in a comparable way to individual stock selection - should be taken into account while building investment strategies based on regression analysis. While the situation in Panel A of below Figure 2 may lead to some distortion, as autocorrelations of single factors seem showing continuous reversal trends, in Panel B it is clear that a persistent *positive cross-correlation* pattern exists on average in the "cross-section" of equity factors, albeit very small in magnitude, with a general upper limit of around 2%. This turns out to be less effective if trying to increase the lagged period. In fact, although this positive trend is not really evident from a numerical perspective, it does give an indication to investors on how to consider correlations when assembling the various factors in one unique investment strategy, whilst keeping volatility limited, and still without feeling the need to give up the diversification benefits – other variables being equal.

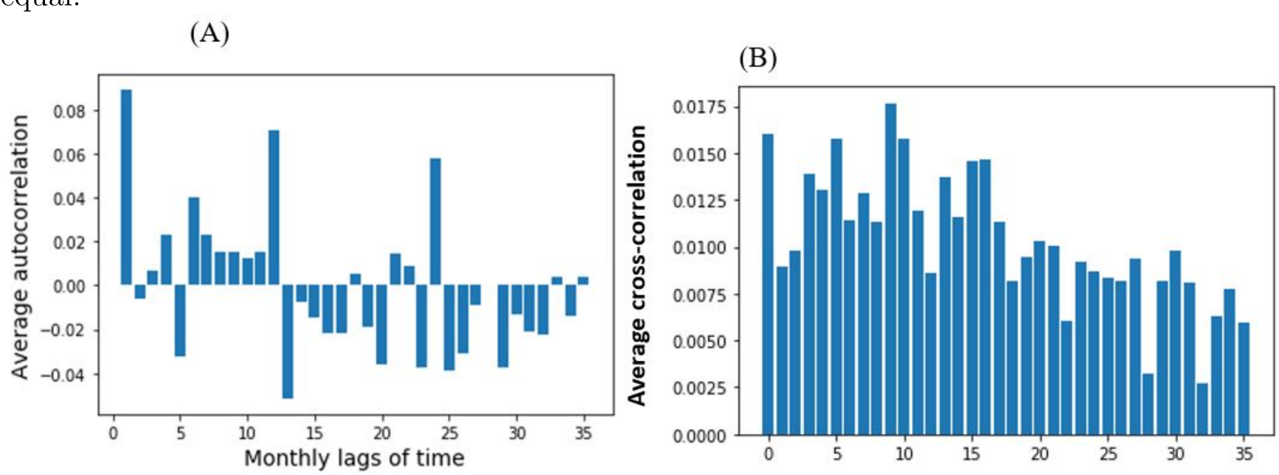

Figure 2: Single-factor autocorrelation and Cross-factor time series correlation

Plotted are the values which express autocorrelation on average between the monthly excess return of each equity factor in my dataset over their own excess returns lagged 1–60 months (on the left: Panel A), and cross-factor correlation on average of monthly excess return of each equity factor in my dataset over other factors' excess returns lagged 1–60 months (on the right: Panel B). The used dataset includes the 156 cross-sectional return predictors (*retrieved from Chen Zimmermann, 2020*). Refer to the Appendix A for more detailed overview and complete list of predictors. The sample period is Jan-1986 to Dec-2016. (A) Panel A: average single-factor autocorrelation figures; (B) Panel B: average multi-factor cross-correlation figures.

Zooming in the actual lead-lag investment strategies themselves using autocorrelation and cross-correlation patterns, the t-statistics of the signs of the lagged returns for each lag are plotted in Figure 3. As in the previous section, the t-statistics are clustered by month. From Panel A, it can be seen that the t-statistics of the signs of the lagged factor returns in Regression (3) are positive for the majority of the 60 months used, though not many lags being statistically significant (mainly lags 1 and 12). Conversely, from Panel B, it can be noticed that the t-statistics of the signs of the lagged equity cross-factor returns from Regression (4) have pretty much alternative sign for the first 15 months, with several lags again being statistically significant. However, after lag 15 most of the t-statistic figures are negative but yet insignificant. Evidence is thus found of past equity anomaly returns being, on average, positive predictors of the outstanding future factor returns in the dataset and of cross-factor predictability being much more powerful in assessing future stock (factor) returns than self-predictability. Panel A of Figure 3 plots the t-values from pooled autoregressions by monthly lag h. The positive t-statistics for most of the months indicate significant return continuation over time. Differently, in Panel B, the negative signs for the longer horizons (from lag 14) indicate reversals in the strategy profitability, the majority of which occurring in the year immediately following the positive trend. As indicated in the Methodology (Section IV), excess returns of the factor strategies are not scaled by their ex-ante volatility. Moskowitz et al. (2012) coupled with the general time series momentum literature agree that results are fairly comparable if running OLS regressions whilst scaling by factor's volatility.

(A) (B)

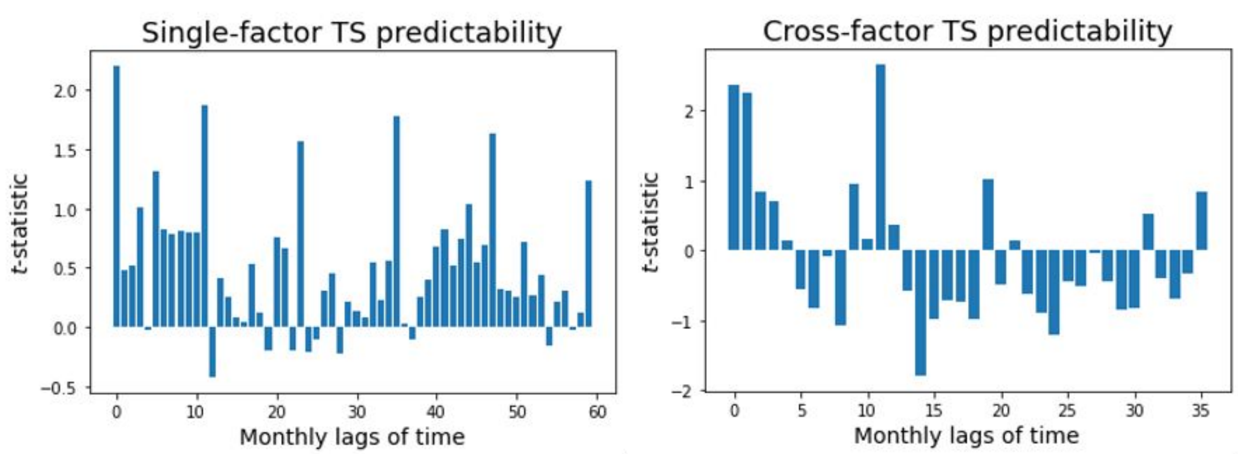

Figure 3: Single-factor and Cross-factor time series predictability

Plotted on the left are the t-statistics clustered by month from pooled panel regressions where I regress the monthly excess returns of each equity factor in my dataset on the sign of its own excess returns lagged 1–60 months. On the right, displayed are the t-statistics clustered by month from pooled panel regressions where I regress the monthly excess returns of each equity factor in my dataset on the sign of its own excess returns lagged 1-36 months and the sign of the similarly lagged excess returns of the other equity factors at disposal. The used dataset includes the 156 cross-sectional return predictors (*retrieved from Chen Zimmermann, 2020*). Refer to the Appendix A for more detailed overview and complete list of predictors. The sample period is Jan-1986 to Dec-2016. (A) Panel A: average single-factor autoregression t-statistics; (B) Panel B: average cross-factor regression t-statistics.

5.2 Equity Factor investment strategies in the time series dimension

The outperformance of cross-asset time series momentum is also consistent across time. For example, the XFTSMOM portfolio has a higher Sharpe ratio than the FTSMOM portfolio in each individual decade, as is also visible from Figure 5 below - besides the annualized Sharpe ratio figures in Table 3. Both on absolute scale and risk-adjusted basis, on average XFTSMOM and FTSMOM achieve a superior performance compared to the long passive investment strategy. This applies to both specifications – investing either in the risk-free asset or going short the factor that expresses negative past return signals. Based on results in Table 3, FTSMOM seems offering superior outperformance opportunities when shorting is limited, if not allowed, as it may very well be the case for factors given their considerably lower tradability in the market compared to e.g. equity market. On the contrary, under the assumption of shorting restrictions, XFTSMOM is the strategy to be preferred, as it is possible to benefit from factor mutually interactive effects and capture the upside potential of dynamic cross-correlation.

To demonstrate the value of these patterns within cross-factor predictability in a time series momentum context, in Table 4 the average monthly excess returns and annualized gross Sharpe ratios of the equity factors are reported in my U.S. dataset during different factor momentum regimes. A factor belongs to a positive (negative) momentum regime in month t if the $t-12$ to $t-1$ cumulative excess return of the same factor was positive (negative). From Panel A of Table 4, it can be detected that the factor excess return is seemingly higher during positive equity momentum regimes, while the being lower during negative equity momentum regimes. This is consistent with past equity factor returns being positive predictors of future returns according to autocorrelation patterns. One finding to note is that factor excess return is on average less negative under the Long/Short specification, testifying this is to be preferred overall to the Risk-free rate one. In Panel B, the same analysis is replicated, but using combined single factor and cross-factor momentum regimes. This allows to see how the auto- and cross-factor returns during different momentum regimes vary depending on the prevailing regime under the other outlook. For instance, while the equity return is 1.10% during positive equity momentum regimes and 1.05% in the case of shorting opportunity, when the cross-factor regime is also positive, the factor return increases on average to 1.24% and 1.37%, respectively. In a similar fashion, while the equity return is -0.19% during negative time series momentum regime (Risk-free) and -0.06% (Long/Short), when the cross-factor regime is also negative, factor returns jump back into the positive domain by being 0.55% and 0.62%, respectively. The usage of the combined regimes thus permits to identify in finer detail those periods when the return is maximized. In particular, the most relevant observation that can be taken away based on the results of Panel B is that the excess returns during periods of simultaneously positive (negative) equity factor momentum regimes are higher (lower) than the returns during any of the other regimes. And just for the sake of remembrance, in two cases out of four where the signs of past own excess returns and average cross-factor excess returns are both negative, an investor's inventory is piled up with the risk-free asset. Overall, the fact that negative past equity returns seem to be a stronger positive predictor of (other) future equity factor returns, as the results in Panel B suggest, highlights the importance of considering cross-factor predictors in the series momentum framework.

Next on the agenda, once the quantitative factor strategies are built and portfolios are diversified, an insightful point of investigation is to look at whether the α generated at the end of the investment is significant for different lookback time horizons, while holding those factors that respect the signals for one month. I am thus interested in seeing if diversified cross-factor time series momentum portfolios generate abnormal performance relative to corresponding factor time series momentum portfolios while also controlling for equity market benchmarks and standard asset pricing factors. I repeat the regressions for different combinations of lookback period k while keeping $h = 1$ month. The t-statistics of the different Alphas from the regression analysis can be found in Table 5. The existence and significance of time series momentum is robust across time horizons, particularly when the look-back period is either 3 or less months, or more extensive than 12 months. There is an observable remarkable difference between the two scenarios. In fact, in Panel B t-values are much more pronounced as the Long/Short strategies actively tries to outperform by looking at both investment sides, whereas at the same time Risk-free rate sets just a low boundary to the strategy payoff and the upside being limited to the Long component of the factor strategy. The represented performance analysis of time series momenta then paves the way for analyzing the efficiency of the quant Time-series strategies on a risk-adjusted basis, which is offered down below in the next Section, both from a graphical and econometric perspective.

Table 3: **Performance of the Analyzed Investment Strategy Specifications**

Reported are the annualised gross Sharpe ratios, mean returns, and volatilities of regular buy-and-hold (*LONG*), equally-weighted factor time series momentum (*FTSMOMrf, FTSMOMshort*) and cross-factor time series momentum (*XFTSMOMrf, XFTSMOMshort*) portfolios diversified across each equity factor in my data set. The two specifications *rf* and *short* represent the re-investment in case the signals from previous k months are not concordant. Each strategy uses a lookback period of twelve months and a holding period of one month. The sample period is Jan-1985 to Dec-2016.

Strategy	*Sharpe Ratio*	*Mean*	*Volatility*
LONG (MSCI USA TR)	0.80	12.34%	15.05%
FTSMOMrf	5.38	17.38%	3.17%
FTSMOMshort	2.31	12.75%	5.38%
XFTSMOMrf	5.53	17.12%	3.03%
XFTSMOMshort	4.91	15.31%	3.05%

Table 4: **Returns by Momentum Regime**

Reported are the number of factor-month combinations, the annualised gross Sharpe ratios, and the average monthly excess returns of the equity factors in my U.S. data set during different equity momentum regimes. In this case, a factor belongs to a positive (negative) regime in month t if the t-12 to t-1 cumulative excess return of the asset was positive (negative). The same logic applies for the cross sign of the other factors on average. Both the possibilities of investing in the risk-free rate and shorting the factor are exploited, in case of non-concording past return signs. The sample period is Jan-1985 to Dec-2016. (A) Panel A: FTSMOM regimes; (B) Panel B: XFTSMOM regimes.

(A) Panel A: FTSMOM regimes

	Positive past Equity Factor	Negative past Equity Factor
Risk-free rate		
N	32639	25393
Factor Monthly Excess Return	1.10%	-0.19%
Factor Sharpe Ratio	1.00	-2.71
Long/Short		
N	32639	25393
Factor Monthly Excess Return	1.05%	-0.06%
Factor Sharpe Ratio	0.93	-0.06

(B) Panel B: XFTSMOM regimes

	Positive past & Negative Cross-past	Negative past & Positive Cross-past	Positive past & Positive Cross-past	Negative past & Negative Cross-past
Risk-free rate				
N	4166	19043	27704	7119
Factor Monthly Excess Return	0.94%	0.30%	1.11%	0.55%
Factor Sharpe Ratio	1.50	4.69	1.00	12.57
Long/Short				
N	4166	19043	27704	7119
Factor Monthly Excess Return	0.97%	0.25%	1.04%	0.42%
Factor Sharpe Ratio	1.55	0.61	0.96	0.73

Table 5: **Cross-Factor Time Series Momentum Alpha t-Statistics**

Reported are the t-statistics of the alphas from regressing both monthly excess return series of cross-factor time series momentum (*XFTSMOM*) portfolios with different lookback periods - holding period assumed to be one month - on passive exposures to the U.S. equity market, the excess returns of a corresponding diversified single-factor time series momentum (*FTSMOM*) portfolio, as well as the Fama-French-Carhart size, value, and (cross-sectional) momentum factors. The sample period is Jan-1986 to Dec-2016. (A) Panel A: XFTSMOM strategy with risk-free rate investment; (B) Panel B: XFTSMOM strategy with possibility of shorting.

(A) Panel A: XFTSMOM - Risk-free strategy Alpha		*(B) Panel B*: XFTSMOM - Long/Short strategy Alpha	
Lookback Period (Months)	Holding Period (Months) 1	Lookback Period (Months)	Holding Period (Months) 1
1	2.08	1	13.25
3	2.07	3	13.10
6	1.99	6	1.76
9	0.26	9	0.93
12	2.53	12	12.16
24	2.88	24	8.85
36	3.74	36	14.51
48	3.99	48	17.20

5.3 Risk-adjusted performance: is there any alpha leftover yet?

As a first indicator of the risk-adjusted performance of the XFTSMOM portfolios, in Figures 3 and 4 plotted are the cumulative excess returns of buy-and-hold, FTSMOM, and XFTSMOM portfolios diversified across each equity factor in the dataset. The graphs cover the researched period and are based on a log scale. To allow for an equitable performance comparison in order to have an equal amount of risk in each factor, the returns of each portfolio have been scaled so that their realized annualized volatilities are 10% (Pitkäjärvi et al. (2020)). Since each strategy is scaled by the same constant volatility, the three represented portfolios have the same ex ante volatility except for differences in correlations among the two factor time series momentum strategies and the passive long strategy. As it can be noticed, the cross-factor time series momentum portfolio delivers consistently higher returns than the factor time series momentum and buy-and-hold positions in all equity factors (at the same ex ante volatility). Furthermore, coherent with results obtained in Table 6 discussed further below, cross-anomaly time series momentum strategies yield significant improvements in risk-adjusted performance that are not captured by single-anomaly time series momentum, providing room for superior alpha.

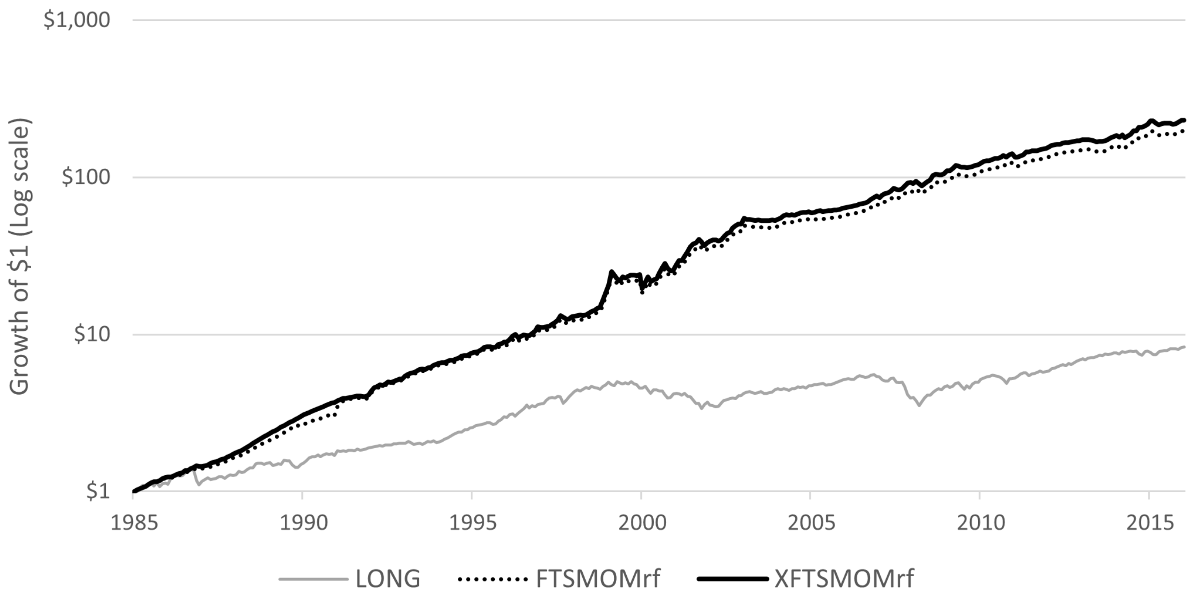

Figure 4: Cumulative Excess Returns of Diversified Portfolios (Risk-free rate)

Plotted are the cumulative excess returns of MSCI USA Total Return index buy-and-hold (LONG), factor time series momentum (FTSMOM), and cross-factor time series momentum (XFTSMOM) portfolios equally diversified across each equity factor in my data set. Both strategies go invest in the risk-free rate (J.P. Morgan 1-month U.S. Cash index) in case past factor returns are negative (for FTSMOM), and factor past excess returns and other factors' average past excess returns are both negative (for XFTSMOM). Each strategy uses a lookback period of twelve months and a holding period of one month. The returns of each portfolio are scaled so that their ex-post annualised volatilities are 10%. The sample period is Jan-1986 to Dec-2016.

