FROG IN THE FACTOR PAN:

CONTINUOUS INFORMATION IN FACTOR MOMENTUM

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Frog in the Factor Pan: Continuous information in factor momentum

Abstract:

Since stock momentum stems from momentum within common risk factors, as shown through recent studies, we test whether Da et al. (2014)'s frog-in-the-pan hypothesis of limited attention is able to explain the persistence of the momentum within factor risk premia. Indeed, our results show that information arriving slowly and in small amounts is overlooked by investors and leads to persistent momentum in factor risk premia. Factor momentum decreases from the continuous information portfolio to the discrete information portfolio regardless of factor construction and portfolio conditioning method. The frog-in-the-pan hypothesis of investor limited attention is robust when applied to factor momentum.

Keywords:

Momentum, Factor momentum, Cross-sectional factor momentum, Time-series factor momentum, Frog-in-the-pan hypothesis, Limited attention, Continuous information

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1. Introduction

Stock momentum, the consistency of stock performance, has been a pervasive and persistent phenomenon in the global financial market. Among a wide range of behavioral explanations, limited investor attention (which is called the "Frog In the Pan" theory by Da et al., 2014) seems to be robust (Goyal et al., 2022). Unlike other behavioral explanations for stock momentum, the Frog-In-the-Pan hypothesis focuses on the continuity of information flow. Due to the investor's limited attention to new information, investors underreact in series of continuous and small information compared to discrete and large information. This leads stock with continuous information to generate significant momentum against stock with discrete information.

Recent studies argue that stock momentum stems from momentum within common risk factors (Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2021). Central finding is that momentum exists in factor returns, and this factor momentum transmits into individual stock returns through variation in factor loadings of individual stocks.

However, it is not yet clear why factor momentum exists, and what causes factor momentum. Most researchers who have previously explored the rational of momentum have focused only on stock momentum itself, not factor momentum. The question remains: If the limited attention is a prevailing explanation for stock momentum, and if stock momentum is a byproduct of factor momentum, does the limited attention explain the rationale of factor momentum? Inspired by this gap in the literature, we investigate whether the explanation for stock momentum also has an explanatory power for factor momentum.

Following Da et al. (2014), we investigate if the limited attention of investors, as theorized through the frog-in-the-pan hypothesis, transmits into factor risk premia as underreaction to continuous information and therefore delayed incorporation. We further dissect factor momentum by conditioning on information discreteness (ID), the proxy for continuous and discrete information. Throughout our study we find that continuous information translates into stronger and more persistent returns regardless of sorting method, independent or sequential on momentum and ID. Our results uniformly support the frog-in-the-pan hypothesis as we can observe that the Winner minus Loser (H-L) portfolio return decreases steadily from the continuous portfolio to the discrete portfolio while the continuous portfolio earns the highest return and alpha with both being statistically significant. Moreover, we test the conditional relationship between the formation period returns and ID and find that indeed there is a negative interaction where lower (negative) ID, corresponding to continuous information, leads to higher and more persistent returns.

2. Literature Review

In this section, we review previous literature on momentum and the frog-in-the-pan hypothesis. The review begins with how momentum works in the financial markets and how persistent and pervasive it is. Next is a literature review of time-series momentum and factor momentum, which are derivatives of cross-sectional momentum, the original concept of momentum. This literature review is followed by the frog-in-the-pan hypothesis, one of the behavioral explanations for momentum's pervasiveness and persistence in the markets. Finally, the section ends by showing how this paper expands and contributes to the existing findings.

2.1. Momentum

Cross-sectional Momentum

Momentum is the tendency of an asset's prior return to continue into its future return. With momentum, assets that performed well will continue to perform well in the future, and assets that performed poorly will continue to perform poorly. Trading strategy relying on momentum was first documented by Jegadeesh and Titman (1993), who observed that the strategy of going long winners and shorting losers can generate significant returns. In Jegadeesh and Titman's test, sorting stocks by their recent 3-12 month returns then going long top 30% of stocks and shorting bottom 30%, generates significant returns.

Several other studies maintain that momentum can explain market anomalies well. Asness (1995) asserts that momentum, in addition to size and value, is essential in explaining the cross-sectional expected return of common stocks. Carhart (1997) suggests a four-factor model including momentum as a new factor in addition to the three factors (beta, size, and value) of Fama-French's (1993) model. In this paper, evidence indicates that this four-factor model explain mutual fund returns better than the existing three-factor model.

Since the initial research on momentum focused on the U.S market was published, many studies have examined whether momentum is a pervasive phenomenon stretching to financial markets outside the U.S. Rouwenhorst (1998, 1999), in the analysis of the markets in 12 European countries and 20 emerging countries, found that momentum is significant in the international stock market as well.

Studies exist about momentum effect in a wide range of asset classes, beyond the stock market. Momentum strategies generate profit in six major government bond markets (Luu and Yu, 2012). Success of momentum strategies are documented in both future markets (Erb and Harvey, 2006) and spot markets (Gorton et al., 2008). Further, momentum is solid and persistent within industry components of equity returns (Moskowitz and Grinblatt, 1999).

Momentum is not only pervasive in the financial market, but also persistent over long periods of time. Fama and French (2012), during their study of stock returns in global market from 1989 to 2011, found strong evidence of momentum. Geczy and Samonov (2015) demonstrate the effects of momentum across various asset classes between 1802-2012, a period of study where the authors find consistent momentum within six asset classes namely domestic stocks, currencies, government bonds, commodities, global sectors, and US equities. In the 2010s, long after the foremost publishing of momentum research, evidence of momentum is still visible. Asness (2013) concluded that momentum exists across eight regions and various asset classes. Moskowitz (2010) documented that momentum exists in 40 countries and in various asset classes.

The type of momentum so far discussed is cross-sectional momentum. Cross-sectional momentum is the strategy used by the first documenters of the momentum effect, Jegadeesh and Titman (1993), and is also the most frequently discussed type of momentum in existing literature. Cross-sectional momentum means building a strategy by comparing the relative return of stocks. The strategy looks at recent performance of assets, then long relatively good performing assets and short relatively bad performing assets. Even if all assets perform positively, a cross-sectional momentum strategy is to short the assets with relatively low returns.

Time-Series Momentum

Another concept of momentum is time-series momentum. Unlike cross-sectional momentum, time-series momentum is based on a single asset's absolute performance trend, thus it is called a trend-following strategy. For example, when all assets rise in value, cross-sectional momentum strategy is to short relatively low-performing assets, whereas time-series momentum strategy is to long all assets. Moskowitz et al. (2012) were the first to document the term time-series momentum. The authors found strong and consistent time-series momentum in equity index, as well as currency, bond futures, and commodity, and argue that time-series momentum strategies can generate significant abnormal returns.

Several studies provide evidence that time-series momentum is persuasive and persistent across various asset classes and regions. Baltas et al. (2013) show time-series momentum in the future markets. By examining 71 future contracts in multiple asset classes such as commodity and currency between 1974 and 2011, the authors found strong evidence of momentum in time-series. This evidence stands out during both the entire period as well as the partial periods of the study. Hurst et al. (2017) show strong evidence of time-series momentum after conducting studies in 67 markets and 4 asset classes of commodity, bond, equity indices and currency within the 1880-2016 time period. They found that time-series momentum has consistently generated significant returns for the 137 years.

D’Souza et al. (2016) focused on individual stock momentum and analyzed the U.S market during the years 1927-2014 and 13 major international markets during the years 1975-2014. As a result, the authors show that time-series momentum created a significant profitability over both markets. This contradicts random walk theory which maintains that historical price trends cannot predict future return. D’Souza et al. (2016) also noticed that time-series momentum, in contrast to cross-sectional momentum, does not go through January losses. This 2016 study shows time-series momentum, besides being different, can be related to cross-sectional momentum. That is, time-series stock momentum captures cross-sectional stock momentum, but not vice versa.

Factor Momentum

In recent years, research on momentum paid attention to momentum within portfolios or risk factors. For example, McLean and Pontiff (2016) argue that momentum exists in well-diversified portfolios. Avramov et al. (2016) show that a trading strategy that buys past top-performing portfolios and sells past poor-performing portfolios can generate significant returns. Zaremba and Shemer (2018) show that cross-sectional momentum exists in the returns of five well-known factors. These empirical findings imply that momentum exists in factor returns as well as individual stock returns.

Building on previous work, Ehsani and Linnainmaa, in their 2019 study "Factor Momentum and Momentum Factor," explored the relationship between factor momentum and individual stock momentum. As a result of analyzing 15 US factors and seven global factors, the authors found that individual stock momentum stems from momentum in factor returns. In other words, momentum within factor returns transmits into individual stock returns through their factor loadings, and generates cross-sectional momentum of individual stocks. In addition, they also found that stock momentum trading strategies fail when factor autocorrelation breaks down. These results led the authors to conclude that stock momentum is not an independent factor. It is just the sum of factor momentum.

These findings are consistent with the 2019 paper "Factor Momentum Everywhere" by Gupta and Kelly. By constructing and analyzing a large collection of 65 commonly studied US and global factors from 1965 to 2017, the authors found that, in general, individual factors exhibit solid time-series momentum. Of 65 factors, 59 were reliably timed based on their own prior returns and 49 of them were statistically significant. Strong momentum among the factors indicates that stock momentum phenomenon is largely driven by the momentum of common factors, not because of the firm-specific information. In their analysis, factor momentum trading strategy, buying high-performing factors and selling low-performing factors, outperform traditional stock momentum strategy and also industry momentum, value, and other widely studied factors in terms of the Sharpe ratio. Since factor momentum generates significant alpha even after controlling for stock momentum, factor momentum strategy and stock momentum strategy can be used as complement. From these results, the authors concluded that factor momentum is a persistent and pervasive phenomenon in the global financial market.

Arnott et al., authors of the 2021 study "Factor momentum," also provide strong evidence to momentum among factors. They explored industry momentum, and they found that prior returns of industry predict the cross section of industry returns, and this industry momentum stems from momentum among factors, not from industry-specific news. Factor momentum transmits into the industry returns through differences in industries' factor exposures. In their investigation, industry momentum strategy based on one month horizon achieves an annual return of 8.7%, but after controlling for factor momentum, the alpha falls close to zero. Another finding of their investigation is that factor momentum strategy generates significant profit in terms of average returns and five-factor model alphas. Factor momentum is a pervasive phenomenon of all factors, so it can be captured by trading almost any combination of factors. Some factors like distress, illiquidity, and market beta contribute more towards the profits of factor momentum than other factors, but none of the factors significantly lower the profits. Their conclusion is that there is little or no pure industry momentum excluding factor momentum, therefore industry momentum is a by-product of factor momentum, supporting Ehsani and Linnainmaa (2019)'s explanation.

