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U.S. Mutual Fund Performance in Recessions and Expansions, 1977 to 2019.

Navn: Thomas Holtvedt, Håkon Skogseid

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U.S. Mutual Fund Performance in Recessions and Expansions, 1977 to 2019.

Supervisor:

Professor Bruno Gerard

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Abstract

Using a sample of 2680 U.S. actively managed open-end mutual funds in the period from January 1977 through December 2018, we investigate whether actively managed mutual funds are able to outperform a passive benchmark over a 504-month sample. We highlight whether mutual funds are able to generate abnormal returns during NBER expansions and recessions. We find that an equal-weighted portfolio of net returns has a statistically significant abnormal return in expansion, but not in recession. Further, we find evidence of strong superior performance and underperformance by a small group of actively managed mutual funds.

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Introduction

Investing in passive index funds seems to have become the default investment strategy for investors in recent years. In 2018, mutual funds experienced the highest annual recorded outflows since this data have been gathered, and is expected to be surpassed by passive product by 2021 (Moody´s, 2019). After more than 40 years since the late John C. Bogle created the first low-cost index fund, there has been a significant shift to passive investments, but mutual fund performance still remains as one of the most popular topics in the field of finance.

Hendricks, Patel and Zeckhauser (1993) find that persistence in relative performance exists, with the evidence for “hot-hands” among mutual fund managers, while Carhart (1997) claims that the persistence in mutual fund performance cannot be credited to managers superior stock-picking ability, but can be explained by common factors in stock returns and persistent differences in mutual fund expenses and transaction costs. Daniel, Grinblatt, Titman and Wermers (1997) contributes to the research by examining whether active mutual funds can earn back their fees and expenses by systematically picking stocks that earn abnormal returns, and find that particularly aggressive-growth funds exhibit some selectivity ability, but exhibit no characteristic timing ability. In more recent studies, Barras, Scaillet and Wermers (2010) implement a new approach to control for luck in estimated alphas and find that there exist managers that exhibit persistence over short intervals. Berk and van. Binsbergen (2014) find that the average mutual fund manager has used their skill to generate $3.2 million per year and that large cross-sectional differences in skill persist for as long as ten years.

Our contribution to this discussion is to investigate if the extra cost of active management is beneficial to the investor in a different economic climate. We expand on the existing research and test whether or not actively managed U.S. mutual funds are able to outperform a low-cost benchmark index from 1977 through 2018. Especially, we would like to highlight if there exist any evidence of superior performance among mutual fund managers in recessions. The full time-series of monthly net returns is divided into sub-samples of expansions and recessions based on US Business Cycle Expansion and Contraction provided by the National Bureau of Economic Research (NBER, 2010). We first apply the model-free performance measures Sharpe ratio and M^2, then we perform individual fund and portfolio regressions by single- and multifactor models CAPM, Carhart 4-factor model (1997) and Fama and French 5-factor model (2015). Finally, we perform persistence testing with contingency ranking and bootstrap simulations. This work is done in order to answer the following hypothesis:

H_0: *Actively managed mutual funds do not outperform index funds net of costs during NBER recessions*

H_A: *Actively managed mutual funds outperform index funds net of costs during NBER recessions*

We study a sample of 504 monthly net returns for 2680 U.S. actively managed open-end funds in the period from January 1977 through December 2018. We do not find evidence that U.S. mutual funds on average are able to statistically significantly outperform the benchmark index portfolio during NBER recessions. The results indicate that on aggregate, mutual funds perform statistically significantly better in expansion than in recession. However, we do find both evidence of statistically significant superior performance and underperformance by a small group of funds during recessions when we perform individual regressions. The evidence of strong out- and underperformance by a small group of funds are further confirmed by our findings of persistence in contingency and bootstrap models.

The remainder of this paper is organized as follows. Section 1 provides a literary review of previous research on mutual fund performance. Section 2 presents an overview of the data used in the paper, such as the collected sample of funds, benchmark portfolio, regression factors and business cycle dates. Section 3 presents the methodology. Section 4 presents the performance of the model-free performance measures and regression model. Section 5 presents persistence through contingency tables and bootstrap simulations. Section 6 concludes.

1. Literary review

Hendricks, Patel and Zeckhauser (1993) find that persistence in relative performance exists, with the evidence for "hot-hands" among mutual fund managers. The meaning of the expression "hot-hand" comes from the sport of basketball, claiming that a player that has made many baskets in row will also continue to do so. Translating this into an economic setting, Hendricks et al. (1993) claims that performance in the near-term is persistent, with the strongest evidence found when evaluating fund managers on a one-year horizon. Recent poor-performing portfolios continue to significantly underperform standard benchmarks, and recent top performers continue to do better, but not significantly so.

Carhart (1997) finds that persistence in mutual fund performance cannot be credited to managers superior stock-picking ability. He states that the predictability in mutual fund returns found by Hendricks et al. (1993) can be explained by common factors in stock returns and persistent differences in mutual fund expenses and transaction costs. The article finds that funds with higher one-year returns infrequently repeat their abnormal returns, and their abnormal returns are due to the fact that funds by chance happen to hold relatively larger positions in last year´s winning stock, not because managers successfully follow momentum strategies. Carhart (1997) demonstrates that expenses have a negative impact on fund performance, and turnover negatively impacts performance. Further, the analysis provides evidence for negative correlation between fund performance and load fees, with load funds underperforming no-load funds by approximately 80 basis points per year. Finally, Carhart (1997) finds that funds with past high alphas seems to demonstrate higher alphas in subsequent periods, but these funds also earn expected future alphas that are insignificantly different from zero.

Daniel, Grinblatt, Titman and Wermers (1997) examines whether active mutual funds can earn back their fees and expenses by systematically picking stocks that earn abnormal returns. Based on the stock characteristics of market capitalization, book-to-market and prior-year returns, Daniel et al. (1997) constructs benchmarks from passive portfolios of stocks with the above-mentioned characteristics. The authors state that there are several advantages to directly evaluating the portfolio holdings of the mutual funds, most importantly that the method makes it easier to capture the investment style of the fund managers, and the fact that hypothetical returns do not include fees, expenses and trading cost of the mutual funds. This will lead to an overestimation of returns from holding the funds, but are appropriate in determining whether mutual fund managers have stock-picking selection or timing abilities.

Berk and Green (2004) claims that despite of fierce competition and little evidence of superior performance among managers, mutual fund managers are still highly rewarded. They claim that from an economic view it would be troubling to reward managers, when the evidence for performance is widely regarded to be attributable to luck, and not managerial skill. The authors state that investments in mutual funds do not outperform passive benchmarks. With the use of their 3-part model they find that in a highly competitive environment, investors supply managers with funds and that there are decreasing returns to scale for managers to deploy their superior ability. Investors see past high performance as evidence of mutual fund managers superior ability and funds that have had past superior returns will experience an inflow of money. To increase their compensation, managers will increase the size of their fund, to the point where expected excess returns are competitive going forward. Managers must be able to find undervalued securities and exploit this knowledge without moving prices too much, and this becomes more difficult when the size of the fund increases. Berk and Green (2004) conclude that mutual fund managers do not lack skill, and the lack of persistence in performance does not imply that differential ability amongst managers is unrewarded. It only implies provision of capital by investors to the mutual fund industry is highly competitive.

Kosowski (2006) finds that the risk-adjusted performance between recessions and expansions is statistically and economically significant at 3 to 5 percent per year. He states that the average underperformance by mutual funds documented in the literature "*stems from expansion periods when funds have statistically significant negative risk-adjusted performance and not from recession periods when risk-adjusted performance is positive*" (Kosowski, 2006, p. 1). The findings are based on a multivariate regime-shifting performance methodology and concludes that mutual fund performance is undervalued in recessions, when investors marginal utility of wealth is higher than in expansion.