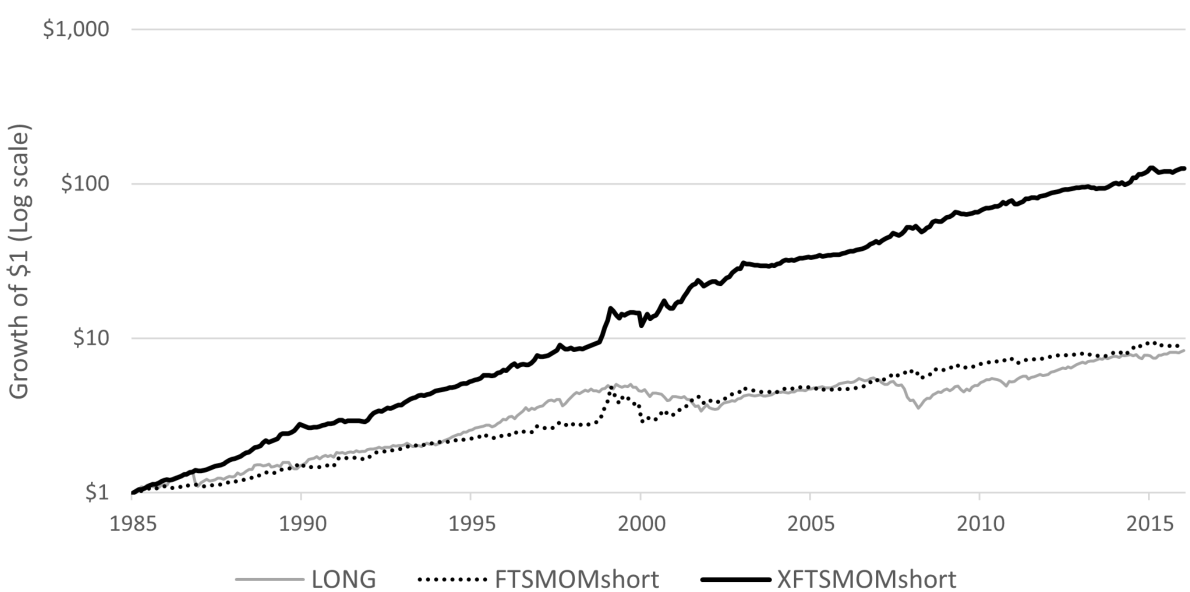

Figure 5: Cumulative Excess Returns of Diversified Portfolios (Long/Short)

Plotted are the cumulative excess returns of MSCI USA Total Return index buy-and-hold (LONG), factor time series momentum (FTSMOM), and cross-factor time series momentum (XFTSMOM) portfolios equally diversified across each equity factor in my data set. Both strategies are allowed to go short in case past factor returns are negative (for FTSMOM), and factor past excess returns and other factors' average past excess returns are both negative (for XFTSMOM). Each strategy uses a lookback period of twelve months and a holding period of one month. The returns of each portfolio are scaled so that their ex-post annualised volatilities are 10%. The sample period is Jan-1986 to Dec-2016.

As Figures 4 and 5 show, the performance over time of the diversified time series momentum strategy provides a relatively steady stream of positive returns that outperforms a diversified portfolio of passive long positions in a general U.S. equity index (at the same ex ante volatility). The dominance in performance of XFTSMOM is particularly evident especially when considering the short side of factor investing (Figure 5) – i.e. in case when both single factor's and cross factors' past cumulative excess returns express a negative sign. Here XFTSMOM generates a total (gross) growth in the invested capital of 10x the one produced by FTSMOM during the considered 31-year period. The latter in turn steadily delivers positive returns over the years, although it does not add high-caliber value to a "conservative" investment in the MSCI USA (Total Return index). One possible explanation for this can be that a (factor) time-series momentum strategy relies more on the raw potential of a bunch of stocks that proved to show a certain anomaly, whereas a cross-factor strategy clearly aims to bring additional value by exploiting the correlation motives. Therefore, XFSTMOM has a further "signal" to consider before delving in portfolio construction and, as such, permits a more diversified allocation to factors in the long term. This finding can say something about the value added of employing an "active" approach in investing compared to a more passive one, particularly in the current discussion involving investing actively in Mutual Funds versus investing in Exchange-Traded funds (ETFs). However, it is not in my intent to stimulate a discussion in this direction, nor is the attempt to prompt investment advice in active strategies which ultimately require more time and effort, as this lies outside the scope of this dissertation. In addition, the returns of the (cross-) factor time series momentum factor from 1966 to 1985 can also be computed, despite the more limited number of equity anomalies with available data from Chen & Zimmermann (from originally 156 to 89). Over this earlier sample, time series momentum has a statistically significant return and an annualized Sharpe ratio of 2.25 for FTSMOM and 2.36 for XFTSMOM in the shorting scenario, providing uplifting out-of-sample evidence of time series momentum on factor level.

On the contrary, the huge performance difference between FTSMOM and XFTSMOM is almost bootless in the case of investing in the risk-free rate when both past cumulative return signals turn out to be negative (Figure 4). Here both strategies deliver remarkably greater returns over the long MSCI USA index, achieving even a 200x multiplier of the initial invested capital. A likely reason for such enormous outperformance over the considered timeframe is twofold. Firstly, with respect to the Long/Short scenario, risk-free asset is by definition an instrument which always carries a (constant) positive return and cannot default. Henceforth, investors can decide to ultimately go safe, reduce volatility in their own portfolio and "settle" with a low stream of income in case both signals show a negative sign. This way, they would not incur in a loss should the short strategy not yield a certain compensation as expected. Secondly, and perhaps most importantly, it is crucial to remind that both FTSMOM and XFTSMOM are originally characterized by a much higher amount of volatility by construction. After having scaled strategy returns to the same lower volatility level – e.g. 10% - returns undoubtedly became more prominent at the benefit of the factor strategy themselves, which aggregate several different factors. Yet this justifies the magnitude of excess returns also in the Long/Short scenario.

5.3.1 Regression analysis: Efficacy of factor time-series momentum strategies

Next the main part of the analysis is treated, and the econometric part deeply analyzed. In the following regressions, only the Long/Short scenario has been used as this is the most immediate way to verify whether active investment strategies based on factor excess return are able to provide some powerful additional value, instead of being safeguarded with the more conservative risk-free asset. In fact, the risk-adjusted performance of the XFTSMOM portfolio is evaluated by regressing its excess returns on the excess returns of a similarly diversified FTSMOM portfolio, the MSCI World Total return index, and either the Fama–French–Carhart size, value, and momentum factors or the Asness et al. (2013) value and momentum everywhere factors. In the latter specifications, controlling for a cross-country momentum factor (XSMOM) is also considered, where the risk factor is constructed from the equity factor time series in my sample using the Asness et al. (2013) methodology. The results can be seen beneath in Table 6.

From Panel A, it can be seen that the XFTSMOM portfolio generates a highly significant alpha of 0.47% per month while also loading significantly and positively on the size SMB factor. When controlling for the FTSMOM portfolio in the second regression specification, we see that the FTSMOM portfolio is able to explain a large portion of the returns, but the XFTSMOM portfolio still generates a significant and positive alpha of 0.23% per month that is not captured by the FTSMOM portfolio. This time only SMB is able to significantly explain a part of the variation in returns, yet at the 90% confidence level only, whereas HML and UMD cannot. Coming out of Panel B, it can be seen that the results are very similar with the value and momentum everywhere factors. The XFTSMOM portfolio generates a statistically significant monthly α of 0.25% or 0.47% depending on whether controlling for the FTSMOM portfolio return or the XSMOM factor is carried out, respectively. The results of the two specifications are similar. From the regression results and the country-level Sharpe ratios, it shall be acknowledged that cross-factor time series momentum is not just a way to repackage the familiar time series momentum effect. Instead, cross-factor time series momentum yields significant improvements in risk-adjusted performance that are not captured by (factor) time series momentum. Certainly, some other versions of the same strategies may also need to be examined – i.e. considering return- and rank-weighted versions of the single- and cross-factor strategies and eventually show how the risk-adjusted performance varies, if any eventual differences, across the different strategy variants. This may allow to understand and establish whether the performance results of the specified quant investment strategy are thus robust to reasonable changes in the way strategies are defined.

Finally, under Panel C, I consider how XFTSMOM and FTSMOM excess returns co-vary in aggregate with the time series of liquidity and sentiment factors. In particular, the first three rows of Panel C of Table 3 report results using the Treasury Eurodollar (TED) spread, a proxy for funding liquidity as suggested by Brunnermeier and Pedersen (2009), Asness, Moskowitz, and Pedersen (2010), and Garleanu and Pedersen (2011). As the table shows, there is no significant relation between the TED spread and XFTSMOM returns, suggesting little relationship with funding liquidity. Also after trying to separate the TED Spread from the other controlling risk factors, results do not change much as it is a negative load factor but still insignificant (t-stats = -0.25). Meanwhile, the last three rows of Panel C of Table 6 repeat the analysis using the VIX index to capture the level of market volatility, which also seems to correspond with funding liquidity circumstance. According to the regression results, there is no significant relationship between XFTSMOM profitability and market volatility either, nor between the latter and FTSMOM. Last but not least, an integral part of Panel C within Table 6, I also examine the relationship between XFTSMOM returns and the sentiment index measures used by Baker and Wurgler (2006, 2007), by only taking into consideration the level of monthly changes in market sentiment. As the regressions indicate, we find no significant relationship between XFTSMOM profitability and sentiment measures. Going forward, factor investing-related research may take into account the possibility of analyzing extreme values, for example by considering top 10%/20% of liquidity, VIX and sentiment indices and their effect on total XFTSMOM and FTSMOM performance. This would be useful to understand whether and how most extreme realizations of those three control variables help capture the most illiquid funding, volatile and sentimental environments, as well as if they can provide additional value for alpha-seeking opportunities.

Table 6: **Cross-Asset Time Series Momentum Risk-Adjusted Performance**

Reported are the results from regressing the monthly excess returns of the diversified cross-factor time series momentum portfolio (*XFTSMOM*) on the excess returns of the diversified single-factor time series momentum portfolio (*FTSMOM*), the excess returns of the MSCI World total return index, and standard asset pricing factors taken from Fama & French. The sample period is Jan-1985 to Dec-2016. The scenario of the risk-free rate investment in case of non-concordant return signals has been adopted. Controls in Panel A: Monthly Fama-French-Carhart size, value, and momentum factors; in Panel B: Monthly Asness, Moskowitz, and Pedersen (2013) value and momentum "everywhere" factors, and a momentum (XSMOM) factor constructed using their methodology from the equity factor returns in the data set; and in Panel C: Monthly general market return (MSCI World Total Return Index), volatility index (VIX), funding liquidity (TED spread), and the orthogonalized version of sentiment variables taken from Baker and Wurgler (2006, 2007) - in order to make the two variables statistically independent. Following Asness, Moskowitz, and Pedersen (2013) and Pitkajarvi et al. (2020), the XSMOM factor is based on the relative ranking of each asset's past 12-month returns, and is long or short the assets in proportion to their ranks relative to the median rank. As in Asness, Moskowitz, and Pedersen (2013), the most recent month has been skipped when computing 12-month cross-sectional momentum. The scenario of the risk-free rate investment in case of non-concordant return signals has been adopted. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is Jan-1985 to Dec-2016.

(A) Panel A: Fama-French-Carhart factors

	Alpha	FTSMOMrf	MSCI World	SMB	HML	UMD	Adj. R^2
Coefficient	0.47%***		0.21	3.23**	-1.15	-0.09	0.019
(t-Stat)	(9.84)		(0.19)	(2.12)	(-0.68)	(-0.84)	
Coefficient	0.23%**	0.52***	0.41	1.04	0.45	-0.29*	0.839
(t-Stat)	(2.36)	(43.65)	(0.94)	(1.67)	(0.66)	(-1.60)	

(B) Panel B: Asness, Moskowitz, and Pedersen (2013) factors

	Alpha	FTSMOMrf	MSCI World	VAL Everywhere	MOM Everywhere	XSMOM	Adj. R^2
Coefficient	0.44%***		0.08	-0.02	0.04		0.062
(t-Stat)	(8.82)		(0.80)	(-0.65)	(1.28)		
Coefficient	0.25%*	0.93***	0.00	0.03	0.03		0.936
(t-Stat)	(2.82)	(74.16)	(-0.05)	(0.30)	(0.41)		
Coefficient	0.47%***		0.04	-0.07**		-0.10	0.013
(t-Stat)	(9.84)		(0.43)	(-2.09)		(-0.81)	
Coefficient	0.32%**	0.93***	-0.01	-0.09		-0.05*	0.936
(t-Stat)	(2.42)	(74.56)	(-0.39)	(-1.05)		(-2.73)	

(C) Panel C: Market, volatility, liquidity, and sentiment factors

	Alpha	FTSMOMrf	MSCI World	TED Spread	VIX	Sentiment	Adj. R^2
Coefficient	0.32%**	0.93***	0.00	-0.03		-0.08	0.914
(t-Stat)	(2.29)	(74.86)	(0.09)	(-1.22)		(-0.42)	
Coefficient	0.45%***		0.01	-0.08	0.02	-0.02	0.141
(t-Stat)	(8.71)		(1.00)	(-1.71)	(0.77)	(-0.16)	
Coefficient	0.03%**	0.89***		-0.23*	0.05		0.836
(t-Stat)	(2.24)	(50.01)		(-2.11)	(1.56)		
Coefficient	0.34%***		0.01		0.01	-0.03	0.005
(t-Stat)	(6.74)		(0.91)		(0.81)	(-0.19)	

5.4 The factor time series momentum strategy smiles

To demonstrate that the analyzed time series momentum strategies perform well in both up and down markets, I show that cross-factor time series momentum exhibits a similar "smile", following the methodology adopted by Moskowitz et al. (2012). Concretely, in Figures 6 and 7 the non-overlapping quarterly returns of diversified FTSMOM and XFTSMOM portfolios are plotted against the corresponding non-overlapping quarterly returns of the CRSP value-weighted index. To allow for a fair comparison, the returns of the portfolios have been scaled so that their ex-post volatilities are the same. From the two graphs below it is noticeable both FTSMOM and XFTSMOM exhibit smiles, though these are not symmetric. In fact, trendlines in both scenarios – Risk-free rate (on the left) and Long/Short (on the right) – assume a marked upward shape towards the positive domain. Moreover, the FTSMOM smile is more pronounced in the positive return domain than the XFTSMOM smile in both scenarios. At first glance, the magnitudes of the differences between the smiles are much more evident in the Short scenario. Here the FTSMOM strategy seems suffering zero- or negative compensations in case the market underperforms slightly, yet being able to deliver around 5% return per quarter in case of big market dips overall – i.e. 10% drop in S&P returns.

These results suggest that from a portfolio diversification perspective, the FTSMOM portfolio is more valuable in the Risk-free scenario because of the slightly higher returns it offers during periods when the market return is negative while showing more concavity in its shape. However, in the Long/Short scenario the XFTSMOM portfolio compensates for this by offering higher returns during periods when the market return is near zero or positive, yet offering a more stable pattern and more consistent performance with respect to FTSMOM. Because the XFTSMOM portfolio outperforms the FTSMOM portfolio in terms of risk-adjusted performance on average, this seems to be a trade-off worth making. In both situations, given its more pronounced and concave outline, FTSMOM thus displays payoffs similar to an option straddle on the market. Fung and Hsieh (2001) discuss why trend following has straddle-like payoffs and apply this insight to describe the performance of hedge funds. According to them and Moskowitz et al. (2012), FTSMOM strategy generates this payoff structure because it tends to go long when the market has a major upswing and short when the market crashes. Historically, FTSMOM does well during market crashes because crises often happen when the economy goes from normal to bad (making FTSMOM go short risky assets all of a sudden), and then from bad to worse (leading to FTSMOM profits), with the recent 2007-2008 global financial crisis being a prime example.

