1/N – Does it have momentum?

Bachelor thesis

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Abstract

This study compares the momentum strategy with the naive benchmark, also known as the 1/N rule, proposed by DeMiguel, Garlappi, & Uppal (2009). The strategies formed based on monthly data over the period of 2000 to 2018 retrieved from the CRSP/Compustat Merged Database. Three performance criteria are used to compare the performance of the momentum strategies with the naive rule. The average monthly excess return of each strategy, the monthly Sharpe ratio of each strategy and the certainty equivalent return of each strategy. The results from the analysis of this study show that the naive strategy did not constituently outperform the momentum strategies. Stock momentum was still present in the sample used on the subsequent momentum strategies performed relatively well compared to the naive benchmark.

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1. Introduction

If you want to start investing today there many strategies you can adapt to, to invest your wealth in an optimal manner. Some of these strategies include pairs trading, momentum strategies, mean-variance assets allocation and minimum-variance. A lot of these models claim, and prove, they can achieve abnormal returns. This means that the return these models perform significantly better than what is expected based on the standard asset pricing model.

In 2009 DeMiguel, Garlappi, & Uppal wrote a paper were they tested the performance of 14 strategic asset allocation models against a naive rule. All the 14 models compared with the naive rule were consistently outperformed by the naive rule. The naive rule, also known as the 1/N rule or 1/N strategy, simply states that for the construction of your portfolio, you assign 1/N weight to each of the N assets in your portfolio. This means that all N assets are equally weighted into the investment portfolio. For example, if you have a total wealth of 100 euro at your disposal and there are 5 assets to invest in, according to the 1/N rule you need to invest 20 euro in each asset. To compare the performance of these 14 models with each other and with the naive rule they used a number of performance measurements, these include the out-of-sample Sharpe ratio, the turnover for each portfolio strategy and the certainty-equivalent (CEQ) return for the expected utility of a mean-variance investor. One of the suggestions DeMiguel et al. (2009) provided for further research is to use the 1/N strategy as a benchmark for other portfolio optimization models. Creating a simple benchmark to test the performance of optimal asset allocation models can be of value since it makes comparison simpler and more intuitive to understand and thus can be used by more investors than just the professional investors.

One of the models DeMiguel et al. did not cover in their paper is the momentum strategy developed by Jegadeesh & Titman (1993). During the literature research no literature was found that compared the 1/N benchmark proposed by DeMiguel et al. (2009) with the momentum strategy. The momentum strategy is a strategy were an investor goes long in stocks that have performed good in the past 3 to 6 months, so called winners, and short in stocks that have performed bad in the past 3 to 6 months, so called losers. Jegadeesh & Titman (1993) found that constructing these momentum portfolios generate significant abnormal returns. That is, returns that are significantly greater than the expected return based on the asset pricing model. Considering the suggestion by DeMiguel et al. (2009) and that no literature has been written on the comparison of the momentum strategies with the naive rule and the apparent superior performance of the naive rule, the following central research question will be studied in this paper:

How does the momentum strategy perform relative to the 1/N benchmark proposed by DeMiguel et al. (2009)?

The rest of this paper will be structured as follows. First, a theoretical framework will be constructed to see what relevant research has already been performed on this topic. Based on the knowledge gained in the literature review several hypotheses will be formed. Next, there will be a description of the data that is used in this research and the methodology applied in the analysis. After this the results of the analysis will be described and discussed. Finally, a conclusion will be drawn based on the results and there will be a last critical look casted on the paper and its results.

2. Theoretical framework

2.1 What is asset allocation?

Before asset allocation can be described, it is necessary to first define what an investment portfolio is. An investment portfolio is the collection of all the securities an investor has invested in. There is a large variety of securities to invest in. However, the most common investments are in stocks and bonds. To optimize the performance of an investment portfolio Markowitz (1952) proposed to value a portfolio based on the risk, measured as the variance of the portfolio, and the return of the portfolio. One key element of his portfolio theory involves the diversification of a portfolio. Diversification means that you invest in different assets such that you minimize the exposure to specific assets within your portfolio. For example, when you invest in the stocks of a ski-resort you should also invest part of your wealth in the stocks of an ice-cream factory. In this case the stock specific risk, the weather, will be compensated by the diversification. Markowitz (1952) argued, and proved, that by diversifying a portfolio, an investor can achieve the same or even a higher return on a diversified with the same risk as the undiversified portfolio. Over the years this mean-variance optimization has been researched by many economists and investors.

