The active vs passive: smart factors, market portfolio or both?

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Abstract

While there may be debates about passive and active investing, and even blogs about the numbers of active funds that were outperformed by the market, the history taught us that the outperformance of active or passive investing is cyclical. As a proxy for the active investing, the paper examines factor strategies and their smart allocation using fast or slow time-series momentum signals, the relative weights based on the strength of the signals and even blending the signals. While the performance can be significantly improved, using those smart approaches, the factors still got beaten by the market in both US and EAFE sample. However, the passive approach did not show to be superior. The factor strategies and market are significantly negatively correlated and impressively complement each other. The combined Smart Factors and market portfolio vastly outperforms both factors and market throughout the sample in both markets. With the combined approach, the ever-present market falls can be at least mitigated or profitable thanks to the factors.

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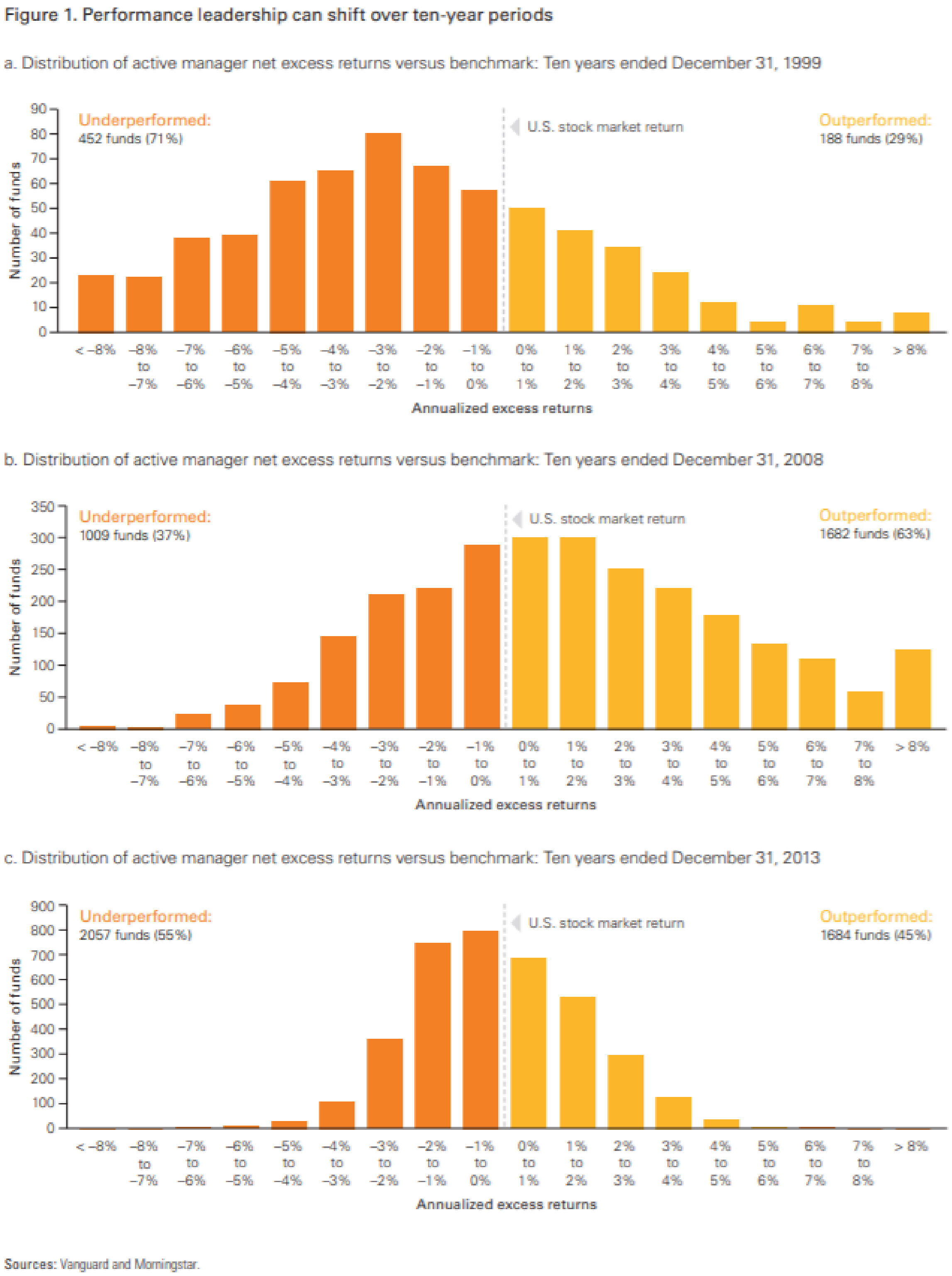
1. Introduction

In the equity market, there are two types of investing: active and passive. The aim of passive investors is to track the market with all the "ups" and "downs". The passive investing is simple; after all, the strategy consists of tracking the market by a buy-and-hold. Nowadays, it is easy to implement with the numerous ETFs, for example, by buying SPY ETF and getting exposure to the S&P500 index. Proponents state that in the long run, the equity market is going up. They do not try to beat the market, they bet on the market in the long run.

On the other hand, there is active management. The main aim of active investing should be to beat the market. Therefore, active investors aim to achieve better returns or risk-adjusted returns since the equity markets tend to be volatile. The passive investors should aim for a long horizon, and therefore, they should not panic when they experience the first drawdown. However, for many, it is desired that their investment would be more stable or safe. A major part of active investment management consists of factor (or smart beta) strategies. Equity factors include, for example, value, size, volatility, momentum or quality. With the numerous ETFs, it is also easy to get exposure to these factors through smart beta ETFs.

Having established that there are two major management styles and many factors, numerous questions arise. Firstly, there is a debate that is as old as investing itself, is active or passive investing better? There seems to be an unreasonable debate, many investing "experts" shame active investing stating that active managers often cannot beat the market. Indeed, the active management requires skill and knowledge, which can bring success, and outperform the market (either in total or risk-adjusted returns). On the other hand, passive management does not require much of the skill or knowledge and with low-cost brokers, and ETFs, it is widely accessible to retail investors. The truth lies somewhere in the middle. The performance of active and passive investing is cyclical. The periods of active (passive) outperformance rotate (see the following figure). Therefore, the answer to the question of which investing is better, changes in time. We should find a solution to a different problem, in which state of the market is it better to invest passively and in which state of the market is it better to invest actively? Another question that arises is whether we can use our active investing strategy to outperform the market consistently.



Active vs Passive investing leadership. Source: [4]

Considering active investing, if we get back to the factor investing, we have a similar ongoing debate. It is widely recognized that equity factors also have cyclical performance. Many argue that value is dead (which has already happened in the past), yet Blitz and Hanauer (2020) claim that value can be resurrected. Momentum is notoriously known for its crashes (Hanauer and Windmüller, 2020). Also, the size factor seems to have its problems (Blitz and Hanauer, 2020). On the other hand, quality appears to be emerging as a popular investment style, and it has even enjoyed outperformance compared to the other factor during the recent first Covid wave (Quantpedia, 2020).

