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Erasmus School of Economics

Bachelor Thesis [Econometrics and Operations Research]

Time-series versus Cross-sectional versus Dual momentum strategies.

Which is the most profitable?

Name student: Fayyaz Sheikh

Student ID number: 484438

Supervisor: Kleen, O.

Second assessor: Kole, H.J.W.G.

Abstract

This research extends on the findings of Goyal and Jegadeesh (2017) who compare the performance of two trading strategies, namely time-series and cross-sectional strategies. We investigate whether a third trading strategy, dual momentum, performs better or worse than the previous two. In doing so we also do a robustness check by using multiple subsamples in order to see if the performance of these strategies are constant over time or fluctuate a lot. When comparing the time-series against the cross-sectional strategy we find that the time-series strategy outperforms the cross-sectional strategy. The dual momentum strategy performs worse than both the time-series and the cross-sectional strategy. The time-series strategy is the only one out of the three that proves to be robust, since the performance for different ranking and holding periods do not fluctuate a lot. In times of crisis all three strategies perform worse when compared to the full sample, especially the dual momentum. The trading strategy which seems the most viable for investing appears to be a time-series strategy with a ranking period of nine months and a holding period of six months.

Contents

1 Introduction

Using a good trading strategy has always been something many traders and investors are interested in. Having low risk and high return is preferred. Over the years many trading strategies have been created and some of them are still being used nowadays, like time-series (TS) strategies and cross-sectional (CS) strategies. This paper looks at the TS, CS and also the dual momentum (DUAL) strategy. The latter is a combination of the other two. The three trading strategies are compared and a recommendation is given, which of these strategies will be the most profitable.

TS is a trading strategy that looks back on its past returns in order to make a decision if you need to go long or short in that stock when creating your portfolio. It compares the return of the stock with zero, because you want to know if the returns are positive or negative before making a decision. This idea is the same for CS, but with one difference. This difference is that for CS one does not look at the fixed value zero but a cross-sectional average which is the average of the returns of all the stock that are being traded within that timeframe. Trying to find out which of these two strategies edges the other Bird et al. (2017) test different ways of implementing TS and CS strategies. They conclude that TS is the best strategy for implementing momentum. TS momentum does exist in intraday trading according to Li et al. (2020), showing that the trading strategies also work on a small time window. Asness et al. (2013) study cross sectional momentum strategies and the returns to value across different markets. Cheema et al. (2020) conclude that the performance of TS and CS are country based, by this they mean that TS and CS perform similar in the US but they are different in China. Ham et al. (2019) confirm this and add to this that the duration of momentum differs per country.

In order to make the TS and CS strategies more comparable Goyal and Jegadeesh (2017) add a time-varying investment component to the CS strategy and they name this CS_{TVM}. This CS_{TVM} is each month set equal to the difference between short and long from the TS strategy. Goyal and Jegadeesh (2017) find that when implemented within three individual asset classes, namely commodities, equities and currencies the CS_{TVM} and TS strategies perform rather similar. They also find that within these asset classes the net long positions that are taken by TS strategies are the main cause of any of the differences between CS and TS strategies. On the other hand, they find that TS strategies are outperformed by CS_{TVM} strategies when investing into bonds. Which let them to the conclusion that for under and overvalued bonds the CS approach is preferred over the TS approach. Goyal and Jegadeesh (2017) also look at cross-alpha regressions in which they

regress the returns from TS on CS and vice versa. In these regressions they test whether the alphas are significantly different from zero. Kim et al. (2016) show that the TS alphas are largely driven by volatility scaling.

Trying to find a better trading strategy than TS and CS Lim et al. (2018) come up with two alternatives, namely dual momentum and revised time-series momentum. In this paper we will only take a closer look at the dual momentum. According to them these two strategies generate higher profits than standard TS and CS strategies. In implementing this DUAL strategy Lim et al. (2018) is followed. Where there are two stages to make a DUAL strategy. First stocks are split into groups with positive or negative return. Then these are further split up into five quintiles. According to D'Souza et al. (2016), TS strategies do not suffer from market crashes and have a good performance in both bull and bear markets. This however, is not the case for cross-sectional momentum strategies. They also discuss the DUAL strategy and they come to the conclusion that it generates around 1.88% returns on a monthly basis which is relatively high.

The ranking period, formation period, is self-explanatory since it is a period in which we rank the stocks based on its previous returns, with these periods ranging from 1 to 60 months. We do this for TS, CS and DUAL strategies. When a stocks market capitalization is above the 20th percentile of the NYSE market capitalization we speak of non-micro cap stocks. For the ranking period we refit the model every month in order to keep all the non-micro cap stocks in our portfolio. The stocks that are micro-cap and non-micro-cap can change every month, since as stated earlier, it is based on the market capitalization and this fluctuates. These portfolios are being held for some period of time before it is being sold, this is also known as the holding period. Like Jegadeesh and Titman (1993), we will use overlapping portfolios when the holding period is larger than one month. Overlapping portfolios are visualized in Figure 1. A strategy that has a ranking period Y and a holding period Z is referred to as a Y × Z strategy, with Y and Z in months. Goyal and Jegadeesh (2017) have Y and Z $\in \{1, 3, 6, 12, 36, 60\}$. In this paper we add 9 and 24 which extends the set for Y and Z to $\in \{1, 3, 6, 9, 12, 24, 36, 60\}$. This means we extend the number of strategies we have from 36 to 64.

This research is mainly relevant for traders and investors and it is interesting for practical applications. The IDE that is used is R-studio 4.0.5. Knowing more and better trading strategies improves the variety of trading strategies, this causes people to make better decisions, e.g. less risk and higher returns. This has always been important and now even more because of the Covid-19 pandemic, which caused a crisis, which at the time of writing is still ongoing. This brings us to the main research question, namely: *Which out of the three trading strategies, time-series, cross-*
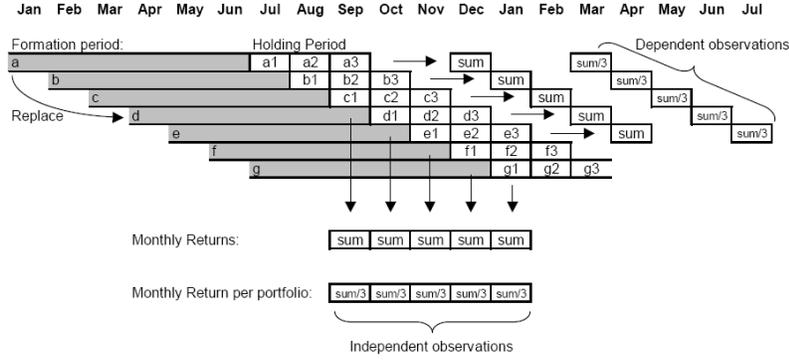
Figure 1: Overlapping portfolios for holding periods that are larger than one month

sectional and dual momentum, is the most profitable and what is the best ranking/holding period that belongs to this strategy? To answer this main research question we answer three sub-questions. First of all, *How do time-series and cross-sectional strategies compare to one another?* Secondly, *How does the dual momentum strategy compare to time-series and cross-sectional strategies?* Finally, *Is it robust, so how different is the performance of the different $Y \times Z$ strategies in multiple subsamples for time-series, cross-sectional and dual momentum?*

When comparing the TS and CS, like Goyal and Jegadeesh (2017) we find that for CS the 1 $\times$ 1 strategy gives a return of -4.75% whereas this is -0.41% for TS. For a 60 $\times$ 60 strategy the differences are bigger, TS is significantly positive with returns of 9.42%. However, the CS is -1.39%. For yearly based strategies, so a 12 $\times$ 12 strategy we get a return of 4.34% and 1.54% for TS and CS, respectively. This is in line with Goyal and Jegadeesh (2017) and Moskowitz et al. (2012). For the cross-alpha regressions, we find that when CS is the dependent variable, the alphas are negative for the short and long ranking and holding periods. When TS is the dependent variable, all the alphas are positive. The addition from the time-varying investment component to the CS strategy makes the CS_{TVM} strategy which is an improvement.

The DUAL has returns -16.20%, 3.49% and -2.62% for a 1 $\times$ 1, 12 $\times$ 12 and 60 $\times$ 60 strategy, respectively. So, in short and long ranking and holding periods the DUAL performs worse than the TS and CS, which is not in line with Lim et al. (2018). In Lim et al. (2018) the DUAL outperforms the TS. For a medium ranking and holding period the returns are much closer. For the cross-alpha comparison of DUAL with TS or CS the alphas are mostly positive and significant, when DUAL is the explanatory variable. When DUAL is the dependent variable, the alphas are negative and significant.

For the robustness check with two subsamples and another sample period corresponding to only crises, the TS proves to be the only strategy that is robust. In Lim et al. (2018), TS and DUAL are robust. For example for our TS, the 9×6 strategy is 6.09% for the first subsample and 6.68% in the second. In times of crisis it is 3.17%, which is lower than the two subsamples. This is expected since returns are most of the time much lower in times of crisis.