Kosowski, Timmerman, Wermers and White (2006) apply a statistical bootstrap technique to examine performance in the U.S. mutual fund industry from 1975 to 2002. Kosowski et al. (2006) conduct a comprehensive examination of mutual fund performance that explicitly controls for luck, something the authors believes is lacking in previous studies. They find that the bootstrap test consistently indicates that the top 10 percent of the largest positive alphas are extremely unlikely to arise due to luck. The test also finds strong evidence of mutual funds with negative and significant alphas, controlling for luck. When applying the bootstrap to a group of 1788 mutual funds, net-of-cost, Kosowski et al. (2006) find overwhelming evidence that some fund managers have superior stock-picking abilities. The results also show that these superior fund managers survive and that their returns are not due to luck alone. Their findings also suggest that a small amount of funds have stock-picking abilities that more than compensate for their cost, while most funds cannot. Further, Kosowski et al. (2006) finds stronger evidence of superior stock-picking abilities before 1990 than after. After 1990, the funds that display superior performance, after controlling for luck, is located in the extreme right tail of the alpha distribution. Kosowski et al. (2006) also test for significance by using the framework of Carhart (1997), but applying the bootstrap instead of the standard parametric *t*-tests. The finding shows significant persistence in net return alphas (using bootstrapped *p*-values) for the top decile and sometimes for the top two deciles. The results are significant for several different ranking periods.

Barras, Scaillet and Wermers (2010) implement a new approach to control for luck in estimated alphas among 2076 actively managed U.S open end mutual funds from 1975 to 2006. The approach estimates more precisely the proportions of unskilled and skilled funds in the sample. Using a Monte Carlo simulation, Barras et al. (2010) demonstrate that their approach provides a more accurate partition of zero-alpha, unskilled and skilled mutual funds than previous studies with a priori assumptions imposed on the zero-alpha funds. The study finds that 75.4 percent of the funds in the sample are zero-alpha funds, net of trading costs and expenses. This means that the funds have some stock-picking abilities but no more than to cover their management fees. The number of skilled managers (true $\alpha > 0$) is only 0.6 percent but not statistically significant different from zero, while 24.0 percent of the funds are unskilled (true $\alpha < 0$). The highest proportion of skilled managers is found in the funds investing in aggressive growth, while no skilled is found among managers in growth and income. Barras et al. (2010) also find that the number of skilled mangers decreases severely from early 1990 when 14.4 percent of managers showed skill to only 0.6 percent in 2006. The number of funds has increased substantially over the sample period but the results show that is has become rare to find a skilled fund manager that pick stocks well enough cover his costs. Further, Barras et al. (2010) conducts tests over five-year sub-intervals to check for persistence and finds that 2.4 percent of managers have “hot hands” over these short intervals. These skilled funds are concentrated in the extreme right tail of the cross-sectional estimated alpha distribution, which is a good signal for short-run manager skill. Further, older and larger funds seem to consist of less skilled managers than smaller and newer funds.

Fama and French (2010) examines if actively managed mutual funds are able to produce significant alphas due to actual managerial skill, or simply due to luck. They state that traditional persistence testing to distinguish skill and luck has a weakness because funds are only ranked short-term and is largely based on noise. Similar to Kosowski et al. (2006) they apply bootstrap simulations to randomize residuals with replacement over the full time-series. Further, Fama and French (2010) make the assumption that a true zero alpha for net returns imply that mutual funds do not only generate the market rate of return, but also enough return to justify the cost of management. The distribution of bootstrapped simulated alphas shows the existence of skill among some mutual fund managers. Fama and French (2010) finds evidence of both superior and negative skill amongst mutual funds, but where the majority of funds show neither.

Berk and van. Binsbergen (2014) find that the average mutual fund manager has used their skill to generate $3.2 million per year and that large cross-sectional differences in skill persist for as long as ten years. They also find that investors are able to recognize this skill and reward it by investing more with better funds, and find a strong positive correlation between current compensation and future performance. Further, Berk and van. Binsbergen (2014) argue that neither the gross or net alpha is a good measure for skill, and that the gross alpha is only a good measure under the assumption that all funds are exactly the same size. Instead, they argue that the skill of a manager equals the fund´s gross excess return over its benchmark multiplied by assets under management. To evaluate managers against an alternative investment opportunity set, the authors use all available Vanguard index funds as they proclaim that Vanguard is in a market-leading position in the index fund space. The strongest evidence of manager skill is found in the persistence of cross-sectional differences in value added. The authors find evidence of persistence up to as much ten years, which is far longer than previous studies have shown. As mentioned above, Berk and van. Binsbergen (2014) find strong correlation between managerial skill and managerial compensation. This implies that investors are able to infer managerial quality, and this is confirmed by demonstrating that current compensation better predicts future value than past value added does. In addition, the authors find that half of the value added by mutual funds is attributable to diversification services and the other half to market timing and stock picking.

2. Data

2.1 Fund selection

Our data sample consists of 504 monthly net returns of 2680 U.S. actively managed open-end funds in the period from January 1977 through December 2018. The data sample, obtained from investment research firm Morningstar, originally included 2962 large-cap mutual funds but we omit funds that passively replicate indices and/or is not U.S. domiciled. In an average month, the sample includes 518 funds, a median annual management fee of 0.70 percent and an average annual expense ratio of 1.06 percent.

2.2 Portfolios

For all performance evaluation models, we construct the following portfolios for the full time-series and the sub-samples expansions and recessions:
Firstly, an equal-weighted (EW) portfolio of monthly net returns based on reported returns from Morningstar of all funds in the sample. Secondly, we apply the framework of Hendricks, Patel and Zeckhauser (1993) andCarhart (1997)

where we form ten synthetic EW portfolios of mutual funds, ranked on last years reported net returns. The portfolios are held for one-year, and are then re-formed.

2.3 Benchmark

In order to measure and understand the relative performance of the mutual funds returns, an appropriate benchmark needs to be selected. The benchmark will work as a proxy for index funds on an aggregate level so it is important to choose a benchmark that we believe will pick up the variation in fund returns in the best possible way. We have created a NAV-weighted benchmark that consists of 34 low-cost index funds which has an investment objective to track the performance of Standard & Poor´s 500 Index that measures the investment return of U.S. large-capitalization stocks.

2.4 Risk-free rate

For all performance evaluation models, we measure portfolio returns in excess of risk-free rate. Therefore, we need a proxy for the risk-free rate. Since we are working with monthly returns, the one-month Treasury bill is chosen as an appropriate proxy. This is in line with previous work by researchers Fama and French (1993) and Carhart (1997). We obtain the risk-free rate from the Kenneth R. French Data Library (French, 2019).

2.5 Regression factors

The regression models used in this thesis is Capital Asset Pricing Model (CAPM), Carhart 4-factor model (1997) and Fama-French 5-factor model (2015). The models will be described in more detail in section 3. The NAV-weighted portfolio of low-cost index funds will be used as proxy for the market portfolio in excess of the risk-free rate. The remaining factors, small minus big (SMB), high minus low (HML), momentum (MOM), robust minus weak (RMW) and conservative minus aggressive (CMA) is also obtained from the Kenneth R. French Data Library (French, 2019).

2.6 NBER business cycle dates

To define periods of expansion and recession we use the National Bureau of Economic Research´s (NBER) US Business Cycle Expansion and Contraction (NBER, 2010). NBER define recession as “a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales”. From January 1977 through December 2018 there have been 56 months of recession spread across five recession, the longest one being “The Financial Crisis” of 2007. The last expansion, which we are currently in, began when the Financial Crisis ended in June 2009 (NBER, 2010).

