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Industrial Time Series Momentum Strategies

Performance of Industrial Time Series Momentum strategies

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Abstract

This thesis documents significant profits for the Industrial Time Series Momentum strategies, using data from 17 industry portfolios in the US stock market, during time period from January 1985 to December 2018. Given 1 dollar investing in the Industrial Time Series Momentum strategies from the beginning of sample period, January 1985, an investor could end up with a maximum cumulative return of 126.75 dollars in December 2018. This cumulative return is around two times higher than that from a passive long strategy in all industries, and that from Fama-French market proxy. Among four Industrial Time Series Momentum strategies been studied in this thesis, the 1-month look back equally weighted and 12-month look back value weighted strategies are the most profitable ones. These two strategies deliver maximum significantly positive abnormal returns of 1.05 and 0.68 percent per month, respectively, after controlling for several risk factors. Also, the returns of Industrial Time Series Momentum strategies are not fully explained by any of the momentum factors that have been studied before. Furthermore, the performance of Industrial Time Series Momentum strategies is improved during extreme market conditions, making these strategies attractive for investors as a hedge tool.

1. Introduction

Momentum strategies, defined by acquiring past winning stocks and selling past losing stocks, are one of the most interesting of stock return persistence anomalies. Many researches study the profitability of these strategies and show that these strategies deliver abnormal returns. For example, using the US stock data from 1965 to 1989, Jagadeesh and Titman (1993) first show groundbreaking findings on the momentum strategies (commonly known as "cross-sectional momentum"), which still are an important source for many studies on Momentum effects. Using their results, an investor could construct several momentum portfolios, which yield a maximum significant annual return about 25 percent. This return is higher than the annual 10 percent return of a normal stock index like the S&P 500. This high reward later inspires researchers and investors to study and examine the momentum strategies in both academic and practical aspects.

More recently, Moskowitz et al. (2012) document "Time Series Momentum", which refers to purely investing in certain assets based on their own past performance (not relative to their peers). They document significant ''Time Series Momentum'' return of 1.58 percent per month from diverse futures and forward contracts that include country equity indexes, currencies, commodities, and sovereign bonds from 1985 to 2009. Besides, the Time Series Momentum strategy exhibits strong and consistent performance across many asset classes, has small loadings on standard risk factors, and performs well in extreme market conditions. Moreover, Moskowitz et al. (2012) also find that the Time Series Momentum captures the returns associated with individual stock (cross-sectional) momentum, and most notably Fama-French's factor - *UMD*.[1] Also, recent evidence on momentum returns, for example from Asness et al. (2013), suggests that the time series strategy outperforms the cross-sectional strategy, when investing in the same assets. Thus, in this thesis, I am motivated to analyze the performance of Industrial Time Series Momentum strategies. The fundamental idea of these strategies is that I invest monthly in each of all industries in the market, where the long (short) position on each industry is based on its individual past performance.

[1] *UMD*, stands for *Up Minus Down*, is a cross-sectional momentum factor, stands for the monthly premium on winners minus losers from Fama-French (1993) and Carhart (1997).

The main purpose of this thesis is to examine the profitability of Industrial Time Series Momentum strategies, which monthly investing in 17 industries' returns in the US stock from January 1985 to December 2018. In addition, in this thesis, I examine the performance of Industrial Time Series Momentum strategies during extreme market conditions.

Based on the monthly equally weighted and value weighted return series of 17 industries in the US stock market, I construct and analyze the performance of four different Industrial Time Series Momentum strategies: 12-month look back equally weighted (*12-m ITSM, EW*), 1-month look back equally weighted (*1-m ITSM, EW*), 12-month look back value weighted (*12-m ITSM, VW*), 1-month look back value weighted (*1-m ITSM, VW*), with 1-month holding period strategies.

To construct the equally weighted Industrial Time Series Momentum strategies, I use the equally weighted return series of 17 industries in the US stock market. More specifically, I build these strategies by looking at the last 12-month (or 1-month) cumulative return of each of all industries, to decide the investing position for that industry. Here each industry shares an equal weight in the portfolios. Next, to construct the value weighted Industrial Time Series Momentum strategies, I use the value weighted return series of 17 industries in the US stock market. Here, I look at the previous 12-month (or 1-month) cumulative return of each of all industries to decide the investing position for that industry. However, for these value weighted strategies, the weight of each industry in the portfolios is based on its market capitalization relative to that of all 17 industries.

The reason why I choose 1 month or 12 months for looking back and 1 month for holding period is based on the results from previous researches and my data analysis. Jegadeesh and Titman (1993) find that the cross-sectional momentum strategies, in which long (short) positions are taken in securities that have performed well (poorly) over the past 3- to 12- month period, generate significant positive returns over up to 12- month holding period. Moskowitz et al. (2012) conclude that 12-month look back with 1-month holding time series momentum strategy is the most profitable one, for future and forward contracts of various asset classes. Moreover, the return predictability research of the sample data in this thesis shows that current return of an industry has a significant impact only on next month's return. Also, in this sample data, there is a tendency of reversal returns after 12-month horizon, despite this phenomenon is not significantly clear. Therefore, I choose to construct the Industrial Time Series Momentum strategies with holding period of 1 month, and look back period of 1- or 12- month.

After constructing four Industrial Time Series Momentum strategies, I analyze the performance of these strategies by looking at their returns' descriptive statistics, cumulative returns during the sample period, as well as investigating their profitability when controlling for several risk factors. First, for two equally weighted Industrial Time Series Momentum strategies, the 12-month look back one ends up with 3.83 dollars in December 2018 for 1 dollar investing in this strategy in January 1985. Also, this strategy yields a low annualized gross Sharpe ratio of 0.338, and does not provide any significant abnormal returns after controlling for several risk factors. The 1-month look back equally weighted Industrial Time Series Momentum strategy, however, performs better by ending up with 126.75 dollars in December 2018 from 1 dollar investing in this strategy in January 1985. This strategy also outperforms the market, when comparing its cumulative return to that from several market proxies. Moreover, the 1-month look back strategy yields a high annualized gross Sharpe ratio of 0.9420 and provides a maximum significant abnormal return of 1.05 percent per month, after controlling for various risk factors.

Next, for two value weighted Industrial Time Series Momentum strategies, the 12-month look back one ends up with 106.14 dollars in December 2018 for 1 dollar investing in this strategy in January 1985. Also, this strategy yields an annualized gross Sharpe ratio of 1.0837, and provides a maximum significant abnormal return of 0.68 percent per month, after controlling for several risk factors. For the 1-month look back value weighted Industrial Time Series Momentum strategy, there is no significant abnormal returns in any case, after controlling for the risk factors. In addition, this strategy does not beat the market and only provides a cumulative revenue of 6.10 dollars in December 2018 for 1 dollar investing in this strategy in January 1985, with an annualized gross Sharpe ratio of 0.4877.

From these results, note that when changing from an equally weighted to a value weighted method of investing, there is an improvement in the performance of 12-month look back Industrial Time Series Momentum strategies. Also, the 1-month look back value weighted Industrial Time Series Momentum strategy underperforms the 12-month look back value weighted and the 1-month look back equally weighted ones. These findings raise a concern that size has an impact on Industrial Time Series Momentum. However, I will not go further into explaining this phenomenon in this thesis, and leave this to future studies.

This thesis also documents that the performance of Industrial Time Series Momentum strategies is improved during extreme market conditions. By plotting against the S&P 500 index returns and the VIX index, all the Industrial Time Series Momentum strategies show a "smile" pattern, which proves that these strategies perform better during extreme events. Furthermore, when regressing on the squared S&P 500 returns or the squared VIX index, the results for the 1-month look back equally weighted and the 12-month look back value weighted strategies support that these strategies' performance are significantly improved during extreme time.

In a nutshell, this thesis finds that the Industrial Time Series Momentum strategies, investing in 17 industries in the US stock market are profitable, especially for the 1-month look back equally weighted and the 12-month look back value weighted ones. Moreover, these two Industrial Time Series Momentum strategies perform well under extreme markets, making these strategies attractive as a hedge for investors.

This thesis contributes to the research topic in several aspects. First, most of the studies on Time Series Momentum examine the strategies based only on equally weighted investing. For example, Moskowitz et al. (2012) investigate performance of Time Series Momentum strategy that equally weighted investing in 58 futures and forward contracts of 5 different asset classes, Baltas and Kosowski (2013) study performance of Time Series Momentum strategy that equally weighted investing in 71 futures and forward contracts of 4 different asset classes. However, this thesis is different in the way of it investigate the performance of Time Series Momentum strategies which invested by both equally and value weighted ways. Especially, significant abnormal returns provided by the 12-month look back value weighted Industrial Time Series Momentum strategy suggests for future researches that size has an impact on Industrial Time Series Momentum.

Second, most of the studies in Time Series Momentum topic focus on strategies that investing in futures and forward contracts from different individual asset classes. Regarding to researches that study the performance of momentum strategies investing in industries, Moskowitz and Grinblatt (1999) find that at the industry level, there is a short term cross-sectional momentum and the abnormal returns are largest for the 1-month look back and 1-month holding period cross-sectional momentum strategy. Also, they find that in comparison with the individual cross-sectional momentum strategies, the industrial cross-sectional momentum ones are more profitable.

However, different from Moskowitz and Grinblatt (1999), in this thesis, I focus on studying the performance of Time Series Momentum strategies, not the cross-sectional momentum ones.

Finally, the good performance of Industrial Time Series Momentum strategies during extreme events, documented in this thesis, could inspire future researchers to investigate the explanations for this phenomenon. In fact, there are several other researches that reach the same finding. For example, besides results from Moskowitz et al. (2012) stated above, Georgopoulou and Wang (2016) document that a diversified long-short time series momentum portfolio, investing in 67 equity and commodity indices from 1969 to 2013, realizes its largest profits in extreme market conditions.

This thesis is organized as follows. Section 2 briefly describes the data construction as well as its descriptive statistics and choice of several market return proxies to compare with performance of the Industrial Time Series Momentum strategies. Section 3 presents the predictability of price continuation for the industry portfolios' return series and describes the process of constructing the Industrial Time Series Momentum strategies. Section 4 then analyzes the performance and profitability of four Industrial Time Series Momentum strategies, and studies the performance of those strategies during extreme market conditions. Finally, Section 5 concludes the thesis by summarizing all the findings and offering several extensions for future researchers.