The paper is structured as follows: Section 2 gives the description of the data that is used. The following section, which is Section 3 explains the three different trading strategies in more detail. The results from these three trading strategies and their comparison are shown in Section 4. Section 5 gives the conclusion and discussion of this paper.

2   Data

2.1   Database and variables selection

We use a dataset from the Center for Research in Security Prices (CRSP) which is obtained from Wharton Research Data Services (WRDS). This dataset contains monthly data for all American stocks between December 1925 up and until December 2020, but we only use data from January 1946–December 2020.
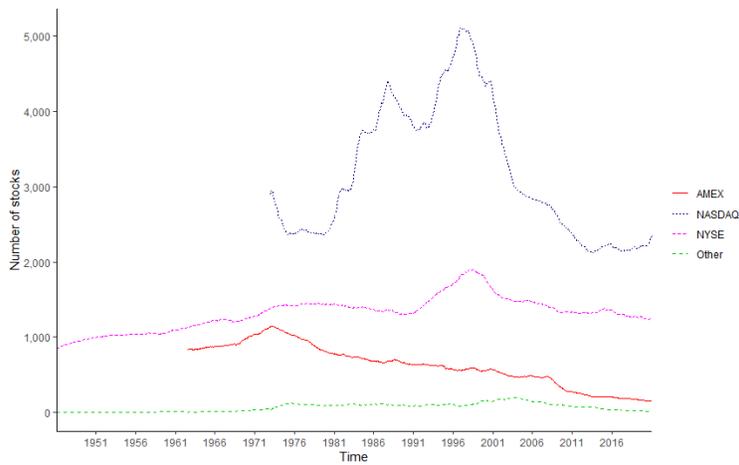
Figure 2: Number of stocks per stock exchange between 1946–2020

Figure 2 shows the number of available stocks between 1946 and 2020 per stock exchange. There are a total of 3,515,503 observations. When we want to split data into two parts which are roughly the same size the split needs to be after June 1992. This gives two subperiods, namely January 1946–June 1992 and July 1992–December 2020.

We select nine different variables from the database and briefly explain their definition (more details can be found on the WRDS site). First of all the exchange code, which is used to make a distinction between the stock exchanges. It filters for the index, 1 and 31 for NYSE, 2 and 32 for AMEX, 3 and 33 for NASDAQ and if it is neither of these they will be categorised as "OTHER". Secondly, the share code which is 10 and 11. This filters out closed-end funds, real estate investment trusts, American trust components, American depository receipts, units and preferred stocks. The delisting code indicates whether a security is still trading or it provides a specific reason for the delisting of that stock. The price alternate is an alternate monthly price which contains the last non-missing price in the month. The delisting return is the return of the stock after it is delisted. The holding period return is the change per dollar in the total value of a stock over some period of time. The number of shares outstanding, which is the number of publicly held shares in thousands. The equal-weighted return which includes distributions is the monthly returns on an equally-weighted market portfolio. Finally, the value-weighted return which also includes distributions is the monthly returns on a value-weighted market portfolio.

Since we want to compare the returns for these stocks and the prices have changed over time, we will need to adjust for the Consumer Price Index (CPI). The Federal Reserve Economic Data (FRED) database is used for this. The third and final database that is going to be used is the Fama-French database. This has the risk-free rate on a monthly basis which is used to calculate excess returns. The summary statistics of the returns that are adjusted for CPI and are in excess of the risk-free rate are shown in Table 1.

Table 1: Summary statistics of returns that are CPI adjusted and in excess of the risk-free rate

max	min	st.dev	mean	skewness	kurtosis
2399.66	-101.31	18.23	0.63	6.50	352.31

For calculating the portfolio returns of the trading strategies we need to define the way we calculate this. We do this using the holding period return formula given in Equation (1). This equation calculates the annualized holding period returns which are the results in the tables in Section 4 and in Appendix A. Where, $strat$ is the trading strategy, so TS, CS or DUAL. The R_t is the return of the trading strategy in month t, this will be explained in more detail in Section 3.

$$\text{Annualized holding period return } strat = 12 \times \text{mean}(R_t^{strat}) \tag{1}$$

2.2 Data cleaning

We will look at all the stocks that are available in the dataset of CRSP, but we first have to clean the dataset in order to make use of it. The description of the code that is used for this is in Appendix B. To cope with missing data and the delisting of some of the stocks we follow Shumway (1997) for the adjustment of the returns. We look at past returns, when there is no data for the past returns but there is for the delisted returns we take that value. So in a sense we merge these two variables and call it the adjusted returns. This might not be exactly the same as Goyal and Jegadeesh (2017), since it was not specifically specified by them what they do. However, as will become more clear in Section 4 these differences are negligible.

Market capitalization is calculated as the current market price per share times the total number of outstanding shares. This market capitalization is calculated because we do not want micro-cap stocks in our sample. The reason for this is that micro-cap stocks can provide potential biases in computed returns. This is mostly the case for low priced stocks. Non-micro-cap stocks are defined as stocks that are above 20th percentile of the NYSE market capitalization.

3 Methodology

3.1 The three trading strategies

3.1.1 Time-series

The first of three different trading strategies is TS. TS is a strategy that follows the trend of a stock. It looks back on its past performance, during a ranking period, which defines if we need to go long or short in that stock. Since the TS strategy only looks at its own performance, the decision between going long or short is based on a positive or negative return. Hence, this gives us Equation (2).

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

where $R_{\text{it-1}}$ is the ranking period excess return of the ith stock. Here excess return is defined as the return in excess of the risk-free rate. N is the total number of stocks. The excess return of a stock in the month the portfolio is created is given by R_{it}. R_t^{TS} is the return of the TS strategy in month t. In order to make a better comparison with the CS strategy we multiply by two. This factor makes sure that the total long plus short position of TS and CS are equal.

3.1.2 Cross-sectional

The CS approach is similar to the TS approach, but the big difference is that the CS approach compares the stocks performance to a cross-section. In this cross-section there are multiple other stocks. According to its relative performance (rank), a decision will be made if we go long or short in this asset. If the stock outperforms its competitors from the cross-section, it has a more positive return than average for that cross-section, we take a long position in that stock. Otherwise, we go short and this is illustrated in mathematical notation in Equation (3).

$$R_t^{CS} = \frac{1}{N^+} \sum\nolimits_{R_{it-1} \geq \bar{R}_{t-1}} R_{it} - \frac{1}{N^-} \sum\nolimits_{R_{it-1} < \bar{R}_{t-1}} R_{it} \tag{3}$$

The cross-sectional equal-weighted average of the ranking period is given by $\bar{R}_{t-1}$. N^+ represents the number of stock which have returns higher than the cross-sectional average and N^- is the number of stock with lower returns than the cross-sectional average. R_t^{CS} is the return of the CS strategy in month t. The other variables have the same meaning as for the TS strategy. The way the CS strategy is constructed makes us invest one unit of currency (dollar) in the long side of the portfolio and one in the short side. This happens every month.

3.1.3 Dual momentum

As previously stated DUAL is a combination of TS and CS. This strategy is involves sequential double sorts. For the return of the ranking period we first look at the sign of that return. Secondly, we rank the returns from all the available stocks within that ranking period. These stocks are put into two distinct time-series groups. If the return from the ranking period is negative then this stock is assigned to T1, which is also known as the "loser group". When the return is positive the stock goes into the "winner group", namely T2. Within both groups the stocks are ranked into quintiles (Q1-Q5), again based on the return of the ranking period. Q1 is the value-weighted portfolio of the stocks below the 20th percentile and Q5 is the value-weighted portfolio of stocks above the 80th percentile. The DUAL goes long in the strongest winner (*T2Q5*) and short in the weakest loser (*T1Q1*). This is also shown in Equation (4).

$$R_t^{DUAL} = \sum\nolimits_{R_{it-1}} T2Q5 - \sum\nolimits_{R_{it-1}} T1Q1 \tag{4}$$

3.2 Robustness

3.2.1 Data split into two parts

In order to find out if the performance of these strategies change over time, the dataset will be split into two distinct parts. The full dataset has a range from 1946 up and until 2020. For a somewhat fair comparison the cutoff will be placed where the number of stock in both sample periods will roughly be the same, see Figure 2. This is after June 1992, so the two subperiods are January 1946–June 1992 and July 1992–December 2020.

3.2.2 Crisis

Some questions one can come up with when thinking about stock returns and performance in times of crisis are: How well do these strategies perform in crisis? Should you switch strategies and or holding/ranking periods when there are crisis? Why might this be the case, because returns fluctuate a lot over time and especially in times of crisis when most stocks are spiralling downwards.