2.7 Survivorship and incubation bias

Survivorship bias can occur when the existing funds in the market is believed to be representative for a larger, more comprehensive sample of funds. This happens when defunct funds are omitted from the sample, by either exterminating the fund completely or by merging the fund into a more successful fund. In both cases, the fund´s bad record is “buried” and this might lead to an overestimation in aggregate fund returns. The importance of survivorship bias has been debated, and researcher have come to different conclusions. Brown, Goetzmann, Ibbotson and Ross (1992) and Brown, Goetzmann and Ross (1995) finds evidence for significant survivorship bias in the U.S. market, arguing that survivorship bias in mutual fund data may give rise to spurious indications of performance persistence. Meanwhile, Malkiel (1995) asserts that previous studies underestimate the impact survivorship bias has on performance, finding an average annual difference of 4.2 percent between surviving funds and all funds including non-surviving funds for a 15-year sample ending in 1991. Wermers (1997) contributes to the existing literature on the subject and finds that surviving funds have average returns only slightly higher than non-surviving funds, making this bias a relatively small concern.

Incubation bias can occur when returns of companies conducting a trial process of a single fund or a group of funds privately, is part of the fund sample. Generally, only the best performing funds during this trial period is later opened to the public. This is a problem because only the return of the best fund will be presented to the public and lead to an upward bias in the sample. Evans (2010) examines the difference between incubated and nonincubated funds, after removing the performance in the incubation period. Evidence for superior manager or investment strategy could be found if the incubated funds would continue to outperform nonincubated funds, but this difference is found to be statistically insignificant. Secondly, Evans (2010) performs the same test *including* the incubated funds and finds a return difference of 3.5 percent which suggest that including incubated funds upwardly biases returns. Testing is done for a four-factor model and an equal-weighted model with a sample of 1048 funds where approximately 23 percent is incubated. The results show a biased four-factor alpha and equal-weighted returns annually of 0.43 percent and 0.84 percent, respectively. Value-weighted returns show no signs of bias.

The presence of either survivorship- or incubation bias is our sample could influence our results in several different ways. Having a significant portion of these two biases in our sample of mutual funds will first of all make the average return of the EW funds higher than what is a true representation of the average return of these funds. This will in turn impact our regression results. If the mutual funds have higher average return than what is true, then we might find statistically significant alphas in favor of managerial skill when this is not the case. It will then be more difficult for the passive index funds to outperform the mutual funds. Possible findings of underperformance by mutual funds would also be affected in the presence of the two biases, where underperformance by mutual funds would be even stronger, or results that are insignificant might become significant for a bias-free sample. Lastly, the number of funds that are statistically significant for the individual regression would be affected by these biases. The number of funds that are statistically significantly positive or negative and their respective return would be biased. The number of funds that are statistically significant positive alphas would be too many and the number of funds with statistically significant negative alphas would be too few.

3. Methodology

In order to investigate the performance of mutual funds in our sample, we apply a number of performance measures and factor models that are well-established in financial literature. This section presents a review of these measures, beginning with the model free performance measures Sharpe ratio and M^2, before we move on to single-factor model Capital Asset Pricing Model (CAPM) and the linked model measure Jensen´s alpha. Secondly, we review the factor 4- and 5-factor models of Carhart (1997) and Fama and French (2015), and lastly, we explain persistence in terms of Carhart´s (1997) ranked contingency portfolios and Kosowski et al.´s (2006) and Fama and French´s (2010) bootstrap simulation.

3.1 Sharpe ratio

Sharpe (1966) wanted to add to the existing work on capital theory and behavior of stock market prices. His goal was to introduce a "simple yet theoretically meaningful measure" of risk and return (Sharpe, 1966, p. 119). The measure, popularly known as the Sharpe ratio, divides a stock or a portfolio´s return in excess of risk-free rate by the asset´s standard deviation. The result is an estimate of risk-adjusted return, where risk is defined in standard deviation.

$$S_p = \frac{E(r_p) - r_f}{\sigma_p}$$

$E(r_p)$ is the one-period expected return on portfolio p, r_f is the one-period risk-free rate and σ_p is the standard deviation of portfolio p.

Some advantages of the Sharpe ratio are that it can easily be used to measure relative performance for e.g., a portfolio or a manager against vis à vis a relevant peer, and whether a manager has generated sufficient excess returns to compensate for the risk assumed. A weakness of the Sharpe ratio is that it uses standard deviation as a measure of risk, which assumes a normal distribution, a feature that a stock or a portfolio may not always be in possession of.

3.2 Risk-Adjusted Return (M^2)

The easiest readable measure in evaluating performance is by comparing returns, but returns by itself is an incomplete measure to a risk-averse investor because it does not take the risk assumed into account. The importance of risk in relation to returns is the understanding that investors can achieve greater expected returns by simply accepting more risk. When evaluating the performance of active management, we would like to know if abnormal returns are due to managerial skill or because the fund manager has undertaken higher systematic risk.

In 1997 Modigliani and Modigliani developed a new measure of risk-adjusted returns, published in the article Risk Adjusted Performance. The authors state that the basic idea of risk-adjusted returns is to adjust all portfolios to the level of an unmanaged market benchmark. The excess return of a risk-adjusted portfolio compared to the average return of the market equals the portfolio surplus, popularly known as the M^2-measure. If the difference in return between the portfolio and the market is positive over the same period, then the portfolio has outperformed the market. If it is negative, the portfolio has underperformed.

$$M^2 = ((r_p - r_f)\frac{\sigma_m}{\sigma_p}) - (r_m - r_f)$$

σ_m is the standard deviation of the market portfolio and r_m is the return on the market portfolio.

Since we are working with monthly returns and is risk-adjusting every individual month, and not an entire period, we need to create a proxy for the standard deviation of a single month. This is calculated as the standard deviation of a moving average over the previous 36-months in order to capture the variation in overall volatility.

$$\sigma_{it} = \sigma(r_{i,t-36} - r_{f,t-36}, r_{i,t-1} - r_{f,t-1})$$

When Vanguard 500 Index Fund Investor Shares (ticker: VFINX) was created in the second half of 1976, it was the first index fund open to the public, and because our time-series regression starts is 1977 we also need a proxy for the benchmark´s standard deviation in 36 months preceding the first month of our time-series. The proxy that we find appropriate and have chosen for the benchmark´s volatility is the standard deviation of what the benchmark is tracking, the S&P 500 Index. The 36 months of returns of the S&P 500 Index used to calculate the standard deviation is obtained from Yahoo! Finance (2019).

3.3 CAPM

The foundation of modern portfolio management was laid by Harry Markowitz (1952), and another milestone was reached in the 1960´s when the Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The CAPM is an equilibrium model, in the sense that is it imposes a number of assumptions that describes a fully efficient market where all investors have the same information, they maximize returns while minimizing volatility. In a simple form it describes the relationship between systematic risk and expected return for any asset.

$$E(r_i) = r_f + b_i(E(r_m) - r_f)$$

b_i is the volatility of the stock to the market and equals $\frac{cov(r_i, r_m)}{\sigma^2(r_m)}$.

Advantages of the CAPM is that the model provides investors with a simple way of calculating the expected return of different assets, and that the model has been accepted through empirical research of testing. The biggest disadvantage of the model is the number of assumptions it makes, some being difficult to achieve in a real-world setting.

3.4 Jensen´s alpha

Based on the CAPM, Jensen (1968) developed a measure for a portfolio´s deviation from the security market line. This abnormal return of a portfolio or investment is called the Jensen measure or popularly, Jensen´s alpha. A statistically significant non-zero alpha indicates that the fund manager is able to earn abnormal risk-adjusted in excess of the risk-free rate. A statistically significant positive alpha implies that the manager´s portfolio has outperformed the market and a negative one implies underperformance.

$$\alpha_p = r_p - (r_f + b_p(r_m - r_f))$$

α_p is the abnormal return of portfolio p.