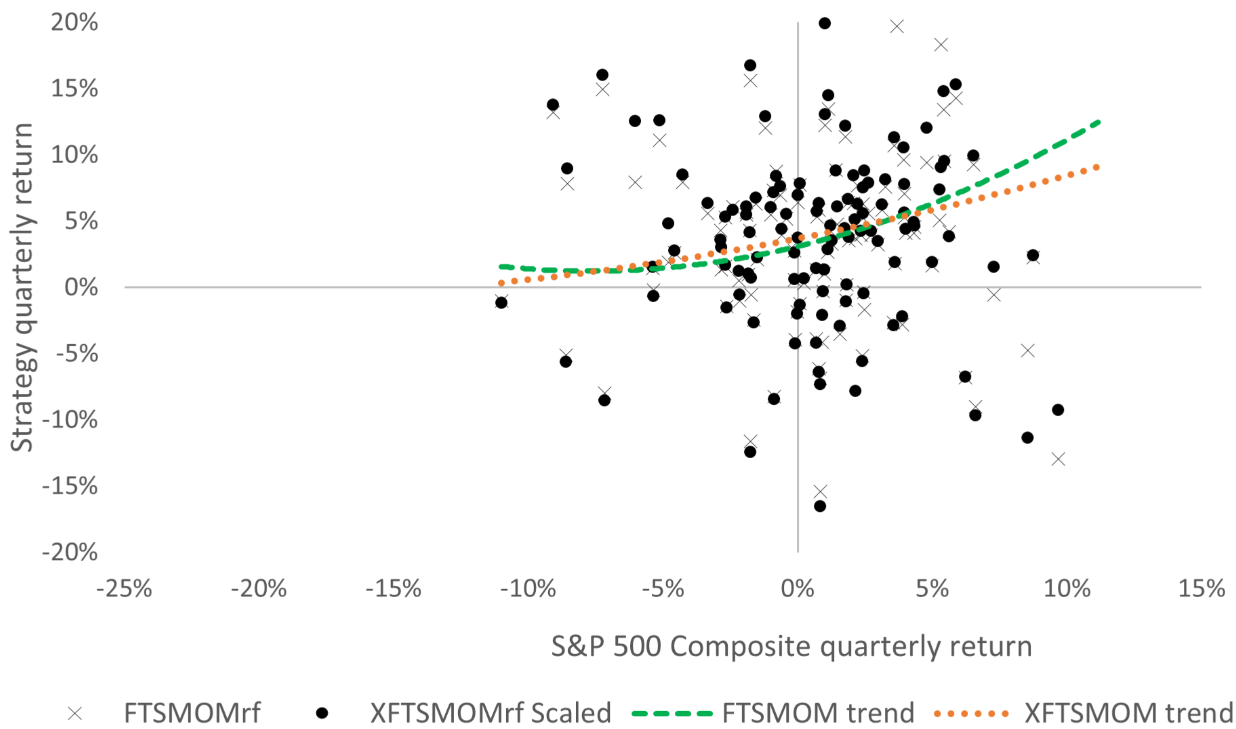

Figure 6: The XFTSMOM Smile for Risk-free rate re-investment strategy

Plotted are the non-overlapping quarterly returns of diversified factor time series momentum (FTSMOM) and cross-factor time series momentum (XFTSMOM) portfolios against the corresponding non-overlapping quarterly returns of the CRSP value-weighted index. The investment is re-directed to the U.S. risk-free rate in case of both negative signals from past returns. Also plotted are the trendlines for both the FTSMOM and XFTSMOM schemes. The quarterly returns of the portfolios are scaled so that their ex-post volatilities are the same. The sample period is Jan-1986 to Dec-2016.

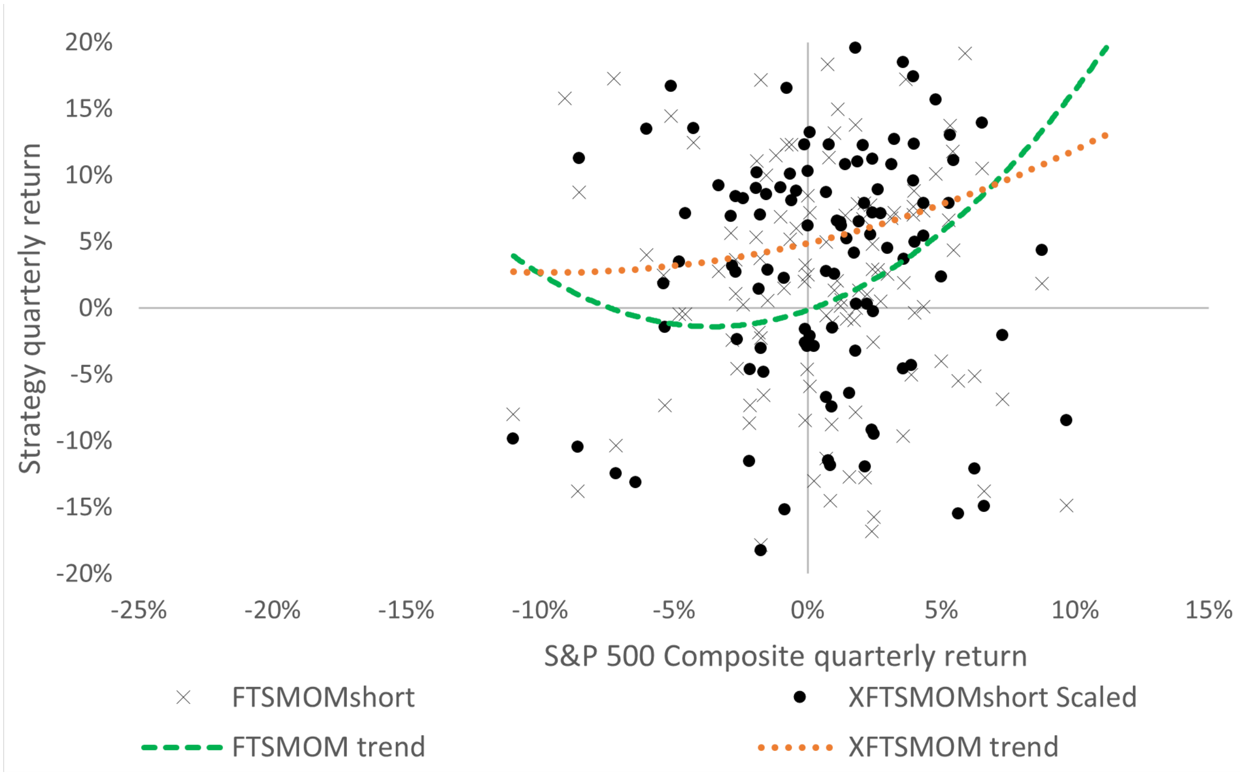

Figure 7: The XFTSMOM Smile for Long/Short strategy

Plotted are the non-overlapping quarterly returns of diversified factor time series momentum (FTSMOM) and cross-factor time series momentum (XFTSMOM) portfolios against the corresponding non-overlapping quarterly returns of the CRSP value-weighted index. The investment strategy allows to short specific factors in case of both negative signals. Also plotted are the trendlines for both the FTSMOM and XFTSMOM schemes. The quarterly returns of the portfolios are scaled so that their ex-post volatilities are the same. The sample period is Jan-1986 to Dec-2016.

5.5 Spanning tests

In Table 7 on page below, results from spanning tests of the diversified XFTSMOM, FTSMOM, and XSMOM portfolio returns are disclosed, in order to investigate whether the researched investment strategies are able to mutually explain each other. As already described before, the XSMOM portfolio is constructed using the methodology of Asness et al. (2013). The below table is composed of two separate panels, the first of which considers investing in the risk-free asset and the second allowing to short one's investments in a factor, in case past cumulative single factor and cross-factor returns have both negative signs, whereas XSMOM time series returns remain the same in both cases. This allows a direct comparison between a conservative investment procedure and a more active Long/Short approach.

Looking at Panel A in Table 7 first, from the first three rows it can be seen that returns of the diversified *XFTSMOMrf* portfolio are not spanned by the *FTSMOMrf* and

XSMOMrf returns. Instead, the XFTSMOM portfolio generates a highly significant monthly alpha between 0.27% and 0.46% (t-statistic in the range between 2.12 and 10) depending on the specification. XFTSMOM thus seems to be capturing something novel that FTSMOM and XSMOM do not capture in the framework of equity factors instead of individual stocks. In particular, it seems that the significative positive XSMOM effect on XFTSMOM ($\alpha =$ 0.53% with $t = 2.78$) is muffled when taking FTSMOM into account.

While the XFTSMOM excess returns are not spanned by FTSMOM and XSMOM, in the opposite direction the *FTSMOMrf* returns are unambiguously spanned by *XFTSMOMrf* . Specifically, from the fourth row of both Panels, it is noticeable that XFTSMOM explains away the returns of FTSMOM ($\alpha = 0.02\%$ with $t = 0.16$). From the seventh row of Panel A, instead, we can see that XFTSMOMrf is also significant in explaining the returns of XSMOM in the used sample of equity factors, leaving XSMOM a positive but statistically insignificant α of 0.37% ($t = 2.16$). Most effects are recognized also in the other scenario in Panel B where the remaining α's turn out to be much larger in magnitude while spanning *XFTSMOMshort* and *FTSMOMshort* , except from the seventh row where XFTSMOMshort seems not predicting XSMOM, nor do the other two momentum strategies at any confidence levels.

The strong performance of XFTSMOM and FTSMOM in both scenarios and their ability to explain some of the prominent factors in asset pricing, namely, cross-sectional momentum as well as other well-known ones present in Table 6, suggests that both strategies are significant features of asset pricing behaviour of stock (excess) returns. Future research may well consider what other asset pricing phenomena might be related to factor time series momentum.

Table 7: **Spanning Test with Equity Factor Portfolios in the Cross-sectional dimension**

Reported are the results from regressing the monthly returns of cross-factor time series momentum (*XFTSMOM*), single-factor time series momentum (*FTSMOM*), and cross-sectional momentum (*XSMOM*) portfolios on each other. The portfolios are diversified across each equity factor in my data set, and use lookback periods of twelve months and holding periods of one month. The XSMOM portfolios are constructed using the methodology taken from Asness, Moskowitz, and Pedersen (2013). The sample period is Jan-1986 to Dec-2016. (A) Panel A: Spanning test taking the risk-free rate version of the investment; (B) Panel B: Spanning test taking shorting possibility of the investment.

(A) Panel A: Risk-free rate scenario if non-concordant past return signals

Dependent Variable	XFTSMOMrf	FTSMOMrf	XSMOM	Alpha	Adj. R^2
XFTSMOMrf		0.93*** (73.56)		0.27%** (2.12)	0.936
XFTSMOMrf			0.53** (2.57)	0.46%*** (10.00)	0.020
XFTSMOMrf		0.93*** (73.61)	-0.03 (-1.33)	0.29%** (2.20)	0.936
FTSMOMrf	1.01*** (73.56)			0.02% (0.16)	0.915
FTSMOMrf			0.09 (0.94)	0.47%*** (9.70)	0.054
FTSMOMrf	1.01*** (73.62)		0.04 (1.53)	0.01% (0.06)	0.936
XSMOM	0.17 (0.57)			0.37% (1.26)	0.005
XSMOM		0.26 (0.94)		0.32% (1.11)	0.007
XSMOM	-1.53 (-1.33)	1.68 (1.53)		0.36% (1.25)	0.014

(B) Panel B: Long/Short scenario if non-concordant past return signals

Dependent Variable	XFTSMOMshort	FTSMOMshort	XSMOM	Alpha	Adj. R^2
XFTSMOMshort		0.52*** (43.87)		0.24%*** (12.41)	0.839
XFTSMOMshort			0.71** (2.76)	0.41%*** (8.90)	0.017
XFTSMOMshort		0.52*** (43.80)	-0.03 (-0.70)	0.24%*** (12.42)	0.839
FTSMOMshort	1.62*** (43.87)			-0.32%*** (-8.99)	0.817
FTSMOMshort			0.19 (1.13)	0.34%*** (4.15)	0.036
FTSMOMshort	1.62*** (43.80)		0.01 (1.10)	-0.33%*** (-9.05)	0.839
XSMOM	0.22 (0.76)			0.35% (1.24)	0.002
XSMOM		0.18 (1.13)		0.38% (1.44)	0.004
XSMOM	-0.50 (-0.70)	0.45 (1.10)		0.50% (1.59)	0.010

6 Robustness checks

As suggested in the Methodology section, it is certainly constructive practice to eventually check some meaningful sources that can potentially explain the outperformance of the FTSMOM and XFTSMOM investment strategies. In fact, given that the explanatory effect of the Cross-sectional XSMOM factor on XFTSMOM in Table 7, also cited as Carhart's UMD, is being almost entirely crowded out by FTSMOM (in both scenario specifications), it is beneficial to understand if the Time series component (*TSMOM*) of the momentum effect does play a role in rendering XFTSMOM's superior excess returns. For this reason, Table 8 below has been built to illustrate eventual predictive power of TSMOM which will add up to the studied asset pricing model.

Likewise, several economic variables are going to be employed to try to explain the exceptional alpha effect of time-series (cross-)factor performance. Although the set of potentially meaningful macroeconomic covariates can be extended to a much broader scope, I am hereby employing the most influential and widely used variables, to be able to keep it consistent across the time-series momentum literature[4]. This is done because what I am trying to carry out is a single robustness check only, leaving the pure macro-econometric side of analysis outside the scope of this thesis, which would imply looking at factor investing from a completely different angle. The selected control variables are namely: **i)** monthly percentage change in equity mutual fund flows; **ii)** U.S. monthly historical inflation (consumer price index) rate; **iii)** U.S. historical unemployment rate; **iv)** monthly percentage change in industrial production; **v)** monthly percentage change in gross private domestic investment; **vi)** monthly percentage change in federal funds rate (which represents the Federal Reserve's central monetary policy tool); **vii)** monthly percentage rate in the US Dollar index[5] (referred to as USDX, DXY or, more informally, the "Dixie"), and finally **viii)** the quarterly seasonally-adjusted ratio of GDP growth of the U.S. economy against GDP growth of emerging market economies, to help check whether this implicitly drives upwards the performance of advanced economies. All relevant variables data has been taken from Thomson Reuters Datastream. Results are analyzed both graphically and empirically, by employing a linear approach as well as a linear-log regression model – to allow for more flexibility in controlling percentage interaction effects of more than two variables – and carrying out the analysis on both strategy specifications (i.e. Risk-free rate and Long/Short).

Additionally, the results in the previous section strongly suggest that volatility in the market is not one of the main drivers of XFTSMOM phenomenon, nor is sentiment,

[4]Here references are collected from Arnott et al. (2019), Asness, Moskowitz, and Pedersen (2013), Moskowitz et al. (2012), Baltas and Kosowski (2020), Ehsani et al. (2019), Gupta et al. (2019) and Pitkäjärvi et al. (2020).

[5]Which measures the strength of US dollar against a basket of U.S. main trade partners' foreign currencies.

as measured by Baker and Wurgler's sentiment index, unlike are FTSMOM, XSMOM and sometimes illiquidity. The results are continued being examined on the sensitivity to a couple of insightful robustness checks, which are centred around the role of sentiment in predicting future stock (factor) returns. From an individual investor, both measures represent an indication of general sentiment existing in the market. Therefore it is certainly fascinating to evaluate the role of the sentiment-based factor in asset pricing to explain prominent equity market anomalies. As sentiment is related with different attributes, there is no universal definition accepted by literature. According to De Long et al. (1990), sentiment is investors' formation of beliefs about future cash flows and investment risks that are not justified by existing evidence. Barberis and Shleifer (2000) opine that sentiment is not about merely uncorrelated random mistakes but reflects the common judgment errors made by a large number of investors. Brown and Cliff (2004) believe that sentiment is the manifestation of expectations of market participants relative to a benchmark – a bullish (bearish) investor expects returns to be above (below) the average. In Baker and Wurgler (2006), it is the propensity of investors to speculate which determines waves of optimism and pessimism. The two soundness tests are further described in more details in Sections 6.2 and 6.3, which the reader is able to consult beneath.

While the S&P 500 CBOE's Volatility Index (*VIX*) is a unique contrarian indicator that not only helps investors look for tops, bottoms, and lulls in the trend but allows them to get an idea of large market players' sentiment. Yet, this argument cannot be brought forward in case of general sentiment item. Therefore, in order to measure the fortitude of the above-explained factor time series momentum models, I focus on the time series of the combined Baker and Wurgler's (BW) sentiment, as this index pulls monthly data from a series of macroeconomic variables, making the estimate pretty inaccurate unlike other sentiment factors which are impinged by common behavioural biases that occur during surveys (Hudson & Green, 2015). *VIX* monthly returns are taken from Datastream whereas BW from Baker's website.

6.1 What drives cross-factor time series momentum effect?

6.1.1 "Traditional" Time-series momentum strategy

Both Panels A and B of Table 8 below further use TSMOM as a right-hand-side covariate, testing its ability to explain performance against the other used factors, especially if they can significantly load on FTSMOM and XFTSMOM returns. Nevertheless, TSMOM is not able to significantly capture the return premium of the hereby studied strategy; this has indeed a meaningless negative loading on XFTSMOM in the risk-free rate scenario and a positive loading in the Long/Short scenario. In the two cases, the effects yet lead to a significant +0.47% and +0.42% α component (t-stat = 9.96 and 8.89), respectively. Likewise, in the case of FTSMOM (both risk-free rate and Long/Short scenarios), TSMOM is not capable to add predictive power to the factor momentum element on average.

Furthermore, I also examine XSMOM to see if TSMOM can capture the returns to cross-sectional momentum across equity factors. As the fourth row of Panel A of Table 8 shows, TSMOM is able to fully explain cross-sectional momentum effect for equity factor strategies – this in line with what demonstrated my Moskowitz et al. (2012). The intercepts or alphas of XSMOM are statistically no different from zero, suggesting TSMOM captures the return premiums of XSMOM in the equity space. Interestingly, the same cross-sectional momentum anomaly is able to significantly predict time-series momentum (last row in Panel A), even though the strategy α still remains significantly positive. This is to be expected, as Moskowitz et al. (2012) and Georgopoulou and Wang (2015) prove in their studies, where they also document that time-series momentum on average outscores its cross-sectional peer in the current market. The obtained results for the Long/Short strategies in Panel B are similar and comparable to what Panel A documents, both in magnitude and sign of the mutual effects of underlying covariates.

Table 8: **Spanning Test with Equity Factor Portfolios in the Time-series dimension**

Reported are the results from regressing the monthly returns of cross-factor time series momentum (XFTSMOM), single-factor time series momentum (FTSMOM), and cross-sectional momentum (XSMOM) portfolios on each other. The portfolios are diversified across each equity factor in my data set, and use lookback periods of twelve months and holding periods of one month. The XSMOM portfolios are constructed using the methodology taken from Asness, Moskowitz, and Pedersen (2013). Contrarily to the afore-shown table, this Spanning test has been run by taking into consideration the time series component, as TSMOM dependencies with the studied strategies are analyzed. The sample period is Jan-1986 to Dec-2016. (A) Panel A: Spanning test taking the risk-free rate version of the investment; (B) Panel B: Spanning test taking shorting possibility of the investment.