2. Data description and choice of comparable market proxies

In this section, I describe the process of collecting, cleansing and properties of my data sample, as well as describe several market proxies that used to compare with the Industrial Time Series Momentum strategies' performance in empirical analysis section. Using the CRSP and COMPUSTAT data files, 17 industry portfolios by equally-weighted and 17 industry portfolios by value-weighted are formed every month from January 1985 to December 2018.[2] Four-digit Standard Industrial Classification (SIC) codes of NYSE, AMEX and NASDAQ stocks are used to form industry's returns each month. The SIC codes are those of 17 Industry portfolios of Fama-French's database library.[3] The constructing process of portfolios is described as following:

First, on the last day of each month in my sample period, I collect stocks data for each of 17 industries, including price, share outstanding to define market capitalization for computing value-weighted return, holding period returns and delisting returns for stocks' returns. Next, after cleansing eventual errors of the stock returns, I compute market capitalization for each stock as product of price and share outstanding, then sum up all stocks' market capitalizations within an industry to define each industry's capitalization. Finally, I compute equally weighted industry returns for each industry by taking average returns of all stocks within that industry. For value weighted industry returns, for each of 17 industries, I sum up all products of each stock's return and weight within that industry. After constructing the equally and value weighted monthly returns for 17 industries, each month when comparing with Fama-French database library's 17 industry portfolios return series, the difference in absolute monthly return is only around ± 100 to 200 basis points for both 17 equally weighted and 17 value weighted industry return series.[4]

Table I reports descriptive statistics of the equally and value weighted monthly returns of 17 industry portfolios. Through the whole time period, there are total of 17,597 individual stocks for all 17 industries. The number of stocks within an industry in the sample are different, with the highest amount of 5993 stocks from Other (variable's name: Other) industry and the lowest of 151

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[2] CRSP data are collected from Wharton Research Data Services: https://wrdsweb.wharton.upenn.edu/wrds/ds/crsp/stock_a/msf.cfm?navId=128

[3] SIC codes source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/Siccodes17.zip

[4] Fama-French library's 17 industry portfolios' returns: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/17_Industry_Portfolios_CSV.zip

stocks from Fabricated Products (FabPr) industry. Despite the difference in number of stocks across industries, there is not much difference among annualized return and volatility of each industry portfolio.

Regarding to the equally weighted industries' return series, average annualized returns range from 8.11 to 18.88 percent per year and annualized volatilities range from 12.13 to 28.54 percent per year. As seen from Table I, the highest annualized return is 18.88 percent, obtained from Drugs, Soap, Perfumes, Tobacco (Cnsum) industry, where the lowest return is 8.11 percent per year, obtained from Mining and Minerals (Mines) industry. The highest annual volatility is 28.54 percent from Oil and Petroleum Products (Oil) industry, where the lowest one is from Utilities (Utils) industry with 12.13 percent per year. Besides, when I test whether the means returns of industry portfolios are significantly different from 0, most of the t-statistics are highly positive significant (except for Mining and Minerals (Mines) industry).

For the value weighted industrial return series, in general, all annualized returns of each industry are higher than those from the equally weighted return series, with higher positive significant t-statistics of the test whether means of time series returns of industry portfolios are significantly different from 0, at 5% level. Besides, when looking through all industry portfolios, all annualized volatilities are lower when comparing those from the equally weighted return series. In specific, average value weighted annualized returns range from 14.73 to 21.88 percent per year and annualized volatilities range from 13.50 to 26.49 percent per year. Also, the highest annualized return is 21.88 percent, obtained from Other (Other) industry, where the lowest return is 14.73 percent per year, obtained from Utilities (Utils) industry. In terms of volatility, the highest annualized volatility is 26.49 percent from Mining and Minerals (Mines) industry, where the lowest one is from Utilities (Utils) industry with 13.50 percent per year.

In the next sections, when analyzing the performance of Industrial Time Series Momentum strategies over time, I choose several benchmarks which represent market portfolio's performance to compare with my strategies. For this purpose, I use three portfolios as proxies for market returns. All of the market proxies' performance used to compare are cumulative monthly returns of buy-and-hold strategies, in which investor starts by going long 1 dollar in each of the market proxies on January 1st 1985. For the first market proxy, I use excess returns on the market from Fama-

French library, $R_m - R_f$, which is a well-known risk factor in Fama-French 3 factor model.[5] For the second proxy, I use the 17 equally weighted industry portfolios to construct an equally weighted buy-and-hold proxy for market return, then compare performance of this proxy with the equally weighted Industrial Time Series Momentum strategies. For the third proxy, I use the 17 value weighted industry portfolios to construct a value weighted buy-and-hold proxy for the market, then compare performance of this proxy with the value weighted Industrial Time Series Momentum strategies.

In specific, for the second proxy, using 17 industries equally weighted return series, I construct cumulative return of a diversified buy-and-hold portfolio, $Passive\ long\ [EW]$, in which an investor will invest 1 dollar, by equally weighted in all 17 industries on January 1st 1985. Then I compare the performance of this proxy with the equally weighted Industrial Time Series Momentum strategies. For the third proxy, I use 17 value weighted industry portfolios to construct cumulative return of a diversified buy-and-hold portfolio, $Passive\ long\ [VW]$, in which an investor will invest 1 dollar, by value weighted in all 17 industries on January 1st 1985. Then I compare the performance of this proxy with the value weighted Industrial Time Series Momentum strategies.

[5] Excess returns on the market is defined by value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month *t*, good shares and price data at the beginning of *t*, and good return data for *t* minus the one-month Treasury bill rate (from Ibbotson Associates)

Table I

Descriptive Statistics of 17 Industries' return series

Summary statistics of 17 industry portfolios are presented below. The industry portfolios are formed monthly, both equally and value weighted, from January 1985 – December 2018 using CRSP four-digit SIC codes of NYSE, AMEX and NASDAQ stocks. Reported are the annualized mean return and volatility (standard deviation), total stocks of each industry portfolio, as well as t-statistics in the parentheses for whether the mean monthly return of each industry is different from zero.

Industry	Variable Names	Total stocks	Equally weighted returns		Value weighted returns	
			Annualized mean	Annualized volatility	Annualized mean	Annualized volatility
1. Automobiles	Cars	240	12.00 % (3.05)	22.93 %	17.63 % (5.04)	22.16 %
2. Chemicals	Chems	285	13.33 % (3.78)	20.59 %	18.21 % (6.01)	19.18 %
3. Textiles, Apparel & Footwear	Clths	295	11.87 % (3.19)	21.71 %	21.85 % (6.73)	20.56 %
4. Construction and Construction Materials	Cnstr	533	12.62 % (3.43)	21.45 %	20.18 % (6.27)	20.37 %
5. Drugs, Soap, Perfumes, Tobacco	Cnsum	828	18.88 % (4.06)	27.09 %	19.90 % (8.40)	14.99 %
6. Consumer Durables	Durbl	484	9.87 % (2.79)	20.61 %	19.17 % (5.83)	20.83 %
7. Fabricated Products	FabPr	151	16.71 % (4.66)	20.93 %	20.26 % (6.29)	20.39 %
8. Banks, Insurance Companies, and Other Financials	Finan	3515	13.27 % (4.99)	15.50 %	18.52 % (6.43)	18.22 %
9. Food	Food	404	12.82 % (5.16)	14.48 %	17.90 % (8.03)	14.11 %
10. Machinery and Business Equipment	Machn	2069	15.50 % (3.54)	25.52 %	21.22 % (5.74)	23.39 %
11. Mining and Minerals	Mines	218	8.11 % (1.72)	27.45 %	18.77 % (4.48)	26.49 %
12. Oil and Petroleum Products	Oil	616	11.87% (2.43)	28.54 %	16.50 % (5.32)	19.62 %
13. Retail Stores	Rtail	1013	11.94 % (3.15)	22.12 %	20.25 % (7.22)	17.76 %
14. Steel Works Etc	Steel	184	11.53 % (2.58)	26.10 %	17.57 % (4.40)	25.29 %
15. Transportation	Trans	465	12.69 % (3.73)	19.83 %	19.84 % (6.60)	19.03 %
16. Utilities	Utils	304	12.47 % (5.99)	12.13 %	14.73 % (6.91)	13.50 %
17. Other	Other	5993	14.54 % (3.60)	23.55 %	21.88 % (7.89)	17.55 %

3. Predicting price continuation and construction of Industrial Time Series Momentum strategies

3.1. Predicting price continuation

In this section, following initial analyzing process from Moskowitz et al. (2012), I study the time series predictability of industry return series across different time horizons. Moskowitz et al. (2012) stack all futures contracts and dates, then run a pooled panel regression and compute t-statistics that account for group-wise clustering by time (at the monthly level). Their regressions are run using lags of $h = 1, 2, \dots, 60$ months, as following

$$\frac{r_t}{\sigma_{t-1}} = \alpha + \beta_h * \frac{r_{t-h}}{\sigma_{t-h-1}} + \epsilon_t$$

In this equation, returns are scaled by ex ante volatilities in order to make meaningful comparisons across assets, since Moskowitz et al. (2012) study time series momentum across various asset classes including bonds, equity index futures, commodity futures… These instruments have various annualized volatilities, range from 2% to 40%. Thus, returns of these instruments have to be scaled by volatilities to have the same level of volatility. However, Moskowitz et al. (2012) claim that regression results are still qualitatively unchanged when they run regressions without adjusting for each asset's volatility. In this thesis, since I only study the US stocks data instead of various asset classes, in which the industries' volatilities do not vary. I therefore do not scale returns by volatilities and using both equally and value weighted return series, the regressions are:

$$r_t^{all,EW} = \alpha + \beta_h * r_{t-h}^{all,EW} + \epsilon_t^{all,EW} \quad \text{(i)}$$

and

$$r_t^{all,VW} = \alpha + \beta_h * r_{t-h}^{all,VW} + \epsilon_t^{all,VW} \quad \text{(ii)}$$

The regressions are run using lags of $h = 1, 2, \dots, 60$ months and t-statistics of predictor's coefficient are reported, for monthly equally and value weighted portfolios of all industries. Moskowitz et al. (2012) find that from their size regressions, there is a strong return continuation for the first year, proven by highly positive significant t-statistics at 5% level, and weaker reversals for the next 4 years, using their sample of various asset classes. However, the results are slightly different for equally and value weighted industrial returns from US stock data.