Establishing that factor investing is not that straightforward and has cyclical performance, the aim of this paper is to find a profitable way how to invest in plenty of equity factors. Factors are obtained from the Alpha Architect's Factor Investing Data Library. The factors include Asset Growth, Beta, Book/Price, Cash Flow/Price, Debt Paydown Yield, Dividend/Price, Earnings/Price, EBIT/TEV, EBITDA/TEV, Financial Strength Score, Gross Profit, various Momentum measures (1m, 6m, 12m and 12m with the last month skipped), Repurchase Yield, Return on Assets, Return on Equity, Sales/Price, Shareholder Yield, Shareholder Yield with Debt, Size and Volatility. Therefore, the factor library includes all the major styles: Value, Momentum, Volatility, Quality and Size. We are interested in two markets: the US market that is represented by the top 1500 stocks and developed market (EAFE). Through the paper, the analysis is made for both markets.

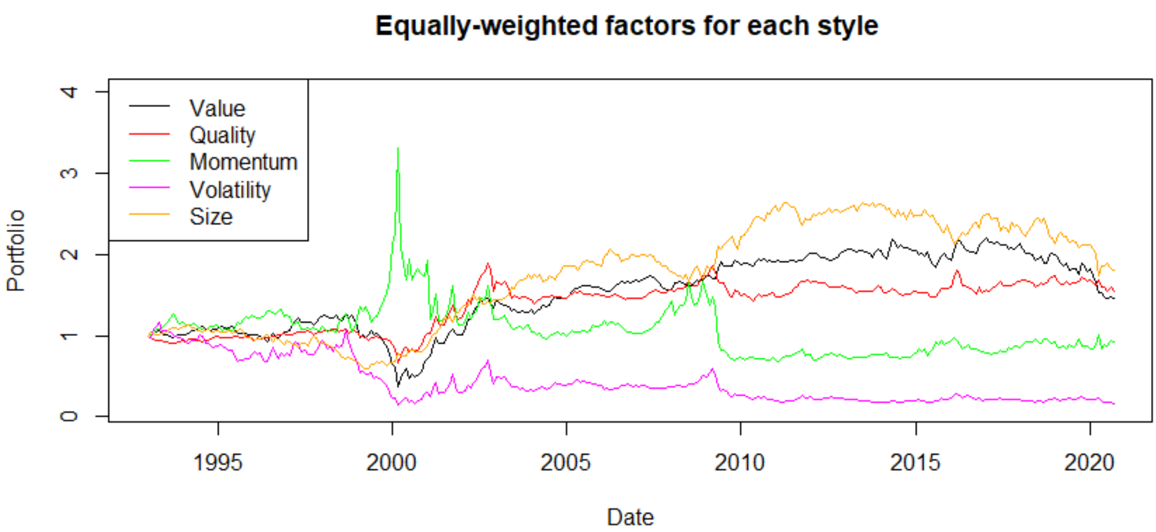
Since the performance of the factors is cyclical, the hypothesis of the paper is that each factor could be a vital part of the final portfolio. However, the weight of each factor in the portfolio should be changing in time. A possible way is to react to the actual market situation. Garg et al. (2019) examined the time-series momentum strategies and the momentum turning points. According to the research, turning points are the Achilles' heel of time-series momentum portfolios. The reason is straightforward, slow signals tend to be unreactive to changes in trend, and fast signals are often false alarms. The authors examine fast and slow momentum signals and different blending approaches to construct more profitable momentum strategies. The weight of the long (short) position depends on both fast and slow signals, and whether they agree or disagree. We follow a similar approach for the construction of the factor momentum strategies, but there are major differences. For the active factor strategy, we first examine two signals: fast, which is 1-month momentum and slow, which is 12-month momentum. Moreover, we examine the strategy which is traded only if both signals agree and blended strategy similar to the Garg et al. (2019).

Nextly, separately for each type of signal and for each factor, we cross-sectionally rank the absolute value of the signal to obtain the strength of the signal. The ranks act like weights – stronger the signal greater the weight. After establishing cross-sectional strength, the factor strategies that utilize the slow and fast signals can be further enhanced. The detailed strategies and results can be found in the sections 3, 4 and 5.

The dynamic weighting outperforms the baseline strategies. The outperformance of dynamical weighting compared to all other strategies is present on each market and each type of portfolio sort (quintiles, deciles and ventiles). Moreover, the results of the dynamic weighting of signals outperform other strategies in two distinct approaches. Firstly, when we consider the relative strength of the signals for all factors together or in the other case, when we firstly, break all the factors into individual investment styles separately. The results are almost exactly the same (since the breaking the factors into individual styles does not alter the results, for the simplicity, results for such variant are unpublished).

It is worth mentioning that by the construction, all of the strategies are "immune" to problems like value versus growth or short-term momentum/short-term reversal. For example, if the value tends to be profitable, the strategy would tilt its exposition to the value factors. If the value tends to be unprofitable (growth is profitable), the strategy shorts the value factors (in other words, it reverses deciles, quintiles or any other sorted portfolios).

Having established that it is possible to utilize the factors better in a relative-strength dynamically weighted factor momentum strategies, it is time to get back to the active versus passive investing debate. In the recent period, it is well-known that many factors have underperformed.



Therefore, it seems that in the past, proponents of passive investing were right. However, that conclusion would not be correct. Later, we show that active investing, using the relative-strength dynamically blended factor momentum strategy could be a great addition to the market portfolio. The combined strategy looks back on the past twelve months, and twelve moving averages (MA) of the returns: one month, two months, three months and so on. Suppose the MA for active investing (factor momentum) is larger than MA for market portfolio, then the active investing scores one point. Otherwise, the market portfolio gets one point. Therefore, each month, the weight of the factor momentum and market portfolio is determined by the number of "winning" (loosing) moving averages. Combining active and passive investing largely outperforms passive investing only. Moreover, if we have a rule that we follow for investing into factors and market, it is definitely an active investing strategy.

Although the relative-strength dynamically blended factor momentum strategy and its combination with the market portfolio might seem to be tangled, the rules are straightforward and transparent. It is possible to ex-post choose the best lookback periods for fast and slow indicators, or the best blending rule, however, such overfitting is not in the interest of this paper. Strategies should be transparent, and the aim of this paper is to show a set of transparent rules to find answers to two questions. Firstly, which factor to invest in (factor allocation problem), and secondly, to have a rule-based solution to the active versus passive clash.

The paper is mainly related to the work of Gupta and Kelly (2018), which examine the time-series factor momentum, and the paper of Arnott et al. (2020), that explores the cross-sectional factor momentum strategy. Naturally, the paper is also related to the researches about the individual factors. However, there is an abundant amount of research papers connected to the factors of the Alpha Architect's data library.

