Erasmus University Rotterdam

Erasmus School of Economics

Bachelor Thesis

Department of Econometrics and Operations Research

Cross-Sectional versus Time-Series: which is the better momentum trading strategy on a weekly frequency?

Author:

Melih Samutoglu

Student ID:

501628

Supervisor:

Dr. O. Kleen

Second assessor:

Dr. H.J.W.G. Kole

4th of July 2021

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

Abstract

This paper investigates the performance of momentum strategies using rankings based on cross-section and time-series. We create overlapping portfolios in order to compare both strategies. In addition, a time-varying investment is examined to account for the net investment made in the time-series momentum strategy. Results show that the time-series momentum strategy outperforms the cross-sectional momentum strategy. However, the returns of the strategies seem to be marginally equal when the net investment is taken into consideration.

Contents

1 Introduction

Investors want to optimize their returns by applying different investment strategies. Consequently, researching and proposing investment strategies are popular aspects in the academic world. In particular, Jegadeesh and Titman (1993) state that the cross-sectional momentum (CS) strategy, which means going long in assets that have performed relatively well in the recent past and short in assets that have performed relatively poorly, realizes abnormal returns. These results became a basis for other researchers in developing other strategies, such as the time-series momentum (TS) strategy proposed in Moskowitz et al. (2012) and the return signal momentum (RSM) strategy mentioned in Papailias et al. (2021). As stated, all these strategies are examples of momentum strategies. Here, "Momentum" refers to the phenomenon in which assets that have a good (poor) performance in the past are likely to rise (fall) in the future.

Conventionally, investors want the "best" investment strategy to achieve the highest returns. Hence, the momentum strategies need to be compared to each other. The comparison could result in one strategy outperforming the other, leading to the creation of portfolios with higher returns and better risk management for fund managers.

The purpose of this paper is to replicate and extend the research on common stock returns with momentum strategies presented by Goyal and Jegadeesh (2018). The replication part can be found in the appendix. Specifically, the extension includes more recent data that results in a better representation of the present, weekly data instead of monthly, returns without the delisting bias in data of the Center for Research in Security Prices (CRSP) stated by Shumway (1997) and variations of the cross-sectional momentum strategy with a time-varying investment in the market (CS_{TVM}) proposed by Goyal and Jegadeesh (2018). Namely, instead of a time-varying investment in the market, we utilize a time-varying investment in stocks with returns above the 95th percentile in the ranking period (CS_{w} strategy) and stocks with returns below the 5th percentile in the ranking period (CS_{l} strategy). The CS_{w} strategy represents momentum and the CS_{l} strategy return reversal. Therefore, the central research question of this paper is: 'Does the TS strategy outperform the CS strategy based on weekly returns for the period of January 1992 up to and including December 2019?'. In addition, we inspect whether the difference is justified or if it is accountable to the net investment of the TS strategy.

The data in this research is provided by the CRSP and consists of daily stock data from the period January 1992 up to and including December 2019. Furthermore, we use Ken French's data library for the daily risk-free rates. The data set for the analyses is created with the transformation of the daily data to weekly data.

We examine the CS, TS, CS_{TVM}, CS_w and CS_l strategies in this paper. Specifically, we investigate the annualized mean of the portfolios created with these strategies and test if these returns differ from one another. Thereafter, the Capital Asset Pricing Model (CAPM) and Fama and French Three-Factor Model (FF3M) are used to examine the risk adjusted returns of the various strategies (Sharpe, 1964; Lintner, 1965; Fama and French, 1993). Moreover, we evaluate the significance of our results by performing Student's t-tests.

We find that our results are mostly in accordance with the results of Goyal and Jegadeesh (2018), namely that the TS strategy returns exceed the CS strategy returns due to the net investment of the TS strategy. The CS strategy results in only significantly negative annualized returns. In contrast, the TS strategy attains several significantly positive annualized returns, which indicates that the TS strategy outperforms the CS strategy. Although, the returns are relatively similar when we account for the net investment of the TS strategy by adding a time-varying investment to the CS strategy. Specifically, we observe the difference between the TS strategy and the CS strategies with a time-varying investment rarely being significantly positive.

This paper contributes to the current literature as corporate quantitative researchers and portfolio managers can use the "best" trading strategy determined by our results. Consequently, leading to better decision making in portfolio management. Thus, possibly achieving better returns from the portfolios. Our research differs from other researchers in terms of variations of the proposed CS_{TVM} strategy and the usage of weekly data, which is corrected for the delisting bias of the CRSP stated by Shumway (1997), from the period January 1992 up to and including December 2019.

The remainder of the paper proceeds as follows. In Section 2, we provide a brief literature review. Section 3, the relevant data is described. Next, our methods are introduced in Section 4. Afterwards, the results are presented in Section 5. Finally, we conclude and discuss our results in Section 6.

2 Literature

This section provides the main findings of previous research conducted on similar topics. We also introduce some concepts that are crucial to understanding the research process.

The focus of this research field lies on the predictability of future returns with the help of past returns. Extensive research has been done on this topic. For example, De Bondt and Thaler

(1985, 1987) state that long-run past losers outperform long-run past winners when the holding period is between 3 and 5 years inclusive, in other words long-run return reversals. They rank stocks in specific moments of time based on their past returns. Furthermore, using the same method of ranking stocks, Jegadeesh (1990) and Lehmann (1990) provide evidence for short-run return reversals. In contrast, Jegadeesh and Titman (1993) prove that buying past winners and selling past losers in the short run result in significant abnormal returns due to the anomaly called "momentum". Most of these studies implemented cross-sectional tests in order to choose the winners and the losers.

The fundamentals of Jegadeesh and Titman (1993) led to Moskowitz et al. (2012) proposing a momentum strategy based on time-series instead of cross-section. The TS strategy differs from the CS strategy in the sense that the TS strategy does not rank the stocks based on its relative rank across a cross-section. In particular, the TS strategy goes long on an asset if the return of that asset in the ranking period is higher than or equal to zero and short otherwise. In contrast, the CS strategy goes long on an asset if the return of that asset is higher than or equal to cross-sectional average return and short otherwise. Moskowitz et al. (2012) present evidence of the TS strategy significantly outperforming the CS strategy. However, Goyal and Jegadeesh (2018) document that the reason for the performance of the TS strategy originates from the net long or short investment. In contrast, the CS strategy is a zero long investment. Therefore, Goyal and Jegadeesh (2018) introduce a CS strategy with a time-varying investment in order to rightfully compare both strategies. Consequently, the TS strategy returns do not significantly differ from the CS strategy returns with a time-varying investment.

"Momentum" is extensively discussed in the literature. Grinblatt and Titman (1989, 1993) state that most mutual funds incorporate some variation of momentum in their decision making regarding the portfolio management. On the contrary, Huang et al. (2020) utilize the same data as Moskowitz et al. (2012) and extend the sample period to 2015 and show that the evidence of TS momentum is weak. Hence, the existence of TS momentum seems questionable. Asness et al. (2013) propose to combine momentum with value in order to obtain better analyses. In this paper, we research if using more recent weekly data with returns corrected for delisting changes the results presented in Goyal and Jegadeesh (2018). In addition, two unique variations of the CS_{TVM} are examined.

3 Data

In this section, we introduce the data used in our research. We explain the data choice, transformations and summarize the most important variables.

