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Cross-Sectional and Dual Momentum: A Comparative Analysis Under Simulated Trading

By: Nikolas Kjeldsen Mengel

443758

Supervisor: Sjoerd van den Hauwe

Second Assessor:

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TABLE OF CONTENTS

1. INTRODUCTION

Cross-sectional momentum is a well-known phenomenon in financial markets. The effect can very briefly be explained as winners keep on winning and losers keep on losing. A distinction can be made between cross-sectional and time-series momentum. With time-series momentum, one only looks at the sign of the past return of the asset in question, versus the relative differences in past returns between several assets (Moskowitz et al. 2012; He & Li 2015; Antonacci 2017). Among practitioners, the combination of these two effects is dubbed "dual momentum" but due to the contemporary nature of such a strategy, limited results on its efficacy are available. To date, only one paper explores the possibility of applying a dual momentum strategy to individual stocks (D'Souza et al. 2016) and their results were promising, finding that the dual momentum strategy produced an annualized return three times that of the time-series momentum strategy but the author does not compare the performance of dual momentum with cross-sectional momentum which is the momentum variant that is historically given the most amount of attention in the literature. This paper aims to fill that gap by fully operationalizing a cross-sectional and a dual momentum equity strategy and simulate realistic strategy execution in the market, in order to compare their viability from an implementation point of view.

A majority of equity momentum literature, including D'Souza et al. (2016), employs a methodology that is very much similar to that of Jagadeesh & Titman (1993, 2001), who first documented momentum. This methodology is not very representative of how strategies are implemented by industry professionals and given that a majority of quantitative fund managers and even fundamental managers incorporate momentum in their trading strategy (Swaminathan, 2010), and given that the aim is to empirically assess the viability of the investment strategy, not the momentum effect itself, it makes sense to approach a comparative analysis from a realistic point of view, via trading simulations.

Cross-sectional momentum strategies have been shown to be subject to substantial tail risk (Daniel et al. 2012; Barroso & Santa-Clara 2015; Daniel & Moskowitz 2016) meaning they suffer infrequent but large losses, especially in times of turbulent markets with high volatility. Daniel & Moskowitz (2016) show that the momentum crashes are very much related to the static holding periods often seen in momentum literature which highlights some of the benefits of a more dynamic and realistic approach to momentum strategy assessment. The case for dual momentum is particularly interesting as it attempts to incorporate time-series momentum which has been shown to be especially potent in the sort of turbulent markets where cross-sectional momentum suffers (Moskowitz et al. 2012).

Due to the emphasis on realism, this paper primarily adds value for practitioners in the asset management industry, but it may also complement the existing body of momentum literature due to the modernity of dual momentum as well as add a perspective on whether or not momentum still even exists. The paper is structured as follows: Section 2 explores some of the pertinent momentum literature and theory, Section 3 briefly describes the data, followed by a description of the methodology used. Section 5 presents the empirical results and Section 6 concludes the paper.

2. THEORETICAL FRAMEWORK

As briefly mentioned in the introduction, the first seminal paper on momentum was published in 1993 and authored by Jagadeesh & Titman. They found that a strategy that buys stocks that have performed well over the past 3-12 months and sells stocks that have done poorly over the last 3-12 months to be extremely profitable. The methodology they employed in their paper has since become somewhat of a standard when researching this effect. The key points of this methodology are overlapping equal and/or value-weighted portfolios that are formed at the beginning of every month and held for different fixed periods of time with no transaction costs. While such a methodology is appropriate for studying and quantifying the actual effect, it is not ideal for evaluating investment strategies built on the same effect(s), as it is far from representative of actual trading practices.

Inexplicably (at the time), stocks that did well over the 3-12-month horizon continued to do well over the same horizon and vice versa for the losers, before a reversal occurred. This finding was significant because, as Jagadeesh & Titman (1993, 2001) point out, it could not be explained by the systematic risk factors proposed by Fama & French (1993). In 1996 Fama & French themselves, the main proponents of the risk doctrine, acknowledged the elusive nature of stock price momentum, describing it as "*the main embarrassment of the three-factor model"*.

The discovery of cross-sectional momentum arguably loosened the stranglehold the *efficient market hypothesis* had on empirical finance at that time, as researchers broadened their horizons in search for answers to this puzzle. Although the effect was originally studied on US equities, it has since then been found to be a global effect that can be observed in and across multiple asset classes including bonds, currencies and futures (Asness et al. 2013; Blitz & Vliet 2008; Rouwenhorst 1998).

2.1 CROSS-SECTIONAL VS. TIME-SERIES MOMENTUM

At this point, it is appropriate to elaborate on the conceptual differences between cross-sectional and time-series momentum. The momentum effect described above is often referred to as cross-sectional momentum, where relative differences in returns between assets determine who is a winner and who is a loser. Jagadeesh & Titman's (1993, 2001) long-short equity strategy ranks stocks based on their past performance and goes long in the top decile and short in the bottom decile. In other words, the return differences in the cross section determine which assets are winners and which are losers. This is distinct from time-series momentum, where only an asset's past return determines whether it is a winner or not. Specifically, an asset is considered a winner if its past 12-month return is above some threshold and a loser if it is below another threshold. The winner-loser thresholds can be equal in absolute values or they may differ. Typically, the threshold is set to 0 which is also the value used here.

Time-series momentum was first documented in Moskowitz et al. (2012), where the authors find persistent abnormal returns in the future market, on broad asset classes including, bonds, equity indices, currencies and commodities. Interestingly, their results indicate that their time-series momentum portfolios outperform similar cross-sectional momentum portfolios comprised of the same assets. They also find that time-series momentum captures cross-sectional momentum associated with individual stocks. In other words, time-series momentum explains cross-sectional equity momentum but not vice versa.

The last point above brings us to two open questions in momentum literature, namely which of the two momentum-based strategies is best and are the two effects distinctively different from each other or just two sides of the same coin? As mentioned, Moskowitz et al. (2012) found that time-series momentum portfolios were superior to their cross-sectional cousins. This sentiment was echoed by Bird, Gao & Yeung (2017) who test various implementations of cross-sectional and time-series momentum strategies in 24 major equity markets. They attribute the superior performance of time-series momentum to the observation that performance deterioration of time-series strategies appeared to be much less severe in down markets, compared to cross-sectional strategies. This, they postulate, is because the time-series strategy imbues the stock selection decision with a timing element which consequently makes the asset holdings "*more in tune with market conditions*" (Bird, Gao & Yeung 2017). Specifically, a time-series strategy will have a net long position when markets are up and a net short position when markets are down, whilst a cross-sectional strategy will have zero net exposure, regardless of market conditions.