2. Data

Factors are obtained from the Alpha Architect's Factor Investing Data Library[1]. The factors include Asset Growth, Beta, Book/Price, Cash Flow/Price, Debt Paydown Yield, Dividend/Price, Earnings/Price, EBIT/TEV, EBITDA/TEV, Financial Strength Score, Gross Profit, various Momentum measures (1m, 6m, 12m and 12m with the last month skipped), Repurchase Yield, Return on Assets, Return on Equity, Sales/Price, Shareholder Yield,

[1] https://alphaarchitect.com/2020/04/17/factor-return-library-beta-release/

Shareholder Yield with Debt, Size and Volatility. Therefore, the factor library includes all the major styles: Value, Momentum, Volatility, Quality and Size.

All factors are either value-weighted or equally-weighted. We are interested in two markets: the US market that is represented by the top 1500 stocks and developed market (EAFE). The data spans from 31.1.1993 to 31.8.2020, therefore, it includes many major financial crises, e.g. the dot-com bubble, the financial crisis of 2007–2008, recent COVID crisis (the first wave, including the recovery) and many other market downturns.

3. Factor Momentum

For each factor i, at time t, we first compute the fast and slow momentum signals as follows:

$$s_{slow,i} = \left(\prod_{k=t-1}^{t-12} 1 + r_{i,k}\right) - 1 \ , \qquad (1)$$

$$s_{fast,i} = r_{i,t-1} \ . \qquad (2)$$

Where $r_{i,t}$ denotes the monthly return for month t and factor i, $s_{slow,i}$ is the slow signal, and $s_{fast,i}$ is the fast signal. Signals can be used in time-series momentum strategies. We also consider weighted relative-strength signals. The raw weight is found as follows: we take the cross-sectional rank of the signal divided by the sum of all ranks, multiplied by the sign of the signal. The computation can be denoted by the following equation:

$$w_{slow,i} = \frac{rank(s_{slow,i})}{\sum_j rank(s_{slow,j})} \times sign(s_{slow,i}) \ , \qquad (3)$$

$$w_{fast,i} = \frac{rank(s_{fast,i})}{\sum_j rank(s_{fast,j})} \times sign(s_{fast,i}) \ . \qquad (4)$$

Therefore, the long or short position is scaled by the cross-sectional strength of the signal. The idea is that the stronger signal should have a bigger weight in the portfolio. Moreover, by the construction, traditional factor portfolios (long-short) can be flipped. For example, investing into value factor does not need to consist of a long position in value stocks and short position in growth stocks, given the equations (1) and (2), the positions can be flipped.

With established signals and weights, we can now form all the variants of examined strategies. Given the equations (1)-(4) there are two options. Firstly, strategies can utilize the signs as signals and factors are equally-weighted in the portfolio. Secondly, the strategy also employs the raw weights of (3) and (4) to ensure that the factor strategy with a stronger signal gets a larger weight in the portfolio. Throughout the paper, n is the number of traded factors.

Nextly we define strategies based on the slow signals and on the fast signals:

$$ret_{slow,t} = \frac{1}{n}\sum_{j=1}^{n} r_{j,t} \times sign(s_{slow,j}) \ , \tag{5}$$

$$ret_{dyn.slow,t} = \sum_{j=1}^{n} r_{j,t} \times w_{slow,i} \ , \tag{6}$$

$$ret_{fast,t} = \frac{1}{n}\sum_{j=1}^{n} r_{j,t} \times sign(s_{fast,j}) \ . \tag{7}$$

$$ret_{dyn.fast,t} = \sum_{j=1}^{n} r_{j,t} \times w_{fast,i} \ . \tag{8}$$

The returns for the neutral strategy or a strategy that only opens positions if both signals agree can be defined as:

$$ret_{neutral,t} = \frac{1}{n}\sum_{j=1}^{n} r_{j,t} \times \frac{sign(s_{fast,j})+sign(s_{slow,j})}{2} = \frac{ret_{slow,t}+ret_{fast,t}}{2} \ . \tag{9}$$

A next strategy is a dynamically neutral strategy. The strategy is similar to the blended strategy (8), but it also employs the raw weights of (3) and (4) to ensure that the factor strategy with a stronger signal gets a larger weight in the portfolio.

$$ret_{dyn.neutral,t} = \sum_{j=1}^{n} r_{j,t} \times \left(\frac{1}{2} w_{fast,i} + \frac{1}{2} w_{slow,i}\right) \ . \tag{10}$$

The blended strategy reduces the weight in the times when the slow and fast indicator do not agree – in the correction state (when the slow signal is positive but the fast is negative) or in the rebound state (when the slow signal is still negative, but the fast is already positive). In the correction state, there is not opened the "full" short position, but the weight is scaled to the half (the weight of the factor is -0.5). In the rebound state, there is not opened the "full" long position, but the weight is scaled to the half again (the weight of the factor is 0.5).

$$ret_{blended,t} = \frac{1}{n}\sum_{j=1}^{n} r_{j,t} \times \left(\frac{3}{4} sign(s_{fast,j}) + \frac{1}{4} sign(s_{slow,j})\right) \ . \tag{11}$$

The final strategy is the dynamically blended strategy.

$$ret_{dyn.blended,t} = \sum_{j=1}^{n} r_{j,t} \times \left(\frac{3}{4} w_{fast,i} + \frac{1}{4} w_{slow,i}\right) \ . \tag{12}$$

4. Combined strategy

In the introduction, we have outlined that the passive market investing would outperform the factors. In this section, we show that it might be even better to combine the previously mentioned dynamically blended factor momentum strategy and the market portfolio. The combination is straightforward, the combined strategy looks back on the past twelve months, and twelve MAs of the returns. If the MA for active investing (factor momentum) is larger than MA for market portfolio, the active investing scores one point. Otherwise, the market portfolio gets one point. Therefore, each month, the weight of the factor momentum and market portfolio is determined by the number of "winning" (loosing) moving averages. At time t, the weight of the market portfolio and factor portfolio (fport) is given by the following equations:

$$w_{market,t} = \frac{1}{12}\sum_{j;MA_{market,j}>MA_{fport,j}} 1 \ , \tag{12}$$

$$w_{fport,t} = \frac{1}{12}\sum_{j;MA_{fport,j}>MA_{market,j}} 1 = 1 - w_{market,t} \ , \tag{13}$$

where $j = 1,2,3, \ldots ,12$; $MA_{market,j}$=$\frac{1}{j}\sum_{k=1}^{j} ret_{market,t-k}$ and $MA_{fport,j}$=$\frac{1}{j}\sum_{k=1}^{j} ret_{fport,t-k}$.

Return of the combined portfolio at month t is equal to:

$$ret_{combined,t} = ret_{fport,t} \times w_{fport,t} + ret_{market,t} \times w_{market,t} \ . \tag{14}$$

5. Results

Throughout the research, results were qualitatively the same for both options of weighting inside of factors. The equally-weighted or value-weighted stocks in each of the factor did not change the results. Therefore, only the value-weighted individual factors are examined in the proposed strategies. Also, the sorting method (deciles, quintiles, ventiles) did not largely change the results, and the results were qualitatively the same. While the individual needs for diversification can significantly influence the number of traded stocks, the study opts for deciles as a "middle ground". The results are divided into two sections: for US stocks and for international EAFE stocks.