2.2. Relationship between asset allocation and performance: empirical results

Creating a portfolio and investing requires a lot of decisions. An investor needs to set a goal and decide on an investment policy. Moreover, an investor also needs to select securities and find a good timing in the market to trade the selected securities. According to Brinson, Hood, & Beebower (1995) the most important determinant of portfolio performance is the investment policy. That is, the selection of assets and the assignment of weights to each of these assets. What is more, Brinson et al. (1995) also found that the asset allocation decision accounts for 90 percent of the portfolio return variation. However, this percentage has been widely debated in the literature. In their paper Xiong, Ibbotson, Idzorek & Chen (2010) conducted a time-series analysis on the determinants of the variability in the performance of portfolios. In their research only about 20 percent of the variation in performance is due to the asset allocation policy. The reason for this large difference is because they also included market movement as one of the determinants. Ibbotson (2010) concluded, after reviewing the literature including the research of Xiong et al. (2010), that investors should discard the idea that asset allocation policy can account for up to 90 percent of the portfolio performance variation. Nevertheless, asset allocation policy is still an important determinant portfolio performance variation. When comparing different strategic asset allocation strategies with each other one should take the market movement into account and look in the differences the variation that are not explained by the market. Since these are most likely the variations that can be influenced by an individual investor. Market variation is a given since it cannot be influenced by an individual investor. So even though the asset allocation policy might not be the most influential factor for the performance variation of a portfolio, it is one of the most important decisions an investor can decide on that influences the return variation of a portfolio.

As briefly mentioned before, there are a lot of investment strategies developed over the years. Each trying to optimize the performance of the portfolio. Moreover, some strategies that have been developed over the years also state that they can beat the market. That is, getting a significantly higher return than the market. The relative strength strategy or momentum strategy developed by Jegadeesh & Titman (1993) claims that by going long in stocks that have performed well over the last 3 to 12 months will continue to perform well for the next 3 to 12 months and the opposite holds for the stocks that have performed bad over the last 3 to 12 months. Buying these “winner” stocks and selling these “loser” stocks a resulted in a significant positive return in excess of the market. Both the naive strategy and the momentum strategy do not advise on security selection, rather, they state what the weights of the securities in a portfolio should be. This makes the naive rule an interesting benchmark since it does not follow a strategy for security selection, this is solely dictated by the sample chosen. The momentum strategy, on the contrary, does follow a strategy to specify the weights of each of the assets in the portfolio since it matters whether a stock has a positive or negative momentum.

Since there is no estimation needed for the naive rule there is no risk of an estimation error. That is, the difference between the estimated return and the actual return. In their research Klein & Bawa (1976) show that when taking estimation risk into consideration investors can choose different portfolios than when estimation risk is not taken into consideration. Estimation risk can be a serious problem to strategic asset allocation models as DeMiguel et al. (2009) also demonstrated in their research. They looked at the severity of the estimation error by looking at the differences between the returns of the in-sample estimation and out-of-sample estimation error. Even for model's that explicitly try to minimize this estimation error, the difference can still be large.

Although the momentum strategy takes a 3 to 12 months to estimate the optimal portfolio, there is no exact estimation of the return, only a prediction on the relative performance of stocks. Thus, there is no estimation risk. However, it does make predictions on the future performance of stocks, and hence, it can be empirically tested if these predictions are true. Neither Jegadeesh & Titman (1993) nor Rouwenhorst (1998) examine the performance of the momentum strategy out-of-sample by constructing a rolling window. This leaves the risk of an estimation error. In fact, in their paper Chan, Jegadeesh, & Lakonishok (1996) argue that the momentum strategy might not even work out-of-sample. The reasons to concern for this estimation risk is that the model you are using for asset allocation might lead to inefficient use of capital and thus another model might have been more . There is however some positive literature on the estimation error. Lewellen & Shanken, (2000) argue in their paper that estimation risk can be of predictive value to an asset pricing model. The world is inherently noisy which will inevitably lead to wrong predictions.

2.3 What is the momentum strategy

As mentioned in the introduction, the momentum strategy is a strategy were an investor goes long in stocks that have performed good in the past 3 to 6 months, so-called winners, and short in stocks that have performed bad in the past 3 to 6 months, so called losers. The reason for constructing this strategy is because Jegadeesh & Titman (1993) found that there is return persistence on the medium term. That is, the stocks with a relatively high performance continue to perform well over the next 3- to 12-months. The momentum strategy defies the weak form of the efficient market hypothesis (EMH) developed by Malkiel & Fama, (1970). Most importantly, because it should be possible to predict the direction of future stock prices based on their past performance in the weak form of the EMH. Since, the performance of the momentum strategy seems to contradict the EMH it is called a market anomaly. In the weak form of the EMH historic stock prices does not contain any information about the future performance of these stocks. This level of information efficiency makes it impossible to outperform the market since all information us already incorporated into the stock prices. More evidence against the EMH was provided by Jegadeesh (1990) he constructed 10 decile portfolios based on predicted performance of stocks and found a significant difference between the extreme decile portfolios. This research provided more evidence for the later formed Momentum strategy developed by Chan et al. (1996).

