MACRO-ECONOMICS AND THE FACTOR MOMENTUM EFFECT

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Abstract

Macro-economic effects and investor sentiment are both regarded as possible drivers of the stock momentum effect. Given the fact that stock momentum is an indirect form of factor momentum, because factor momentum explains stock momentum but not vice versa, these factors could also be possible drivers of the factor momentum effect. However only investor sentiment has been considered in the research until now and the difference in factor momentum returns between high sentiment and low sentiment periods was not found to be significant in any paper. This thesis therefore proposes macro-economic variables as predictors of future factor momentum returns. Volatility and long term treasury yield were found to have a strong significant positive effect and the term spread was found to have a strong significant negative effect on factor momentum returns. Inflation and unemployment rate were not significant predictors. The adjusted R^2 of this predictive model is 5.6%.

Keywords: Macro-Economics; Prediction; Factor Momentum; Stock Momentum; Sentiment

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1. Introduction and Theoretical Framework

1.1 Inefficient Markets

Although research about the outperformance of either active or passive investing is somewhat mixed in its conclusions in the shorter term, active investment managers and their funds do not seem to consistently outperform the market over longer time periods (French, 2008). This is in line with the efficient market hypothesis (EMH), because if the stock market reflects all available information a long-term outperformance through individual stock selection should be impossible (Fama,1970). In this case individual stock returns are mainly a function of the exposure to market risk and they should follow the standard capital asset pricing model (CAPM) (Sharpe, 1964).

Researchers found however that by investing in firms with certain characteristics a significant outperformance could be achieved relative to the CAPM. These *"abnormal returns"* that are achieved by (mainly) creating zero-cost long-short portfolios cannot be explained by the CAPM and should therefore be considered as stock market anomalies. Banz (1981) found for example that smaller firms had higher risk-adjusted returns in comparison to bigger firms and that this "size effect" or "size premium" had been in existence for at least 40 years. Basu (1977) on the other hand found that firms with a low price-to-earnings ratio outperformed firms with a high price-to-earnings ratio and that this "value premium" also violated the strong form of the efficient market hypothesis and the standard capital asset pricing model.

Fama and French (1993) followed these new discoveries and also argued that the exposure to market risk or the market β's does not reliably explain the cross-section of average returns and that other variables have considerable explanatory power. Following (among others) the earlier research of Banz (1981), Bhandari (1988), Basu (1983) and Rosenberg, Reid and Lanstein (1985), they researched multiple variables on their own and jointly and constructed the so-called "Fama-French 3-factor model" (FF3). This model uses the exposure to market risk (β); a size premium (SMB), where smaller companies are expected to outperform bigger companies and a value premium (HML), where value stocks are expected to outperform growth stocks.

This model and related research into factors inspired researchers to find multiple other factors that gave "risk-adjusted" or "abnormal" returns and to create statistically significant models with variations of those factors. A well-cited example of this is the research of Jegadeesh and Titman (1993). They found that there was a certain "*momentum effect*" in the stock market.

Selling stocks that performed poorly and buying stocks that performed well in the past (creating a net-zero investment portfolio) resulted in a significant positive excess return for certain holding periods. A variation of this anomaly was later added as a factor to the Fama-French 3-factor model to create the Carhart 4-factor model (Carhart, 1997).

However as more and more anomalies were discovered, they could not be simply added as a factor to an existing multi-factor model. There could be overlapping factors like the fact that value-companies often have low volatility or even contradicting factor findings, like different momentum holding periods and different stock reversal periods that would overlap each other. Hou et al. (2015) even argued that half of the found "factors" up to the point of their research were actually insignificant in the cross-section. In addition to the market factor and the size factor, they themselves added an investment factor and a profitability factor to create a 4-factor model (q^4-model) to try and capture the remaining statistically significant anomalies that were challenging for the Fama-French 3-factor model.

This discussion within the anomaly and factor-model research turned into an optimization problem to minimize the amount of factors in the model, while maximizing the explanatory and predictive power of the model, where every team of researchers had a different answer. Fama and French (2015) for instance also found a profitability factor and investment factor to be statistically significant, but could not find a good reason behind the omission of a value premium factor (HML) in the q^4-model of Hou et al. (2015). Therefore they created the Fama-French five-factor model (FF5) by adding the profitability factor and the investment factor to their original three-factor model of the exposure to market risk factor, the size premium factor and the value premium factor, which was essentially similar to adding the value premium factor (HML) to the q^4-model.

Blitz et al. (2018) had in response some concerns with this new Fama-French five-factor model questioning the addition of the profitability factor and the investment factor. Furthermore, they added that the existence of a low-volatility or low-beta anomaly challenged both the original FF3-model and the new FF5-model and wondered why the significant momentum effect already discovered by Jegadeesh and Titman in 1993 and integrated into a model by Carhart in 1997 was not considered as an additional factor. Fama and French (2018) did in their own words "*despite theoretical justification*" and *"somewhat reluctantly"* add a momentum-factor to their FF5-model, but warned that to prevent factor modeling becoming "*meaningless dredging"* the number of factors should be limited and that multiple comparison issues could arise due to the comparison of a large amount of models. Recently Hou et al. (2021) still added an expected growth factor to their q^4-model, creating a q^5-model that according to their research methods outperforms all the other latest models. The underlying issue however still remained; the research and discovery of more and more stock market anomalies relative to the already existing models had created an untamed *"zoo of factors"*.

1.2 The Factor Zoo

This term, which was first used by Cochrane (2011), describes the fact that there has been an inflationary growth of factors especially in the last few years. Harvey et al. (2016) showed that there had been at least 316 unique factors tested and that most of these factors were proposed in the last decade. Follow-up research by Harvey and Liu (2019) indicates furthermore that this trend is not slowing down. This quantity of researched factors intuitively raises the question if these stock market anomalies can really all be considered lasting factors.

The first issue according to Harvey et al. (2016) is the amount of data mining or data dredging in this space. This means that the same limited amount of data is analyzed repeatedly to find any significant relationship between variables often without having a clear hypothesis in mind beforehand. The result could be that a lot of the historically discovered factors are actually significant by chance. In addition to this, some discovered weaker relationships in the data could also be made significant through p-hacking and data manipulation. Harvey (2017) noted that in financial economics the selection of certain time periods and the exclusion of certain outliers have led to the discovery of many factors that would not be significant otherwise.

Because of all these issues Chordia, Goyal, and Saretto (2020) estimated that up to 45% of the findings could be false if multiple hypothesis testing is not taken into account by the researchers. Hou, Xue and Zhang (2020) even claimed that half of the research into factors cannot be replicated. To restore the credibility of cross-sectional asset pricing Chen and Zimmermann (2021) launched an open source dataset, where the returns of 319 characteristics are provided. Their research showed that all (100%) of the predictors were replicable and they found that the significance level in most cases was comparable to the original papers. However this does not mean that all critique is unfounded. Data-mining and p-hacking are still reasonable concerns and organization of factors is difficult. It still remains an untamed *"zoo of factors"*.

This is also an important issue for the practical side of this research. The finding of consistent factors is apart from a statistical exercise also relevant for investors that want to get higher risk-adjusted returns. The amount of available factors however makes it difficult to make the right choice. Hsu et al. (2015) from the asset management firm *Research Affiliates* proposed that for a factor to be investable it should be studied enough times over many years; it should be persistent across different time periods and countries and it should retain a robust definition. They found that only the value and the low-beta or low-volatility factors were investable. In their research the momentum and the illiquidity factors showed promise, but the transaction costs might be too high in practice in their view.