Our data incorporates stocks provided by the CRSP covering the period of January 1992 to December 2019. Specifically, it contains daily data of U.S.-based common stocks with share code 10 and 11. This criterion excludes American depository receipts, units, American trust components, closed end funds, preferred stocks, and real estate investment trusts. In addition, we utilize the daily risk-free security return rates obtained from Ken French's data library[1] to calculate the excess returns. The excess return of a stock is determined by the difference between the stock return and the risk-free security return over the same period. These are commonly used in the literature instead of the simple returns (Goyal and Jegadeesh, 2018; Moskowitz et al., 2012). Moreover, Bali et al. (2016) state that, following the asset pricing theory, investors demand, on average, the return of a stock to surpass the risk-free rate in order to buy that specific stock due to the risk connected to it. Therefore, our analyses are applied on excess returns and, henceforth, are referred as returns in this paper, unless otherwise stated. We also include the daily factor variables of the three-factor Fama French model found in Ken French's data library (Fama and French, 1993) in our reseach. Furthermore, the post-delisting value of many stocks is not determined by the CRSP. Hence, we solve this situation by adjusting the returns for delisting with a method described by Shumway (1997). Precisely, the return of a stock is equal to the delisting return when the stock is delisted. However, if the delisting return is not available, the return depends on the reason for the delisting that is explained by the delisting code. When the delisting code is 500, 520, 580, 584 or between 551 and 574 inclusive, we set the return of the stock during the delisting day to -30%. Moreover, if the delisting return is not available and the delisting code is not equal to the codes mentioned before, the return is set to -100%. Our analyses are based on these adjusted returns. At last, we exclude micro-cap stocks in our sample to avoid possible biases in the returns due to stocks with low prices stated by Blume and Stambaugh (1983) and Lyon et al. (1999). Micro-cap stocks are defined as stocks below the 20th percentile of the New York Stock Exchange (NYSE) market capitalization at the end of the ranking period following literature (e.g. Jegadeesh and Titman (1993); Goyal and Jegadeesh (2018)).

The data provided by the CRSP and Ken French's data library are on a daily basis. However, transformations are performed to this data set in order to obtain weekly data. In preparation

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

for this process, we define weekly returns as the compounded daily returns of five consecutive trading days, since weekends are considered non-trading days. Therefore, the dates after each fifth trading day starting from January 2, 1992 up to and including December 31, 2019, are relevant, including the date of the first day. For example, the first week starts on January 2, 1992, and ends on January 8, 1992. The second week starts on January 9, 1992 and ends on January 15, 1992. In addition, the market capitalization of a firm is equal to the shares outstanding times the stock price on the relevant dates.

The weekly risk-free security rate from July 1926 up to and including March 2021 is presented on the left in Figure 1. In addition, the risk-free security rate from January 1992 up to and including December 2019, which is our sample period, is shown on the right in Figure 1. The sample period is chosen in such a way that, first, more recent years are included as these are more prone to reflect the present. However, the Covid-19 crisis period is not included as this is still an ongoing event. Therefore, we believe that performing analysis on this period is questionable at this point of time. Second, the risk-free rate peaks with a rate of 0.31% in June 1981. We omit these periods with high risk-free rates to acquire a sample period with risk-free rates representing the risk-free rates of more recent years. Thus, our sample incorporates the period of January 1992 up to and including December 2019.

Figure 1

Weekly risk-free security rate of the period July 1926 - March 2021 (left) and January 1992 - December 2019 (right)

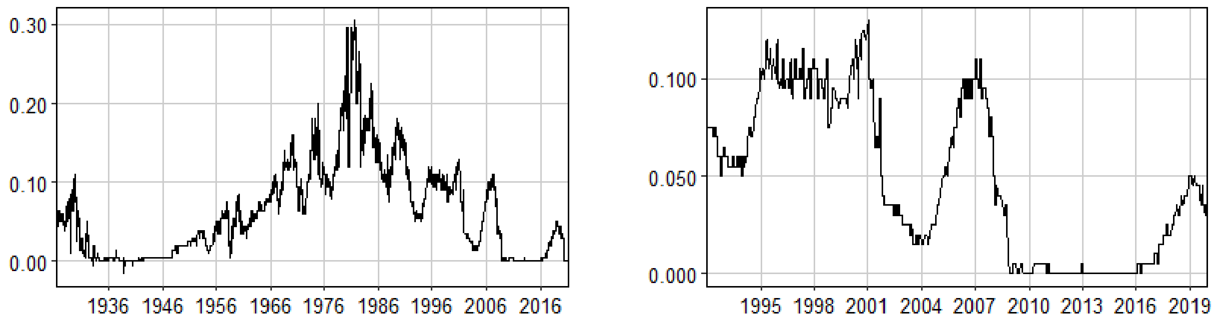


Table 1 shows the summary statistics of the returns and the adjusted returns. We observe the number of weekly stock returns (N), mean, standard deviation, minimum and maximum value. The mean and the maximum value of the two returns are the same. In addition, the standard deviation and the minimum value are similar. The maximum and minimum value are quite large in absolute value when compared to the mean of the returns. The minimum value of the adjusted returns is the consequence of a certain company's delisting. Values that are similar to the minimum value are caused by the same phenomenon mentioned in the previous sentence. In contrast, the maximum value is attained in January 2014. Similar returns are observed in the year 2009, the end of 1999 and the beginning of 2000. These periods refer to the Dot-Com bubble that occurred in the late 1990s and the recovery after the financial crisis in 2008/2009.

Table 1

Summary statistics of weekly returns

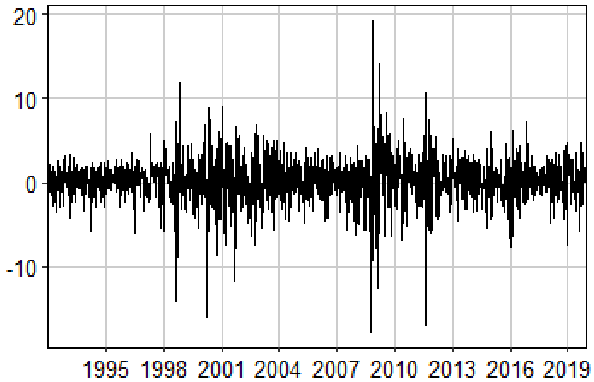
Variable	N	Mean	St. Dev.	Min	Max
Return	2,938,620	0.202	6.735	-98.551	544.542
Adjusted return	2,938,620	0.202	6.737	-100.035	544.542

Note. The summary statistics of the returns and adjusted returns for the period January 1992 up to and including December 2019 are included. The minimum value of the adjusted return is less than -100 due to it being an excess return.

Figure 2 shows the average weekly adjusted returns of all the stocks over the course of the sample period. We observe some high volatility periods, as mentioned before, referring to the Dot-Com bubble and the financial crisis. Moreover, there is not a real trend visible in the figure due to alternating periods of positive and negative average returns.

Figure 2

Average weekly adjusted returns of the period January 1992 up to and including December 2019



We observe the 20th percentile of the NYSE in millions during our sample period in Figure 3. The figure shows an upwards trend until 2008 followed by a dip due to the financial crisis. After the crisis, the upwards trend resurfaces with smaller dips over time and the 20th percentile reaches the same values as in 2007.

Figure 3

Weekly 20th percentile of the NYSE in millions of dollars of the period January 1992 up to and including December 2019

4 Methodology

First, the matter of ranking and holding stocks in overlapping portfolios is discussed in this section. Second, we define the CS strategy. Next, the TS, $\mathrm{CS_{TVM}}$, $\mathrm{CS_w}$ and $\mathrm{CS_l}$ strategy are introduced. Third, the method for determining the relative importance of the CS and TS strategies is presented. Thereafter, the Capital Asset Pricing Model and Fama-French three-factor model are described. At last, we explain how the results are evaluated. In our study a result is referred to as significant when a significance level of 5% holds and we perform all the analysis in the statistical software R (RStudio Team, 2020). In addition, we follow the notation of Goyal and Jegadeesh (2018).