Jensen´s alpha has received some criticism that an informed investor should keep in mind. One of these criticisms is the mismatch of portfolio returns and benchmarks used in calculating superior performance or underperformance. More specifically, that there is no appropriate benchmark portfolio with which to compute beta from. With this in mind, we construct a benchmark portfolio that we believe is the most appropriate in measuring mutual fund performance in this study.

3.5 Generalized alpha

Similar to the methodology presented by Jensen (1968), we can reformulate the CAPM model to isolate the alpha, and the same method can be applied to any factor model. Formulating a generalized factor model:

$$r_{it} - r_{ft} = \alpha_i + \sum_{j=a}^{K} \beta_{ij} f_{jt} + \varepsilon_{it}$$

β_i is the factor loading of f_t, which represent the different factors at time t.
A simple rearrangement of the model, gives the formulation of the generalized alpha:

$$\alpha_i = r_{it} - r_{ft} - \sum_{j=a}^{K} \beta_{ij} f_{jt} + \varepsilon_{it}$$

The properties of the generalized alpha are the same as Jensen's alpha, it captures the abnormal returns after accounting for exposure towards the factors used in the model.

3.6 Carhart 4-Factor Model

Carhart states that the construction of his 4-factor model was motivated by Fama and French´s 3-factor model´s (1993) “inability to explain cross-sectional variation in momentum-sorted portfolios returns” (Carhart, 1997, p. 61).

For more than two decades the CAPM was the most common academic model to evaluate risk-adjusted performance. In 1993, Fama and French constructed a multifactor model, adding two risk-factors that would explain more of the cross-sectional returns than the single-factor model CAPM could. The two factors were small-minus-big (SMB) and high-minus-low (HML), and was created based on the findings that small-capitalization stocks tended to outperform large-capitalization stocks, and stocks with high book-to-market ratio tended to outperform stocks with low book-to-market ratios. The two risk-factors were constructed by creating a portfolio going long small-capitalization stocks and short large-capitalization stock for the SMB, and going long in value stocks and short in growth stocks for the HML.

Carhart (1997) added a fourth factor to the three-factor model by Fama and French (1993), creating a portfolio that would go long stocks that had the highest one-year return and short the stocks that had the lowest one-year returns, the previous year. The factor was called PR1YR and would capture the one-year momentum anomaly in stock returns first introduced by Jagadeesh and Titman (1993). The model:

$$r_{it} - r_{ft} = \alpha_i + b_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + p_i PR1YR_t + e_{it}$$

s_i is the factor loading on the *SMB*-factor, h_i is the factor loading on the *HML*-factor and p_i is the factor loading on the *PR1YR*-factor. We use the momentum-factor (MOM) provided by Kenneth French´s Data Library (French, 2019) as a proxy for the PR1YR factor. MOM is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

3.7 Fama and French 5-factor model

After having received a fair amount of criticism, Fama and French (2015) revamped their 3-factor, adding two more risk factors. The criticism they received was due to their 3-factor model not being able to capture much of the variation in average returns related to profitability and investment. Fama and French (2015) included these factors in the new 5-factor model, arguing that the new model performed better than the 3-factor model.

$$r_{it} - r_{ft} = \alpha_i + b_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$$

r_i is the factor loading on the *RMW*-factor, *RMW* is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, c_i is the factor loading on the *CMA*-factor and *CMA* is average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios.

3.8 Persistence

To study persistence in mutual fund performance, we apply the framework used by Hendricks, Patel and Zeckhauser (1993) and Carhart (1997). For the full time-series of 504 months, we form ten EW portfolios of mutual funds, based on last years reported net returns. The portfolios are held for one year, and are then re-formed. In addition to the one-year holding period which captures the persistence from year to year, we also use shorter holding periods. We measure the one-year return of mutual funds prior to the first month of a recession, and the return after three and six months into recession. The reason for doing this to investigate if mutual funds are able to react when the economic climate changes from expansion to recession. The initial ranking period will therefore the defined as

$$r_i^e = r_{i,t-12}^e, r_{i,t-1}^e$$

r_i^e is the return on asset i in excess of the risk-free rate.

prior to the first month of recession. The subsequent period of fund returns three months into recession is defined as

$$r^e_{i,3} = r^e_{i,t}, r^e_{i,t+3}$$

Finally, the subsequent period of fund returns six months into recession is defined as

$$r^e_{i,6} = r^e_{i,t}, r^e_{i,t+6}$$

If we can find significant abnormal returns for either the best or worst portfolio, then we confirm the presence of persistence.

3.9 Bootstrap

We perform a bootstrap simulation to examine whether he alphas obtained from the ranked deciles portfolios are due to actual managerial skill or if performance is simply due to luck. One of the key assumptions of the OLS estimates is that the residuals are normally distributed around zero. However, Kosowski et al. (2006) claims that this does not always hold in reality. We apply the bootstrap procedure as presented by Kosowksi et al. (2006) and later modified by Fama and French (2010). This enables us to find the distribution of possible alphas and t-statistics, which allows us to examine if the true alphas are due to skill or market-timing (luck). The adjustment that we make to the bootstrap simulation compared to Kosowski et al. (2006) and Fama and French (2010) is that the previous studies have been carried out with Carhart´s 4-factor model while we perform the bootstrap on the Fama-French 5-factor model. The second adjustment is that we perform the bootstrap on ranked portfolios instead of individual mutual funds.

The procedure starts by OLS-regressing our aggregate time-series of equal weighted actively managed mutual funds net of costs against the Fama-French 5-factor model.

We then store the alphas and factor loadings, and construct a vector containing the residuals (ε_{it}). For each simulation S, we draw a number of random residuals with replacement that matches the length of the original time-series and place them in a new vector. The formulation for the new residual vector:

$\varepsilon_{i,t_\varepsilon}^B, t_\varepsilon = S_{T_{i0}}^B, \ldots, S_{T_{i1}}^B,$

where B is an index for the bootstrap number.

The saved coefficients are used to construct the pseudo time-series, which is the sum of the products of the Fama-French 5-factor loadings and the corresponding factors at time *t* and a randomly drawn residual from our vector. We set the true alpha to zero, by subtracting the true alpha from the average aggregate fund returns. The pseudo time-series is formulated:

$$r_{i,t}^B = b_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{i,t_\varepsilon}^B$$

In line with Fama-French (2010), we perform 10,000 simulations, which should be sufficient to avoid under-sampling. We store the bootstrapped alphas and corresponding t-statistics and present the average simulated alpha, t-statistic and the fraction of bootstrapped alphas and t-statistics that is larger than the actual statistic. The formulas used to calculate the fraction of simulated alphas and t-statistics:

$$P(\alpha^B) = \frac{1}{S}\sum_{S=1}^{S} 1\,[\alpha^B(S) > \alpha^{act}]$$

$$P\left(t_{\alpha^B}^B\right) = \frac{1}{S}\sum_{S=1}^{S} 1\left[t_{\alpha^B}^B(S) > t^{act}\right]$$

$P(\alpha^B)$ and $P\left(t_{\alpha^B}^B\right)$ are presented as % (sim>Act) in the results. We replicate the process for each of the deciles with the decile portfolio as the dependent variable in the original regression. Lastly, we bootstrap the sub-samples for both expansion and recession periods.

4. Performance

We measure the mutual performance by first comparing the raw returns in excess of the risk-free rate for the EW-portfolio of fund returns and the decile portfolios, against the benchmark portfolio of NAV-weighted index funds. We further measure the model-free portfolio performance when adjusted for risk by utilizing the Sharpe ratio and the M^2-measure. Further, we OLS-regress the time-series return of the EW portfolio of fund and the decile portfolios against the benchmark portfolio. We regress on the single-factor model CAPM (1964) and multi-factor models Carhart 4-factor model (1997) and Fama-French 5-factor model (2015). Lastly, we investigate the persistence of our portfolios to see if we can rely on past performance in the future by testing persistence through contingency tables and bootstrap simulations of the portfolios. For all performance measures or regression model, we first rapport the results of the particular model for the full time-series and subsamples. Then we highlight the difference between recession and expansion, and compared the results of different model with each other.