(A) Panel A: Risk-free rate scenario if non-concordant past return signals

Dependent Variable	XFTSMOMrf	FTSMOMrf	XSMOM	TSMOM	Alpha	Adj. R^2
XFTSMOMrf				-0.01 (-0.15)	0.47%*** (9.96)	0.256
XFTSMOMrf		0.93*** (73.55)	-0.03 (-0.98)	-0.11 (-0.72)	0.03%** (2.27)	0.936
FTSMOMrf	1.01*** (73.55)		0.31 (1.19)	0.10 (0.64)	-0.01% (-0.04)	0.936
XSMOM	-1.06 (-0.98)	1.23 (1.19)		0.22*** (7.35)	0.04% (0.13)	0.134
TSMOM	-0.07 (-0.15)				1.46*** (3.16)	0.129
TSMOM		0.07 (0.15)			1.40%*** (3.04)	0.200
TSMOM	-1.23 (-0.72)	1.05 (0.64)	0.57*** (7.35)		1.25%*** (2.89)	0.131

(B) Panel B: Long/Short scenario if non-concordant past return signals

Dependent Variable	XFTSMOMshort	FTSMOMshort	XSMOM	TSMOM	Alpha	Adj. R^2
XFTSMOMshort				-0.01 (-0.16)	0.42%*** (8.89)	0.260
XFTSMOMshort		0.52*** (43.74)	-0.33 (-0.81)	0.11 (0.43)	0.24%*** (12.17)	0.838
FTSMOMshort	1.62*** (43.74)		0.09 (1.26)	-0.03 (-0.67)	-0.33%*** (-8.83)	0.838
XSMOM	-0.54 (-0.81)	0.48 (1.26)		0.24*** (7.46)	0.18% (0.60)	0.128
TSMOM	-0,08 (-0.16)				1.46%*** (3.23)	0.130
TSMOM		-0.06 (-0.24)			1.45%*** (3.46)	0.202
TSMOM	0.46 (0.43)	-0.40 (-0.67)	0.58 (7.46)		1.13%** (2.40)	0.133

6.1.2 Is the Macro-economy completely uninfluential on systematic quant investing?

Hutchinson and O'Brien (2015) show that the returns to time series momentum depend on the macroeconomic cycle, being larger in economic expansions, and argue that the returns are there- fore compensation for business cycle risk. In this Sub-section, following the existing literature on the matter – i.e. Hutchinson and O'Brien (2015) and Pitkäjärvi et al. (2020) especially – I partially confirm the above statement. Indeed, I am demonstrating that FTSMOM and XFTSMOM strategy effectiveness in the U.S. equity market is to a certain extent dependant on the GDP trend, especially when comparing this to that of several Emerging market countries. Likewise, the U.S. Dollar index does play a role in predicting the two strategy excess returns, reinforcing the idea of currency movements being able to effect stock returns. On the other hand, the other 6 macro covariates employed are ultimately not able to anticipate the trend of neither of the two time-series momentum schemes. The other way round is also true: DXY and GDP country ratio are the only variables that are somewhat influenced by the two time-series momentum regimes, whereas the latter strategies cannot forecast the other same 6 variables. This poses a question on the yet existing parallelism between (quantitative) financial markets and the real economy, as the two do not seem closely following each other.

Going step by step in order of graphs and analysis employed, I begin by illustrating the relation between returns and flows of equities in and out of mutual funds at the aggregate level. Specifically, in Figure 8 the 12-month past cumulative excess returns of FTSMOM and XFTSMOM are plotted against the detrended 12-month past cumulative equity mutual fund flows. From here, it can be seen that returns and flows are not closely related, with feeble contemporaneous correlations of -0.13 between the FTSMOM scheme and equity fund flows, and -0.19 between the XFTSMOM scheme and equity fund flows, respectively. Moreover, size and significance of the mutual fund industry growth over the sample period seem not affecting the comovement of returns and flows, as during periods of big inflows time-series momentum returns stay relatively low, and vice versa. Although results are not very appealing in this case, it has already been proven that there is no statistically significant relationship between aggregate mutual fund flows and subsequent stock market returns, as recently argued by Edelen and Warner (2001), among the others. The analytical proof with econometric regressions will be shown down below in Table 9.

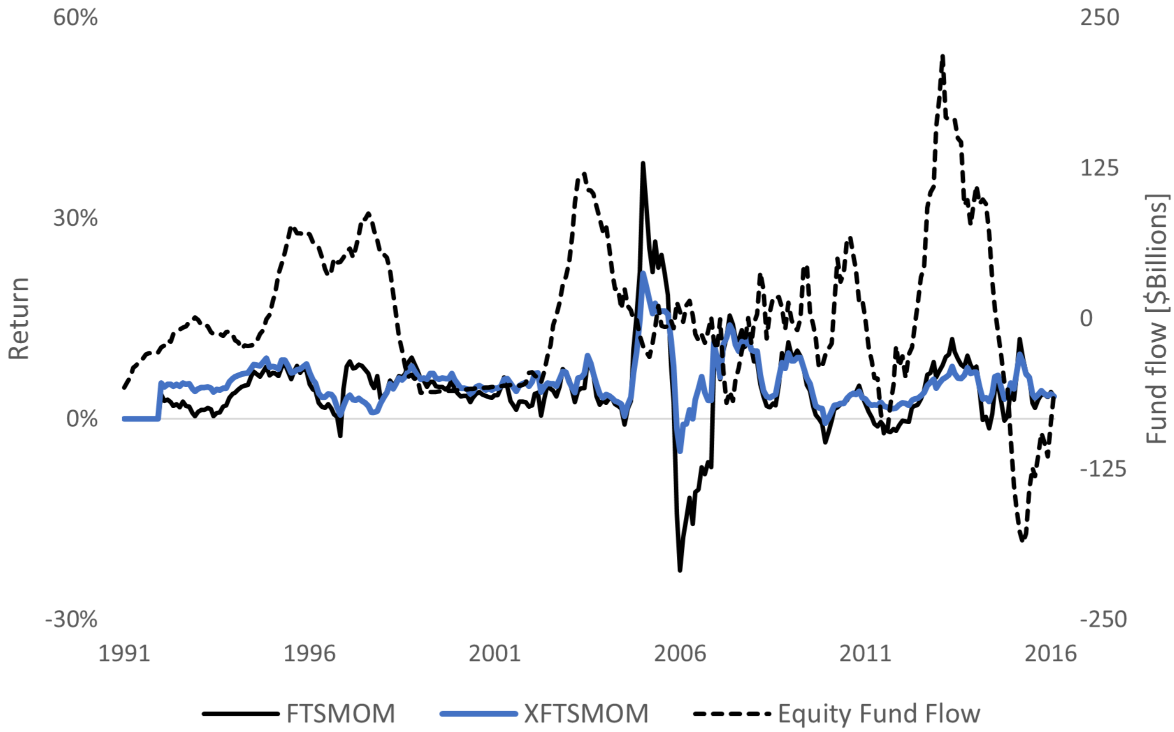

Figure 8: Comovement of Factor Time series Momentum Returns and Equity Fund Flows

Plotted are the twelve-month cumulative excess returns of the FTSMOM and XFTSMOM investment strategies (left axis) and detrended twelve-month cumulative equity mutual fund flows (right axis), taken from Thomson Reuters Datastream. The correlation between the series is -0.13 and -0.19, respectively. Only the Long/Short specification is here displayed. Results are very similar in the risk-free rate scenario; correlation between the series is -0.23 and -0.21. The sample period is Nov-1991 to Dec-2016.

Relating this finding to time series momentum, I next present along the lines evidence that mutual fund flows does not actually chase performance at the aggregate level. Specifically, in Figure 9 two correlation series between involved FTSMOM and XFTSMOM 12-month past cumulative returns and equity mutual fund flows are displayed, for 1 to 24 months taken in the future. From Figure 9 it can be deduced that past returns are negatively correlated with future fund flows in both time-series momentum schemes, and that the relationship is significant only for the first 6-8 months (with magnitude turning progressively less negative) while becoming insignificant afterwards. The correlations are initially significant and peak at one to three months and then persist in the negative spectrum for about 14 months before reversing at longer lags multiple times. This evidence is consistent with the "feedback trading" hypothesis discussed in Edelen and Warner (2001). Generally speaking, unlike documented in most of the outstanding literature – including Pitkäjärvi et al. (2020) and Ben-Rephael et al. (2011, 2012) – if we see persistent meaningful correlations between equity fund flows and performance on the *stock level*, this fact is not confirmed by investigating *equity factors.*

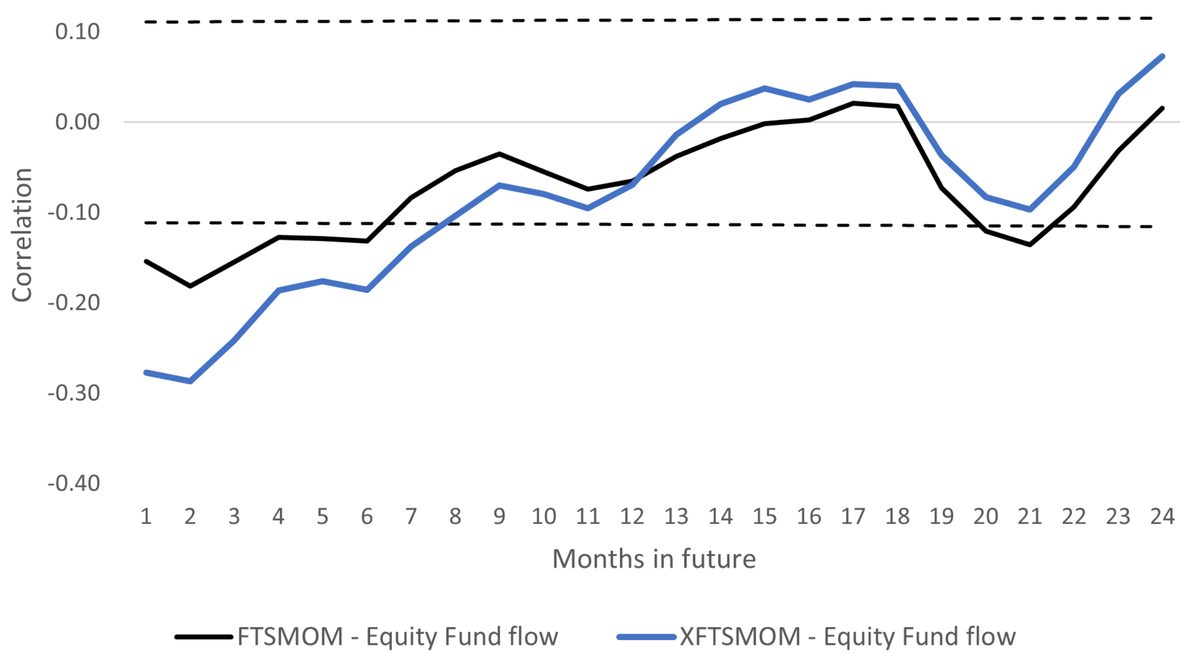

Figure 9: Correlations Between Factor Time series Momentum Returns and future Equity Fund Flows

Plotted are the two series of correlations between FTSMOM and XFTSMOM twelve-month cumulative returns and equity mutual fund flows, for one to 24 months in the future. The equity fund flows are normalised by traditional monthly updated equity mutual fund assets under management (AuM), following Pitkajäärvi et al. (2020). Horizontal lines indicate approximate 5% critical values per each month forward. Only the Long/Short specification is here displayed. Results are almost identical in the risk-free rate scenario. The sample period is Jan-1986 to Dec-2016.

A second channel through which factor time-series momentum returns – particularly, the cross-factor performance - can affect the real economy is the monetary policy channel, for instance, whether FTSMOM and XFTSMOM returns can explain the ongoing changes in the Federal Reserve's central monetary policy tool, the Federal funds rate. In below Figure 10 two correlation series between involving FTSMOM and XFTSMOM 12-month past cumulative returns and monthly percentage rate changes are shown, for the Federal funds rate taken 1–24 months in the future. From Figure 10, it can be deduced that equity market returns are basically uncorrelated with future changes in the federal funds rate, and the effect stay plummeted to zero even at longer lags. It thus appears that, although the Federal Reserve conditions its monetary policy on past stock market returns, this effect is once again not visible by assuming the perspective of equity factors. Despite increases in the federal funds rate will typically increase yields across the entire yield curve, and ultimately affect the whole bond market returns, any spillover effect from the equity framework to future monetary policy decisions is thus quite cumbersome to predict.

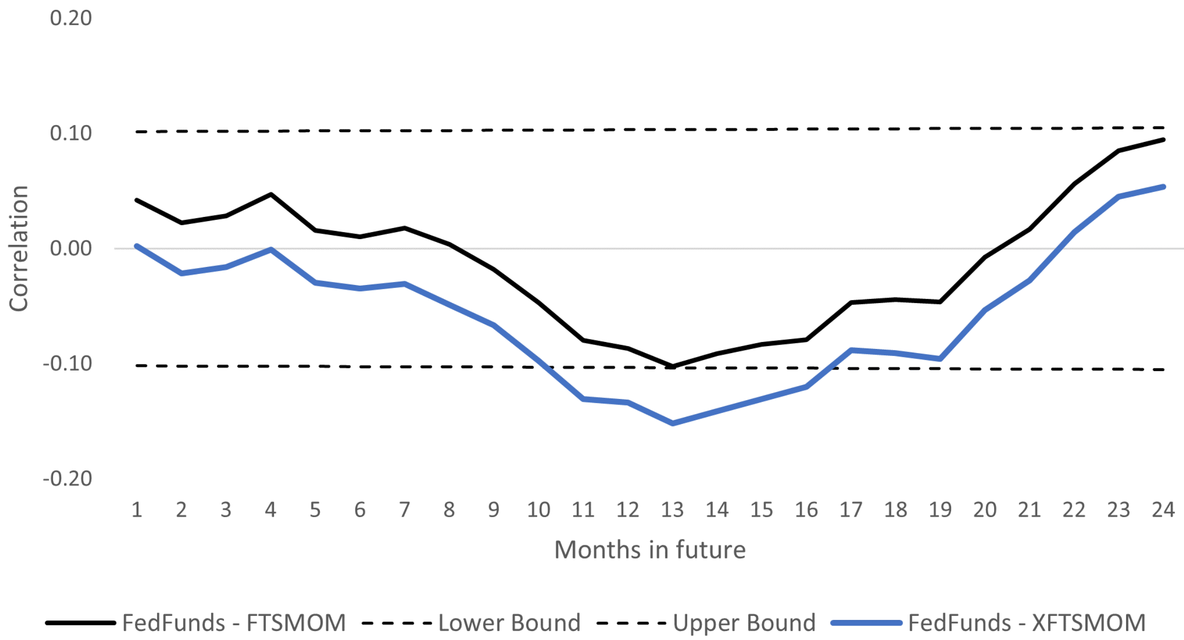

Figure 10: Correlations Between Factor Time Series Momentum Returns and future Fed Funds Rate Changes

Plotted are the two series of correlations between FTSMOM and XFTSMOM twelve-month cumulative returns and monthly percentage changes in the federal funds rate one to 24 months in the future. Horizontal lines indicate approximate 5% critical values. Only the Long/Short specification is here displayed. Results are almost identical in the risk-free rate scenario. The sample period is Jan-1986 to Dec-2016.

The following step now is to relate factor time series momentum to the real economy by showing how future changes in industrial production, investment, inflation, unemployment, U.S. Dollar index GDP ratio versus EM economies depend on equity FTSMOM and XFTSMOM regimes. I hereby show that factor time series momentum and cross-factor time series momentum both contain information about real economic activity, in addition to the information they contain about risk premiums in equity markets, thereby opening some real potential frontier in asset pricing studies.

To start, in Figure 11 the average next 12-month percentage changes in industrial production, gross private domestic investment and equity mutual fund flows, and the average next 12-month changes in GDP country ratio, U.S. Dollar index, inflation, unemployment and Fed funds rates, for different FTSMOM and XFTSMOM regimes. Next 12-month changes in these macroeconomic variables are mapped out for 55 double sorts of cumulative past 12-month FTSMOM and XFTSMOM excess returns. Then, to complement this macro-based analysis, in Table 9 the opposite perspective is taken – i.e. effects of the various macroeconomics control variables on the actual performance of the two strategies (by means of individual linear regressions) are represented.

From below Figure 11, it can be seen that the majority of the adopted economic variables is closely influenced by FTSMOM and XFTSMOM, represented along the two axes. This is particularly evident for industrial production, equity fund flows, DXY and GDP U.S. proportion to EM – depicted in Panels A, E, G and H, respectively. Future changes in inflation and unemployment seem being only mildly affected instead, while for Fed funds rate equity investment strategies have controversial effects on the main Central Bank's monetary policy tool, further highlighting the difficulty in settling forecasts on future interest rate policies. Regarding the increased industrial production as the strategies' excess returns surge, intuitively positive past equity returns are primarily associated with lower costs of equity, and thus higher net present values for firms' investment projects which, at the margin, should increase investment (hence production and employment as well). However, because corporate investments take time to be planned and executed, the economic indicators react with a lag, thus creating predictability from past returns to reflect future economic activity. Secondly, positive past returns increase investors' wealth which leads to higher real activity as firms react to investors' increased capacity to consume. Because reaction also takes time, the result is a predictable relation between equity (factor) returns and real bread-and-butter activity. Furthermore, Panel E shows that outperformance in FTSMOM and XFTSMOM are likely to enlarge flows of equity in mutual funds ever so slightly. This goes in contrast to what dispatched in Figure 9 above, where dependency was largely insignificant. Yet the magnitude of the bars needs to be tested, as the scaling of the effects on the macroeconomic variables differs across all the panels.