4.1 Overlapping portfolios

In order to research the returns of different strategies we create overlapping portfolios following Jegadeesh and Titman (1993). Accordingly, each strategy has a ranking period and holding period equal to m and p, respectively. Henceforth, these strategies will be referred to as m-p-strategies. First, the ranking period determines the number of past weekly returns that are taken into account when the relevant stocks are ranked. Second, the holding period is the number of weeks a portfolio is held. Specifically, when the ranking (holding) period is greater than one, the return over multiple weeks is calculated with the individual weekly returns. Thereby, we use the equation for multi-period returns

$$r_{t,h} = (1 + r_t) * (1 + r_{t+1}) * \cdots * (1 + r_{t+h-1}) - 1, \tag{1}$$

where r is the return, t a given week and h the horizon. The horizon in our case is equal to p. Thus, we close out the portfolio created in week $t-p$ at the start of each week t. Thereafter, the stocks are ranked based on the returns of the ranking period m and the specific condition of a certain strategy. For example, the condition of a TS strategy could require a return greater than zero in the ranking period of a certain stock in order to take a long position in that specific stock or otherwise a short position is initiated. The stocks with a long position are referred to as "winners" and in the short position "losers". Subsequently, a new portfolio is constructed with the use of "winners" and "losers" and is held for p weeks. The m-p-strategies require lagged returns up to m weeks, which varies from 1 up to 156 weeks in our research.

4.2 Momentum strategies

In this subsection, we describe the specific momentum strategies that are used in our research. We consider cross-sectional, time-series and cross-sectional with time-varying investment strategies.

4.2.1 Cross-sectional

The first strategy uses cross-sectional analysis in order to rank the stocks and, eventually, create a portfolio. The ranking is based on the cross-sectional average returns. Consequently, "winners" are stocks with returns higher than or equal to to the cross-sectional average return, otherwise the stocks are "losers". We take a long position in the "Winners" and a short position in the "losers". This leads to the following portfolio returns

$$r_t^{CS} = \frac{1}{N^w} \sum_{r_{it-1} \geq \bar{r}_{t-1}} r_{it} - \frac{1}{N^l} \sum_{r_{it-1} < \bar{r}_{t-1}} r_{it}, \tag{2}$$

where r_t^{CS} is the return of the CS strategy, r_{it-1} the return in the ranking period of stock i, $\bar{r}_{t-1}$ the cross-sectional average return in the ranking period, N^w the number of "winners" and N^l the number of "losers".

4.2.2 Time-series

The second strategy ranks the return of stocks based on it's own performance. Therefore, "winners" are stocks with returns higher than or equal to zero, otherwise the stocks are "losers". We take a long position in the "Winners" and a short position in the 'losers". Consequently, the equation for the relevant return is

$$r_t^{TS} = \frac{2}{N}\left(\sum_{r_{it-1} \geq 0} r_{it} - \sum_{r_{it-1} < 0} r_{it}\right), \tag{3}$$

where r_t^{TS} is the return of the TS strategy, r_{it-1} the return in the ranking period of stock i and N the number of stocks.

4.2.3 Cross-sectional with time-varying investments

The last strategy is the cross-sectional strategy with a time-varying investment. Specifically, the CS strategy is constructed such that it requires a zero-net investment contrary to the TS strategy, which demands a net investment calculated as follows

$$\text{NetInvestment}_t = \sum_i w_{it-1}^{TS}, \tag{4}$$

where w_{it-1}^{TS} is the investment in stock i and NetInvestment_t the total net investment at time t. The net investment of the TS strategy is utilized in a time-varying investment and added to the CS strategy in order to compare both strategies. This creates the CS_{TVM} strategy. We investigate three variations of the time-varying investment, namely an equally weighted market index, an equally weighted index of the top five best performers of the ranking period and an equally weighted index of the top five worst performers of the ranking period.

First, we look at the variation with the equally weighted market index, which is calculated as follows

$$r_t^{CS_{TVM}} = r_t^{CS} + (\text{NetInvestment}_t * \bar{r}_t), \tag{5}$$

where $r_t^{CS_{TVM}}$ is the return of the CS_{TVM} strategy utilizing the equally weighted market index, r_t^{CS} the return of the CS strategy, NetInvestment_t the total net investment and $\bar{r}_t$ the return of the equally weighted market index. As mentioned before, the CS_{TVM} includes the addition of the CS strategy and a time-varying investment. Hence, the second term in (5) is the return of the time-varying investment.

Second, we have the CS_{w} strategy, which utilizes the stocks above the 95th percentile in the ranking period instead of the equally weighted market index as a time-varying investment. In particular, the strategy relies on the momentum of the return of top performing stocks. This leads to the equation

$$r_t^{CS_w} = r_t^{CS} + (\text{NetInvestment}_t * r_t^{best}), \tag{6}$$

where $r_t^{CS_w}$ is the return of the $\mathrm{CS_w}$ strategy, r_t^{CS} the return of the CS strategy, NetInvestment_t the total net investment and r_t^{best} the return of the stocks above the 95th percentile.

Last, we introduce the $\mathrm{CS_l}$ strategy, which uses the stocks under the 5th percentile in the ranking period instead of the equally weighted market index as a time-varying investment. Specifically, this strategy depends on the return reversal of the worst performing stocks. Consequently, the equation equals

$$r_t^{CS_l} = r_t^{CS} + (\text{NetInvestment}_t * r_t^{worst}), \tag{7}$$

where $r_t^{CS_l}$ is the return of the $\mathrm{CS_w}$ strategy, r_t^{CS} the return of the CS strategy, NetInvestment_t the total net investment and r_t^{worst} the return of the stocks under the 5th percentile.

4.3 Relative importance of the CS and TS strategy

The method to establish what the relative importance is of the CS and TS strategy is explained in this subsection. In particular, we follow the specific method stated by Moskowitz et al. (2012). They regress the TS returns against the CS returns and the CS returns against the TS returns. This leads to the following regressions

$$r_t^{CS} = \alpha_1 + \beta_1 r_t^{TS} + \varepsilon_{1t}, \tag{8}$$

$$r_t^{TS} = \alpha_2 + \beta_2 r_t^{CS} + \varepsilon_{2t}, \tag{9}$$

where r_t^{CS} is the CS strategy return, r_t^{TS} the TS strategy return, α_1 (α_2) a constant, ε_{1t} (ε_{2t}) the residual of week t. The constant of the regressions represent the relative importance of the strategies.

4.4 Risk models

This subsection describes the two risk models applied in our research, namely the CAPM stated by Sharpe (1964); Lintner (1965), independently, and the FF3M introduced by Fama and French (1993). We use these models in order to calculate the average abnormal return of the portfolios created by the mentioned strategies. First, we explain the CAPM and, second, the FF3M.

4.4.1 Capital Asset Pricing Model

The CAPM represents the relationship between expected return and systematic risk of stocks. The regression is specified as

$$r_t = \alpha_3 + r_{Mt} + \varepsilon_{3t}, \tag{10}$$

where r_t is the return of a specific strategy, r_{Mt} the return of the market, α_3 a constant and ε_{3t} the residual during week t. The abnormal return of the strategy is known as the constant of the regression. Therefore, in order to determine if a strategy produces abnormal returns according to the CAPM, we test if the constant is significantly different from zero, which is explained later on.

4.4.2 Fama-French three-factor model

The FF3M extends the CAPM regarding the factors in the model. Particularly, size and value risk are added as additional risk factors to the CAPM. This is due to value stocks and stocks of companies with a small market capitalization regularly exceeding the market regarding returns. Therefore, the regression is as follows

$$r_t = \alpha_4 + r_{Mt} + smb_t + hml_t + \varepsilon_{4t}, \tag{11}$$

where r_t is the return of a specific strategy, r_{Mt} the return of the market, α_4 a constant, smb_t the size stock factor, hml_t the value stock factor and ε_{4t} the residual during week t. Specifically, smb_t stands for small minus big and is equal to the excess return of companies with a small market capitalization minus that of companies with a higher market capitalization. Moreover, hml_t refers to high minus low and equals to the excess return of value stocks minus the excess return of growth stocks, because of the fact that value stocks have a high book-to-market ratio and growth stocks have a low book-to-market ratio.