According to the classic investment theory a stock should always return to its intrinsic value in the long-run. Markowitz (1991) argued that, following the logic of John Burr Williams book; *The Theory of Investment Value*, investors want to maximize the expected value of their portfolio by optimizing the trade-off between risk and return.
A stock can however deviate from its intrinsic value. One reason why stocks seem to deviate from their intrinsic value is because most people seem to overreact to random, unexpected, dramatic events. De Bondt & Thaler, (1985) found evidence for this systematic overreaction hypothesis. They found that portfolios consisting of stocks that have performed bad over the past 36 months, so called losers portfolios, outperform portfolios of stocks that have performed well over the past 36 months, 36 months after formation. Interestingly, the opposite holds for a shorter period of time as explained by Jegadeesh & Titman, (1993), Chan, Jegadeesh, & Lakonishok, (1996), Rouwenhorst, (1998). However, both papers could not explain as to why there seem to be a systematic over or underreaction by the market and why it appears in the patterns that these anomalies show. Jegadeesh & Titman (1993) suggest that one area where this explanation might be found is the behavior of individual investors. Further research done by Jegadeesh & Titman (2001) found the momentum strategy also still worked in an updated sample, providing more evidence in favor of the momentum strategy. What is more, their research also strengthens the idea that one of the most important cause of the momentum anomaly is to be found in the behavior of investors.

2.4 Relationship between momentum strategy and performance: empirical results

Following the literature reviewed so far it might seem that there is no strategic asset allocation model that is able to outperform the simple naive benchmark so far. Based on the literature so far, it looks as if the 1/N benchmark is very hard to outperform. DeMiguel et al. (2009).

Bloomfield, Leftwich, & Long (1977) also compared the naive strategy to more complex asset allocation strategies and found that the complex strategies were not able to outperform the naive strategy in-sample. The research by Bloomfield et al. (1977) seems to strengthen the case that the naive benchmark is still the most superior strategy. However, the results from these two papers are interesting because they both use more complex mean-variance optimization models.

The momentum strategy is not a complex strategy since it does not rely on any elaborate statistical procedures or predictions, just like the naive benchmark. In their paper Jegadeesh & Titman (1993) state that the profit of their relative strength portfolios is not due to systematic risk. So how will it compare to the naive benchmark against the performance criteria used by DeMiguel et al. (2009)? Another reason to be skeptical about the performance of the momentum strategy is because the behavior of investors can change over time. As mentioned by Jegadeesh & Titman (2001) one of the most important reasons for the momentum strategy to exist is the behavior of investors. Hence, if markets are efficient, and investors thus notice that the momentum strategy can achieve abnormal higher returns, they might start to anticipate on this phenomenon and thus reducing the effect of the momentum strategy.

There is, however, also critique on the naive benchmark as used by DeMiguel et al. (2009), Kirby & Ostdiek (2012) They argue that the results of DeMiguel et al. (2009) are mainly due to the design of their research and create a negative bias towards the mean-variance optimization. Kirby & Ostdiek (2012) propose two new sets of strategies that do seem to outperform the naive benchmark, both in-sample and out-of-sample, even after adjusting for the transaction costs of the portfolios.

2.5 Benchmark: 1/N vs. price momentum

In short, the naive benchmark is a useful benchmark because it is simple to interpret and simple to execute as well. Moreover, its remarkably good performance relative to the more sophisticated models appears to make it a relevant strategy to take into consideration when an investor needs to decide on optimal asset allocation. Now, it should be emphasized that the naive benchmark should not be the only benchmark used when choosing a specific asset allocation model. Rather, it should be complimentary to the strategic asset allocation decision and help to improve current and optimal asset allocation models. Moreover, as Kirby & Ostdiek (2012) demonstrate, we should be looking critical to the results of the naive benchmark and make sure the research is designed in such a way that it does not has a bias towards any of the strategies tested. To conclude this literature review, based on the literature, the following three hypothesizes are expected to hold:

H1: The naive strategy will consistently outperform the momentum strategy in terms of excess returns

H2: The momentum strategy will not be able to consistently outperform the naive benchmark based the Sharpe ratio

H3: The momentum strategy will not be able to consistently outperform the naive benchmark based the certainty equivalent return

3. Data & Methodology

In this study the methodology for performance evaluation of DeMiguel et al. (2009) will be replicated as closely as possible. This section will start with a brief overview of the data used and the transformation applied to this data to make it operational for the analysis. Next the methodology behind the construction of the portfolios will be presented. Finally, the methodology of the performance criteria will be discussed.

3.1 The Data

The data used for this research was retrieved from the CRSP/Compustat Merged Database and contains all stocks from the listed on the New Yorks Stock Exchange, American Stock Exchange and the NASDAQ Stock Market for the period 2000 – 20018. The dataset contains a total of 11135 stocks. It should be noted that not all stocks are present over the entire length of the sample period. Some stocks will be listed during the sample period, and some stocks will be delisted during the sample period. Figure 1 displays the total number of stocks listed each month for the entire sample. The average number of stocks listed per month is 5264, the minimum number of stocks listed per month is 4945, the maximum number of stocks listed per month is 5918. For each stock the total return per month will be used for this research.