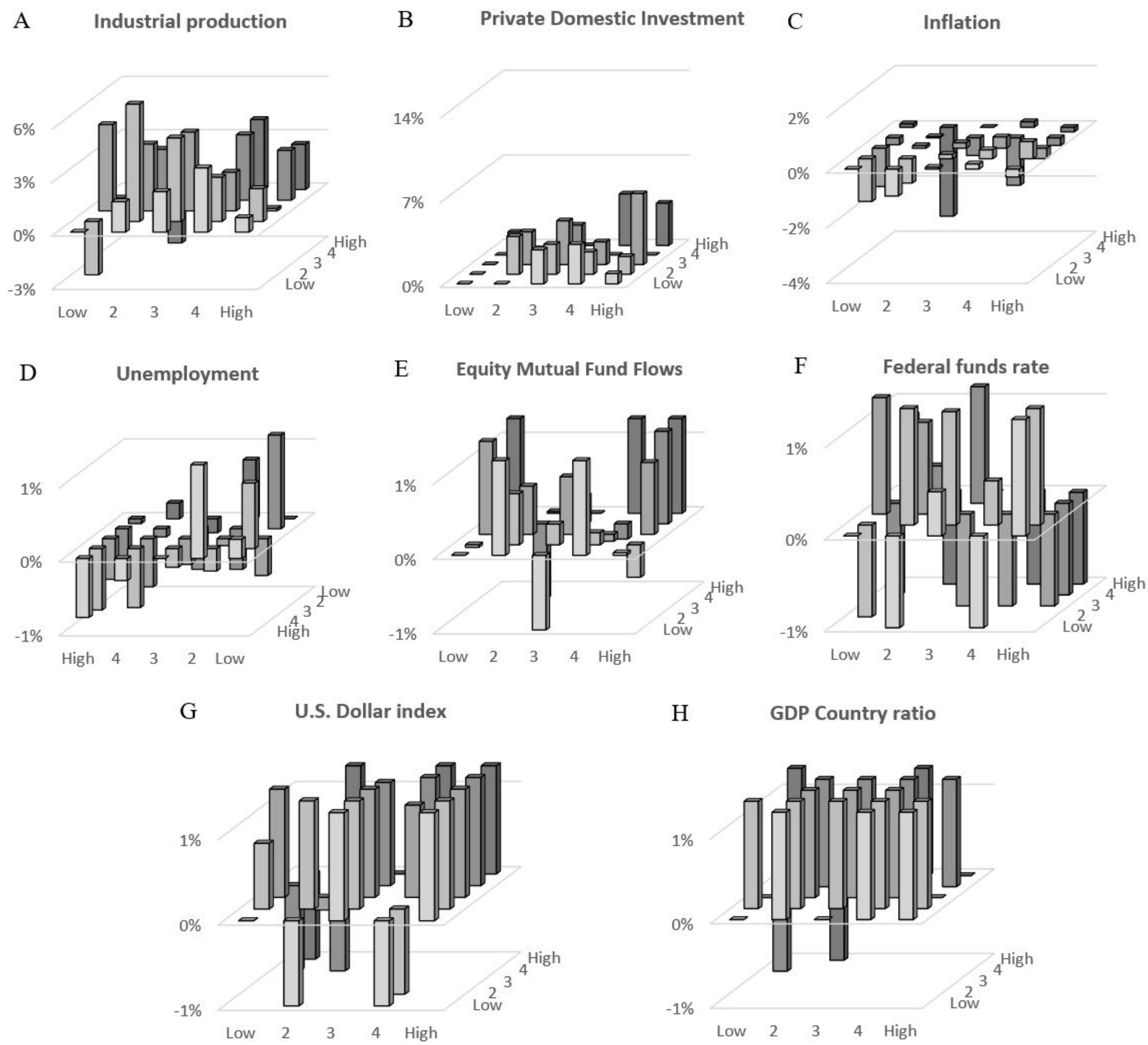

Figure 11: Economic Indicators by Past FTSMOM and XFTSMOM Return Quintiles

Plotted are the average next twelve-month percentage change in industrial production, percentage change in gross private domestic investment, change in the inflation rate, change in the unemployment rate, percentage change in equity mutual fund flows, percentage change in the Federal funds rate, change in DXY index and percentage change in the ratio between the U.S. GDP and the GDP of Emerging Markets for 5x5 sorts of past twelve-month cumulative excess returns of FTSMOM and XFTSMOM factor strategies. In each panel the equity XFTSMOM return quintiles are on the horizontal axis whereas the equity FTSMOM return quintiles are on the depth axis. In Panels A, B, E and G the vertical axis is the percentage change, and in Panels C, D, F and H it is the percentage point change. Note the reversed axes in Panel D. Only the Long/Short specification is here displayed. Results are very similar in the risk-free rate scenario. The sample period is Jan-1987 to Dec-2016. (A) Panel A: Industrial production; (B) Panel B: Investment; (C) Panel C: Inflation; (D) Panel D: Unemployment; (E) Panel E: Equity Mutual Fund Flows; (F) Panel F: Federal funds rate; (G) Panel G: U.S. Dollar index; (H) GDP USA/EM ratio.

Last but not least, taking an asset pricing mindset in FTSMOM and XFTSMOM analysis, from Table 9 a few facts can be derived on reliability and robustness of the two strategies. Overall results have been checked under both investment specifications – i.e. Risk-free rate and Long/Short scenario, and they express pretty similar results, although for brevity's sake only the linear regression approach has been shown here. Most of the outstanding effects are statistically meaningless at any confidence interval. Moreover, I attempted to combine individual variables in different multiple regression analysis, though the effects have been crowded out even more and strictly tending to zero. The only two effects truly deserving a bigger note are related to DXY (USD index) and GDP country ratio, which is to be expected, also looking at the bar graph analyzed above. In fact, their coefficients are both positive and significant at 95% level for risk-free rate scenario and even at 99% level for Long/Short scenario. However, this does not fully explain the Alpha excess return and does not pose a threat to the effectiveness of FTSMOM and XFTSMOM strategies in the utilized dataset. This finding is further confirmed in Panels G and H of the bar plot (Figure 11), where most of the bars are displayed above the horizontal axis for every excess return quintile. A likely rationale for this is that, although some countries depreciate their currency in an attempt to fuel growth particularly in periods of downturn, as a currency generally strengthens (USD in this case) investors in stocks see this as a signal of not yet captured potential in the financial markets, thus picking this cherry as an opportunity and naturally allowing equity (factor) returns to surge. Investopedia in fact documents that on average around 35% to 40% of the stock indexes' movement is attributable to movements in U.S. Dollar, when measuring the correlation between DXY and major stock indexes. This has in turn direct consequences on the real economy, where investments do stimulate money circulation while GDP and purchasing power are promoted overall.

Table 9: **Effect of (Macro-)Economic Indicators on Factor Time-series Momentum strategies**

Reported are the average effects of the past cumulative twelve-month percentage change in Industrial Production, percentage change in Gross Private Domestic Investment, change in the Inflation rate, change in the Unemployment rate on (single- and cross-) factor time series momentum regimes, percentage change in Equity Mutual Fund flows, percentage change in the Federal funds rate, change in DXY index and percentage change in the Ratio between the U.S. GDP and the GDP of Emerging Markets. Each and every response is accompanied by its respective t-statistic value in parentheses. Only the Simple Linear regression analysis is taken into consideration, as results for the Linear-Log specification are very similar and mostly insignificant. The outline for Alpha % is not hereby displayed as the excess performance is not cancelled out in any of the investment specifications and covariates, nor does it lose its significance power in explaining the factor times series momentum strategies. (A) Panel A: Risk-free rate investment scenario (in case both past return signals have negative sign); (B) Panel B: Long/Short investment scenario (in case both past return signals have negative sign). The sample period is Jan-1986 to Dec-2016.

(A) Panel A: Simple Linear Regressions (Risk-free Rate scenario)

*α effect remains persistent in every specification, staying always ****

β effects of individual independent variables. Multivariate linear regressions have also been run, but covariates are dynamically insignificant

	Industrial Production	Gross Private Domestic Investment	Inflation Rate	Unemployment Rate	Equity fund flows	Federal funds Rate	U.S. Dollar index	GDP U.S.A. / EM ratio
FTSMOMrf	0.08	0.00	0.07	-0.15	-0.02	0.01	0.45	0.60**
	(-0.27)	(-0.01)	(-1.00)	(-0.84)	(-0.32)	(-0.21)	(-1.28)	(-2.28)
XFTSMOMrf	0.25	-0.02	0.10	-0.24	-0.01	0.00	0.16	0.52**
	(-0.28)	(-0.15)	(-0.37)	(-1.26)	(-0.05)	(-0.05)	(-1.41)	(-2.16)

(B) Panel B: Simple Linear Regressions (Long/Short scenario)

*α effect remains persistent in every specification, staying always ****

β effects of individual independent variables. Multivariate linear regressions have also been run, but covariates are dynamically insignificant

	Industrial Production	Gross Private Domestic Investment	Inflation Rate	Unemployment Rate	Equity fund flows	Federal funds Rate	U.S. Dollar index	GDP U.S.A. / EM ratio
FTSMOMshort	0.13	0.00	0.06	-0.03	-0.01	0.01	0.48	0.81***
	(-0.63)	(-0.05)	(-1.18)	(-0.31)	(-0.26)	(-0.41)	(-1.46)	(-2.76)
XFTSMOMshort	0.45	-0.04	0.16	-0.02	0.00	0.00	0.31*	0.69***
	(-0.38)	(-0.48)	(-0.56)	(-0.46)	(-0.10)	(-0.10)	(-1.65)	(-2.60)

6.2 Does volatility play a role in equity factor correlation pattern?

As a further control, it is interesting to analyze whether volatility has a distinguishable impact on the correlation between equity factors. VIX index is to capture the level of market volatility and the most extreme market volatility environments, which also seem to correspond with illiquid episodes. Although there is no significant relationship between XFTSMOM profitability and market volatility, the same can be said for the dependency between cross-factor correlation and volatility, which turns out to be pretty flat, as shown in Figure 13.

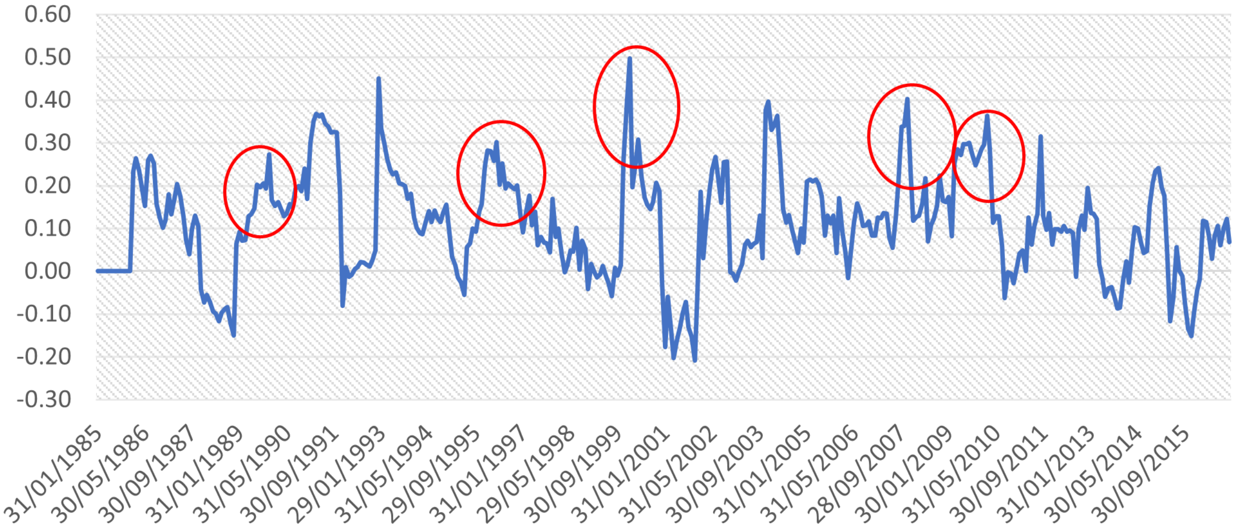

Figure 12: 12-month Rolling Cross-factor correlation of excess returns

Plotted is the average 12-month time-series rolling cross-correlation pattern of the equity factor excess returns at disposal. Each rolling correlation observation is taken from t-13 to t-1. The surrounding loops put in evidence significant dips in average cross-correlation measures at several specific moments in time for the global economy. The sample period is Jan-1986 to Dec-2016.

Although the correlation across factor returns on a rolling basis and level of market volatility is negative (-0.17), the model is overall statistically meaningless as the R-squared value just about reaches 0.20. Rather, Figure 12 aims nonetheless to investigate whether some facts can be inferred in times of economic downturn. Bear periods have been taken in correspondence of historical events that have negatively affected worldwide economy for several years before triggering some significant recovery signs. Those events are namely the OPEC Oil crisis and Post-war early 90's U.S. recession (1990), Asian Flu (1997), the Dot-com tech bubble (2001), the GFC (2007), and the European debt crisis (2009).

In this case, it can be noticed that as we approach those negative events, the factor cross-correlation also increases on average, while diminishing in periods of strong economic recovery. By regressing the VIX index values on the factor cross-correlation, as expected the latter positively predicts the general volatility level existing in the market, although it is not statistically significant to infer a lead-lag effect between the two ($t = 0.378$). The opposite is equally true, being that market VIX index is a positive predictor for average cross-dependency between anomalies, although insignificant from a statistical standpoint. This finding therefore does not reject Thesis Hypothesis #2 and goes along with what depicted in Table 6 above, where the subordinate product of cross-factor correlation – i.e. XFTSMOM – is positively related to, although not explained by, VIX index values for any confidence level.

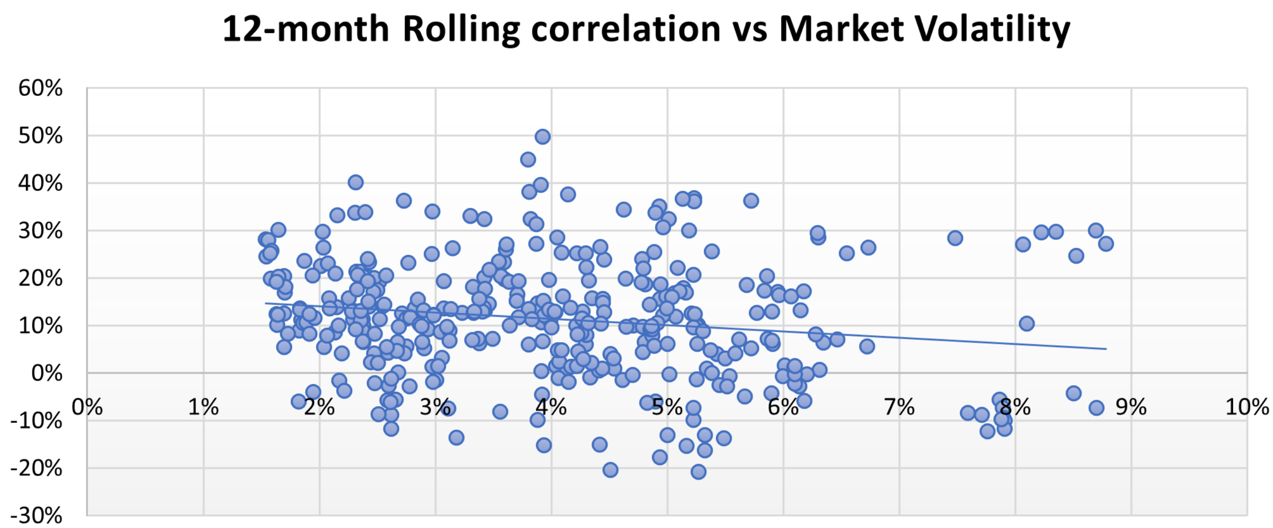

Figure 13: Relationship between 12-month rolling cross-correlation and market volatility

Plotted is the correlation between the previously computed average 12-month rolling correlation of equity factor excess returns at disposal – y axis, expressed in % – and the level of overall 12-month rolling stock market volatility (calculated from the equity index of reference – MSCI USA Total return Index) – x axis, expressed in %. The sample period is Jan-1986 to Dec-2016.

6.3 Does sentiment index measures positively load on cross-factor correlations during crises periods?

Along with the first check, it is even more interesting to make a deep dive as far as the sentiment index is concerning, and whether this somehow influences cross-factor correlation patterns over time in periods of economic crisis. The same procedure has been adopted as in Section 6.2, by regressing the two variables on each other. In Figure 14 it is possible to visualize a negative relationship between the composite sentiment index and the factor cross-correlation on average, particularly in downturn periods – namely the OPEC Oil crisis and Post-war early 90's U.S. recession (1990), the Dot-com tech bubble (2001), the Global financial crisis (2007), and the European debt crisis (2009). In agreement with the above graph, regression analysis tells us that 1% increase in the average cross-factor correlation negatively anticipates the sentiment existing in the market by almost the same magnitude on log scale – the orthogonalized version – and that this relationship is significant (t = -3.824). Likewise, composite sentiment index measure is able to significantly predict a lower cross-correlation between different factors on average when investor confidence is boosted, with an overall pooled β = -0.039.

Interestingly, this differs from what seen in Table 6 on the strategy level, where sentiment was not a significant predictor for XFTSMOM. This implies that, as findings have been of comparable sign and magnitude with FTSMOM and XFTSMOM strategies, cross-factor correlations do play a remarkable role in assessing future stock returns. Hence, they prove to have indicative predictive power also from a portfolio construction perspective. However, it can be argued that the dependence relationship existing between the two may be asymmetric, meaning a non-linear effect of investor sentiment and stock market returns, and vice versa, as documented by He et al. (2020). Nonetheless, this finding is proven to be consistent with Fisher and Statman (2003) who reveal the level of investor sentiment in one month is negatively related to the stock returns over the next month and the next 6 or 12 months.