4.5 Evaluation

This subsection presents the methods, which are used for the evaluation of the results that are obtained. The specific returns are annualized and then tested for significance with the Student t-test using Newey-West standard errors (Newey and West, 1987).

We determine the returns of different holding periods. Afterwards, these returns are annualized for comparison purposes and further analyses. The process for creating an annualized return is multiplying the return of a strategy with

$$x = \frac{52}{p}, \tag{12}$$

where x is the multiplication term, 52 the number of weeks in a year and p the holding period.

The results are also checked on significance. Specifically, we make use of the Student's t-test with Newey-West standard errors due to heteroskedasticity and autocorrelation of returns of overlapping portfolios. The relevant hypothesis is testing

$$H_0 : \mu = 0 \quad \text{vs.} \quad H_a : \mu \neq 0, \tag{13}$$

where μ is the mean of the returns.

First, the annualized returns are regressed on a constant, which results in the following regression

$$R_i = x_i'\beta + \varepsilon_{3i}, \tag{14}$$

where R_i is the annualized return, x_i' the $1 \times k$ vector of regressors and ε_{3i} the residual during week i. Particularly, k is equal to one in our case due to only including a constant in the regression. Second, the Newey-West standard errors are calculated. Therefore, we note a preliminary equation used in calculating the relevant errors following the notation of Heij et al. (2004). This equation is as follows

$$\hat{V} = \frac{1}{n}\widehat{X'\Omega X} = \frac{1}{n}\sum_{i=1}^{n} e_i^2 x_i x_i' + \frac{1}{n}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} w_{j-i} e_i e_j (x_i x_j' + x_j x_i'), \tag{15}$$

where n is the number of returns, e_i the estimated residual of observation i, w_{j-i} the Bartlett kernel weight factor described in Newey and West (1987, 1994), x_i the $k \times 1$ vector of regressors in (14). Furthermore, the equation for the standard errors is equal to

$$\widehat{var}(b) = \frac{1}{n}(X'X)^{-1}\hat{V}(X'X)^{-1}, \tag{16}$$

where b is the vector of regressor coefficient estimates, X the $n \times k$ matrix $[x_1, x_2, \ldots, x_n]$. At last, we have the equation for the t-statistic

$$t = \frac{\mu - \mu_0}{\frac{\sigma}{\sqrt{n}}} = \frac{\mu}{\frac{\sigma}{\sqrt{n}}}, \tag{17}$$

where μ is the mean of the returns, μ_0 the mean of H_0, n the number of observations and σ the Newey-West standard error obtained by taking the square root of (16). Moreover, the t-statistic in (17) follows a $t(n-1)$-distribution that converges to the standard normal distribution when $n-1 \longrightarrow \infty$ (Heij et al., 2004). Hence, significance on a 5% level follows from the condition

$$|t| \geq 1.96, \tag{18}$$

where $|t|$ is the absolute value of the t statistic and 1.96 the critical value of the 5% significance level.

5 Results

The results of our research are discussed in this section. We look at the profitability, difference and risk adjusted returns of the various strategies.

5.1 Profitability

Table 2 reports the annualized returns of the different momentum strategies. In addition, the holding and ranking periods vary from one week up to and including 156 weeks. For example, the annualized returns of the CS and TS strategy with a ranking and holding period equal to one week (1-1-strategy) are -8.87% and -12.2-%, respectively. We observe the returns and holding periods increasing in tandem up to a certain point. Specifically, returns seem to decrease after the jump from a holding period of 52 to 156 weeks or the jump from 26 to 52 weeks. For instance, the 1-1 CS strategy has a return of -8.87%, the 1-52 CS strategy a return of 0.22% and 1-156 CS strategy a return of 0.06%. The same sort of pattern can be seen with the returns when increasing the ranking period while the holding period stays equal.

Panel A presents the annualized returns for the TS strategy. These are all positive, except for the 1-1, 1-4 and 1-13 strategy. However, only the 1-1 and 1-4 TS strategy are significantly negative. Furthermore, most TS strategy returns in Goyal and Jegadeesh (2018) are significantly different than zero contrary to our TS strategy returns. In addition, the 26-26 TS strategy, which is equivalent to a holding and ranking period of six months, earns significantly positive annualized returns, which corresponds with the proof of momentum by Jegadeesh and Titman (1993) and the results in Goyal and Jegadeesh (2018). Furthermore, panel B includes the annualized returns for the CS strategy. As mentioned before, the 1-1 CS strategy leads to a significantly negative annualized return of -8.87%, which is in line with the short-run return reversals mentioned by

Jegadeesh (1990). Although, the 156-156 CS strategy, which corresponds with a holding and ranking period of three years, does not result in a significant negative annualized return, contrary to the long-run return reversals recorded by De Bondt and Thaler (1985). Moreover, 26-26 CS strategy is also not significant. This is inconsistent with the significantly positive returns from the 6-6 monthly CS strategy presented by Goyal and Jegadeesh (2018) and Jegadeesh and Titman (1993).

Table 2

Annualized mean returns of the CS and TS strategy of the different m-p-strategies

	Holding period					
Ranking period	1	4	13	26	52	156
A. *Time-series strategy*						
1	**-12.20**	**-2.77**	-0.64	0.02	0.22	0.06
	(-3.56)	(-2.18)	(-0.61)	(0.02)	(0.42)	(0.13)
4	0.24	0.02	1.04	1.42	**2.18**	**1.75**
	(0.09)	(0.01)	(0.56)	(1.19)	(1.99)	(2.11)
13	2.73	3.77	3.44	3.65	**3.88**	2.87
	(0.88)	(1.16)	(1.36)	(1.69)	(2.00)	(1.88)
26	4.06	4.65	5.57	**6.40**	5.10	3.59
	(1.08)	(1.29)	(1.82)	(2.15)	(1.82)	(1.81)
52	5.85	6.36	5.76	5.34	4.06	4.05
	(1.32)	(1.55)	(1.45)	(1.41)	(1.23)	(1.73)
156	3.31	3.38	3.63	3.35	3.95	4.50
	(0.80)	(0.86)	(0.92)	(0.90)	(1.22)	(1.85)
B. *Cross-sectional strategy*						
1	**-8.87**	**-3.28**	-0.77	-0.07	0.16	-0.28
	(-6.14)	(-4.01)	(-1.15)	(-0.17)	(0.50)	(-1.77)
4	-3.07	-1.05	-0.03	0.37	0.79	-0.33
	(-1.54)	(-0.68)	(-0.02)	(0.48)	(1.15)	(-0.99)
13	-0.12	1.43	1.37	1.71	1.59	-0.41
	(-0.05)	(0.65)	(0.78)	(1.23)	(1.19)	(-0.67)
26	1.50	2.60	2.84	3.29	1.37	-0.66
	(0.53)	(0.95)	(1.28)	(1.58)	(0.73)	(-0.78)
52	1.86	2.34	1.41	0.60	-0.70	-1.50
	(0.66)	(0.80)	(0.50)	(0.23)	(-0.33)	(-1.44)
156	-3.20	-2.80	-2.73	-2.72	-2.51	-1.74
	(-1.21)	(-1.10)	(-1.12)	(-1.23)	(-1.38)	(-1.69)

Note. Annualized means of the time-series and cross-sectional strategy with student's t-statistics between parentheses. The holding and ranking period vary from 1 week up to and including 156 weeks. The values in bold are significant on a 5% level.