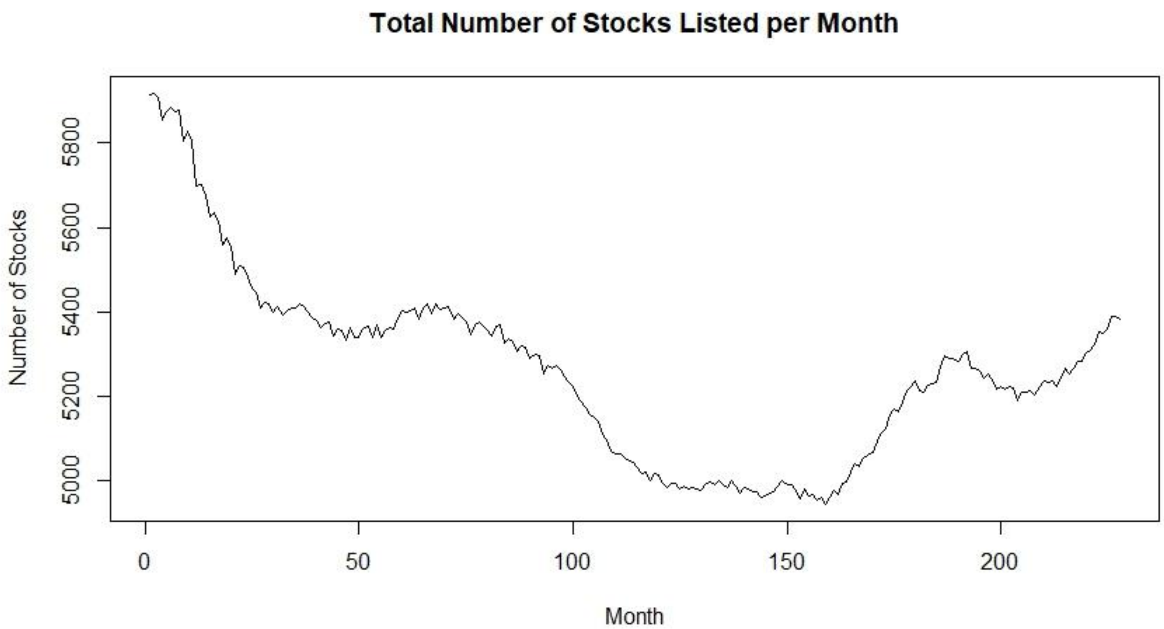

Figure 1: Total Number of Stocks Listed per month. This figure contains the total number of stocks listed per month over the period 2000 to 2018. Each month is displayed as number. Month 0 is 01/01/2000 and month 228 is 31/12/2018.

Total return includes the changes in price of the stock plus the return of cash equivalent distributions and the compounding effect of reinvested dividend of the stock. Two transformations will be applied to the data. First, the total return will be transformed into total excess returns by subtracting the monthly risk-free rate provided by the Kenneth. R. French library. Next, variables will be created containing the compounded 3-, 6-, 9-, and 12-month total excess return for each stock for each month using the following formula:

$$Cr_{s,i,k} = \prod_{k}^{i}(1 + tter_{s,i})$$

Here s is the stock, i is the month and k is the number of months to compound. Thus k = i - x, where x can be either 3, 6, 9, or 12. Moreover, $tter_{s,i}$ is the total excess return of stock s in month i and finally $Cr_{s,i,k}$ is the k month compounded return for stock s from month k to i.

3.2 Portfolio Construction

1/N Strategy

The 1/N Portfolio will be solely based on the number of stocks available each month in the dataset used for this analysis. Every month the weight of each asset in the portfolio will be determined by $\frac{1}{N_i}$ where N_i is the number of stocks N available in month i.

For each of the momentum strategies there will be a 1/N portfolio constructed over the same period. The reason for this is that not all momentum strategies will be able to be applied over the entire sample period duo to both the ranking and holding periods.

The Momentum Portfolios

The momentum portfolios or relative strength portfolios will be constructed as described in the paper of Jegadeesh & Titman (1993). First, all stocks will be ranked based on their past k performance ranking periods, where k can be 3-, 6-, 9-, and 12-months. Based on their past k-month performance each stock will be put into a decile. With this data two portfolios will be constructed for each of the k performance ranking periods, a winner and a loser portfolio.
A winner portfolio which consists of all the stocks in the highest performing decile, that is the 10% highest performing stocks of the past k performance ranking period. A loser portfolio consists of the stocks in the worst performing decile, that is the 10% worst performing stocks of the past k performance ranking period. All stocks within these two portfolios will be equally weighted. Next, both portfolios will be held for 3, 6, 9, and 12 months. As a result of this methodology 32 portfolios will be constructed, 16 winner portfolios and 16 loser portfolios. This process will be repeated for each possible month in the sample. For example, the winner strategy with a ranking period of 3 months and a holding period of 3 months can be repeated for 223 out of the 228 months in the sample. After this, the average monthly performance of each strategy will be calculated. The following formula will be used to calculate the average monthly performance:

$$AMR_{i,h} = \left(\frac{SD_{d,i,h}}{N_d}\right)^{\frac{1}{h}}$$

Here i is the month, h is the holding period, d is the decile, h is the holding period and N_d is the number of stocks in the decile d. $SD_{d,i}$ is calculated as follows:

$$SD_{d,i,h} = \sum Cr_{s,i,h,d}$$

Here d is the decile, i is the month, s is the stock, h is the holding period and $Cr_{s,i,h,d}$ is the average compounded return of decile d, h month after month i. Following this the average monthly excess return of 32 strategies will be calculated. According to Jegadeesh & Titman

(1993) the winner strategy should outperform the loser strategy on the medium term, that is, up to 12 months.