4.1 Average portfolio returns

Full time-series

Table 1 reports descriptive statistics of the returns and higher moments of the benchmark portfolio, ten decile portfolios, EW portfolio of all the funds in our sample and the EW alpha-coefficients based on the individual fund regressions. The benchmark index portfolio reports an average monthly net return of 0.51 percent while the EW portfolio has an average monthly net return of 0.56 percent per month. The top portfolio has an average monthly net return close to twice that of the benchmark portfolio, with a net return of 1.02 percent. The worst performing portfolio underperforms the benchmark by more than 17 percentage points on average, returning 0.36 percent to investors monthly.

The top performing portfolio has the highest observed monthly return of have 26.67 percent but also the lowest of negative 35.27 percent.

All portfolios have a negative skewness ranging from negative 0.77 to negative 0.68, with no particular outliers. This describes that the distribution of returns contains more negative than positive return values compared to the mean. The top decile has a kurtosis of 3.50 while the bottom decile has a kurtosis of 3.13, meaning a higher density of observed returns around its mean than a normal distribution. The rest of the deciles and the EW portfolio of returns have kurtosis values ranging from 2.9 to 1.9, which indicates less consistency in the returns than a normal distribution.

Expansion

Table 2 reports the descriptive statistics during expansions. From the table, we can see that the EW-portfolio of all funds has approximately the same average monthly return as the benchmark. The difference is only 0.06 percent per month in favor of the EW portfolio. The top decile outperforms the benchmark by close to 0.67 percentage points on average each month, while the bottom decile underperforms the benchmark portfolio by approximately 19 percentage points.

The highest observed return in expansion belongs to decile 1 with a monthly observation of 26.67, and the lowest observation belongs to decile 5 with an observed return of negative 23.72 percent.

In expansions, the skewness is negative for all portfolios. The top decile reports a skewness on negative 0.33 while the bottom decile has a negative skewness of 0.92. The rest of the portfolios have distributions ranging from negative 0.91 to negative 0.67. The kurtosis is higher than 3.0 for the bottom five deciles and slightly less for the top five and the EW full sample of funds.

Recession

Table 3 reports the descriptive statistics during recessions. The average monthly net return for the EW-portfolio is negative 1.00 percent compared to the benchmark portfolio which reports an average monthly net return of negative 1.05 percent. More interestingly, the top portfolio underperforms the benchmark portfolio by 0.76 percentage points per month. The bottom decile underperforms by only 0.025 percentage points per month while the remaining eight decile portfolios outperforms the benchmark portfolio by 0.09 to 0.24 percentage points per month.

In recession, decile 9 has the highest observed return with a monthly observation of 13.11 percent. The lowest observation belongs to decile 1 with an observed monthly return of negative 35.27 percent.

The distribution skewness in the top decile is negative 1.17, the next four deciles and the EW portfolio have a negative skewness negative 0.30 to negative 0.11 and the bottom five have a positive ranging from zero to 0.15. The kurtosis is 2.32 for the top decile and the rest of the portfolios are in the range of negative 0.45 to negative 0.21. This indicates large variations in the distribution of returns among the bottom five deciles.

Findings

When we compare the average returns of the EW portfolio of mutual funds, we find an economically insignificant monthly difference of only 0.01. However, we find that there are several differences in the performance of the decile portfolios compared to the benchmark in the two defined periods. During expansions there is an almost geometrically declining performance when going from the top to bottom decile, with the top five deciles outperforming the benchmark and the bottom five deciles underperforming the benchmark. However, during recessions the top decile turns into the worst performing portfolio and is joined by the bottom decile as the only two portfolios that is underperforming the benchmark. We find that 80 percent of the deciles have outperformed the benchmark, which might indicate that mutual fund managers, on aggregate, can perform better in recession than in expansion, when only looking at the average returns.

With the exception of the top decile, every portfolio has experienced both their maximum and minimum monthly return during recession. Comparing the distribution of the returns, we see that the EW sample of all funds report much smaller, albeit still negative skewness in recessions compared to expansion. The top five deciles have a negative skewness in both periods, while the skewness for the bottom five deciles turn from negative in expansion to positive in recession. The kurtosis goes to negative for all portfolios except decile 1, indicating a wide range of observations in recessions compared to the more compact distribution in expansion. For decile 1, the kurtosis shows almost the same distribution in recession compared to expansion.

4.2 Sharpe ratio and M^2

Full time-series

Table 4 reports the Sharpe ratio and M^2-measure for the full time-series, and the subsamples of expansions and recessions. The EW-portfolio of all the funds in the sample has a higher Sharpe ratio than the benchmark index portfolio, measuring 13.50 percent against the benchmark of 12.49 percent. The top five decile portfolios all have a higher Sharpe ratio than the benchmark index portfolio, while the bottom five has a lower Sharpe ratio than the benchmark.

The story is the same when looking at the M^2-measure. The top five deciles outperform the benchmark after risk-adjusting the returns while the bottom five underperform the benchmark. Decile 1, the top decile, outperforms the benchmark with a monthly average of 0.224 percentage points while the bottom decile underperforms by a monthly average of 0.109 percentage points. The EW portfolio also outperforms the benchmark by a small margin of 0.031 percentage points per month.

Expansion

During expansions, the EW-portfolio of all funds in sample reports a higher Sharpe ratio than the benchmark index portfolio, measuring 19.80 percent against the benchmark´s 18.62 percent. The top five deciles all have higher Sharpe ratios than the benchmark index portfolio, while the bottom five deciles have lower Sharpe ratios than the benchmark. Decile 1 obtains a Sharpe ratio of 23.00 percent while the bottom decile obtains a Sharpe ratio of only 15.30 percent.

The result of the M^2-measure is similar to those of the Sharpe ratio; the EW-portfolio outperforms the benchmark by a small margin, while the top and bottom five deciles outperforms and underperforms the benchmark, respectively. The best five deciles have an average risk-adjusted monthly return that outperforms the benchmark by 0.020 to 0.232 percentage points, while the bottom five deciles underperform the benchmark by negative 0.024 to negative 0.104 percentage points.

Recession

During recessions, the EW portfolio has a reported Sharpe ratio of negative 16.75 percent which is higher than the Sharpe ratio of the benchmark of negative 18.24 percent. Interestingly, decile 1 is the only portfolio to underperform the benchmark while all the other portfolios obtain higher all Sharpe ratios than the benchmark.

All of the decile portfolios obtain a positive M^2-measure during recession, except the bottom decile. Deciles 2 and 4, which had the best Sharpe ratios also have the best M^2-measures, and outperform the benchmark portfolio after risk-adjusting the monthly average returns by 0.25 and 0.22 percent. The top decile has a lower Sharpe ratio than the benchmark but still has a positive M^2-measure, and the case is the opposite for the bottom portfolio. This does not seem feasible but is due to the fact that the two risk-measures use standard deviation from different sources. The standard deviation used in calculating the Sharpe ratio is obtained from the associated return from the sub-sample. However, the standard deviation used in calculating the M^2-measure is obtained from a proxy, as explained in section 3. This is the reason for why e.g., the bottom decile has a Sharpe ratio higher than the benchmark, but still has a negative M^2.

Findings

Why find differences in the distribution of Sharpe ratios among the decile portfolio when we compare expansions to recessions. During expansions, the Sharpe ratios are evenly distributed among the top five and bottom five deciles, which is expected. The top five portfolios outperform the benchmark on terms of Sharpe ratio and the bottom five underperform. However, this changes in recessions. As reported in Table 4, all but one of the ten decile portfolios produce better Sharpe ratios than the benchmark index portfolio. Judging only on this risk-measure, the evidence seems to indicate that most mutual fund managers are able to produce better risk-adjusted returns for investors than index funds in recessions compared to expansion. It is worth mentioning that the top portfolio folio goes from having the best Sharpe Ratio during expansions to having the worst one during recessions, confirming that risk and return go hand-in-hand.