5.1 US Stocks

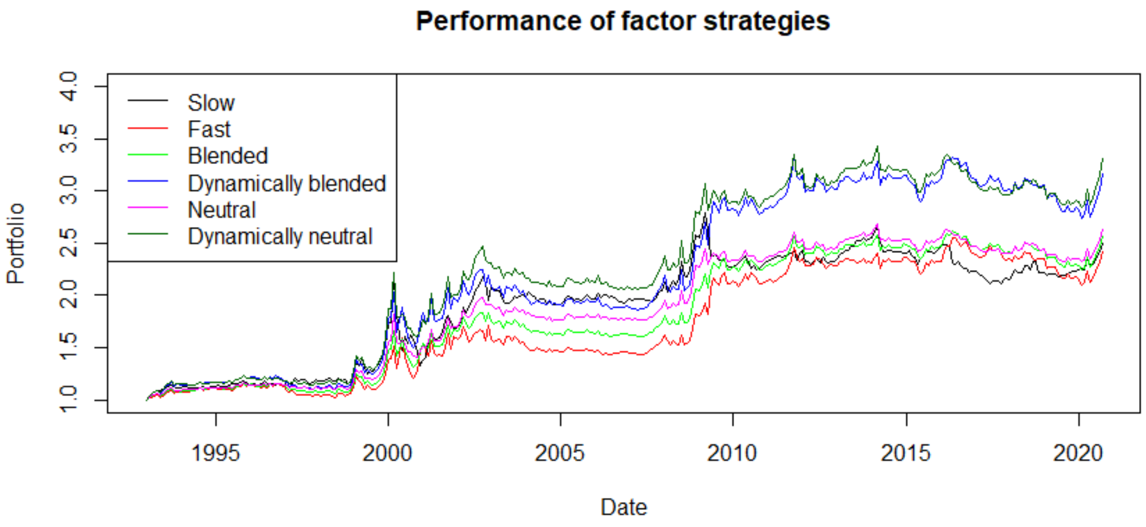
Table 1 Performance metrics for strategies mentioned in section 3 in the US market. Returns and volatilities are annualized. Risk-adjusted performance is return divided by the volatility. The sample consists of returns for the period of 31.12.1992 to 31.8.2020. Individually, each factor is value-weighted. The factor portfolios are weighted according to section 3.The Slow is the long term momentum signal (12 months), Fast signal is the short term momentum signal (1 month), Neutral trades only if both signals agree, Blended strategy reduces the weight in the times when the slow and fast indicator do not agree (equation 11). Dynamic strategies employ relative weights (the strength of each signal – equations 3 and 4).

Strategy	**Return**	**Volatility**	**Max Drawdown**	**Risk-adjusted performance**
Slow	3.362%	10.969%	-38.075%	0.306
Fast	3.235%	11.032%	-24.445%	0.293
Neutral	3.547%	8.464%	-22.83806	0.419
Dynamically neutral	4.402%	11.224%	-27.783%	0.392
Blended	3.451%	9.183%	-20.911%	0.376
Dynamically blended	4.235%	12.133%	-26.303%	0.349

The dynamical approach improves the performance of both neutral and blended strategies. However, by the construction, both strategies are blended with different weights for short and fast signals. As expected, dynamical strategies are the most profitable. The blending of the signals adds some performance (measured by the returns) compared to slow or fast signals. Therefore, the blending of time-series factor momentum signals seems to be profitable. Even larger returns were obtained with dynamic strategies that are similar to the cross-sectional momentum.

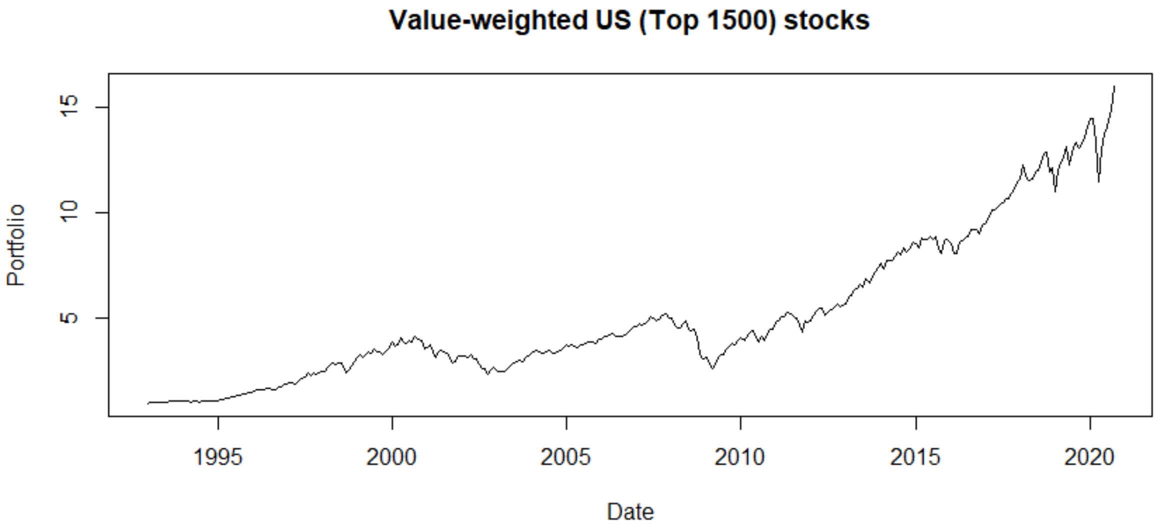
The performance can also be inspected visually, by looking at the equity lines for the unit portfolios.

Figure 1 Comparison of US active strategies unit portfolios



All of the strategies are profitable, do not have large drawdowns or volatilities, but they do not seem to be that profitable. There are many periods where the performance is flat.

Figure 2 Performance of unit US market portfolio



Compared to the factor strategies, a buy-and-hold approach for top 1500 US stocks would have skyrocketed. A natural question arises, is there any reason to invest in factors?

Common knowledge is that the outperformance of active and passive investing is cyclical. The edge is changing based on market conditions. Therefore, we suggest that both the active factor strategy and market portfolio should be utilized in the investor's portfolio. However, there needs to be set a rule for the allocations. This common-sense can also be backed by the correlations between active and passive strategies. Spearman's correlation coefficient between the market portfolio and dynamically blended strategy is -0.185 (*p-val 0.0006969*). Coefficient between dynamically neutral strategy and market portfolio is -0.143 (*p-val 0.009194*). Both correlations are negative and highly statistically significant using non-parametric (therefore robust in this case) tests. These results suggest that it should be beneficial to combine those strategies. The performance of active and passive investing is cyclical and slightly negatively correlated. The straightforward rules based on simple moving averages were established in section 4.

Throughout the next section, the combination is presented for the market portfolio and dynamically blended strategy that would be called the Smart Factors.