5.2 Difference in strategies

Table 3 presents the intercept estimates of the regressions (8) and (9). We present the results with the holding period equal to the ranking period and one week. The intercept estimates are almost all negative and significant for the short-run and long-run when the CS return is the dependent variable. For example, the intercept estimates for the 1-1 and 156-156 strategies are -5.55% and -2.74%, respectively. In contrast, the intercept estimate of the 26-26 strategy is not significant, which is not in line with the significantly positive intercept estimate of the strategy with a holding and ranking period of six months presented by Goyal and Jegadeesh (2018). The regression with the TS return as the dependent variable results in all positive and significant intercept estimates for the long-run. For instance, the intercept estimates for the 52-52 and 156-156 strategies are, respectively, 4.90% and 6.61%. These significantly positive intercept estimates are in line with the results of Moskowitz et al. (2012) and Goyal and Jegadeesh (2018). However, Goyal and Jegadeesh (2018) also state significantly positive intercept estimates for the short run, which is not the case in our findings. Moreover, the significant intercept estimates indicate that the CS and TS strategy are not the same for the relevant holding and ranking periods.

Table 3

Cross-alphas of portfolio returns based on time-series and cross-sectional strategies

	Holding period = Ranking period		Holding period = 1 week	
Dependent variable	CS	TS	CS	TS
Independent variable	TS	CS	TS	CS
Ranking period				
1	**-5.55**	4.89	**-5.55**	4.89
	(-4.18)	(1.34)	(-4.18)	(1.34)
4	-1.06	1.50	**-3.15**	4.88
	(-0.85)	(0.67)	(-1.98)	(1.58)
13	-0.15	2.00	-1.16	2.90
	(-0.12)	(0.97)	(-0.60)	(1.03)
26	0.25	2.56	-0.16	2.00
	(0.19)	(1.15)	(-0.08)	(0.65)
52	-2.61	**4.90**	-0.50	3.47
	(-1.84)	(2.33)	(-0.23)	(1.03)
156	**-2.74**	**6.61**	**-4.21**	**6.91**
	(-2.82)	(3.33)	(-2.00)	(2.11)

Note. Annualized intercepts of regressing the returns of the time-series strategy on the returns of the cross-sectional strategy and vice versa. We present the student's t-statistics between parentheses. The holding and ranking period varies from 1 week up to and including 156 weeks. The values in bold are significant on a 5% level.

Table 4 and 5 include the performances of the TS, CS, CS_{TVM}, CS_w and CS_l strategy when the holding period is, respectively, equal to the ranking period and one week. In addition, the tables include the differences between the TS strategy return and all other strategies. We notice a U-shaped pattern in the TS−CS and TS−CS_{TVM} strategies, which means that the largest differences are on the short-run and long-run. This pattern is also found by Goyal and Jegadeesh (2018) for the TS−CS strategy. However, the differences are only significant when the ranking period is 52 or 156 weeks. The TS−CS_w and TS−CS_l strategy show an inverse of the mentioned U-shape pattern. Although, the annualized returns for the TS−CS_w strategy are not significant. In contrast, TS−CS_l results in mostly significant annualized returns. All in all, the TS, CS, CS_{TVM} and CS_w perform somewhat the same.

Furthermore, the last two columns document the average dollar long and short investments for the TS strategy. For example, the net investment of the 1-1 TS strategy is equal to $Long - |Short| = 1.02 - 0.98 = \$0.04$. The net investment increases along with the ranking period, namely from \$0.04 to \$0.82 in Table 4 and from \$0.04 to \$0.84 in Table 5.

Table 4

Time-series and cross-sectional strategies with the ranking period equal to the holding period

	Holding period = Ranking period										
Ranking period	TS	CS	CS_{TVM}	CS_w	CS_l	TS−CS	TS−CS_{TVM}	TS−CS_w	TS−CS_l	Long	Short
1	**-12.20**	**-8.87**	**-14.31**	**-14.46**	**-14.94**	-3.33	**2.12**	2.27	2.74	**1.02**	**-0.98**
	(-3.56)	(-6.14)	(-3.51)	(-3.17)	(-1.98)	(-1.17)	(2.50)	(1.10)	(0.73)	(2.00)	(2.00)
4	0.02	-1.05	-0.54	2.19	-4.65	1.07	0.56	-2.17	4.66	**1.10**	**-0.90**
	(0.01)	(-0.68)	(-0.17)	(0.52)	(-1.05)	(0.49)	(0.90)	(-0.90)	(1.82)	(9.43)	(9.43)
13	3.44	1.37	2.45	4.11	-4.58	2.07	0.99	-0.67	**8.02**	**1.16**	**-0.84**
	(1.36)	(0.78)	(0.84)	(1.15)	(-1.08)	(0.99)	(1.60)	(-0.33)	(3.60)	(15.75)	(15.75)
26	**6.40**	3.29	5.20	**9.27**	-7.03	3.11	1.20	-2.86	**13.44**	**1.21**	**-0.79**
	(2.15)	(1.58)	(1.33)	(2.30)	(-0.91)	(1.47)	(1.05)	(-1.26)	(2.57)	(20.54)	(20.54)
52	4.06	-0.70	1.89	1.79	-9.55	**4.76**	**2.18**	2.27	**13.61**	**1.29**	**-0.71**
	(1.23)	(-0.33)	(0.47)	(0.49)	(-1.37)	(2.14)	(2.37)	(1.10)	(3.20)	(27.59)	(27.59)
156	4.50	-1.74	3.24	2.07	1.06	**6.24**	1.25	2.43	3.43	**1.41**	**-0.59**
	(1.85)	(-1.69)	(1.18)	(0.62)	(0.28)	(2.94)	(1.55)	(1.04)	(1.60)	(36.33)	(36.33)

Note. Annualized means of the time-series strategy and the cross-sectional strategy with and without the time-varying investment. We present the student's t-statistics between parentheses. The holding and ranking period vary from 1 week up to and including 156 weeks. The values in bold are significant on a 5% level. Long is the share of long investment in the TS strategy. Short is the share of short investment in the TS strategy. Long and short are tested if they are equal to 1 and -1, respectively.

Table 5

Time-series and cross-sectional strategies with the holding period equal to one week

	Holding period = 1 week										
Ranking period	TS	CS	CS_{TVM}	CS_{w}	CS_{l}	TS−CS	TS−CS_{TVM}	TS−CS_{w}	TS−CS_{l}	Long	Short
1	**-12.20**	**-8.87**	**-14.31**	**-14.46**	**-14.94**	-3.33	**2.12**	2.27	2.74	**1.02**	**-0.98**
	(-3.56)	(-6.14)	(-3.51)	(-3.17)	(-1.98)	(-1.17)	(2.50)	(1.10)	(0.73)	(2.00)	(2.00)
4	0.24	-3.07	-1.54	0.32	-6.09	3.30	**1.77**	-0.08	6.33	**1.10**	**-0.90**
	(0.09)	(-1.54)	(-0.48)	(0.07)	(-1.21)	(1.34)	(2.29)	(-0.03)	(1.64)	(9.61)	(9.61)
13	2.73	-0.12	1.27	2.91	-6.46	2.85	1.46	-0.18	**9.19**	**1.17**	**-0.83**
	(0.88)	(-0.05)	(0.36)	(0.64)	(-1.15)	(1.13)	(1.45)	(-0.07)	(2.38)	(16.51)	(16.51)
26	4.06	1.50	2.60	6.22	-8.58	2.56	1.46	-2.16	**12.64**	**1.22**	**-0.78**
	(1.08)	(0.53)	(0.55)	(1.18)	(-1.13)	(0.94)	(1.12)	(-0.76)	(2.59)	(21.83)	(21.83)
52	5.85	1.86	4.03	8.48	-12.09	4.00	1.83	-2.62	**17.94**	**1.28**	**-0.72**
	(1.32)	(0.66)	(0.71)	(1.27)	(-1.43)	(1.28)	(1.24)	(-0.74)	(3.37)	(27.60)	(27.60)
156	3.31	-3.20	2.20	4.99	-9.02	**6.52**	1.12	-1.68	**12.34**	**1.42**	**-0.58**
	(0.80)	(-1.21)	(0.41)	(0.77)	(-1.13)	(1.99)	(0.64)	(-0.47)	(2.36)	(42.50)	(42.50)

Note. Annualized means of the time-series strategy and the cross-sectional strategy with and without the time-varying investment. We present the student's *t*-statistics between parentheses. The ranking period varies from 1 week up to and including 156 weeks while the holding period is equal to one week. The values in bold are significant on a 5% level. Student's *t*-statistics between parentheses. Long is the share of long investment in the TS strategy. Short is the share of short investment in the TS strategy. Long and short are tested if they are equal to 1 and -1, respectively.