2.2. Frog-in-the-Pan hypothesis

There are both risk-based explanations and behavioral explanations for why momentum is persistent and robust in the financial markets. Most of the literature supports the behavioral explanations that momentum profit results from investors' behavioral bias. For example, Daniel et al. (1998) argue that investors tend to overconfident about their investing skills and their private information, and this overconfidence leads overreaction and creates momentum. Hong et al. (2000) suggest that information about fundamentals diffuses slowly to investors, therefore, some investors cannot use all available information in the market, which leads to create momentum. George and Hwang (2004) argue that investor may use the 52-week high price as the anchor, thus investors consider stocks below 52-week high price to be cheap, so they tend to invest these stocks regardless of their fundamental and this creates momentum effect.

Da et al. (2014) also present a behavioral model, but unlike the above models, their model focuses on the continuous flow of the information provided. Among various behavioral explanations, recent studies prove that investors' limited attention bias and consequent underreaction create momentum (Goyal et al., 2022). Hou et al. (2009) observed that as investor's attention increased, price underreaction to earning decreased. They suggest that limited investor attention results in profit from momentum strategy. Hirshleifer et al. (2009) also investigated whether limited investor attention causes market underreaction. They found when multiple corporations make simultaneous earning announcements, price and volume reaction for each company's stock was much lower, because investors got overwhelmed and distracted by too much information.

Since investors have limited attention and there is so much information available in the market, investors only pay attention to large-scale and dramatic information. In other words, investors are inattentive to small and continuous information, hence small and continuous information cannot be incorporated to stock prices immediately. The authors argue that this limited attention create robust and persistent momentum in the market, and they call this model 'Frog-In-the-Pan' hypothesis. According to the frog-in-the-pan story, a frog in a pan jumps out of the water immediately when the temperature rises dramatically. However, when the temperature rises gradually, the frog does not perceive the danger and gets boiled. Relating the frog-in-the-pan hypothesis to the financial markets, suggests that investors are more inattentive to continuous information than they are to discrete information, even if the cumulative information remains the same. By measuring the level of continuous information based on the number of days the stock price changes, the authors examined momentum profit from continuous and discontinuous information during the 1927-2007 time period. From their test, stocks with continuous information create significant momentum (5.94%) compared against stocks with discrete information (-2.07%). These observations support the frog-in-the-pan hypothesis.

Since the proposal of the frog-in-the-pan hypothesis, several studies have backed the theory. Goyal et al. (2022) conducted a cross-sectional "horse race" across all the previous behavioral explanations for momentum: frog-in-the-pan hypothesis, overconfidence (Daniel et al., 1998), slow diffusion of information (Hong et al., 2000), anchoring bias (George and Hwang, 2004); and also risk-based explanations for momentum of Sagi and Seasholes (2007). The test results showed that the FIP hypothesis is the winner. In addition, Goyal et al. (2022) explored the relationship between momentum and volatility and found that momentum is robust in a low volatility market. As information flows gradually in low volatility conditions, this empirical finding strongly supports the frog-in-the-pan theory.

Huang et al. (2021) examined lead-lag return pattern of economically linked firms, like customer-supplier firms. Lead-lag return pattern is a phenomenon in which information about the customer firm is not immediately incorporated into the supplier firm's stock price even though the performance of suppliers is linked to that of customers. The authors found that investors underreact to continuous information from customers while discrete amounts of information is rapidly absorbed into price and enhances investor attention, an observation which also supports the frog-in-the-pan hypothesis.

All momentum used in the above studies for the frog-in-the-pan hypothesis are cross-sectional stock momentum. In addition, there is evidence that the frog-in-the-pan hypothesis explains time-series momentum as well as cross-sectional stock momentum. D'Souza et al. (2016), by analyzing the U.S markets during 1927-2014 period and the international markets since 1975, show that the time-series momentum of stocks with continuous information (1.17%) is much stronger than that of stocks with discrete information (0.20%). That is, the more gradual the information flows, the more profitable the time-series momentum strategy is, an observation consistent with the frog-in-the-pan hypothesis.

2.3. Thesis contribution to the literature

According to the literature reviewed so far, stock momentum is pervasive and persistent worldwide in both cross-sectional and time-series approach. Such stock momentum is a by-product of factor momentum and is transmitted through factor loading. Recent studies show that factor momentum strategies generate higher returns than stock momentum strategies.

Although the dynamics of momentum have been explored in previous studies, further research is necessary. There are still unknown parts, the explanation of why factor momentum exists. Ehsani and Linnainmaa (2019) state the following:

> We leave questions for future research. ... Although, factor momentum is consistent with Kozak et al.'s (2018) model of sentiment investors, this consistency does not imply that factor momentum must stem from mispricing. The point of Kozak et al. (2018) ... provides no clues as to whether factor premiums compensate for risks or reflect mispricings. (Ehsani and Linnainmaa, 2019)

The thesis aims to contribute to the preliminary literature in two ways. First, we explore why factor momentum is pervasive and persistent in the financial market. We test whether factor momentum can be explained through the frog-in-the-pan hypothesis, which is the robust explanation for individual stock momentum, both time-series and cross-sectional approach. Using the indicator for measuring continuous information by Da et al. (2014), we examine whether investors' underreaction to information in the U.S stock market creates factor momentum.

Second, as continuous information contributes to improving traditional stock momentum strategies, we examine whether the quality of cross-sectional factor momentum strategies and time series factor momentum strategies can be improved by reflecting the limited investor attention through continuous information.

3. Data and methodology

3.1. Data

We take daily factor returns from the publicly available data source[1] of Chen and Zimmerman (2021) from 01 January 1927 to 31 December 2021. The original dataset has 207 factors; however, 5 factors were removed from the study due to high number of missing data throughout the sample period. Other 25 factors had missing variables in the first part of the time series and therefore data was cleaned up to the date where time series was continuous. Chen and Zimmerman (2021) implement the data in their study following the original factor construction as closely as possible, nonetheless there are certain deviations due to standardization of methods, as noted by the authors. Also worth noting is that previous studies on factor momentum have created factors through Fama French style long short portfolios and value weighting methods. Therefore, both the original factors and the ones created through value weights are taken from the database.

[1] Factor data available at:
https://drive.google.com/drive/folders/1O18scg9iBTiBaDiQFhoGxdn4FdsbMqGo

The full list of the factors used in the study is in the **Appendix 1**. Choosing a large set of factors allows us to minimize factor selection bias and study both the source that drives factor momentum and its pervasiveness. Market return, SMB and HML factors are taken from Fama-French database[2]. Similar to Fama and French we calculate one year as 252 trading days and one month as 21 trading days.

3.2. Methodology

Factor Momentum

Factors experience serial correlation in returns, marking the basic premise for factor momentum (Ehsani and Linnainmaa, 2019; Gupta and Kelly, 2019). The cross-sectional factor momentum is created in the spirit of Jegadeesh and Titman (1993) as long-short portfolios of "winners" minus "losers". The cross-sectional momentum strategy (CSFM) compares prior returns among factors, and to ensure comparability to Da et al. (2014), they are separated in quintiles based on their formation period return and assigned to a category from Low to High. The Winner minus Loser portfolio is represented by the 20% largest return factors minus the 20% lowest return factors and therefore the cross-sectional momentum filters the factor universe. On the other hand, a time-series factor momentum strategy (TSFM) is long factors with positive return during the formation period and short factors with negative return during the period, deciding each factor's inclusion in the High or Low portfolio based solely on their own past performance and therefore invests in the whole factor universe available at that date.

Frog-in-the-Pan – information discreteness

We construct the measure of quality within momentum through continuous or discrete information by using the information discreteness (ID) proposed by Da et al. (2014). Specifically, we construct the information discreteness as follows:

$$ID = sign(PRET) * [\%neg - \%pos] \quad (1)$$

where:

[2] FF3 factor data available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

- PRET is the cumulative return during the formation period;
- sign(PRET) determines the sign of the return as +1 or -1;
- %neg is the percentage of days with negative returns in the formation period;
- %pos is the percentage of days with positive returns in the formation period;

The ID measure does not take into account the magnitude of the past cumulative return, PRET, it simply measures if a positive (negative) PRET is formed by a multitude of small positive (negative) returns or a sparse number of large positive (negative) returns. Equation (1) implies that when a factor has a positive cumulative return during the formation period and the number of positive return days is larger than the negative return days then the ID factor is negative and closer to -1 with an increasing difference between the positive and negative days. Similarly, when PRET is negative and the number of negative days is higher than positive days, then ID becomes negative.

When ID is closer to -1, PRET is created by a large number of small returns with the same sign and the factor experiences continuous information, while when ID is closer to +1, PRET is created by a small number of large returns with the same sign as PRET. Da et al. (2014) show that stock momentum following continuous information persists longer. Therefore ID, allows us to assign quality to momentum by conditioning each factor on its prior return and its information flow.

Conditional factor momentum

Respecting the same fashion cross-sectional factor momentum was constructed, we assign group factors into quintiles based on their ID, denoting continuous information for low ID and discrete information for high ID, quality or poor momentum respectively.

To study the robustness of frog-in-the-pan theory in explaining factor momentum, we construct portfolios through multiple double sorts on momentum and ID. We first create independent sorts on momentum and ID by assigning each factor into momentum and ID quintiles, then we create 25 portfolios for Cross-Sectional Factor Momentum and 10 portfolios for Time-Series Factor Momentum. Second, we create portfolios on sequential sorts where each momentum category from H to L is further divided into quintiles from Discrete to Continuous. Third, we examine a sequential sort on momentum and then ID with ID sorted in Fama-French style into 3 groups 30-40-30%.

Stock momentum strategies require skipping the last month in the formation period due to the short-term reversal effect, however as noted in the previous studies, the factor momentum does not experience similar reversals and therefore the last month is not skipped (Ehsani and Linnainmaa, 2019; Gupta and Kelly,2019). The formation period is twelve months while the holding period returns are six months and twelve months. Since holding period is longer than one day and we are creating portfolios each day to improve our tests, we use the Newey-West (1987) adjustment on standard errors to deal with overlapping observations and ensure comparability with Da et al. (2014). On the other hand, previous studies on factor momentum have used the overlapping portfolio approach of Jegadeesh and Titman (1993).