Beck et al. (2016) agreed with the conclusions from Hsu et al. (2015) that the value and the low-beta factor are robust and suitable for investment, while factors like size and quality are less promising. They argued however that although momentum and illiquidity factors might not be suitable for indexation, active management could still deliver significant returns when pursuing these strategies. Blitz and Van Vliet (2018) from the asset management firm *Robeco* proposed however that factor investing should simply be focused on low return volatility, high net payout yield and strong price momentum, because according to their research these factors are responsible for the most important factor premiums. The selection framework made by Gupta et al. (2022) from the asset management firm *Invesco* also suggests selecting the low-volatility and momentum factors. They however also find compelling evidence for investing in the value and quality factors.

These proposed selections of factors are reflected in the current Exchange Traded Funds (ETFs) that these asset management companies offer. Low-volatility, Momentum, Quality and Value factor-funds are offered at almost all big asset management firms, while Size and Dividend Yield or Income factor-funds are also prevalent.[1] Although most firms offer multi-factor ETF choices, investors still have to make a selection of which factors to include in their investing strategy and when to invest.

[1]) These current offerings can be found on the internet site of the firms, such as:
https://www.ishares.com/us/strategies/smart-beta-investing (BlackRock) ;
https://www.invesco.com/us/resources/factor-investing (Invesco) ;
https://www.robeco.com/en-int/products/strategies/factor-quant-equity (Robeco)
https://advisors.vanguard.com/investments/all?strategy=Factor (Vanguard)

1.3 Factor Momentum

In an ideal scenario investors would want to invest in the best performing factors and possibly even go short (if their risk-profile allows this) in the worst performing factors to maximize possible returns and repeat this process for every optimal time period. Although this seems impossible, Haddad et al. (2020) argued that by unifying cross-sectional factor estimation and time-series predictability of returns it should be possible to construct an optimal factor timing portfolio. This is however still mostly statistical theory, which is difficult to put into practice. Nevertheless, factor timing was still found to be very valuable and capable of superior returns. Although it might be suboptimal; one of the possible ways to still be able to use this strong combination of factor investing and factor timing is to make use of the concept of "*Factor Momentum Investing".*

Recent research shows that individual factors can in general be reliably timed on their own recent past performance, which shows that factors exhibit momentum (Ehsani & Linnainmaa, 2022; Gupta & Kelly, 2019). Gupta and Kelly (2019) found that the use of this strategy adds significant performance to not only the commonly used factors, like the value factor, but to standard "*normal*" momentum strategies as well. Arnott et al. (2021) later found that this factor momentum fully explains industry momentum. By studying this concept further, Ehsani and Linnainmaa (2022) found that factor momentum actually explains not only industry momentum, but all other forms of momentum as well, which means that industry momentum, individual stock momentum, intermediate momentum and Sharpe momentum do exist, because factor momentum exists. Their conclusion was that stock momentum strategies actually time factors. This means that stock momentum strategies are an indirect form of a factor timing strategy.

It is important to note that although research shows that factor momentum fully explains all other different forms of momentum, that this effect does not exist vice versa (Arnott et al, 2021; Ehsani & Linnainmaa, 2022). The fact that factor momentum is more than stock momentum becomes especially clear at shorter lags. Falck et al. (2022) show that a big portion of the strength of factor momentum comes from just the first lag and argue that if this lag is excluded factor momentum is almost equal to normal stock momentum. In contrast to this, the first lag is normally excluded in the calculation of normal stock momentum, because of short term reversal effects. Factor momentum does therefore not have a short term reversal effect, but instead has significant returns in the first month after the formation period.

This complicated relationship between factor momentum and stock momentum (and short term reversal) in the first period does not undermine the fact that factor momentum fully explains stock momentum. This is because as earlier stated stock momentum normally excludes this first lag. The question therefore still remains what the reason is for the existence of the factor momentum concept and why this persists over time.

1.4 Macro-economic Prediction, Investor Sentiment and Stock Momentum

Because of the fact that factor momentum is a relatively novel concept and the amount of research is still limited, there is currently no specific paper that looks into the reason for the existence of factor momentum yet. There is however research into the underlying mechanism of "normal" stock momentum, which could be extrapolated to factor momentum if the economic theory and logic is sound. Balakrishnan and Barik (2021) explain that there are two major sides as it comes to explaining "normal" stock momentum. One group argues that stock momentum exists mainly because of "*rational"* sources and that macro-economic factors can explain the phenomenon. The other group attributes the stock momentum returns to irrational investor behavior or investor sentiment.

Financial theory suggests that (a selection of) macroeconomic variables should systematically impact stock market returns. Chen, Roll and Ross (1986) found that interest rate spread, unexpected and expected inflation, industrial production and default risk are indeed priced in. Following these results Chordia and Shivakumar (2002) argued that the stock momentum effect might not be due to investor irrationality like other researchers hypothesized, but that macro-economic variables could explain this phenomenon. They found that a model ($R^2 \approx 6\%$) of the lagged macro-economic variables short term treasury bond yield, yearly dividend yield, the term spread (difference in long term and short term treasury bond yield) and the default spread could fully explain stock momentum. The term spread and the short term yield variables both had a strong significant positive effect on the stock momentum returns, while the dividend yield and default spread variables were not significant in every period and were on average positive and negative respectively.

Recently Cooper, Mitrache and Priestley (2022) also looked at the effect of macro-economic variables on the momentum strategy returns (among others) on a more global scale. Using the variables from Chen, Roll and Ross (1986) they found that the effect of the different macro-economic variables was generally the same across different stock markets. The effects of industrial production; unexpected inflation; change in expected inflation and default spread were all positive on stock momentum returns for U.S. stocks, U.K. stocks, European stocks and Japanese stocks. The only exception was the term spread variable, which was zero in the U.K. market and negative in all other markets, where it only reached significance in the European stock market.

Apart from the aforementioned variables, volatility was also studied as a possible macro-economic variable influencing stock momentum returns. Wang and Xu (2015) found that market volatility had a significant negative effect on stock momentum payoffs and that this effect remained significant after adding dividend yield (negative effect and not significant); default rate (negative effect and significant); term spread (positive effect and significant) and short term yield (positive effect and significant) to the model (R^2 = 5.6%). When studying the phenomenon of momentum crashes Daniel and Moskowitz (2016) also found a significant negative effect of market variance on momentum returns. This effect was however no longer significant when an interaction effect with a bear market indicator was added, suggesting a limited predictive effect in low-volatility markets. The findings of Hutchinson and O'Brien (2020) deepened this researched connection between volatility, market states, macro-economic variables and momentum returns. They found that a model consisting of default rate (negative effect and not significant); dividend yield (negative effect and not significant); GDP growth (positive effect and not significant); inflation (negative effect and not significant); market factor (positive effect and significant); short term yield (positive effect and significant); term spread (positive effect and not significant) and unemployment rate (negative effect and not significant) could actually not explain momentum returns.[2] However by combining the volatility of each factor into an index of economic uncertainty a strong significant effect on momentum payoffs was found.