The five crises in the full sample period are:

1. The OPEC Oil Price Shock, from October 1973 up and until March 1974.

2. Black Monday, 19 October 1987.

3. The Dotcom bubble, from January 1995 up and until December 2001.

4. The Financial Crisis (Creditcrisis), from October 2007 up and until March 2009.

5. Covid-19, ongoing but started in February 2020.

For the subsample with only crises, we take all these months from the five crises.

4 Results

4.1 TS and CS comparison

Table 2 shows the annualized excess returns for TS and CS strategies for different ranking and holding periods, with the Newey-West t-statistics in parentheses. The sample period is from January 1946 up and until December 2020. For TS all portfolio returns are positive with the exception of the 1×1 strategy. When the ranking period increases and the holding period stays the same, the portfolio return tends to increase. When the ranking period stays the same and we keep increasing

the holding period up and until twelve months, the returns keep on increasing. This is in line with He and Li (2015), where they state that when the holding period is longer the momentum strategies tend to do better. After twelve months there is a decline, which is followed by a series of increases in portfolios returns.

For the CS the 1×1 strategy is -4.75% which is significantly less than zero, at the 5% level. This is in line with Goyal and Jegadeesh (2017) and Jegadeesh (1990). They refer to this as the short-horizon contrarian profits and our result confirms this. The 60×60 strategy is -1.39% which is significantly less than zero, which is consistent with the long-horizon return reversals from Goyal and Jegadeesh (2017) and De Bondt and Thaler (1985). The strategies with medium ranges (six, nine and twelve months) in both their ranking and holding period for both the TS and CS produces positive returns. This is in line with the momentum evidence from Jegadeesh and Titman (1993). Overall TS outperforms CS which coincides with the findings of Cheema et al. (2018). This has to do with the state of the market (up or down) and according to them this leads to the conclusion that the market state is constant.

Table 3 shows the intercepts/alphas from the regression of the CS excess returns on the TS excess returns and the other way around. This comparison is to show the relative importance from the strategies to one another. When CS returns are the dependent variable, the intercept is negative for the short and long ranking and holding periods, but for the medium ranges it is positive. The alphas for the 1×1 strategy and the 60×60 strategy are -4.52% and -3.72%, respectively. These negative alphas for the short and long ranking and holding periods are in line with Goyal and Jegadeesh (2017). For the strategy 9×1 and 12×1 the alphas are the same when rounded to two decimals, however both of these are not significant at the 5% level. When TS returns are the dependent variable, all the intercepts are positive just as in Goyal and Jegadeesh (2017). The alpha for the 1×1 strategy is 5.69% and for the 60×60 is 12.09%. Both of these are significant. For TS as the dependent variable, eight out of fifteen of the intercepts are not significantly different from zero. This is rather similar for CS, where it is nine insignificant intercepts. The magnitude of the intercept is almost always larger in the case where TS is dependent variable. Moskowitz et al. (2012) also do this cross-alpha comparison and they conclude that TS explains CS, but CS does not fully explain TS. We obtain results that are similar to them, hence our conclusion is the same.

Table 4 presents the comparison of the TS, CS and CS_{TVM} strategy. As stated in Section 1, this CS_{TVM} is each month set equal to the difference between short and long from the TS strategy. This difference is then multiplied by the cross-sectional average and added to the CS strategy. The

Table 2: Portfolio returns for Time-series and Cross-sectional strategies

Ranking period	Holding period							
	1	3	6	9	12	24	36	60
Time-series								
1	-0.41*	1.72*	1.77	1.88	2.10	0.91	0.79	0.81
	(-0.13)	(1.40)	(1.98)	(2.61)	(3.37)	(2.02)	(2.10)	(2.33)
3	2.61*	2.84	2.98	3.86	3.63	2.40	2.29	2.54
	(0.93)	(2.16)	(3.16)	(4.98)	(5.39)	(4.89)	(5.48)	(6.88)
6	2.71*	3.89	4.90	5.44	4.81	2.71	3.12	3.18
	(0.86)	(2.72)	(5.21)	(6.98)	(6.96)	(5.31)	(7.72)	(8.85)
9	3.67*	6.54	6.55	6.12	4.78	3.07	3.71	3.80
	(1.11)	(4.67)	(6.54)	(7.32)	(6.55)	(5.77)	(8.57)	(10.07)
12	7.19	7.13	7.11	5.67	4.34	3.21	4.00	4.12
	(2.50)	(4.82)	(7.02)	(6.82)	(5.91)	(6.22)	(9.42)	(11.19)
24	4.27*	6.06	6.20	6.11	5.67	5.63	6.33	6.26
	(1.34)	(3.96)	(5.79)	(7.03)	(7.53)	(9.72)	(14.37)	(16.79)
36	5.73*	7.40	6.70	6.76	6.60	6.59	7.37	6.85
	(1.66)	(4.31)	(5.60)	(7.00)	(7.64)	(10.77)	(16.31)	(17.04)
60	6.06*	10.95	11.96	11.49	10.88	9.52	9.19	9.42
	(1.22)	(4.84)	(8.13)	(9.90)	(10.77)	(14.60)	(16.32)	(19.75)
Cross-sectional								
1	-4.75	-1.04	0.35*	0.67	1.07	0.26*	-0.05*	-0.22
	(-4.86)	(-2.01)	(1.04)	(2.35)	(4.42)	(1.63)	(-0.48)	(-2.57)
3	-1.24*	0.84*	1.77	2.08	2.12	0.66	0.17*	-0.02*
	(-1.09)	(1.44)	(4.70)	(6.42)	(7.51)	(3.69)	(1.29)	(-0.19)
6	1.57*	2.78	3.20	3.17	2.52	0.60	0.15*	-0.03*
	(1.30)	(4.28)	(7.59)	(8.45)	(7.90)	(3.12)	(1.11)	(-0.28)
9	2.64	3.86	3.91	3.18	2.26	0.34*	0.02*	-0.12*
	(2.10)	(5.73)	(8.33)	(7.86)	(6.74)	(1.67)	(0.14)	(-1.09)
12	4.06	4.14	3.29	2.40	1.54	-0.10*	-0.26*	-0.34
	(3.23)	(5.88)	(6.70)	(5.84)	(4.49)	(-0.47)	(-1.82)	(-2.97)
24	0.83*	1.26*	0.87*	0.39*	-0.07*	-0.76	-0.61	-0.82
	(0.66)	(1.76)	(1.83)	(1.00)	(-0.21)	(-3.33)	(-4.00)	(-6.43)
36	-0.05*	0.44*	0.31*	0.08*	-0.27*	-0.67	-0.82	-1.03
	(-0.05)	(0.64)	(0.66)	(0.20)	(-0.81)	(-2.99)	(-5.15)	(-7.96)
60	-0.15*	0.26*	0.12*	-0.19*	-0.59*	-1.29*	-1.38	-1.39
	(-0.14)	(0.41)	(0.26)	(-0.51)	(-1.86)	(-6.20)	(-8.83)	(-11.29)

Portfolio returns for TS and CS strategies for ranking and holding periods between 1 and 60 months, with Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is 1946–2020. Returns that have a * are not significant at the 5% level.

column with *$Long* is calculated as two times the fraction of stocks one goes long in divided by the total available stocks. The reason for this factor of two is explained in Section 3.1.1. By construction the *$Short = $Long - 2* and they both have the same t-statistic. The *$Long* is always significantly different from one and the *$Short* is always significantly different from minus one. The net long position is the difference between *$Short* and *$Long*. For every ranking and holding period in Table 4 the net long position is positive, this means that number of stocks in which we go long is bigger than the number of stocks we go short in. For example, the 1×1 strategy has a net long position of 1.07 - 0.93 = 0.14 dollar. The net long position increases as the ranking and holding period become larger. According to Goyal and Jegadeesh (2017), it can be stated that the overall markets excess

Table 3: Cross-alphas for Time-series and Cross-sectional strategies

	Holding period = Ranking period		Holding period = 1 month	
Dependent variable →	TS	CS	TS	CS
Explanatory variable →	CS	TS	CS	TS
Ranking period				
1	5.69	-4.52	5.69	-4.52
	(1.97)	(-4.95)	(1.97)	(-4.95)
3	1.83*	-0.04*	4.05*	-1.82*
	(1.76)	(-0.09)	(1.67)	(-1.73)
6	0.64*	1.61	0.88*	0.99*
	(0.88)	(4.58)	(0.32)	(0.86)
9	2.38	1.37	0.16*	2.04*
	(3.41)	(3.81)	(0.05)	(1.74)
12	2.63	0.21*	2.13*	2.04*
	(4.36)	(0.68)	(0.92)	(1.83)
24	6.98	-2.50	3.88*	-0.62*
	(14.82)	(-11.34)	(1.41)	(-0.51)
36	9.45	-3.28	6.85	-2.07*
	(25.14)	(-18.44)	(2.23)	(-1.65)
60	12.09	-3.72	7.62*	-2.02*
	(23.56)	(-17.06)	(1.61)	(-1.43)

The intercepts/alphas from regressions TS on CS strategies (vice versa) for ranking and holding periods between 1 and 60 months, Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is 1946–2020. Alphas that have a * are not significant at the 5% level.

return has been positive during the sample period of 1946–2020.