For each holding period we calculate mean return of the portfolios and the alpha in respect to the Fama French three-factor model as in Equation (2).

$$r_{i,t,t+h} = a_i + b_i\left(MRF_{t,t+h}\right) + s_i\left(SMB_{t,t+h}\right) + h_i\left(HML_{t,t+h}\right) + \varepsilon_i \qquad (2)$$

where h is the holding period six months or twelve months.

To ensure the robustness of the study we examine the frog-in-the-pan hypothesis on the portfolios' six and twelve months holding return with overlapping observations and one month formation period.

According to the frog-in-the-pan hypothesis, the ID measure has a conditional relationship with momentum (Da et al., 2014). We study the interaction between the formation period returns (PRET) and ID through cross-sectional regressions in the form of Fama-MacBeth regressions as specified in Equation (3). The momentum literature implies a positive coefficient for the formation return while the frog-in-the-pan hypothesis implies a negative β_3 coefficient for the interaction variable $PRETxID$ since a high ID leads to discrete information and weaker momentum continuation while a low (negative) ID corresponding to continuous information would lead to persistent momentum.

$$r_{i,t,t+h} = \beta_0 + \beta_1(PRET) + \beta_2(ID) + \beta_3(PRETxID) + \varepsilon_{i,t} \qquad (3)$$

Moreover, to study the implications of ID as a quality measure for momentum we create monthly factor time series and double sequentially sorted portfolios based on twelve-month look back period and one month lookback period, with one month holding period return and no overlapping observations.

4. Results

In this section we present the empirical findings of applying the frog-in-the-pan hypothesis of continuous information on factor momentum. The theory predicts that momentum with continuous information will be more persistent than momentum with discrete information (Da et al., 2014). Throughout our study we find that indeed investor limited attention to frequent and small amounts of information leads to underreaction which translated into increasingly persistent factor risk premia momentum.

First, we examined similar construction to Da et al. (2014) with twelve-month formation period and six-month holding return from buying winners and selling losers. The results are reported in **Table 1**. Panel A reports results for winner and loser portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from H to L and then each momentum quintile sorted based on ID into quintiles ranging from discrete to continuous. In the original factors for the CSFM, the winner portfolio decreases from 6.99% in the continuous portfolio to 5.62% in the discrete portfolio while the loser portfolio increases from 0.16% in the continuous portfolio to 1.77% in the discrete portfolio. The H-L portfolio six-month return decreases by more than 40% from the continuous portfolio to the discrete portfolio. This difference of 2.98% in the factor momentum is statistically significant with a t-statistic of 3.47. The alpha, in respect to the Fama French three-factor model, is statistically significant for all portfolios and the difference of continuous minus discrete momentum portfolios shows a six- month alpha of 4.34% with a t-statistic of 4.82. Similar results are seen in the TSFM. Winner portfolio decreases from 5.37% to 3.06% and loser portfolio increases from 0.49% to 2.01%. The H-L portfolio decreases from 4.88% to 1.05% with a statistically significant difference between continuous and discrete of 3.83% for the six-month return.

Table 1. Conditional Factor Momentum – 12x6 [3]

Panel A: Sequential sort on momentum and ID 5x5

Original paper factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	5.62	1.77	-0.02	3.85	*4.74*	3.10	*3.51*	3.06	2.01	0.02	1.05	*2.32*	0.13	*0.28*
2	6.26	1.26	-0.07	5.00	*5.39*	3.46	*3.97*	3.54	1.61	-0.03	1.93	*4.78*	1.42	*3.53*
3	6.01	1.26	-0.10	4.75	*5.40*	4.04	*4.82*	3.75	1.51	-0.07	2.24	*4.56*	1.85	*3.89*
4	6.48	0.75	-0.14	5.73	*6.77*	5.83	*6.60*	4.35	1.10	-0.11	3.25	*4.94*	3.04	*4.78*
continuous	6.99	0.16	-0.19	6.83	*6.28*	7.44	*6.53*	5.37	0.49	-0.18	4.88	*5.38*	5.74	*5.63*
continuous - discrete				2.98	*3.47*	4.34	*4.82*				3.83	*4.04*	5.61	*5.50*

Value weighted factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	3.62	0.87	-0.01	2.75	*3.12*	1.54	*1.78*	1.79	1.30	0.02	0.50	*1.00*	-0.68	*-1.38*
2	4.15	0.81	-0.06	3.34	*4.24*	2.47	*3.00*	2.31	1.12	-0.03	1.19	*2.66*	0.43	*0.96*
3	4.40	0.41	-0.09	3.99	*5.21*	4.05	*4.85*	2.77	0.88	-0.06	1.90	*4.28*	1.73	*3.61*
4	4.35	0.27	-0.12	4.08	*4.64*	4.96	*5.67*	3.31	0.63	-0.09	2.68	*4.37*	3.28	*5.24*
continuous	5.32	-0.31	-0.17	5.62	*5.03*	7.19	*6.40*	4.19	-0.01	-0.15	4.20	*4.11*	5.81	*6.23*
continuous - discrete				2.88	*2.73*	5.65	*5.32*				3.70	*3.42*	6.49	*6.60*

[3] Table reports the six-month holding returns of portfolios constructed with a twelve-month formation period.

Panel B: Independent sort on momentum and ID 5x5

Original paper factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	4.03	1.62	0.00	2.41	*3.08*	1.21	*1.55*	3.08	2.06	0.03	1.02	*2.13*	0.02	*0.03*
2	5.50	1.20	-0.06	4.30	*4.79*	3.42	*3.60*	3.21	1.43	-0.03	1.78	*4.31*	0.96	*2.27*
3	6.03	0.59	-0.10	5.44	*5.87*	4.82	*5.33*	3.62	1.10	-0.07	2.51	*4.59*	2.14	*3.99*
4	6.04	0.59	-0.14	5.45	*5.62*	5.71	*5.79*	4.17	0.77	-0.11	3.40	*5.05*	3.55	*5.31*
continuous	6.77	-0.27	-0.21	7.04	*6.73*	7.53	*6.84*	5.22	0.23	-0.18	4.98	*5.12*	5.80	*5.65*
continuous - discrete				4.63	*4.89*	6.32	*6.51*				3.97	*3.98*	5.79	*5.56*

Value weighted factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	3.02	0.93	0.00	2.08	*2.64*	0.73	*0.98*	1.82	1.32	0.03	0.49	*0.94*	-0.88	*-1.70*
2	3.89	0.74	-0.05	3.15	*3.81*	2.56	*2.89*	2.00	1.01	-0.02	0.98	*2.31*	0.25	*0.59*
3	4.26	0.23	-0.09	4.03	*4.82*	4.51	*5.26*	2.73	0.87	-0.06	1.87	*3.78*	1.89	*3.70*
4	4.11	-0.03	-0.13	4.14	*4.68*	5.16	*5.79*	3.16	0.51	-0.09	2.65	*4.13*	3.43	*5.23*
continuous	5.10	-0.50	-0.18	5.60	*5.47*	6.80	*6.76*	3.93	-0.24	-0.15	4.17	*4.37*	5.66	*6.43*
continuous - discrete				3.52	*3.55*	6.08	*6.42*				3.68	*3.36*	6.54	*6.47*

Panel C: Sequential sort on momentum and ID 5x3

Original paper factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	5.82	1.59	-0.03	4.22	*5.14*	3.22	*3.66*	3.14	1.96	0.01	1.18	*2.85*	0.36	*0.91*
2	6.18	1.25	-0.10	4.92	*5.17*	4.17	*4.74*	3.79	1.49	-0.07	2.30	*4.55*	1.90	*3.97*
continuous	6.86	0.37	-0.17	6.49	*6.31*	6.99	*6.36*	5.07	0.62	-0.16	4.45	*4.68*	4.85	*4.99*
continuous - discrete				2.27	*3.03*	3.77	*4.97*				3.27	*4.02*	4.49	*5.21*

Value weighted factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	3.76	0.90	-0.02	2.86	*3.37*	1.69	*1.99*	1.85	1.24	0.02	0.61	*1.33*	-0.48	*-1.05*
2	4.41	0.45	-0.09	3.96	*4.68*	3.82	*4.39*	2.74	0.92	-0.05	1.82	*3.83*	1.57	*3.18*
continuous	5.03	-0.08	-0.16	5.11	*4.46*	6.51	*6.02*	3.89	0.21	-0.13	3.67	*3.45*	4.96	*5.38*
continuous - discrete				2.25	2.50	4.82	5.46				3.06	3.22	5.44	6.16

This table reports **six-month** holding returns from double-sorted portfolios on the prior **twelve-month** return and information discreteness ID. An ID closer to -1 signifies continuous information while an ID closer to +1 signifies discrete information. Each panel reports results for both factors constructed as in original papers and the factors constructed by value-weighting stocks. Moreover, each panel reports both cross-sectional and time-series factor momentum with average six month holding return for winner and loser portfolios, H-L momentum portfolio and the risk-adjusted alpha through the Fama French three-factor model. Panel A reports results for portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from H to L and then each momentum quintile sorted based on ID into quintiles ranging from discrete to continuous. Panel B reports results for portfolios through factors independently sorted on prior twelve month into quintiles ranging from L to H and sorted based on ID into quintiles ranging from discrete to continuous. Panel A reports results for portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from L to H and then each momentum quintile sorted based on ID Fama French style 30/40/30% groups ranging including discrete, neutral and continuous.

Across all ID portfolios TSFM has a lower six-month return than CSFM. This finding contrasts with the findings of Ehsani and Linnainmaa (2019) who use the same construction method for the time-series factor momentum but defines cross-sectional factor momentum through going long factors above the median and going short under the median return on the formation period. However, when taking continuous H-L minus discrete H-L both the six-month return and alpha are higher for TSFM than CSFM which is in line with the findings of Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019).

Regardless of factor construction, we can observe that the Winner minus Loser (H-L) portfolio decreases steadily from the continuous portfolio to the discrete portfolio while the continuous portfolio earns the highest return and alpha with both being statistically significant. Previously mentioned research on factor momentum construct factors in Fama French Style and value weigh stocks in factor construction. The value weighted factors used in our study have lower returns than original across all portfolios six-month return but higher alphas. This finding is unexpected since we would have expected value weighted factors to be explained more by the Fama French SMB factor.

In Panel B we can report the returns of independently sorted portfolios on momentum and ID. The results have the same pattern as in sequential sorts, suggesting robust behavior of the ID measure. Across all portfolios regardless of factor construction the return decreases in the winner portfolio from continuous to discrete and increases in the loser portfolio from continuous to discrete. The Fama French style sort on ID presented in Panel C shows robustness irrespective of the number of ID groups used to sort portfolios.