5.3 Returns adjusted for risk

Table 6 and 7 present the constants of the CAPM and FF3M when the holding period is, respectively, equal to the ranking period and one week. The time-varying investment of the CS_{TVM} strategy includes the weighted market index. Hence, the market factor should account for this.

First, we look at the CAPM constants. The constant of the TS strategy is only significantly negative for the 1-1 TS strategy. In contrast, positive constants are attained for the other TS strategies. Thereafter, the constants of the CS strategy are only significant for the 1-1, 26-26 and 156-156 strategies. Specifically, the 1-1 and 156-156 CS strategies are significantly negative and the 26-26 CS strategy is significantly positive. The differences of the TS strategy and other strategies show some significant constants. In particular, the differences between the TS strategy and the strategies with a time-varying investment have significantly positive constants for the 52-52 and 156-156 strategy, which is in line with the results of Goyal and Jegadeesh (2018).

Second, we focus on the FF3M constants. The differences between the TS strategy and the strategies with a time-varying investment are mostly not significant for the 13-13 and 26-26 strategy. Jegadeesh and Titman (1993) state momentum strategy profitability for these horizons. On the contrary, there are significantly positive constants for the 1-1, 52-52 and 156-156 strategy. Jegadeesh (1990) and De Bondt and Thaler (1985) proved the existence of return reversals over these horizons. Moreover, Goyal and Jegadeesh (2018) also state a significantly positive constant for the TS−CS_{TVM} strategy with a holding and ranking period of three years (156-156 strategy in our case).

Table 6

CAPM and Fama-French 3-factor model alphas with the ranking period equal to the holding period

	Holding period = Ranking period								
Ranking period	TS	CS	CS_{TVM}	CS_{w}	CS_{l}	TS−CS	TS−CS_{TVM}	TS−CS_{w}	TS−CS_{l}
A. CAPM alpha									
1	**-7.08**	**-7.30**	**-8.51**	**-10.95**	-5.13	0.22	1.43	3.86	-1.95
	(-2.23)	(-4.51)	(-2.29)	(-2.57)	(-0.92)	(0.08)	(1.84)	(1.70)	(0.56)
4	4.20	1.23	3.96	4.15	2.50	2.97	0.23	0.04	1.70
	(1.26)	(0.83)	(1.02)	(0.92)	(0.48)	(1.36)	(0.33)	(0.02)	(0.67)
13	**5.76**	2.73	4.59	5.15	-0.50	3.03	1.17	0.61	**6.26**
	(2.38)	(1.67)	(1.64)	(1.34)	(-0.13)	(1.37)	(1.84)	(0.31)	(2.90)
26	**7.64**	**4.51**	**6.67**	**8.80**	-0.04	3.14	0.97	-1.16	**7.68**
	(3.36)	(2.72)	(2.36)	(2.41)	(-0.01)	(1.56)	(1.21)	(-0.56)	(2.22)
52	4.61	-0.95	2.48	0.56	-2.44	**5.56**	**2.14**	**4.06**	**7.06**
	(1.61)	(-0.32)	(0.70)	(0.14)	(-0.52)	(3.30)	(2.45)	(1.98)	(2.58)
156	-2.30	**-4.50**	**-5.07**	**-8.62**	**-5.37**	2.20	**2.77**	**6.32**	3.07
	(-1.51)	(-2.99)	(-3.02)	(-4.79)	(-2.22)	(1.10)	(3.79)	(3.89)	(1.92)
B. FF 3-factor alpha									
1	**-7.23**	**-7.46**	**-8.73**	**-11.53**	-5.19	0.23	1.50	**4.30**	-2.04
	(-2.27)	(-4.45)	(-2.35)	(-2.72)	(-0.89)	(0.08)	(1.93)	(2.04)	(-0.59)
4	4.88	1.75	5.00	5.23	4.09	3.13	-0.11	-0.34	0.80
	(1.86)	(1.14)	(1.23)	(1.15)	(0.74)	(1.15)	(-0.17)	(-0.18)	(0.31)
13	**6.16**	3.75	5.27	5.78	0.30	2.41	0.89	0.38	**5.86**
	(2.48)	(1.94)	(1.87)	(1.49)	(0.07)	(0.94)	(1.49)	(0.18)	(2.73)
26	**8.01**	**5.45**	**7.66**	**9.74**	2.12	2.56	0.35	-1.72	5.89
	(3.22)	(2.85)	(2.35)	(2.72)	(0.31)	(1.19)	(0.37)	(-0.94)	(1.24)
52	**6.58**	1.15	5.26	3.28	1.32	**5.43**	**1.32**	3.30	5.27
	(2.57)	(0.61)	(1.76)	(1.03)	(0.23)	(2.81)	(2.02)	(1.71)	(1.40)
156	1.12	**-2.07**	-1.43	-4.88	-2.12	3.19	**2.55**	**6.00**	3.24
	(0.39)	(-2.02)	(-0.46)	(-1.64)	(-0.43)	(1.15)	(3.44)	(2.96)	(1.16)

Note. Annualized intercepts of the Capital Asset Pricing Model and the Fama-French 3-factor model. We present the student's t-statistics between parentheses. The holding and ranking period varies from 1 week up to and including 156 weeks. The values in bold are significant on a 5% level.

Table 7

CAPM and Fama-French 3-factor model alphas with the holding period equal to one week

	Holding period = 1 week								
Ranking period	TS	CS	CS_{TVM}	CS_{w}	CS_{l}	TS−CS	TS−CS_{TVM}	TS−CS_{w}	TS−CS_{l}
A. CAPM alpha									
1	**-7.08**	**-7.30**	**-8.51**	**-10.95**	-5.13	0.22	1.43	3.86	-1.95
	(-2.23)	(-4.51)	(-2.29)	(-2.57)	(-0.92)	(0.08)	(1.84)	(1.70)	(0.56)
4	6.31	-0.57	5.34	4.83	4.96	**6.88**	0.97	1.48	1.35
	(1.75)	(-0.28)	(1.25)	(0.95)	(0.81)	(2.24)	(1.10)	(0.60)	(0.36)
13	7.16	1.73	5.89	5.03	1.66	5.43	1.27	2.13	5.50
	(1.91)	(0.69)	(1.33)	(0.94)	(0.27)	(1.85)	(1.27)	(0.79)	(1.47)
26	7.11	2.74	5.57	5.71	-1.63	4.37	1.54	1.41	**8.75**
	(1.76)	(1.05)	(1.15)	(0.98)	(-0.24)	(1.31)	(1.32)	(0.49)	(2.13)
52	6.52	2.26	3.88	4.99	-9.29	4.26	2.64	1.53	**15.81**
	(1.24)	(0.82)	(0.61)	(0.62)	(-1.09)	(0.97)	(1.71)	(0.40)	(3.50)
156	0.50	-3.73	-2.44	-2.59	-13.03	4.23	2.93	3.09	**13.52**
	(0.12)	(-1.34)	(-0.46)	(-0.39)	(-1.73)	(1.19)	(1.80)	(0.84)	(2.93)
B. FF 3-factor alpha									
1	**-7.23**	**-7.46**	**-8.73**	**-11.53**	-5.19	0.23	1.50	**4.30**	-2.04
	(-2.27)	(-4.45)	(-2.35)	(-2.72)	(-0.89)	(0.08)	(1.93)	(2.04)	(-0.59)
4	6.50	-0.69	5.59	4.86	5.74	**7.19**	0.91	1.64	0.76
	(1.74)	(-0.34)	(1.26)	(0.94)	(0.89)	(2.31)	(1.02)	(0.67)	(0.20)
13	**7.66**	2.17	6.69	5.71	3.11	5.49	0.97	1.95	4.55
	(2.06)	(0.90)	(1.56)	(1.08)	(0.51)	(1.80)	(1.07)	(0.73)	(1.21)
26	**7.99**	3.45	6.85	6.38	0.84	4.54	1.14	1.61	7.14
	(1.99)	(1.44)	(1.47)	(1.16)	(0.12)	(1.26)	(1.15)	(0.57)	(1.69)
52	8.17	3.60	6.24	7.13	-5.14	4.57	1.93	1.05	**13.31**
	(1.57)	(1.48)	(1.05)	(0.97)	(-0.62)	(0.97)	(1.68)	(0.31)	(3.02)
156	2.42	-2.10	0.35	0.85	-9.78	4.52	2.06	1.57	**12.19**
	(0.62)	(-1.15)	(0.08)	(0.17)	(-1.39)	(1.22)	(1.90)	(0.58)	(2.81)