The difference between TS and CS (TS-CS) and between TS and CS_{TVM} (TS-CS_{TVM}) is also shown in Table 4. For a holding period of one month the TS-CS_{TVM} is negative and most of the time insignificant. For a 1×1 strategy the difference in absolute terms is 3.58% and this fluctuates a bit when the ranking period increases. For the 60×1 strategy the difference is 0.53%. For TS-CS the difference is 4.33% for the 1×1 strategy and 6.21 % for the 60×1 strategy. For the other strategies with an one month holding period the difference is lower than 4.33% and Goyal and Jegadeesh (2017) refer to this as a U-shaped pattern. This has to do with the short and long horizon contrarian. However, most of these difference are not significant. When ranking and holding periods are the same the difference is still negative but more of these differences are significant. For example, for the 12×12 strategy the difference between TS and CS_{TVM} is -2.38%. This indicates that the CS_{TVM} has better returns than the TS strategy. For TS-CS, all the results are positive and significant except for the 1×1 strategy. This indicates that the TS does have better returns than CS. However, we need to keep in mind that these differences are not always statistically different from zero. We can thus state that the TVM part of CS_{TVM} is decisive in the conclusion that CS_{TVM} outperforms TS and in some sense also CS. This is different from Goyal and Jegadeesh (2017), where it is concluded that TS and CS_{TVM} perform the same.

Table 4: Comparison of Time-series and Cross-sectional strategies

Ranking period	Holding period = Ranking period							Holding period = 1 month						
	TS	CS	CS_{TVM}	TS-CS	$TS\text{-}CS_{TVM}$	$Long	$Short	TS	CS	CS_{TVM}	TS-CS	$TS\text{-}CS_{TVM}$	$Long	$Short
1	-0.41*	-4.75	3.17	4.33*	-3.58*	1.07	-0.93	-0.41*	-4.75	3.17	4.33*	-3.58*	1.07	-0.93
	(-0.13)	(-4.86)	(2.83)	(1.45)	(-1.16)	(4.91)	(4.91)	(-0.13)	(-4.86)	(2.83)	(1.45)	(-1.16)	(4.91)	(4.91)
3	2.84	0.84*	6.36	2.00	-3.53	1.15	-0.85	2.61*	-1.24*	5.45	3.85*	-2.84*	1.16	-0.84
	(2.16)	(1.44)	(8.78)	(1.96)	(-3.10)	(10.82)	(10.82)	(0.93)	(-1.09)	(5.79)	(1.59)	(-1.13)	(11.11)	(11.11)
6	4.90	3.20	7.28	1.71	-2.38	1.21	-0.79	2.71*	1.57*	6.50	1.14*	-3.79*	1.22	-0.78
	(5.21)	(7.59)	(13.48)	(2.37)	(-3.21)	(15.00)	(15.00)	(0.86)	(1.30)	(7.45)	(0.42)	(-1.32)	(15.68)	(15.68)
9	6.12	3.18	7.28	2.94	-1.16*	1.25	-0.75	3.67*	2.64	6.81	1.03*	-3.14*	1.25	-0.75
	(7.32)	(7.86)	(16.26)	(4.23)	(-1.82)	(17.83)	(17.83)	(1.11)	(2.10)	(8.12)	(0.30)	(-1.04)	(17.96)	(17.96)
12	4.34	1.54	6.72	2.80	-2.38	1.29	-0.71	7.19	4.06	7.67	3.13*	-0.49*	1.29	-0.71
	(5.91)	(4.49)	(18.35)	(4.75)	(-4.15)	(21.24)	(21.24)	(2.50)	(3.23)	(9.85)	(1.33)	(-0.19)	(21.48)	(21.48)
24	5.63	-0.76	5.80	6.39	-0.17*	1.42	-0.58	4.27*	0.83*	6.35	3.44*	-2.08*	1.43	-0.57
	(9.72)	(-3.33)	(23.49)	(14.02)	(-0.36)	(33.84)	(33.84)	(1.34)	(0.66)	(8.79)	(1.43)	(-0.72)	(35.69)	(35.69)
36	7.37	-0.82	5.72	8.19	1.66	1.50	-0.50	5.73*	-0.05*	6.00	5.78	-0.27*	1.52	-0.48
	(16.31)	(-5.15)	(28.19)	(23.78)	(4.86)	(41.53)	(41.53)	(1.66)	(-0.05)	(9.27)	(2.19)	(-0.09)	(46.09)	(46.09)
60	9.42	-1.39	4.73	10.81	4.69	1.57	-0.43	6.06*	-0.15*	5.54	6.21*	0.53*	1.62	-0.38
	(19.75)	(-11.29)	(26.19)	(27.02)	(12.87)	(41.19)	(41.19)	(1.22)	(-0.14)	(8.87)	(1.59)	(0.11)	(55.33)	(55.33)

Portfolio returns for TS and CS strategies for ranking and holding periods between 1 and 60 months, Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. CS_{TVM} is the sum of CS and TVM. $Long and $Short are the dollar positions of TS, with null hypothesis for t-statistic that $Long = 1 and $Short = -1. Sample period is 1946–2020. Values that have a * are not significant at the 5% level.

4.2 DUAL versus TS and CS

Table 5 shows the annualized excess returns for the DUAL strategy for different ranking and holding periods, with the Newey-West t-statistics in parentheses. The sample period is from January 1946 up and until December 2020. For the 1×1 strategy the portfolio return is -16.20% which is very low and significantly different from zero at the 5% level. Just as the TS and CS for medium ranges the DUAL produces positive returns. For example, the 12×12 strategy has a return of 2.53% and is significant. For returns with a ranking period larger than a year the returns are mostly negative and significant. The 60×60 strategy is -2.62% which is significantly less than zero. This reversed U-shaped pattern, with negative portfolio returns for short and long ranking and holding periods together with positive portfolio returns for medium ranges, is in line with the previously mentioned long-horizon return reversals from De Bondt and Thaler (1985) and Goyal and Jegadeesh (2017).

The DUAL has only 22 out of 64 strategies with positive returns whereas it is 63 out of 64 for TS and 38 out of 64 for CS. From these 22 positive returns 18 are significant, whereas this is 56 for TS and 21 for CS. These findings contradict Lim et al. (2018), which stated that DUAL should increase the profitability when compared to TS. This is not the case.

Table 5: Portfolio returns Dual momentum strategy

Ranking period	Holding period							
	1	3	6	9	12	24	36	60
1	-16.20	-6.07	-2.41	-1.16	-0.60*	-0.99	-1.23	-1.18
	(-9.92)	(-7.93)	(-4.83)	(-2.89)	(-1.76)	(-4.60)	(-7.71)	(-10.01)
3	-8.55	-0.47*	1.67	2.41	2.24	0.60	-0.20*	-0.55
	(-4.33)	(-0.53)	(2.84)	(5.16)	(5.53)	(2.65)	(-1.16)	(-4.22)
6	-3.95	2.52	4.12	4.15	3.20	0.86	-0.04*	-0.42
	(-1.96)	(2.55)	(6.37)	(7.97)	(7.20)	(3.51)	(-0.19)	(-3.02)
9	-2.91*	3.45	4.45	3.86	2.98	0.58	-0.23*	-0.49
	(-1.38)	(3.35)	(6.53)	(7.10)	(6.42)	(2.30)	(-1.23)	(-3.50)
12	-1.17*	3.83	4.36	3.49	2.53	0.36*	-0.40	-0.91
	(-0.56)	(3.66)	(6.28)	(6.18)	(5.40)	(1.38)	(-2.12)	(-6.04)
24	-6.70	-0.01*	0.85*	0.59*	0.30*	-0.75	-1.30	-1.60
	(-3.26)	(-0.01)	(1.28)	(1.13)	(0.67)	(-2.60)	(-5.98)	(-9.20)
36	-8.74	-2.78	-1.30*	-1.17	-1.50	-1.94	-2.03	-2.11
	(-4.54)	(-2.80)	(-1.94)	(-2.17)	(-3.29)	(-6.26)	(-8.21)	(-11.79)
60	-14.37	-6.84	-4.06	-3.58	-3.52	-3.46	-3.07	-2.62
	(-6.82)	(-6.03)	(-5.18)	(-5.63)	(-6.50)	(-9.17)	(-10.50)	(-13.30)

Portfolio returns for DUAL strategy for ranking and holding periods between 1 and 60 months, with Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is 1946–2020. Returns that have a * are not significant at the 5% level.