3.3 Portfolio Performance Methodology

Winner – Loser

Once the winner and loser portfolios are formed, they can be compared with each other. To do this, the average monthly excess return of the loser strategy will be subtracted from the average monthly excess return of the winner strategy with the same ranking and holding period.

In the absence of transaction costs, this strategy could be considered a zero-investment strategy. If a short position is taken into the loser portfolio and this money is subsequently used finance a long position in the winner portfolio of the same strategy, a portfolio will be created that requires no investment. For the rest of this paper, this portfolio will be referred to as the winner – loser strategy. To compare this winner – loser strategy with the 1/N strategy, a t-test will be performed to check whether the difference between the performance of the 1/N portfolios and the winner – loser portfolios is significantly different from zero.

Sharpe Ratio

A Sharpe ratio will be computed for each of the portfolios to gain a better insight into the relationship between the risk and return of each of these strategies. The following formula will be used to calculate the Sharpe ratios for each of the strategies

$$SR_k = \frac{\mu_k}{\sigma_k}$$

Where SR_k is the Sharpe ratio of strategy k, μ_k is the mean excess return of strategy k and σ_k is the standard deviation of strategy k.

Certainty Equivalent Units (CEQ) return

For each strategy a certainty equivalent return (CEQ return) will be calculated. The CEQ return can be interpreted as the risk-free return that would make an investor indifferent between investing in the strategy k and the CEQ return. The following formula will be used to calculate the CEQ:

$$CEQ_k = \mu_k - \frac{\gamma}{2}\sigma_k^2$$

Here CEQ_k is the certainty equivalent unit return of strategy k, μ_k is the mean of the excess return of strategy k , σ_k^2 is the variance of excess returns of strategy k. γ is the risk aversion of an investor who only takes the mean and the variance of a portfolio into consideration. Risk aversion is inherently difficult or even impossible to measure and thus γ should not be interpreted as a precise measurement of the risk aversion of an individual investor, but rather as the degree of risk-aversion of an investor. The higher γ, the more risk-averse an investor is. For the rest of the analysis it is assumed that γ=1 for every strategy. This is in line with the methodology of DeMiguel et al. (2009) and thus makes comparison with their paper more intuitive. Moreover, for the analysis in this paper it is more important to see the differences between each strategy for a given degree of risk-aversion instead of the effect of risk aversion on the strategies.

4. Results

The results of the analysis will be discussed in three parts. First, the returns of each strategy will be evaluated and compared to the other strategies. Next, to gain more insight into the risk-return relationship of each of the strategies the Sharpe ratios of each strategy will be discussed. Lastly, to get a better insight in the risk aversion of investors for each of the strategies, the certainty equivalent returns of each strategy will be discussed.

4.1 Returns Performance

Table 1: Returns of all Strategies. In this table the average excess returns per month of all strategies can be found. Moreover, for each winner – loser strategy a t statistic has been computed to test whether the difference between the winner – loser strategy and the 1/N strategy is significantly different from 0. The sample period is January 2000 to December 2018

		Returns of all Strategies			
		Holding Period			
Ranking Period	Strategy	3	6	9	12
3	1/N	0.012	0.012	0.012	0.012
	Loser	0.005	0.009	0.012	0.016
	Winner	0.021	0.014	0.015	0.019
	Winner - Loser	0.016	0.005	0.003	0.003
	(t-stat)	*1.09*	*-1.74*	*-2.17*	*-2.04*
6	1/N	0.012	0.012	0.012	0.012
	Loser	-0.034	0.007	0.011	0.016
	Winner	0.059	0.018	0.016	0.017
	Winner - Loser	0.093	0.011	0.005	0.000
	(t-stat)	*20.46*	*-0.26*	*-1.79*	*-3.00*
9	1/N	0.012	0.012	0.012	0.012
	Loser	-0.030	-0.008	0.008	0.017
	Winner	0.057	0.033	0.019	0.018
	Winner - Loser	0.086	0.041	0.011	0.001
	(t-stat)	*19.02*	*7.94*	*-0.28*	*-2.72*
12	1/N	0.013	0.013	0.013	0.013
	Loser	-0.020	-0.020	0.003	0.014
	Winner	0.046	0.045	0.025	0.020
	Winner - Loser	0.067	0.064	0.023	0.006
	(t-stat)	*13.85*	*13.72*	*2.45*	*-1.78*

In table 1 the average monthly excess returns of all the strategies researched in this paper can be found. The performance of the 1/N strategy is in the range of .012 and .013. The average monthly excess return of the 1/N strategies does only slightly increase for the strategies with a ranking period of 12 months. For all the other strategies the monthly excess returns are approximately .012. They are, however, not exactly the same due to the differences in the sample period used to calculate each of the returns.

All the loser strategies show an increase in average monthly excess returns with an increase in the holding period. An increase in the ranking period does not result in an increase in an average monthly return for all the loser portfolios. The profit maximizing loser strategy is the strategy with a ranking period of 3 months and a holding period of 12 months.