In contrast to this rational explanation of stock momentum with macro-economic variables was the argument that stock momentum exists because of investor sentiment. Antoniou,

[2]) It is important to note that they did not use lagged values of the variables, but only the current values of the variables (Hutchinson & O'Brien (2020)).

Doukas, and Subrahmanyam (2010) showed for instance that momentum returns are only significant in periods of high sentiment. By regressing sentiment on different anomalies including the momentum effect Stambaugh, Yu and Yuan (2012) showed in a different way that a higher sentiment was significant predictor of higher anomaly returns. A deeper look at the results however revealed that the positive effect from investor sentiment on momentum returns was very low and not significant. This effect became even smaller after controlling for macro-economic variables.

Recently however Ashour, Hao and Harper (2023) repeated the findings of Antoniou, Doukas and Subrahmanyam (2010) by showing that momentum returns are only significant in periods of high sentiment (with the additional use of style investing as a variable). These papers that show the significance of investor sentiment treat the sentiment variable however only as a dummy variable (low/high sentiment), while the paper that does not find significance uses sentiment as a continuous variable in the regression. To rule out interference from investor sentiment in the prediction of momentum returns with volatility and macro-economic variables Wang and Xu (2015) also performed a regression with just investor sentiment as a predictor; regressions with investor sentiment and volatility as predictors and a regression with investor sentiment, volatility and macro-economic variables as predictors. They found first of all that investor sentiment on its own was a significant positive predictor of momentum returns. Secondly they found that investor sentiment stayed significant when volatility (negative effect and significant) was added as a predictor. In the last regression however they found that investor sentiment was no longer significant when volatility and macro-economic variables were added as predictors of stock momentum. Cooper, Gutierrez and Hameed (2004) found the exact opposite result. After dividing up the market in high sentiment (UP) and low sentiment (DOWN) periods, macro-economic variables were not significant predictors in either period.

It is in conclusion still difficult to give an answer to the question what the primary driver is of stock momentum returns, whether it is macro-economic variables, investor sentiment or an unknown third option. In my opinion following the economic theory based off of Chen, Roll and Ross (1986), the results from Chordia and Shivakumar (2002) combined with the controlling regressions from Wang and Xu (2015) and the global effect result from Cooper, Mitrache and Priestley (2022) still provide a strong argument for the influence and predictive power of macro-economic variables in relation to momentum returns. That is why these variables should also be tested in predicting factor momentum.

1.5 Prediction of Factor Momentum Returns

The current research into factor momentum returns however seems to be more of a proponent of the theory that investor sentiment is an important driver of the factor momentum returns. The research of Ehsani and Linnainmaa (2022) measures this interaction between investor sentiment and factor momentum by classifying each factor as a winner or loser based on the average return of the past year and calculating the differences between the “winner factors” and “loser factors” for high sentiment periods and low sentiment periods. They found that the difference is significant in the low sentiment period, but not significant in the high sentiment period. Their explanation for this finding is that following Stambaugh, Yu and Yuan (2012) the returns of anomalies/ factors are all higher in a high-sentiment environment. They do however not calculate if the difference between the high sentiment and low sentiment periods is significant. In addition to this, they use an one-year factor momentum calculation, while the factor momentum effect is generally stronger in shorter lags.

Avramov et al. (2017) also looked the interaction between investor sentiment and factor momentum. They found that there was a difference between the factor momentum returns in the high sentiment period and the factor momentum returns in the low sentiment period. They used short lags in the factor momentum calculation, which is (in my opinion) superior to the method of Ehsani and Linnainmaa (2022), but also did not calculate if the discovered difference was significant. Furthermore all factor momentum returns were strongly significant (significant at 1%) for both the high sentiment and low sentiment periods.

Finally, a recent paper by Grobys, Kolari, and Rutanen (2022) looked at the influence of investor sentiment and option implied volatility on factor momentum returns. Their results also showed that there was a difference in factor momentum returns between high and low sentiment periods. However this difference was not significant for all versions of factor momentum and every variation of formation and holding period. Apart from this the option implied volatility scaling was found to increase both the economic magnitude and statistical significance of the factor momentum effect.

Although this research showed an effect of investor sentiment on factor momentum, the difference in factor momentum returns between high sentiment and low sentiment periods was not found to be significant in any paper. Moreover, apart from a small part in the research of Grobys, Kolari, and Rutanen (2022) about the effect of option implied volatility on factor momentum returns, there is still no research into the predictive power of macro-economic variables in factor momentum returns. Following the economic theory based off of Chen, Roll and Ross (1986), the results from Chordia and Shivakumar (2002) combined with the controlling regressions from Wang and Xu (2015) and the global effect result from Cooper, Mitrache and Priestley (2022) with respect to normal stock momentum, this thesis will examine this gap in the research by answering the question:

To what extent can macro-economic variables predict factor momentum returns?

To answer this question, firstly the variation of factor momentum strategy has to be chosen and the returns of that strategy have to be calculated. After that these returns will be regressed on different Fama-French regressions to determine if the factor momentum strategy remains significant after controlling for these factors. By adding a momentum effect and a short-term reversal effect, the relation between the factor momentum effect and momentum (especially at short lags) can also be further analyzed. Lastly, a cross-sectional regression with the factor momentum returns and lagged values of selected macro-economic variables will be done to determine the predictive power of these variables and these results will be compared with aforementioned similar research on normal stock momentum.

2. Data

2.1 Factor Data

Before the returns of a factor momentum strategy can be calculated the underlying factors have to be selected and their individual returns have to be calculated. One way to achieve this is to include every factor by reproducing them in the way of their original paper and calculate their returns for a chosen time period. However recent criticism suggests that a lot of factors should not be considered "real" factors, because they are possibly the result of data-mining, *p*-hacking or they are not even replicable (Harvey, Liu & Zhu, 2016; Hou, Xue & Zhang, 2020). To ensure the quality of the factor momentum returns and this research only "real", consistent and statistically significant factors should be used. Simply replicating every factor for a chosen time period is therefore not an option and a selection of factors has to be made.

To address this criticism about asset pricing research and to create a transparent and organized overview of the current research into factor returns Chen and Zimmerman (2021) looked at 319 cross-sectional stock return predictors from 153 different papers. By replicating the factors in the way of their original research paper, they found that for (almost) all of them the standardized statistics were in line with the original research and also showed a similar level of significance. After replication they sorted these factors in their paper into 161 "clear predictors", that had clear evidence of significant return predictability in their original papers; 44 "likely predictors", that had only mixed evidence for predictability; 14 "not-predictors", that had insignificant evidence for predictability and 100 factors, that only suggested predictability. Furthermore they updated (where possible) the factor returns of all the replicated factors for the years outside of the scope of their original papers and made this dataset publicly available.[3] The 161 "clear predictors" from this dataset are used as a starting point of the research for this thesis.

It is important on one hand to keep this thesis relevant to choose a time-period within this dataset that is current. However on the other hand there has to be enough data to get stronger prediction conclusions and to be able to generalize the results over multiple different economic periods or market cycles. To satisfy both of these conditions the available data from the last 25 years (January 1996 – December 2021) is selected. This led to the exclusion of 17 factors, which meant that there were 144 factors remaining on the basis of which the returns of a Factor Momentum strategy could be calculated.

[3]) This dataset is available at https://www.openassetpricing.com/.