Table 6: Cross-alphas for Dual momentum together with Time-series and Cross-sectional strategies

(a) Dual momentum and Time-series strategies

	Holding period = Ranking period		Holding period = 1 month	
Dependent variable →	TS	DUAL	TS	DUAL
Explanatory variable →	DUAL	TS	DUAL	TS
Ranking period				
1	6.77	-16.46	6.77	-16.46
	(2.09)	(-10.17)	(2.09)	(-10.17)
3	3.17	-1.37*	6.60	-9.94
	(2.56)	(-1.56)	(2.46)	(-5.02)
6	2.79	2.48	5.07*	-5.44
	(3.17)	(3.83)	(1.70)	(-2.64)
9	4.34	2.12	5.43*	-4.25
	(5.39)	(3.80)	(1.75)	(-2.00)
12	3.43	0.83*	8.60	-5.01
	(4.93)	(1.73)	(3.24)	(-2.41)
24	6.01	-1.70	7.50	-9.70
	(10.40)	(-5.36)	(2.41)	(-4.41)
36	8.02	-2.69	8.68	-12.27
	(17.22)	(-9.25)	(2.50)	(-5.51)
60	9.58	-3.17	7.39*	-15.43
	(16.54)	(-10.31)	(1.44)	(-5.89)

(b) Dual momentum and Cross-sectional strategies

	Holding period = Ranking period		Holding period = 1 month	
Dependent variable →	DUAL	CS	DUAL	CS
Explanatory variable →	CS	DUAL	CS	DUAL
Ranking period				
1	-10.83	1.81	-10.83	1.81
	(-8.88)	(2.39)	(-8.88)	(2.39)
3	-1.34	1.05	-6.85	2.65
	(-2.07)	(2.46)	(-5.62)	(3.72)
6	0.66*	1.31	-6.04	3.47
	(1.40)	(4.28)	(-4.97)	(4.74)
9	0.90	1.19	-6.46	4.04
	(2.22)	(3.97)	(-5.11)	(5.36)
12	1.11	0.29*	-6.45	4.61
	(3.17)	(1.13)	(-4.88)	(5.85)
24	-0.35*	-0.51	-7.67	3.75
	(-1.33)	(-2.46)	(-5.33)	(4.25)
36	-1.65	-0.43	-8.68	3.47
	(-6.87)	(-2.70)	(-5.97)	(3.83)
60	-1.94	-0.89	-14.21	3.71
	(-9.58)	(-6.84)	(-7.98)	(4.04)

The intercepts/alphas from regressions DUAL on only CS or TS strategies (vice versa) for ranking and holding periods between 1 and 60 months, Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is 1946–2020. Alphas that have a * are not significant at the 5% level.

Table 6a and Table 6b present the intercepts/alphas from the regression of the TS/CS excess returns on the DUAL excess returns and vice versa. These two tables help explain the relative importance from the DUAL compared to TS and CS. For the TS and DUAL comparison where the TS is the dependent variable, almost all of the alphas are positive and significant. The alpha for the 1×1 strategy is 6.77% and for the 60×60 is 9.58%. When DUAL is the dependent variable, the alphas are only positive for medium ranges and fourteen out of fifteen are significant. For the 1×1 strategy the alpha is -16.46% and for the 9×9 it is 2.12%. For the CS and DUAL comparison where CS is the dependent variable, most alphas are positive and all but one are significant. The alpha for the 1×1 strategy is 1.81% and for the 60×60 is -0.89%. When DUAL is the dependent variable almost all alphas are negative and all but one are significant. For the 1×1 strategy the alpha is -10.83%, for the 9×9 it is 0.90% and for the 60×60 it is -1.94%. So, we see a reversed U-shaped pattern. We can thus state that DUAL can explain TS and CS. The reverse, that CS and TS explain DUAL is also true.

4.3 Robustness

As stated in Section 3.2 the performance from the three trading strategies in the two subsamples will be analyzed, as well as in times of crisis. Table 7 shows the annualized excess returns for the TS, CS and DUAL strategies for different ranking and holding periods, with the t-statistics in parentheses. The (first) sample period is from January 1946 up and until June 1992. Table 8 shows the same but for the (second) sample period July 1992–December 2020. The portfolio returns in times of crisis are presented in Table 9. These three tables are a shortened version of the full tables, they have the most interesting results. Table A1, Table A2 and Table A3 in Appendix A show the full versions.

For the first sample period most portfolio returns are positive, especially the TS returns which are all positive. For example, the 60×60 strategy of TS is 3.66% and significant. For the second sample period for TS there are five negative returns, but all are insignificant. Around three quarters of the CS returns are negative and all but one of the returns for the DUAL are negative. The positive one is insignificant. For the TS strategy, the portfolio returns in the first (second) sample for the 6×6 strategy, 9×9 strategy and 12×12 strategy are respectively, 4.63% (5.27%), 5.28% (6.79%) and 3.38% (4.96%). So, the second subsample has returns that are around 1% better than the first subsample. The difference for the other TS strategies is approximately the same. The difference of 1% is not considered big. Hence, the TS is robust since almost all returns have around the same value in both subsamples. However, this is not the case for the CS and DUAL, they are not robust.

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Table 7: Portfolio returns for Time-series, Cross-sectional and Dual momentum strategies for the sample period January 1946–June 1992

		Holding period			
Ranking period	1	6	9	12	60
Time-series					
1	1.84*	2.88	2.22	2.52	0.76*
	(0.80)	(2.55)	(2.40)	(3.18)	(1.77)
6	4.87*	4.63	4.84	4.22	2.34
	(1.77)	(3.83)	(4.96)	(4.85)	(5.43)
9	6.37	6.09	5.28	4.09	2.57
	(2.01)	(4.67)	(4.90)	(4.38)	(5.46)
12	9.00	6.45	4.86	3.38	2.56
	(2.76)	(4.87)	(4.50)	(3.69)	(5.64)
60	8.03*	10.76	9.77	8.34	3.66
	(1.80)	(5.42)	(6.07)	(6.15)	(5.45)
Cross-sectional					
1	-6.14	0.60*	1.05	1.55	0.01*
	(-7.10)	(1.86)	(3.81)	(6.65)	(0.13)
6	1.96*	4.14	4.35	3.65	0.19*
	(1.73)	(9.73)	(12.26)	(12.21)	(1.41)
9	3.00	5.24	4.52	3.51	0.05*
	(2.48)	(11.74)	(12.41)	(11.34)	(0.38)
12	5.11	4.88	3.89	2.80	-0.21*
	(4.20)	(10.76)	(10.42)	(9.02)	(-1.46)
60	0.07*	0.36*	-0.01*	-0.50*	-2.21
	(0.06)	(0.72)	(-0.01)	(-1.40)	(-13.52)
Dual momentum					
1	-10.01	-0.49*	0.59*	1.09	-0.51
	(-7.34)	(-1.08)	(1.52)	(3.37)	(-4.06)
6	2.11*	6.64	6.87	5.83	0.43
	(1.23)	(11.50)	(14.58)	(14.23)	(2.64)
9	3.67	7.87	7.18	5.95	0.40
	(1.96)	(12.68)	(14.51)	(14.19)	(2.40)
12	6.86	8.51	7.22	5.80	0.13*
	(3.69)	(13.90)	(14.70)	(13.77)	(0.70)
60	-5.80	0.21*	-0.05*	-0.40*	-1.38
	(-2.56)	(0.25)	(-0.07)	(-0.68)	(-5.80)

Portfolio returns for TS, CS and DUAL strategies for ranking and holding periods between 1 and 60 months, with Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is January 1946–June 1992. Returns that have a * are not significant at the 5% level.

In times of crisis (Table 9) the TS is negative with a holding period of one month, this is understandable since returns often drop in times of crisis. For CS this is less the case, which again is as expected since the decision of going long or short is based on the cross-sectional average and not just a fixed number like zero. Most of the portfolio returns for TS and CS are not significant. This is not the case for DUAL, where around half of the returns are significant. The DUAL for the 1 × 1 strategy is -30.73% which is relatively a big negative number. This is comprehensible, since the DUAL goes long in the best winners and short in the worst losers and in times of crisis the best winners will most likely take a hit which results in these negative portfolios returns.

This 1×1 strategy for the DUAL in times of crisis is the worst portfolio return out of all the strategies in this paper. However, the magnitude of this strategy is also the highest. This might give reason to investigate this particular strategy more in future research since it has the potential to be altered in a way which might make it the best strategy in times of crisis. The reason for this is that the best winner can have a relatively good period but might return to some regular levels afterwards which sees the stock price moving down. The reverse can be said for the worst loser. An idea is then that going short in the best winner and going long in the worst loser would make this particular strategy more interesting.