Panel A of Figure I plots the t-statistics from the equally and value weighted portfolios investing in all 17 industries' regressions. For the equally weighted return series, when jointing 17 industries every month, there is an only highly significant positive t-statistics for lagging 1 month, while the rest time horizon laggings result in mostly insignificant and random signs t-statistics. In terms of reversal, the trend or return continuation of my sample is weak and only occurs for 1 month lagging. In addition, after 12 months the reverse of return from positive to negative is weak and not significant. For value weighted return series, when jointing 17 industries every month, in this case there is still positive t-statistics for lagging 1 month, however all t-statistics across all time horizons are insignificant. Regarding to the return reversal, the return continuation of value weighted sample is weak and after 12 months the reverse of return from positive to negative still occurs but not significant. [6]

Besides size regression specification, Moskowitz et al. (2012) also explore another regression to look at time series predictability, which is to simply focus only on the sign of the past excess return. They note that this specification is even simpler way of looking at time series momentum, which underlies their trading strategies. Also, they find that results from this specification are similar to those from previous specification, which is strong return continuation occurs only for the first year, then there is reversals for the next 4 years. Following sign regressions' setting from Moskowitz et al. (2012), the regression setting for my sample is examined using following specification, with same lags of $h = 1, 2, \dots, 60$ months:

$$r_t^{all,EW} = \alpha + \beta_h * \ sign(r_{t-h}^{all,EW}) + \epsilon_t^{all,EW} \quad \text{(iii)}$$

and

$$r_t^{all,VW} = \alpha + \beta_h * \ sign(r_{t-h}^{all,VW}) + \epsilon_t^{all,VW} \quad \text{(iv)}$$

For this specification, $sign\left(r_{t-h}^{all,EW}\right)$ or $sign\left(r_{t-h}^{all,VW}\right)$ are defined as $+1$ if return at month *t-h* is positive and -1 if return at month *t-h* is negative. The t-statistics from the equally and value

[6] Same results and patterns obtained when I rerun the regressions for each industry's return series, for both equally and value weighted return series of each industry.

weighted portfolio investing monthly in all 17 industries' regressions of equation (iii) and (iv) are reported in Panel B of Figure I. First, for the equally weighted return series, I obtain similar results to those from the size equation (i). In specific, the strong, highly significant positive return continuation only occurs for the first 1 month and the return continuation becomes weaker, more random reversals for most of the rest of time horizons. Second, for the value weighted return series, the sign regressions' results are slightly different from those from the size regressions. As seen from Panel B of Figure I, in this case all t-statistics across all time horizons are insignificant and surprisingly the t-statistics for 1-month lagging regression is negative. Regarding to return reversal, the return continuation of value weighted sample is weak and random, as well as after 12 months the reverse of return from positive to negative still occurs but not significant. [7]

A

B

Figure I. Time series predictability across industry portfolios. We regress the monthly return of equally and value weighted of all industries on their own lagged return over various horizons. Panel A uses the size of the lagged return as a predictor, Panel B uses the sign of the lagged return as a predictor (+1 or -1). Sample period is January 1985 to December 2018.

[7] Similarly, for sign regressions, when run regressions for each industry's return, both equally and value weighted return's sample, I obtain similar results and patterns as those from joint of 17 industries' regressions.

Table II similarly reports the results from Figure I, in a numerical aspect, which exhibits t-statistics from regressions (i) to (iv) for all industries, both equally and value weighted. To highlight the occurrence of returns' reversal after the first year, I choose to report t-statistics for 1-month to 15-month lagging regressions. As described from Figure I, from Table II, for the equally weighted return series, there are only highly significant positive t-statistics at 5% level for lagging 1 month of both size and sign regressions, with t-statistics of 4.60 and 4.09 respectively. For the regressions using the value weighted return series, t-statistics for 1-month lagging of both size and sign regressions are low and insignificant at 5% level, with t-statistics of 1.15 and -0.01 respectively. In terms of returns' reversal after the first year, this phenomenon still occurs, proven by changing signs of t-statistics from positive to negative after 12-month lagging for all regressions. However, this effect is ambiguous since the t-statistics around 12-month lagging are low and insignificant, range from -0.91 to 0.66. In conclusion, from this section, with the equally and value weighted industrial returns from the US stock data, the price continuation predictability is significantly strongest only from 1-month look back and from the equally weighted return series. Besides, regarding to the reversal of return after first 12 months, known as a property of Time series momentum, this feature still maintains across the equally and value weighted return series of 17 industry portfolios.

Table II

Industrial time series predictability

T-statistics of regressions for return of all industries' portfolio on its lagging predictors are presented below. Left hand side are equally or value weighted returns of portfolio that investing in all industries. Predictor is laggings of returns from 1-month to 15-month for size regressions, or signs of those laggings for sign regressions. Sample period is from January 1985 – December 2018.

Month lag	Equally weighted return series		Value weighted return series	
	Size regression	Sign regression	Size regression	Sign regression
1	4.60	4.09	1.15	-0.01
2	0.06	-0.01	-1.10	-0.37
3	-0.38	-1.52	0.05	-0.01
4	-0.64	-1.23	-0.57	-1.08
5	-1.66	-1.42	0.02	-1.00
6	-2.75	-1.61	-0.74	-1.85
7	-1.07	0.25	0.15	0.99
8	-0.23	0.06	0.19	0.50
9	-1.34	-0.75	-1.12	-0.37
10	0.46	0.76	1.05	1.85
11	0.89	0.60	0.63	1.04
12	0.66	0.16	0.14	0.18
13	-0.24	-0.57	-0.36	-0.91
14	-0.29	0.04	-0.07	0.09
15	0.38	0.66	0.18	-0.31

3.2. Construction of Industrial Time Series Momentum strategies

In this section, I describe the process to construct several Industrial Time Series Momentum strategies, using the equally and value weighted return series of 17 industries from the US stock market. Note that I will use the equally weighted return series to construct the equally weighted Industrial Time Series Momentum strategies. To construct the value weighted Industrial Time Series Momentum strategies, I will use the value weighted return series of 17 industries.

Two most important factors when constructing the time series momentum strategies are look back and holding periods, which are both normally high profitable at intermediate horizons (up to 24 months look back, with strongest in the 6- to 12- month range). For the individual time series momentum, Moskowitz et al. (2012) find that the 12-month look back with 1-month holding period strategy is the strongest one and they focus on analyzing that strategy to study the time series momentum effect. Besides, Moskowitz and Grinblatt (1999) find that the strongest cross-sectional industrial momentum strategy is the 1-month look back with 1-month holding period strategy. These studies have a common factor that a momentum strategy would perform better when being constructed by 1-month holding period. Therefore, based on these findings, I choose to construct the Industrial Time Series Momentum investing strategies, with a holding period of 1 month.

In terms of the look back period, most of the studies on this topic conclude that investors should choose the look back period of 12 months, based on the reversal of price continuation of asset. Indeed, time series momentum effect tends to be strong over short and intermediate investment horizons (1 to 12 months), then dissipate or reverse after first 12 months. However, as seen from Figure I, the reversal effect of returns after the first year is weak and only strongest at one-month lagged horizon. Therefore, for each of the equally and value weighted return series of 17 industry portfolios in the US stock market, I construct two Industrial Time Series Momentum strategies: 12-month look back, 1-month holding strategy and 1-month look back, 1-month holding strategy.

Initially, the Industrial Time Series Momentum strategies are formed monthly as following: For each industry *s* and month *t*, from each of the equally and value weighted industrial return series, I consider whether the cumulative return for that industry over the past *k* months ($k = 1$ or $k = 12$) is positive or negative. To compute the cumulative return for 12-month look back strategy at time *t* for industry *s*, I use the following formula:

$$Cumulative\ return_t^{s,12} = CR_t^{s,12} = exp\left[\sum_{i=1}^{12} \ln(1 + r_{t-i}^s)\right] - 1$$

For 1-month look back strategy, $CR_t^{s,1}$, cumulative return of industry *s* at time *t*, is simply defined by lagging 1 month return (last month's return), or $CR_t^{s,1} = r_{t-1}^s$. After computing the cumulative returns for each industry, at time *t*, I then go long in industry *s* if its cumulative return is positive and short *s* if its cumulative return is negative. To minimize size effect on the strategies, I use the equally weighted industries' return series to invest in the equally weighted Industrial Time Series Momentum strategies. Also, I use the value weighted industries' return series to invest in the value weighted Industrial Time Series Momentum strategies.

Using the equally weighted industrial return series, to diversify the equally weighted Industrial Time Series Momentum portfolios, each month I invest equally weighted in all industries, and hold the position for one month. In specific, for instance, on January 1st 1985, an investor will compute cumulative return of each industry from January 1st 1984 to December 31st 1984 (for 12-month look back strategy) or check the industry's return of December 1984 (for 1-month look back strategy). If the cumulative return is positive, the investor will go long in that industry and short otherwise, and take average of all positions on January 31st 1985 to report the equally weighted Industrial Time Series Momentum strategy's return of January 1985. In formula, returns of the equally weighted Industrial Time Series Momentum strategies at month *t* is computed as following:

$$r_t^{12-m\,ITSM,EW} = \frac{\sum_{s=1}^{17} r_t^{s,EW} * sign\left(CR_t^{s,EW,12}\right)}{17}$$

for the 12-month look back equally weighted Industrial Time Series Momentum strategy and

$$r_t^{1-m\,ITSM,EW} = \frac{\sum_{s=1}^{17} r_t^{s,EW} * sign\left(CR_t^{s,EW,1}\right)}{17}$$

for the 1-month look back equally weighted Industrial Time Series Momentum strategy, where $r_t^{s,EW}$ is equally weighted return of industry *s* at month *t*. Note that signs of cumulative equally weighted returns, $sign\left(CR_t^{s,EW,12}\right)$ or $sign\left(CR_t^{s,EW,1}\right)$, are defined as $+1$ if cumulative return of industry *s* at month *t* is positive and -1 if return at month *t* is negative.