The average of the average return of all these factors over this time-period was 44 basispoints (bp) per month, with the highest average return being the Efficient Frontier Index-factor (a firm efficiency factor) with an average return of 150 bp per month and the lowest average return being the Order Backlog-factor with an average return of negative 9 bp per month. In addition to the Order Backlog-factor two other factors (Abnormal Accruals and Mean Revenue Growth Ranking) had an average negative return in this time-period, while all other factors provided a positive average monthly return.

Although all these factors were significant in the selected time-period of their own studies, it is also interesting to find out if these factors were strong predictors in the chosen time-period in this paper. After performing 144 t-tests there were 68 significant strong predictors ($t > 1.96$), which represent 47% of all factors. In addition there were 13 more relatively strong predictors ($t > 1.645$) for a total of 56% of all factors. This is however not an issue that impacts the quality of the data. The not-significant predictors cannot be excluded after this analysis, because in a real investing scenario the strength of the predictors is not known beforehand. The complete predictor or factor list with their original paper as well as the results of all t-tests can be found in Appendix A.

2.2 Fama-French Factors and Macro-Economic Data

To be able to determine if these factor momentum strategy returns remain significant after controlling for the Fama-French 3-factor model and 5-factor model factors, the excess return of the market factor (MKT-rf), the size factor returns (SMB), value factor returns (HML), profitability factor returns (RMW) and the investment factor returns (CMA) are pulled directly from the Kenneth French online library. To do further analysis of the relation between the factor momentum effect and momentum (especially at short lags), the momentum factor and short term reversal factor returns were also selected.

The selection of macro-economic variables that are used in the prediction models is made based on aforementioned research into the predictive factors of stock momentum and data availability. The selected macro-economic variables that are more directly linked with the stock market are the option implied volatility (VIX-index), term spread (or slope of the yield curve) and the long term treasury bond yield (Chordia & Shivakumar (2002); Cooper, Mitrache and Priestley (2022); Grobys, Kolari, & Rutanen (2022); Wang & Xu (2015)). The more general selected macro-economic variables are the inflation rate and unemployment rate (Cooper, Mitrache and Priestley (2022); Hutchinson and O'Brien (2020)). The data for all of these variables is gathered from the site of the Federal Reserve Bank of Saint Lewis (FRED).

Table 1. Correlation Matrix

	Factor Momentum	Inflation Rate	Volatility	Long Term Yield	Yield Curve	Unemployment Rate
Factor Momentum	1	-.019	.158	.027	-.111	-.144
Inflation Rate	-.019	1	-.076	.227	.090	-.208
Volatility	.158	-.076	1	-.238	.128	-.135
Long term Yield	.027	.227	-.238	1	.423	-.095
Yield Curve	-.111	.090	.128	.423	1	.016
Unemployment Rate	-.144	-.208	-.135	-.095	.016	1

To ensure the quality of the prediction model it is important to confirm that each macro-economic factor is its own independent factor. This can be done by looking at the correlations between the different factors. Table 1 shows that the highest correlation of 42.3% is between the long term yield factor and the yield curve factor. Because of the fact that the long term yield value is used to calculate the slope of the yield curve this connection is logical and does not present a problem. Other notable correlations are the correlation between the VIX and the long term yield; the correlation between inflation and the long term yield and the correlation between inflation and the unemployment rate. These correlations are however expected and not high enough to have a significant (negative) effect on the quality of the predictive model.

3. Methodology

3.1 Factor momentum Construction

Using the gathered factor data, the research of Jegadeesh and Titman (1993) into *"normal"* momentum can also be followed to define a factor momentum strategy. The factors are ranked each month by their average returns over a prior formation period F. After this ranking equal long and short positions are taken in the best and worst performers, which are held for a holding period H. Although there are a lot of different F/H pairs possible, earlier research suggests that a simple F=1/H=1 (1/1) strategy is the best choice. Arnott et al. (2021) found that a 1/1 strategy strongly outperforms a 6/6 strategy by more than 100%. Furthermore, research from Falck et al. (2022) suggests that a big part of the factor momentum return comes from its first lag (F=1) and that any F/H combination other than 1/1 up to the combination 6/6 has actually a lower Sharpe ratio. In contrast to standard stock momentum, the factor momentum strategy therefore does not show a short-term reversal effect, but it shows actually the complete opposite with the strongest return in the first holding month.

Apart from the F/H decision the amount of long positions and opposite short positions also has to be decided. Although a lot of factors have been constructed using this method, there is not an official statistically efficient recommendation. Previous research articles show percentages that vary from selecting 10% up to 30% of the top and bottom performers. To include enough factors, while still maximizing a long-short result the top and bottom 20% are chosen to be included. In the case of 144 factors, this means that the long and short positions contain 29 factors each and that 58 factors are included in total each period.

3.2 Fama-French regressions

After the construction of the factor momentum strategy and calculating their results, it is important to research if these results are still significant after controlling for the Fama-French factors. This can be done by using the following formula's for the Fama-French 3 factor model and Fama-French 5 factor model respectively.

$$R_{i,t} = \alpha + \beta_{MKTRF} * (MKT_t\text{-}rf_t) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t \quad (1)$$

$$R_{i,t} = \alpha + \beta_{MKTRF} * (MKT_t\text{-}rf_t) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{RMW} * RMW_t + \beta_{CMA} * CMA_t \quad (2)$$

In the first formula the factor momentum returns are regressed on the Fama-French 3-factor model with an intercept (α), the excess return of the market factor (MKT-rf), the size factor (SMB) and the value factor (HML). In the second formula the profitability factor (RMW) and investment factor (CMA) are added, which creates a regression of the factor momentum returns on the factors of the Fama-French 5-factor model.

$$R_{i,t} = \alpha + \beta_{MKTRF} * (MKT_t\text{-}rf_t) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{RMW} * RMW_t + \beta_{CMA} * CMA_t + \beta_{MOM} * MOM_t \quad (3)$$

$$R_{i,t} = \alpha + \beta_{MKTRF} * (MKT_t\text{-}rf_t) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{RMW} * RMW_t + \beta_{CMA} * CMA_t + \beta_{MOM} * MOM_t + \beta_{STREV} * STREV_t \quad (4)$$

By adding a momentum factor to the regression (formula 3), it can be analyzed if the factor momentum returns are still significant after controlling for the momentum effect and a possible interaction between the factor momentum returns at short lags and the momentum effect can be determined. Lastly, because of the fact that momentum has a short-term reversal effect, while factor momentum does not display this effect and could be hypothesized to be the opposite, the addition of the short-term reversal factor in formula 4 could also provide further insights into the relation between factor momentum and stock momentum.