Figure 3 The weights (proportions in the combined portfolio) of active strategy (Smart Factors) and market portfolio (Market) using a combined approach from section 4. US market.

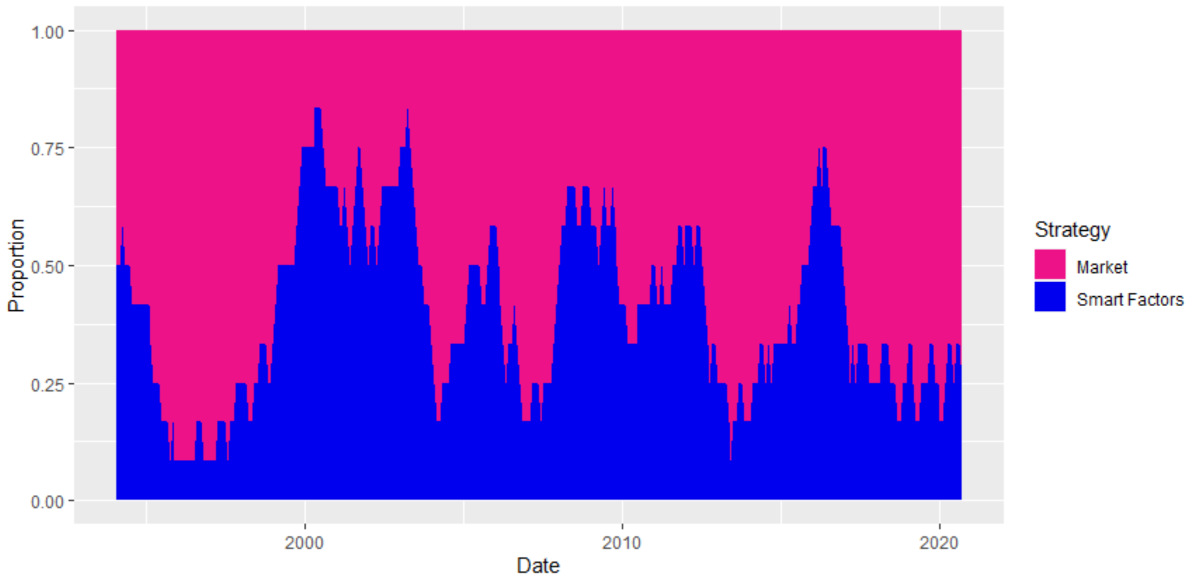


Table 2 Performance metrics for strategies mentioned above in the US market. Returns and volatilities are annualized. Risk-adjusted performance is return divided by the volatility. The sample consists of returns for the period of 31.12.1993 to 31.8.2020.

Strategy	**Return**	**Volatility**	**Max Drawdown**	**Risk-adjusted performance**
Smart Factors	3.884%	12.282%	-26.303%	0.316
Market	10.519%	15.086%	-50.007%	0.697
Smart Factors + Market	11.909%	10.460%	-16.95%	1.138

The combination of Smart Factors + market demonstrates the potential of the factor strategies. Gathering information from Figure 1-3, factors are profitable when the market is not, and by the construction (section 4), the combination strategy has the biggest allocation into factors when there is a market downturn. On the other hand, the factors tend to be flat when the market is largely profitable. As a result, the combination has the largest return, the lowest volatility and max drawdown, and the highest risk-adjusted-performance. A dollar invested in the 31.12.1993 would result in the 20.28 dollars by the 31.8.2020 compared to only 14.52 dollars for the Market portfolio.

Figure 4 Comparison of Smart Factors, Market and Smart Factors + Market, US market

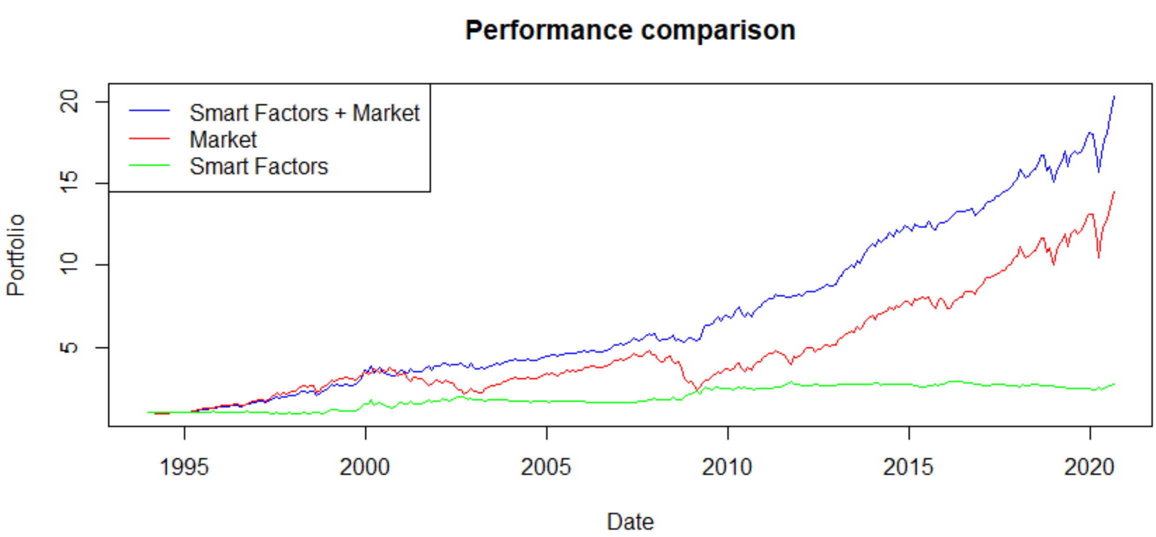
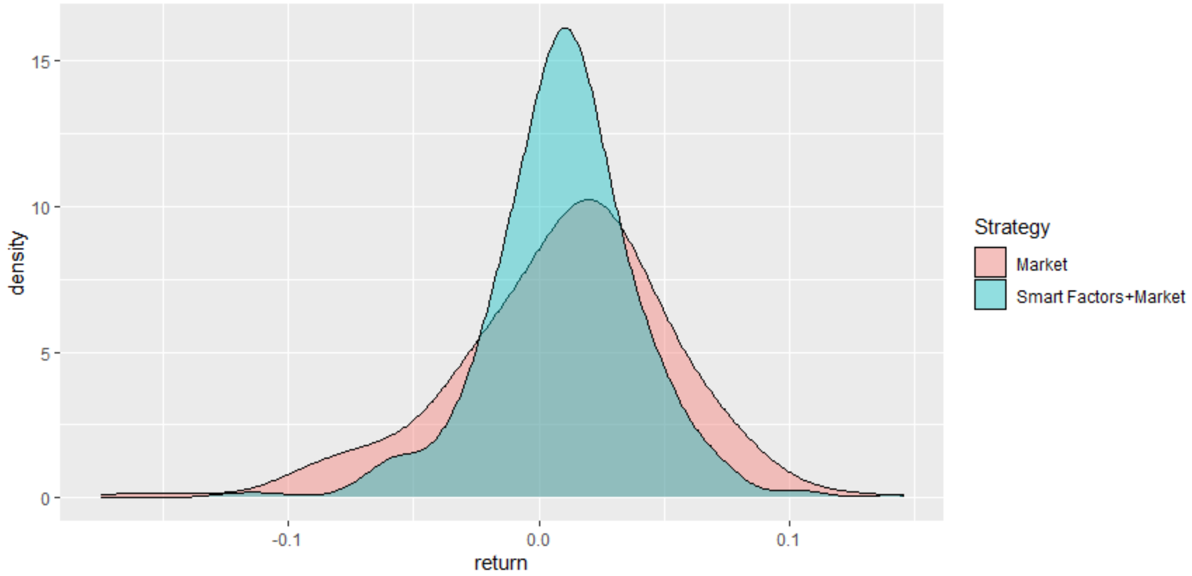