Using the value weighted industrial return series, to diversify the value weighted Industrial Time Series Momentum portfolios, in general, I invest value weighted in all industries each month, and hold the position for one month. In specific, for example, on January 1st 1985, an investor will compute cumulative return of each industry from January 1st 1984 to December 31st 1984 (for 12-month look back strategy) or check industry's return of December 1984 (for 1-month look back strategy). If the cumulative return is positive, the investor will go long in that industry and short otherwise, proportioned by its value weight. Then, the investor sums up weighted returns of all industries on January 31st 1985 to report the value weighted Industrial Time Series Momentum strategy's return of January 1985. In formula, returns of the value weighted Industrial Time Series Momentum strategies at month *t* is computed as following:

$$r_t^{12-m\,ITSM,VW} = \sum_{s=1}^{17} r_t^{s,VW} * w_t^{s,VW} * sign\left(CR_t^{s,VW,12}\right)$$

for the 12-month look back value weighted Industrial Time Series Momentum strategy and

$$r_t^{1-m\,ITSM,VW} = \sum_{s=1}^{17} r_t^{s,VW} * w_t^{s,VW} * sign\left(CR_t^{s,VW,1}\right)$$

for the 1-month look back value weighted Industrial Time Series Momentum, where $r_t^{s,VW}$ is value weighted return of industry *s* at month *t*, and $w_t^{s,VW}$ is value weight of industry *s* at month *t*, defined by market capitalization of industry *s* divided by total market capitalization of all 17 industries at month *t*. Also, the signs of cumulative value weighted returns, $sign\left(CR_t^{s,VW,12}\right)$ or $sign\left(CR_t^{s,VW,1}\right)$, are defined as $+1$ if cumulative return of industry *s* at month *t* is positive and -1 if return at month *t* is negative.

4. Empirical analysis on performance of Industrial Time Series Momentum strategies

After constructing four Industrial Time Series Momentum strategies, in this section I analyze the performance of the 1-month and 12-month look back, with 1-month holding Industrial Time Series Momentum strategies, based on both equally weighted and value weighted investing.

4.1. Performance of equally weighted Industrial Time Series Momentum strategies

Figure II plots the performance of two equally weighted Industrial Time Series Momentum strategies from January 1985 to December 2018, together with the performance of two market return benchmarks, including the diversified equally weighted passive long strategy ($Passive\ long\ [EW]$) and Fama-French excess return of market factor. All performance plotted are cumulative returns where an investor starts investing 1 dollar in each strategy or market proxy by buy-and-hold from January 1985.

As can be seen from Figure II, in general the 12-month look back Industrial Time Series Momentum strategy (*12-m ITSM, EW*) underperforms two market proxies, while the 1-month look back Industrial Time Series Momentum portfolio (*1-m ITSM, EW*) outperforms the market proxies. This figure supports the prediction referred from Figure I, that the Industrial Time Series Momentum strategy based on 1-month look back will outperform 12-month look back one. Given 1 dollar investing in the strategies from January 1985, in December 2018 an investor ends up with 3.83 dollars using the 12-month look back equally weighted Industrial Time Series Momentum strategy. This revenue is even lower than that from the passive long equally weighted in all industries (*Passive long, EW*) and Fama-French's excess market return factor $R_m - R_f$, with revenues of 43.28 and 32.44 dollars in December 2018, respectively. However, from Panel B of Figure II, the 1-month look back equally weighted Industrial Time Series Momentum strategy outperforms the 12-month look back strategy and market benchmarks, with cumulative revenue of 126.75 dollars in December 2018.

Besides, from Figure II, while the volatility of cumulative returns from the 12-month look back equally weighted Industrial Time Series Momentum strategy does not vary, the volatility of cumulative returns from the 1-month look back one fluctuates significantly, especially in the time period from 2008 to 2013. Through the time period from 2000 to 2013, cumulative revenue of the 1-month look back equally weighted Industrial Time Series Momentum strategy rises sharply from 15.05 to 173.55 dollars. Meanwhile, that of the 12-month look back strategy only increases slightly from 1.83 to 3.48 dollars, although annualized volatilities of these strategies' return series are mostly equal at around 15 percent per year (as shown in Table III). In addition, during the Global Financial Crisis in 2008 and 2009, while all proxies for market return dramatically decrease in revenue, two equally weighted Industrial Time Series Momentum strategies perform well. In specific, from August 2008 to February 2009, cumulative revenue of the 12-month look back strategy increases from 2.90 to 5.03 dollars and that of the 1-month look back strategy rises from 63.53 to 88.42 dollars. Through this time period, cumulative revenues of the equally weighted Passive long and Fama-French excess market return strategies decrease from 19.54 to 9.51 dollars and from 13.09 to 7.64 dollars, respectively. These findings suggest that the equally weighted Industrial Time Series momentum strategies perform well in extreme events.

Table III reports descriptive statistics of two equally weighted Industrial Time Series Momentum strategies' returns, together with the equally weighted passive long in all industries strategy and Fama-French market factor return series. Reported are annualized mean with *t*-statistics of the two-sided test whether mean return is different from 0, standard deviation, Gross Sharpe ratios, minimum and maximum monthly return, skewness and kurtosis of the return series.

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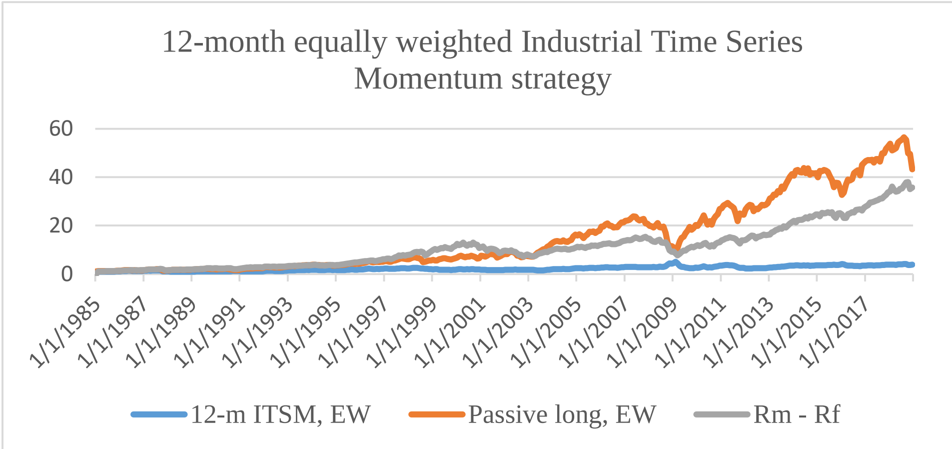

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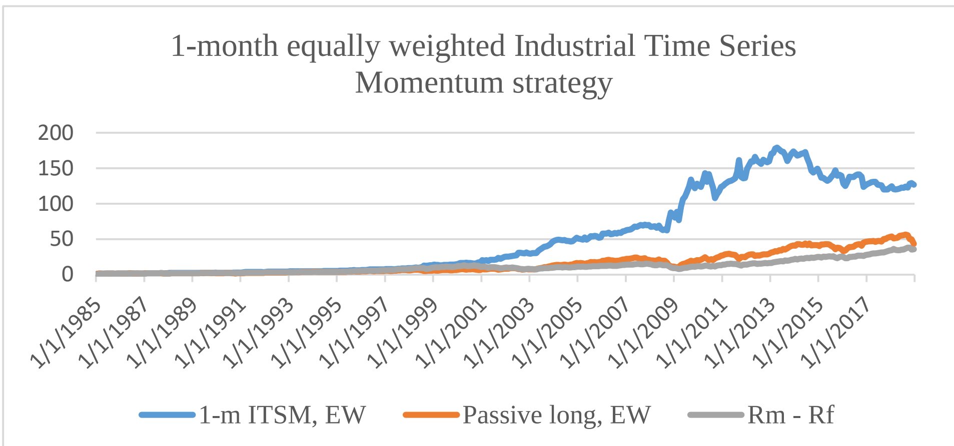

Figure II. Cumulative returns of two equally weighted Industrial Time Series Momentum strategies, diversified equally weighted passive long strategy and Fama-French excess return of market factor, sample period is January 1985 to December 2018. Panel A reports results for the 12-month look back equally weighted Industrial Time Series Momentum strategy, while Panel B reports results for the 1-month look back equally weighted Industrial Time Series Momentum strategy.

As seen from Table III, the 12-month look back equally weighted Industrial Time Series Momentum strategy exhibits an annualized mean return of 5.23 percent with 15.66 percent annualized volatility, which results in yearly gross Sharpe ratio of 0.3338. The two-sided test whether mean return of 12-month look back strategy is different from zero results in a significant t-statistics at 10% level. These numbers are lower than those from market proxies, supports the statement that 12-month look back strategy underperforms the market. For the 1-month look back equally weighted Industrial Time Series Momentum strategy, its performance is better than market proxies and 12-month look back strategy’s one, with annualized return of 13.81 percent per year and annualized volatility of 14.66 percent, results in gross Sharpe ratio of 0.9420. Besides, the two-sided test of whether mean return of the 1-month look back strategy is different from zero yields t-statistics of 5.49, which is significant for all 1%, 5% and 10% level. Because annualized gross Sharpe ratios for both strategies are relatively low, there is a concern that the equally weighted Industrial Time Series Momentum returns are compensation for risk taking.

Table III

Descriptive Statistics of Equally weighted Industrial Time Series Momentum returns

Summary statistics of returns from two equally weighted Industrial Time Series Momentum portfolios are presented below. The portfolios are formed monthly, from January 1985 – December 2018. Reported are the annualized mean return, volatility (standard deviation) and gross Sharpe ratio, min, max, skewness and kurtosis of the return series. In parentheses are *t*-statistics with *, ** and *** stand for statistical significance based on two-sided tests whether the mean is different from zero, at the 1%, 5% and 10% level, respectively.

Parameter	12-month look back strategy (*12-m ITSM, EW*)	1-month look back strategy (*1-m ITSM, EW*)	Passive long, equally weighted (*Passive long, EW*)	Fama-French market factor ($R_m - R_f$)
Annualized mean return	5.23 % *(1.94)**	13.81 % *(5.49)****	12.94 % *(4.01)****	11.45 % *(4.41)****
Min	-29.05 %	-14.74 %	-29.05 %	-22.64 %
Max	23.01 %	25.28 %	25.28 %	12.89 %
Annualized standard deviation	15.66 %	14.66 %	18.81 %	15.13 %
Annualized gross Sharpe ratio	0.3338	0.9420	0.6881	0.7565
Skewness	-0.9980	0.8488	-0.6434	-0.8959
Kurtosis	8.1130	5.4258	4.1603	2.7171

In terms of range, return series of the 12-month look back strategy ranges from minimum return of -29.05 to 23.01 percent per month, while the range of the 1-month look back strategy's return series is from -14.74 to 25.28 percent per month. Besides, skewnesses of 12-month look back and 1-month look back strategies are -0.9980 and 0.8488 respectively, means that the 12-month look back strategy has a left-tailed distribution of return, while that of the 1-month look back strategy is a right-tailed distribution. In conclusion, although the 1-month look back strategy has higher min, max and mean monthly return than those figures of the 12-month look back strategy, most of the returns of 1-month look back strategy are distributed below the mean return.