Note. Annualized intercepts of the Capital Asset Pricing Model and the Fama-French 3-factor model. We present the student's t-statistics between parentheses. The ranking period varies from 1 week up to and including 156 weeks while the holding period is equal to one week. The values in bold are significant on a 5% level.

6 Conclusion & Discussion

This section covers the conclusion and discussion of our research. Originally, literature ranked stocks based on cross-section in order to create portfolios with the purpose of predicting returns. A more recent method is using time-series to rank stocks, which is introduced by Moskowitz et al. (2012).

In this paper, we research the performance of the CS strategy, TS strategy and CS with three variations of a time-varying investment strategy. Specifically, the time-varying investment variations are investing in an equally weighted market index, stocks with returns above the 95th percentile in the ranking period and stocks with returns below the 5th percentile in the ranking period. The central research question in this paper is: 'Does the TS strategy outperform the CS strategy based on weekly returns for the period of January 1992 up to and including December 2019?'. We observe significant differences in the returns of the TS and CS strategy. Specifically, the TS strategy seems to achieve higher returns compared to the CS strategy. In particular, the 26-26 TS strategy has a significantly positive annualized return of 6.40% while the CS strategy only has significantly negative returns for the 1-1 and 1-4 strategy. However, the comparisons between the TS strategy and CS strategies including a time-varying investment indicate that the TS strategy likely outperforms the CS strategy due to the net investment made in the TS strategy. We find that the difference between the TS and the CS strategies with a time-varying investment only lead to a few significantly positive returns. Therefore, it seems that the TS and CS strategy are somewhat equal when we adjust for the aforementioned net investment. In addition, the risk adjusted returns of the TS and CS strategy with a time-varying investment are also relatively equal. All things considered, the CS strategy is likely outperformed by the TS strategy. However, the difference seems to occur due to the net investment of the TS strategy. The TS and CS strategy with a time-varying investment perform somewhat equally. This is consistent with the results in Goyal and Jegadeesh (2018).

Nevertheless, we have some suggestions for further research. For instance, it might be interesting to use daily data for the research. In addition, varying conditions of the TS and CS strategy for "winner" stocks can be used. For example, the TS strategy calls stocks "winners" if they have a return exceeding zero in the ranking period. Instead, stocks might be called "winners" when their return exceeds five. Therefore, future research could look into which condition maximizes the return. Furthermore, we suggest utilizing other financial assets instead of stocks.

References

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, 68(3):929–985.

Bali, T. G., Engle, R. F., and Murray, S. (2016). *Empirical asset pricing: The cross section of stock returns*. John Wiley & Sons.

Blume, M. E. and Stambaugh, R. F. (1983). Biases in computed returns: An application to the size effect. *Journal of Financial Economics*, 12(3):387–404.

De Bondt, W. F. and Thaler, R. (1985). Does the stock market overreact? *The Journal of finance*, 40(3):793–805.

De Bondt, W. F. and Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of finance*, 42(3):557–581.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33:3–56.

Goyal, A. and Jegadeesh, N. (2018). Cross-sectional and time-series tests of return predictability: What is the difference? *The Review of Financial Studies*, 31(5):1784–1824.

Grinblatt, M. and Titman, S. (1989). Mutual fund performance: An analysis of quarterly portfolio holdings. *Journal of business*, pages 393–416.

Grinblatt, M. and Titman, S. (1993). Performance measurement without benchmarks: An examination of mutual fund returns. *Journal of business*, pages 47–68.

Heij, C., de Boer, P., Franses, P. H., Kloek, T., van Dijk, H. K., et al. (2004). *Econometric methods with applications in business and economics*. Oxford University Press.

Huang, D., Li, J., Wang, L., and Zhou, G. (2020). Time series momentum: Is it there? *Journal of Financial Economics*, 135(3):774–794.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of finance*, 45(3):881–898.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1):65–91.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, 105(1):1–28.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, 47(1):13–37.

Lyon, J. D., Barber, B. M., and Tsai, C.-L. (1999). Improved methods for tests of long-run abnormal stock returns. *The Journal of Finance*, 54(1):165–201.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of financial economics*, 104(2):228–250.

Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708.

Newey, W. K. and West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653.

Papailias, F., Liu, J., and Thomakos, D. D. (2021). Return signal momentum. *Journal of Banking & Finance*, 124:106063.

RStudio Team (2020). *RStudio: Integrated Development Environment for R*. RStudio, PBC., Boston, MA.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442.

Shumway, T. (1997). The delisting bias in crsp data. *The Journal of Finance*, 52(1):327–340.

Appendix A Table 1 through 4 of Goyal and Jegadeesh (2018)

Table 8

Portfolio returns to prior return sorts based on time-series and cross-sectional strategies

	Holding period					
Ranking period	1	3	6	12	36	60
A. *Time-series strategy*						
1	4.02	2.39	2.42	2.66	1.00	0.98
	(2.52)	(1.99)	(2.52)	(3.27)	(1.70)	(1.51)
3	6.12	4.72	4.32	4.46	2.34	2.62
	(2.87)	(2.49)	(2.85)	(3.20)	(2.33)	(2.25)
6	7.68	6.29	5.90	5.07	2.81	3.30
	(3.33)	(2.92)	(2.84)	(2.92)	(2.22)	(2.12)
12	9.55	7.75	6.33	3.58	2.98	3.98
	(3.55)	(3.07)	(2.71)	(1.71)	(1.82)	(1.98)
36	5.98	5.57	4.59	4.16	5.64	7.02
	(2.34)	(2.08)	(1.61)	(1.53)	(2.20)	(2.74)
60	6.23	5.89	5.56	5.36	7.03	8.44
	(2.19)	(2.04)	(1.89)	(1.89)	(2.73)	(3.24)
B. *Cross-sectional strategy*						
1	-5.11	-1.07	0.36	1.42	0.18	0.01
	(-5.43)	(-1.68)	(0.82)	(4.08)	(0.83)	(0.04)
3	-0.76	1.31	2.31	3.06	0.64	0.38
	(-0.72)	(1.72)	(3.20)	(4.77)	(1.69)	(0.86)
6	2.33	3.63	4.31	3.68	0.69	0.50
	(1.96)	(3.36)	(4.18)	(4.16)	(1.29)	(0.82)
12	5.00	5.18	4.25	2.37	0.04	-0.25
	(3.52)	(3.87)	(3.34)	(3.58)	(0.06)	(-0.31)
36	-0.07	0.39	0.15	-0.26	-1.21	-2.28
	(-0.05)	(0.28)	(0.11)	(-0.21)	(-1.19)	(-2.11)
60	-0.46	-0.08	-0.03	-0.63	-2.09	-3.20
	(-0.40)	(-0.07)	(-0.02)	(-0.59)	(-2.22)	(-2.99)

Note. Student's t-statistics between parentheses.