2.2 IS TIME-SERIES MOMENTUM *REALLY* BETTER?

While the *"timing element"* described above was portrayed as an inherent advantage to the time-series strategy, Goyal & Jagadeesh (2017) describe this "*time varying investment in the market"* as a problematic feature that distorts the comparison of the two momentum strategies. In their recent paper, they argue that the results obtained in Moskowitz et al. (2012) are driven by two factors, namely a net long position throughout the sample period and a methodological discrepancy between the time-series and cross-sectional portfolios that related to position scaling. Addressing the former first, the authors argue that the superior performance of time-series momentum is driven by the risk associated with a net long position. The time-series portfolios, on average, had a net long exposure because markets, on average, were up during the sample period. The risk of this net long position was not accounted for and the problem was exacerbated by the second factor, namely that the positions in the time-series portfolios were scaled inversely to volatility whilst the positions in the cross-sectional portfolios were equal-weighted. In order to control for the time-varying investment in the market exhibited by the time-series strategy, the authors add the return earned from investing or shorting the net position in an equal-weighted market index, to the return earned from the classical zero net exposure cross-sectional strategy.

By correcting the portfolio positions discrepancy and accounting for the time-varying net investment in the market, Goyal & Jagadeesh show that time-series momentum is in fact not vastly superior to cross-sectional momentum when considering both the broader asset classes originally investigated in Moskowitz et al. (2012) as well as individual stocks. Regarding individual stocks, the authors conclude there are no real differences between the two strategies, but one could argue the authors are painting with too broad of a brush. There are instances where the time-series strategy did produce a statistically significant higher return than its cross-sectional counterpart that controls for the time-varying net long/short exposure, as well as a higher Sharpe ratio. Goyal & Jagadeesh (2017) proceed to demonstrate that when the abovementioned corrections are in place, time-series momentum does not explain cross-sectional momentum and vice versa and one can cautiously infer they hold the belief that the two strategies reflect the same market-wide phenomenon.

Regardless of whether or not time-series momentum and cross-sectional momentum are two incarnations of the same effect, the respective investment strategies devised around momentum do behave differently, as has been outlined above. D'souza et al. (2016) is the only paper to date that explores the idea of combining the two momentum strategies to form a dual momentum trading strategy that is applicable to individual stocks. As the focus of their paper is on time-series momentum, a comparative analysis of dual momentum and cross-sectional momentum is not presented. It should also be noted that they do not make any corrections for the time-varying investment in the market inherent to time-series momentum strategies.

2.3 EXPLAINING MOMENTUM

Although this paper will make no attempts at explaining momentum, it is nevertheless appropriate to briefly discuss some possible explanations. The debate concerning why momentum can even be observed to begin with is a lengthy one and to date, no satisfactory answer has been presented. That being said, the most compelling evidence over the past two decades seems to be in favour of a behavioural explanation as opposed to a risk-based explanation rooted in market efficiency.

Jagadeesh & Titman (1993) initially conjectured that cross-sectional momentum might be explained by investors underreacting to firm-specific news. Later, Chen, Jagadeesh & Lakonishok (1996) examined if the predictability of future returns from past returns stems from an initial underreaction to earnings surprises, causing an upward return drift. They found that past earnings surprises and past return each had predictive power for future returns, but that cross-sectional momentum and earnings momentum were two distinct phenomena and that price momentum is not subsumed by momentum in earnings.

De Bondt & Thaler (1985) had already documented long-term overreaction in stock markets. Specifically, they document how losers over a 3-5-year lookback period become winners over the next 3-5 years (essentially the opposite of momentum) and so Lee & Swaminathan (2000) suggest that both underreaction to firm-specific news as well as long-term overreaction are pertinent in explaining cross-sectional momentum. Although the possible causes of the initial underreaction and subsequent overreaction are still hotly contended, most explanations relate to one or several behavioural biases such as self-attribution bias & overconfidence (Daniel et. al 1998), the disposition effect (Grinblatt & Han 2005) and cognitive dissonance (Antoniou & Doukas 2013).

There are of course also several rational pricing stories to consider. One such story revolves around the idea of news diffusing gradually (Hong & Stein 1999; Hong, Lim & Stein 2000). Holden and Subrahmanyam (2002) builds on this idea and construct a formal model that suggests momentum can be explained by uncertainty due to news diffusing slowly which consequently reduces risk premia in an autocorrelated fashion. They posit that traders become informed after the revelation of a public signal and that as more and more investors become informed, risk premia steadily decline which gives rise to momentum.

Chordia & Shivakumar (2002) examines the explanatory power of lagged common macroeconomic factors that have been used in the past to explain stock returns and find that a parsimonious specification of macro-variables related to the business cycle can explain momentum profits. The variables they consider are yield on three-month T-bills, default spread, term spread and value-weighted market dividend yield, on which they also build a conditional forecasting model. Griffin, Ji & Martin (2003) tests this model internationally and find that those variables do a poor job at explaining momentum profits internationally.

Last but not least, it is worth mentioning that a significant portion of the papers mentioned thus far assume that the return distribution is time invariant. Hwang & Rubesam (2015) devise a model that allows for multiple structural breaks and find that while momentum strategies were profitable from the 1940s to 1960s and from 1970s to 1990s, its profitability has largely dissipated in recent times, especially since the *"quant meltdown"* of 2007. They also speculate that the explanation for momentum profits is multifaceted and that it is not strictly only behavioural, or risk based.

3. DATA

All required data is provided by Quantopian (see Section 4 for a description of Quantopian) and their database runs from 2002 to present day. The algorithms will use closing prices that are adjusted for dividends and stock splits in its decision-making process instead of prevailing market prices so that these events do not affect the past return figures on which the algorithms will place their trades. However, resulting gains and losses (realized or otherwise) are computed using prevailing market prices.

The algorithms will use the same tradeable universe of stocks throughout the simulations. The tradeable universe is derived using three "*filters*". The first filter only selects stocks that pass the following rules: First, the stock must be common stock (i.e. not preferred stock). It also cannot be a depository receipt or a stock for a limited partnership and the stock must not be traded over the counter. Companies with more than one share class can pass through this filter, in order to pick only one share class, the most liquid is chosen. Liquidity is measured using the 200-day median daily dollar volume. The third filter is based on the following dynamic attributes: The 200-day median daily dollar volume must be in excess of 2.5 million USD and have a market capitalization in excess of 350 million USD over a 20-day simple moving average. The market capitalization and dollar volume restriction eliminate potential problems that could arise with stocks that are illiquid and difficult to short. Lastly, the stock cannot be an active M&A target.

At any given time, this tradeable universe will contain roughly 8000 US equities, but the exact number of stocks in the tradeable universe will be time varying. Both algorithms will ultimately produce a time series with daily discrete returns that account for both realized and unrealized gains/losses as well as dividend payments if applicable. These returns will be log-transformed and resampled to monthly returns. The monthly return series will be the cornerstone of the empirical analysis. Part of the analysis will involve factor regressions and the relevant factor data is downloaded from Kenneth R. French's website.

4. METHODOLOGY

This section has two parts to it. Firstly, I will detail how the algorithms will trade and ultimately produce the resulting return series that the empirical analysis will be conducted on. Following this, the empirical side of the methodology will be presented along with two hypotheses.