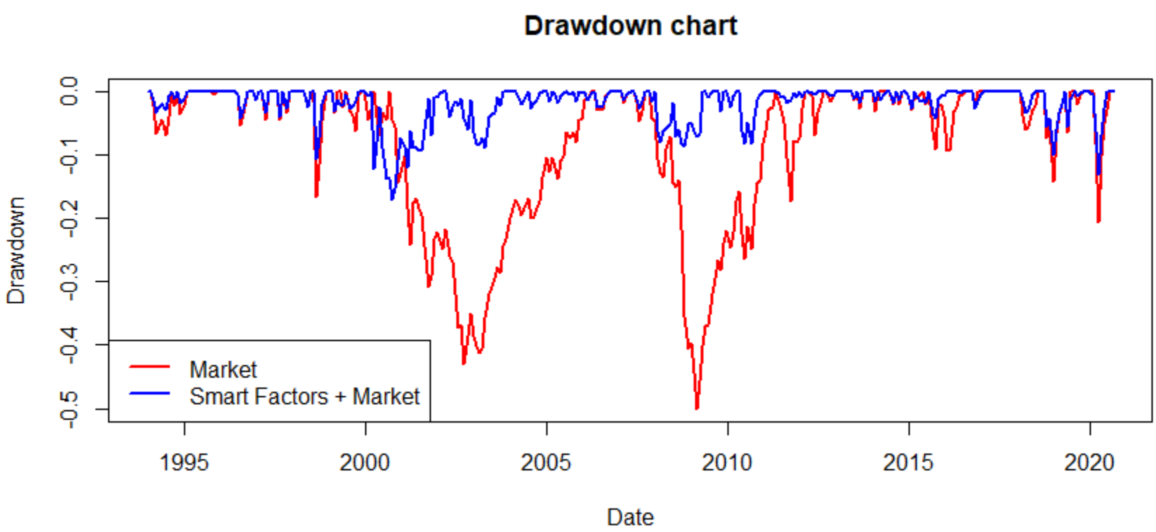
Figure 5 Distribution of the returns, US stocks



Returns of the combination strategy also tend to be more favourably distributed. The left tail is shorter and thin, not as heavy as for market portfolio. As expected, the same can be said about the right tail, but overall, the combination is better.

The list of favourable properties does not end; the following chart shows the much lower drawdowns for the combined portfolio. While one could say that the passive approach is better than some factor (smart beta) strategies, and passive investing is superior to the active, their active combination and dynamic allocation largely outperforms the passive buy-and-hold approach of the market.

Figure 6 Drawdown chart, US stocks



5.2 EAFE Stocks

Table 3 Performance metrics for strategies mentioned in section 3 in the EAFE stocks. Returns and volatilities are annualized. Risk-adjusted performance is return divided by the volatility. The sample consists of returns for the period of 31.12.1992 to 31.8.2020. Individually, each factor is value-weighted. The factor portfolios are weighted according to section 3.The Slow is the long term momentum signal (12 months), Fast signal is the short term momentum signal (1 month), Neutral trades only if both signals agree, Blended strategy reduces the weight in the times when the slow and fast indicator do not agree (equation 11). Dynamic strategies employ relative weights (the strength of each signal – equations 3 and 4).

Strategy	**Return**	**Volatility**	**Max Drawdown**	**Risk-adjusted performance**
Slow	2.182%	7.195%	-28.947%	0.303
Fast	4.188%	8.021%	-13.069%	0.522
Dynamically fast	5.701%	10.813%	-15.369%	0.527
Neutral	3.301%	5.874%	-17.062%	0.562
Blended	3.773%	6.598%	-11.082%	0.572
Dynamically blended	5.165%	8.917%	-14.599%	0.579

The performance of strategies in the EAFE universe is comparable to the US sample. However, the fast signals tend to be significantly more profitable, indicating that the short term factor momentum outperforms the long term factor momentum. On a risk-adjusted basis, the dynamically blended strategy is the winner.

Figure 7 Comparison of EAFE active strategies unit portfolios

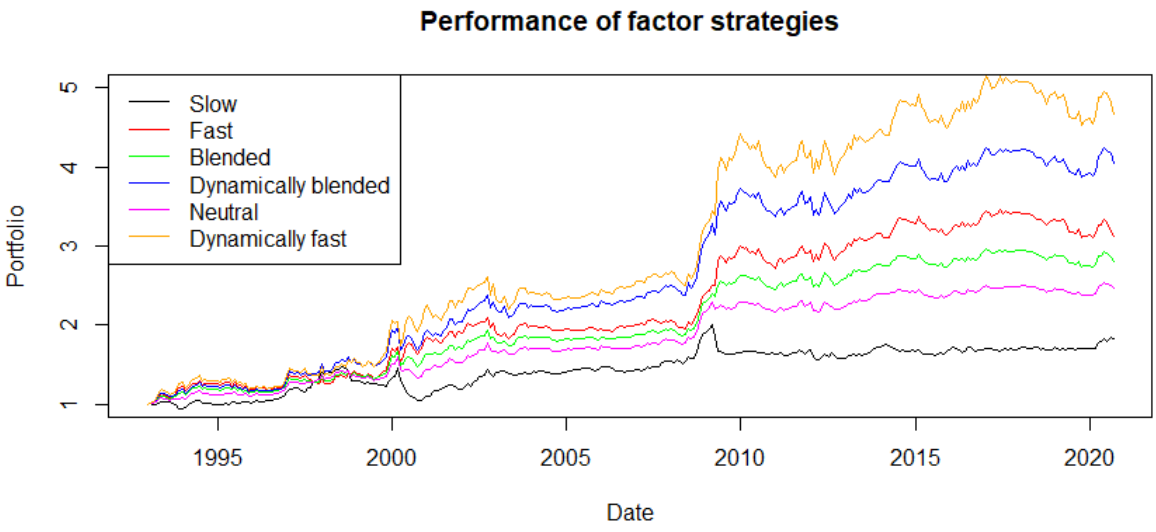
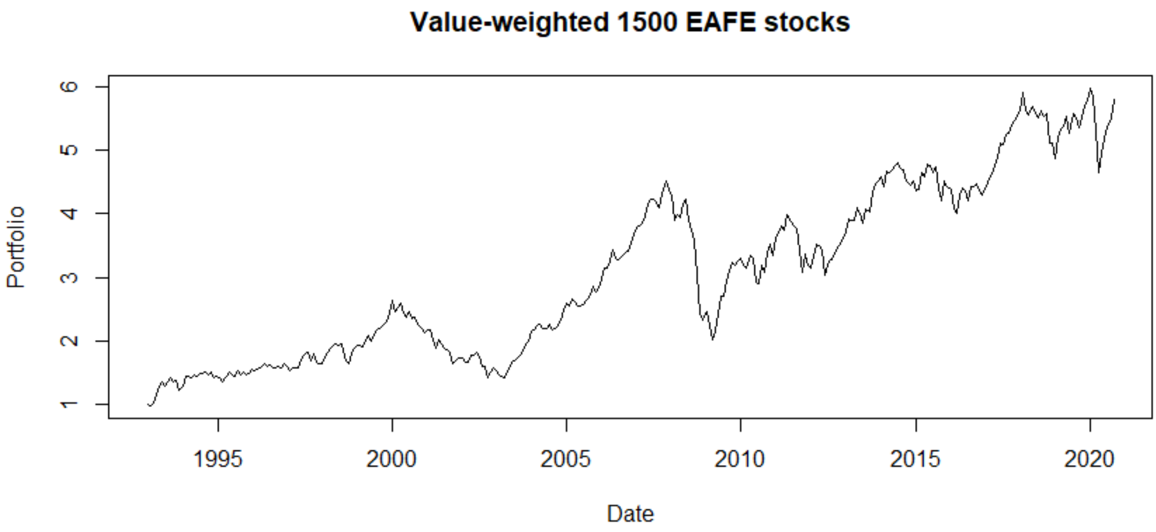