The holding period appears to have the opposite effect on the returns of the winner strategies. Although not as clear as with the loser strategy, for most strategies there appears to be a decrease in the average monthly return with an increase in the holding period. The effect of the ranking period, again, is more difficult to interpret. There does not seem to be a relationship between the performance of a strategy and the ranking period. The winner – loser, or zero-costs, strategy seems to follow the opposite pattern as the loser strategy. That is, the performance decreases with an increase in the holding period. This holds for all the strategies. Again, the ranking period does not have a clear effect on the performance of the strategies. Lastly, the t-statistics were computed to see whether the difference between the returns of the momentum strategy were significantly different than those of the 1/N strategy. The null hypothesis here was that the difference is between the two strategies is equal to 0. The first thing to notice is the large dispersion in t-stats. The smallest t-stat is -3 whilst the largest is 20.46. Results like these should be handled with prudence since the difference may be caused by other factors than the strategy itself. For example, the risk factors used in the multifactor model of Fama & French (1993). The results might also be caused by individual, one-time cases instead of actual momentum. What is more, some strategies have a significantly negative difference, meaning that the momentum strategy is outperformed by the 1/N strategy. In general, the results of the t-stats show an inconsistent performance pattern for the momentum strategy. It should be noted however, that the momentum strategy is a zero-investment strategy in this setting, and thus that only looking at the returns would not yield an optimal performance comparison of these strategies. Economically it would be more interesting to invest minimal for a maximal return and so in this context the momentum strategy might outperform the 1/N strategy. One caveat however is the lack of the transaction costs in this analysis.

The results in table 1 have some differences with the findings of Jegadeesh & Titman (1993) and Rouwenhorst (1998). For example, neither found any negative average monthly excess returns for any of the strategies conducted in their research. While in this research 5 out of the 16 loser strategies have a negative monthly excess return. Despite the differences with the loser strategies, the winner strategies perform relatively the same as in the literature except for the winner strategies with a ranking period of 12 months. These winner strategies perform better than those found in previous literature.

One possible reason for this, is the difference in the samples used. Both Jegadeesh & Titman (1993) and Rouwenhorst (1998) use samples that of stock returns from before 2000, the first year of the dataset used for the analysis in this paper. Moreover, the difference needs to be significant. A significance test could be performed to see whether the differences are significantly different from each other. The true nature of the differences, however, is a topic for further research. For the 1/N strategy I was not able to find literature with a similar dataset used to compute the returns for the 1/N strategy. This would make a comparison prone to errors due to the differences in the datasets and thus no comparison could be conducted.

When comparing the returns of all strategies with that of the 1/N strategy one can see two clear patters. The first, is that the 1/N strategy does not always yield a higher return than the loser strategies. In fact, all loser strategies with a holding period of 12 months outperform the 1/N strategy. The opposite is true for the loser strategies with a holding period of 3 and 6 months. The winner strategies perform consistently better than the 1/N strategy in terms of monthly excess returns. Lastly, the 1/N strategy only outperform the winner – loser strategies in 7 out of the 16 cases. Thus, the 1/N strategy is not able to consistently outperform the momentum strategies in terms of excess return.

4.2 Sharpe Ratios of the Strategies

Table 2: Sharpe Ratios of all Strategies. For all the strategies constructed the Sharpe ratios are computed. Sharpe ratios are calculated by dividing the mean of the monthly excess returns of each strategy by the standard deviations of the monthly excess returns of that strategy. The higher the Sharpe ratio the better the trade-off between risk and return. The sample period is January 2000 to December 2018.

		Sharpe Ratios			
		Holding Period			
Ranking Period	Strategy	3	6	9	12
3	1/N	0.2298	0.2295	0.2260	0.2291
	Loser	0.1221	0.3418	0.5136	0.6834
	Winner	0.6600	0.5816	0.5179	0.6090
	Winner - Loser	0.7291	0.2241	0.1015	0.0847
6	1/N	0.2413	0.2411	0.2376	0.2408
	Loser	-0.7040	0.2367	0.4707	0.6601
	Winner	1.5488	0.8968	0.5667	0.9088
	Winner - Loser	3.1475	0.6137	0.1740	0.0186
9	1/N	0.2322	0.2319	0.2284	0.2315
	Loser	-0.6936	-0.2606	0.3335	0.6229
	Winner	1.4091	1.5341	0.6667	0.9465
	Winner - Loser	3.0873	2.1554	0.3593	0.0315
12	1/N	0.2527	0.2525	0.2491	0.2525
	Loser	-0.4997	-0.6345	0.1006	0.5803
	Winner	1.1679	1.6252	0.8936	1.0623
	Winner - Loser	2.4778	3.1186	0.7854	0.2698