Both strategies will be deployed using the freely available and open source technologies developed by Quantopian, a Boston-based quantitative hedge fund. While Quantopian's technologies are quite flexible, the underlying algorithmic logic for both momentum strategies is quite trivial. In its simplest form, each strategy will compute a signal for each individual stock in the tradeable universe and then rank them, based on this numerical signal. The algorithm will then go long in the stocks with the highest signal and short in the stocks with the lowest signal whilst being as dollar neutral as possible. In order to make the signal as clean as possible, it will be calculated using the adjusted closing prices described in Section 3. Since this is a comparative analysis of two investment strategies all technical aspects of the trading algorithms will be identical except in the ranking of stocks from most to least attractive.

4.1 DEFINING THE CROSS-SECTIONAL STRATEGY

The signal for the cross-sectional momentum strategy will simply be the percent change in adjusted closing prices over the past 12 months. Stocks are then ranked on this signal and divided into deciles. Five simulations will be run, where the algorithm first goes long in stocks that place in the top decile and short in stocks that place in the bottom the bottom decile, then long stocks in the decile second from the top and short stocks in the decile second from the bottom and so forth.

4.2 DEFINING THE DUAL MOMENTUM STRATEGY

In order to form dual momentum portfolios, it is first necessary to define time-series momentum. Both Moskowitz et al. (2012), Antonacci (2017) and D'Souza et al. (2016) restrict time-series momentum to a binary classification where only the sign of the signal matters and not the magnitude. Both the singular analysis of time-series momentum in Moskowtiz et al. (2012) and the definition of time-series momentum in Antonacci (2017) simply uses the sign of the percent change in price over a year to identify if the time-series momentum is positive or negative. However, classifying stocks with this measure and then ranking them on cross-sectional momentum will produce the exact same ranking as ranking them on cross-sectional momentum alone, so an alternative definition of time-series momentum is required. The preferred option is to deploy the definition in D'Souza et al. (2016) which uses the sign of the cumulative product of monthly returns over the past year.

Once assets are classified as a time-series winner or a time-series loser, the cross-sectional momentum over a year is computed on time-series winners and losers separately and sorted into quintiles and this momentum serves as the signal in the dual momentum strategy as well. In line with D'Souza et al. (2016) I will not apply any additional filtering, meaning that the bottom quintile of the time-series winners contains stocks that are cross-sectional losers and the top quintile of time-series losers contain stocks that are cross-sectional winners. The primary purpose of this is to exacerbate any differences between stocks deemed to be very attractive and stocks deemed to be not so attractive. Finally, the two sets of quintiles (one set for each time-series classification) will be combined to form the final ranking of stocks, such that the top (bottom) five deciles are all time-series winners (losers).

4.3 STOCK PICKING AND CAPITAL ALLOCATION

Before outlining how capital will be allocated, an important point of attention is due: Due to the binary nature of time-series momentum and due to the fact that the cross-sectional momentum in the dual momentum strategy will be calculated on time-series winners and losers separately, the sizes of the resulting quintiles will not be symmetrical across the two time-series classifications. The sizes will also be time-varying and different than the size of the pure cross-sectional strategy deciles. This is essentially (part of) the critique Goyal & Jagadeesh (2017) present as the relevant time-series focused papers use a methodology that buys all stocks in a given decile. In the spirit of eliminating a persistent net long positions in the market ("net long" because the market, on average, trended up in the sample period) both strategies will be restricted to only a maximum of 100 long and 100 short positions when picking stocks from a given decile. 100 is somewhat arbitrary but chosen to err on the side of caution as every decile will contain *at least* 100 stocks at any given point in time.

After each tradeable universe has been identified, signals computed for every stock and (maximum) 200 stocks have been picked based on the signals, the algorithms need to allocate capital. There is a large repository of different methods one can consider in order to compute portfolio weights, but for this investigation, it will be kept simple. DeMiguel et al. (2007) shows that naïve diversification consistently outperforms 14 more sophisticated models. Naïve diversification is simply the $\frac{1}{n}$ rule, where n is the total number of assets. It is worth mentioning, however, that their results were subject to criticism in Kirby et al. (2012) who claimed their results were largely due to the research design used.

Assuming the signal is somewhat predictive of future returns, i.e. past returns predict future returns, then it would be beneficial for a given portfolio weight to reflect the corresponding signal. One way to achieve this is as follows: Let $\boldsymbol{s} = [s_1, s_2, \dots, s_n]$ be a vector of computed signals for n assets in the tradeable universe and let $\boldsymbol{w} = [w_1, w_2, \dots, w_n]$ be a vector of unknown weights. Then, the optimization problem is

$$\begin{array}{lll} Maximize & \boldsymbol{w} * \boldsymbol{s}' & \\ Subject\ to & |w_i| \leq w_{max} & 0 \leq i \leq n \\ & \displaystyle\sum_{i=0}^{n} |w_i| \leq W_{max} & \end{array}$$

where w_{max} is the maximum position concentration and W_{max} is the maximum total portfolio weight. Both restrictions are expressed as a percentage of the allotted capital an algorithm can trade with. In the interest of avoiding unnecessary complexities, neither algorithm will have access to leverage and so $W_{max} = 1$. The maximum position concentration, w_{max}, will be set equal to $\frac{1}{n}$. Keep in mind however, that this does not constitute a perfect equally weighted portfolio and only serves as an upper bound.

4.5 PORTFOLIO REBALANCING

A total of 20 simulations will be run, 10 with monthly rebalancing and 10 with quarterly. Rebalancing is relatively straight forward. At the start of every month/quarter, the algorithms identify the tradeable universe and assign every asset a signal by which it ranks them. Depending on the simulation running, the relevant 200 stocks in the two (long and short) deciles will be identified and corresponding weights calculated as described above. It then compares this "optimal portfolio" to its existing holdings and then places the appropriate market orders required to move the existing portfolio towards this "optimal portfolio" whilst obeying all constraints specified, including that of dollar neutrality with a tolerance of 0.0001. Whilst rebalancing, the algorithm incurs commissions which are drawn from the allotted capital. The commissions will be set at 0.005 USD per share, with a minimum order of 1.00 USD but orders that are not filled by the end of the day are not charged and subsequently cancelled. This corresponds to the fixed pricing regime charged by Interactive Brokers LLC which operate the largest electronic trading platform in the U.S. Next, the empirical side of this paper will be discussed.

4.6 HYPOTHESIS 1 AND RETURN DIFFERENCES

Perhaps the most obvious element to examine is that of the actual returns generated by the two trading algorithms. The first hypothesis is that the dual momentum strategy will outperform the classical cross-sectional momentum strategy. The dual momentum strategy incorporates more information than the cross-sectional one. Assuming this additional information is informative with respect to future returns, it seems intuitive that it will generate a higher return. To test this hypothesis, I first examine the returns generated by doing a one-sample t-test on the monthly mean return from both algorithms. Additionally, several performance metrics will be reported as well.