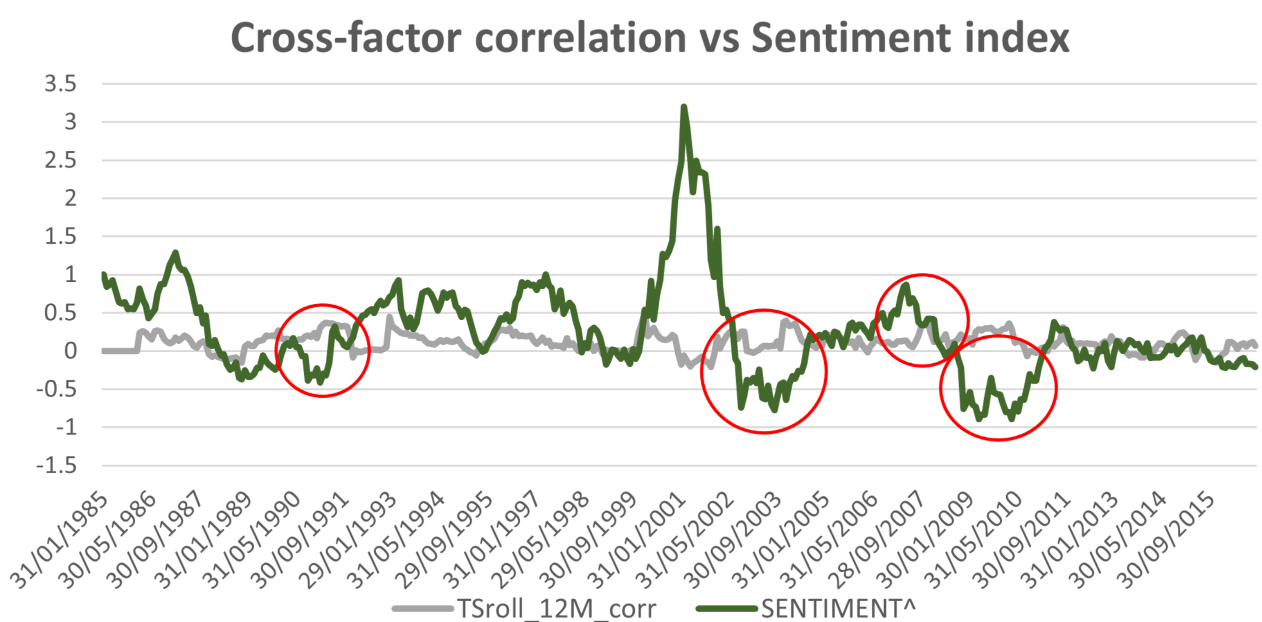

Figure 14: Relationship between 12-month rolling cross-correlation and sentiment index returns

Plotted is the interaction between the previously computed 12-month rolling correlation of equity factor excess returns at disposal and the orthogonalized return of the sentiment index measure, as defined by Baker and Wurgler (2006, 2007). Both variables are expressed in % terms. The surrounding loops put in evidence declines in the sentiment index at several specific points in time. The sample period is Jan-1986 to Dec-2016.

7 Conclusion

Factor timing has been a field for researchers and investors exploited for decades which is increasingly gaining attention by academics and on-field practitioners. Prior to the Global Financial Crisis, the typical active manager would have been in the “do not bother” spectrum given the robustness of all-weather static models. In the years after the crisis, factor timing became a “keep it monitored”. The possibility for the numbers to speak has to be given by a correct rational approach in quant factor investing and rigorous willingness of progressing, without wasting what has been achieved and kept track of. Only this way, this rollercoaster spectrum of investor behavior can turn into a “must have”. The goal of this thesis was indeed to investigate the presence of significant effects in the U.S. equity market during 1985-2016 between same or different factors that can lead to superior factor future excess return.

This paper contributes to the existing literature by analyzing time series momentum and building sound investment strategies by exploiting time-varying correlations. It has been proven that it is possible to consistently outscore the benchmark and beat the “traditional” equity investments by systematically betting on factor strategies over a 32-year period adopting a correlation approach which makes use of past historical returns to predict the world to come. I have not considered bet sizing strategies for this thesis, as the main goal is not about bankroll management and how to get rich, but whether or not it is feasible to apply an econometric approach to essentially better predict future returns in the equity framework.

Specifically, this thesis is among the first ones to explore the cross dynamics occurring between equity factors instead of individual securities. The main findings in this thesis indicate that cross-factor time series momentum positively predicts equity factor returns on average. This result persists even after controlling for factor time series momentum, cross-sectional momentum, return in the market, liquidity, volatility, sentiment factors, and other factors commonly used in the financial research, such as the Fama & French and Asness et al. (2013). Likewise, several covariates from markets and macroeconomy have been used, namely inflation, unemployment, Fed funds rate, relative value of Dollar, equity fund flows, strength of American GDP relative to classified emerging economies, industrial production and private domestic investments. A large set of control variables has been employed to limit the omitted variable bias, and hence the endogeneity issue incorporated in it. All in all, in the case in which stock anomalies express a certain correlation pattern, when one factor’s lagged returns positively impact their own and other factors’ future returns, this thesis steers to increase the exposure to that specific factor, while diminishing it in case of both negative predictive signals. This approach, which converges to investing in the risk-free asset in case of opposite signs, delivers a remarkably higher return over time with respect to the MSCI USA Total Return index of reference (Zakamulin et al., 2020) when considering this dataset.

Some limitations, however, of this paper need to be addressed. Firstly, and perhaps most obviously, the quality of the equity factors is worth a note. The more factors are used the higher the amount of observations at disposal: this would be the first thought for a research to be statistically relevant, as this enforces the reasonableness of a study in a more quantitative-tilted framework. However, these relationships are observed with the benefit of hindsight, and thus suffer from the age-old problem of data mining. Being able to identify signals that have worked well at predicting factors historically is not the same as picking signals today that will work well at predicting factors in the future. Even familiarizing with models as much as possible in strong theory and academic backing is not sufficient as academic research tends to cluster around signals that appear predictive; those that do not usually do not receive a lot of attention. Secondly, different versions of the long-short portfolio excess returns, related to both portfolio allocation schemes – e.g. value-weighted returns – and portfolio construction schemes – e.g. deciles or binaries – need to be examined more accurately in future studies related to timing factors. In fact, a recent research conducted by Russell on portfolio allocation schemes (2020) showed that an Equal Exposure approach to factor allocation is unlikely to achieve factor risk parity outcomes so long as the volatility of factor risk premia differ; it will overweight high volatility factors, such as Low Volatility and Momentum, and underweight less volatile factor attributes, such as Quality and Value. Hence, an equally-weighted factor allocation scheme will potentially deliver sub-optimal levels of factor diversification. In contrast, a Risk Exposure (value-weighted) approach appears to provide reasonably balanced risk contribution outcomes. However, to achieve true parity of risk contributions, factor correlations are a necessary consideration, which are employed in an Equal Risk Contribution approach – each equity factor contributes equally towards active risk. Therefore, it would be truly appealing to delve into several other alternative allocation strategies of factors in the time series dimension, particularly in the case of XFTSMOM, where mutual factor interaction does play a role in assessing the most suitable strategy and generate superior excess returns. Lastly, performing further analysis on which are the main drivers of FTSMOM and XFTSMOM would allow to understand how equity factor returns affect their own and other factors' returns. The studies conducted by Pitkäjärvi et al. (2020), Moskowitz et al. (2011) and Gupta et al. (2019) prove that mutual fund flows, credit conditions and monetary policy conditions are effective in explaining the effects studied in this research. Future research may shed a light on whether there are other events which systematically pull factor correlations and returns in a certain direction and pronounce the findings of this research. The same outline may be also achieved by aggregating factor strategies across different asset classes, such as fixed income and commodities

(Moskowitz et al. (2012) and Asness et al. (2013)); in this scenario, returns of different asset classes should be scaled in order to obtain a comparable, if not the same, level of volatility.

Irrespective of the above-mentioned limitations and considerations, the presented results provide practical implications for practitioners in the risk and asset management industry, as well as for retail investors who are keen on achieving superior returns using a systematic investment approach, as there is no actual need to time the stock market as a whole but rather specific factors whose returns change dynamically based on how correlations change in one's outstanding portfolio. The half time score is therefore (Time-Series) Factor investing 1 – 0 Securities investing, with all the 3 stated Hypotheses not being rejected, hence fully reaching the pre-set target. Certainly, bigger samples will be needed to verify the obtained results further, but even though it is still early days, the positive trends of Figures 4 to 7 and the outstanding outcomes of Tables 6 to 8 hold promise of a bright future in the field of factor timing and systematic predictability in future equity premia.

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Appendix A: Full List of Equity Predictors Used

Table A.1 List of cross-sectional predictors and Description of their Construction.

This table provides details of the construction of return predictors used in the research, and taken originally from *Chen & Zimmermann (2020)*. Data comes from the CRSP stock return database, Compustat North America Annual and Quarterly databases, IBES earnings estimates database, OptionMetrics, Thomson SDC and a number of additional databases noted in the descriptions of specific anomalies. The final database which I inherited from the initial authors is set up at monthly frequency. Specifically, annual Compustat data is lagged by five months and quarterly Compustat data by 3 months to assure availability of relevant data at the time of trading.

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
AbnAccr	Abnormal Accruals	Xie	2001	1971	1992	Define Accruals as net income (ib) minus operating cash flow (oancf), divided by average total assets (at) for years *t*-1 and t. If oancf is missing, replace operating cash flow with funds from operations (fopt) minus the annual change in total current assets (act) plus the annual change in cash and short-term investments (che) plus the annual change in current liabilities (lct) minus the annual change in debt in current liabilities (dlc). For each year t, regress Accruals on: the inverse of average total assets for years *t*-1 and t, the change in revenue (sale) from year *t*-1 to t divided by average total assets, propery plant and equipment (ppegt) divided by average total assets, industry dummies for Fama-French's 48 industry classification. AbnormalAccrual is the residual from this cross-sectional regression.
Accruals	Accruals	Sloan	1996	1962	1991	Annual change in current total assets (act) minus annual change in cash and short-term investements (che) minus annual change in current liabilities (lct) minus annual change in debt in current liabilities (dlc) minus change in income taxes (txp). All divided by average total assets (at) over this year and last year. Exclude if abs(prc) < 5.
AccrualsBM	Book-to-market and accruals	Bartov and Kim	2004	1980	1998	Binary variable equal to 1 if stock is in the highest Accrual quin- tile and the lowest BM quintile, and equal to 0 if stock is in the lowest Accrual quintile and the highest BM quintile. Exclude if book equity (ceq) is negative.
AdExp	Advertising Expense	Chan et al	2001	1975	1996	Advertising expense (xad) over market value of equity (shrout*abs(prc))
AnnounceR	Earnings announcement return	Chan et al	1996	1977	1992	Get announcement date for quarterly earnings from IBES (fpi = 6). AnnouncementReturn is the sum of (ret - mktrf + rf) from one day before an earnings announcement to 2 days after the announcement.
AssetGrowth	Asset Growth	Cooper et al	2008	1968	2003	Annual growth rate of total assets (at)
AssetTurnover	Asset Turnover	Soliman	2008	1984	2002	Sales (sale) divided by two year average of net operating assets. Net operating assets is the sum of receivables (rect), inventories (invt), current assets other (aco), net property, plants and equip- ment (ppent) and intangibles (intan), minus accounts payable (ap), other current liabilities (lco) and other liabilities (lo). Ex- clude if abs(prc) < 5 or AssetTurnover < 0.
Beta	CAPM beta	Fama and MacBeth	1973	1926	1968	Coefficient of a 60-month rolling window regression of monthly stock returns minus the riskfree rate on market return minus the risk free rate (ewretd - rf). Exclude if estimate based on less than 20 months of returns.
BetaSquared	CAPM beta squared	Fama and MacBeth	1973	1926	1968	Square of Beta (defined above).

Continued on next page

Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
BetaTailRisk	Tail risk beta	Kelly and Jiang	2014	1963	2010	Each month, compute the 5th percentile over daily returns over all firms. For all daily return observations with return below that 5th percentile, compute the average of (log(ret/5th per- centile of cross-sectional return distribution). Call that average tailEX. BetaTailRisk is the coefficient of a 120-month rolling re- gression of a firm's stock return on tailEX. Exclude if price less than 5 or share code greater than 11.
BidAskSpread	Bid-ask spread	Amihud and Mendelsohn	1986	1961	1980	Spread estimates from Shane Corwin's website (https://www3.nd.edu/ scorwin/) divided by price (abs(prc)).
BM	Book to market	Fama and French	1992	1963	1990	Log of annual book equity (ceq) over market equity (see above).
BMent	Enterprise component of BM	Penman Richardson Tuna	2007	1961	2001	(ceq + che - dltt - dlc - dc - dvpa+ tstkp) / (mve_c + che - dltt - dlc - dc - dvpa+ tstkp). Exclude if price less than 5.
BPEBM	Leverage component of BM	Penman Richardson Tuna	2007	1961	2002	BP - EBM, where BP = (ceq + tstkp - dvpa)/(shrout*abs(prc)), and EBM is defined above. Exclude if price less than 5.
Cash	Cash to assets	Palazzo	2012	1972	2009	Ratio of quarterly cash and short-term investments (cheq) and total assets (atq).
CBOperProf	Cash-based operating profitability	Ball et al	2016	1963	2014	Revenue (revt) minus cost (cogs) - (administrative expenses (xsga) - R&D expenses (xrd)) minus annual change in receivables (rect), annual change in investment (invt) and annual change in prepaid expenses, plus annual change in current deferred rev- enue (drc), long-term deferred revenue (drlt), accounts payable (ap) and accrued expenses (xacc), all divided by total assets (at) in year *t*-1. Replace all variables in the numerator with 0 if they are missing. Exclude if share code is greater 11, market value of equity, BM or total assets are missing, or if SIC code between 6000 and 6999.
CFPcash	Operating Cash flows to price	Desai, Rajgopal, and Venkatachalam	2004	1973	1997	Operating cash-flow (oancf) divided by market value of equity. If operating cash-flow is missing, replace by difference betwee net income (ib) and level of accruals, where the latter is the an- nual change in current assets (act) minus the annual change in cash and short-term investments (che), minus the annual change in current liabilities (lct) plus the annual change in debt in cur- rent liabilities (dlc) plus the annual change in payable income taxes (txp) plus depreciation (dp).
CFPinc	Cash flow to market	Lakonishok et al	1994	1968	1990	Net income (ib) plus depreciation (dp) divided by market equity. Exclude NASDAQ stocks.
ChATurn	Change in Asset Turnover	Soliman	2008	1984	2002	Annual change in AssetTurnover (defined above). Exclude if price less than 5.
ChCOA	Change in current operating assets	Richardson et al	2005	1962	2001	Difference in current operating assets (total current assets (act) minus cash and short-term investments (che)) between years *t*-1 and t, scaled by average total assets (at) in years *t*-1 and t.

Continued on next page

Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
CCChCol	Change in current operating liabilities	Richardson et al	2005	1962	2001	Difference in current operating liabilities (total current liabilities (lct) minus debt in current liabilities (dlc)) between years *t*-1 and t, scaled by average total assets (at) in years *t*-1 and t.
ChDeprToPPE	Change in depreciation to gross PPE	Holthausen and Larcker	1992	1978	1988	Annual percentage change in the ratio of depreciation (dp) to property, plant and equipment (ppent).
ChDRC	Deferred Revenue	Prakash and Sinha	2012	2002	2007	Annual change in deferred revenue (drc) scaled by average total assets (at) in *t*-1 and t. Exclude if negative book equity (ceq), deferred revenue equal to 0 in both years, revenue less than 5m, or SIC code between 6000 and 6999.
ChEQ	Sustainable Growth	Lockwood and Prombutr	2010	1964	2007	Ratio of book equity (ceq) to book equity in the previous year. Include only if book equity is positive this year and last year.
ChEqu	Change in equity	Richardson et al	2005	1962	2001	Difference in book equity (ceq) between years *t*-1 and t, scaled by average total assets (at) in years *t*-1 and t.
ChFAccrual	Change in Forecast and Accrual	Barth and Hutton	2004	1981	1996	Within upper half of Accruals distribution, equal to 1 if mean earnings estimate increased relative to the previous month. 0 if it decreased.
ChFinLiab	Change in financial liabilities	Richardson et al	2005	1962	2001	Difference in financial liabilities (sum of long-term debt (dltt), current liabilitites (dlc) and preferred stock (pstk)) between years *t*-1 and t, scaled by average total assets (at) in years *t*-1 and t.
ChInventory	Inventory Growth	Thomas and Zhang	2002	1970	1997	12 month change in inventory (invt) divided by average total assets.
ChInvestInd	Change in capital inv (ind adj)	Abarbanell and Bushee	1998	1974	1988	Growth in capital expenditure (capx) minus average growth in capital expenditure in the same industry (two-digit SIC). If capx is missing, capital expenditure is defined as the annual change in property, plant and equipment (ppent). Capital expenditure growth is defined as the percentage growth of capx today rela- tive to the average capx over the previous two years (.5*(capx$_*t*- 1$ + capx$_*t*-2$), or as percentage growth relative to the previous year only if *t*-2 is missing.
ChLTI	Change in long-term investment	Richardson et al	2005	1962	2001	Difference in investment and advances (ivao) between years *t*-1 and t, scaled by average total assets (at) in years *t*-1 and t.
ChNAnalyst	Decline in Analyst Coverage	Scherbina	2008	1982	2005	Binary variable equal to 1 if the number of analysts (numest) for next quarter's EPS estimate decreased relative to three months ago, and 0 if it increased.
ChNCOA	Change in Noncurrent Operating Assets	Soliman	2008	1984	2002	Twelve-month change in noncurrent operating assets. Noncur- rent operating assets is ((at - act - ivao) - (lt - dlc - dltt))/at.
ChNWC	Change in Net Working Capital	Soliman	2008	1984	2002	Twelve-month change in net working capital. Net working capi- tal is ((act - che) - (lct - dlc))/at
ChOptVol	Option Volume relative to recent average	Johnson and So	2012	1996	2010	Based off of OptionVolume1. OptionVolume2 = OptionVolume1 / average of OptionVolume1 from months *t*-6 to *t*-1.