3.2 Macro-Economic Prediction

The prediction with macro-economic variables can be done in a similar way as the Fama-French regressions. First the macro-economic predictors are made stationary by taking the first difference. After this, the lagged values of these variables can be used in a regression to predict the factor momentum returns. Formula 5 shows that the predictive model of factor momentum returns at time t ($R_{i,t}$) consists of an intercept (α), the lagged value of inflation (CPI_{t-1}), the lagged value of volatility (VIX_{t-1}), the lagged value of the long term treasury yield ($DGS10_{t-1}$), the lagged value of the term spread ($T10Y2Y_{t-1}$) and the lagged unemployment rate ($UNRATE_{t-1}$).

$$R_{i,t} = \alpha + \beta_{CPI} * CPI_{t-1} + \beta_{VIX} * VIX_{t-1} + \beta_{DGS10} * DGS10_{t-1} + \beta_{T10Y2Y} * T10Y2Y_{t-1} + \beta_{UNRATE} * UNRATE_{t-1} \quad (5)$$

4. Results

4.1 Factor Momentum Returns

Using the described methodology first of all the factor momentum returns were calculated by using a one month formation period (F=1) and an one month holding period (H=1) and going long in the top 20% of factors and going short in the lowest 20% of factors in terms of performance . This strategy earns an average monthly return of 58 basis points during the sample period of the last 25 years, with a *t*-value of 3.06. The mean annualized return of this strategy is 6.96% with an (annualized) standard deviation of 11.47. This return is somewhat on the lower side compared to the returns found in similar research. For a strategy with the same formation and holding period Arnott et al (2021) found a relatively similar mean annualized return of 7.68%, but Ehsani and Linnainmaa (2022) found a significantly higher mean annualized return of 10.49% and Gupta and Kelly (2019) even found a mean annualized return of 11.3%.

Although the difference in returns can somewhat be explained by the selection of the time-period, the most probable reason for the difference is the selection of underlying factors that are the basis of the factor momentum returns. It is logical that the selection of different factors result in a different factor momentum strategy result. Additionally, it is important to note that the amount of factors used in their research is less than half of the factors used in this thesis (43, 51, 65 and 144 respectively). The effect of this is that a lower amount of top-performing and lowest-performing factors each month are weighted heavier in the determination of the factor momentum strategy results, so less factors drive the factor momentum returns.

This is theoretically not a problem, because Ehsani and Linnainmaa (2022) found for instance through randomizing the set of factors of varying size that all of the factor momentum strategy profits could be captured by just rotating among the ten factors that contributed to their strategy profits the most out of the 51 factors they researched. In practice however, it is not possible to know beforehand which and how many factors explain (most of) the strategy. A point could be made to lower the amount of factors by for instance removing one of the factors from a factor-pair that explain a very similar anomaly and that have a very high correlation. In the end however, other than extremes that include the whole universe of researched factors or that include a very low amount of factors (for example $n < 5$) to execute the factor momentum strategy, it is difficult to say if one choice is significantly better than the other.

Table 2. Regression of factor momentum returns on different variations of descriptive and predictive (1st lag) Fama-French models. The * and ** signify that the weight estimate is statistically significantly different from zero at the 5% and 1%, respectively.

	Dependent variable: Factor Momentum							
	Descriptive Models				Predictive Models			
Variable	FF3	FF5	FF6	FF6+R	FF3	FF5	FF6	FF6+R
α	0.67	0.57	0.56	0.69	0.52	0.42	0.45	0.44
	(3.49)**	(3.00)**	(2.89)**	(5.66)**	(2.74)**	(2.10)*	(2.25)*	(2.18)*
β_{MKTRF}	-0.14	-0.08	-0.07	0.08	0.09	0.13	0.10	0.09
	(-3.31)**	(-1.76)	(-1.43)	(2.44)*	(2.05)*	(2.62)**	(2.08)*	(1.75)
β_{SMB}	0.11	0.03	0.03	0.06	-0.06	-0.002	0.01	0.005
	(1.79)	(0.49)	(0.39)	(1.48)	(-0.94)	(-0.04)	(0.12)	(0.07)
β_{HML}	0.03	-0.14	-0.12	-0.003	0.14	0.05	0.01	-0.0001
	(0.52)	(-1.81)	(-1.45)	(-0.07)	(2.47)*	(0.65)	(0.13)	(-0.00)
β_{RMW}		-0.12	-0.13	-0.11		0.16	0.17	0.17
		(-1.46)	(-1.54)	(-2.12)*		(1.79)	(1.94)	(1.92)
β_{CMA}		0.57	0.56	0.40		0.10	0.12	0.13
		(4.93)**	(4.84)**	(-5.37)**		(0.82)	(0.95)	(1.08)
β_{MOM}			0.04	-0.04			-0.07	-0.06
			(0.97)	(-1.67)			(-1.69)	(-1.48)
β_{STREV}				-0.68				0.07
				(-20.64)**				(1.26)
N	299	299	299	299	299	299	299	299
Adjusted R^2	3.11%	10.81%	10.79%	63.67%	2.21%	2.76%	3.37%	3.57%

It is however possible to determine if the factor momentum returns remain significant after controlling for often used and invested-in factors. The results of these regressions, where factor momentum is controlled for the market factor (β_{MKTRF}), the size factor (β_{SMB}), the value factor (β_{HML}), the profitability factor (β_{RMW}), the investment factor (β_{CMA}) , the momentum factor (β_{MOM}) and a short-term reversal factor (β_{STREV}) can be found in table 2 above. The statistically significant intercept or alpha of 67 basis points per month (*t*-value = 3.49) from the first regression suggests that the factor momentum strategy returns remain significant after controlling for the factors of the Fama-French 3-factor model. As expected the alpha and significance do decline after controlling for the added factors of the Fama-French 5-factor model and 6-factor model. An interesting observation is that the addition of the investment factor has a significantly higher impact on the alpha and the significance than the addition of the momentum factor.

It seems counterintuitive that the alpha increases with 13 basis points and in significance after the addition of the short-term reversal factor to the Fama-French 6-factor model. However, as was already discussed in the methodology, research from Falck et al. (2020) found that, unlike stock momentum, factor momentum does not exhibit a short term reversal effect. Moreover the fact that most of the strength of factor momentum comes from the first lag and the fact that a factor momentum strategy with a one month formation and one month holding period (F=1/H=1) is used in this thesis, provides an explanation for this finding. Factor momentum shows almost the exact opposite result as the short-term reversal factor. By adding a very similar opposite factor as an explanatory variable in the regression with other variables the intercept or alpha will increase and the strength or significance will also increase. It is important to note however that Factor Momentum even with only using a 1/1 model is more than the opposite of short-term reversal. In that case the α and all the β's would be 0 except for the β of Short Term Reversal, which would be -1. Additionally, although the adjusted R^2 is high at 63.67%, there is still 36.33% of the variation remaining that the model (including the short-term reversal factor) cannot explain.

An analysis of the predictive power of the factors from the Fama-French 6-factor model and the short-term reversal factor is also possible by using identical regressions with the first lags of these factors. The Adjusted R^2-values of these models in Table 2 show that these predictors explain a significantly lower amount of the variation of factor momentum, varying from 2.21% to 3.57%. By using lags the logic behind an increase in alpha and significance because of the addition of the short-term reversal factor is no longer applicable. The short-term reversal factor turned positive and is not significant or close to significant. Although the addition of the normal stock momentum factor does increase the alpha by 3 basis points, the factor is not significant and does not follow the logic either.

4.2 Macro-economic Prediction

By regressing the monthly factor momentum returns on the first lags of the selected macro-economic variables an estimation of the predictive power of these variables can be made. Analysis of the model as a whole shows that the combination of variables is significant (F (5,293) = 4.74, p <.001). Although an adjusted R^2 of 5.91% (non-adjusted R^2 = 7.49%) seems to suggest that the predictive power is low, because the lags of the macro-economic variables only explain 5.91% of the variation of factor momentum, this percentage is actually in line with expectations. Similar predictive research shows that these values in predictive models of stock momentum are often significantly similar (Chordia & Shivakumar 2002; Wang & Xu, 2015).