Figure 8 Performance of unit EAFE market portfolio



The case is not same as in the US market, the EAFE market portfolio has not skyrocketed compared to the factor strategies. The market portfolio is very volatile compared to the factors, and the returns are similar. Spearman's correlation coefficient between the market portfolio and dynamically blended strategy is -0.122 (*p-val 0.02661*). Therefore, the result is the same as in the US case. The correlation is slightly negative and statistically significant. These results point to the same conclusion as in the US case. It should be beneficial to combine those strategies. The straightforward rules based on simple moving averages were established in section 4.

Throughout the next section, the combination is presented for the market portfolio and dynamically blended strategy that would be called the Smart Factors.

Figure 9 The weights (proportions in the combined portfolio) of active strategy (Smart Factors) and market portfolio (Market) using a combined approach from section 4. EAFE market.

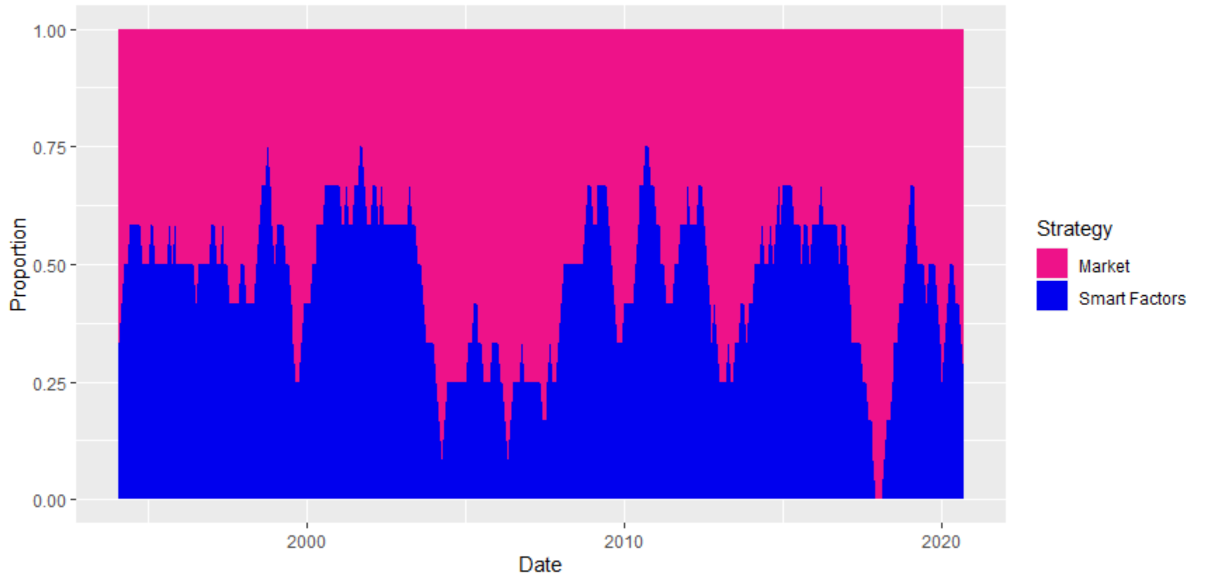
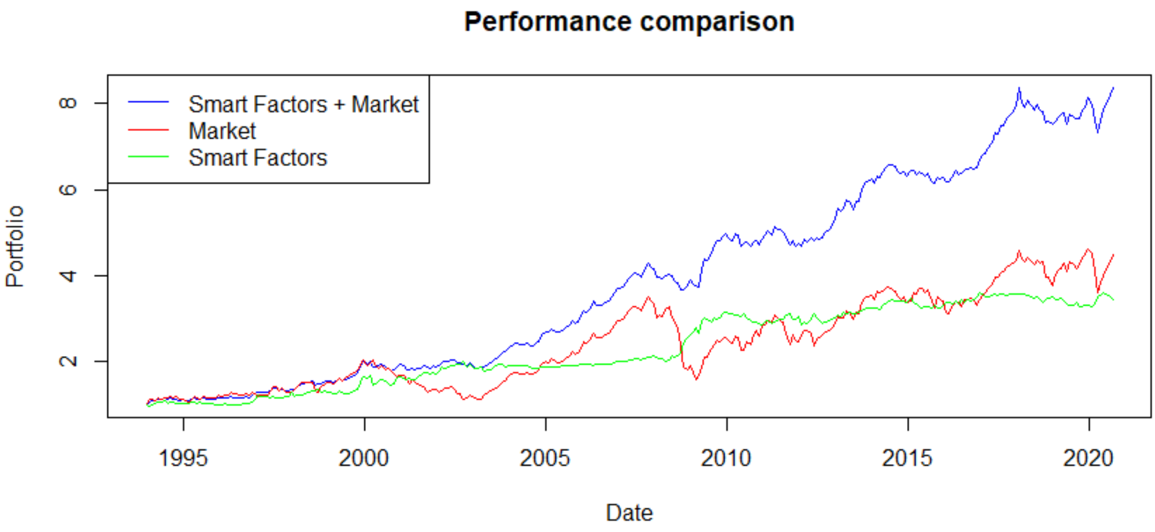


Table 4 Performance metrics for strategies mentioned above in the EAFE market. Returns and volatilities are annualized. Risk-adjusted performance is return divided by the volatility. The sample consists of returns for the period of 31.12.1993 to 31.8.2020.

