**ERASMUS UNIVERSITY ROTTERDAM**
**ERASMUS SCHOOL OF ECONOMICS**
**Bachelor Thesis Economics & Business**

# Momentum Strategies in the S&P 500: Can Small Investors Exploit the Momentum Effect?

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**Finish date:** 31 August 2023

## ABSTRACT

This paper studies the extent to which small investors can exploit the momentum effect among stocks listed in the S&P 500 Index. This thesis offers a practical alternative to strategies presented in the existing literature, focusing on a widely accessible range of stocks with relatively high liquidity. Furthermore, winners-only strategies are the focus of the investigation, disregarding the short selling of losers which is typically applied in momentum investing literature. Using S&P 500 data from 2010 to 2021, this study investigates the excess returns of 208 strategies formed based on formation periods, holding periods, and the number of stocks included over the S&P 500 Index. Risk-adjusted returns were calculated to analyse the strategies from another angle. They were also tested against the existing CAPM and three-factor models, ultimately proving that these strategies present excess returns for lower initial investments which are not explained by factors in the models. This study therefore promotes a more enterprising investment strategy for retail investors which remains intuitive and accessible.

**Keywords:** momentum investing, retail investing, investment strategy

**JEL codes:** G11, G14

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# CHAPTER 1 Introduction

Momentum investing is a popular and widely researched investment strategy in recent decades. Jegadeesh & Titman (1993) were the first to propose a significant strategy in the field, sparking further interest to investigate the extent to which the momentum anomaly can generate excess returns. The existing literature surrounding momentum investing typically caters to the institutional investor, building winner-loser portfolios that can consist of hundreds of positions. Little research has been done on the feasibility of momentum strategies for smaller average investors. Siganos (2010) investigates whether a momentum strategy can be exploited using portfolios consisting of a small number of stocks, using UK stocks to construct winner-loser portfolios. Foltice & Langer (2015) construct winners-only portfolios for US stocks listed on the NYSE for the individual investor. This thesis constructs portfolios based on stocks in the S&P 500 Index with the highest positive momentum, implementing a winners-only strategy for retail investors. This investigation aims to decipher whether the average retail investor can generate excess returns with momentum strategies including the 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, and 30 best-performing stocks from the index, using an equal-weighted approach. The risk-adjusted returns of these portfolios will be measured against the similar returns of the S&P 500 Index over the corresponding periods.

This investigation aims to replicate that of Foltice & Langer (2015) in investigating the performance of momentum trading strategies for a small number of positions against a benchmark. Their study utilizes monthly return information for all listed and delisted NYSE companies reported by Thomson Reuters Datastream between July 1991 and December 2010. By comparing different trading strategies based on a winners-only approach, the paper builds up from a framework presented in Jegadeesh & Titman (1993) which tests for varying holding periods between one to four quarters. Foltice & Langer (2015) find that investors can outperform the benchmark after accounting for transaction costs and risks with a smaller number of stocks. Their investigation elucidates the feasibility of momentum investing for the average retail investor while avoiding the downside risks associated with short selling, offering new findings which could prompt greater adoption of such strategies.

This study combines elements of the frameworks used in Siganos (2010), Foltice & Langer (2015) and Jegadeesh & Titman (1993) while catering towards the average global retail investor. The work of Siganos (2010) investigates the momentum effect on UK companies specifically, conducting a robust analysis of transaction costs, using winner-loser strategies. Foltice & Langer (2015) and Jegadeesh & Titman (1993) presented findings revolving around stocks listed on the NYSE, fabricating winners-only and winner-loser strategies, respectively. When formulating strategies this investigation focuses on the S&P 500 Index, a collection of the biggest US-listed companies by market cap. These stocks are globally accessible, have high liquidity, and therefore lower bid-ask spreads which prompt less detrimental transaction costs which harm small scale investments disproportionately.

The approaches to transaction costs vary across the literature, Jegadeesh & Titman (1993) which use a fixed rate, Siganos (2010) uses a flat-fee, and Foltice & Langer (2015) combine a rate for average bid-ask spreads per market cap and a flat-fee. Therefore, there is an element of ambiguity with regards to the method with which to account for transaction costs in momentum investing. This study incorporates elements from each of the three frameworks, ultimately providing a holistic overview of the impacts of transaction costs on returns.

This investigation focuses on winners-only strategies due to the unlimited downside risk exposure associated with short selling that is undesirable for the small investor (Foltice & Langer, 2015). Furthermore, the average retail investor may not be as well versed in short selling. Hence, reinforcing the notion that a winners-only strategy would be easiest to implement for the average investor, requiring only simple long positions on given stocks. This rationale leads to the central question of this paper: *Can a winners-only momentum investing strategy generate excess returns over the S&P 500 Index for the average investor?*

The investigation therefore contributes to the existing literature by basing strategies around globally accessible companies with larger market caps which entail only going long on winners and disregarding losers. This minimizes both theoretical transaction costs which are calculated through bid-ask spreads and downside risks posed by short selling. S&P 500 historical constituent lists and price information are extracted from the Yahoo Finance application programming interface accessed through Python. The sample size contains all constituents of the S&P 500 Index and their corresponding monthly returns between January 2010 and December 2021, documenting the monumental rise of retail investing following the 2008 financial crisis. The biggest 30 winners are selected as it represents the maximum number of positions in the strategy which aims to cater specifically to the smaller retail investor. The list of winners fluctuates monthly and therefore strategies differ in attractiveness across the sample period. This study puts forth an easily implemented trading strategy that requires little understanding of investing, following an intuitive approach to going long on previous winners. The intuitive nature of the strategies proposed can potentially inspire average retail investors to take more enterprising roles when investing in their personal portfolios, provided the returns and downside risk warrant doing so.

The investigation finds that the momentum strategies conducted generate excess returns over the S&P 500 Index, with the best-performing portfolios consisting of fewer positions and lower trading frequency. Therefore, the detrimental effects of transaction costs are felt acutely by the small investor. Nevertheless, an analysis of Sharpe ratios highlights the sub-optimal risk-adjusted returns achieved by the strategies which improves with number of positions per portfolio. Therefore, prompting a trade-off between returns and risk-adjusted performance when deciding how many positions a momentum portfolio ought to be comprised of.

The remainder of this paper will be structured as follows. A theoretical framework will be established to discuss the existing literature in the field of momentum investing. Next, the data section describes the data set used, the number of observations, and some descriptive statistics. To continue, a methodology is presented to explain the steps conducted in the analysis to test the proposed hypotheses. Furthermore, the results are analysed and discussed in relation to the existing literature. Finally, the findings of this investigation are concluded, and the potential limitations and extensions are addressed.

# CHAPTER 2 Theoretical Framework

## 2.1 The Momentum Effect

Jegadeesh & Titman (1993) define momentum strategies as strategies which buy stocks that have performed well in the past and sell stocks with have performed poorly in the past. These strategies therefore bet on the continuation of a previous upward or downward trend in stock prices which is known as its momentum.