Next, I analyze the performance of two equally weighted Industrial Time Series Momentum strategies under risk. Table IV reports the risk-adjusted performance of two equally weighted Industrial Time Series Momentum strategies and its factor exposures. I regress the excess return of the 12-month look back and 1-month look back strategies on excess returns of the US stock market, $(R_m - R_f)$, and standard Fama-French factors *SMB*, *HML*, and *UMD*, representing the size, value, and cross-sectional momentum premium among individual US stocks. I also include cross-sectional and time series momentum factors, (*XSMOM* and *TSMOM*, respectively), from Asness, Moskowitz, and Pedersen (2010), Moskowitz et al. (2012), separately and together with Fama-French factors.[8] The process is as following: first, with each $k = 1\ or\ k = 12$ – month look back, I use Fama-French three factors model to test if both strategies deliver abnormal return

$$r_t^{k-m\ ITSM,EW} - r_{f,t} = \alpha + \beta_1 * \left(R_{m,t} - R_{f,t}\right) + \beta_2 * SMB_t + \beta_3 * HML_t + \epsilon_t \quad \text{(i)}$$

Next, I add Fama-French momentum factor *UMD* to Fama-French 3 factors model to test if the equally weighted Industrial Time Series Momentum strategies still deliver abnormal return

$$r_t^{k-m\ ITSM,EW} - r_{f,t} = \alpha + \beta_1 * \left(R_{m,t} - R_{f,t}\right) + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * UMD_t + \epsilon_t \quad \text{(ii)}$$

With regards to momentum risk factors, I run equation (iii) to test whether the strategies result in alpha when controlling for cross-sectional and time series individual momentum risk factors

$$r_t^{k-m\ ITSM,EW} - r_{f,t} = \alpha + \beta_1 * TSMOM_t + \beta_2 * XSMOM_t + \epsilon_t \quad \text{(iii)}$$

Finally, I add up all risk factors to check risk-adjusted performance of the strategies, as shown in equation (iv)

$$r_t^{k-m\ ITSM,EW} - r_{f,t} = \alpha + \beta_1 * \left(R_{m,t} - R_{f,t}\right) + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * UMD_t + \beta_5 * TSMOM_t + \beta_6 * XSMOM_t + \epsilon_t \quad \text{(iv)}$$

In Table IV, line (1) and (5) represent results of regression (i), line (2) and (6) represent results of regression (ii), line (3) and (7) represent results of regression (iii), line (4) and (8) represent results of regression (iv), for the 12-month look back and 1-month look back equally weighted Industrial Time Series Momentum strategies, respectively.

[8] *XSMOM* and *TSMOM* factors are formed from long-short portfolios of cross-sectional and time series momentum across individual equities index, bond futures, currencies, and commodities futures from several international markets. In this case, two cross-sectional individual momentum risk factors, *UMD* and *XSMOM*, are different since those were constructed using different sources of assets. While *UMD* is built using US stocks data, *XSMOM* is constructed by various asset classes through several international exchange markets.

Table IV

Performance of Equally weighted Industrial Time Series Momentum strategies

Risk-adjusted performance of two equally weighted Industrial Time Series Momentum portfolios are presented below. Reported are coefficients from time series regressions of monthly excess returns of 12-month and 1-month look back, 1-month holding Industrial Time Series Momentum strategies on several risk factors, which are Fama-French 3 factors $R_m - R_f$, *SMB*, *HML* and *UMD*, representing the market, size, value, and cross-sectional momentum premiums in US stocks. Cross-sectional and time series momentum factors, *XSMOM* and *TSMOM* respectively, from Asness, Moskowitz, and Pedersen (2010), Moskowitz et al. (2012) are also used as risk factors. In parentheses are *t*-statistics associated with each coefficient.

	$R_m - R_f$	SMB	HML	UMD	TSMOM	XSMOM	Intercept	R^2	
12-month look back strategy (*12-m ITSM*, *EW*)	0.08 (1.58)	0.25 (3.39)	-0.10 (-1.25)				0.11 % (0.5)	5.41 %	(1)
	0.21 (4.71)	0.23 (3.60)	0.10 (1.41)	0.54 (12.58)			-0.31 % (-1.60)	32.09 %	(2)
					0.32 (5.32)	0.32 (7.37)	-0.36 % (-1.72)	23.61 %	(3)
	0.22 (5.00)	0.40 (5.98)	0.24 (0.62)	1.01 (9.07)	0.26 (4.84)	-0.57 (-5.32)	-0.61 % (-3.23)	39.77 %	(4)
1-month look back strategy (*1-m ITSM*, *EW*)	-0.17 (-3.47)	0.11 (1.49)	0.06 (0.85)				0.98 % (4.65)	3.48 %	(5)
	-0.19 (-3.82)	0.11 (1.55)	0.03 (0.41)	-0.09 (-1.85)			1.05 % (4.91)	4.29 %	(6)
					0.17 (2.62)	-0.05 (-1.09)	0.71 % (3.21)	1.68 %	(7)
	-0.22 (-4.44)	0.03 (0.40)	0.09 (1.13)	-0.51 (-4.01)	0.22 (3.60)	0.37 (3.03)	0.86 % (3.96)	9.36 %	(8)

In general, Table IV highlights that the 12-month look back equally weighted Industrial Time Series Momentum strategy does not provide abnormal returns in comparison with the 1-month look back one, when controlling for risk. On the one hand, from equation (1), (2) and (3), 12-month strategy provides monthly alphas of 0.11, -0.31 and -0.36 percent respectively, with none of those is statistical significant at 5% level, despite high model fitness (R^2 at around 25-30 percent). However, when taking all risk factors into one model, equation (4) shows that 12-month look back strategy provides a negative abnormal return of -0.61 percent per month, with t-statistics of -3.23 that is significant at 5% level. From equation (1), (2) and (4), 12-month look back strategy is fully explained by size factor, *SMB*. Size factor's ability in explaining the Industrial Time Series Momentum inspires me to analyze the Industrial Time Series Momentum strategies by value-weighted investing. Besides, from equation (2), (3) and (4), 12-month look back strategy is fully captured by individual cross-sectional and time series momentum factors, *UMD*, *XSMOM* and *TSMOM*, proven by highly significant t-statistics.

On the other hand, 1-month look back strategy delivers significant abnormal returns for all four regressions, which proves that this strategy performs well. Through equation (5) to (8), 1-month look back Industrial Time Series Momentum strategy delivers significant abnormal returns of 0.98, 1.05, 0.71 and 0.86 percent per month (with significant t-statistics of 4.65, 4.91, 3.21 and 3.96 at 5% level, respectively). Therefore, one can conclude that the equally weighted Industrial Time Series Momentum is not fully captured by any risk factors and provides alphas, when constructing strategy by 1-month look back with 1-month holding period.

In the aspect of being captured by momentum risk factors, except for coefficient of *XSMOM* in equation (7), the coefficients of all momentum risk factors in equations (3), (4), (7) and (8) are significant at 5% level. This finding suggests that the individual cross-sectional and time series momentum risk factors can explain the equally weighted Industrial Time Series Momentum. Moreover, the intercept in equation (3) is insignificant, shows that the 12-month look back equally weighted Industrial Time Series Momentum is fully explained by two individual momentum factors. Besides, all coefficients of individual time series momentum factor, *TSMOM*, are significant, from equation (3), (4), (7) and (8), for both 12-month look back and 1-month look back strategies. This result shows a strong relation between Individual and Industrial Time Series Momentum. However, the intercepts from equation (4), (7) and (8) are significant, proves that the equally weighted Industrial Time Series Momentum is not fully explained by either individual cross-sectional or time series momentum factors.

Other interesting finding from the 1-month look back strategy performance's results is that from equation (5) to (8), all betas for market factor, $R_m - R_f$, are negative and highly significant at 5% level. In specific, these betas are -0.17, -0.19 and -0.22, associated with t-statistics of -3.47, -3.82 and -4.44 respectively. This suggests that the 1-month look back equally weighted Industrial Time Series Momentum moves reversely against the market, which makes these strategies to be a good hedge tool when market crashes. This suggestion is similar to conclusions from Figure II, that the equally weighted Industrial Time Series Momentum perform well in extreme events.

To conclude, the equally weighted Industrial Time Series Momentum strategies perform better when constructing by 1-month look back strategy than 12-month look back one, with 1-month holding period. While the 12-month look back strategy does not provide any positive significant abnormal returns, the 1-month look back strategy provides a maximum alpha of 1.05 percent per month, when controlling for risk. When taking all risk factors into account, the 1-month look back strategy also delivers significant alpha of 0.86 percent per month. In addition, the equally weighted Industrial Time Series Momentum strategies are explained by the individual momentum risk factors. However, those factors cannot fully explain the 1-month look back strategy. Besides, these strategies are explained by the market factor, and it is shown that the equally weighted Industrial Time Series Momentum strategies move reversely against the market, which raises a concern of using these strategies as hedge tools.

4.2. Performance of value weighted Industrial Time Series Momentum strategies

From previous section, I analyze the performance of equally weighted Industrial Time Series Momentum strategies, using 17 industries' equally weighted return series of the US stock market. It turns out that the 1-month look back, 1-month holding strategy is the strongest one, which yields significant risk-adjusted abnormal return of 0.86 percent per month at 5% level after controlling for all risk factors. In this section, I analyze the performance of Industrial Time Series Momentum strategies based on value weighted investing, using the 17 industries' value weighted return series of the US stock market.

Figure III plots the performance of two value weighted Industrial Time Series Momentum strategies from January 1985 to December 2018, together with the performance of two market return benchmarks, including the diversified value weighted passive long strategy ($Passive\ long\ [VW]$) and Fama-French excess return of market factor. All performance plotted are cumulative returns where an investor starts investing 1 dollar in each strategy or market proxy by buy-and-hold from January 1985.