To make results somewhat comparable to that of Jagadeesh & Titman (1993, 2001) and to attempt to be somewhat consistent with existing momentum literature, the risk-free rate will be set to 0, as these momentum strategies will be (quasi) dollar neutral investment strategies with very little net capital invested. I say "very little" because the algorithm will simulate real trading on real prices so it is likely that at times the algorithm will be slightly more long than short (in monetary terms) or vice versa, in which case it can temporarily draw on the pool of allotted capital. Additionally, the net exposure will likely alternate between long and short and I thusly assume that the exposures cancel out on average.

4.7 COMPLEMENTARY: A SMALL BRIDGE TO EXISTING MOMENTUM LITERATURE

I will also attempt to bridge this practically oriented paper with existing momentum literature, by forming equally weighted overlapping portfolios from each decile, every day and calculating the mean monthly forward log returns. Forward returns at time t is defined as the return realized at time t, having held an asset for a set period of time. The fixed holding periods used in this section of the analysis are 10, 11 and 12 months. The overlapping portfolios are constructed as follows: For each given day, the 10, 11- and 12-month forward log returns are calculated for all assets in a decile and then averaged to produce the forward log return of an equal weighted portfolio for that given day. Ultimately, the average over all the days in the sample is calculated and reported.

For each holding period, I will also report the spearman rank correlation coefficient. This is a measure of how well the signal predicts returns. The spearman rank correlation coefficient for a given asset is the correlation between the ranks of the signal and the ranks of the forward returns, which ultimately accounts for any non-linear relationship between the signal and forward returns. This metric is calculated for all assets and averaged out and reported for each holding period.

4.8 HYPOTHESIS 2 AND RISK ADJUSTED RETURNS

As mentioned earlier in this paper, the question regarding whether cross-sectional momentum and time-series momentum reflect the same broader phenomenon is not fully answered. I implicitly assume that the two momentum effects only differ by the means of which they reflect the same general momentum effect in markets and that the momentum factor used can capture both cross-sectional and time-series momentum equally well.

Since this effect has been shown to be a viable way to generate returns in the past, it makes sense to investigate which of the two strategies best capitalizes on the broader momentum effect. Additionally, only examining the overall returns does not shed any light on whether momentum is driving those returns or not. My second hypothesis is that the dual momentum strategy is more suitable to capitalize on this effect due to it incorporating more information. To test this, I will run a four-factor regression model similar in spirit to that of Carhart (1997) on the different return series and examine how each strategy loads on the momentum factor. Note that Carhart's UMD factor has been replaced by a MOM factor on Kenneth R French's website, but the construction of the factor is similar[1]. The functional form of the regressions can be represented as

$$R_i = \alpha + \beta_1(R_m - r_f) + \beta_2 HML + \beta_3 SMB + \beta_4 MOM + \varepsilon_i \tag{1}$$

With corresponding Newey-West standard errors to correct for any heteroskedasticity and serial correlation. Note that the dependent variable is not return in excess of the risk-free rate due to the assumption outlined in Section 4.6.

[1] For details on how the factors are constructed, please see Kenneth R. French's website.

5. RESULTS

Running the algorithms on the entire sample revealed that none of them were profitable. At best, some simulations broke even. Examining the time-series of the cumulative returns, a general pattern occurred. The algorithms would generally incur losses and be more volatile in the early 2000s and become profitable leading up to the crash in 2007. As the crisis erupted, every simulation incurred substantial losses, some in the magnitude of 60%. Post crisis times, the strategies incurred far less volatile yet positive returns, but those returns were still modest and insufficient to recoup previous losses. It is possible that the substantial losses incurred during the crisis are a manifestation of the tail risk believed to be associated with momentum strategies (Daniel et al. 2012; Barroso & Santa-Clara 2015; Daniel & Moskowitz 2016). In order to get a more accurate view of how these strategies perform in "normal times" the analysis will be conducted on both pre and post-crisis times. Pre-crisis is defined as start of 2003 through the end of 2007 where post-crisis is from the start of 2010 to end of 2018. However, the pre-crisis analysis uses a much smaller sample and consequently the results contain a lot of noise. Additionally, it did not tell a very different story than the post-crisis analysis and is therefore presented in the appendix on this paper.

5.1 POST CRISIS ANALYSIS

Table 1 displays a general overview of the performance of both strategies, executed with both monthly and quarterly rebalancing. Turning to the upper panel with monthly rebalancing first, the most immediate observation is that the all five dual momentum simulations appear to underperform the cross-sectional counterparts when looking at the mean return only, although none of the simulations generated a mean return that was positive and significantly different than zero. Only one of the dual momentum simulations in this panel is profitable, namely the 6-5 simulation which according to the theory should be worst of them. This simulation generated a modest total return of 24.47% over the sample which interestingly is higher than the best (10-1) cross-sectional simulation. In addition to this dual momentum simulation having a lower maximum drawdown, it also has a higher Sharpe ratio but also higher daily turnover rate.

Generally, however, if one compares the Sharpe ratios pairwise, it appears that the cross-sectional momentum strategy generates higher risk adjusted returns than the dual momentum strategy although the highest Sharpe ratio of 0.0615 is generated by the 6-5 dual momentum simulation. One interesting thing to note are the CAPM parameters. All but one of the betas are marginally negative but none are significantly different than zero. The same statement generally applies to the alphas as well. Only two alphas are significant at conventional levels and their effects are negative yet only marginally so. It seems possible that transaction costs incurred via the relatively high rebalance frequency erodes returns to the point where the CAPM intercepts and mean returns are not significantly different than zero.

Focusing on the bottom panel, we are told a similar story. None of the mean returns are significantly different than zero and neither are the betas. Two alphas are significant, but their effects are (marginally) negative. The cross-sectional momentum Sharpe ratios are again higher than the dual momentum counter parts with the exception for the 6-5 dual momentum simulation which again turned out to be the most profitable one among the dual momentum simulations. One interesting thing to note is that while the 10-1 cross-sectional simulation was the most profitable overall, generating a return of 64.02%, the Sharpe ratio for the 9-2 simulation is higher. A possible explanation for this is that the cross-sectional winners in the 10-1 simulation contains relatively more stocks that are about to undergo the reversal documented in the literature (De Bondt & Thaler 1985; Jagadeesh & Titman 1993; Jagadeesh & Titman 2001).

Table 1

Descriptive statistics of monthly returns and general performance, post crisis. Upper panel is with monthly rebalancing, lower panel is with quarterly rebalancing. α and β are parameters from standard CAPM regressions with Newey-West standard errors, where a lag length of 10 months was chosen, and p-values are given in parenthesis. The excess market return is the excess return on a value-weighted portfolio with all CRSP firms incorporated in the US and listed on AMEX, NYSE or NASDAQ. The risk-free rate is set to 0 due to market neutral nature of the strategies. Each column shows relevant information from returns from the long leg minus returns from the short leg of a given strategy.