We show results for twelve-month formation period and twelve-month holding return from buying winners and selling losers in **Table 2**. Similar results can be observed regardless of factor construction and the sorting method. In Panel A, where we report the sequential sorts, the CSFM winner minus loser return decreases from 11.95% twelve month return in the continuous portfolio to 7.62% in the discrete one, while the TSFM winner minus loser portfolio decreases from 8.23% in the continuous portfolio to 2%. Similar results are obtained for the value weighted construction of the factors and other type of sorts. The information discreteness measure is able to further condition momentum based on the formation of its past return and dissect momentum into higher persistence for continuous information and lower persistence for discrete information. Across all sorts, continuous momentum has higher return than discrete momentum. All continuous portfolios and continuous minus discrete have a positive twelve month return and statistically significant alphas in respect to the Fama French three-factor model. Although, we can observe that the ID measure is able to dissect the TSFM momentum better thus providing a better return and alpha for the continuous minus discrete portfolio.

In **Table 3** we provide further robustness checks in regard to the change in formation period. The table shows results for the one-month formation period and six-month holding period. Panel A presents the sequentially sorted portfolios on momentum and then ID. The CSFM decreases from the continuous portfolio to the discrete from 3.53% to 1.64% with a six-month return for the continuous minus discrete of 1.89% and a t statistic of 4.16. Compared to the twelve-month formation period, the conditional factor momentum on one month formation period realizes lower returns. Although, worth noting is the difference between regular stock momentum where last month is skipped due to the short-term reversal effect. Regardless of factor construction or ID sorts, all continuous portfolios display higher persistence than the discrete portfolio. However, when momentum and ID are constructed on a one-month formation period, the value weighted construction yields higher returns for the sequentially sorted portfolios. We present the results for one month formation period and twelve month-holding return in the **Appendix 2.** Overall, we can observe through our empirical evidence that the information discreteness is able to further condition momentum and dissect it into higher persistence for continuous information and lower persistence for discrete information as theorized by Da et al. (2014) in the stock momentum.

Table 2. Conditional Factor Momentum - 12x12

Panel A: Sequential sort on momentum and ID 5x5

Original Paper factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	-0.02	7.62	*4.58*	7.22	*3.33*	0.02	2.00	*2.60*	0.86	*0.95*
2	-0.07	8.04	*4.41*	7.34	*4.08*	-0.03	3.21	*4.10*	2.56	*3.49*
3	-0.10	8.02	*4.53*	7.74	*4.89*	-0.07	3.62	*3.60*	3.67	*4.13*
4	-0.14	10.04	*5.28*	11.43	*5.15*	-0.11	5.18	*4.04*	5.45	*4.61*
continuous	-0.19	11.95	*5.60*	13.59	*6.56*	-0.18	8.23	*4.77*	10.50	*5.57*
con-dis		4.33	*2.27*	6.37	*3.76*		6.23	*3.66*	9.64	*5.37*

Value weighted factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	-0.01	4.25	*3.19*	3.52	*2.34*	0.02	0.63	*0.77*	-0.63	*-0.87*
2	-0.06	5.18	*3.91*	5.33	*3.58*	-0.03	1.86	*2.73*	1.41	*1.76*
3	-0.09	6.04	*4.34*	7.33	*4.39*	-0.06	2.90	*3.76*	3.41	*3.83*
4	-0.12	6.71	*4.09*	9.00	*4.95*	-0.09	4.33	*3.97*	5.53	*4.53*
continuous	-0.17	9.62	*4.52*	13.48	*5.74*	-0.15	6.97	*3.79*	10.28	*5.14*
con-dis		5.37	*3.03*	9.96	*5.41*		6.34	*3.42*	10.91	*5.69*

Panel B: Independent sort on momentum and ID 5x5

Original weighted factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	0.00	4.05	*2.83*	2.90	*2.01*	0.03	1.81	*2.08*	0.31	*0.33*
2	-0.06	7.63	*4.23*	8.24	*3.57*	-0.03	2.99	*4.07*	2.29	*3.00*
3	-0.10	9.28	*4.68*	9.33	*4.58*	-0.07	4.28	*3.55*	4.37	*3.85*
4	-0.14	9.27	*4.86*	10.29	*5.31*	-0.11	5.25	*4.10*	6.04	*5.22*
continuous	-0.21	11.96	*5.97*	14.37	*7.11*	-0.18	8.26	*4.81*	10.73	*5.87*
con-dis		7.92	*4.19*	11.47	*5.89*		6.45	*3.63*	10.42	*5.56*

Value weighted factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	0.00	2.93	*2.19*	2.15	*1.69*	0.03	0.55	*0.62*	-1.00	*-1.28*
2	-0.05	4.70	*3.39*	4.92	*2.89*	-0.02	1.53	*2.22*	1.18	*1.48*
3	-0.09	6.18	*4.39*	7.58	*4.94*	-0.06	2.84	*3.32*	3.52	*3.66*
4	-0.13	6.54	*4.27*	9.32	*5.76*	-0.09	4.17	*3.79*	5.64	*4.63*
continuous	-0.18	9.19	*4.37*	12.54	*5.90*	-0.15	6.70	*3.73*	9.74	*5.48*
con-dis		6.26	*3.35*	10.39	*5.89*		6.15	*3.21*	10.74	*5.69*

Panel C: Sequential sort on momentum and ID 5x3

Original Paper factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	Raw return H-L		Fama-French 3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	-0.03	7.89	*4.69*	7.33	*3.28*	0.01	2.19	*2.99*	1.20	*1.45*
2	-0.10	8.20	*4.52*	8.22	*4.88*	-0.07	3.78	*3.88*	3.55	*4.22*
continuous	-0.17	11.31	*5.49*	12.93	*5.98*	-0.16	7.31	*4.16*	8.75	*5.11*
con-dis		3.42	*2.14*	5.60	*3.95*		5.11	*3.41*	7.56	*5.02*

Value weighted factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	-0.02	4.33	*3.33*	3.67	*2.49*	0.02	0.85	*1.17*	-0.28	*-0.42*
2	-0.09	6.03	*4.22*	7.15	*4.32*	-0.05	2.85	*3.62*	3.19	*3.59*
continuous	-0.16	8.72	*4.21*	12.11	*5.45*	-0.13	6.05	*3.50*	8.61	*4.77*
con-dis		4.39	*2.85*	8.44	*5.34*		5.21	*3.42*	8.89	*5.78*

This table reports **twelve-month** holding returns from double-sorted portfolios on the prior **twelve-month** return and information discreteness ID. An ID closer to -1 signifies continuous information while an ID closer to +1 signifies discrete information. Each panel reports results for both factors constructed as in original papers and the factors constructed by value-weighting stocks. Moreover, each panel reports both cross-sectional and time-series factor momentum with average six month holding return for winner and loser portfolios, H-L momentum portfolio and the risk-adjusted alpha through the Fama French three-factor model. Panel A reports results for portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from H to L and then each momentum quintile sorted based on ID into quintiles ranging from discrete to continuous. Panel B reports results for portfolios through factors independently sorted on prior twelve month into quintiles ranging from L to H and sorted based on ID into quintiles ranging from discrete to continuous. Panel A reports results for portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from L to H and then each momentum quintile sorted based on ID Fama French style 30/40/30% groups ranging including discrete, neutral and continuous.

Table 3. Conditional Factor Momentum 1x6

Panel A: Sequential sort on momentum and ID 5x5

Original paper factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	4.25	2.61	-0.06	1.64	*4.27*	1.46	*3.91*	3.04	2.54	0.04	0.50	*2.71*	0.38	*1.92*
2	3.81	2.09	-0.21	1.71	*5.32*	1.71	*5.14*	2.91	2.23	-0.11	0.68	*4.29*	0.67	*4.17*
3	3.56	1.70	-0.30	1.87	*5.30*	2.02	*5.47*	3.03	1.97	-0.21	1.06	*4.90*	1.15	*5.14*
4	4.03	1.83	-0.39	2.20	*5.13*	2.59	*5.41*	3.52	2.00	-0.31	1.52	*4.88*	1.76	*5.04*
continuous	5.01	1.48	-0.52	3.53	*6.80*	4.09	*6.73*	4.48	1.78	-0.47	2.71	*5.76*	3.30	*6.11*
continuous - discrete				1.89	*4.16*	2.63	*4.84*				2.21	*4.78*	2.92	*5.30*

Value weighted factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	2.36	1.93	-0.06	0.43	*1.24*	0.22	*0.52*	1.69	1.67	0.05	0.02	*0.12*	-0.19	*-0.95*
2	2.42	1.14	-0.20	1.28	*4.23*	1.22	*3.83*	1.78	1.29	-0.10	0.49	*3.09*	0.52	*2.94*
3	2.26	0.85	-0.29	1.41	*4.56*	1.63	*4.97*	1.93	1.08	-0.20	0.85	*4.45*	0.96	*4.67*
4	2.81	0.99	-0.37	1.82	*4.63*	2.30	*5.72*	2.39	1.05	-0.29	1.34	*4.55*	1.67	*5.34*
continuous	3.63	0.87	-0.50	2.76	*5.98*	3.21	*6.38*	3.29	1.08	-0.44	2.21	*5.08*	2.83	*6.24*
continuous - discrete				2.33	*5.65*	2.99	*6.00*				2.19	*4.93*	3.02	*6.31*

Panel B: Independent sort on momentum and ID 5x5

Original paper factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	3.54	2.60	0.02	0.93	*2.91*	0.73	*2.25*	2.94	2.50	0.11	0.45	*2.15*	0.27	*1.24*
2	4.31	2.40	-0.17	1.92	*4.90*	1.80	*4.71*	3.12	2.50	-0.07	0.62	*3.49*	0.56	*3.20*
3	3.55	1.66	-0.30	1.89	*5.21*	2.00	*5.05*	2.96	1.96	-0.21	1.00	*4.59*	1.10	*4.75*
4	3.99	1.72	-0.39	2.27	*5.29*	2.79	*5.82*	3.50	1.91	-0.31	1.59	*4.95*	1.80	*5.17*
continuous	5.04	1.28	-0.53	3.76	*7.05*	4.37	*7.06*	4.39	1.62	-0.47	2.77	*5.87*	3.33	*6.14*
continuous - discrete				2.83	*5.71*	3.64	*6.06*				2.32	*4.66*	3.06	*5.09*