Strategy	**Return**	**Volatility**	**Max Drawdown**	**Risk-adjusted performance**
Smart Factors	4.708%	8.944%	-14.599%	0.473
Market	5.769%	15.957%	-55.15%	0.361
Smart Factors + Market	8.264%	8.308%	-14.747%	0.995

Results are similar to the US market; factors are largely profitable when the market is in the downturn. For example, after the year 2000, the factor strategies have one of the best periods, while the market is falling. A similar situation is before 2010. Therefore, the factors and markets complement each other and using straightforward rules, and the active approach beats the market again.

Figure 10 Comparison of Smart Factors, Market and Smart Factors + Market, EAFE market



The density plot and drawdown chart bear the same results as in the US case. The density plot even shows that the left tail is even heavier than in the US case. However, the tail disappears when the strategies are combined. Moreover, the distribution of monthly returns of Smart Factors + Market evokes the normal distribution, and we cannot reject the null hypothesis (Shapiro–Wilk test) that returns are normally distributed on the 1% significance level. The mean monthly return is 0.69%.

Figure 11 Distribution of the returns, EAFE stocks

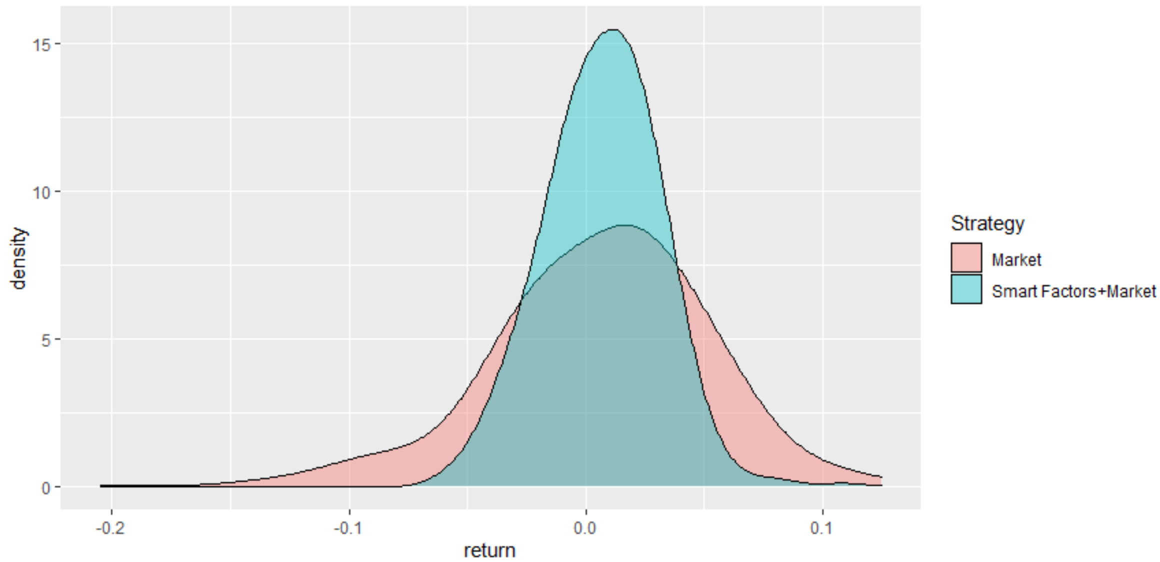
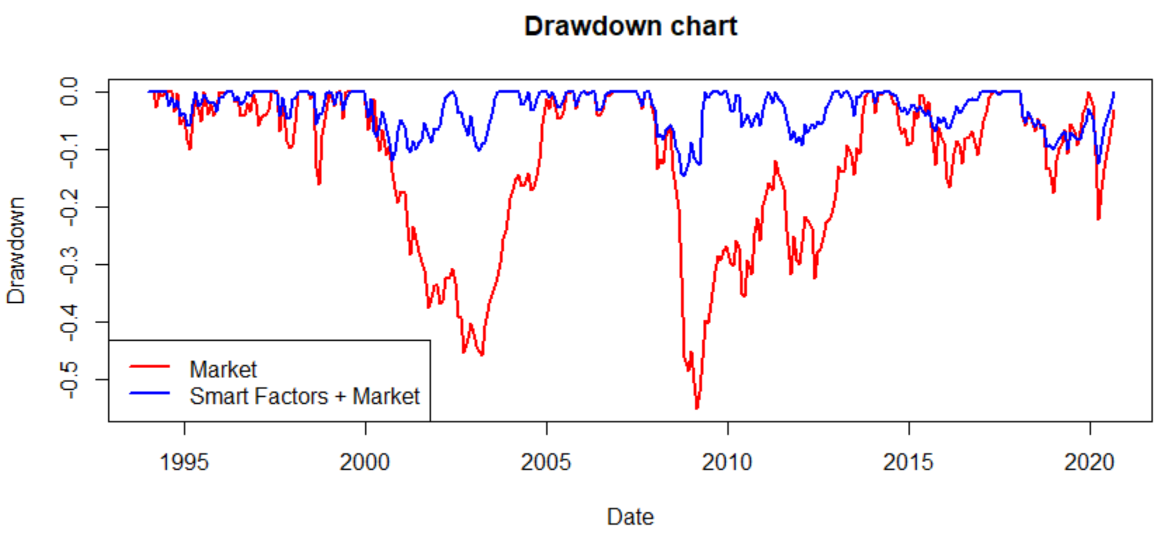


Figure 12 Drawdown chart, EAFE stocks



6. Conclusion

We conclude that the results are qualitatively the same for both investments universes. In both EAFE and US stocks, the market portfolio in terms of returns outperforms the factor strategies. The results hold even if we use time-series, cross-sectional factor momentum or blending the fast and slow momentum signals. However, the blending of the fast and slow signals proved to be superior to using the fast or slow signals only. Overall, the results are in line with the known results for momentum anomalies in the individual stocks.

It might look like that the passive approach of buy-and-hold market indices outperforms the active investing, and the active investing is pointless, but we show that this simply is not true. The active approach that consists of smart allocation into both Smart Factors strategy and market portfolio significantly outperforms either market or factors. Smart Factors and market are in both cases, slightly negatively correlated. The performance of both is cyclical, and factors have an outstanding performance during market downturns. Therefore, by allocating into market and factors using a scoring system based on moving averages, it is possible to create much more profitable portfolio, with lower volatility or drawdowns.

These results are applicable to both markets – US and EAFE. In both cases, the risk-adjusted return dramatically improves switching from market portfolio to the combined portfolio (from

0.361 to 0.995 for EAFE stocks and from 0.697 to 1.138 for US stocks). Lastly, comparing the factors and markets, the EAFE factors outperform US factors, but US market outperforms the EAFE market. Therefore, the combined portfolio in the connected samples could be an interesting idea for a further research.

Related literature

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