	Cross-Sectional Momentum Portfolios					**Dual Momentum Portfolios**				
Variable	**10-1**	**9-2**	**8-3**	**7-4**	**6-5**	**10-1**	**9-2**	**8-3**	**7-4**	**6-5**
Mean	0.0010	-0.0004	-0.0017	-0.0011	-0.0009*	-0.0002	-0.0018*	-0.0012**	-0.0014	0.0016
	(0.751)	(0.808)	(0.181)	(0.208)	(0.087)	(0.942)	(0.071)	(0.030)	(0.197)	(0.524)
Std. Dev.	0.0323	0.0165	0.0128	0.0086	0.0053	0.0255	0.0103	0.0057	0.0111	0.0267
β	-0.0010	-0.0010*	-0.0006	-0.0005	0.0000	-0.0012*	-0.0005	-0.0002	-0.0006	-0.0008
	(0.278)	(0.075)	(0.125)	(0.204)	(0.918)	(0.065)	(0.141)	(0.157)	(0.164)	(0.376)
α	0.0019	0.0006	-0.0010	-0.0006	-0.0009***	0.0010	-0.0013	-0.0001**	-0.0008	0.0024
	(0.472)	(0.629)	(0.319)	(0.363)	(0.001)	(0.647)	(0.110)	(0.010)	(0.379)	(0.269)
Sharpe Ratio	0.0306	-0.0234	-0.1295	-0.1220	-0.1661	-0.0070	-0.1753	-0.2116	-0.1240	0.0615
Daily Turnover	3.3%	6.8%	7.7%	8.0%	8.1%	7.1%	8.1%	8.0%	7.9%	6.2%
Max Drawdown	-29.0%	-16.6%	-18.3%	-12.5%	-13.7%	-21.6%	-25.3%	20.4%	-16.0%	-22.9%
Total Return	24.4%	-1.1%	-15.6%	-9.2%	-12.0%	-12.2%	-24.8%	-18.7%	-12.7%	24.8%
Annual Return	2.4%	-0.2%	-1.9%	-1.1%	-1.4%	-1.5%	-3.1%	-2.3%	-1.6%	2.7%
	Cross-Sectional Momentum Portfolios					**Dual Momentum Portfolios**				
Mean	0.0037	0.0020	-0.0002	0.0007	-0.0001	0.0018	-0.0006	-0.0003	0.0003	0.0013
	(0.213)	(0.169)	(0.827)	(0.374)	(0.919)	(0.440)	(0.524)	(0.518)	(0.771)	(0.609)
Std. Dev.	0.0306	0.0150	0.0118	0.0082	0.0063	0.0246	0.0102	0.0055	0.0101	0.0256
β	-0.0001	-0.0003	-0.0002	0.0000	0.0000	-0.0006	-0.0002	0.0001	-0.0002	-0.0002
	(0.875)	(0.554)	(0.564)	(0.890)	(0.952)	(0.285)	(0.478)	(0.441)	(0.505)	(0.811)
α	0.0038	0.0023	0.0000	0.0007	-0.0001	0.0024	-0.0004	-0.0004	0.0005	0.0014
	(0.121)	(0.038)	(0.989)	(0.265)	(0.886)	(0.248)	(0.605)	(0.335)	(0.435)	(0.558)
Sharpe Ratio	0.1205	0.1334	-0.0210	0.0859	-0-0098	0.0746	-0.0615	-0.0623	0.0281	0.0493
Daily Turnover	1.8%	2.7%	2.8%	2.9%	2.9%	2.5%	2.9%	2.9%	2.9%	2.5%
Max Drawdown	-24.3%	-10.8%	-12.6%	-5.6%	-7.2%	-18.9%	-13.6%	-7.3%	-8.4%	27.2%
Total Return	64.0%	21.4%	-1.6%	8.4%	-0.1%	25.8%	-6.4%	-3.1%	3.5%	26.0%
Annual Return	5.7%	2.9%	-0.2%	0.9%	0.0%	2.6%	-0.7%	-0.3%	0.4%	2.6%

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

It is entirely possible that the superior returns of the simulations with quarterly rebalancing are only driven by the fact that the stocks are held for longer, which is reflected in the daily turnover rate. In order to see which of the strategies best capitalize on momentum, factor regressions were undertaken, and the results can be found in Table 2.

All loadings on the momentum factor are positive and significant at the 1% level. Turning our attention to the upper panel, we see that the intercepts are largely either negative or not significantly different than 0, which makes sense given the relatively poor performance of the simulations with monthly rebalancing. Examining the momentum parameters for the cross-sectional simulations, we a see linear relationship between the coefficient and the set of deciles the algorithm traded, the 10-1 simulation having the highest coefficient. For the dual momentum simulations, the relationship between the coefficients and the deciles being traded seems more parabolic. The coefficients initially decline in value as we move away from the less extreme set of deciles (10-1) but then increases again as we approach the 6-5 simulation. In fact, that simulation had the highest momentum parameter, which is consistent with this simulation also being the most profitable despite theory suggesting otherwise.

Looking at the lower panel with quarterly rebalancing, all intercepts are not significantly different from zero except for two, which are significantly negative. The momentum parameters follow the same pattern as described above. When comparing each coefficient in the lower panel pairwise to the parameters in the upper panel, we see they tend to be the same in magnitude albeit slightly lower.

If we rank the momentum parameters from highest to lowest for monthly and quarterly rebalancing separately and for each strategy or if we just sum them up in a similar fashion, it appears that the cross-sectional algorithm better captures momentum than the dual momentum counterpart.

Table 2

Four-factor regressions in the form of $R_i = \alpha + \beta_1(R_m - r_f) + \beta_2 HML + \beta_3 SMB + \beta_4 MOM$ with Newey-West standard errors and a corresponding lag length of 10 months. The upper panel are coefficients with monthly portfolio rebalancing and the bottom panel are coefficients from quarterly rebalancing. The factor data is downloaded from Kenneth R. French's website and the excess market return is the excess return on a value-weighted portfolio with all CRSP firms incorporated in the US and listed on AMEX, NYSE or NASDAQ. The risk-free rate is set to 0 due to market neutral nature of the strategies. Each column shows relevant information from returns from the long leg minus returns from the short leg of a given strategy. P-values are given in parenthesis and a joint test for significance is presented on the bottom row of each panel.