Table 8: Portfolio returns for Time-series, Cross-sectional and Dual momentum strategies for the sample period July 1992–December 2020

	Holding period				
Ranking period	1	6	9	12	60
Time-series					
1	-3.88*	0.04*	1.46*	1.45*	0.97*
	(-0.54)	(0.03)	(1.24)	(1.40)	(1.50)
6	-0.61*	5.27	6.10	5.38	4.60
	(-0.09)	(3.42)	(4.59)	(4.55)	(6.94)
9	-0.62*	6.68	6.79	5.17	5.57
	(-0.09)	(4.13)	(4.90)	(4.20)	(8.06)
12	3.66*	7.38	6.13	4.96	6.20
	(0.68)	(4.50)	(4.47)	(3.87)	(9.11)
60	-0.61*	11.19	11.21	11.69	14.93
	(-0.05)	(4.17)	(5.45)	(6.29)	(27.74)
Cross-sectional					
1	-2.51*	-0.10*	0.07*	0.24*	-0.58
	(-1.17)	(-0.15)	(0.11)	(0.45)	(-3.80)
6	0.94*	1.71*	1.22*	0.61*	-0.31*
	(0.36)	(1.95)	(1.50)	(0.88)	(-1.51)
9	2.00*	1.46*	0.77*	0.06*	-0.34*
	(0.74)	(1.45)	(0.86)	(0.09)	(-1.58)
12	1.90*	0.35*	-0.23*	-0.71*	-0.50
	(0.70)	(0.32)	(-0.25)	(-0.92)	(-2.22)
60	-0.80*	-0.34*	-0.47*	-0.68*	-1.20
	(-0.33)	(-0.35)	(-0.56)	(-0.96)	(-6.77)
Dual momentum					
1	-26.36	-5.51	-4.01	-3.38	-2.21
	(-7.27)	(-5.09)	(-4.77)	(-4.69)	(-9.34)
6	-13.44	0.15*	-0.37*	-1.13*	-1.82
	(-2.98)	(0.10)	(-0.33)	(-1.19)	(-6.84)
9	-13.28	-1.22*	-1.70*	-1.96	-2.01
	(-2.84)	(-0.83)	(-1.46)	(-1.96)	(-7.43)
12	-14.25	-2.53*	-2.70	-2.89	-2.59
	(-3.08)	(-1.67)	(-2.19)	(-2.86)	(-9.17)
60	-29.18	-11.11	-9.33	-8.44	-4.95
	(-6.31)	(-6.48)	(-6.72)	(-7.12)	(-13.72)

Portfolio returns for TS, CS and DUAL strategies for ranking and holding periods between 1 and 60 months, with Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is July 1992–December 2020. Returns that have a * are not significant at the 5% level.

Table 9: Portfolio returns for Time-series, Cross-sectional and Dual momentum strategies for the sample period in times of crisis

Ranking period	Holding period				
	1	6	9	12	60
Time-series					
1	-6.49*	-0.91*	1.20*	1.47*	-0.80*
	(-0.32)	(-0.27)	(0.46)	(0.69)	(-0.72)
6	-13.10*	2.34*	4.03*	2.26*	1.10*
	(-0.73)	(0.68)	(1.30)	(0.88)	(0.96)
9	-13.00*	3.17*	4.55*	1.89*	1.70*
	(-0.70)	(0.93)	(1.49)	(0.72)	(1.40)
12	-3.10*	7.00	4.73*	1.25*	2.02*
	(-0.23)	(2.00)	(1.50)	(0.46)	(1.64)
60	-13.73*	6.96*	6.04*	6.69	14.09
	(-0.63)	(1.53)	(1.71)	(2.28)	(10.31)
Cross-sectional					
1	-1.45*	-0.45*	-0.17*	0.66*	-1.44
	(-0.26)	(-0.25)	(-0.10)	(0.47)	(-4.54)
6	1.71*	2.50*	1.32*	0.21*	-1.24
	(0.26)	(1.07)	(0.59)	(0.11)	(-2.84)
9	4.10*	1.83*	0.22*	-1.21*	-1.22
	(0.61)	(0.70)	(0.09)	(-0.61)	(-2.53)
12	4.09*	0.23*	-1.65*	-2.81*	-1.46
	(0.60)	(0.08)	(-0.68)	(-1.37)	(-2.91)
60	-2.40*	-3.41*	-4.40	-4.54	-0.03*
	(-0.45)	(-1.60)	(-2.45)	(-3.06)	(-0.06)
Dual momentum					
1	-30.73	-5.93	-3.64*	-2.79*	-3.76
	(-3.18)	(-2.04)	(-1.65)	(-1.51)	(-8.19)
6	-6.70*	5.67*	3.71*	1.85*	-2.83
	(-0.57)	(1.54)	(1.27)	(0.77)	(-5.28)
9	-3.55*	4.35*	1.77*	0.20*	-2.90
	(-0.30)	(1.14)	(0.58)	(0.08)	(-5.30)
12	-2.46*	2.54*	0.17*	-1.74*	-3.67
	(-0.21)	(0.65)	(0.05)	(-0.69)	(-6.60)
60	-23.02	-11.20	-9.95	-10.15	-5.19
	(-2.74)	(-3.51)	(-3.96)	(-4.91)	(-7.52)

Portfolio returns for TS, CS and DUAL strategies for ranking and holding periods between 1 and 60 months, with Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is October 1973–March 1974, October 1987, January 1995–December 2001, October 2007–March 2009 and February 2020–December 2020. Returns that have a * are not significant at the 5% level.

4.4 Future research

One can use the findings of this paper for follow up research. For that research we give some advice and ideas one might want to use. Lim et al. (2018) come up with two alternatives for TS but in this paper we will not use revised time-series momentum. For future research one can try this strategy and compare it with the results from this paper and see how the strategies compare to one another.

Another way of creating the DUAL can be used, e.g. different order of the two steps or not using five quintiles but maybe four quartiles or ten deciles. Jain et al. (2020) use a triple momentum

strategy which is an enhanced version of the DUAL. Instead of ranking on past returns, ranking on inverse volatility can be used, like in Moskowitz et al. (2012).

5 Conclusion

In order to answer our main research question we first answer our three sub research questions. By using the findings of Table 2, Table 3 and Table 4 we can answer our first sub research question: *How do time-series and cross-sectional strategies compare to one another?* We can say that TS outperforms CS, however the differences are not always significant.

Table 5, Table 6a and Table 6b show the results from the DUAL strategy and its cross-alpha comparison with TS and CS. It can be stated that the DUAL performs worse than the TS and CS in short and long ranking and holding periods. For ranking and holding periods of medium size the DUAL performs roughly the same as the CS, but still worse than the TS. Hence, in answering the second sub research question: *How does the dual momentum strategy compare to time-series and cross-sectional strategies?* We conclude that the DUAL strategy performs worse than the TS and CS strategies.

As a means to test whether the results are somewhat constant through time the third and final sub research question is made: *Is it robust, so how different is the performance of the different $Y \times Z$ strategies in multiple subsamples for time-series, cross-sectional and dual momentum?* Table 7, Table 8 and Table 9 show the results that are used for this robustness check. The conclusion that can be draw from these tables is that the TS strategy is robust. The CS and DUAL strategies are not robust.

Finally, using the three sub research questions we can answer the main research question: *Which out of the three trading strategies, time-series, cross-sectional and dual momentum, is the most profitable and what is the best ranking/holding period that belongs to this strategy?* The time-series strategy has proven to be the best strategy out of the three, since it has almost always positive returns and it is the only one which is robust. As for the best ranking and holding period, the medium ranges (six, nine and twelve months) have the best returns and least fluctuations. From these the 9×6 strategy has the edge over the others but this is very marginal.

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A   Appendix tables

Table A1: Portfolio returns for Time-series, Cross-sectional and Dual momentum strategies for the sample period January 1946–June 1992