The momentum effect is a phenomenon that challenges the efficient market hypothesis presented by Fama (1970) which – through its association with random walks – hypothesises that prices fully reflect all known information and news about the stock and price changes are unpredictable and random. Momentum investing arises from the notion that future stock prices are somewhat predictable based on a combination of past stock price patterns and certain "fundamental" valuation metrics, according to Malkiel (2003). It constitutes an investing strategy highlighting some psychological and behavioural elements of price determination.

Using NYSE and AMEX stock data from 1965 to 1989, Jegadeesh & Titman (1993) were among the first to investigate the momentum effect on stock returns in a seminal paper that brought the investing strategy to the limelight. They formulated a J-Month / K-Month strategy to select stocks based on their returns in the preceding 3, 6, 9, or 12 months (J-Months), and to hold them for 3, 6, 9 or 12 months (K-Months), ultimately yielding 16 unique strategies. At the beginning of a given month stocks were ranked in ascending order in based on their returns in the past J months and allocated to one of ten decile portfolios (1 being the best performers, 10 being the worst). The strategy then buys the best performing decile and short sells the worst performing decile. They ultimately found that such strategies realized significant abnormal returns of around 1% over the 1965 to 1989 period (Jegadeesh & Titman, 1993). This seminal work laid the foundation for further research on momentum investing and the root of these abnormal returns.

## 2.2 Transaction Costs

To more accurately reflect the true profitability of the momentum strategies investigated, market frictions in the form of transaction costs are factored into returns. Transaction costs are essential when analysing the performance of a given strategy as variables such as trading frequency and portfolio size can heavily influence the realised returns.

To continue, the seminal work of Jegadeesh & Titman (1993) adopts a 0.5% one-way transaction cost. This was a relatively conservative estimate of market frictions which posed questions among critics. Carhart (1997) concludes that the momentum returns presented by Jegadeesh & Titman (1993) dissipate after factoring in transaction costs.

There are various approaches to implementing transaction costs in the literature, for example, Siganos (2010) implements a £10 flat fee for one-way transactions, whilst Foltice & Langer (2015) combine a flat fee of $10 for one-way transactions with an average bid-ask spread rate for small, mid, and large cap stocks respectively. Given that the S&P 500 Index consists of the largest US stocks by market cap and these constituents are relatively liquid, this investigation assumes that the consideration of bid-ask spreads in transaction costs is less significant than for small or mid cap companies. Erwin & Miller (1998) investigates that effect of the inclusion of a stock into the S&P 500 on its corresponding bid-ask spread, finding significant decrease in bid-ask spreads upon addition to the index. Due to the ambiguity involved in the discussion of transaction costs, this investigation conducts analysis with three different calculations drawn from Jegadeesh & Titman (1993), Siganos (2010), and Foltice & Langer (2015).

### 2.3 Small Investors and the Momentum Strategy

A benefit of momentum strategies is their simplicity. Any investor can survey the best (worst) performers in each market or index and take long (short) positions on them. Hence, it makes momentum investing a plausible strategy for a retail investor which is generally uninformed and prone to making systematic mistakes when investing in equities (Barber & Odean, 2000, 2008). Furthermore, Statman (2004) highlights the average investor's tendency to maintain overdiversified portfolios and Odean (1998) remarks on the aversion to sell loser shares. With retail investors holding relatively small portfolios compared to institutional investors (Boehmer, 2021), most trading strategies evaluated not through the lens of the smaller counterparts. This reinforces this investigation's imperative to build portfolios that are both affordable and founded on very intuitive strategies for the average investor.

Several institutional managers implement the momentum strategy by increasing their holdings of previous winner shares and slightly reducing the number of loser shares (Burch & Swaminathan, 2001). However, according to Siganos (2010), it is unlikely that institutional managers employ such strategies in their purest form. Moreover, Carhart (1997) reveals that said increase in fund managers' positions of previous winners is more accidental than a conscious effort to adopt the momentum strategy.

It follows that small investors must invest in individual stocks to follow the momentum strategy. Existing literature in the field of momentum is not representative for individual traders (Siganos, 2010). Many US studies (e.g. Jegadeesh & Titman. 1993) obtain data from the CRSP database, boasting data for over 32.000 securities listed with primary listings on NYSE. Amex. and NASDAQ markets (*CRSP US Stock Databases,* n.d.). Most UK studies (e.g. Lui, Strong & Xu, 1999) derive data from LSPD or Datastream which involve analysing hundreds or thousands of stocks listed on the LSE. Such studies define winner and loser portfolios based on deciles, quintiles, or terciles, investigating hundreds of companies as a result (Siganos. 2010). Retail investors simply do not have the capacity to emulate such portfolios. For example, Goetzmann & Kumar (2008) find that most retail investors only hold three or four stocks in their portfolios, with only 5% of trader portfolios consisting of more than 10 securities. A strategy which focuses on buying few shares of many large companies is unlikely to become profitable since investors pay commission either as a flat fee or as a percentage of total amount invested. Since retail investors are unlikely buy or short sell hundreds of companies at a time, this paper will investigate the profitability of momentum strategies when much fewer positions are included in the portfolios. Siganos (2010) finds that after accounting for transaction costs and risk small investors can exploit the momentum effect with only a limited number of stocks, constructing such portfolios for prices ranging from £5,000 to £1,000,000. Similarly. Foltice & Langer (2015) find that after factoring in transaction costs and risks a simplified momentum strategy still outperforms the benchmark for investors with initial investment amounts of at least $5,000. Moreover, their investigation finds that increasing the trading frequency initially increases risk-adjusted returns to a certain degree whereafter transaction costs detract from these profits. Foltice & Langer (2015) affirm this investigation's choice to disregard the short selling of loser portfolios to eliminate the exposure to unlimited downside risk for the average investor.

Overall, findings from Siganos (2010) and Foltice & Langer (2015) suggest that momentum effects can still be exploited by retail investors which are constrained to holding fewer stocks in their portfolios. Moreover, both studies highlight an association between higher trading frequency and risk-adjusted returns to a certain extent. Thus, with respect to the "winners only" momentum strategies constructed from the S&P 500 Index this investigation expects to see significant excess risk-adjusted returns over the benchmark – the value-weighted S&P 500 Index itself. This study expects these findings to uphold in the face of transaction costs, which will have a progressive influence on excess returns following trading frequency.

# CHAPTER 3 Data

This paper uses monthly return data for all listed and delisted stocks comprising the S&P 500 Index as reported from Yahoo Finance between January 1st, 2010, and December 31st, 2021. Resulting in a total 84,960 observations collected. The sample period is chosen to encapsulate the historic rise of retail investing following the onset of the 2008 financial crisis, giving insight into which momentum strategies performed strongest, and whether these generated excess returns. The number of observations is slightly conservative given the more contemporary time frame selected.

Monthly price data, book-to-market ratios, and market capitalizations from the S&P 500 Index and its constituents are obtained using the Yahoo Finance application programming interface on Python. Delisted stocks are incorporated to address potential survivorship bias.

The monthly returns of the value-weighted S&P 500 Index are collected against said momentum strategies, attempting to deduce whether they outperform these benchmarks. The S&P 500 Index is a market-capitalization-weighted index of the 500 leading publicly traded companies in the US. This index is specifically chosen for its wide accessibility through global exchanges and the lower liquidity associated with the companies included. Thus, ensuring the replicability of the investigated strategies in the average retail investor's portfolio and a lower exposure to high bid-ask spreads affecting the transaction costs associated with carrying out said strategies.