	Cross-Sectional Momentum Portfolios					**Dual Momentum Portfolios**				
Variable	**10-1**	**9-2**	**8-3**	**7-4**	**6-5**	**10-1**	**9-2**	**8-3**	**7-4**	**6-5**
α	-0.0025*	-0.0017**	-0.0026***	-0.0013***	-0.0012***	-0.0024**	-0.0024***	-0.0014***	-0.0022***	-0.0013
	(0.099)	(0.010)	(0.000)	(0.007)	(0.000)	(0.029)	(0.000)	(0.000)	(0.000)	(0.416)
$(R_m - r_f)$	-0.0000	-0.0004*	-0.0003	-0.0003	0.0001	-0.0005	-0.0003*	-0.0001	-0.0003	0.0000
	(0.931)	(0.063)	(0.228)	(0.199)	(0.682)	(0.130)	(0.082)	(0.317)	(0.184)	(0.948)
HML	-0.0016**	-0.0002	0.0001	0.0003	0.0001	-0.0016***	0.0002	0.0000	0.0003	-0.0006
	(0.023)	(0.672)	(0.830)	(0.281)	(0.787)	(0.004)	(0.663)	(0.869)	(0.322)	(0.466)
SMB	-0.0006	-0.0009***	-0.0003	-0.0001	0.0001	-0.0001	-0.0001	-0.0001	-0.0005**	-0.0006
	(0.424)	(0.004)	(0.295)	(0.802)	(0.554)	(0.800)	(0.616)	(0.681)	(0.022)	(0.263)
MOM	0.0092***	0.0048***	0.0035***	0.0018***	0.0008***	0.0071***	0.0026***	0.0010***	0.0031***	0.0080***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F-test	0.000***	0.000***	0.000***	0.000***	0.003***	0.000***	0.000***	0.000***	0.000***	0.000***
	Cross Sectional Momentum Portfolios					**Dual Momentum Portfolios**				
α	-0.0003	0.0003	-0.0014**	-0.0002	-0.0006	-0.0007	-0.0015**	-0.0007	-0.0008	-0.0022
	(0.859)	(0.661)	(0.049)	(0.670)	(0.196)	(0.593)	(0.016)	(0.134)	(0.089)	(0.167)
$(R_m - r_f)$	0.0008**	0.0002	0.0001	0.0003	0.0001	0.0000	0.0000	0.0002	0.0001	0.0008***
	(0.036)	(0.297)	(0.770)	(0.118)	(0.442)	(0.927)	(0.894)	(0.194)	(0.518)	(0.003)
HML	-0.0021**	-0.0000	0.0000	-0.0003	0.0000	-0.0012*	0.0001	-0.0002	0.0002	-0.0004
	(0.025)	(0.972)	(0.930)	(0.174)	(0.950)	(0.061)	(0.860)	(0.517)	(0.387)	(0.384)
SMB	-0.0004	-0.0006**	-0.0004	-0.0004	-0.0002	-0.0001	-0.0003	0.0000	-0.0005**	-0.0016**
	(0.475)	(0.030)	(0.261)	(0.298)	(0.432)	(0.785)	(0.214)	(0.901)	(0.015)	(0.018)
MOM	0.0082***	0.0044***	0.0030***	0.0016***	0.0011***	0.0066***	0.0025***	0.0006***	0.0027***	0.0076***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F-test	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

* p < 0.1 ** p < 0.05 *** p < 0.01

Table 3

Mean log forward return per decile of the base universe of approximately 8000 equities. Decile 10 contains the top 10% of stocks with the highest past 12-month return. Each mean forward return is the mean forward return on overlapping equally weighted portfolios formed every day and held for 10, 11 and 12 months, with no transaction costs. P-values from a two-sided t-tests on a given sample mean being different from zero are given in parenthesis. The mean correlation is the mean spearman rank correlation between the ranks of 12-month past returns and ranks of forward returns 10, 11 and 12 months later. For the dual momentum strategy, decile 6 through 10 are time-series winners where decile 6 contains the biggest cross-sectional losers and decile 10 the biggest cross-sectional winners. Similarly, decile 1 through 5 contains time-series losers with decile 1 containing the largest cross-sectional losers and decile 5 the largest cross-sectional winners.

	Cross-Sectional Momentum Holding Periods			**Dual Momentum Holding Periods**		
Decile	**10**	**11**	**12**	**10**	**11**	**12**
10	0.0276***	0.0289***	0.0296***	0.0483***	0.0519***	0.0546***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
9	0.0695***	0.0757***	0.0803***	0.0765***	0.0838***	0.0898***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
8	0.0742***	0.0811***	0.0866***	0.0758***	0.0826***	0.0888***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
7	0.0786***	0.0861***	0.0922***	0.0590***	0.0644***	0.0690***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
6	0.0762***	0.0834***	0.0895***	-0.0157***	-0.0174***	-0.0203***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
5	0.0742***	0.0810***	0.0872***	0.0498***	0.0537***	0.0564***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4	0.0663***	0.0729***	0.0785***	0.0764***	0.0837***	0.0893***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
3	0.0520***	0.0564***	0.0601***	0.0750***	0.0821***	0.0882***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2	0.0286***	0.0311***	0.0327***	0.0595***	0.0652***	0.0700***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1	-0.0623***	-0.0682***	-0.0759***	-0.0171***	-0.0185***	-0.0216***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Correlation	0.050	0.053	0.054	0.051	0.053	0.055

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 3 shows mean log forward returns from equally weighted portfolios comprised of stocks from ten deciles, sorted by their 12-month past return, for three different holding periods. The first thing to note is that the mean return tends to increase with the holding and that all means are significantly different from zero. The latter is not surprising given the length of the holding periods and the fact that 2010-2018 was a bull market in the US. When analysing the strategy performances in Table 1, it was noted that for the cross-sectional strategy with quarterly rebalancing, the 9-2 simulation had a higher Sharpe ratio than the 10-1. Here we again see decile 10 (for both strategies) earning a lower mean return than several of the lower deciles. It seems possible this is a reflection of the 1-month short term reversal due to a microstructural bias reported in Jagadeesh (1990) and

Grinblatt & Moskowitz (2004) or the long-term reversal documented in much of the momentum literature (De Bondt & Thaler 1985; Jagadeesh & Titman 1993; Jagadeesh & Titman 2001; Asness, Moskowitz & Pedersen 2014). Regardless, it is a feature of momentum that was not incorporated into the strategy[2].

Another interesting observation is that the decile 8 through 10 (long legs) generated a higher mean return with dual momentum than with cross-sectional momentum. The opposite is true for decile 1 through 3 (short legs) where cross-sectional momentum earns a lower return. A possible explanation for this is that due to the sequential double sorting used with dual momentum, the most extreme cross-sectional losers are divided into two deciles (1 and 6) depending on whether they are time-series losers or winners, whereas all extreme losers under cross-sectional momentum are grouped together in decile 1. If one considers the results in Table 3 in isolation, it appears that using dual momentum to construct the long leg and cross-sectional momentum to construct the short leg would be a superior approach than strictly using only one of them, even though dual momentum already incorporates cross-sectional momentum (at least theoretically).

It is possible that the results in Table 3 pertaining to the long leg dual momentum deciles (decile 6 through 10) having a higher mean return is due to markets trending up in this period and thus, deciles 6 through 10 under dual momentum have more equities in it than the cross-sectional deciles. If we construct an equally-weighted portfolio by going long in a time-series winner decile (decile 6 through 10) and short in a time-series loser decile (decile 1 through 5), our portfolio would on average suffer from a net long position, which is the basis of the criticism against time-series momentum in Goyal & Jagadeesh (2017). For that reason, doing factor regressions on forward returns will likely be misleading, as it was argued to be in Moskowitz et al. (2012).