In table 2 the Sharpe ratios of each strategy tested in this research are presented. The Sharpe ratios of the 1/N strategy are in the range from .2260 to .2527. The difference is caused by the way the 1/N strategy is constructed as explained in the methodology section of this paper. The Sharpe ratios of the 1/N strategy in this research are in some cases almost twice as large as most of the Sharpe ratios found by DeMiguel et al. One possible reason for this difference can be the sample. Not only is the sample period different, but DeMiguel et al. also makes use of portfolios that account for certain risk factors such as the three-factor model developed by Fama & French (1993). For the loser strategy an increase in the holding period will, in general, lead to an increase in the Sharpe ratio. This holds for all ranking periods except the 12 month ranking period strategies as can be seen in the table. The Sharpe ratio of the loser portfolio first decreases from -.4997, for the loser strategy with a holding period of 3 months, to -.6345, for the loser strategy with a holding period of 6 months. Economically this makes sense. In table 1 you can see that the average excess return of both strategies is about the same. However, one strategy only needs 3 months to get the same returns as the one who needs 6 months.
Due to the longer investment period you will take more risk, however, this does not result in a higher return. Hence, your risk-return trade-off must be worse.
In general, however, the pattern makes somewhat less sense. A longer holding period will lead to greater risk and hence, one would expect the Sharpe ratios of the loser strategies to decrease with an increase in the holding period. One reason for this patterns is offered by De Bondt & Thaler (1985). They state that these loser stocks are underperforming in the short run and that in the long run there will be a reversal pattern were the underperforming stocks become the winning stocks and the winning stocks will become the losing stocks.
This, however, is true for the long run, that is at least three years after the formation period. Here there already seems to be a reversal of the loser strategy returns 6 months after the portfolio formation. However, this research does not contain any strategy with a holding period of more than 12 months and hence, it is not clear whether the performance of the loser portfolios keeps increasing with an increase in the holding period. More research seems to be necessary in the period between the 12- and 36-months holding period.
What is more, 5 out of the 16 loser strategies have a negative Sharpe ratio. This means that the trade-off between risk and return is negative, and that it makes economically no sense to invest in these strategies. However, shorting such a strategy, like the winner-loser strategy does, and investing that money into a winner strategy might yield a better performance than to simply go long in the winner strategy.

The winner strategies do not show any pattern related to the holding period. There does seem to be some pattern related to the ranking period, that is an increase in the ranking period leads to an increase in the Sharpe ratio. This, however, does not hold for the strategies with a holding period of 3 months. What is more, some increases seem to be very marginal and thus further research is needed to see if this pattern is significant. Sharpe ratios of the winner strategies are consistently better than those of the 1/N strategy. If the tradeoff between risk and return is your main concern, investing in a winner strategy is always more optimal than investing in the 1/N strategy. Again, transaction costs are not considered, and thus further research is needed to see whether it is also the most efficient strategy.

The winner – loser strategies appears to have to opposite pattern of the loser strategy. That is, an increase in the holding period will, in general, lead to a decrease in the Sharpe ratio. This is true for all strategies except winner – loser strategies with a 12-months ranking period. Here there is an increase in the Sharpe ratio from 2.4778, for the winner – loser strategy with a holding period of 3 months, to 3.1186, for the winner – loser strategy with a holding period of 6 months. In fact, the Sharpe ratio of the 12 months ranking and 6 months holding winner – loser strategy is one of the highest Sharpe ratios of all strategies. Economically this pattern makes sense since the returns of the winner – loser strategies are decreasing whilst the holding period increases. This decreasing the risk-return tradeoff and thus the Sharpe ratio.

Comparing the results of the 1/N strategy with the results of the momentum strategies it becomes clear that 1/N strategy does not consistently outperform any of the momentum strategies constructed in this research. Most notably are the results of the loser strategies. By increasing the holding period these strategies can turn a negative Sharpe ratio in one that outperforms the 1/N strategy. Moreover, the winner-loser strategy outperforms 11 out of the 16 cases. The ranking period appears to influence the Sharpe ratios. It is, however, difficult to state in what way the ranking period influences the performance of the strategies.

4.2 Sharpe Ratios of the Strategies

Table 3: Certainty Equivalent Returns (CEQ). In this table the monthly CEQ returns of all strategies constructed in this research. The number should be interpreted as the monthly risk-free return that makes the investor indifferent between the risky strategy and the risk-free return.

		Certainty Equivalent Returns (CEQ)			
		Holding Period			
Ranking Period	Strategy	3	6	9	12
3	1/N	0,010	0,010	0,010	0,010
	Loser	0,004	0,009	0,011	0,016
	Winner	0,020	0,014	0,014	0,019
	Winner - Loser	0,015	0,005	0,003	0,002
6	1/N	0,011	0,011	0,011	0,011
	Loser	-0,035	0,006	0,011	0,016
	Winner	0,059	0,018	0,015	0,017
	Winner - Loser	0,093	0,011	0,005	0,000
9	1/N	0,010	0,011	0,010	0,011
	Loser	-0,031	-0,008	0,008	0,016
	Winner	0,056	0,033	0,018	0,017
	Winner - Loser	0,086	0,041	0,010	0,000
12	1/N	0,011	0,011	0,011	0,012
	Loser	-0,021	-0,020	0,002	0,013
	Winner	0,046	0,044	0,025	0,019
	Winner - Loser	0,066	0,064	0,022	0,006

The results in table 3 show that the 1/N strategy performs within a range of .010 and .012. Reasons for these small deviations are most likely due to the differences in the samples used for each of the 1/N strategies. From the results of table 3 it is also clear that there are some differences with the CEQ returns of the 1/N strategy with the research done by DeMiguel et al. Just as with the results of the Sharpe ratios, the results from the 1/N CEQ returns from this research are sometimes twice as large as the ones resulted from the research of DeMiguel et al. The results from table 3 show the same similar patterns as the results from table 1 and 2 for the loser strategies. That is, the performance of the loser strategies increases with an increase in the holding period. Thus, an investor with the assumed risk-aversion experiencing a decrease in the risk of the loser strategy with an increase in the holding period.