Although the sample period could be extended a further 57 years back, it is not done for such a large range would be beyond the scope of this investigation, which focuses on the employability of such strategies for the contemporary retail investor. A contemporary retail investor is assumed to have begun investing following the monumental rise in popularity of investing in recent years. which reportedly increased by 75% in 2020 (Arora. 2022).

# CHAPTER 4 Methodology

## 4.1 Framework

This investigation combines elements of the frameworks proposed by Jegadeesh & Titman (1993) and Siganos (2010). Using the J-Month / K-Month strategy of Jegadeesh & Titman (1993) discussed in the theoretical framework, we construct portfolios with formation periods of 3, 6, 9, or 12 months (J-months). with corresponding holding periods of 3, 6, 9, and 12 months (K-months). Where the formation periods refer to the time frames in which stocks within the index are ranked in descending order based on their returns. Holding periods simply represent the duration for which a given strategy will be held. This yields 16 unique combinations of formation periods and holding periods. Moreover, each strategy will choose the 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, or 30 best performing stocks for its respective formation period. This ultimately leads to 208 unique strategies based on formation periods, holding periods, and number of positions. To illustrate this, a 6 / 6 / 15 strategy will derive the 15 best performing stocks in the index, over the previous 6 months from a given time stamp and proceed to hold these positions for the following 6 months from said time stamp. For this analysis, overlapping periods will be used. While this has the potential to positively skew returns, the method increases the power of the tests performed. This investigation implements a lag of one month between the formation period and the holding period in accordance with the findings of Jegadeesh (1990), which highlights that doing so can avoid some of the bid-ask pressure, price pressure, and lagged reaction effects documented in their study.

Using the returns from the Yahoo Finance application programming interface on Python. the returns over formation periods are calculated as follows:

$$R_{i,\,(t-J,\,t-1)} = \frac{R_{i(t-1)} - R_{i(t-J)}}{R_{i(t-J)}} \quad . \tag{1}$$

Where $R_{i,\,(t-J,\,t-1)}$ is the return of stock $i$ during the formation period $J$ (note again that the last month of each formation period is skipped), $R_{i(t-1)}$ represents the return of stock $i$ at time $t$ and $R_{i(t-J)}$ is the return of stock $i$ at time $t-J$. The reason that this investigation caps the maximum number of stocks at 30 – a number lower than that of both Foltice & Langer (2015) and Siganos (2010) – is due to the assumption that more than 30 positions is unrealistic for a smaller investor. reiterating that Goetzmann & Kumar (2008) find that only 5% of trader portfolios hold more than 10 positions in their portfolios. Therefore, holding more than 30 positions would be unrepresentative of a retail investor's hypothetical portfolio. If a stock within a portfolio is delisted from the S&P 500 Index during the holding period of the strategy, it remains part of the portfolio until the conclusion of the holding period for the sake of simplicity for the retail investor.

In order to deduce whether the strategies generate excess returns over the benchmark the following hypothesis will be tested:

$$H_0 : Portfolio_i \ = \ S\&P\, 500\, Index$$
$$H_\alpha : Portfolio_i \ > \ S\&P\, 500\, Index.$$

Where the value-weighted S&P 500 Index is used as the benchmark. The hypothesis is tested with a Welch's t-test for the equal means of the population. The difference between the Welch's t-test and a standard t-test is the assumption of normality, as the former assumes unequal variances and is therefore a non-parametric equivalent of the two-sample t-test (Zach, 2020). The P-value obtained from this test is measured against a predetermined critical value to test whether there is sufficient evidence to reject the null hypothesis. In this investigation a confidence interval of 95% is chosen and hence the critical value equals 0.05. If the one-tailed Welch's t-test for the alternative hypothesis returns a P-value less than 0.05, the investigation concludes that the average returns of momentum strategies outperform the benchmark, in other words, the momentum strategies on average achieve excess returns over the S&P 500 Index.

### 4.2 Risk-Adjusted Returns

In addition to analysing the excess returns of momentum strategies, the Sharpe ratios of strategies are calculated to assess the returns relative to the risk they assume. The sharpe ratios are calculated using the following formula:

$$S_i = \frac{E[R_i - R_f]}{\sigma_i}. \tag{2}$$

Where $S_i$ is the Sharpe ratio of portfolio *i*, $E[R_i - R_f]$ is the expected excess return of portfolio *i* over the risk-free rate, and $\sigma_i$ is the volatility of strategy *i*. The Sharpe ratio effectively indicates how much excess return a given portfolio generates for the added risk it assumes. Therefore, a Sharpe ratio of 1 suggests that the excess return is on par with the excess risk assumed over the risk-free asset. Any Sharpe ratio <1 therefore indicates that the excess returns over the risk-free asset are lower than the associated risk, meaning the investment achieves less return per unit of risk.

### 4.3 Alphas

To assess the robustness of the strategy, the analysis conducts a significance test of Jensen's alpha in the Capital Asset Pricing Model (CAPM). Where the alpha indicates the return in excess of the expected rate of return of the CAPM. The CAPM equation can be written as follows:

$$E(R_i) - R_f = \beta_i\left[E(R_m) - R_f\right]. \tag{3}$$

Where $E(R_i)$ is the expected return of portfolio $i$, $R_f$ *is* the risk-free rate, β is the systematic risk of portfolio $i$, and $E(R_m)$ is the expected return of the market portfolio. It should be noted that the risk-free rate in this investigation takes the yield of US 10-year treasury bond yields as a proxy. Jensen's alpha is defined as the difference between the realised return $R_i$ and the risk-adjusted return of the CAPM model. This can be calculated as follows:

$$\alpha_i = R_i - \left[R_f + \beta_i\left(R_m - R_f\right)\right]. \tag{4}$$

If $\alpha_i$ is positive and significant, it implies that portfolio $i$ generates abnormal returns in excess of what would be predicted by the model. This insinuates that the momentum returns are not fully explained by the risk factor alone. Jensen's alpha helps an investor determine to what extent a portfolio's returns differ from the expected returns in theory.

For the sake of robustness, this paper also makes use of the Fama & French (1996) three-factor model, comprising of the market return, the value factor (high book-to-market ratio minus low book-to-market ratio) and the size factor (small market capitalisation minus big market capitalisation). To clarify, the S&P 500 Index return serves as a proxy for market return. The following regression will be used to test the significance of alpha:

$$R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i SMB + h_i HML + \varepsilon_i\,. \tag{5}$$

Where $R_i - R_f$ represents the risk-adjusted returns of portfolio $i$, $\alpha_i$ is the alpha, $\beta_i$ is the coefficient for the exposure which the portfolio has to the market factor, $s_i$ gives the exposure to the size factor, $h_i$ gives the exposure to the value factor, and $\varepsilon_i$ represents the error term in the regression. By incorporating additional factors, the 3 factor model aims to explain any excess returns generated through size and value and therefore challenges the notion that these returns result from momentum. Thus, the alpha retrieved from the regression would highlight the portfolio's capacity to outperform the expected return given the market, size, value, profitability, and risk factors. Regression (4) will test the following hypothesis:

$$H_0 : \alpha_i = 0$$
$$H_\alpha : \alpha_i > 0.$$

If the alpha is significant and positive, it implies that there is variation in the excess returns which are not explained by the risk factors proposed by Fama & French (1996). Hence, suggesting that these returns can be explained by other factors such as momentum.