The M^2-measure tells the same story as the Sharpe ratio when comparing expansions and recessions. During expansion, the EW portfolio of funds returns and the top five deciles outperform the benchmark while the bottom five percent underperform it. However, the risk-adjusted returns also change during recessions, according to the results from the M^2-model. Nine out of ten decile portfolios outperform the index which again seems to indicate that mutual fund managers can produce better risk-adjusted returns than index funds in recessions compared to expansions.

4.3 Capital Asset Pricing Model

The first factor model we will discuss is the single-factor model CAPM (1964). Firstly, we perform one regression on a portfolio of EW-returns against the benchmark index portfolio. Secondly, we perform ten regressions against the same benchmark, one for each of the decile portfolios. Lastly, we perform regressions for each mutual fund individually against the benchmark and report EW averages of the alpha coefficients, and calculate fractions of significantly positive and negative alphas.

Full time-series

Based on the returns of all mutual funds in the sample, we find that the portfolio of EW returns has an average monthly alpha coefficient of 0.053 percent in the full time-series from 1977 through 2018. The alpha is not statistically significant though, as shown in Table 5. The top four deciles all have statistically significant alphas on a 5 percent significance level, with average monthly alphas ranging from 0.098 to 0.296 percent. That equals an annual abnormal positive return of 3.55 percent for the top portfolio which is economically significant.

On aggregate, the more than 2600 funds that make up EW portfolio of fund returns has a beta coefficient to the market of close to 1 (0.997), which can be expected for a sample of this size. Decile 4 is the only statistically significant decile that has a factor to the market of less than one.

The bottom three deciles produce negative alphas, but they are all statistically insignificant. The three deciles also have the lowest beta factor loadings of the ten portfolios, which seems to have affect the average returns negatively.

When running regression for each individual mutual fund against the benchmark index portfolio, we find that the EW alpha coefficient of all funds is negative with an average monthly alpha negative 0.050 percent per month. This is an economically insignificant difference compared to the EW portfolio of fund returns which has a positive, yet statistically insignificant monthly alpha coefficient of 0.053 percent. 3.62 percent of the total number of funds in the sample have statistically significant positive alphas on a 5 percent significance level, which constitutes 82 funds. The same number for the funds with statistically significant *negative* alphas on the same significance level is 6.98 percent which amounts to 158 funds. The monthly alpha of those with statistically significantly positive alphas is on average 0.312 percent while the statistically significant negative average alpha is negative 0.484 percent per month.

Expansion

The portfolio of monthly EW fund returns has a statistically insignificant average alpha of 0.062 percent in expansions, as can be seen in Table 6. Four decile portfolios have statistically significant alphas, but only two of them on a 5 percent significance level, while the other two are statistically significant on a 10 percent level. Decile 1 has a statistically significant alpha of 0.390 percent which is also economically significant, outperforming the benchmark by 4.685 percent annually. Four decile portfolios also have negative alphas but these are all statistically insignificant.

The EW portfolio has a beta coefficient to the market of 0.987, while the two deciles with statistically significant alphas on a 5 percent significance have beta coefficients of 1.392 and 0.977, respectively.

Looking at the EW alpha coefficient for the individual fund regressions, we find that the average monthly alpha coefficient is negative 0.066 percent. This is very similar to the average monthly alpha of 0.062 percent found in the regression for the EW fund returns. The percentage of funds with statistically significant alphas is 3.71 percent on a 5 percent significance level, which amounts to a total number of 90 mutual funds. These funds have an average positive alpha of 0.317 percent per month in expansion. The number of funds that are statistically significant positive on a 1 percent level is 1.11 percent of the total sample (27 funds), and these funds generate an average positive alpha of 0.310 percent.

The corresponding number for those funds with statistically significant negative alphas on a 5 percent significance level is 9.23 percent of the total funds in expansion, which amounts to 224 funds and 3.01 percent (73 funds) on a 1 percent significance level. These funds have average monthly alphas of negative 0.471 and negative 0.485 percent on the two significance levels, respectively.

Recession

Table 7 shows that the monthly EW portfolio of fund returns has a positive, but statistically insignificant average alpha of 0.073 percent in recessions. None of the decile portfolios have statistically significant alphas during recessions, but there are only two portfolios that generate negative alphas. Although statistically insignificant, it is interesting to see that the top decile is the portfolio that performs worst in recession with an average negative alpha of 0.269 percent per month. The second worst portfolio is the decile 10 which on a monthly basis has an economically insignificant negative alpha of 0.006 percent on average.

The EW portfolio of fund returns has a beta coefficient of 1.029 during recessions while decile 1 undertakes most risk of all the portfolios with a beta coefficient of 1.467.

For the EW alpha coefficient based on individual regressions, we find that the average monthly alpha coefficient is 0.085 percent in recession, compared to the alpha of 0.073 by the EW fund returns. Only 2.42 percent of the total number of funds have statistically significant positive alphas on a 5 percent level which amounts to 44 funds. These funds have an average positive alpha of 1.040 percent per month in recession. The number of funds that are statistically significant positive on a 1 percent level is 0.60 percent (11 funds), and these funds generate an average positive alpha of 1.592 percent per month. The results show that the average returns of these funds are highly economically significant in recession.

The number of funds that generate statistically significant negative alphas on a 5 percent significance level is 1.37 percent of the total number of funds in the sample which amounts to 25 funds. Corresponding numbers on a 1 percent significance level is 0.16 percent (3 funds), and the average monthly alpha on those significance levels are negative 1.280 and negative 1.780 percent, respectively.

Findings

When comparing the result from expansion and recession, we find a number of differences between the two subsamples. The most prominent finding is that we find decile portfolios that show signs of manager skill with significant alphas in expansions, but not in recessions. We find four decile that are statistically significant in expansion (although two of them on a 10 percent level), but these four portfolios show no signs of managerial skill in recessions. The regressions also show that 40 percent of the decile portfolios underperform in expansion compared to only two in recession. However, we cannot conclude that this is evidence for better overall performance in recession because of statistically insignificant alphas.

Nor the results from the individual fund regressions provide evidence for superior mutual fund performance in recessions. The number of funds that outperform the benchmark goes down from 90 in expansion to 44 in recession on a 5 percent significance level, and from 27 to 11 on a 1 percent significance level. However, the funds that do outperform the benchmark perform better in recession than in expansion. The average alpha of the funds with statistically significant alphas on a 5 percent significance level is 1.040 percent in recession, more than three times larger compared to the average alpha of 0.317 percent in expansion.

In recession, we find that also the number of funds that significantly underperform the benchmark go down compared to expansion. We find 224 funds that underperform the benchmark on a 5 percent significance level in expansion, but only 25 in recession. This might support the theory that some mutual fund managers do better in recession compared to expansion. However, the funds that do underperform in recession do considerably worse in recession compared to expansion. Average monthly underperformance is measured to negative 0.471 percent in expansion but is more than three times that in recession, with an average monthly underperformance of 1.592 percent. Conclude?

4.4 Carhart 4-factor model

The second factor model we perform OLS-regression on in this thesis is the Carhart 4-factor model. In addition to regressing the mutual funds on the benchmark index portfolio, we add three more factors; Small-Minus-Big (SMB), High-Minus-Low (HML) and PR1YR (MOM). Like we did for the CAPM, we first perform one regression on a portfolio of EW fund returns against the benchmark index portfolio. Then we perform ten regressions against the benchmark, one for each of the decile portfolios and lastly, we perform regressions for each mutual fund against the benchmark and report EW averages of the alpha coefficients, and calculate fractions of significantly positive and negative alpha coefficients.