Value weighted factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	2.05	1.97	0.02	0.07	*0.23*	-0.15	*-0.39*	1.69	1.67	0.12	0.02	*0.11*	-0.25	*-1.08*
2	2.55	1.42	-0.16	1.13	*3.27*	1.07	*2.88*	1.82	1.46	-0.06	0.37	*2.23*	0.31	*1.73*
3	2.27	0.94	-0.29	1.33	*4.18*	1.56	*4.69*	1.91	1.04	-0.20	0.87	*4.29*	1.03	*4.58*
4	2.77	0.97	-0.37	1.79	*4.60*	2.21	*5.47*	2.38	1.15	-0.29	1.23	*4.01*	1.65	*5.12*
continuous	3.69	0.84	-0.51	2.85	*6.10*	3.28	*6.41*	3.22	1.01	-0.44	2.21	*5.18*	2.71	*5.97*
continuous - discrete				2.78	*6.25*	3.43	*6.45*				2.19	*4.57*	2.97	*5.60*

Panel C: Sequential sort on momentum and ID 5x3

Original paper factor construction

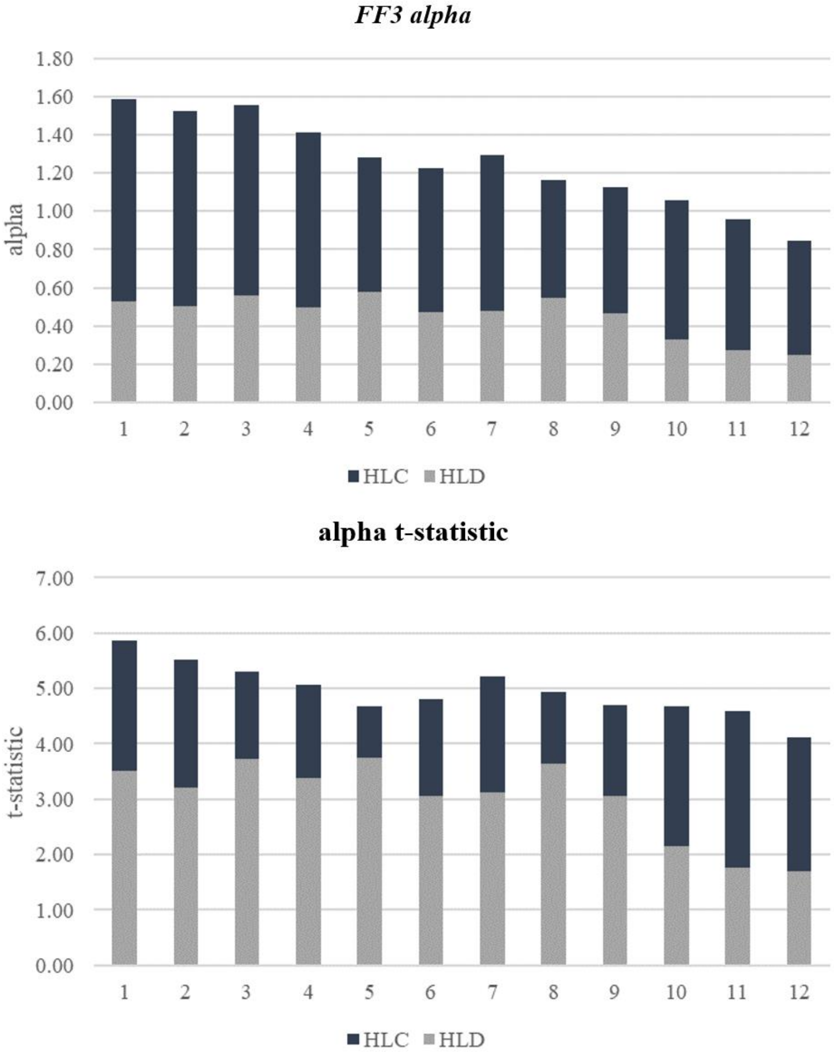
ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	4.21	2.68	-0.04	1.53	*4.26*	1.40	*3.85*	2.97	2.56	0.07	0.42	*2.27*	0.32	*1.57*
2	4.46	2.33	-0.25	2.13	*4.96*	2.16	*4.91*	3.35	2.40	-0.16	0.95	*4.40*	0.96	*4.34*
continuous	5.06	1.81	-0.48	3.25	*6.16*	3.83	*6.32*	4.24	1.92	-0.41	2.31	*5.33*	2.77	*5.66*
continuous - discrete				1.72	*3.93*	2.43	*4.50*				1.89	*4.46*	2.45	*4.80*

Value weighted factor construction

ID	Cross Sectional Factor Momentum							Times Series Factor Momentum						
			average	raw ret H-L		FF3				average	raw ret H-L		FF3	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	2.33	2.04	-0.03	0.29	*0.87*	0.04	*0.10*	1.67	1.67	0.08	0.00	*0.01*	-0.22	*-1.04*
2	2.86	1.27	-0.24	1.59	*4.25*	1.74	*4.41*	2.09	1.34	-0.15	0.74	*3.75*	0.83	*3.88*
continuous	3.66	1.02	-0.46	2.64	*5.53*	3.15	*6.19*	3.07	1.11	-0.39	1.96	*4.90*	2.44	*5.89*
continuous - discrete				2.35	*5.70*	3.11	*6.31*				1.96	*4.67*	2.66	*5.88*

This table reports **six-month** holding returns from double-sorted portfolios on the prior **one-month** return and information discreteness ID. An ID closer to -1 signifies continuous information while an ID closer to +1 signifies discrete information. Each panel reports results for both factors constructed as in original papers and the factors constructed by value-weighting stocks. Moreover, each panel reports both cross-sectional and time-series factor momentum with average six month holding return for winner and loser portfolios, H-L momentum portfolio and the risk-adjusted alpha through the Fama French three-factor model. Panel A reports results for portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from H to L and then each momentum quintile sorted based on ID into quintiles ranging from discrete to continuous. Panel B reports results for portfolios through factors independently sorted on prior twelve month into quintiles ranging from L to H and sorted based on ID into quintiles ranging from discrete to continuous. Panel A reports results for portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from L to H and then each momentum quintile sorted based on ID Fama French style 30/40/30% groups ranging including discrete, neutral and continuous.

Figure 1. CSFM 12month formation - FF3 alpha persistence



The previously discussed results suggest that continuous portfolios have higher persistence than discrete portfolios. In **Figure 1** and **Figure 2,** we report the high minus low momentum alpha in respect to the Fama French three-factor model for each month after portfolio construction. The momentum portfolios are created through original weighting factors and sequential sort on momentum and ID. The alpha represents the holding period alpha within each of the twelve months after portfolio construction.

In **Figure 1** we observe that, for the CSFM with a twelve-month formation period, the continuous information momentum alpha steadily declines from the first month to the last with all being statistically significant. However, the discrete information momentum alpha is much lower than the continuous and less persistent since it becomes statistically insignificant after the tenth month. This finding provides evidence to the suggestions in previous results.

We present the CSFM with one month formation period and sequentially sorted momentum and ID in **Figure 2**. Similarly, even if the formation period is lower (1 month), the continuous momentum alpha is much higher than the discrete momentum across all twelve months. However, with a shorter formation period, the alpha is much higher in the first months while alpha in the other months are ranging between 0.4 and 0.6 and not steadily declining. We can observe that the continuous momentum alpha is statistically significant across all months, while the discrete momentum alpha is statistically in insignificant in seven out of the twelve months starting right from the second month. Overall we can observe that continuous momentum has higher persistence.

Figure 2. CSFM 1 month formation - FF3 alpha persistence

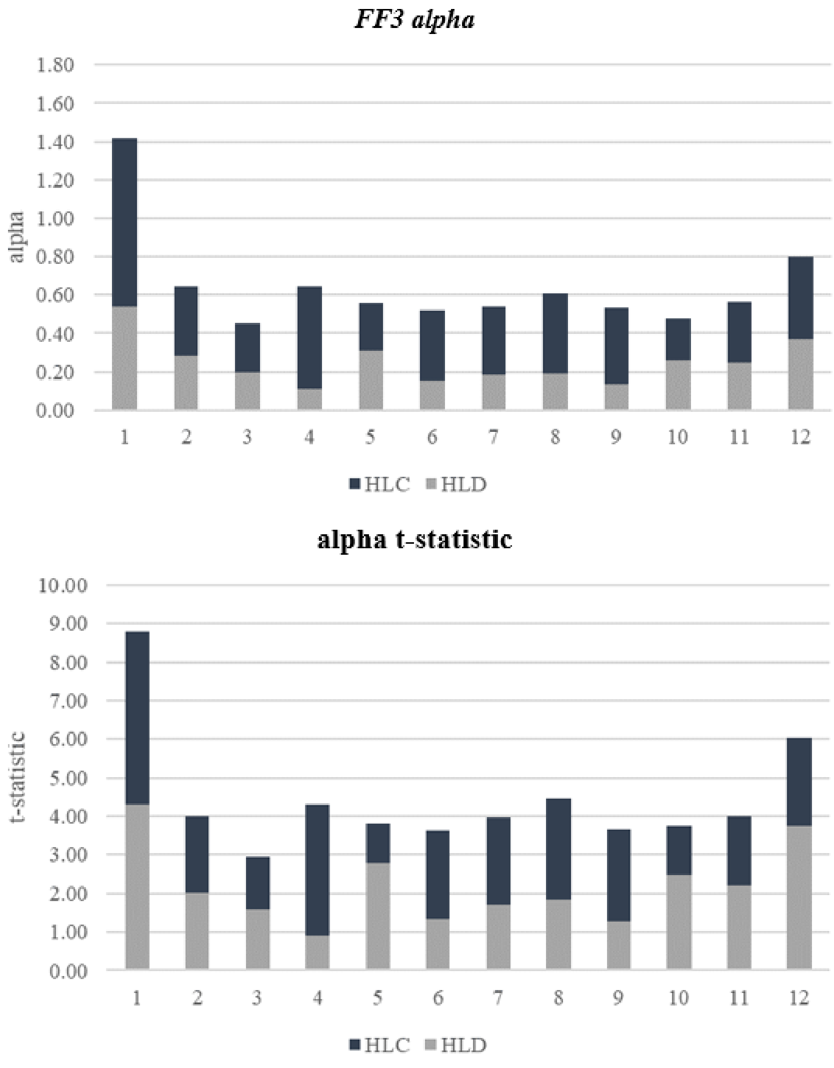


Table 4. Fama-MacBeth regressions

	Cross Sectional Factor Momentum				Times Series Factor Momentum			
	intercept	PRET	ID	PRET x ID	intercept	PRET	ID	PRET x ID
Panel A: Sequential sort - twelve-month formation period.								
Original paper	0.0233	0.1294	0.0358	-0.2899	0.0242	0.1161	0.0313	-0.3369
	12.83	*6.70*	*2.92*	*-2.63*	*13.00*	*5.87*	*1.95*	*-2.43*
Value weighted	0.0156	0.0712	0.0051	-0.4260	0.0159	0.0648	0.0094	-0.5164
	8.72	*4.12*	*0.44*	*-3.30*	*8.23*	*3.70*	*0.64*	*-3.56*
Panel B: Sequential sort - one-month formation period.								
Original paper	0.0206	0.2658	-0.0195	-0.2620	0.0243	0.2213	-0.0123	-0.3588
	17.26	*6.21*	*-10.15*	*-2.87*	*17.09*	*5.35*	*-5.82*	*-3.57*
Value weighted	0.0123	0.1264	-0.0166	-0.3807	0.0143	0.1320	-0.0136	-0.3714
	11.67	*3.78*	*-9.45*	*-5.18*	*11.35*	*3.92*	*-7.21*	*-4.65*