### 4.4 Transaction Costs

Regarding transaction costs, this investigation adopts the methods of Jegadeesh & Titman (1993), Siganos (2010), and Foltice & Langer (2015) – in which they factor in a 0.5% fee, a $10 flat-fee, and a flat fee $10 plus a rate of 0.212%, respectively. The rate of 0.212% represents the bid-ask spread for large cap stocks presented in Foltice & Langer (2015). Through applying these differing stress tests this investigation assesses robustness of results against market frictions.

The following provides an illustration of the different kinds of transaction costs applied to the results:

$$c_1 = 0.5\% \cdot portfolio\ value$$
$$c_2 = 10$$
$$c_3 = 10 + 0.212\% \cdot portfolio\ value\ .$$

Where $c_i$ represents the one-way transaction cost for a given method. Therefore, for a given portfolio $c_i$ will be deducted upon both formation and liquidation. These transaction costs are applied to the returns of the best performing strategies per holding duration to illustrate the various effects on returns. These results are expressed in nominal terms to give a practical insight into the detrimental effects of transaction costs.

### 4.5 Value-at-Risk

To analyse the risk involved in employing certain momentum strategies for the retail investor, the value at risk (VaR) is calculated to measure risk of loss of capital. It serves as an indication of the maximum amount an investor is set to lose on a given investment. Comparing the VaR across strategies will help deduce how feasible select strategies may be for the small investor. This study aims to provide insights for investors with differing attitudes towards risk, allowing them to select their momentum strategies accordingly. The VaR will be calculated as follows:

$$VaR = -1.65 \cdot \sigma_i \tag{6}$$

Where 1.65 is the measure of volatility for a 95% confidence interval, and $\sigma_i$ is the standard deviation of portfolio $i$. This represents the maximum loss below the expected return of a given portfolio. Note that the greater the volatility of a portfolio, the higher the maximum loss will be for that strategy. The maximum loss will be calculated as a percentage before being multiplied by the average cost of portfolio construction. This will ultimately yield an average maximum loss from employing these strategies.

# CHAPTER 5 Results & Discussion

## 5.1 Momentum Returns

This section of the investigation will delve into the general performance of the momentum strategies employed. Each strategy is compared against the S&P 500 Index as the benchmark. Strategies are referred to in the J / K / N form where J represents the formation period in months, K indicates the holding period in months, and N signifies the number of positions selected for the portfolio.

Table 1 presents the average annualized returns and standard deviations per portfolio size, showing a steady negative correlation between portfolio size and returns realized. The best-performing portfolios on average were those that comprised of a singular stock, attaining annualized returns of 21.6%. The worst-performing portfolios on average were those with 30 positions with achieved an annualized return of 10.4%. These findings could be attributed to the notion that the greater the portfolio size, the greater the similarities between that portfolio and the underlying. Hence, the average return will approach that of the S&P 500 Index.

Similarly, Table 1 highlights a negative correlation between standard deviations and portfolio sizes. On average, portfolio volatility steadily decreases as number of stocks increases, with the singular stock portfolios attaining average annualised standard deviations of 1.497 while the largest portfolios had 0.263 in comparison. Greater portfolio size also implies a higher degree of diversification. This has a negative influence on the standard deviation, as the portfolio reduces idiosyncratic risks posed by specific stocks or sectors, consequently dampening volatility.

Another impeding factor on returns which is associated with number of positions is the influence of transaction costs. Such market frictions accumulate which each added position, as these portfolios are constructed with individual long positions rather than by buying a basket of stocks e.g. indexes.

*Average Annualized Returns and Standard Deviations of Portfolios per Number of Positions*

| $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 15 | 20 | 30 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $R_n$ | 0.216 | 0.202 | 0.183 | 0.173 | 0.166 | 0.160 | 0.158 | 0.154 | 0.149 | 0.146 | 0.130 | 0.120 | 0.104 |
| $\sigma_n$ | 1.497 | 1.097 | 0.829 | 0.705 | 0.627 | 0.576 | 0.540 | 0.511 | 0.480 | 0.457 | 0.369 | 0.323 | 0.263 |

Table 1: *The average annualized returns and standard deviations for each portfolio size are collected. Portfolio size is based on the number of positions from which it is comprised. These figures are derived from the cumulative returns and standard deviations across all 208 possible strategies.*

To continue, Table 2 shows the annualized average returns and standard deviations per J / K strategy – referring to the unique combination of formation and holding periods in months. It is apparent that the average annualized returns tend to increase with the duration of the strategies. The formation period is particularly influential in the returns, as there is a more ambiguous trend in holding periods. For example, the 12 / 3 strategy invokes 7% higher annualized return than the 3 / 3 strategy whereas the

3 / 12 strategy only realises 1.5% higher returns. These findings suggest that imposing a longer formation period is more effective than a holding period in producing momentum returns. The intuition behind this is that the longer formation periods will pinpoint stocks that outperform more consistently, which would suggest a comparatively robust growth trend in the long term. Longer formation periods also eliminate stocks with short term mean reversions which tend to be more volatile.

Moreover, Table 2 also highlights that standard deviation increases with strategy duration. Mathematically, standard deviation increases with the square root of time, this is due to the conception that certain fluctuations negate each other, leading to a less than proportional relationship between time and volatility.

*Average Annualized Returns and Standard Deviations per J / K Strategy*

| **J / K Strategy** | $\boldsymbol{R_n}$ | $\sigma_n$ |
|---|---|---|
| 3 / 3 | 0.116 | 0.365 |
| 3 / 6 | 0.131 | 0.437 |
| 3 / 9 | 0.114 | 0.345 |
| 3 / 12 | 0.131 | 0.413 |
| 6 / 3 | 0.133 | 0.450 |
| 6 / 6 | 0.150 | 0.542 |
| 6 / 9 | 0.139 | 0.462 |
| 6 / 12 | 0.166 | 0.621 |
| 9 / 3 | 0.159 | 0.598 |
| 9 / 6 | 0.186 | 0.870 |
| 9 / 9 | 0.160 | 0.561 |
| 9 / 12 | 0.196 | 0.947 |
| 12 / 3 | 0.186 | 0.850 |
| 12 / 6 | 0.188 | 0.890 |
| 12 / 9 | 0.193 | 0.948 |
| 12 / 12 | 0.188 | 0.885 |

Table 2: *The average annualized returns and standard deviations for each J / K strategy are collected. The leftmost column indicates the unique combination of formation and holding periods, the middle column presents average annualized returns and the rightmost column presents the average annualized standard deviations per strategy.*