Ranking period	Holding period							
	1	3	6	9	12	24	36	60
Time-series								
1	1.84*	2.38*	2.88	2.22	2.52	0.74*	0.81*	0.76*
	(0.80)	(1.61)	(2.55)	(2.40)	(3.18)	(1.33)	(1.75)	(1.77)
3	4.83*	3.61	3.78	3.72	3.82	1.88	1.93	1.99
	(1.89)	(2.16)	(3.26)	(3.73)	(4.39)	(3.13)	(3.79)	(4.37)
6	4.87*	4.60	4.63	4.84	4.22	1.98	2.54	2.34
	(1.77)	(2.80)	(3.83)	(4.96)	(4.85)	(3.20)	(5.10)	(5.43)
9	6.37	6.40	6.09	5.28	4.09	2.29	2.97	2.57
	(2.01)	(3.48)	(4.67)	(4.90)	(4.38)	(3.43)	(5.43)	(5.46)
12	9.00	6.89	6.45	4.86	3.38	2.33	2.98	2.56
	(2.76)	(3.64)	(4.87)	(4.50)	(3.69)	(3.69)	(5.57)	(5.64)
24	4.38*	4.21	5.08	5.47	5.20	4.92	5.17	4.40
	(1.31)	(2.13)	(3.54)	(4.73)	(5.39)	(6.58)	(8.97)	(9.53)
36	6.25*	6.67	5.68	5.25	5.20	4.33	4.63	3.88
	(1.70)	(3.03)	(3.51)	(3.92)	(4.41)	(5.26)	(7.49)	(7.17)
60	8.03*	10.41	10.76	9.77	8.34	4.85	3.85	3.66
	(1.80)	(3.83)	(5.42)	(6.07)	(6.15)	(5.02)	(4.88)	(5.45)
Cross-sectional								
1	-6.14	-1.05	0.60*	1.05	1.55	0.62	0.29	0.01*
	(-7.10)	(-2.14)	(1.86)	(3.81)	(6.65)	(3.64)	(2.22)	(0.13)
3	-1.72*	1.31	2.46	2.84	3.05	1.22	0.65	0.22*
	(-1.66)	(2.24)	(6.44)	(8.77)	(11.08)	(6.19)	(4.49)	(1.73)
6	1.96*	3.65	4.14	4.35	3.65	1.34	0.72	0.19*
	(1.73)	(5.68)	(9.73)	(12.26)	(12.21)	(6.71)	(4.94)	(1.41)
9	3.00	4.66	5.24	4.52	3.51	1.24	0.61	0.05*
	(2.48)	(6.80)	(11.74)	(12.41)	(11.34)	(6.21)	(3.96)	(0.38)
12	5.11	5.79	4.88	3.89	2.80	0.90	0.33	-0.21*
	(4.20)	(8.40)	(10.76)	(10.42)	(9.02)	(4.34)	(2.04)	(-1.46)
24	1.58*	2.00	1.80	1.48	0.96	-0.01*	-0.30*	-1.06
	(1.28)	(2.79)	(3.66)	(3.71)	(2.85)	(-0.03)	(-1.53)	(-6.07)
36	0.95*	1.62	1.45	1.03	0.50*	-0.21*	-0.78	-1.54
	(0.80)	(2.28)	(2.86)	(2.47)	(1.41)	(-0.83)	(-3.72)	(-8.64)
60	0.07*	0.61*	0.36*	-0.01*	-0.50*	-1.38	-1.90	-2.21
	(0.06)	(0.87)	(0.72)	(-0.01)	(-1.40)	(-5.30)	(-8.85)	(-13.52)
Dual momentum								
1	-10.01	-3.18	-0.49*	0.59*	1.09	0.16*	-0.20*	-0.51
	(-7.34)	(-5.04)	(-1.08)	(1.52)	(3.37)	(0.79)	(-1.28)	(-4.06)
3	-3.08*	2.24	3.62	4.34	4.32	1.94	1.00	0.15*
	(-1.84)	(2.72)	(6.87)	(10.01)	(11.65)	(8.47)	(5.71)	(0.97)

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Table A1 – *Continued from previous page*

Ranking period	Holding period							
	1	3	6	9	12	24	36	60
6	2.11*	5.71	6.64	6.87	5.83	2.70	1.43	0.43
	(1.23)	(6.45)	(11.50)	(14.58)	(14.23)	(11.33)	(7.80)	(2.64)
9	3.67	7.17	7.87	7.18	5.95	2.63	1.34	0.40
	(1.96)	(7.62)	(12.68)	(14.51)	(14.19)	(11.10)	(6.90)	(2.40)
12	6.86	8.74	8.51	7.22	5.80	2.75	1.40	0.13*
	(3.69)	(9.01)	(13.90)	(14.70)	(13.77)	(11.34)	(6.80)	(0.70)
24	1.73*	5.45	5.54	5.07	4.32	1.84	0.38*	-0.65
	(0.89)	(5.48)	(8.31)	(9.64)	(9.42)	(5.86)	(1.33)	(-2.89)
36	-0.44*	3.86	4.06	3.35	2.55	0.35*	-0.59*	-0.92
	(-0.22)	(3.58)	(5.70)	(6.02)	(5.35)	(0.96)	(-1.81)	(-3.97)
60	-5.80	-0.84*	0.21*	-0.05*	-0.40*	-1.31	-1.37	-1.38
	(-2.56)	(-0.69)	(0.25)	(-0.07)	(-0.68)	(-3.11)	(-3.91)	(-5.80)

Note: Portfolio returns for TS, CS and DUAL strategies for ranking and holding periods between 1 and 60 months, with Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is January 1946–June 1992. Returns that have a * are not significant at the 5% level.

Table A2: Portfolio returns for Time-series, Cross-sectional and Dual momentum strategies for the sample period July 1992–December 2020

Ranking period	Holding period							
	1	3	6	9	12	24	36	60
Time-series								
1	-3.88*	0.67*	0.04*	1.46*	1.45*	1.09*	0.94*	0.97*
	(-0.54)	(0.31)	(0.03)	(1.24)	(1.40)	(1.40)	(1.39)	(1.50)
3	-0.76*	1.63*	1.97*	4.13	3.28	3.11	3.09	3.30
	(-0.13)	(0.76)	(1.22)	(3.26)	(2.96)	(3.67)	(4.22)	(4.84)
6	-0.61*	2.87*	5.27	6.10	5.38	3.73	4.31	4.60
	(-0.09)	(1.10)	(3.42)	(4.59)	(4.55)	(4.14)	(6.09)	(6.94)
9	-0.62*	6.31	6.68	6.79	5.17	4.01	4.93	5.57
	(-0.09)	(2.83)	(4.13)	(4.90)	(4.20)	(4.34)	(6.50)	(8.06)
12	3.66*	6.55	7.38	6.13	4.96	4.35	5.50	6.20
	(0.68)	(2.66)	(4.50)	(4.47)	(3.87)	(4.68)	(7.35)	(9.11)
24	3.08*	7.94	7.41	6.74	6.02	6.60	7.88	8.46
	(0.47)	(3.09)	(4.30)	(4.69)	(4.52)	(6.21)	(9.74)	(11.36)
36	3.40*	7.37	7.16	7.92	7.56	8.97	10.57	9.54
	(0.48)	(2.43)	(3.59)	(5.06)	(5.21)	(8.31)	(14.55)	(13.49)
60	-0.61*	9.01	11.19	11.21	11.69	14.53	14.35	14.93
	(-0.05)	(1.99)	(4.17)	(5.45)	(6.29)	(14.63)	(17.52)	(27.74)
Cross-sectional								
1	-2.51*	-1.07*	-0.10*	0.07*	0.24*	-0.37*	-0.61	-0.58
	(-1.17)	(-0.97)	(-0.15)	(0.11)	(0.45)	(-1.14)	(-2.79)	(-3.80)

Continued on next page

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Table A2 – *Continued from previous page*

	Holding period							
Ranking period	1	3	6	9	12	24	36	60
3	-0.55*	0.03*	0.75*	0.85*	0.58*	-0.26*	-0.55	-0.35
	(-0.22)	(0.02)	(0.97)	(1.26)	(0.96)	(-0.72)	(-2.18)	(-2.01)
6	0.94*	1.54*	1.71*	1.22*	0.61*	-0.58*	-0.67	-0.31*
	(0.36)	(1.13)	(1.95)	(1.50)	(0.88)	(-1.46)	(-2.31)	(-1.51)
9	2.00*	2.36*	1.46*	0.77*	0.06*	-1.13	-0.86	-0.34*
	(0.74)	(1.68)	(1.45)	(0.86)	(0.09)	(-2.52)	(-2.95)	(-1.58)
12	1.90*	0.99*	0.35*	-0.23*	-0.71*	-1.69	-1.14	-0.50
	(0.70)	(0.66)	(0.32)	(-0.25)	(-0.92)	(-3.53)	(-3.89)	(-2.22)
24	-0.80*	-0.30*	-0.77*	-1.35*	-1.70	-1.78	-0.89	-0.40*
	(-0.29)	(-0.20)	(-0.75)	(-1.58)	(-2.32)	(-3.60)	(-3.14)	(-1.70)
36	-2.02*	-1.83*	-1.68*	-1.51*	-1.57	-1.25	-0.73	-0.56
	(-0.77)	(-1.24)	(-1.64)	(-1.75)	(-2.17)	(-2.67)	(-2.56)	(-2.51)
60	-0.80*	-0.58*	-0.34*	-0.47*	-0.68*	-0.96	-0.83	-1.20
	(-0.33)	(-0.42)	(-0.35)	(-0.56)	(-0.96)	(-2.23)	(-3.30)	(-6.77)
Dual momentum								
1	-26.36	-10.81	-5.51	-4.01	-3.38	-2.77	-2.89	-2.21
	(-7.27)	(-6.31)	(-5.09)	(-4.77)	(-4.69)	(-6.06)	(-8.67)	(-9.34)
3	-17.49	-4.82	-1.32*	-0.68*	-1.14*	-1.55	-2.16	-1.63
	(-3.96)	(-2.51)	(-1.02)	(-0.67)	(-1.30)	(-3.40)	(-6.39)	(-6.55)
6	-13.44	-2.48*	0.15*	-0.37*	-1.13*	-2.06	-2.38	-1.82
	(-2.98)	(-1.15)	(0.10)	(-0.33)	(-1.19)	(-4.11)	(-6.56)	(-6.84)
9	-13.28	-2.50*	-1.22*	-1.70*	-1.96	-2.68	-2.74	-2.01
	(-2.84)	(-1.11)	(-0.83)	(-1.46)	(-1.96)	(-5.15)	(-7.52)	(-7.43)
12	-14.25	-4.38*	-2.53*	-2.70	-2.89	-3.32	-3.27	-2.59
	(-3.08)	(-1.94)	(-1.67)	(-2.19)	(-2.86)	(-6.18)	(-9.26)	(-9.17)
24	-20.53	-8.68	-6.39	-6.31	-5.85	-4.60	-3.98	-2.83
	(-4.54)	(-4.18)	(-4.73)	(-6.04)	(-6.63)	(-8.57)	(-11.82)	(-8.78)
36	-22.33	-13.62	-9.92	-8.34	-7.93	-5.43	-4.27	-4.07
	(-5.37)	(-6.93)	(-7.66)	(-7.84)	(-8.87)	(-9.32)	(-10.24)	(-13.43)
60	-29.18	-16.89	-11.11	-9.33	-8.44	-6.94	-6.53	-4.95
	(-6.31)	(-6.87)	(-6.48)	(-6.72)	(-7.12)	(-8.33)	(-10.98)	(-13.72)