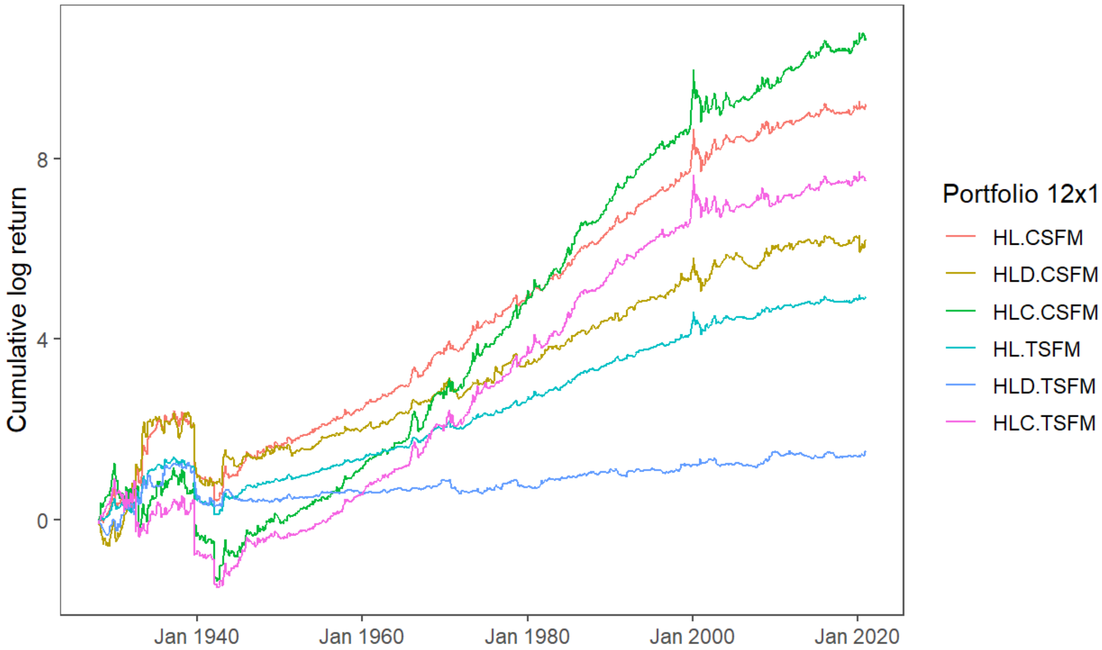
This table reports the Fama-Mac Beth regression coefficients as specified in Equation (3):

$$r_{i,t,t+h} = \beta_0 + \beta_1(PRET) + \beta_2(ID) + \beta_3(PRETxID) + \varepsilon_{i,t}$$

To examine the interaction between ID and the formation period return on which momentum relies (PRET) we have estimated the Fama-MacBeth regressions and reported the results in **Table *4***. The results, regardless of the formation period, indicate support for the frog-in-the-pan hypothesis as the β_3 coefficient is negative and statistically significant implying that a low ID (negative) that corresponds to continuous information will create persistence in momentum returns.

As noted by Da et al. (2014), the positive coefficient for the ID, in Panel A, shows the existence of a risk premium to hold positive ID factors that have discrete information, lower persistence and are more susceptible to jump risk. An interesting aspect is seen in Panel B where the formation period is one month. The β_2 of the ID is negative, implying a risk premium for holding continuous factors in the face of a short-term reversal risk. As shown through previous factor momentum literature, the factor momentum is not susceptible to short-term reversal risk, on the contrary they show that factor momentum is strongest with a one-month formation period (Gupta and Kelly,2019). However, worth noting is that their factor momentum construction is different by including timing abilities and different holding periods and therefore a clear connection and conclusion cannot be drawn.

Figure 3. Original paper - factor momentum 12x1



While in the previous part we have undertaken a similar strategy to Da et al., (2014) in studying the six-month and twelve-month holding returns with overlapping observations, we have created a non-overlapping strategy with monthly rebalancing based on either one month or twelve months look-back periods and one month holding return. We present a visualization of the conditional factor momentum, i.e. momentum conditional on ID. In order to visualize the impact on momentum of introducing the information discreteness variable we have created benchmark Winner-Loser (HL) momentum portfolios that abstract from further conditioning.

In **Figure 3** we can observe that in both CSFM and TSFM the HL continuous portfolio has a larger cumulative return than the benchmark portfolio while the discrete portfolio has lower cumulative return than the benchmark portfolio. Worth noting is that when the formation period is large, i.e. twelve months, the continuous TSFM portfolio has lower cumulative return than the CSFM benchmark portfolio. However, as seen in **Figure 4**, when the formation period is based on the previous month, the continuous TSFM performs better. Overall, regardless of the formation period or factor construction, the information discreteness variable is able to further condition momentum such that the continuous momentum has a higher quality in respect to persistence and therefore higher cumulative returns.

Figure 4. Original paper - factor momentum 1x1[4]

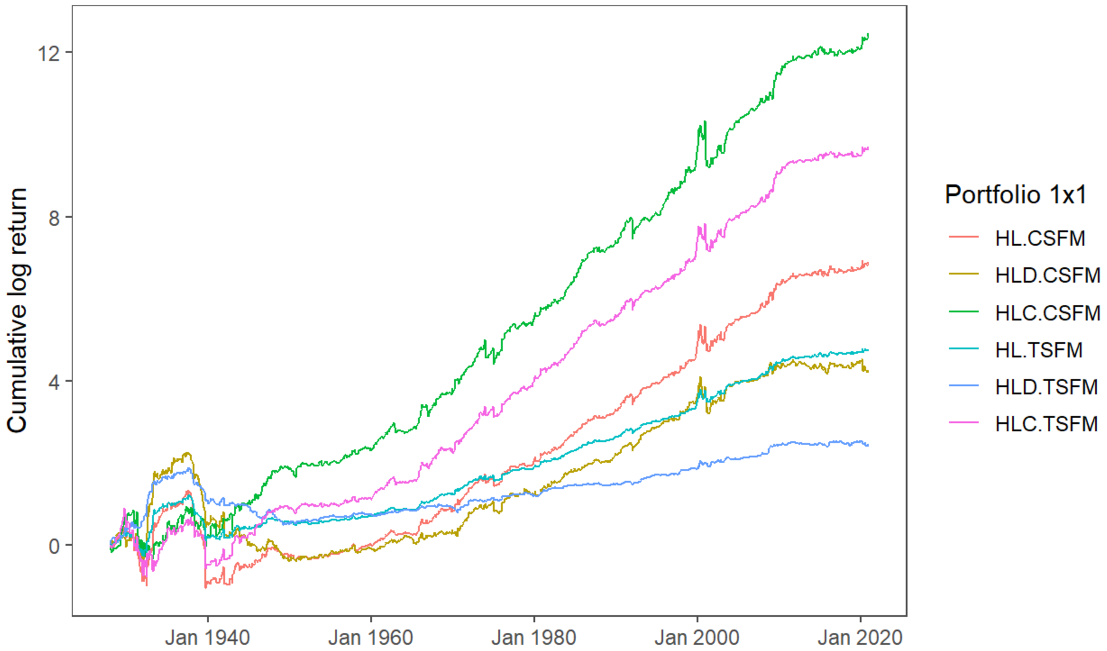
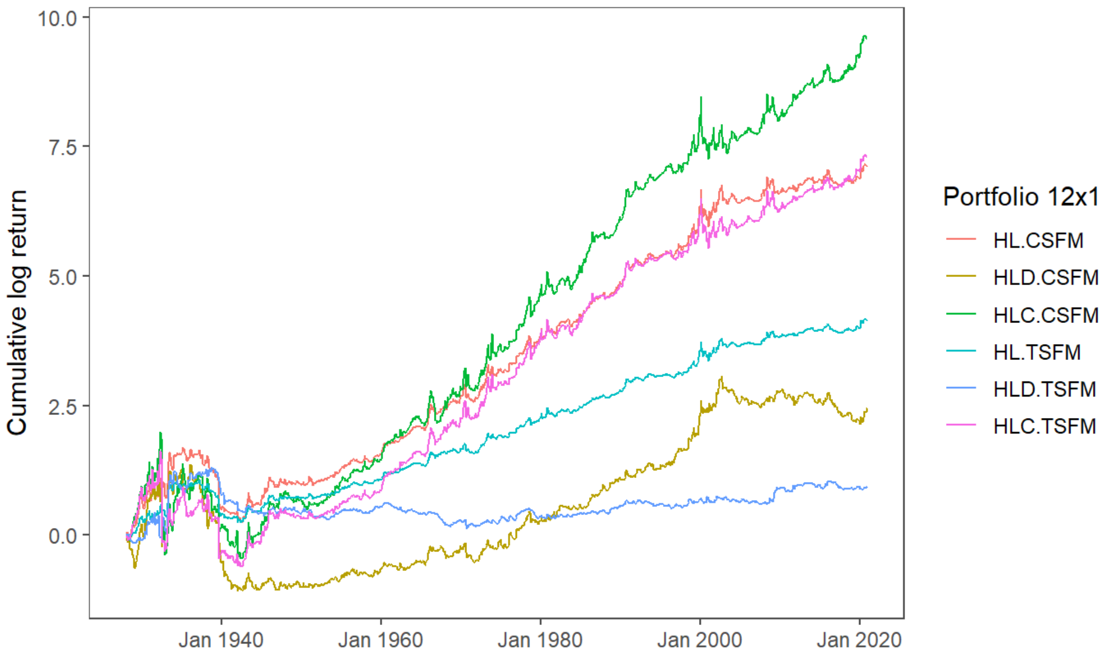


Figure 5. Value weighted - factor momentum 12x1



[4] H-High, L-Low, D-Discrete, C-Continuous, HL- High-Low, CSFM-Cross-Sectional Factor Momentum, TSFM – Time-Series Factor Momentum.