Full time-series

We find no signs of superior performance for mutual funds under the Carhart 4-factor model in the full time-series, as shown in Table 8. All portfolios, including the EW portfolio of fund returns have positive, but statistically insignificant alpha coefficients.

All portfolios have highly statistically significant and positive SMB-coefficients. The regressions also show that all portfolios have negative HML-coefficients, but only the EW portfolio and deciles 2 through 5 are statistically significant on a 5 percent level. The EW portfolio has statistically insignificant exposure to the MOM-factor, but eight out of ten deciles have highly statistically exposure to the MOM-factor in the full time-series. Deciles 1 through 4 have statistically significant positive alpha coefficients on a 1 thousandth significance level. Deciles 8 through 10 have the same statistical significance, but with negative MOM-coefficients while decile 7 is statistically significant negative on a 1 percent significance level.

The EW alpha coefficient based on the individual fund regressions has an average monthly alpha of negative 0.081 percent. 72 of 2263 mutual funds have a statistically significant alpha on a 5 percent significance level. These funds have an average positive alpha of 3.12 percent annually which is economically significant. The number of funds that statistically significantly underperform the benchmark portfolio is 176 on the same significance level. Average underperformance generated by these funds is economically significant, underperforming the benchmark by 5.952 percent annually. Those funds with statistically significant negative underperformance on a 1 percent significance level are naturally fewer, but their underperformance is stronger with and annual underperformance of 7.176 percent.

For the Carhart 4-factor model, we find that adding three factors reveals that the statistically significant alphas found in the CAPM can be explained by other characteristics than managerial skill in the full time-series. The average alpha based on the individual fund regressions is less negative under CAPM than for the 4-factor, emphasizing again that the performance by mutual fund are better explained by characteristic risk-factor rather than managerial skill. The number of funds that have statistically significant positive alphas decrease when going from the CAPM to the 4-factor model and so does their average outperformance. The difference for the underperformers is largest among the number the funds that underperform on a 1 percent level, but the average negative return are economically insignificant when comparing the two factor models.

Expansion

In expansion, we do not find statistically significant alphas for the EW portfolio of fund returns in expansion, nor for any of the decile portfolios. The top five deciles have positive alphas and the bottom five negative alphas, none are statistically significant as previously stated.

The regressions show that the SMB-coefficients are highly statistically significant for the EW portfolio and for the top nine deciles, as can be seen in Table 9. The HML-coefficients are negative and statistically significant for deciles 2 through 4, but otherwise statistically insignificant. The top five deciles are highly statistically significant to the MOM-factor with all five having positive MOM-coefficients, while the bottom three deciles have statistically significant negative coefficients.

The average EW alpha coefficient based on individual fund regressions under the Carhart 4-factor model is negative 0.082 percent per month, which is more negative than the EW alpha coefficient of the CAPM. 67 funds have a statistically significant positive alpha on a 5 percent significance level, and 22 on a 1 percent level during expansions. Average monthly alpha of these funds is 0.309 and 0.357 percent, respectively, which is very similar to the CAPM even though the number of funds has decreased. We find 263 and 89 funds with statistically significant negative alpha coefficient during expansions, with average alphas that is economically insignificant to the CAPM

We find that the returns attributed to manager skill in the CAPM seems to be explained by other factors as alphas go from statistically significant under CAPM to statistically insignificant under the 4-factor model. Adjusted R^2 increases for all portfolios going from CAPM to Carhart 4-factor model as can be expected.

Recession

During recessions, we do not find evidence of managerial skill under the Carhart 4-factor model as can be seen by all the insignificant alpha coefficients in Table 10. All portfolios except decile 10 have highly statistically significant positive SMB-coefficients while the only decile that does not have a statistically significant negative HML-coefficient is decile 10. Decile 2 and 3 have highly statistically significant positive MOM-coefficient while the bottom half of the deciles have statistically significant negative MOM-exposure.

In recession, we find that the average EW monthly alpha coefficient based on the individual fund regressions, has a negative alpha of 0.010 compared to the positive average alpha of 0.085 under CAPM. The number of funds that statistically significantly outperform the benchmark on a significance level of 5 percent during recession is 38 for the 4-factor model, with an economically significant alpha of 0.891 percent per month. 9 funds are statistically significant on a 1 percent significance level, with an average monthly alpha 0.740. Both the number of funds and their average alphas are lower under the 4-factor model than for CAPM. The number of funds that statistically underperform the benchmark increases by close to 70 percent on a 5 percent significance level while the average underperformance of these funds is very similar to those in CAPM. The number of that statistically significantly underperform on a 1 percent level doubles from CAPM to the 4-factor model, but the average negative alpha is approximately the same.

Findings

Under the Carhart 4-factor model, we do not find evidence for better average managerial skill during recessions compared to expansions. The EW portfolio of fund returns has an alpha 0.027 percent during expansions and increases to 0.042 in recessions, but is statistically insignificant. The distribution of decile alpha coefficients seems to more random in recessions compared to the almost geometrically declining performance among deciles in expansions, but we cannot say that the performance is evidence of neither superior performance or underperformance since all deciles are statistically insignificant.

As explained above, the SMB-factor is statistically significant for all of the portfolios except decile 10 but has decreased substantially from expansion to recession. The HML-factor becomes statistically significantly negative for all deciles except decile 1 in recession, compared to only three deciles in expansion. The bottom five portfolios have higher negative exposure to the MOM-factor during recessions compared to expansions, while the decile 1 goes from statistically significant positive exposure in expansions to insignificant negative in recessions. The adjusted R^2 explain more of the returns in recession than during expansion, except for decile 1.

We find that the EW alpha from the individual fund regressions goes from being negative 0.082 in expansion to negative 0.010 in recession, which equals a monthly difference of 0.072 or 0.864 annually. The difference between those funds that have statistically significant alphas on a 5 percent difference level in expansion and recession is even bigger. These funds have average monthly alphas that are 0.588 percent better in recession or a highly economically significant annual difference of 7.056 percent. Comparing those funds that significantly underperform, we find a larger difference but with opposite sign. The difference in average underperformance between expansion and recession is negative 0.861 per month or 10.332 percent annually. Imagine an investor who is consistently buying the wrong group of funds, investing in the funds with statically significant negative alphas during expansion, but is also invested in those funds with statistically significant negative alphas during recession. He will have a negative return of 1.695 percent per month. Then imagine a second investor who invest only in the group of funds that has statistically significant positive alphas during the two periods. She will have a monthly average return of 1.200 percent. The difference in returns between the two investors are 2.895 percent per month or 34.740 percent annually!

4.5 Fama-French 5-factor model

The final model we perform OLS-regressions on is the Fama and French 5-factor model (2015). This model is an extension of the well-known 3-factor model by the same authors in 1993, adding the factor Robust-Minus-Weak (RMW) and Conservative-Minus-Aggressive (CMA). Like we did for the Carhart 4-factor model, we first perform one regression on a portfolio of EW-returns against the benchmark index portfolio. Then we perform ten regressions against the benchmark, one for each of the decile portfolios and lastly, we perform regressions for each mutual fund against the benchmark and report EW averages of the alpha coefficients, and calculate fractions of significantly positive and negative alpha coefficients.

Full time-series

For the full time-series, we find that the EW portfolio of aggregate fund returns has a statistically significant alpha of 0.064 on a 5 percent significance level. So does decile portfolio 3 while deciles 1, 2 and 4 have alphas that are statistically significant on a 1 percent significance level. Table 11, shows that the bottom five deciles have negative alphas, but are all statistically insignificant.

Decile 1 is the portfolio taking most risk out of all the portfolios with a beta-coefficient of 1.335 against the market. The EW portfolio of funds has a beta-coefficient of 0.964 while the rest of the deciles have beta-coefficients between 0.972 and 0.822.