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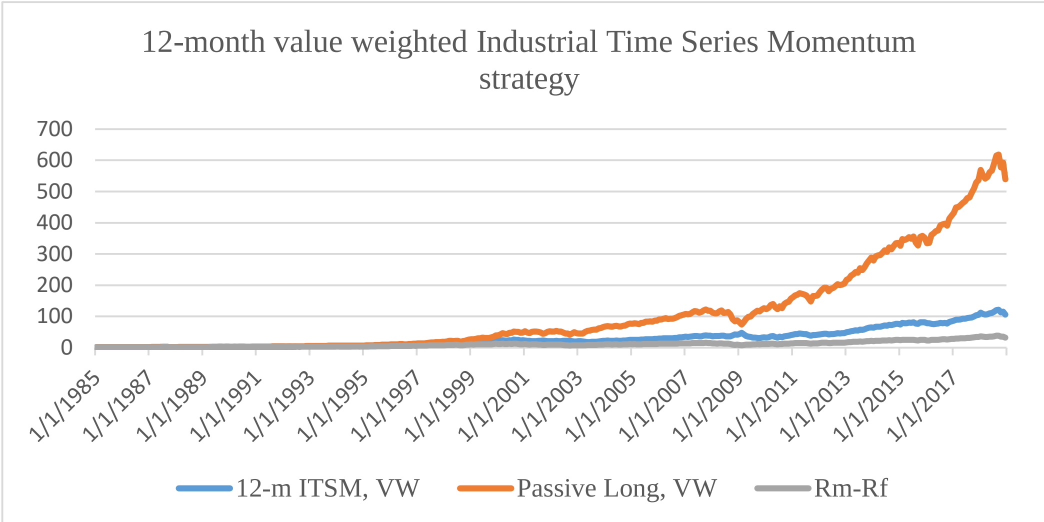

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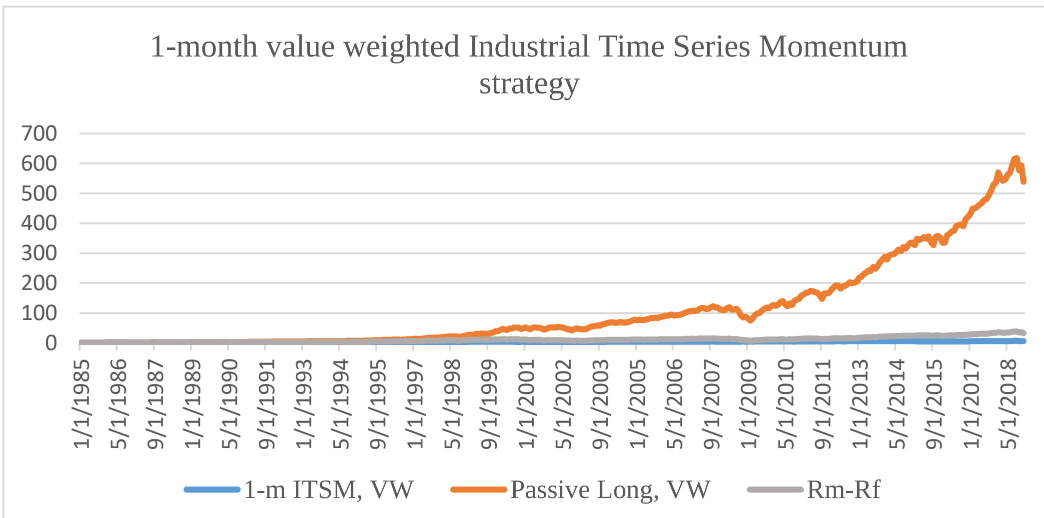


Figure III. Cumulative returns of value weighted Industrial Time Series Momentum strategies, together with value weighted diversified passive long strategy and Fama-French excess return of market factor, from January 1985 to December 2018. Panel A reports results for the 12-month look back value weighted Industrial Time Series Momentum strategy, while Panel B reports results for the 1-month look back one.

As seen from Figure III, two value weighted Industrial Time Series Momentum strategies underperform passive long strategy that investing in all industries' value weighted returns. However, the 12-month look back value weighted Industrial Time Series Momentum strategy (*12-m ITSM*, *VW*) outperforms Fama-French market proxy, while the 1-month look back strategy (*1-m ITSM*, *VW*) underperforms all market proxies. Therefore, in terms of cumulative return, the 12-month look back value weighted Industrial Time Series Momentum strategy outperforms the 1-month look back one. This finding is totally different from that I obtained from the equally weighted Industrial Time Series Momentum strategies' analysis, in which the 1-month look back equally weighted strategy outperforms the 12-month look back one.

In specific, given 1 dollar investing in the value weighted Industrial Time Series Momentum strategies from January 1985, in December 2018 an investor ends up with 106.14 dollars using 12-month look back value weighted Industrial Time Series Momentum strategy. This revenue is higher than that from Fama-French's excess market return factor, $R_m - R_f$, with revenue of 32.44 dollars in December 2018. However, from Panel B of Figure III, the 1-month look back value weighted Industrial Time Series Momentum strategy underperforms the 12-month look back one and all market benchmarks, with cumulative revenue of 6.10 dollars in December 2018. In this time period, until December 2018, cumulative revenues of Fama-French's excess market return factor ($R_m - R_f$) and the value weighted Passive long strategy (*Passive long*, *VW*) are 32.44 and 538.95 dollars, respectively. Comparing to those from the equally weighted Industrial Time Series Momentum strategies, two value weighted Industrial Time Series Momentum strategies yield higher cumulative revenues than 12-month look back equally weighted strategy but lower than 1-month look back one.

In terms of the performance during the extreme time, from Figure III, the 12-month look back value weighted strategy shows a rise in cumulative return during Global Financial Crisis, while 1-month look back strategy does not perform better during that time period. From August 2008 to February 2009, cumulative revenue of 12-month look back value weighted industrial time series momentum strategy slightly rises from 35.92 to 47.53 dollars, while that of 1-month look back strategy only increases from 4.11 to 4.47 dollars. Through this time period, cumulative revenues of value weighted Passive long and Fama-French excess market return strategies decrease from 114.32 to 74.62 dollars and from 13.09 to 7.64 dollars, respectively. These figures suggest that only 12-month look back value weighted Industrial Time Series Momentum strategy performs well in extreme events.

Table V reports descriptive statistics of two value weighted Industrial Time Series Momentum's returns, together with value weighted passive long in all industries strategy and Fama-French market factor return series. Reported are annualized mean with *t*-statistics of the two-sided test whether mean return is different from 0, standard deviation, Gross Sharpe ratios, minimum and maximum monthly return, skewness and kurtosis of the return series.

Table V

Descriptive Statistics of Value weighted Industrial Time Series Momentum returns

Summary statistics of returns from two value weighted Industrial Time Series Momentum portfolios are presented below. The portfolios are formed monthly, from January 1985 – December 2018. Reported are the annualized mean return, volatility (standard deviation) and gross Sharpe ratio, min, max, skewness and kurtosis of the return series. In parentheses are t-statistics with *, ** and *** stand for statistical significance based on two-sided tests whether the mean is different from zero, at the 1%, 5% and 10% level, respectively.

Parameter	12-month look back strategy (*12-m ITSM, VW*)	1-month look back strategy (*1-m ITSM, VW*)	Passive long, value weighted (*Passive long, VW*)	Fama-French market factor ($R_m - R_f$)
Annualized mean return	14.73 % *(6.31)****	6.12 % *(2.84)****	19.79 % *(7.61)****	11.45 % *(4.41)****
Min	-21.19 %	-12.51 %	-21.19 %	-22.64 %
Max	13.57 %	12.71 %	13.83 %	12.89 %
Annualized standard deviation	13.59 %	12.55 %	15.14 %	15.13 %
Annualized gross Sharpe ratio	1.0837	0.4877	1.3076	0.7565
Skewness	-0.6254	-0.2101	-0.6149	-0.8959
Kurtosis	3.0906	1.0499	2.1882	2.7171

As seen from Table V, the 12-month look back value weighted Industrial Time Series Momentum strategy exhibits an annualized mean return of 14.73 percent with 13.59 percent annualized volatility, which results in yearly gross Sharpe ratio of 1.0837. The two-sided test whether mean return of 12-month look back strategy is different from zero results in a significant t-statistics at all 1%, 5% and 10% level. These numbers shows that 12-month look back value weighted strategy outperforms all other Industrial Time Series Momentum strategies and even Fama-French market proxy. For the 1-month look back value weighted Industrial Time Series Momentum strategy, its performance is only better than the 12-month look back equally weighted strategy's one, with annualized return of 6.12 percent per year and annualized volatility of 12.55 percent, results in gross Sharpe ratio of 0.4877. Besides, the two-sided test of whether the mean return of 1-month look back strategy is different from zero results in a t-statistics of 6.31, which is significant at all 1%, 5% and 10% level. In conclusion, in terms of strategy performance measured by the Sharpe ratio, the best strategy is the 12-month look back value weighted Industrial Time Series Momentum, followed by the 1-month look back equally weighted, the 1-month look back value weighted and the 12-month look back equally weighted ones.

In terms of range, the return series of 12-month look back value weighted strategy ranges from minimum return of -21.19 to 13.57 percent per month, while the range of 1-month look back strategy's return series is from -12.51 to 12.71 percent per month. These ranges are smaller than those from the equally weighted Industrial Time Series Momentum strategies. Besides, from Table V, skewnesses of 12-month look back and 1-month look back strategies are -0.6254 and -0.2101 respectively, suggests that both two value weighted Industrial Time Series Momentum strategies have left-tailed distributions of return.

Next, I analyze the performance of two value weighted Industrial Time Series Momentum strategies under risk. Table VI reports the risk-adjusted performance of two value weighted Industrial Time Series Momentum strategies and its factor exposures. In Table VI, I regress similar equations that have been done in Table IV, for each of the value weighted strategies. In general, Table VI highlights that the 12-month look back value weighted Industrial Time Series Momentum strategy provides abnormal returns when controlling for risk, while the 1-month look back one is fully explained by risk factors and does not deliver any alphas.

For the 12-month look back value weighted Industrial Time Series Momentum strategy, from equation (1), (2) and (3) of Table VI, this strategy provides monthly alphas of 0.68, 0.35 and 0.55 percent respectively, with all of those alphas are statistical significant at 5% level and consists of high model fitness (R^2 ranges from around 20 to 60 percent). However, when controlling for all risk factors, from equation (4), alpha disappears for the 12-month look back strategy, with intercept of 0.17 percent, but insignificant t-statistics of 1.34 at 5% level. From equation (1), (2) and (4), the 12-month look back strategy is fully explained by $R_m - R_f$, *HML, UMD* and *TSMOM* factors.

Besides, in terms of explaining by other momentum factors, as seen from equation (2), (3) and (4), the 12-month look back strategy is fully captured by individual cross-sectional and time series momentum factors, *UMD*, *XSMOM* and *TSMOM*, proven by highly significant t-statistics.