[2] To avoid the 1-moth short term reversal one typically skips the most recent month when calculating the past return such that there is a 1-month gap between lookback period and portfolio formation.

6. CONCLUSION

In conclusion it appears that the cross-sectional momentum strategy is a more viable choice than the dual momentum strategy, when controlling for the time-varying investment in the market inherent to time-series (and dual momentum) strategies. It not only delivers better raw and risk adjusted returns but also captures the general momentum effect better than the time-series counterpart which means that both hypotheses posited in Section 4 are rejected. However, the main takeaway is that even though momentum seems to have been present, neither algorithm on its own could be considered a viable investment strategy in the sample periods studied (2003-2007 & 2010-2018) and that just holding the S&P500 would have been a superior approach.

There are however a few limitations that needs to be discussed. The first is regarding the differences in returns generated. Ideally, I would have performed statistical tests on the difference in Sharpe ratios produced by the different strategies, but this proved too challenging, which leaves inferences regarding the first hypothesis in lack of statistical power. The second limitation pertains to the differences (if any) between cross-sectional and time-series momentum. If the two are in fact different at a non-superficial level, then given how the momentum factor is constructed, it makes sense that is relatively ill equipped to reflect time-series momentum and thus the validity of the comparison of momentum coefficients across the two strategies can be called into question. Additionally, the comparison of the momentum coefficients also lacks statistical power. It should also be mentioned that my assumption regarding dollar-neutrality on average may not hold, in which case some figures pertaining to the performance of the algorithms are overstated, though it is unlikely this would affect the conclusions drawn.

As mentioned in Section 2, there is no clear consensus about whether cross-sectional and time-series momentum are different from each other. If they are, further research is needed to clarify if and how the two effects can be combined optimally. Additionally, this investigation has strictly focused on individual equities and it is not clear if examining other asset classes would lead to a different conclusion about what kind of momentum strategy is superior.

7. APPENDIX: PRE-CRISIS RESULTS

The following pages contain the same tables as Section 5 but for the pre-crisis sample. As mentioned, this sample is smaller, and the results are generally noisier as well and I cannot reliably ascertain that the analysis from this sample tells a significantly different story than the analysis from the post-crisis sample. However, two differences are apparent. In Table 6, the mean log forward return decreases with the holding period whereas in Table 3 it increases. Additionally, the mean spearman rank correlation coefficient is negative for all holding periods in this sample, but positive in the post-crisis sample.

Table 4

Descriptive statistics of monthly returns and general performance, post crisis. Upper panel is with monthly rebalancing, lower panel is with quarterly rebalancing. α and β are parameters from standard CAPM regressions with Newey-West standard errors, where a lag length of 10 months was chosen, and p-values are given in parenthesis. The excess market return is the excess return on a value-weighted portfolio with all CRSP firms incorporated in the US and listed on AMEX, NYSE or NASDAQ. The risk-free rate is set to 0 due to market neutral nature of the strategies. Each column shows relevant information from returns from the long leg minus returns from the short leg of a given strategy.

	Cross-Sectional Momentum Portfolios					**Dual Momentum Portfolios**				
Variable	**10-1**	**9-2**	**8-3**	**7-4**	**6-5**	**10-1**	**9-2**	**8-3**	**7-4**	**6-5**
Mean	-0.0076***	0.0000	0.0000	-0.0008	-0.0013*	-0.0035	-0.0011	-0.0019**	-0.0007	-0.0005
	(0.000)	(0.987)	(0.976)	(0.451)	(0.098)	(0.393)	(0.398)	(0.013)	(0.544)	(0.860)
Std. Dev.	0.0000	0.0171	0.0111	0.0084	0.0059	0.0311	0.0101	0.0056	0.0094	0.0217
β	0.0000*	-0.0010	-0.0004	-0.0008	-0.0005	-0.0030**	-0.0006	-0.0004	-0.0005	-0.0015
	(0.097)	(0.385)	(0.628)	(0.190)	(0.154)	(0.048)	(0.529)	(0.203)	(0.487)	(0.330)
α	-0.0076***	0.0009	0.0004	-0.0001	-0.0009	-0.0008	-0.0006	-0.0015***	-0.0003	0.0008
	(0.000)	(0.702)	(0.841)	(0.920)	(0.164)	(0.789)	(0.704)	(0.005)	(0.787)	(0.810)
Sharpe Ratio	-437.1502	0.0021	0.0040	-0.0980	-0.2172	-0.1111	-0.0011	-0.3320	-0.0788	-0.0230
Daily Turnover	3.5%	6.8%	7.6%	7.8%	8.0%	6.3%	7.8%	8.0%	7.8%	6.3%
Max Drawdown	-38.5%	-12.0%	-10.3%	-10.5%	-9.7%	-31.0%	15.6%	-12.9%	-11.6%	-21.5%
Total Return	-23.9%	0.8%	0.8%	-4.4%	-7.2%	-18.0%	-6.0%	-10.4%	-4.0%	-2.4%
Annual Return	-5.3%	0.2%	0.2%	-0.9%	-1.5%	-3.9%	-1.2%	-2.2%	-0.8%	-0.5%
	Cross-Sectional Momentum Portfolios					**Dual Momentum Portfolios**				
Mean	-0.0031	-0.0012	-0.0005	-0.0001	0.0008	-0.0028	-0.0008	-0.0013	-0.0017	-0.0005
	(0.410)	(0.545)	(0.742)	(0.936)	(0.305)	(0.483)	(0.495)	(0.112)	(0.171)	(0.848)
Std. Dev.	0.0293	0.0155	0.0116	0.0077	0.0058	0.0309	0.0087	0.0061	0.0096	0.0202
β	-0.0035*	-0.0011	-0.0004	0.0001	-0.0002	-0.0035*	-0.0004	0.0002	-0.0007	-0.0014
	(0.055)	(0.288)	(0.596)	(0.892)	(0.446)	(0.057)	(0.452)	(0.641)	(0.286)	(0.401)
α	-0.0000	-0.0002	-0.0001	-0.0001	0.0009	0.0003	-0.0004	-0.0015**	-0.0011	0.0007
	(0.991)	(0.898)	(0.949)	(0.888)	(0.103)	(0.921)	(0.760)	(0.012)	(0.272)	(0.793)
Sharpe Ratio	-0.1071	-0.0427	-0.0427	-0.0104	0.1336	-0.0912	-0.0886	-0.2083	-0.1788	-0.0249
Daily Turnover	2.0%	2.7%	2.9%	2.9%	2.9%	2.5%	2.9%	2.9%	2.9%	2.5%
Max Drawdown	-32.9%	-16.0%	-12.4%	-6.5%	-4.4%	31.7%	-10.6%	-10.6%	-14.2%	-24.9%
Total Return	-17.1%	-7.0%	-2.9%	-0.5%	4.8%	15.5%	-4.5%	-7.4%	-9.8%	-3.0%
Annual Return	-3.7%	-1.5%	-0.6%	-0.1%	0.9%	-3.3%	-0.9%	-1.5%	-2.0%	-0.6%