Table 3. Predictive model of Factor Momentum with Macro-Economic Variables

Variable	Coefficient	Standard Error	*t*-statistic	*p*-value
α	0.633	0.187	3.39	0.001
β_{CPI}	-0.334	0.446	-0.75	0.455
β_{VIX}	0.147	0.044	3.33	0.001
β_{DGS10}	2.520	1.066	2.36	0.019
β_{T10Y2Y}	-4.621	1.501	-3.08	0.002
β_{UNRATE}	-0.546	0.298	-1.83	0.068

The results of the regressions in Table 3 show that three out of the five factors in the regression are significant, which are the VIX factor or the Chicago Board Options Exchange Volatility Index as an indication of market expectation of near term volatility; the DGS10 factor or the market yield on U.S. treasury securities at 10-year constant maturity as an indication of the long term interest rates and the T10Y2Y factor or the 10-year treasury constant maturity minus the 2-year treasury constant maturity as an indication of the slope of the yield curve. The other two variables, the CPI factor or consumer price index and the UNRATE factor or unemployment rate are not significant.

One of the explanations why the VIX factor, the DGS10 and the T10Y2Y factor are significant, while the CPI factor and UNRATE factor are not, could be that the link between the first three variables and the stock market is more direct. The values of the VIX factor, DGS10 factor and T10Y2Y factor are available daily and tradeable on the stock market in different forms, while the CPI factor and UNRATE factor values are only available monthly and not directly tradeable. This difference in availability of daily versus monthly might also reflect the way they influence the stock market. The publication of the consumer price index values and unemployment rates can create a monthly shock effect if they differ from expectations or they can have no effect at all, while the other factors might have a more underlying continuous influence.

Although not all variables are significant the sign of the coefficient (positive or negative) can still give an indication of the relation between the macro-economic variable and the factor momentum strategy returns. First of all, the CPI variable has a negative effect on the factor momentum returns. This suggest that a rise in prices and inflationary periods lower the returns of the factor momentum strategy and that this might not be suitable to hedge against inflation. The relation between the VIX variable and factor momentum returns is on the other hand positive. An increase in (the market's expectation of) volatility might therefore result in higher factor momentum returns. The factor momentum strategy could be useful in unsure and volatile market conditions.

A rise in long term interest rates (DGS10 variable) also seems to have a positive effect on factor momentum returns. In general however an increase in interest rates does have negative effects on stock prices. The factor momentum strategy might therefore be a possible defensive strategy in this market scenario to protect against these falling prices. The difference between the 10 year interest rate (long term) and the 2 year interest rate (short term), which is an indicator for the slope of the yield curve, has however a negative effect on the returns of the factor momentum strategy. This inversely means that a flattening or even inversion of the yield curve positively impacts factor momentum returns. Given the fact that flattening and especially inverting yield curves are often indications of an upcoming recession, this again suggests that the factor momentum strategy performs better in troubled times.

The sign of the coefficient of the last variable, unemployment rate, seems to go against this statement. That is because an increase in unemployment has a negative impact on the returns of the factor momentum strategy. Although low unemployment is generally seen as a sign of a strong and growing economy, data shows that unemployment often is at the lowest point of the market cycle just before a recession begins (World Economic Forum, 2023). This statistic combined with the fact that the unemployment rate variable is actually not significant might be explanations for this found relation between unemployment rate and factor momentum returns.

In contrast to all these findings, the significant coefficients of the predictive models of stock momentum in the literature have the exact opposite signs. Cooper, Mitrache & Priestley (2022) found that inflation had both nationally and internationally a significant positive effect on stock momentum returns. Moreover Chordia and Shivakumar (2002) as well as Hutchinson and O'Brien (2020) and Wang and Xu (2015) found that a steepening yield curve also had a significant positive effect on these returns. Market volatility on the other hand had a significant negative effect on the stock momentum returns (Daniel & Moskowitz, 2016; Wang & Xu, 2015). These results in combination with the existence of momentum crashes suggest that the stock momentum strategy has therefore a more offensive nature (Daniel & Moskowitz, 2016). It is however important to note that the results from this thesis are based on a factor momentum strategy with a one-month formation period and a one-month holding period, while the results from these studies are based on stock momentum strategies that skip the last month in their formation period and have significantly longer formation and holding periods, which has an influence on how well a comparison between the two strategies can be made.

All in all, the regression results of this research suggest that the factor momentum strategy seems overall to be a defensive strategy based on the signs of the coefficients. In volatile periods with high interest rates and a flattening yield curve the factor momentum strategy will deliver the best returns according to the prediction model.

5. Discussion

The goal of this thesis was to find an answer to the question to what extent macro-economic variables can predict the returns from a factor momentum strategy. A secondary objective was to take a look at the relationship between factor momentum and stock momentum and compare the findings of the calculated predictive model for factor momentum with earlier research into the macro-economic predictors of stock momentum. The first major result is that the factor momentum effect remains significant after controlling for the Fama-French 5-factor model; the momentum factor and the short-term reversal factor. The momentum factor returns itself were not a significant descriptor or predictor of factor momentum returns. The addition of the short-term reversal factor, which was a significant descriptive factor with a negative sign, increased the strength and significance of the factor momentum returns notably, implying that factor momentum is partly the opposite of short term reversal. However even by including this factor, a large part of factor momentum returns variance remained unexplained.

The other major result is that the lagged values of volatility, long term treasury yield and term spread are significant predictors of factor momentum returns. Both volatility and the long term treasury yield had a positive effect on returns, while the term spread (or slope of the yield curve) had a negative effect on returns. This suggests that the factor momentum strategy performs better in stressed markets and can be considered defensive. Volatility and term spread were also significant in predicting normal stock momentum, but had the opposite effect, suggesting that stock momentum performs better in unstressed markets instead of stressed markets and is more offensive. These findings combined with the fact that the momentum effect was insignificant in the Fama-French regressions and the lack of short-term reversal effects and momentum crashes show that factor momentum is different from and more than stock momentum at least in short lags.

With these results this thesis adds value and fills a gap in the current research into factor momentum by considering macro-economic effects as possible drivers of this phenomenon. A strong point of this thesis is that there is a significant higher amount of factors included in the calculation of factor momentum compared to the current research, while still only including consistent factors based on the research of Chen and Zimmermann (2021). Another strong point is that the chosen macro-economic variables and method of analysis are similar to the earlier research into the predictors of stock momentum, which means that a more accurate comparison can be made.

A point of critique for this thesis could be that only one variation of factor momentum was used as a dependent variable in the regressions. This choice was made because the research from Arnott et al. (2018) and Falck et al. (2020) suggest that this variant of factor momentum is the strongest and that most of the returns come from the first lag. Nevertheless the results that were found could be different for other variations of factor momentum, which leaves room for further research. Another point of criticism could be that investor sentiment was not included as a variable and predictor in the model. This was done deliberately because the focus of this thesis was on the macro-economic predictors only and the relation between stock momentum and factor momentum on this point, which no research paper had done before, while investor sentiment was already studied in other papers. The difference in macro-economic predictive strength between high sentiment and low sentiment periods could however also be an avenue for further research.

All in all, this research shows that macro-economic variables can be used to partly explain and predict not only the stock market as a whole (Chen, Roll and Ross, 1986) or the anomalies/factors themselves, but even the momentum in these factors.