For the winner strategies there does not appear to be a specific pattern in the CEQ returns.

The winner – loser strategy follows the opposite pattern of the loser strategy. An increase in the holding period leads to a decrease in the performance of the winner – loser strategy. Investors with the risk aversion assumed in this research are thus experiencing an increase in the risk of the winner – loser strategies with an increase in the holding period.

Another notable result in table 3 are the negative CEQ returns. This means that investors with the assumed risk-aversion in this paper are in these cases willing to except a negative risk-free rate, rather than investing in the risky strategy.

The ranking period appears to influence the performance of the momentum strategies. However, there is no clear pattern and thus further research is needed to see if the changes in CEQ returns are caused by a change in the ranking period.

The 1/N does not consistently outperform is momentum strategy in terms of the CEQ returns. It only outperforms 7 out of the 16 winner – loser strategies. Moreover, the winner strategy does consistently outperform is 1/N strategy in terms of the CEQ returns.

5. Conclusion

This paper investigated the performance of the momentum strategy relatively to the naive benchmark. The following central research question was investigated:

> *How does the momentum strategy perform relative to the 1/N benchmark proposed by DeMiguel et al. (2009)?*

The performance of the momentum strategy was compared to 1/N strategy using three performance criteria, the average monthly excess return, the monthly Sharpe ratio and the certainty equivalent return.

Based on the literature review three hypotheses were formulated who were further investigated in the analysis of this study. The first hypothesis stated that: *The naive strategy will consistently outperform the momentum strategy in terms of excess returns*. Based on the results of this study, it is concluded that the 1/N strategy did not yield a consistently outperformed the momentum strategy in terms of average monthly return. In fact, all loser strategies with a holding period of 12 months outperformed the 1/N strategy. Moreover, the winner strategies performed consistently better than the 1/N strategy in terms of monthly excess returns. Hypothesis 1 is thus rejected.

The second hypothesis developed based on results of other studies stated that: *The momentum strategy will not be able to consistently outperform the naive benchmark based the Sharpe ratio.* The results of this study show that the 1/N strategy did not consistently outperform the momentum strategies when using the Sharpe ratio as a performance criterion. What is more, the winner – loser strategy was able to outperform the naive benchmark in more than half of the cases. The second hypothesis is thus rejected.

The third and final hypothesis stated that: *The momentum strategy will not be able to consistently outperform the naive benchmark based the certainty equivalent return.*
The results of the analysis in this study show that the naive benchmark was also not able to consistently outperform any of the momentum strategies when comparison is done with the certainty equivalent return criterion. Thus, the third hypothesis is rejected. The 1/N strategy was not able to outperform the winner – loser strategy in over half of the cases. Another important finding of this research is the behavior of the loser strategies. For all the performance criteria in this researched the performance increased with an increase in the holding period. This indicated that the return reversal as identified by De Bondt & Thaler (1985) might start to develop before the 36 months. The winner – loser strategy shows the opposite pattern of the loser strategy. That is, in general there is a decrease in performance with an increase in the holding period. The ranking period on the other hand did not show any clear patterns in the performance of the strategies. There are, however, differences between the strategies with the same holding period but with different ranking periods.

Based on the results of the analysis, the 1/N benchmark preformed relatively poor compared to the momentum strategy. The 1/N strategy was not able to consistently outperform any of the momentum strategies using any of the performance criteria. Moreover, in most cases the 1/N strategy was outperformed by the momentum strategies. What is more, the persistence of stock returns was still present in the data used for this analysis, suggesting that it has still not disappeared from the market. Which could still make the winner – loser strategy an interesting strategy to investigate for investor who are interested in arbitrage and zero-investment strategies. The performance of the winner strategy does too make it an interesting strategy for investors to take into considerations when the investment strategy is being established. The naive strategy does make an interesting benchmark due to its simplicity. It can makes comparison with other strategies, like the momentum strategy, intuitive and straightforward.

Next to the possible implications of this study, it is also important to discuss the limitations of this study. The most important limitation of this study is the assumption of zero transaction costs. This makes it difficult to determine whether the strategies analyzed in this research have any practical implications. Hence, a suggestion for further research is to add a performance criterion that gives an indication of possible transaction costs of each strategy.

Another limitation of this research is the sample period used for the analysis. To be able to correctly compare the results with other studies, the sample period should be matched. This makes comparison prone to differences in the data used instead of differences in the results of the analysis of this study. A suggestion for further research would be to match the sample period of future research with at least one other study.

Lastly, some comparison could be improved by adding statistical power with more significance testing. For example, the differences between the results of the momentum strategies and the naive strategy could be tested. A suggestion for further research is thus, to add more significance tests when comparing a strategy with the naive benchmark.

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