Table 9

Cross-alphas of portfolio returns based on time-series and cross-sectional strategies

	Holding period = Ranking period		Holding period = 1 month	
Dependent variable	CS	TS	CS	TS
Independent variable	TS	CS	TS	CS
Ranking period				
1	-6.32	10.79	-6.32	10.79
	(-8.75)	(5.30)	(-8.75)	(5.30)
3	-0.02	2.94	-2.97	7.05
	(-0.03)	(1.63)	(-3.27)	(3.46)
6	2.55	-0.17	-0.63	4.71
	(2.87)	(-0.10)	(-0.68)	(2.35)
12	1.33	0.80	1.29	3.22
	(1.38)	(0.43)	(1.16)	(1.49)
36	-2.81	7.65	-2.04	6.07
	(-3.73)	(4.35)	(-1.86)	(2.90)
60	-5.17	12.40	-2.00	6.80
	(-6.13)	(5.81)	(-2.04)	(3.04)

Note. Student's t-statistics between parentheses.

Table 10

Cross-alphas of portfolio returns based on time-series and cross-sectional strategies

	Holding period = Ranking period							Holding period = 1 month						
Ranking period	TS	CS	CS_{TVM}	TS−CS	$TS-CS_{TVM}$	$Long	$Short	TS	CS	CS_{TVM}	TS−CS	$TS-CS_{TVM}$	$Long	$Short
1	4.02	-5.11	2.83	9.13	1.19	1.06	-0.94	4.02	-5.11	2.83	9.13	1.19	1.06	-0.94
	(2.52)	(-5.43)	(1.47)	(6.28)	(2.83)	(4.14)	(4.14)	(2.52)	(-5.43)	(1.47)	(6.28)	(2.83)	(4.14)	(4.14)
3	4.72	1.31	4.30	3.41	0.41	1.13	-0.87	6.12	-0.76	4.96	6.88	1.12	1.14	-0.86
	(2.49)	(1.72)	(2.00)	(2.03)	(1.02)	(8.17)	(8.17)	(2.87)	(-0.72)	(2.00)	(3.59)	(2.07)	(8.43)	(8.43)
6	5.90	4.31	5.81	1.59	0.09	1.17	-0.83	7.68	2.33	6.97	5.35	0.71	1.18	-0.82
	(2.84)	(4.18)	(2.35)	(0.93)	(0.16)	(10.25)	(10.25)	(3.33)	(1.96)	(2.62)	(2.87)	(1.15)	(10.80)	(10.80)
12	3.58	2.37	3.04	1.22	0.55	1.22	-0.78	9.55	5.00	9.73	4.55	-0.18	1.23	-0.77
	(1.71)	(2.25)	(1.24)	(0.69)	(1.01)	(13.92)	(13.92)	(3.55)	(3.52)	(3.14)	(2.09)	(-0.25)	(14.74)	(14.74)
36	5.64	-1.21	5.26	6.85	0.38	1.37	-0.63	5.98	-0.07	5.71	6.05	0.27	1.37	-0.63
	(2.20)	(-1.19)	(1.71)	(3.51)	(0.55)	(25.44)	(25.44)	(2.34)	(-0.05)	(1.78)	(2.91)	(0.33)	(26.88)	(26.88)
60	8.44	-3.20	7.31	11.63	1.12	1.47	-0.53	6.23	-0.46	6.60	6.69	-0.37	1.49	-0.51
	(3.24)	(-2.99)	(2.52)	(5.28)	(1.54)	(35.89)	(35.89)	(2.19)	(-0.40)	(1.92)	(2.92)	(-0.35)	(34.31)	(34.31)

Note. Student's t-statistics between parentheses.
$Long is the share of long investment in the TS strategy.
$Short is the share of short investment in the TS strategy.

Table 11

Alphas based on time-series and cross-sectional strategies

	Holding period = Ranking period					Holding period = 1 month				
	TS	CS	CS_{TVM}	TS−CS	TS−CS_{TVM}	TS	CS	CS_{TVM}	TS−CS	TS−CS_{TVM}
Ranking period										
A. *CAPM alpha*										
1	6.65	-4.17	5.68	10.82	0.97	6.65	-4.17	5.68	10.82	0.97
	(3.31)	(-4.83)	(2.60)	(6.03)	(2.32)	(3.31)	(-4.83)	(2.60)	(6.03)	(2.32)
3	4.75	1.76	4.29	3.00	0.47	7.33	0.17	6.34	7.16	0.99
	(2.42)	(2.39)	(1.95)	(1.77)	(1.17)	(3.14)	(0.17)	(2.37)	(3.54)	(1.77)
6	6.69	4.67	6.63	2.03	0.07	8.70	3.02	7.98	5.68	0.73
	(3.80)	(5.42)	(3.27)	(1.28)	(0.15)	(3.62)	(2.74)	(2.93)	(2.61)	(1.22)
12	3.77	2.00	3.02	1.78	0.75	9.23	5.20	9.03	4.03	0.20
	(2.07)	(1.68)	(1.34)	(1.23)	(1.28)	(3.70)	(4.52)	(3.27)	(1.75)	(0.29)
36	-0.14	-3.42	-1.64	3.28	1.49	3.01	-0.74	1.48	3.75	1.53
	(-0.08)	(-3.10)	(-0.81)	(2.02)	(2.38)	(1.36)	(-0.53)	(0.57)	(2.14)	(1.95)
60	0.12	-5.50	-2.64	5.62	2.76	1.92	-1.20	0.55	3.12	1.36
	(0.08)	(-5.30)	(-1.68)	(3.01)	(3.81)	(0.81)	(-1.10)	(0.20)	(1.41)	(1.31)
B. *FF 3-factor alpha*										
1	6.84	-3.80	6.02	10.63	0.82	6.84	-3.80	6.02	10.63	0.82
	(3.62)	(-3.79)	(2.86)	(6.24)	(1.94)	(3.62)	(-3.79)	(2.86)	(6.24)	(1.94)
3	4.61	2.74	4.40	1.87	0.21	7.05	0.65	6.26	6.40	0.79
	(2.30)	(2.80)	(1.95)	(1.01)	(0.55)	(2.77)	(0.48)	(2.14)	(3.01)	(1.31)
6	6.09	5.78	6.59	0.31	-0.50	8.79	3.89	8.53	4.90	0.26
	(3.43)	(5.55)	(3.02)	(0.20)	(-1.02)	(3.47)	(2.91)	(2.94)	(2.14)	(0.44)
12	4.58	4.39	4.73	0.19	-0.15	9.87	6.86	10.44	3.01	-0.57
	(2.49)	(4.62)	(2.21)	(0.12)	(-0.33)	(3.60)	(4.76)	(3.41)	(1.15)	(-0.89)
36	2.86	0.29	3.06	2.57	-0.20	5.56	2.41	5.36	3.15	0.20
	(1.27)	(0.37)	(1.11)	(1.38)	(-0.26)	(2.55)	(2.49)	(2.20)	(1.63)	(0.31)
60	2.34	-0.45	2.12	2.79	0.22	3.46	1.66	3.85	1.80	-0.39
	(1.22)	(-0.64)	(1.06)	(1.45)	(0.20)	(1.46)	(1.80)	(1.33)	(0.90)	(-0.41)

Note. Student's t-statistics between parentheses.

Appendix B Description of the programming code

Each m-p-strategy has its' own file for the replication and extension part of this paper. In addition, the extension contains extra files that include the figures and summary statistic table as the output. Moreover, one of the extra files is the data file. This file is run before each m-p-strategy in the extension part as the output of this file is our data.