5. Conclusion

In this thesis we set out to investigate whether the frog-in-the-pan hypothesis, that explains stock momentum through underreaction to continuous information, is a robust explanation for momentum within factor risk premia. We take a large set of factors and show that indeed investor limited attention to frequent and small amounts of information leads to underreaction, which translates into increasingly persistent factor risk premia momentum.

We show that the information discreteness proxy of Da et al. (2014) can act as a quality measure for momentum. Regardless of factor construction or sorting method, when momentum is conditioned on information discreteness, it can be dissected into different levels of persistence, with the highest persistence for continuous information.

Our results contribute to the literature with several implications for further research on factor risk premia and factor investing. While factor investing and momentum strategies require high turnover, the investable universe can be reduced by identifying the persistent returns through the continuous information portfolio and therefore turnover could be decreased. High turnover requires large transaction costs and therefore renders some of the strategies unable to capture the risk premia. Although, we suggest further research in order to analyze the impact on turnover and returns of these strategies conditioned on information discreteness. While Goyal et al., (2022) show that the frog-in-the-pan hypothesis explains stock momentum better than other proposed explanations, even though we show that limited attention is a robust explanation for momentum within factors as well, we propose further investigation that includes an extensive cross-sectional analysis that includes all explanations.

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7. Appendix

Appendix 1. Summary of Factors

Description[5]	Authors	Year	Journal
Abnormal Accruals	Xie	2001	AR
Accruals	Sloan	1996	AR
Book-to-market and accruals	Bartov and Kim	2004	RFQA
Takeover vulnerability	Cremers and Nair	2005	JF
Active shareholders	Cremers and Nair	2005	JF
Advertising Expense	Chan, Lakonishok and Sougiannis	2001	JF
IPO and age	Ritter	1991	JF
Total assets to market	Fama and French	1992	JF
EPS forecast revision	Hawkins, Chamberlin, Daniel	1984	FAJ
Analyst Value	Frankel and Lee	1998	JAE
Earnings announcement return	Chan, Jegadeesh and Lakonishok	1996	JF
Analyst Optimism	Frankel and Lee	1998	JAE
Asset growth	Cooper, Gulen and Schill	2008	JF
CAPM beta	Fama and MacBeth	1973	JPE
Frazzini-Pedersen Beta	Frazzini and Pedersen	2014	JFE
Pastor-Stambaugh liquidity beta	Pastor and Stambaugh	2003	JPE
Tail risk beta	Kelly and Jiang	2014	RFS
Systematic volatility	Ang et al.	2006	JF
Bid-ask spread	Amihud and Mendelsohn	1986	JFE
Book to market using most recent ME	Rosenberg, Reid, and Lanstein	1985	JF
Book to market using December ME	Fama and French	1992	JPM
Book leverage (annual)	Fama and French	1992	JF
Leverage component of BM	Penman, Richardson and Tuna	2007	JAR
Brand capital investment	Belo, Lin and Vitorino	2014	RED
Cash to assets	Palazzo	2012	JFE
Cash Productivity	Chandrashekar and Rao	2009	WP
Cash-based operating profitability	Ball et al.	2016	JFE
Cash flow to market	Lakonishok, Shleifer, Vishny	1994	JF
Operating Cash flows to price	Desai, Rajgopal, Venkatachalam	2004	AR
Change in recommendation	Jegadeesh et al.	2004	JF
Change in Asset Turnover	Soliman	2008	AR
Growth in book equity	Lockwood and Prombutr	2010	JFR
Change in Forecast and Accrual	Barth and Hutton	2004	RAS
Inventory Growth	Thomas and Zhang	2002	RAS
Change in capital inv (ind adj)	Abarbanell and Bushee	1998	AR
Change in Net Noncurrent Op Assets	Soliman	2008	AR
Change in Net Working Capital	Soliman	2008	AR
Change in Taxes	Thomas and Zhang	2011	JAR
Composite equity issuance	Daniel and Titman	2006	JF
Composite debt issuance	Lyandres, Sun and Zhang	2008	RFS
Consensus Recommendation	Barber et al.	2002	JF

[5] List adapted from Chen and Zimmermann, (2021). Factor data taken from public source available at https://drive.google.com/drive/folders/1O18scg9iBTiBaDiQFhoGxdn4FdsbMqGo

Description[5]	Authors	Year	Journal
Convertible debt indicator	Valta	2016	JFQA
Coskewness using daily returns	Ang, Chen and Xing	2006	RFS
Coskewness	Harvey and Siddique	2000	JF
Credit Rating Downgrade	Dichev and Piotroski	2001	JF
Customer momentum	Cohen and Frazzini	2008	JF
Debt Issuance	Spiess and Affleck-Graves	1999	JFE
Breadth of ownership	Chen, Hong and Stein	2002	JFE
Change in current operating assets	Richardson et al.	2005	JAE
Change in current operating liabilities	Richardson et al.	2005	JAE
Deferred Revenue	Prakash and Sinha	2012	CAR
Change in equity to assets	Richardson et al.	2005	JAE
Change in financial liabilities	Richardson et al.	2005	JAE
Change in long-term investment	Richardson et al.	2005	JAE
Change in net financial assets	Richardson et al.	2005	JAE
Dividend Initiation	Michaely, Thaler and Womack	1995	JF
Dividend seasonality	Hartzmark and Salomon	2013	JFE
Predicted div yield next month	Litzenberger and Ramaswamy	1979	JF
change in net operating assets	Hirshleifer, Hou, Teoh, Zhang	2004	JAE
Past trading volume	Brennan, Chordia, Subra	1998	JFE
Down forecast EPS	Barber et al.	2002	JF
Earnings consistency	Alwathainani	2009	BAR
Long-vs-short EPS forecasts	Da and Warachka	2011	JFE
Earnings surprise streak	Loh and Warachka	2012	MS
Earnings Surprise	Foster, Olsen and Shevlin	1984	AR
Earnings surprise of big firms	Hou	2007	RFS
Enterprise component of BM	Penman, Richardson and Tuna	2007	JAR
Enterprise Multiple	Loughran and Wellman	2011	JFQA
Earnings-to-Price Ratio	Basu	1977	JF
Equity Duration	Dechow, Sloan and Soliman	2004	RAS
Exchange Switch	Dharan and Ikenberry	1995	JF
Excluded Expenses	Doyle, Lundholm and Soliman	2003	RAS
Analyst earnings per share	Cen, Wei, and Zhang	2006	WP
Long-term EPS forecast	La Porta	1996	JF
Firm age based on CRSP	Barry and Brown	1984	JFE
Firm Age - Momentum	Zhang	2004	JF
EPS Forecast Dispersion	Diether, Malloy and Scherbina	2002	JF
Pension Funding Status	Franzoni and Marin	2006	JF
Efficient frontier index	Nguyen and Swanson	2009	JFQA
Governance Index	Gompers, Ishii and Metrick	2003	QJE
gross profits / total assets	Novy-Marx	2013	JFE
Growth in advertising expenses	Lou	2014	RFS
Change in capex (two years)	Anderson and Garcia-Feijoo	2006	JF
Change in capex (three years)	Anderson and Garcia-Feijoo	2006	JF
Growth in long term operating assets	Fairfield, Whisenant and Yohn	2003	AR
Sales growth over inventory growth	Abarbanell and Bushee	1998	AR
Sales growth over overhead growth	Abarbanell and Bushee	1998	AR
Industry concentration (sales)	Hou and Robinson	2006	JF

Description[5]	Authors	Year	Journal
Industry concentration (assets)	Hou and Robinson	2006	JF
Industry concentration (equity)	Hou and Robinson	2006	JF
52 week high	George and Hwang	2004	JF
Employment growth	Bazdresch, Belo and Lin	2014	JPE
Idiosyncratic risk	Ang et al.	2006	JF
Idiosyncratic risk (3 factor)	Ang et al.	2006	JF
Idiosyncratic risk (AHT)	Ali, Hwang, and Trombley	2003	JFE
Amihud's illiquidity	Amihud	2002	JFM
Initial Public Offerings	Ritter	1991	JF
Industry Momentum	Grinblatt and Moskowitz	1999	JFE
Industry return of big firms	Hou	2007	RFS
Intangible return using BM	Daniel and Titman	2006	JF
Intangible return using CFtoP	Daniel and Titman	2006	JF
Intangible return using EP	Daniel and Titman	2006	JF
Intangible return using Sale2P	Daniel and Titman	2006	JF
Intermediate Momentum	Novy-Marx	2012	JFE
Investment to revenue	Titman, Wei and Xie	2004	JFQA
change in ppe and inv/assets	Lyandres, Sun and Zhang	2008	RFS
Inventory Growth	Belo and Lin	2012	RFS
Inst own among high short interest	Asquith Pathak and Ritter	2005	JFE
Customers momentum	Menzly and Ozbas	2010	JF
Suppliers momentum	Menzly and Ozbas	2010	JF
Market leverage	Bhandari	1988	JFE
Long-run reversal	De Bondt and Thaler	1985	JF
Maximum return over month	Bali, Cakici, and Whitelaw	2010	JF
Revenue Growth Rank	Lakonishok, Shleifer, Vishny	1994	JF
Momentum (12 month)	Jegadeesh and Titman	1993	JF
Momentum without the seasonal part	Heston and Sadka	2008	JFE
Momentum (6 month)	Jegadeesh and Titman	1993	JF
Junk Stock Momentum	Avramov et al	2007	JF
Off season long-term reversal	Heston and Sadka	2008	JFE
Off season reversal years 6 to 10	Heston and Sadka	2008	JFE
Off season reversal years 11 to 15	Heston and Sadka	2008	JFE
Off season reversal years 16 to 20	Heston and Sadka	2008	JFE
Momentum and LT Reversal	Chan and Ko	2006	JOIM
Return seasonality years 2 to 5	Heston and Sadka	2008	JFE
Return seasonality years 6 to 10	Heston and Sadka	2008	JFE
Return seasonality years 11 to 15	Heston and Sadka	2008	JFE
Return seasonality years 16 to 20	Heston and Sadka	2008	JFE
Return seasonality last year	Heston and Sadka	2008	JFE
Momentum in high volume stocks	Lee and Swaminathan	2000	JF
Medium-run reversal	De Bondt and Thaler	1985	JF
Mohanram G-score	Mohanram	2005	RAS
Net debt financing	Bradshaw, Richardson, Sloan	2006	JAE
Net debt to price	Penman, Richardson and Tuna	2007	JAR
Net equity financing	Bradshaw, Richardson, Sloan	2006	JAE
Net Payout Yield	Boudoukh et al.	2007	JF
Net Operating Assets	Hirshleifer et al.	2004	JAE