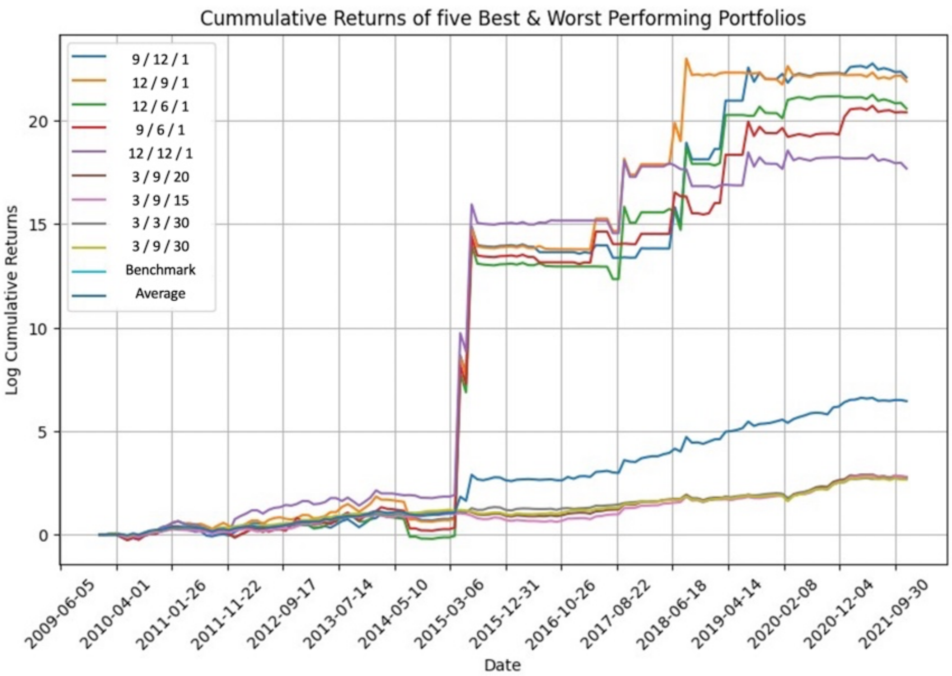
Appendix A shows the annualized risk-adjusted returns for all strategies over the period. Evidently, these returns greatly outperform the benchmark, with the average annualized returns across all strategies being 16.7% against the comparative 9.6% of the S&P over the same period and a standard deviation of 0.617 against the benchmark's 0.219. The 3 / 9 / 30 strategy brought the lowest annualized return of 8.5% across the time analysed, whilst the 9 / 12 / 1 strategy was its best-performing counterpart with a comparative annualized return of 29.4%. This implies a three-fold increase in returns over the benchmark.

The Welch's one-sided t-test differences in means between the average momentum strategy and the S&P 500 Index returns obtained a p-value of 0.015 which is less than the critical value of 0.05. This test result implies that there is significant evidence at the 95% confidence level to reject the null hypothesis outlined in section 4.1. The investigation can therefore reliably conclude that the momentum strategies constructed for small investors on average achieve excess returns over the S&P 500 Index. Hence, answering the central research question and promoting the attractiveness of employing momentum strategies for the retail investor.

Figure 1 shows a plot of the five best & worst performing portfolios in terms of cumulative returns, measuring against the average across all portfolios and the benchmark. The results are positively skewed, with the average portfolio outperforming the benchmark by 7.1% in annualized terms and a mere seven out of the total 208 iterations underperforming the benchmark.

The sudden spike in cumulative returns for single-stock portfolios around the 2015 timestamp is attributed to a singular stock Netflix (NFLX) which achieved a 134.4% return over the course of the year.

Figure 1: *The logarithm cumulative returns of the five best and worst performing portfolios are plotted over time against the benchmark and the average of all strategies. The benchmark used is the S&P 500 Index. The figure encapsulates the entire timeframe of the dataset between January 2010 and December 2021. The legend contains plots for J / K / N strategies, the S&P 500 Index as the benchmark and an average plot across all strategies.*



### 5.2 Risk-Adjusted Returns

Sharpe ratios of the momentum strategies are calculated to investigate the risk-adjusted returns. Table 3 shows the Sharpe ratios of the average momentum strategies based on the number of positions held per portfolio. The S&P 500 has a Sharpe ratio of 0.44, indicating a sub-optimal relationship between returns and risk. Then risk-adjusted returns appear to increase steadily with the number of positions held.

Section 4.2 presents the calculation of the Sharpe ratios, reinforcing that an increase is derived from either heightened returns or decreased risk. Recall that Table 1 showcased a negative correlation between number of positions held in a portfolio and returns, this suggests that the contrasting positive correlation between Sharpe ratios and number of positions is predominantly risk-based. Out of all portfolios, the 3 / 9 / 30 strategy attains the highest Sharpe ratio of 0.44, implying that none of the momentum strategies outperform the S&P 500 Index on a risk-adjusted returns basis. Nevertheless, these findings elucidate that while the annualized returns in Table 1 are higher for portfolios with fewer positions, larger portfolios achieve higher risk-adjusted returns. Therefore, the contradicting returns prompt a trade-off for the smaller investor between absolute returns and risk-adjusted returns.

*Sharpe Ratios for Average Portfolios Based on Number of Positions*

| ***n*** | **S&P** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **15** | **20** | **30** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $S_i$ | 0.44 | 0.16 | 0.20 | 0.24 | 0.26 | 0.28 | 0.29 | 0.31 | 0.31 | 0.32 | 0.33 | 0.36 | 0.38 | 0.40 |

Table 3: *The Sharpe ratios are collected for the S&P 500 Index and the average momentum strategy portfolios based on number of positions.*

### 5.3 Alphas

The strategies are tested through two risk factor models to investigate their robustness. A standard ordinary-least-squares (OLS) regression is conducted.

It is important to note that in the context of a CAPM regression, the alpha is recognised as the excess return over the market, and the beta represents standard measure of systematic risk – reflecting the propensity of the variable to move in tandem with the market. The CAPM therefore implies an alpha of zero, as it assumes no excess returns over the underlying benchmark. In the context of this investigation, a significantly positive alpha would indicate positive excess returns of the given strategy over the S&P 500 Index, allowing us to reject the null hypothesis proposed in section 4.4.

Panel A of Table 4 showcases the results of the CAPM regression for the average momentum strategy based on returns across all portfolios. The alpha of 0.047 proved to be significant at the 1% level. This implies that the momentum strategies generate 4.7% abnormal excess returns. In turn, the results urge a rejection of the null hypothesis, as there is significant evidence to suggest alpha is greater than.  The beta is insignificant, suggesting that it fails to explain the average excess market return and momentum returns are devoid of a systematic relation to the underlying benchmark. This is because the winners only strategies conducted will single out stocks that outperform regardless of market sentiment, so periods of economic downturn will not be felt as acutely in the portfolios constructed.