* p < 0.1 ** p < 0.05 *** p < 0.01

Table 5

Four-factor regressions in the form of $R_i = \alpha + \beta_1(R_m - r_f) + \beta_2 HML + \beta_3 SMB + \beta_4 MOM$ with Newey-West standard errors and a corresponding lag length of 10 months. The upper panel are coefficients with monthly portfolio rebalancing and the bottom panel are coefficients from quarterly rebalancing. The factor data is downloaded from Kenneth R. French's website and the excess market return is the excess return on a value-weighted portfolio with all CRSP firms incorporated in the US and listed on AMEX, NYSE or NASDAQ. The risk-free rate is set to 0 due to market neutral nature of the strategies. Each column shows relevant information from returns from the long leg minus returns from the short leg of a given strategy. P-values are given in parenthesis and a joint test for significance is presented on the bottom row of each panel.

	Cross-Sectional Momentum Portfolios					**Dual Momentum Portfolios**				
Variable	**10-1**	**9-2**	**8-3**	**7-4**	**6-5**	**10-1**	**9-2**	**8-3**	**7-4**	**6-5**
α	-0.0076***	-0.0012	-0.0004	-0.0005	-0.0013	-0.0042	-0.0012	-0.0018***	-0.0011	-0.0020
	(0.000)	(0.343)	(0.757)	(0.534)	(0.104)	(0.168)	(0.165)	(0.007)	(0.300)	(0.328)
$(R_m - r_f)$	-0.0000	-0.0012	-0.0008	-0.0012***	-0.0004	-0.0024*	-0.0008	-0.0006	-0.0009**	-0.0013
	(0.863)	(0.163)	(0.109)	(0.005)	(0.256)	(0.063)	(0.254)	(0.174)	(0.024)	(0.351)
HML	0.0000	0.0012	-0.0005	-0.0002	0.0005	0.0022	-0.0007	0.0003	0.0003	0.0010
	(0.150)	(0.352)	(0.511)	(0.648)	(0.179)	(0.302)	(0.215)	(0.412)	(0.405)	(0.617)
SMB	0.0000**	0.0001	0.0007	0.0008**	-0.0001	-0.0020	0.0004	0.0003	0.0009**	-0.0008
	(0.021)	(0.903)	(0.119)	(0.020)	(0.800)	(0.359)	(0.417)	(0.589)	(0.031)	(0.627(
MOM	-0.0000*	0.0036**	0.0018**	0.0011*	0.0005*	0.0052**	0.0016**	0.0005	0.0014**	0.0048***
	(0.061)	(0.016)	(0.040)	(0.064)	(0.092)	(0.028)	(0.024)	(0.151)	(0.040)	(0.007)
F-test	0.120	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	Cross Sectional Momentum Portfolios					**Dual Momentum Portfolios**				
α	-0.0034	-0.0021*	-0.0012	-0.0005	0.0007	-0.0027	-0.0012	-0.0018**	-0.0019**	-0.0015
	(0.132)	(0.072)	(0.279)	(0.577)	(0.252)	(0.332)	(0.192)	(0.012)	(0.042)	(0.336)
$(R_m - r_f)$	-0.0032*	-0.0017	-0.0006	-0.0001	-0.0004	-0.0032**	-0.0006	0.0002	-0.0008	-0.0011
	(0.079)	(0.097)	(0.302)	(0.770)	(0.233)	(0.049)	(0.134)	(0.753)	(0.186)	(0.463)
HML	0.0013	0.0018***	0.0001	0.0002	0.0004	0.0013	0.0004	-0.0000	0.0002	0.0005
	(0.525)	(0.002)	(0.879)	(0.618)	(0.325)	(0.493)	(0.429)	(0.942)	(0.631)	(0.713)
SMB	-0.0014	0.0009	0.0003	0.0004	0.0004	-0.0013	0.0002	0.0001	0.0001	-0.0010
	(0.550)	(0.284)	(0.616)	(0.558)	(0.327)	(0.517)	(0.692)	(0.877)	(0.872)	(0.430)
MOM	0.0057**	0.0030**	0.0022**	0.0007	0.0003	0.0049**	0.0014**	0.0006*	0.0014***	0.0039**
	(0.014)	(0.044)	(0.030)	(0.326)	(0.483)	(0.037)	(0.047)	(0.081)	(0.008)	(0.024)
F-test	0.000***	0.000***	0.000***	0.326	0.023**	0.000***	0.000***	0.304	0.000***	0.000***

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 6
Mean log forward return per decile of the base universe of approximately 8000 equities. Decile 10 contains the top 10% of stocks with the highest past 12-month return. Each mean forward return is the mean forward return on overlapping equally weighted portfolios formed every day and held for 10, 11 and 12 months, with no transaction costs. P-values from a two-sided t-tests on a given sample mean being different from zero are given in parenthesis. The mean correlation is the mean spearman rank correlation between the ranks of 12-month past returns and ranks of forward returns 10, 11 and 12 months later. For the dual momentum strategy, decile 6 through 10 are time-series winners where decile 6 contains the biggest cross-sectional losers and decile 10 the biggest cross-sectional winners. Similarly, decile 1 through 5 contains time-series losers with decile 1 containing the largest cross-sectional losers and decile 5 the largest cross-sectional winners.

	Cross-Sectional Momentum Holding Periods			**Dual Momentum Holding Periods**		
Decile	**10**	**11**	**12**	**10**	**11**	**12**
10	0.0043	-0.0043	-0.0243***	0.0227***	0.0128***	0.0024
	(0.437)	(0.159)	(0.001)	(0.000)	(0.000)	(0.730)
9	0.0393***	0.0337***	0.0271***	0.0601***	0.0556***	0.0508***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
8	0.0545***	0.0488***	0.0438***	0.0645***	0.0616***	0.0576***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
7	0.0668***	0.0635***	0.0593***	0.0610***	0.0559***	0.0501***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
6	0.0662***	0.0634***	0.0596***	0.0301***	0.0210***	0.0117
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.138)
5	0.0623***	0.0596***	0.0557***	0.0229***	0.0138**	0.0030
	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.656)
4	0.0638***	0.0588***	0.0582***	0.0615***	0.0570***	0.0526***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
3	0.0587***	0.0536***	0.0482***	0.0646***	0.0621***	0.0582***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2	0.0463***	0.0404***	0.0341***	0.0614***	0.0567***	0.0513***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1	0.0151**	0.0026	-0.0095	0.0311***	0.0220***	0.0130*
	(0.034)	(0.749)	(0.288)	(0.000)	(0.001)	(0.097)
Mean Correlation	-0.019	-0.019	-0.020	-0.018	-0.019	-0.020

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

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