However, insignificant t-statistics for *XSMOM*'s coefficient in equation (4) shows that this factor is weaker than other momentum factors in explaining the 12-month look back value weighted strategy. Moreover, significant alpha from equation (3) shows that 12-month look back strategy is not fully explained by individual time series momentum factor, *TSMOM*.

For the 1-month look back value weighted Industrial Time Series Momentum strategy, in general, there are no abnormal returns, as seen from Table VI, proven by intercepts of all four regressions are not significant at 5% level and low model fitness R^2, with maximum R^2 of 5.24 %. Equation (5) and (6) regress excess return of the 1-month look back strategy on Fama-French 3 factors and extend the model with individual cross-sectional momentum factor from Fama-French, *UMD*. These regressions imply that the 1-month look back strategy does not deliver abnormal returns, compared to the 1-month look back equally weighted strategy, or the 12-month look back value weighted one. Moreover, none of coefficients from equation (5) and (6) are significant, which implies that the value weighted Industrial Time Series Momentum bears other sources of risk. When combining all risk factors into one regression, equation (8) shows that the 1-month look back value weighted Industrial Time Series Momentum strategy is fully captured by *UMD* and *TSMOM* factor, proven by significant t-statistics of -2.74 and 3.99 for those factors, in addition with insignificant t-statistics for the intercept.

Besides, in terms of explaining by the momentum factors, as shown from equation (6), the individual cross-sectional momentum factor in US stocks, *UMD*, cannot explain the 1-month look back strategy as its coefficient is not significant at 5% level. However, equation (7) shows that the 1-month look back strategy is totally explained by individual time series and cross-sectional momentum factors, *TSMOM* and *XSMOM*. When combining all risk factors into one regression, equation (8) shows that the 1-month look back strategy is only explained by *TSMOM* and *UMD* factors.

One interesting finding from the performance of equally weighted Industrial Time Series Momentum strategies is that the equally weighted strategies move reversely against the market factor. However, for the value weighted Industrial Time Series Momentum strategies, the market factor has no impact on the 1-month look back value weighted strategy. For the 12-month look back value weighted strategy, the market factor, $R_m - R_f$, still totally explains this strategy, proven by all significant t-statistics from equation (1), (2) and (4), but in this case this factor has positive impact on the 12-month look back strategy.

In conclusion, the value weighted Industrial Time Series Momentum strategies perform better when constructing by 12-month look back than 1-month look back, with 1-month holding period. While the 1-month look back strategy delivers no significant alphas, the 12-month look back one provides a maximum alpha of 0.68 percent per month, when controlling for risk. In addition, the value weighted strategies are not fully explained by the individual momentum risk factors, especially for the 12-month look back value weighted strategy. Besides, while the 1-month look back strategy is not explained by the market factor, the 12-month look back one is fully explained and the market has positive impact on 12-month look back strategy. Note that, these findings are slightly different from those of the equally weighted Industrial Time Series Momentum strategies. There is an improvement in performance for the 12-month look back Industrial Time Series Momentum strategy, after changing from equally to value weighted investing. Also, the 1-month look back value weighted strategy underperforms the 1-month look back equally weighted one. These findings raise a concern that size has an impact on Industrial Time Series Momentum. However, I will not go further into explaining this phenomenon in this thesis, and leave this to future studies.

Table VI

Performance of Value weighted Industrial Time Series Momentum strategies

Risk-adjusted performance of two value weighted Industrial Time Series Momentum portfolios are presented below. Reported are coefficients from time series regressions of monthly excess returns of 12-month and 1-month look back, 1-month holding Industrial Time Series Momentum strategies on several risk factors, which are Fama-French 3 factors $R_m - R_f$, *SMB*, *HML* and *UMD*, representing the market, size, value, and cross-sectional momentum premiums in US stocks. Cross-sectional and time series momentum factors, *XSMOM* and *TSMOM* respectively, from Asness, Moskowitz, and Pedersen (2010), Moskowitz et al. (2012) are also used as risk factors. In parentheses are *t*-statistics associated with each coefficient.

	$R_m - R_f$	SMB	HML	UMD	TSMOM	XSMOM	Intercept	R^2	
12-month look back strategy (*12-m ITSM*, *VW*)	0.48 (13.12)	-0.01 (-0.28)	-0.29 (-5.07)				0.68 % (4.35)	37.73 %	(1)
	0.58 (19.27)	-0.03 (-0.81)	-0.13 (-2.78)	0.43 (14.83)			0.35 % (2.74)	59.72 %	(2)
					0.24 (4.60)	0.27 (7.14)	0.55 % (3.00)	21.06 %	(3)
	0.57 (19.32)	-0.01 (-0.03)	-0.13 (-2.82)	0.45 (5.83)	0.17 (4.65)	-0.08 (-1.02)	0.17 % (1.34)	61.87 %	(4)
1-month look back strategy (*1-m ITSM*, *VW*)	0.01 (0.26)	0.02 (0.29)	0.01 (0.08)				0.23 % (1.24)	0.05 %	(5)
	-0.01 (-0.15)	0.02 (0.35)	-0.02 (-0.32)	-0.07 (-1.76)			0.28 % (1.53)	0.81 %	(6)
					0.19 (3.55)	-0.08 (-2.11)	0.05 % (0.27)	3.22 %	(7)
	-0.03 (-0.62)	-0.01 (-0.11)	0.01 (0.14)	-0.31 (-2.74)	0.22 (3.99)	0.17 (1.63)	0.09 % (0.45)	5.24 %	(8)

4.3. Performance of Industrial Time series momentum strategies in extreme events

As analyzed in the previous sections, the Industrial Time Series Momentum strategies show an interesting feature that these strategies seem to perform well in extreme events, proven graphically by reversal cumulative returns in period of Global crisis in 2008 and 2009. This feature could inspire investors to choose the Industrial Time Series Momentum strategies for hedging. Regarding to this feature, Moskowitz et al. (2012) find that Individual time series momentum strategy performs well in extreme time. They find that individual time series momentum strategy performs well during ‘‘crashes’’ because crises often happen when the economy goes from normal to bad (making the strategies to go short risky assets), and then from bad to worse (leading to the strategy's profits), with the Global crisis of 2008 being a prime example. In this section, I study the performance of both equally and value weighted Industrial Time Series Momentum strategies in extreme market conditions.

First, all four of the equally and value weighted Industrial Time Series Momentum return series are plotted against the returns of the S&P 500 Composite index, with the time period from January 1990 to December 2018. All the plots are depicted in Panel A of Figure IV. As seen from this panel, there is a "smile" pattern shows up for the 1-month look back equally weighted and the 12-month look back value weighted strategy. This "smile" pattern is similar to the one found in Moskowitz et al. (2012), which inspired them to conclude that their individual time series momentum strategy performs well under extreme markets. In this case for the Industrial Time Series Momentum strategies, the returns are largest during the highest up and down market movements, as known as the "smile" figure. Intuitively, these strategies generate these payoff patterns because an investor tends to go long when the market performs well and short when the market crashes. However, for the other two Industrial Time Series Momentum strategies, this "smile" pattern does not show up clearly and even disappears for the 1-month look back value weighted strategy. Indeed, as seen from Panel A of Figure IV, the performance of 1-month look back equally weighted and 12-month look back value weighted strategies are good during extreme markets, making these strategies attractive as a hedge through these time periods.

Next, I use VIX, another source as market condition measurement to investigate the performance of Industrial Time Series Momentum strategies under financial distress. The VIX - CBOE Volatility Index provides a simple measure of the tension in the stock market. Not surprisingly, this index experiences huge swings during financial showdown, such as the financial crisis in 2008 or the dot-com bubble. Panel B of Figure IV plots all four Industrial Time Series Momentum return series against the VIX index on the time horizon from January 1990 to December 2018. Surprisingly, when plotted against the VIX index, the volatility "smile" shows up in all four figures from Panel B of Figure IV. This finding suggests that the performance of Industrial Time Series Momentum strategies is improved during periods with extreme volatility, generally during financial distress. Note that the performance is likewise ameliorated during extremely quite times with low market volatility.

Moreover, to check whether the patterns shown in Figure IV are significant, I run two regressions of all four strategies on the market index return, S&P 500, and on the VIX index, with the time horizon from January 1990 to December 2018. In specific, for the first regression, the return series of all four Industrial Time Series Momentum strategies are regressed on the market index return, S&P 500, and the squared market index return, as following

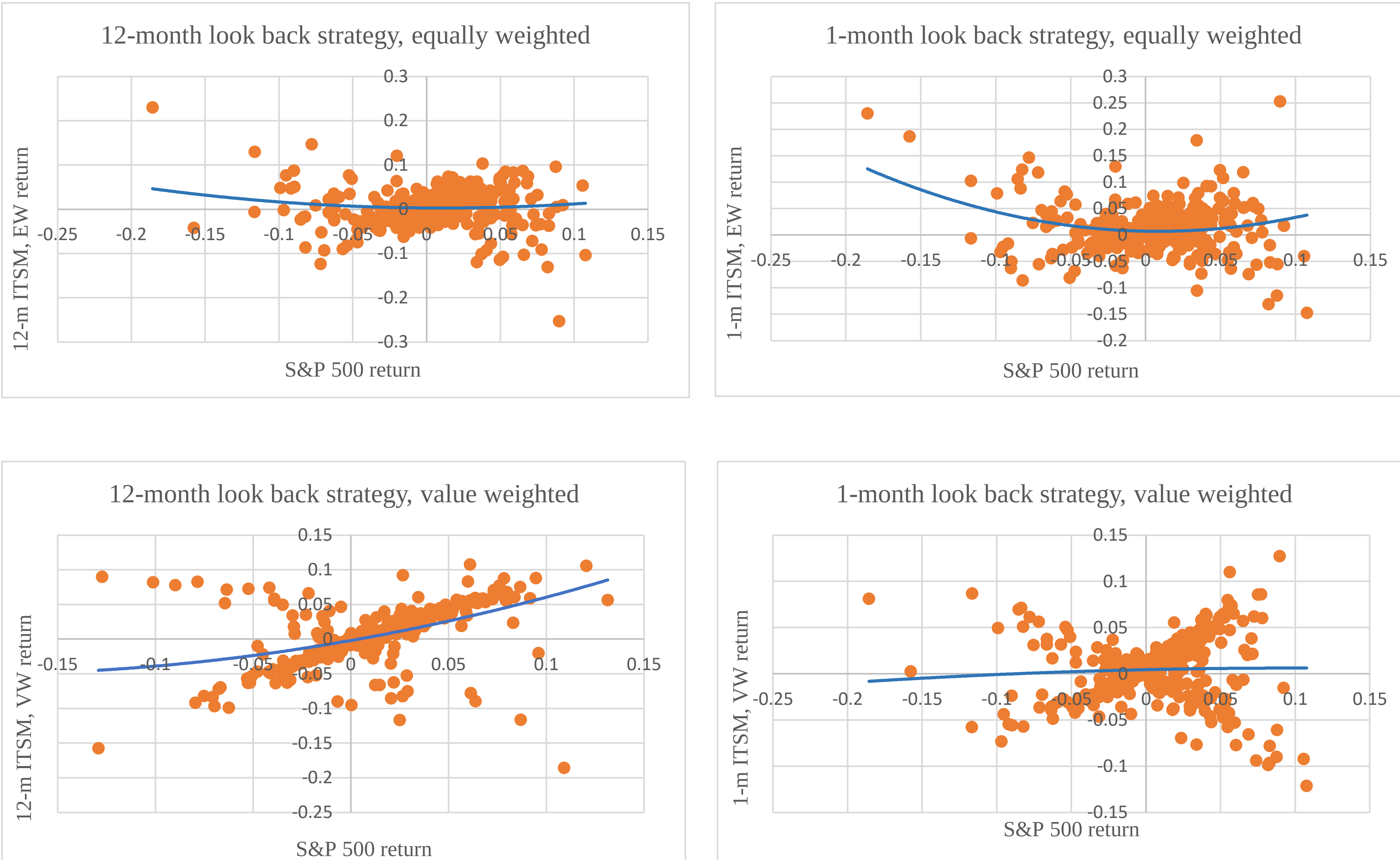
$$r_t^{ITSM} = \beta_0 + \beta_1 * S\&P_t + \beta_2 * S\&P_t{}^2 + \epsilon_t \qquad \text{(i)}$$