Continued on next page

Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
ChPM	Change in Profit Margin	Soliman	2008	1984	2002	Annual change in profit margin PM (profit margin defined be- low). Exclude if price less than 5.
ChRecomm	Change in recommendation	Jegadeesh Kim Krische Lee	2004	1985	1998	(As in MP). If an analyst issues a new strong buy recommen- dation (ireccd == 1), we assign a value of 1 to that event, if an analyst issues any other change in recommendation, we assign a value of -1; we assign 0 if the recommendation is unchanged. The final variable is the average over the constructed variable over all analysts each month.
ChTax	Change in Taxes	Thomas and Zhang	2011	1977	2006	4-quarter change in quarterly total taxes (txtq), scaled by lagged total assets (at).
CompDebtI	Composite debt issuance	Lyandres Sun Zhang	2008	1970	2005	Log of long-term debt (dltt) plus debt in current liabilties (dlc) minus log of the same variable 5 years ago.
ConsRecomm	Consensus Recommendation	Barber Lehavy MicNichols Trueman	2001	1985	1997	Binary variable if the monthly mean of recommendations (ireccd) over analysts is greater than 3, and 0 if it is less or equal than 1.5.
ConvDebt	Convertible debt indicator	Valta	2016	1985	2012	Binary variable equal to 1 if deferred charges (dc) greater than 0 or common shares reserved for convertible debt (cshrc) greater than 0.
CredRatDG	Credit Rating Downgrade	Dichev and Piotroski	2001	1970	1997	A downgrade happens if credit rating (splticrm) decreased by at least one notch relative to the previous month. CredRatDG = 1 if a downgrade happened over the past 3 months.
DebtIssuance	Debt Issuance	Spiess and Affleck-Graves	1999	1975	1989	Equal to 1 if debt issuance (dltis) greater 0 and 0 otherwise. Ex- clude if share code > 11 or missing book-to-market.
DelBreadth	Breadth of ownership	Chen, Hong and Stein	2002	1979	1998	Quarterly change in the number of institutional owners (numin- stowners) from 13F data. Exclude if in the lowest quintile of stocks by market value of equity (based on NYSE stocks only).
DivInd	Dividends	Hartzmark and Salomon	2013	1927	2011	Binary variable equal to 1 if return with dividends (ret) is greater than return without dividends (retx) 11 months ago or 2 months ago, and 0 otherwise or if price less than 5.
DivInit	Dividend Initiation	Michaely Thaler Womack	1995	1964	1988	Define dividend initiation as having paid a dividend in month t (divamt > 0) and not having paid a dividend in the 24 preceding months. DivInit is equal to 1 if a dividend was initiated in the past 12 months and 0 otherwise. Exclude if share code greater 11 and use NYSE stocks only.
DivOmit	Dividend Omission	Michaely Thaler Womack	1995	1964	1988	Define dividend omission as not having paid a dividend in the current month or the two preceding months, but having paid dividends in the 3, 6, 9, 12, 15, 18 months before. DivOmit is equal to 1 if a dividend was omitted in the previous 12 months and 0 otherwise.
DivYield	Dividend Yield	Naranjo et al	1998	1963	1994	4 times latest dividend (divamt) divided by price (prc). Include only if dividend has been paid in all of the past 4 quarters.

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
DolVol	Past trading volume	Brennan Chordia Subrahmanyam	1998	1966	1995	Log of two-month lagged trading volume (vol) times two-month lagged price (prc).
DownForecast	Down forecast EPS	Barber Lehavy MicNichols Trueman	2001	1985	1997	Binary variable equal to 1 if mean earnings forecast (meanest) decreased over the past month.
EarnCons	Earnings Consistency	Alwathainani	2009	1971	2002	Average earnings growth over previous 48 months. Earnings growth is defined as EPS (epspx) minus EPS 12 months ago di- vided by average EPS 12 and 24 months ago. Exclude if price less than 5, absolute value of 12 month earnings growth greater 600%, or earnings growth and earnings growth 12 months ago have different signs.
EarnSupBig	Earnings surprise of big firms	Hou	2007	1972	2001	Average monthly value of EarningsSurprise (defined above) of the 30% largest companies by market value of equity in the same Fama-French 48 industry. Exclude the largest 30% of companies for EarnSupBig (not to compute the anomaly)
EarnSurp	Earnings Surprise	Foster et al	1984	1974	1981	EPS (epspxq) minus EPS twelve months ago - Drift, scaled by standard deviation of that expression. Drift is the average earn- ings growth (EPS - EPS twelve months ago) over the past two years. Exclude if price less than 5
EffFrontier	Efficient frontier index	Nguyen and Swanson	2009	1980	2003	Frontier is the residual of a regression of log(BM) on log(book equity (ceq)), long-term debt (dltt) to assets (at), capital expen- ditures (capx) to revenue (sale), R&D expense (xrd) to revenue, advertising expense (xad) to revenue, property plant and equip- ment (ppent) to assets, EBIT (ebitda) to assets, and dummies for Fama-French's 48 industry definitions. Regression is updated each month with a rolling window of 60 months.
EntMult	Enterprise Multiple	Loughran and Wellman	2011	1963	2009	Market value of equity + long-term debt (dltt) + debt in current liabilities (dlc) + deferred charges (dc) - cash and short-term in- vestments (che) , divided by operating income (oibdp). Exclude if missing book equity or negative operating income.
EP	Earnings-to-Price Ratio	Basu	1977	1957	1971	ib / lag(market value of equity, 6 months). NYSE stocks only. Exclude if EP < 0. Lag simulates the Dec 31 market equity used in original paper
EPforecast	Earnings Forecast	Elgers, Lo and Pfeiffer	2001	1982	1998	Mean earnings estimate (meanest) for next quarter's earnings divided by stock price (prc). Exclude if price less than 1.
EPSForeLT	Long-term EPS forecast	La Porta	1996	1983	1990	Long-term earnings forecast (fgr5yr) lagged by twelve months. Exclude if book equity (ceq), net income (ib), deferred taxes (txdi), dividends (dvp), revenue (sale) or depreciation (dp) is missing.
EPSRevisions	Earnings forecast revisions	Chan et al	1996	1977	1992	Define revisions as the change in the mean earnings estimate (meanest) for the next quarter from month *t*-1 to t, scaled by stock price in month *t*-1. REV6 is the sum of that variable from months *t*-6 to t.

Continued on next page

Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
ExchSwitch	Exchange Switch	Dharan and Ikenberry	1995	1962	1990	Binary variable equal to 1 if a firm switched from AMEX or NASDAQ to NYSE within the past year, or from NASDAQ to AMEX within the past year.
ExclExp	Excluded Expenses	Doyle, Lundholm and Soliman	2003	1988	1999	Difference between unadjusted earnings (EPSActualUnadj) from IBES and quarterly earnings per share (epspiq). Exclude the highest and lowest 1% of values.
FailureProbability	Failure probability	Campbell et al	2008	1981	2003	Failure probability is -9.16 -.058*PRICE + .075*MB - 2.13*CASHMTA -.045*RSIZE + 1.41*IdioRisk - 7.13*EXRETAVG + 1.42*TLMTA - 20.26*NIMTAAVG. PRICE is log(min(abs(prc), 15)); MB is shrout*abs(prc)/ceqq; CASHMTA is cheq/(shrout*abs(prc) + ltq); RSIZE is log(shrout*abs(prc)/ sum of shrout*abs(prc) for the largest 500 companies each month); IdioRisk is defined above, EXRETAVG is the weighted average excess return (log(1 + ret) - log(1 + mktrf)) over the previous 12 months, with weight on month *t*-j being ϕ^j and the sum scaled by $\frac1-\phi1-\phi1^2$; TLMTA is total liabilities (ltq/(shrout*abs(prc)); NIMTAAVG is a weighted average of net income over total assets (ibq/(shrout*abs(prc) + ltq)) over four quarters, with weight $\phiq^ $ on quarter $*t*-q$ and the sum scaled by $\frac1-\phi3^1-\phi1^2$. $\phi = 2^-\frac13$. All input variables are winsorized at the 5th and 95th percentile. Exclude if price less than 1.
FirmAgeMom	Firm Age - Momentum	Zhang	2004	1983	2001	6 month return, restricted to the bottom quintile of the cross-sectional firm age distribution. Exclude if price less than 5 or firm younger than 12 months.
ForecastDispersion	EPS Forecast Dispersion	Diether, Malloy and Scherbina	2002	1976	2000	Standard deviation of earnings estimates (stdev_est) scaled by mean earnings estimate.
GIndex	Governance Index	Gompers et al	2003	1990	1999	Index available from http://faculty.som.yale.edu/andrewmetrick/data.html . The index is only available every 2-3 years for each firm, we replace intermediate missing values with the latest available one. Value-weighted.
GrAdExp	Growth in advertising expenses	Lou	2014	1974	2010	Log of advertising expense (xad) minus log of advertising expense last year. Exclude if price less than 5, xad less than .1 or stock in the lowest decile of market value of equity.
GrCAPX	Change in capex (two years)	Anderson and Garcia-Feijoo	2006	1976	1999	Growth rate of capital expenditures (capx) relative to two years ago. If capx is missing, replace with annual change in property, plant and equipment (ppent).
GrEmp	Employment growth	Bazdresch, Belo and Lin	2014	1965	2010	Change in number of employees (emp) between t -1 and t, scaled by average number of employees in *t*-1 and t. Replace hire with 0 if emp or lagged emp is missing.

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
GrGMToGrSales	Gross Margin growth over sales growth	Abarbanell and Bushee	1998	1974	1988	Define gross margin GM as revenue (sale) minus cost of goods sold (cogs). GrGMToGrSales is the percentage growth of GM relative to average GM in years *t*-1 and *t*-2, minus the percentage growth of revenue relative to average revenue in years *t*-1 and *t*-2. Replace growth rates with growth relative to the previous year only if data for *t*-2 are not available.
GrLTNOA	Growth in Long term net operating assets	Fairfield et al	2003	1964	1993	Annual growth in net operating assets, minus accruals. Net op- erating assets are (rect + invt + ppent + aco + intan + ao- ap- lco- lo) / at. Accruals are (rect- l12.rect + invt - l12.invt + aco - l12.aco - (ap - l12.ap + lco - l12.lco) - dp) / ((at + l12.at)/2)
GrossProf	gross profits / total assets	Novy-Marx	2013	1963	2010	Revenue (sale) - cost of goods solds (cogs), divided by 12 months lagged total assets.
GrSaleToGrInv	Sales growth over inventory growth	Abarbanell and Bushee	1998	1974	1988	Percentage growth in sales (sale) relative to average sales of *t*-1 and *t*-2, minus percentage growth in inventory (invt) relative to average inventory of *t*-1 and *t*-2. Both growth terms are calcu- lated relative to *t*-1 only if *t*-2 is missing.
GrSaleToGrOverhe ad	Sales growth over overhead growth	Abarbanell and Bushee	1998	1974	1988	GrSaleToGrOverHead = Percentage growth in sales (sale) rela- tive to average sales of *t*-1 and *t*-2, minus percentage growth in administrative expenses (xsga) relative to average administra- tive expenses of *t*-1 and *t*-2. Both growth terms are calculated relative to *t*-1 only if *t*-2 is missing. Remove if in the highest quintile of GrSaleToGrOverHead. Returns are nicely monotonic until the highest quintile, consistent with original paper's rank regressions.
Herf	Industry concentration (Herfindahl)	Hou and Robinson	2006	1963	2001	Three-year rolling average of the three digit industry Herfindahl index based on firm revenue (sale). Exclude regulated industries (4011, 4210, 4213 & year $\leq$ 1980; 4512 & year $\leq$ 1978, 4812, 4813 & year $\leq$ 1982, 4900-4999 in any year)
High52	52 week high	George and Hwang	2004	1963	2001	Let temphigh = price / by the maximum daily price over the past twelve months. High52 is the rolling 6 month average of temphigh to simulate the original paper's 6-month holding peri- ods
IdioRisk	Idiosyncratic risk	Ang et al	2006	1963	2000	Standard deviation of residuals from CAPM regressions using the past month of daily data. Value weighted
Illiquidity	Amihud's illiquidity	Amihud	2002	1964	1997	Past twelve month average of: daily return (abs(ret)) divided by turnover((abs(prc)*vol)
IndIPO	Initial Public Offerings	Ritter	1991	1975	1984	1 if IPO in the past 6-36 months. 0 otherwise. IPO dates are taken from Jay Ritter's IPO data available at: http://bear.warrington.ufl.edu/ritter/ipodata.htm . Missing IPO dates imply IndIPO = 0
IndMom	Industry Momentum	Grinblatt and Moskowitz	1999	1963	1995	Weighted average of firm-level 6 month buy-and-hold return. Average is taken over two digit industries each month and weights are based on market value of equity.

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
IndRetBig	Industry return of big firms	Hou	2007	1972	2001	Average monthly return (ret) of the 30% largest companies by market value of equity in the same Fama-French 48 industry. Exclude the largest 30% of companies for IndRetBig (not to com- pute the anomaly!)
IntanBM	Intangible return	Daniel and Titman	2006	1968	2003	In each month, run a cross-sectional regression of a firm's five- year stock return on 5 year lagged BM (defined above) and a constructed regressor that is the change in BM from 5 years ago to today plus the five-year stock return. The residual from that regression is IntanBM.
IntanCFP	Intangible return	Daniel and Titman	2006	1968	2003	In each month, run a cross-sectional regression of a firm's five- year stock return on the 5 year lagged CFP = (net income (ni) plus depreciation (dp))/market value of equity and a con- structed regressor that is the change in CFP from 5 years ago to today plus the five-year stock return. The residual from that regression is IntanCFP.
IntanEP	Intangible return	Daniel and Titman	2006	1968	2003	In each month, run a cross-sectional regression of a firm's five-year stock return on the 5 year lagged EP = net income (ni)/market value of equity and a constructed regressor that is the change in EP from 5 years ago to today plus the five-year stock return. The residual from that regression is IntanEP.
IntanSP	Intangible return	Daniel and Titman	2006	1968	2003	In each month, run a cross-sectional regression of a firm's five- year stock return on 5 year lagged SP (defined above) and a constructed regressor that is the change in SP from 5 years ago to today plus the five-year stock return. The residual from that regression is IntanSP.
IntMom	Intermediate Momentum	Novy-Marx	2012	1926	2010	Stock return between months t-12 and t-6
Investment	Investment	Titman et al	2004	1973	1996	Ratio of capital investment (capx) to revenue (revt) divided by the firm-specific 36-month rolling mean of that ratio. Exclude if revenue less than \$10m.
IO_ShortInterest	Institutional Ownership for stocks with high short interest	Asquith, Pathak and Ritter	2005	1980	2002	Exclude all stocks with short interest (ShortInterest) below .025. IO_ShortInterest is institutional ownership (instown_perc). Keep NYSE Only.
KZ	Kaplan Zingales index	Lamont et al	2001	1968	1997	-1.002* (net income (ni) + depreciation (dp))/total assets (at) + .283*(total assets (at) + market value of equity - book value of eq- uity (ceq) - deferred taxes (txdi))/total assets (at) + 3.319*(debt in current liabilities (dlc) + long-term debt (dltt))/(debt in current liabilities + long-term debt + book value of equity) - 39.368*(Div- idends (divamt)/total assets) - 1.315*(cash and short-term invest- ments (che)/total assets). Replace txdi and divamt with 0 if miss- ing.
Leverage	Market leverage	Bhandari	1988	1946	1981	Total liabilities (lt) divided by market value of equity.
MaxRet	Maximum return over month	Bali et al	2010	1962	2005	Maximum of daily returns (ret) over the previous month
Mom12m	Momentum (12 month)	Jegadeesh and Titman	1993	1964	1989	Stock return between months t-12 and t-1.
Mom1813	Momentum-Reversal	De Bondt and Thaler	1985	1933	1980	Stock return between months t-18 and t-13.

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
Mom1m	Short term reversal	Jegedeesh	1989	1934	1987	Stock return (ret) over the previous month.
Mom36m	Long-run reversal	De Bondt and Thaler	1985	1926	1982	Stock return between months t-36 and t-13.
Mom6m	Momentum (6 month)	Jegadeesh and Titman	1993	1964	1989	Stock return between months t-6 and t-1. Exclude if price less than 5.
Mom6mJunk	Junk Stock Momentum	Avramov et al	2007	1985	2003	Mom6m. Include only stocks with a credit rating (splticrm) of BBB or lower
MomRev	Momentum and LT Reversal	Chan and Kot	2006	1965	2001	Binary variable equal to 1 if firm is in the highest Mom6m quin- tile and the lowest Mom36m quintile, and equal to 0 if firm is in the lowest Mom6m quintile and the highest Mom36m quintile. Exclude if price less than 5.
MomVol	Momentum and Volume	Lee and Swaminathan	2000	1965	1995	Mom6m. Include only stocks in the highest quintile of average trading volume (vol) over the previous 6 months. Exclude NAS- DAQ stocks, if price less than 1 or if stock has been trading for less than 24 months.
Mscore	Mohanram G-score	Mohanram	2005	1978	2001	Examine only stocks in lowest BM quintile. Binary variable based on sum of eight indicator variables which are: 1 if re- turn on assets (ni/average assets) above the two digit indus- try median; 1 i net cash flow to assets (oancf/average assets) above the two digit indstry median; 1 if net cash flow greater than net income; 1 if R&D expense to assets (xrd/average assets) greater than two digit industry median; 1 if capital expenditure (capx/average assets) greater than two digit industry median; 1 if advertising expenses (xad/average assets) greater than two digit industry median; 1 if the volatility of net income over the past 3 years is below the two digit industry median, 1 if the volatility of revenue (revt) over the past 3 years is below the two digit industry median. The final variable is equal to 1 if the sum of the above 8 indicators is greater than 5 and 0 if the sum is less than 2.
NetDebtFinance	Net debt financing	Bradshaw et al	2006	1971	2000	Long-term debt issuance (dltis) minus long-term debt reduction (dltr) minus current debt changes (dlcch), scaled by average total assets (at) in years t-1 and t. Replace missing values of dlcch with 0. Exclude if ratio is greater than 1.
NetDebtPrice	Net debt to price	Penman Richardson Tuna	2007	1961	2001	Long-term debt (dltt) plus debt in current liabilities (dlc) plus preferred stock (pstk) plus preferred dividends in arrears (dvpa) minus treasury stock (tstkp) minus cash and short-term invest- ments (che), scaled by market value of equity. Exclude if SIC between 6000 and 6999, or if missing value for total assets (at), net income (ib), common shares outstanding (csho), book value of equity (ceq) or price close fiscal year (prcc_f). Keep only 3rd B/M Quintile, following Table 4 (and in contrast to Table 1).
NetEquityFinance	Net equity financing	Bradshaw et al	2006	1971	2000	Sale of common stock (sstk) minus purchase of common stock (prstkc), scaled by average total assets (at) from years t and t-1. Exclude if absolute value of ratio is greater than 1.
NetPayoutYield	Net Payout Yield	Boudoukh et al	2007	1984	2003	Dividends (dvc) plus purchase of common and preferred stock (prstkc) minus sale of common and preferred stock (sstk), di- vided by market value of equity.