To continue, Panel B presents the results of the momentum strategies' robustness to the three-factor-model proposed by Fama & French (1996). This model is an extension of the CAPM model, including added explanatory variables for excess returns, including size and value factors. Similarly, the alpha of 0.50 is significant at the 1% level. This indicates an average excess return of 5% which is unexplained by the factors included. The standard error of 0.016 for the alpha is identical to that of the CAPM model, suggesting similar accuracy in prediction across the variables. Moreover, the beta is negative but insignificant. To reiterate the interpretation of this finding, it signals no remarkable tendency to follow the performance of the benchmark. Interestingly, the size factor presents a significant beta of 1.357 at the 5% level, while the value factor proves to be insignificant. Evidently, the difference in market cap between stocks explains some of the excess returns generated by the portfolios. Seeing as the variable is calculated through the difference between market caps (small market cap minus big market cap), it can be interpreted as evidence for stocks with smaller market caps to outperform their larger market caps, on average. Despite the S&P 500 Index being comprised of the largest stocks by market cap in the US, the discrepancies between size prove large enough to warrant higher returns for companies which have relatively low market caps within the index. Overall, the significance of the alpha allows us to reject the null hypothesis for the three-factor model presented in section 4.4. The regression presents evidence that there are significant excess returns for the momentum strategies over the benchmark, whilst accounting for the influence of other factors.

| *The Average Momentum Strategy Applied to the CAPM and 3 Factor Models* | | | | | |
|---|---|---|---|---|---|
| *Panel A - CAPM* | $\alpha_i$ | $\beta_i$ | | | $R^2$ |
| Coefficient | 0.047*** | 0.070 | | | 0.000 |
| Standard Error | 0.016 | 0.376 | | | |
| Test Statistic | 2.871 | 0.187 | | | |
| *Panel B – 3 Factor Model* | $\alpha_i$ | $\beta_i$ | $SMB_i$ | $HML_i$ | $R^2$ |
| Coefficient | 0.050*** | (0.224) | 1.357** | 0.184 | 0.034 |
| Standard Error | 0.016 | 0.398 | 0.666 | 0.527 | |
| Test Statistic | 3.133 | (0.561) | 2.036 | 0.350 | |

Table 4: *The average momentum strategy which generates the average risk-adjusted returns is applied to the CAPM and the 3 Factor Model. Panel A presents the OLS regression results against the CAPM model, while Panel B similarly does so for the 3 Factor Model. The significance of each annualized return is indicated by the asterisk next to the number. One asterisk indicates significance at the 10% confidence interval, whilst two and three do so for the 5% and 1% intervals, respectively. Negative numbers are enclosed in brackets.*

### 5.4 Transaction Costs

Transaction costs are clearly detrimental to returns, as shown by Table 1 and Table 2, the trading frequency and number of positions detract from returns. Portfolios with lower holding periods tend to underperform longer term counterparts and the average annualized returns of portfolios comprised of 30 stocks being less than half of those comprised of a singular company.

This section aims to highlight the magnitude of transaction costs across the different strategies, consequently testing the robustness of returns of some of the best performing strategies against different types of transaction costs. Recall from section 4.2 that the transaction costs are calculated in three different ways; rate, flat-fee, and a combination of both. Similarly to Sepulcri (2020), this paper assumes non-overlapping portfolios for the sake of simplicity for the small investor. Such portfolios vastly minimize the transactions and protect investors' returns.

To illustrate the magnitude of transaction costs, the value of $c_i$ will be compared across the best performing strategies for each holding duration, as it ultimately dictates the frequency of trading. For example, the 12 / 3 strategy is the best performing for strategies using a three-month holding period. This holding period implies that the investor must trade four times per year, incurring transaction costs twice on each occasion. Hence, the total transactions for 3, 6, 9, and 12 month holding periods are 8, 4, 3, and 2 respectively. It follows that over the 12-year period, a maximum of 48 and a minimum of 24 transactions are made for a given stock. These transactions are then multiplied by the number of positions per portfolio to deduce total transactions.

This analysis will use the average stock price of an S&P 500 constituent over the period analysed to calculate the robustness of returns against $c_i$. The average stock price of constituents was \$116.98, implying that an equally weighted portfolio for 30 positions would cost \$3509.40. Assuming an investor has \$5000 to invest – a figure analysed in Siganos (2010) – Table 6 shows the nominal value of their investment after one year while accounting for each method of calculating transaction costs.

The results highlight the extent to which transaction costs deteriorate returns. It shows that strategies with 30 positions are loss-making when accounting for $c_2$ and $c_3$, representing flat-fee and mixed component transaction costs, respectively. Evidently, the 0.5% transaction costs adopted from Jegadeesh & Titman (1993) is most conservative, presenting positive returns for large portfolios. The findings reiterate that strategies involving high frequency trading are less profitable due to the transaction costs incurred, and to make larger portfolios profitable it would require a much greater investment.

| *Nominal Value of a \$5000 Investment per Strategy after Accounting for Transaction Costs* | | | | |
|---|---|---|---|---|
| Strategy | $R_i$ | $c_1$ | $c_2$ | $c_3$ |
| 12 / 3 / 1 | $6290 | $6090 | $6210 | $6104 |
| 12 / 3 / 30 | $5580 | $5380 | $3180 | $3074 |
| 12 / 6 / 1 | $6435 | $6335 | $6395 | $6289 |
| 12 / 6 / 30 | $5585 | $5485 | $4385 | $4279 |
| 12 / 9 / 1 | $6465 | $6390 | $6435 | $6329 |
| 12 / 9 / 30 | $5610 | $5535 | $4710 | $4604 |
| 9 / 12 / 1 | $6470 | $6420 | $6450 | $6344 |
| 9 / 12 / 30 | $5590 | $5540 | $4990 | $4884 |

Table 5: *Spread of the nominal values of a \$5000 investment after a year for different strategies.* $c_i$ *represents the type of transaction cost while* $R_i$ *indicates the annualized return of a \$5000 investment in that strategy without transaction costs.*

### 5.5 Value-at-Risk

Given the average price of an S&P 500 constituent across the dataset is $116.98, this number will be used to calculate the VaR for the worst performing strategies. The purpose of this is to gauge the maximum loss achievable when conducting these momentum strategies, to educate smaller investors about the downside risks they are exposing themselves to. With the average annualized standard deviation across the twenty worst performing portfolios being 0.246, the maximum annual loss in percentage terms is equal to –40.64% (see equation in section 4.4). Given that the largest portfolios consist of 30 stocks, it follows that the average cost of construction for such strategies is $3509.40. Therefore, the maximum annual loss for this hypothetical strategy would be $1426.22.

By virtue of using the average constituent stock price, it allows for a convenient calculation of the cost of construction. Nevertheless, it gives light to the maximum annual downside for an investor looking to create an equally weighted portfolio with the greatest number of positions whilst minimizing the initial investment. The maximum loss will vary with the investor's subjective budget constraints, as a similar strategy can be employed purchasing multiple shares which inflates the nominal value of the potential loss.

### 5.6 Discussion

This section will discuss the similarities and differences between the frameworks and respective results of previous studies and from this investigation.

This study finds returns increase when going from a three-month to a six-month holding period, decrease when increasing to a nine-month period, and finally increase with a yearlong holding period. This signifies a discrepancy in relationships between trading frequency and returns. Foltice & Langer (2015) employ a similar strategy in which winners only portfolios are created with a smaller number of positions. Their investigation found that using data from NYSE between 1991 and 2010, small investors could enjoy significant excess returns with minimum initial investment amounts of $5000. Their findings suggest that increasing trading frequency initially increases returns up to a critical point after which they decline due to overwhelming transaction costs. Despite using the same spreads of formation and holding periods, this investigation finds a contrasting trend in the relationship between trading frequency and returns, as shorter holding periods of three months are associated with lower returns than strategies invoking longer ones. Furthermore, this investigation finds a steady negative correlation between risk-adjusted returns and number of positions, finding that the transaction costs prove too costly when buying many stocks at a time, particularly for strategies with higher trading frequencies. Similarly, Foltice & Langer (2015) find that portfolios with a lower number of positions consisting of between five and eight of the best performers brought much greater returns than portfolios comprising 20-50 stocks.