Panel A of Table VII exhibits results of regression (i) for all four Industrial Time Series Momentum strategies. The betas of the squared market index return, $S\&P^2$, are significantly positive at 5% level with t-statistics of 4.03 and 2.76, only from equation (2) and (3). These betas are for 1-month look back equally weighted and 12-month look back value weighted Industrial Time Series Momentum strategies, respectively. Therefore, this result indicates that these strategies deliver the highest profits during the most extreme market episodes. This finding supports the statement drawn from Panel A of Figure IV, that performance of the 1-month look back equally weighted and 12-month look back value weighted strategies are good during extreme markets.

For second regression, I regress the return series of all four Industrial Time Series Momentum strategies on the volatility index, VIX, and the squared volatility index. The regression for return of each Industrial Time Series Momentum strategy is as following

$$r_t^{ITSM} = \beta_0 + \beta_1 * VIX_t + \beta_2 * VIX_t^2 + \epsilon_t \quad \text{(ii)}$$

A


12-month look back strategy, equally weighted
12-m ITSM, EW return
S&P 500 return
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.25
-0.2
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
1-month look back strategy, equally weighted
1-m ITSM, EW return
S&P 500 return
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.2
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
12-month look back strategy, value weighted
12-m ITSM, VW return
S&P 500 return
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
1-month look back strategy, value weighted
1-m ITSM, VW return
S&P 500 return
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.25
-0.2
-0.15
-0.1
-0.05
0
0.05
0.1
0.15

B

Figure IV. The Industrial Time Series Momentum "smile". All equally and value weighted Industrial Time Series Momentum strategies' return series are plotted against the contemporaneous returns on the S&P 500 (Panel A) and the VIX index (Panel B), from January 1990 to December 2018.

As seen from Panel B of Table VII, all of the regression outputs from equation (5) to (8) show that the squared volatility measure, VIX^2, positively predicts the returns of all four Industrial Time Series Momentum strategies, proven by significantly positive betas for this variable through four equations. This result indicates that the performance of all four Industrial Time Series Momentum strategies are statistically significant higher during extreme market conditions, which supports the conclusion obtained from Panel B of Figure IV.

In conclusion, all equally and value weighted Industrial Time Series Momentum strategies perform well during extreme market conditions. Especially, the 1-month look back equally weighted and 12-month look back value weighted strategies perform better than the other strategies during extreme markets, making these strategies attractive as a hedge for investors during market crashes.

Table VII

Performance of Industrial Time Series Momentum strategies in extreme time

Regression of all equally and value weighted Industrial Time Series Momentum returns on the market index return and on the VIX index, with the time horizon from January 1990 to December 2018. Note that the VIX index is scaled down by a factor of 100. The regression equations are $r_t^{ITSM} = \beta_0 + \beta_1 * S\&P_t + \beta_2 * S\&P_t^{\ 2} + \epsilon_t$ for Panel A, and $r_t^{ITSM} = \beta_0 + \beta_1 * VIX_t + \beta_2 * VIX_t^2 + \epsilon_t$ for Panel B. In parentheses are *t*-statistics associated with each coefficient.

Panel A: Regression on the S&P 500 index return

r_t^{ITSM}	$S\&P$	$S\&P^{\ 2}$	Intercept	R^2	
12-month look back equally weighted strategy (*12-m ITSM, EW*)	-0.023 (-0.39)	1.135 (1.46)	0.003 (1.02)	0.80 %	(1)
1-month look back equally weighted strategy (*1-m ITSM, EW*)	-0.053 (-0.89)	3.137 (4.03)	0.007 (2.56)	5.60 %	(2)
12-month look back value weighted strategy (*12-m ITSM, VW*)	0.455 (10.24)	1.609 (2.76)	0.006 (3.03)	23.30 %	(3)
1-month look back value weighted strategy (*1-m ITSM, VW*)	0.035 (0.74)	-0.176 (-0.28)	0.004 (1.97)	0.23 %	(4)

Panel B: Regression on the VIX index

r_t^{ITSM}	VIX	VIX^2	Intercept	R^2	
12-month look back equally weighted strategy (*12-m ITSM, EW*)	-0.731 (-6.44)	1.303 (6.12)	0.090 (6.65)	10.76 %	(5)
1-month look back equally weighted strategy (*1-m ITSM, EW*)	-0.268 (-2.26)	0.778 (3.51)	0.031 (2.18)	8.00 %	(6)
12-month look back value weighted strategy (*12-m ITSM, VW*)	-0.493 (-5.06)	0.733 (4.02)	0.076 (6.50)	9.47 %	(7)
1-month look back value weighted strategy (*1-m ITSM, VW*)	-0.221 (-2.32)	0.411 (2.30)	0.029 (2.58)	1.55 %	(8)

5. Conclusion

The main purpose of this study is to evaluate the profitability of Industrial Time Series Momentum strategies on 17 equally and value weighted industry portfolios of the US stock market, during the time period from January 1985 to December 2018. The research includes testing the performance of several Industrial Time Series Momentum strategies, which consist of 12-month or 1-month look back, with 1-month holding period, investing by equally weighted or by value weighted in 17 industries from the US stock market. I examine and evaluate the effects of CAPM-beta, size, value, Fama-French momentum risk factors, as well as cross-sectional and time series momentum factors across assets from international markets on the profitability of Industrial Time Series Momentum strategies. I also examine the performance of Industrial Time Series Momentum strategies during extreme market conditions.

The findings from this research contribute to the research field of Time series momentum in a various ways. I have performed an empirical analysis using the same methodology as Moskowitz et al. (2012) but in a new and different setting of momentum investing. These settings include investing in time series return series of 17 industries within the US stock market, and investing monthly by both equally and value weighted in those 17 industries.[9] The results show that the Industrial Time Series Momentum profits are delivered for both equally weighted and value weighted way of investing.

For the equally weighted Industrial Time Series Momentum strategies, the strategy's performance is better when constructing by 1-month look back period than by 12-month look back one, with 1-month holding period. From January 1985, by investing 1 dollar by buy-and-hold in the 1-month look back strategy, an investor would cumulatively come up with an amount of 126.75 dollars. Besides, the 1-month look back strategy provides a maximum significant alpha of 1.05 percent per month, when controlling for risk. When taking into account all risk factors, including momentum factors, the 1-month look back strategy also delivers a significant alpha of 0.86 percent per month. In addition, the equally weighted Industrial Time Series Momentum strategies are explained by several individual momentum risk factors. However, those risk factors cannot fully explain the 1-

[9] Moskowitz et al. (2012) construct their individual time series momentum strategy by equally weighted investing only.

month look back strategy and this strategy still provides a significant abnormal return of 0.71 percent per month, after controlling for the momentum factors.

For the value weighted Industrial Time Series Momentum strategies, however, there is a better performance when constructing by 12-month look back period than 1-month look back one, with 1-month holding period. From January 1985, by investing 1 dollar by buy-and-hold in the 12-month look back strategy, an investor would cumulatively come up with an amount of 106.14 dollars. Besides, while the 1-month look back strategy does not deliver any significant alphas, the 12-month look back strategy provides a maximum significant alpha of 0.68 percent per month, after controlling for risk. When taking all the risk factors into account, the 12-month look back strategy, however, delivers no significant abnormal returns. In addition, similar to the equally weighted Industrial Time Series Momentum strategies, the value weighted ones are not fully explained by the individual momentum risk factors, especially for 12-month look back value weighted strategy.

In terms of performing during extreme events, in general, all of the equally and value weighted Industrial Time Series Momentum strategies perform well during extreme market conditions. This finding is proven by a “smile” pattern, which shows a higher strategies’ returns in extreme market conditions. This pattern is shown up when plotting the equally and value weighted Industrial Time Series Momentum returns on the S&P 500 return series and the VIX index. However, when running regressions for the Industrial Time Series Momentum returns on the squared S&P 500 return series and the squared VIX index, the “smile” pattern is only numerically significant for the 1-month look back equally weighted and the 12-month look back value weighted strategies. This finding proves that these two strategies perform better than the other ones during extreme markets, making these two strategies attractive as a hedge during market crashes.

While performing this research, I have thought of several ways to increase the knowledge in this field of study. In my thesis, I construct investment strategy using 17 industry portfolios in the US stock market. However, it would be interesting to examine the Industrial Time Series Momentum strategies on a bigger number of industry portfolios in the US stock market, or on other international markets. Besides, in this thesis, I have allowed the possibility of short selling all the listed industries, which is limited or even not possible in practice. Moreover, this research also excludes the effects of transaction costs and taxes. These fees would have an impact on the

Industrial Time Series Momentum strategies. However, to examine these effects or extend to bigger dataset is difficult and time consuming. Thus, I leave this concern to future researchers to investigate.

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