Note: Portfolio returns for TS, CS and DUAL strategies for ranking and holding periods between 1 and 60 months, with Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is July 1992–December 2020. Returns that have a * are not significant at the 5% level.

Table A3: Portfolio returns for Time-series, Cross-sectional and Dual momentum strategies for the sample period in times of crisis

Ranking period	Holding period							
	1	3	6	9	12	24	36	60
Time-series								
1	-6.49*	2.84*	-0.91*	1.20*	1.47*	-0.71*	-1.15*	-0.80*
	(-0.32)	(0.55)	(-0.27)	(0.46)	(0.69)	(-0.49)	(-0.99)	(-0.72)
3	-14.71*	-4.91*	-4.68*	1.68*	0.84*	-0.97*	-1.15*	-0.07*
	(-0.93)	(-1.05)	(-1.26)	(0.58)	(0.37)	(-0.66)	(-0.94)	(-0.06)
6	-13.10*	-2.87*	2.34*	4.03*	2.26*	-1.73*	-0.29*	1.10*
	(-0.73)	(-0.45)	(0.68)	(1.30)	(0.88)	(-0.98)	(-0.24)	(0.96)
9	-13.00*	2.46*	3.17*	4.55*	1.89*	-1.71*	-0.25*	1.70*
	(-0.70)	(0.53)	(0.93)	(1.49)	(0.72)	(-0.95)	(-0.20)	(1.40)
12	-3.10*	3.62*	7.00	4.73*	1.25*	-2.49*	-0.18*	2.02*
	(-0.23)	(0.72)	(2.00)	(1.50)	(0.46)	(-1.36)	(-0.14)	(1.64)
24	-8.96*	2.58*	2.30*	1.21*	-1.33*	-0.38*	3.58	6.02
	(-0.61)	(0.50)	(0.65)	(0.41)	(-0.52)	(-0.21)	(2.75)	(4.93)
36	-10.52*	2.35*	2.28*	0.30*	-0.70*	3.82	7.46	9.81
	(-0.72)	(0.43)	(0.63)	(0.11)	(-0.28)	(2.33)	(6.25)	(8.67)
60	-13.73*	3.11*	6.96*	6.04*	6.69	9.43	12.47	14.09
	(-0.63)	(0.40)	(1.53)	(1.71)	(2.28)	(6.55)	(9.04)	(10.31)
Cross-sectional								
1	-1.45*	-1.70*	-0.45*	-0.17*	0.66*	-1.35*	-2.12	-1.44
	(-0.26)	(-0.60)	(-0.25)	(-0.10)	(0.47)	(-1.60)	(-4.22)	(-4.54)
3	-0.66*	-0.93*	0.52*	0.44*	0.32*	-1.85	-2.48	-1.21
	(-0.10)	(-0.30)	(0.26)	(0.24)	(0.20)	(-2.05)	(-4.25)	(-3.20)
6	1.71*	2.06*	2.50*	1.32*	0.21*	-3.05	-3.25	-1.24
	(0.26)	(0.58)	(1.07)	(0.59)	(0.11)	(-3.02)	(-5.03)	(-2.84)
9	4.10*	3.25*	1.83*	0.22*	-1.21*	-4.47	-3.73	-1.22
	(0.61)	(0.91)	(0.70)	(0.09)	(-0.61)	(-3.93)	(-5.83)	(-2.53)
12	4.09*	1.13*	0.23*	-1.65*	-2.81*	-5.91	-4.14	-1.46
	(0.60)	(0.29)	(0.08)	(-0.68)	(-1.37)	(-5.00)	(-6.50)	(-2.91)
24	-3.47*	-3.87*	-4.68*	-6.02	-7.21	-7.07	-3.87	-1.28
	(-0.51)	(-1.02)	(-1.88)	(-2.83)	(-4.11)	(-6.31)	(-6.47)	(-2.49)
36	-3.66*	-4.51*	-5.73	-7.33	-7.95	-5.99	-2.78	-0.93*
	(-0.58)	(-1.28)	(-2.44)	(-3.69)	(-4.90)	(-5.74)	(-4.35)	(-1.76)
60	-2.40*	-2.72*	-3.41*	-4.40	-4.54	-3.13	-1.01*	-0.03*
	(-0.45)	(-0.89)	(-1.60)	(-2.45)	(-3.06)	(-3.37)	(-1.70)	(-0.06)
Dual momentum								
1	-30.73	-11.45	-5.93	-3.64*	-2.79*	-4.95	-5.18	-3.76
	(-3.18)	(-2.56)	(-2.04)	(-1.65)	(-1.51)	(-4.36)	(-7.15)	(-8.19)
3	-15.44*	-1.48*	2.36*	2.44*	1.42*	-2.49	-4.28	-2.96
	(-1.32)	(-0.29)	(0.70)	(0.92)	(0.63)	(-2.35)	(-5.99)	(-6.10)
6	-6.70*	3.22*	5.67*	3.71*	1.85*	-3.76	-4.71	-2.83
	(-0.57)	(0.58)	(1.54)	(1.27)	(0.77)	(-3.22)	(-6.04)	(-5.28)

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Table A3 – *Continued from previous page*

Ranking period	Holding period							
	1	3	6	9	12	24	36	60
9	-3.55*	3.70*	4.35*	1.77*	0.20*	-5.44	-5.62	-2.90
	(-0.30)	(0.65)	(1.14)	(0.58)	(0.08)	(-4.50)	(-7.41)	(-5.30)
12	-2.46*	2.24*	2.54*	0.17*	-1.74*	-7.10	-6.37	-3.67
	(-0.21)	(0.39)	(0.65)	(0.05)	(-0.69)	(-6.12)	(-9.43)	(-6.60)
24	-4.44*	-1.14*	-1.97*	-3.73*	-5.74	-8.29	-5.96	-3.44
	(-0.43)	(-0.25)	(-0.68)	(-1.74)	(-3.47)	(-9.06)	(-10.64)	(-5.65)
36	-5.23*	-6.24*	-5.41	-6.34	-8.36	-9.28	-4.95	-3.69
	(-0.63)	(-1.76)	(-2.43)	(-3.61)	(-5.86)	(-10.00)	(-7.64)	(-6.00)
60	-23.02	-16.37	-11.20	-9.95	-10.15	-9.42	-6.53	-5.19
	(-2.74)	(-3.64)	(-3.51)	(-3.96)	(-4.91)	(-6.53)	(-6.78)	(-7.52)

Note: Portfolio returns for TS, CS and DUAL strategies for ranking and holding periods between 1 and 60 months, with Newey-West t-statistics in parentheses. Annualized excess returns for overlapping portfolios without micro-caps. Sample period is October 1973–March 1974, October 1987, January 1995–December 2001, October 2007–March 2009 and February 2020–December 2020. Returns that have a * are not significant at the 5% level.

B   Appendix code

B.1   Data cleaning

The description of the data cleaning code is as follows: In this script the monthly data from CRSP is loaded in and cleaned. Returns are adjusted for CPI and delisting/missing values. Summary statistics of these adjusted returns are gathered. Number of stocks per exchange on a monthly basis between 1946 and 2020 is plot.

B.2   Results

The description of the code that gathers and computes the results is as follows: In this script the cleaned monthly data from the data cleaning file is loaded in. The 20th percentile for micro caps is calculated. The trading strategies are calculated within the for loop. The order of the trading strategies is: CS, TS, regressions for TS and CS, CS_{TVM}, DUAL, regression for TS, CS and DUAL, Crisis. In the end all the results are printed in matrix form.