While most strategies presented outperform the underlying S&P 500 Index, the optimal degree of portfolio diversification depends on the subjective appetite for risk displayed by the investor. Investors with less initial capital may be able justify delving into riskier strategies while those with relatively deep funds may prefer a portfolio with a greater number of positions which can growth wealth at a lower assumed risk. Sepulcri (2020) finds that when implementing four medium-term winners only momentum strategies based on the AEX, all four of them significantly outperform the underlying. They weigh the trade-off between portfolio diversification and maximizing significant excess returns, ultimately finding that the ultimate portfolio consists of nine positions or higher. It prompts the question about whether the higher returns enjoyed by portfolios containing a single stock outweigh the idiosyncratic risks which can otherwise be reduced through diversification. This investigation highlights that while momentum strategies investing in a minimal number of positions greatly outperform the benchmark and other strategies with more stocks. However, a momentum strategy in which 30 individual stocks are bought achieves much greater risk-adjusted returns and therefore undermines the attractiveness of the singular stock portfolios. Therefore, an investor who is risk seeking may opt for strategies with lower degrees of diversification and higher risk to maximise returns, whilst a risk averse counterpart may invest in more diversified portfolios to the extent which their budget allows them to. The purpose of this investigation was to analyse the extent to which momentum investing strategies outperformed the benchmark on a return basis rather than on a risk-adjusted basis, thus the reporting of risk-adjusted returns merely aims to provide a more holistic analysis of the momentum strategies proposed.

Furthermore, this paper showcases that small investors can exploit the momentum effect without short selling, eliminating prominent risks in its association. Contrastingly, Siganos (2010) used UK stock data to decipher to potential to exploit momentum strategies for the retail investor. They ultimately find that such strategies generate significant risk-adjusted returns which hold up in the face of transaction costs. The study particularly focuses on larger portfolios ranging from $5,000 to $1,000,000 in value, also including the shorting of biggest losers in the construction of its strategies.

# CHAPTER 6 Conclusion

## 6.1 Conclusion

This investigation focuses on the employability of momentum strategies using the S&P 500 Index, and analysing the feasibility of excess returns from the perspective a small investor. Previous research has shown that momentum strategies can be profitable for small investors, with Siganos (2010), Foltice & Langer (2015), and Sepulcri (2020) all demonstrating significant risk-adjusted returns in portfolios focusing on a limited number of positions that are intended to cater to the retail investor rather than institutional investors with deeper pockets. With differing stances on portfolio construction and transaction costs, this study aimed to apply some of the frameworks presented to a widely accessible and relatively liquid dataset in the S&P 500 Index. The purpose was to improve accessibility and reduce market frictions for retail investors, whilst focusing on winners only strategies that eliminated some of the downside risks presented by previous works. The central question studied was *can a winners-only momentum investing strategy generate excess returns over the S&P 500 Index for the average investor?*

To answer this question, price data was collected from stocks in the S&P 500 Index between 2010 to the end of 2021. The price information was used to calculate excess returns and risk-adjusted returns, also calculating their robustness to transaction costs and the renowned CAPM and three-factor models. The results showed that such strategies could indeed generate excess returns over the benchmark, and the alphas of the CAPM and three-factor models indicated that these returns could not be explained by the examined factors. Hence, both null hypotheses proposed were rejected. However, the findings also highlighted the sub-optimal risk-adjusted returns in the form of Sharpe ratios. This prompted the trade-off between returns and risk that a retail investor faces when deciding how many positions their momentum portfolios should comprise of.

This study therefore concludes that the most profitable momentum investment strategies for the retail investor are those which focus on one to five stock positions, selecting them over a longer formation period of a year and proceeding to hold said positions for nine to 12 months thereafter. The strategies with higher trading frequency and shorter holding periods prompt transaction costs which negate these returns heavily for investors without high disposable capital. Combined with previous studies it suggests that momentum investing strategies are plausible and intuitive strategies which can easily be deployed by small investors who wish to outperform the market.

## 6.2 Limitations and Extensions for Future Research

A limitation posed by this study lies in the dataset period. Ideally this study would incorporate data spanning longer than 12 years, maximising the period to enhance the power of the findings. The more contemporary dataset was chosen to make the findings more applicable given the surge in retail investing following the financial crisis, but a longer time span may highlight differing results or additional information that contributes to the findings. A longer time span may also allow for sub-sample analyses to investigate the performance of the momentum strategies proposed on during different business cycles.

A second limitation is the heavy use of averages when conducting transaction cost analysis. A subsample analysis on strategies employing the various transaction costs would provide a valuable extension to the understanding of the robustness of returns against market frictions. Moreover, the transaction costs do not take portfolio turnover into account, doing so would improve the accuracy of the application of such costs and provide a more comprehensive overview of their detrimental effects. These limitations with regards to the application of transaction costs in this investigation are due to time constraints which compromised the deeper analysis of market frictions.

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## APPENDIX A – Annualized Portfolio Returns