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Appendix

A. Factor List and Significance Tests Results

Table 4. Significance Tests for the selected factors for the researched time period

Original Study	**Variable**	**Mean**	***T*-stat**	***p*-value**
Abarbanell and Bushee (1998)	Change in capital inv (ind adj)	0.2576	2.1059	0.036
Ali, Hwang, and Trombley (2003)	Idiosyncratic risk (AHT)	0.191	0.3694	0.7121
Alwathainani (2009)	Earnings consistency	0.259	2.0893	0.0375
Amihud (2002)	Amihud’s illiquidity	0.0653	0.4075	0.6839
Anderson and Garcia-Feijoo (2006)	Change in capex (two years)	0.3097	2.5271	0.012
Anderson and Garcia-Feijoo (2006)	Change in capex (three years)	0.25748	1.9354	0.0539
Ang et al. (2006)	Idiosyncratic risk	0.4506	0.9521	0.3418
Ang et al. (2006)	Idiosyncratic risk (3 factor)	0.4095	0.8613	0.3897
Baik and Ahn (2007)	Change in order backlog	0.3982	1.8565	0.0644
Balakrishnan, Bartov and Faurel (2010)	Return on assets (qtrly)	0.8852	2.406	0.0167
Bali, Cakici, and Whitelaw (2010)	Maximum return over month	0.241	0.4585	0.6469
Bali, Engle and Murray (2015)	Return skewness	0.2216	1.5163	0.1305
Bali, Engle and Murray (2015)	Idiosyncratic skewness (3F model)	0.0874	0.8024	0.4229
Ball et al. (2016)	Cash-based operating profitability	0.6672	2.7567	0.0062
Banz (1981)	Size	0.168	0.8759	0.3818
Barth and Hutton (2004)	Change in Forecast and Accrual	0.1112	1.4143	0.1583
Bartov and Kim (2004)	Book-to-market and accruals	1.2092	4.1712	<0.0001
Basu (1977)	Earnings-to-Price Ratio	0.2525	1.4422	0.1503
Bazdresch, Belo and Lin (2014)	Employment growth	0.4734	3.4755	0.0006
Belo and Lin (2012)	Inventory Growth	0.466	2.7854	0.0057
Bhandari (1988)	Market leverage	0.1697	0.5108	0.6099

Table 4 Continued

Original Study	**Variable**	**Mean**	***T*-stat**	***p*-value**
Blitz, Huij and Martens (2011)	Momentum based on FF3 residuals	0.6686	2.9422	0.0035
Blume and Husic (1972)	Price	0.3597	0.778	0.4372
Boudoukh et al. (2007)	Net Payout Yield	0.9979	2.9985	0.0029
Boudoukh et al. (2007)	Payout Yield	0.2415	1.3274	0.1854
Bradshaw, Richardson, Sloan (2006)	Net debt financing	0.6193	5.8481	<0.0001
Bradshaw, Richardson, Sloan (2006)	Net equity financing	0.7974	2.5925	0.01
Bradshaw, Richardson, Sloan (2006)	Net external financing	1.0011	2.7417	0.0065
Brennan, Chordia, Subra (1998)	Past trading volume	0.4106	1.8468	0.0658
Cen, Wei, and Zhang (2006)	Analyst earnings per share	0.7734	1.8246	0.069
Chan and Ko (2006)	Momentum and LT Reversal	0.6834	1.6871	0.0926
Chan, Jegadeesh and Lakonishok (1996)	Earnings announcement return	1.0726	9.213	<0.0001
Chan, Jegadeesh and Lakonishok (1996)	Earnings forecast revisions	0.1703	0.4471	0.6551
Chan, Lakonishok and Sougiannis (2001)	R&D over market cap	0.9527	2.4289	0.0157
Chandrashekar and Rao (2009)	Cash Productivity	0.1815	0.7325	0.4644
Chordia, Subra, Anshuman (2001)	Share turnover volatility	0.1283	0.292	0.7705
Chordia, Subra, Anshuman (2001)	Volume Variance	0.0202	0.0869	0.9308
Cohen and Frazzini (2008)	Customer momentum	0.4152	0.8891	0.3746
Cohen, Diether and Malloy (2013)	R&D ability	0.2082	1.0615	0.2893
Cooper, Gulen and Schill (2008)	Asset growth	1.022	3.9604	0.0001
Da and Warachka (2011)	Long-vs-short EPS forecasts	0.362	2.0251	0.0437
Daniel and Titman (2006)	Composite equity issuance	0.3333	2.5121	0.0125
Daniel and Titman (2006)	Intangible return using BM	0.2067	0.9275	0.3544
Daniel and Titman (2006)	Intangible return using CFtoP	0.3479	1.4508	0.1479
Daniel and Titman (2006)	Intangible return using EP	0.2714	1.5887	0.1132
Daniel and Titman (2006)	Intangible return using Sale2P	0.4346	1.5185	0.1299
Daniel and Titman (2006)	Share issuance (5 year)	0.343	2.6871	0.0076
Datar, Naik and Radcliffe (1998)	Share Volume	0.1996	1.0434	0.2976
De Bondt and Thaler (1985)	Long-run reversal	0.567	1.8025	0.0725

Table 4 Continued

Original Study	**Variable**	**Mean**	***T*-stat**	***p*-value**
Dechow, Sloan and Soliman (2004)	Equity Duration	0.2134	0.7823	0.4347
Desai, Rajgopal, Venkatachalam (2004)	Operating Cash flows to price	0.4243	1.2391	0.2163
Dharan and Ikenberry (1995)	Exchange Switch	0.9107	3.8849	0.0001
Dichev (1998)	O Score	0.8118	2.2296	0.0265
Diether, Malloy and Scherbina (2002)	EPS Forecast Dispersion	0.1669	0.5276	0.5982
Doyle, Lundholm and Soliman (2003)	Excluded Expenses	0.1631	1.4626	0.1446
Eberhart, Maxwell and Siddique (2004)	Unexpected R&D increase	0.1831	1.4219	0.1561
Eisfeldt and Papanikolaou (2013)	Organizational capital	0.3622	2.072	0.0391
Elgers, Lo and Pfeiffer (2001)	Earnings Forecast to price	0.454	1.0158	0.3105
Fama and French (1992)	Total assets to market	0.2657	0.841	0.401
Fama and French (1992)	Book to market using December ME	0.4426	2.1972	0.0288
Fama and French (1992)	Book leverage (annual)	0.1645	0.5971	0.5509
Foster, Olsen and Shevlin (1984)	Earnings Surprise	0.1808	1.6236	0.1055
Gou, Lev and Shi (2006)	IPO and no R&D spending	0.5769	2.9346	0.0036
Grinblatt and Moskowitz (1999)	Industry Momentum	0.607	2.4384	0.0153
Hafzalla, Lundholm, Van Winkle (2011)	Percent Operating Accruals	0.3061	3.0135	0.0028
Hafzalla, Lundholm, Van Winkle (2011)	Percent Total Accruals	0.3346	3.6556	0.0003
Hahn and Lee (2009)	Tangibility	0.3237	1.1911	0.2345
Hartzmark and Salomon (2013)	Dividend seasonality	0.2566	8.0108	<0.0001
Hawkins, Chamberlin, Daniel (1984)	EPS forecast revision	0.3057	2.8343	0.0049
Heston and Sadka (2008)	Momentum without the seasonal part	0.9785	2.0282	0.0434
Heston and Sadka (2008)	Off season long-term reversal	0.6361	2.0671	0.0396
Heston and Sadka (2008)	Off season reversal years 6 to 10	0.7706	4.2592	<0.0001
Heston and Sadka (2008)	Off season reversal years 16 to 20	0.2206	1.2983	0.1952
Heston and Sadka (2008)	Return seasonality years 6 to 10	0.5207	3.0085	0.0028
Heston and Sadka (2008)	Return seasonality years 11 to 15	0.4143	2.7552	0.0062
Heston and Sadka (2008)	Return seasonality years 16 to 20	0.6072	4.0525	0.0001
Heston and Sadka (2008)	Return seasonality last year	0.2579	1.1192	0.264