Description[5]	Authors	Year	Journal
Earnings streak length	Loh and Warachka	2012	MS
operating profits / book equity	Fama and French	2006	JFE
Operating profitability R&D adjusted	Ball et al.	2016	JFE
Operating leverage	Novy-Marx	2010	ROF
Option to stock volume	Johnson and So	2012	JFE
Option volume to average	Johnson and So	2012	JFE
Order backlog	Rajgopal, Shevlin, Venkatachalam	2003	RAS
Change in order backlog	Baik and Ahn	2007	Other
Organizational capital	Eisfeldt and Papanikolaou	2013	JF
O Score	Dichev	1998	JFE
Payout Yield	Boudoukh et al.	2007	JF
Percent Operating Accruals	Hafzalla, Lundholm, Van Winkle	2011	AR
Percent Total Accruals	Hafzalla, Lundholm, Van Winkle	2011	AR
Predicted Analyst forecast error	Frankel and Lee	1998	JAE
Price	Blume and Husic	1972	JF
Price delay r square	Hou and Moskowitz	2005	RFS
Price delay coeff	Hou and Moskowitz	2005	RFS
Price delay SE adjusted	Hou and Moskowitz	2005	RFS
Probability of Informed Trading	Easley, Hvidkjaer and O'Hara	2002	JF
Piotroski F-score	Piotroski	2000	AR
R&D over market cap	Chan, Lakonishok and Sougiannis	2001	JF
R&D ability	Cohen, Diether and Malloy	2013	RFS
R&D capital-to-assets	Li	2011	RFS
IPO and no R&D spending	Gou, Lev and Shi	2006	JBFA
Real dirty surplus	Landsman et al.	2011	AR
Real estate holdings	Tuzel	2010	RFS
Analyst Recommendations and Short-Interest	Drake, Rees and Swanson	2011	AR
Momentum based on FF3 residuals	Blitz, Huij and Martens	2011	JEmpFin
Return skewness	Bali, Engle and Murray	2015	Book
Idiosyncratic skewness (3F model)	Bali, Engle and Murray	2015	Book
Earnings forecast revisions	Chan, Jegadeesh and Lakonishok	1996	JF
Revenue Surprise	Jegadeesh and Livnat	2006	JFE
Inst Own and Forecast Dispersion	Nagel	2005	JF
Inst Own and Market to Book	Nagel	2005	JF
Inst Own and Turnover	Nagel	2005	JF
Inst Own and Idio Vol	Nagel	2005	JF
Return on assets (qtrly)	Balakrishnan, Bartov and Faurel	2010	JAE
net income / book equity	Haugen and Baker	1996	JFE
Earnings Forecast to price	Elgers, Lo and Pfeiffer	2001	AR
Share issuance (1 year)	Pontiff and Woodgate	2008	JF
Share issuance (5 year)	Daniel and Titman	2006	JF
Share repurchases	Ikenberry, Lakonishok, Vermaelen	1995	JFE
Share Volume	Datar, Naik and Radcliffe	1998	JFM
Short Interest	Dechow et al.	2001	JFE
Sin Stock (selection criteria)	Hong and Kacperczyk	2009	JFE
Size	Banz	1981	JFE

Description[5]	Authors	Year	Journal
Volatility smirk near the money	Xing, Zhang and Zhao	2010	JFQA
Put volatility minus call volatility	Yan	2011	JFE
Sales-to-price	Barbee, Mukherji and Raines	1996	FAJ
Spinoffs	Cusatis, Miles and Woolridge	1993	JFE
Share turnover volatility	Chordia, Subra, Anshuman	2001	JFE
Short term reversal	Jegadeesh	1989	JF
Unexpected R&D increase	Eberhart, Maxwell and Siddique	2004	JF
Tangibility	Hahn and Lee	2009	JF
Taxable income to income	Lev and Nissim	2004	AR
Total accruals	Richardson et al.	2005	JAE
Trend Factor	Han, Zhou, Zhu	2016	JFE
Up Forecast	Barber et al.	2002	JF
Cash-flow to price variance	Haugen and Baker	1996	JFE
Volume to market equity	Haugen and Baker	1996	JFE
Volume Variance	Chordia, Subra, Anshuman	2001	JFE
Volume Trend	Haugen and Baker	1996	JFE
Net external financing	Bradshaw, Richardson, Sloan	2006	JAE
Days with zero trades	Liu	2006	JFE
Days with zero trades	Liu	2006	JFE
Days with zero trades	Liu	2006	JFE

Appendix 2. Conditional Factor Momentum 1x12

Panel A: Sequential sort on momentum and ID 5x5

Original Paper factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	-0.06	3.64	*5.07*	3.13	*4.06*	0.04	1.29	*3.70*	1.03	*2.19*
2	-0.21	3.67	*6.45*	3.41	*6.16*	-0.11	1.68	*6.23*	1.61	*5.59*
3	-0.30	3.77	*7.20*	3.74	*6.26*	-0.21	2.10	*6.55*	2.25	*6.44*
4	-0.39	4.68	*7.65*	4.97	*6.86*	-0.31	2.97	*6.43*	3.16	*5.67*
continuous	-0.52	6.99	*8.58*	6.90	*7.31*	-0.47	5.45	*7.89*	5.51	*6.65*
con-dis		3.36	*4.77*	3.77	*4.52*		4.16	*6.30*	4.48	*5.03*

Value weighted factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	-0.06	1.40	*2.66*	1.12	*1.95*	0.05	0.27	*1.03*	-0.10	*-0.39*
2	-0.20	2.44	*4.73*	2.15	*3.89*	-0.10	0.99	*4.13*	0.98	*3.48*
3	-0.29	2.68	*5.49*	2.65	*4.60*	-0.20	1.54	*5.31*	1.64	*4.86*
4	-0.37	3.16	*5.77*	3.67	*5.39*	-0.29	2.44	*5.71*	2.71	*5.06*
continuous	-0.50	4.87	*6.97*	5.44	*6.53*	-0.44	3.90	*6.45*	4.69	*6.49*
con-dis		3.47	*6.27*	4.32	*7.26*		3.63	*6.09*	4.79	*7.22*

Panel B: Independent sort on momentum and ID 5x5

Original weighted factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	0.02	2.11	*3.63*	1.79	*3.10*	0.11	1.06	*2.83*	0.88	*1.95*
2	-0.17	4.22	*6.55*	3.78	*5.55*	-0.07	1.61	*5.33*	1.44	*4.07*
3	-0.30	3.99	*7.46*	4.02	*6.64*	-0.21	2.00	*5.96*	2.11	*5.74*
4	-0.39	4.89	*8.01*	4.97	*6.96*	-0.31	3.09	*6.78*	3.21	*5.97*
continuous	-0.53	7.57	*9.14*	7.49	*7.80*	-0.47	5.53	*7.99*	5.54	*6.76*
con-dis		5.46	*7.77*	5.70	*7.39*		4.47	*6.25*	4.65	*5.00*

Value weighted factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	0.02	0.62	*1.22*	0.23	*0.41*	0.12	0.14	*0.45*	-0.31	*-1.03*
2	-0.16	2.34	*4.30*	2.15	*3.61*	-0.06	0.83	*3.46*	0.72	*2.59*
3	-0.29	2.68	*5.67*	2.75	*4.72*	-0.20	1.56	*5.38*	1.77	*4.96*
4	-0.37	3.31	*5.63*	3.63	*4.98*	-0.29	2.42	*5.57*	2.68	*4.82*
continuous	-0.51	5.00	*7.19*	5.60	*6.75*	-0.44	3.92	*6.49*	4.56	*6.26*
con-dis		4.38	*6.90*	5.37	*7.69*		3.78	*5.83*	4.88	*6.40*

Panel C: Sequential sort on momentum and ID 5x3

Original Paper factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	Raw return H-L		Fama-French 3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	-0.04	3.52	*5.04*	3.05	*4.06*	0.07	1.15	*3.38*	0.95	*1.98*
2	-0.25	4.41	*6.82*	4.13	*6.11*	-0.16	2.08	*6.00*	1.99	*5.64*
continuous	-0.48	6.65	*8.28*	6.65	*7.09*	-0.41	4.68	*7.48*	4.70	*6.29*
con-dis		3.13	*4.77*	3.60	*4.56*		3.53	*5.66*	3.75	*4.28*

Value weighted factor construction

ID	Cross Sectional Factor Momentum					Time Series Factor Momentum				
	average	raw ret H-L		FF3		average	raw ret H-L		FF3	
	ID	return	t-stat	alpha	t-stat	ID	return	t-stat	alpha	t-stat
discrete	-0.03	1.15	*2.16*	0.71	*1.24*	0.08	0.19	*0.69*	-0.19	*-0.76*
2	-0.24	3.14	*5.28*	3.04	*4.60*	-0.15	1.44	*4.90*	1.50	*4.38*
continuous	-0.46	4.63	*6.73*	5.25	*6.36*	-0.39	3.52	*6.30*	4.04	*5.91*
con-dis		3.47	*6.23*	4.54	*7.37*		3.33	*5.96*	4.23	*6.44*

This table reports **twelve-month** holding returns from double-sorted portfolios on the prior **one-month** return and information discreteness ID. An ID closer to -1 signifies continuous information while an ID closer to +1 signifies discrete information. Each panel reports results for both factors constructed as in original papers and the factors constructed by value-weighting stocks. Moreover, each panel reports both cross-sectional and time-series factor momentum with average six month holding return for winner and loser portfolios, H-L momentum portfolio and the risk-adjusted alpha through the Fama French three-factor model. Panel A reports results for portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from H to L and then each momentum quintile sorted based on ID into quintiles ranging from discrete to continuous. Panel B reports results for portfolios through factors independently sorted on prior twelve month into quintiles ranging from L to H and sorted based on ID into quintiles ranging from discrete to continuous. Panel A reports results for portfolios through factors sequentially sorted first on prior twelve month into quintiles ranging from L to H and then each momentum quintile sorted based on ID Fama French style 30/40/30% groups ranging including discrete, neutral and continuous.