*Annualized Portfolio Returns Adjusted Against the Risk-Free Rate*

| Portfolio Size | S&P | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| 3 / 3 | 0.096 | 0.118 | 0.152 | 0.145 | 0.124 | 0.110 | 0.114 |
| 3 / 6 | - | 0.184 | 0.146 | 0.147 | 0.139 | 0.138 | 0.134 |
| 3 / 9 | - | 0.154 | 0.144 | 0.121 | 0.118 | 0.123 | 0.118 |
| 3 / 12 | - | 0.180 | 0.169 | 0.147 | 0.143 | 0.147 | 0.139 |
| 6 / 3 | - | 0.117 | 0.178 | 0.153 | 0.148 | 0.145 | 0.134 |
| 6 / 6 | - | 0.221 | 0.179 | 0.163 | 0.153 | 0.147 | 0.147 |
| 6 / 9 | - | 0.154 | 0.168 | 0.162 | 0.155 | 0.139 | 0.142 |
| 6 / 12 | - | 0.209 | 0.212 | 0.195 | 0.181 | 0.169 | 0.164 |
| 9 / 3 | - | 0.222 | 0.201 | 0.184 | 0.171 | 0.163 | 0.160 |
| 9 / 6 | - | 0.286 | 0.248 | 0.222 | 0.206 | 0.194 | 0.187 |
| 9 / 9 | - | 0.207 | 0.182 | 0.166 | 0.167 | 0.166 | 0.165 |
| 9 / 12 | - | 0.294 | 0.263 | 0.239 | 0.215 | 0.205 | 0.193 |
| 12 / 3 | - | 0.258 | 0.241 | 0.213 | 0.204 | 0.195 | 0.195 |
| 12 / 6 | - | 0.287 | 0.243 | 0.222 | 0.207 | 0.201 | 0.190 |
| 12 / 9 | - | 0.293 | 0.252 | 0.226 | 0.212 | 0.207 | 0.192 |
| 12 / 12 | - | 0.270 | 0.249 | 0.227 | 0.217 | 0.206 | 0.191 |
| **Portfolio Size** | **7** | **8** | **9** | **10** | **15** | **20** | **30** |
| 3 / 3 | 0.121 | 0.115 | 0.106 | 0.108 | 0.103 | 0.101 | 0.086 |
| 3 / 6 | 0.135 | 0.125 | 0.120 | 0.125 | 0.115 | 0.106 | 0.093 |
| 3 / 9 | 0.117 | 0.113 | 0.109 | 0.105 | 0.088 | 0.089 | 0.085 |
| 3 / 12 | 0.135 | 0.122 | 0.115 | 0.112 | 0.105 | 0.099 | 0.095 |
| 6 / 3 | 0.130 | 0.131 | 0.135 | 0.134 | 0.121 | 0.111 | 0.092 |
| 6 / 6 | 0.144 | 0.150 | 0.147 | 0.145 | 0.132 | 0.122 | 0.099 |
| 6 / 9 | 0.143 | 0.140 | 0.141 | 0.139 | 0.121 | 0.112 | 0.096 |
| 6 / 12 | 0.161 | 0.170 | 0.161 | 0.159 | 0.137 | 0.125 | 0.114 |
| 9 / 3 | 0.168 | 0.159 | 0.153 | 0.146 | 0.128 | 0.115 | 0.093 |
| 9 / 6 | 0.181 | 0.177 | 0.174 | 0.167 | 0.144 | 0.131 | 0.107 |
| 9 / 9 | 0.166 | 0.161 | 0.158 | 0.155 | 0.141 | 0.130 | 0.110 |
| 9 / 12 | 0.190 | 0.184 | 0.180 | 0.174 | 0.154 | 0.140 | 0.118 |
| 12 / 3 | 0.187 | 0.181 | 0.172 | 0.170 | 0.147 | 0.135 | 0.116 |
| 12 / 6 | 0.182 | 0.178 | 0.170 | 0.164 | 0.145 | 0.133 | 0.117 |
| 12 / 9 | 0.187 | 0.184 | 0.173 | 0.169 | 0.151 | 0.138 | 0.122 |
| 12 / 12 | 0.182 | 0.177 | 0.169 | 0.163 | 0.146 | 0.132 | 0.119 |

Table 1: *The annualized returns of each strategy are adjusted against the risk-free rate (10-year US treasury yield). The leftmost column lists the J / K strategies highlighting the formation and holding periods, respectively. The portfolio size rows indicate the number of positions which comprise the portfolio for that given strategy.*

## APPENDIX B – Annualized Portfolio Standard Deviations

| *Annualized Portfolio Standard Deviations of Returns* | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Portfolio Size** | **S&P** | **1** | **2** | **3** | **4** | **5** | **6** |
| 3 / 3 | 0.219 | 0.670 | 0.630 | 0.502 | 0.388 | 0.317 | 0.326 |
| 3 / 6 | | 1.028 | 0.630 | 0.517 | 0.466 | 0.426 | 0.399 |
| 3 / 9 | | 0.739 | 0.571 | 0.385 | 0.364 | 0.334 | 0.307 |
| 3 / 12 | | 0.900 | 0.699 | 0.477 | 0.426 | 0.438 | 0.399 |
| 6 / 3 | | 0.605 | 0.789 | 0.600 | 0.519 | 0.482 | 0.442 |
| 6 / 6 | | 1.275 | 0.803 | 0.682 | 0.561 | 0.486 | 0.494 |
| 6 / 9 | | 0.762 | 0.738 | 0.629 | 0.562 | 0.448 | 0.439 |
| 6 / 12 | | 1.207 | 1.033 | 0.824 | 0.695 | 0.585 | 0.545 |
| 9 / 3 | | 1.223 | 1.039 | 0.804 | 0.657 | 0.593 | 0.561 |
| 9 / 6 | | 2.349 | 1.601 | 1.199 | 0.974 | 0.830 | 0.747 |
| 9 / 9 | | 1.114 | 0.799 | 0.620 | 0.585 | 0.573 | 0.566 |
| 9 / 12 | | 2.596 | 1.743 | 1.300 | 1.015 | 0.902 | 0.785 |
| 12 / 3 | | 2.121 | 1.545 | 1.098 | 0.963 | 0.839 | 0.799 |
| 12 / 6 | | 2.485 | 1.613 | 1.193 | 0.996 | 0.893 | 0.788 |
| 12 / 9 | | 2.668 | 1.699 | 1.234 | 1.055 | 0.958 | 0.837 |
| 12 / 12 | | 2.213 | 1.627 | 1.197 | 1.051 | 0.933 | 0.788 |
| **Portfolio Size** | **7** | **8** | **9** | **10** | **15** | **20** | **30** |
| 3 / 3 | 0.342 | 0.311 | 0.278 | 0.281 | 0.252 | 0.240 | 0.203 |
| 3 / 6 | 0.393 | 0.357 | 0.338 | 0.344 | 0.292 | 0.263 | 0.224 |
| 3 / 9 | 0.302 | 0.299 | 0.280 | 0.265 | 0.223 | 0.218 | 0.195 |
| 3 / 12 | 0.370 | 0.322 | 0.297 | 0.291 | 0.266 | 0.255 | 0.233 |
| 6 / 3 | 0.385 | 0.380 | 0.404 | 0.393 | 0.336 | 0.289 | 0.227 |
| 6 / 6 | 0.450 | 0.473 | 0.452 | 0.441 | 0.364 | 0.322 | 0.242 |
| 6 / 9 | 0.419 | 0.395 | 0.400 | 0.386 | 0.314 | 0.282 | 0.227 |
| 6 / 12 | 0.523 | 0.576 | 0.521 | 0.514 | 0.397 | 0.350 | 0.302 |
| 9 / 3 | 0.570 | 0.515 | 0.492 | 0.441 | 0.351 | 0.300 | 0.232 |
| 9 / 6 | 0.685 | 0.640 | 0.625 | 0.566 | 0.435 | 0.376 | 0.285 |
| 9 / 9 | 0.553 | 0.511 | 0.498 | 0.473 | 0.390 | 0.346 | 0.269 |
| 9 / 12 | 0.751 | 0.696 | 0.680 | 0.619 | 0.489 | 0.413 | 0.319 |
| 12 / 3 | 0.717 | 0.671 | 0.601 | 0.584 | 0.445 | 0.375 | 0.298 |
| 12 / 6 | 0.702 | 0.651 | 0.589 | 0.552 | 0.431 | 0.371 | 0.307 |
| 12 / 9 | 0.767 | 0.712 | 0.627 | 0.592 | 0.462 | 0.389 | 0.324 |
| 12 / 12 | 0.717 | 0.667 | 0.603 | 0.563 | 0.451 | 0.377 | 0.317 |

Table 2: *The annualized standard deviations of risk-adjusted returns are calculated per portfolio. The leftmost column lists the J / K strategies highlighting the formation and holding periods, respectively. The portfolio size rows indicate the number of positions which comprise the portfolio for that given strategy.*