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
NOA	Net Operating Assets	Hirshleifer et al	2004	1964	2002	Difference between operating assets and operating liabilities, scaled by lagged total assets. Operating assets are total assets (at) minus cash- and short-term investments (che), operating li- abilities are total assets minus long-term debt (dltt), minority interest (mib), deferred charges (dc) and book equity (ceq).
NumEarnIncrease	Number of consecutive earnings increases	Loh and Warachka	2012	1987	2009	Number of 4-quarter net income (ibq) increases over the previ- ous 2 years.
OperLeverage	Operating Leverage	Novy-Marx	2010	1963	2008	Sum of administrative expenses (xsga) and cost of goods sold (cogs), scaled by total assets (at). Use xsga = 0 if xsga is missing.
OperProf	operating profits / book equity	Fama and French	2006	1977	2003	Revenue (revt) minus cost (cogs) - administrative expenses (xsga) - interest expenses (xint), scaled by book value of equity (ceq). Exclude smallest size tercile.
OptVol	Option Volume to Stock Volume	Johnson and So	2012	1996	2010	Total monthly option volume (volume) over all puts and calls, divided by monthly stock trading volume (vol). Exclude if price less than 1 or share code greater 11 or option volume or stock volume data are missing for the previous month.
OrderBacklog	Order backlog	Rajgopal et al	2003	1981	1999	Order backlog (ob) divided by average total assets (at) in years *t*-1 and t. Exclude if order backlog is 0.
OrgCap	Organizational Capital	Eisfeldt and Papanikolaou	2013	1970	2008	Defined recursively. Initialize with OrgCap = 4*general expenses (xsga) in the first year, and calculate as .85*OrgCap previous year + xsga current year thereafter. Scale by total assets (at).
OScore	O Score	Dichev	1998	1981	1995	OScore = -1.32 - .407*log(at/GNP deflator) + 6.03*(lt/at) - 1.43*((act - lct)/at) + .076*(lct/act) - 1.72*I(lt > at) - 2.37*(ib/at) - 1.83*(fopt/lt) + .285*(ib + ib$_t-12$ + ib$_t-24$ < 0) - .521*((ib - ib$_t-12$)/(abs(ib) + .abs(ib$_t-12$))). fopt = oancf if fopt is missing. Exclude if SIC code between 3999 and 4999, or greater than 5999. Exclude if price less than 5. Then exclude if OScore is in bottom quintile of OScore (original paper shows non-monotonic returns, as does our replication)
PayYield	Payout Yield	Boudoukh et al	2007	1984	2003	Sum of dividends (dvc), purchase of common and pre- ferred stock (prstkc) and max(preferred stock redemption value (pstkrv), 0), divided by lag(market value of equity, 6 months). Exclude if PayoutYield $\leq$ 0.
PctAcc	Percent Operating Accruals	Hafzalla et al	2011	1989	2008	Income before extraordinary items (ib) minus net cash flow (oancf) divided by absolute value of ib. If oancf is missing, Pc- tAcc is defined as ((act - act$_t-12$) - (che - che$_t-12$) - ((lct - lct$_t-12$) - (dlc - dlc$_t-12$) - (txp - txp$_t-12$) - dp))/abs(ib). In either case, if ib is equal to 0, divide by .01 instead. Exclude if price less than 5.

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
PctTotAcc	Percent Total Accruals	Hafzalla et al	2011	1989	2008	Net income (ni) minus (purchase of common and preferred stock (prstkcc) minus sale of common and preferred stock (sstk) plus dividends (dvt), cash flow from operations (oancf), from financ- ing (fincf) and investment (ivncf)). Scaled by absolute value of net income.
PensionFunding	Pension Funding Status	Franzoni and Marin	2006	1980	2002	FR = (FVPA - PBO), scaled by market value of equity. FVPA is pbnaa from 1980 to 1986, pplao + pplao from 1987 to 1997, and pplao after 1997. PBO is pbnvv from 1980 to 1986, pbpro + pbpru from 1987 to 1997, and pbpro after 1997. Exclude if price less than 5 or shrcd > 11.
Price	Price	Blume and Husic	1972	1932	1971	Log of absolute value of price (prc).
PriceDelay	Price delay	Hou and Moskowitz	2005	1964	2001	Regress daily stock return (ret) on market return (mktrf) in $t, *t*- 1, \ldots, *t*-4$ with observations over the previous year. Trim the highest and lowest 1% of estimated coefficients. Define PriceDe- lay as the ratio of 1*beta on mktrf$_*t*-1$ + 2*beta on mktrf$_*t*-2$ + 3*beta on mktrf$_*t*-3$ + 4*beta on mktrf$_*t*-4$, and beta on mktrf$_t$ + beta on mktrf$_*t*-1$ + beta on mktrf$_*t*-2$ + beta on mktrf$_*t*-3$ + beta on mktrf$_*t*-4$. The final variable is the average of that ratio over the previous month.
Profitability	earnings / assets	Balakrishnan, Bartov and Faurel	2010	1976	2005	Quarterly earnings per share (epspxq) times quarterly shares outstanding used to calculate EPS (cshprq) divided by total as- sets (at). Exclude if price less than 1.
ProfitMargin	Profit Margin	Soliman	2008	1984	2002	Net income (ni) over revenue (revt). Exclude if price less than 5.
Pscore	Piotroski F-score	Piotroski	2000	1976	1996	Sum of nine indicator variables which are: 1 if net income (ib) greater 0; 1 if net cash flow (oancf) greater 0; 1 if return on as- sets (ib/at) increased relative to previous year; 1 if net cash flow greater net income; 1 if long-term debt to assets (dltt/at) de- clined over the previous year; if current assets to current liabili- ties (act/lct) increased over the previous year; 1 if ebit/sale (ebit = ib + txt + xint) increased over the previous year; 1 if revenue to assets increased over the previous year; 1 if shrout $\leq$ shrout last year. Include highest quintile of book-to-market only. Exclude if missing any of the input variables.
RD	R&D over market cap	Chan et al	2001	1975	1995	R&D expense (xrd) over market value of equity.
RDIPO	IPO and no R&D spending	Gou et al	2006	1980	1995	Binary variable equal to 1 if R&D expense (xrd) = 0 and IndIPO=1. 0 otherwise
RDirtSurp	Real dirty surplus	Landsman, Miller, Peasnell and Yeh	2011	1976	2003	Define Dirty Surplus as annual change in marketable securities adjustment msa plus annual change in retained earnings adjustment (recta) + .65 times the annual change in min(Unrecognized prior service cost (pcupsu) – Pension additional minimum liability (paddml),0). Real dirty surplus is the annual change in book dividends preferred (dvp)) + dividends (divamt) - end-of-fiscal- year-stock-price (prcc_f)*annual change in common shares outstanding (csho).

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
RealEstate	Real estate holdings	Tuzel	2010	1971	2005	Industry-adjusted value of real estate holdings. Real estate holdings are calculated as: PPE Buildings at cost (fatb) plus PPE Leases at cost (fatl), divided by PPE (ppegt). Use ppent if ppegt is missing. Subtract monthly industry-mean at the 2 digit SIC level.
RetConglomerate	Conglomerate return	Cohen and Lou	2012	1977	2009	Identify conglomerate firms as those with multiple OPSEG or BUSSEG entries in the Compustat segment data (and require that at least 80% of firm's total assets are covered by segment data). Compute monthly stock return at the 2-digit SIC level for stand-alone (non-conglomerate) firms only, and match those returns to conglomerates' segments. Compute weighted conglomerate return as the industry return of stand-alone companies, weighted with a conglomerate's total sales in each industry.
RevenueSurprise	Revenue Surprise	Jegadeesh and Livnat	2006	1987	2003	Define revenue per share as quarterly revenue (revtq) divided by quarterly common shares outstanding (cshprq). RevenueSurprise is the 4-quarter change in revenue per share minus the average 4-quarter change in revenue per share over the previous 2 years. RevenueSurprise is scaled by its standard deviation over the previous 2 years. Exclude if price less than 5.
RIO_BM	Inst Own and BM	Nagel	2005	1980	2003	Residual institutional ownership (RIO) is defined as log(institutional ownership (instown_perc)/(1-institutional ownership)) + 23.6 - 2.89*log(market value of equity) +.08*log(market value of equity)$2^$. Replace instown_perc with 0 if it is missing, with .9999 if it's above .9999, and with .0001 if it's below .0001. RIO_BM is a binary variable equal to 1 if a firm is in the highest quintile of the monthly RIO distribution and has BM below the cross-sectional median, and 0 if a firm is in the lowest quintile of RIO and has BM below the median.
RIO_Disp	Inst Own and Forecast Dispersion	Nagel	2005	1980	2003	Binary variable equal to 1 if RIO (defined above) is in the highest quintile and ForecastDispersion (defined above) is above the median, 0 if RIO is in the lowest quintile and ForecastDispersion is above the median.
RIO_IdioRisk	Inst Own and Idio Vol	Nagel	2005	1980	2003	Binary variable equal to 1 if RIO (defined above) is in the highest quintile and monthly IdioRisk (defined above) is above the median, 0 if RIO is in the lowest quintile and IdioRisk is above the median.
RIO_Turnover	Inst Own and Turnover	Nagel	2005	1980	2003	Binary variable equal to 1 if RIO (defined above) is in the highest quintile and monthly turnover (vol/shrout) is above the median, 0 if RIO is in the lowest quintile and turnover is above the median.

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
RoE	net income / book equity	Haugen and Baker	1996	1979	1993	Net income (ni) over book value of equity (ceq). Exclude if price less than 5.
SalesGr	Revenue Growth Rank	Lakonishok et al	1994	1968	1990	Rank firms by their annual revenue growth each year over the past 5 years. MeanRankRevGrowth is the weighted average of ranks over the past 5 years, that is, MeanRankRevGrowth = (5*Rank$_t-1$ + 4*Rank$_t-2$ + 3*Rank$_t-3$ + 2*Rank$_t-4$ + 1*Rank$_t-5$)/15. Exclude NASDAQ stocks.
SalesToPrice	Sales-to-price	Barbee et al	1996	1979	1991	Ratio of annual sales (sale) to market value of equity.
Seasonality	Return Seasonality	Heston and Sadka	2008	1965	2002	Average return in the same month over the preceding 5 years. Exclude NASDAQ stocks.
SEO	Public Seasoned Equity Offerings	Loughran and Ritter	1995	1975	1984	Binary variable equal to 1 if seasoned equity offering within the previous 12 months. SEO data are from SDC.
ShareIs1	Share issuance (5 year)	Daniel and Titman	2006	1968	2003	5-year growth in number of shares. Number of shares is calcu- lated as shrout/cfacshr to adjust for splits.
ShareIs5	Share issuance (1 year)	Pontiff and Woodgate	2008	1970	2003	Growth in number of shares between *t*-18 and *t*-6. Number of shares is calculated as shrout/cfacshr to adjust for splits.
ShareRepurchase	Share repurchases	Ikenberry, Lakonishok and Vermaelen	1995	1980	1990	Binary variable equal to 1 if stock repurchase indicated in cash flow statement (prstkc > 0), and 0 if prstkc = 0.
ShareVol	Share Volume	Datar Naik Radcliffe	1998	1962	1991	Sum of monthly share trading volume (vol) over the previous three months, scaled by 3 times common shares outstanding (shrout). Drop if ShareVol is below its median
SinStock	Sin Stock (selection criteria)	Hong and Kacperczyk	2009	1926	2006	Using Compustat Segment data, sinAlgo is defined as a binary variable equal to 1 if at least one segment of a firm is listed as being in at least one of the following industries: sic $\geq$ 2100 & sic $\leq$ 2199, sic $\geq$2080 & sic $\leq$ 2085, NAICS in \7132, 71312, 713210, 71329, 713290, 72112, 721120\. As in the original paper, we assume that the sin stock indicator applies to the entire history and future of the identified firm. sinAlgo is equal to 0 if the firm is not identified in the CS Segment data as a sin stock and if the firm is in one of the following industries: (sic $\geq$ 2000 & sic $\leq$ 2046) OR (sic $\geq$ 2050 & sic $\leq$ 2063) OR (sic $\geq$ 2070 & sic $\leq$ 2079) OR (sic $\geq$ 2090 & sic $\leq$ 2092) OR (sic $\geq$ 2095 & sic $\leq$ 2099).
Size	Size	Banz	1981	1926	1975	Log of monthly market value of equity (abs(prc)*shrout)).

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
Skew1	Volatility smirk	Xing, Zhang and Zhao	2010	1996	2005	Using OptionMetrics data, among options with duration be- tween 10 and 60 days, implied volatility of put option with mon- eyness closest to but above 1 minus implied volatility of call option with moneyness closest to but below 1.
ShortInterest	Short Interest	Dechow et al	2001	1976	1993	Short-interest from Compustat (shortint) scaled by shares out- standing (shrout). Short-interest data are available bi-weekly with a four day lag. We use the mid-month observation to make sure data would be available in real time.
SmileSlope	Slope of smile	Yan	2011	1996	2005	Using OptionMetrics data, average implied volatility of put op- tions with duration between 15 and 30 days and rounded delta of -.5 minus average implied volatility of call options with dura- tion between 15 and 30 days and rounded delta of .5.
Spinoff	Spinoffs	Cusatis et al	1993	1965	1988	Spinoffs are identified as all observations in the CRSP acquisi- tion file with valid acperm entry. Spinoff is a binary variable equal to 1 if a firm is identified in the CRSP Acquisition data and if it has at most one year of history in the CRSP stock return data. Spinoff is equal to 0 otherwise.
StdTurnover	Turnover volatility	Chordia Roll Subrahmanyam	2001	1966	1995	Standard deviation of turnover (vol/shrout) over the past 36 months.
SurpriseRD	Unexpected R&D increase	Eberhart et al	2004	1974	2001	Binary variable equal to 1 if: R&D (xrd) scaled by revenue (revt) is positive, R&D scaled by total assets (at) is positive, annual R&D growth is greater than 5%, annual growth in R&D over total assets is greater than 5%. SurpriseRD is 0 otherwise.
Tangibility	Tangibility	Hahn and Lee	2009	1973	2001	Cash and short-term investments (che) plus .715*receivables (rect) + .547*inventory (invt) + .535* property, plant and equip- ment (ppent), scaled by total assets (at). Only defined for man- ufacturing firms (SIC $\geq$ 2000 and SIC <4000). Exclude the lowest tercile of manufacturing firms by total assets.
Tax	Taxable income to income	Lev and Nissim	2004	1973	2000	Ratio of Taxes paid and tax share of net income. Numerator is defined as the sum of foreign (txfo) and federal (txfed) income taxes. If either one is missing, numerator is defined as total taxes (txt) minus deferred taxes (txdi). Denominator is the product of the prevailing tax rate and net income (ib). Tax rate is .48 before 1979, .46 from 1979 to 1986, .4 in 1987, .34 between 1988 and 1992 and .35 from 1993 onwards. If net income is negative, and the numerator is positive, tax is defined as 1. Exclude if price less than 5.
UpForecast	Up Forecast	Barber Lehavy MicNichols Trueman	2001	1985	1997	Binary variable equal to 1 if mean analyst earnings forecast for the next quarter (meanest) has improved over the previous month, and 0 otherwise.

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Table A.1 (continued)

Acronym	Description	Author(s)	Pub year	Sample Start	Sample End	Description
VarCF	Cash-flow variance	Haugen and Baker	1996	1979	1993	Rolling variance of (ib+dp)/mve_c over the past 60 months (minimum 24 months data required).
VolMkt	Volume to market equity	Haugen and Baker	1996	1979	1993	Average monthly dollar trading volume (vol*abs(prc)) over the previous 12 months, scaled by market value of equity. Exclude if price less than 5.
VolSD	Volume Variance	Chordia Roll Subrahmanyam	2001	1966	1995	Rolling standard deviation of monthly trading volume (vol) over the past 36 months (require at least 24 observations). Include only NYSE stocks.
VolumeTrend	Volume Trend	Haugen and Baker	1996	1979	1993	Rolling coefficient from regressing monthly trading volume on a linear time trend over a window of 60 months (require that at least 30 exist). Scale coefficient by 60-month average of trading volume.
XFIN	Net external financing	Bradshaw et al	2006	1971	2000	Sale of common stock (sstk) minus dividends (dv) minus purchase of common stock (prstkc) plus long-term debt issuance (dltis) minus long-term debt reductions (dltr). Scaled by total assets (at).
ZeroTrade	Days with zero trades	Liu	2006	1960	2003	In each month, count the number of days with no trades. Define zerotrade as the number of days without trades plus (the sum of monthly turnover (vol/shrout) divided by 48*10$5^$), multiplied by 21/number of trading days per month. Zerotrade is the 6-month average of that variable.
ZScore	Altman Z-Score	Dichev	1998	1995	1981	1.2*(current assets (act) - current liabilities (lct))/total assets (at) + 1.4*(Retained earnings (re)/total assets (at)) + 3.3*(net income (ni) + interest expense (xint) + total taxes (txt))/total assets (at) + .6*(market value of equity/Total liabilities (lt)) + revenue (revt)/ total assets (at). Include only NYSE stocks. Exclude if SIC code between 4000 and 4999, or above 5999. Exclude if ZScore is in bottom quintile of ZScore (original paper shows non-monotonic returns, as does our replication)