Table 4 Continued

Original Study	Variable	Mean	*T*-stat	*p*-value
Hirshleifer et al. (2004)	Net Operating Assets	0.8434	3.6467	0.0003
Hirshleifer, Hou, Teoh, Zhang (2004)	change in net operating assets	0.6381	4.7332	<0.0001
Hou (2007)	Earnings surprise of big firms	0.2146	1.0153	0.3108
Hou (2007)	Industry return of big firms	1.4946	4.8625	<0.0001
Hou and Robinson (2006)	Industry concentration (sales)	0.1846	1.1227	0.2624
Hou and Robinson (2006)	Industry concentration (equity)	0.1571	0.9019	0.3678
Jegadeesh (1989)	Short term reversal	1.347	2.8377	0.0049
Jegadeesh and Livnat (2006)	Revenue Surprise	0.4546	3.9844	0.0001
Jegadeesh and Titman (1993)	Momentum (12 month)	0.4908	0.9368	0.3496
Jegadeesh and Titman (1993)	Momentum (6 month)	0.9069	1.7901	0.0744
Jegadeesh et al. (2004)	Change in recommendation	0.5392	6.4124	<0.0001
Kelly and Jiang (2014)	Tail risk beta	0.276	1.2506	0.2121
La Porta (1996)	Long-term EPS forecast	0.0142	0.0435	0.9654
Lakonishok, Shleifer, Vishny (1994)	Cash flow to market	0.2494	0.7964	0.4264
Lakonishok, Shleifer, Vishny (1994)	Revenue Growth Rank	-0.0165	-0.1485	0.882
Landsman et al. (2011)	Real dirty surplus	0.2196	1.6784	0.0943
Lee and Swaminathan (2000)	Momentum in high volume stocks	1.4438	2.3002	0.0221
Lev and Nissim (2004)	Taxable income to income	0.4434	3.1557	0.0018
Li (2011)	R&D capital-to-assets	0.3843	1.559	0.12
Litzenberger and Ramaswamy (1979)	Predicted div yield next month	0.4927	4.289	<0.0001
Liu (2006)	Days with zero trades	0.1311	0.4071	0.6842
Liu (2006)	Days with zero trades	0.2913	0.9516	0.3421
Liu (2006)	Days with zero trades	0.0391	0.1499	0.8809
Lockwood and Prombutr (2010)	Growth in book equity	0.6161	3.3751	0.0008
Loh and Warachka (2012)	Earnings surprise streak	0.6838	6.8126	<0.0001
Lou (2014)	Growth in advertising expenses	0.2603604	1.8796	0.0611
Loughran and Wellman (2011)	Enterprise Multiple	0.7344	2.9484	0.0034
Lyandres, Sun and Zhang (2008)	Composite debt issuance	0.2204	3.4685	0.0006

Table 4 Continued

Original Study	**Variable**	**Mean**	***T*-stat**	***p*-value**
Lyandres, Sun and Zhang (2008)	change in ppe and inv/assets	0.4112	3.5869	0.0004
Menzly and Ozbas (2010)	Customers momentum	0.3968	1.6087	0.1087
Menzly and Ozbas (2010)	Suppliers momentum	0.4652	1.7783	0.0764
Michaely, Thaler and Womack (1995)	Dividend Initiation	0.1624	0.7909	0.4296
Mohanram (2005)	Mohanram G-score	0.6117	3.2833	0.0011
Nagel (2005)	Inst Own and Forecast Dispersion	0.5296	2.3769	0.0181
Nagel (2005)	Inst Own and Market to Book	0.3526	1.6066	0.1092
Nagel (2005)	Inst Own and Turnover	0.5863	2.3981	0.0171
Nagel (2005)	Inst Own and Idio Vol	0.8596	3.1454	0.0018
Nguyen and Swanson (2009)	Efficient frontier index	1.5078	4.4994	<0.0001
Novy-Marx (2010)	Operating leverage	0.4495	2.0675	0.0395
Novy-Marx (2012)	Intermediate Momentum	0.4935	1.1827	0.2379
Novy-Marx (2013)	gross profits / total assets	0.5168	2.6933	0.0075
Palazzo (2012)	Cash to assets	0.5308	1.3922	0.1649
Penman, Richardson and Tuna (2007)	Leverage component of BM	0.0755	0.6355	0.5256
Penman, Richardson and Tuna (2007)	Enterprise component of BM	0.112	1.2089	0.2276
Penman, Richardson and Tuna (2007)	Net debt to price	0.7653	2.6734	0.0079
Piotroski (2000)	Piotroski F-score	0.8053	1.7248	0.0856
Pontiff and Woodgate (2008)	Share issuance (1 year)	0.756	3.9403	0.0001
Rajgopal, Shevlin, Venkatachalam (2003)	Order backlog	-0.0893	-0.6291	0.5298
Richardson et al. (2005)	Change in current operating assets	0.3311	3.2307	0.0014
Richardson et al. (2005)	Change in current operating liabilities	0.2285	2.0714	0.0392
Richardson et al. (2005)	Change in equity to assets	0.5835	3.0057	0.0029
Richardson et al. (2005)	Change in financial liabilities	0.3844	5.1003	<0.0001
Richardson et al. (2005)	Change in long-term investment	0.2011	2.1594	0.0316
Richardson et al. (2005)	Change in net financial assets	0.1192	1.2402	0.2159
Richardson et al. (2005)	Total accruals	0.3285	1.6855	0.0929
Ritter (1991)	Initial Public Offerings	0.3558	1.6279	0.1046

Table 4 Continued

Original Study	**Variable**	**Mean**	***T*-stat**	***p*-value**
Rosenberg, Reid, and Lanstein (1985)	Book to market using most recent ME	0.8731	2.6589	0.0083
Sloan (1996)	Accruals	0.1514	1.4335	0.1527
Soliman (2008)	Change in Asset Turnover	0.0777	1.0957	0.2741
Soliman (2008)	Change in Net Noncurrent Op Assets	0.1339	1.879	0.0612
Soliman (2008)	Change in Net Working Capital	0.0145	0.26	0.7951
Thomas and Zhang (2002)	Inventory Growth	0.4556	3.7033	0.0003
Thomas and Zhang (2011)	Change in Taxes	0.4025	3.2993	0.0011
Titman, Wei and Xie (2004)	Investment to revenue	0.0498	0.2529	0.8005
Valta (2016)	Convertible debt indicator	0.4081	3.8712	0.0001
Xie (2001)	Abnormal Accruals	-0.0441	-0.3056	0.7601