All of the portfolios have positive and highly statistically significant SMB-coefficient in the full time-series, just like for the Carhart´s 4-factor model. Compared to the 4-factor model where the EW portfolio and decile portfolios 2 through 4 had statistically significant negative HML-coefficients, we find that only deciles 2 and 3 are statistically significant negative under the 5-factor model. In addition, decile 10 has a statistically significant positive HML-coefficient.

Table 9 shows all of the factor loadings under the 5-factor model and one can see that deciles 1, 7 and 8 are the only portfolios with statistically significant RMW-coefficients. Decile 1 has a negative factor loading, while the other two portfolios have positive RMW-loadings. For the CML-factor, the table shows that all portfolios except the top to portfolios have statistically significant negative CMA-coefficients.

The EW alpha based on the individual fund regressions shows that the average alpha coefficients of all the funds in the sample is negative 0.040 percent per month which is better than the 4-factor model of negative 0.093. Average monthly alpha of those with statistically significant positive alphas is 0.376 percent on a 5 percent significance level and 0.430 percent per month on a 1 percent significance level. 205 funds have a statistically significant alpha of negative 0.402 percent per month on average. That average is negative 0.434 percent for those 76 funds with statistically significant negative alphas on a 1 percent level.

Compared to Carhart´s 4-factor model, we find that the average EW alpha of the individual funds is less negative under the five-factor model than the 4-factor model, with a monthly difference of 0.041 percent. The average alpha of funds that has statistically significant positive alphas does better on a 5 percent significance level under the 5-factor model compared to the 4-factor model. The average alpha of those funds with statistically significant negative alphas do better on both significance level under the 5-factor model than under the 4-factor.

Expansion

During expansion, we find statistically significant positive alphas for the EW portfolio of fund returns and for the top four decile portfolios. The EW portfolio is significant on a 5 percent level and the four decile portfolios are all significant on a 1 percent level for the 5-factor regression, as can be seen in Table 12.

Decile 1 has the largest beta-coefficient of 1.331, while decile 10 has the smallest of only 0.792. The EW portfolio has a beta-coefficient of 0.964 for the five-factor regression which is a little less than for the 4-factor model. For the SMB-factor, we find that the coefficients are highly statistically significant all portfolios, also for decile 10 which is insignificant under the 4-factor model.

The EW portfolio has statistically insignificant HML coefficients under the 5-factor model but deciles 6 through 9 have gone from statistically insignificant to significantly positive. Only decile 2 has a statistically significant negative HML-coefficient for the five-factor, compared to deciles 2,3,4 and the EW portfolio for the 4-factor model.

Decile 1 has a highly statistically significant negative RMW-coefficient, while decile 8 and 9 are the only other portfolios with any significance, with positive coefficients. All of the portfolios including the EW-portfolio except decile 1 have statistically significant CMA-coefficients. The adjusted R^2 for the portfolios are very similar to those from the 4-factor model.

The average EW alpha based on individual regression is negative 0.043 percent during expansion for the 5-factor, which is better than the alpha coefficients of negative 0.087 under the 4-factor model. The number of funds with statistically significant positive alphas increases by a large amount; from 39 to 187 on a 5 percent level and from 4 to 99 on a 1 percent level. The average alpha of these funds goes from 0.438 and 0.443 under the 4-factor model to 0.406 and 0.472 for Fama-French´s model, respectively. The story is the same for the funds with negative alphas; the number of funds go from 159 to 264 on a 5 percent level and from 39 to 104 on a 1 percent level. The average negative alpha is also better under the 5-factor model than for the 4-factor, with monthly averages of negative 0.387 and 0.404 compared to negative 0.614 and 0.786. We find that the 5-factor attributes more of the returns to managerial skill than the 4-factor model does.

Recession

Table 13 shows the results of the Fama-French 5-factor model during recessions. We find no evidence for managerial skill when looking at the alphas which are statistically insignificant for all portfolios. The results are very different compared to the 4-factor model. Five decile portfolios have superior performance for the 5-factor model and five underperform. Two deciles go from having positive to negative alphas, and two go the opposite way, but we cannot say that this is evidence of either outperformance- or underperformance since they are statistically insignificant.

Most of the portfolios have beta-coefficients to the market that are lower than for the 4-factor model. However, decile 2 through 4 have increased beta-coefficients in the 5-factor model. Just like the 4-factor model, all portfolios are highly statistically significant exposure to the SMB-coefficient except decile 10.

Exposure to the HML-factor decreases for the 5-factor compared to the 4-factor model. The EW portfolio and seven of ten decile portfolios were statistically significant in the 4-factor model, but we only find two that are significant on a 5 percent level while four decile and the EW portfolio are statistically significant on a 10 percent level.

Decile 10 has a negative RMW-coefficient that is highly statistically significant on a 5 percent level and is the only portfolios that is significant to this factor. Deciles 7 and 10 are the only portfolios with that have statistically significant negative exposure CMA-coefficients that are statistically significant. The adjusted R^2 is higher for all portfolios under the 5-factor regression and seems to explain more of the returns compared to the 4-factor model.

Findings

When we compare manager skill with Jensen´s alpha as the preferred measure, we find no evidence of better aggregate performance in recession than expansion. In fact, the results seem to indicate that some portfolios do significantly better in expansion than in recession under the 5-factor model. As mentioned above, the aggregate EW portfolio is statistically significant on a 5 percent significance level and the top four deciles are significant on a 1 percent level in expansion, but all portfolios become insignificant in recession.

The EW portfolio of funds performs very similar in expansion and recession with an economically insignificant difference. However, the bottom five portfolios that all have negative alphas during expansion, become positive during expansion. Although the alphas of these bottom portfolios are statistically insignificant, it is interesting to see that the result changes like this. We believe that the reason for why the bottom deciles do better in recession than expansion is not due to better stock-picking skill during recession, but because these portfolios take less risk than the top portfolios. Their returns suffer during expansion, but is rewarded for this during recession for the same reason. We believe that this is also the reason for why the top decile goes from being the best portfolio during expansions to the worst during recessions. The top portfolio takes a lot of risk which has a large negative impact when the market goes into recession.

The portfolios exposure to the SMB is reduced in recessions compared to expansions, but are still statistically significant for all portfolios except decile 10. As the previous models, exposure to the HML-factor also changes from expansions to recessions under the 5-factor model. Decile 2 shows consistency with statistically significant exposure to the HML-factor while decile 7 through 9 all go from statistically significant positive exposure on 5 percent level in expansion to insignificant negative exposure in recession. Decile 6 stays statistically significant on a 5 percent level and goes from positive in expansion to negative in recession

Only three portfolios have statistically significant exposure to the RMW-factor in expansion and they all become statistically insignificant in recession. The only portfolio that is statistically significant to the RMW-factor in recession is decile 10 which goes from statistically insignificantly positive in expansion to statistically significantly negative on a 1 percent level in recession. All portfolios except decile 1 are highly statistically significant to the CMA-factor in expansion while only deciles 7 and 10 are statistically significant in recession.

We find that the adjusted R^2 is higher for all portfolios in recession than expansion, except for decile 1.

The average EW alpha based on individual fund regressions goes from negative 0.043 to negative 0.067 in recession under the 5-factor model. The number of funds that outperform the index decreases significantly in recession, with close to 75 percent on a 5 percent significance level and almost 90 percent on a 1 percent significance level. However, funds that do significantly outperform the benchmark in recession have average alpha that is more than twice the size of the alpha during expansion.

We find the same pattern for the funds that statistically underperform the benchmark, but with a negative sign. The number of funds with underperformance goes down in recession, but the underperformance is also much stronger in recession compared to expansion. The funds with statistically significant negative alphas underperform the benchmark in recession by more than 14 percent annually on a 5 percent significance level compared to expansion. That number is 21.540 percent on a 1 percent significance level.

5. Persistence

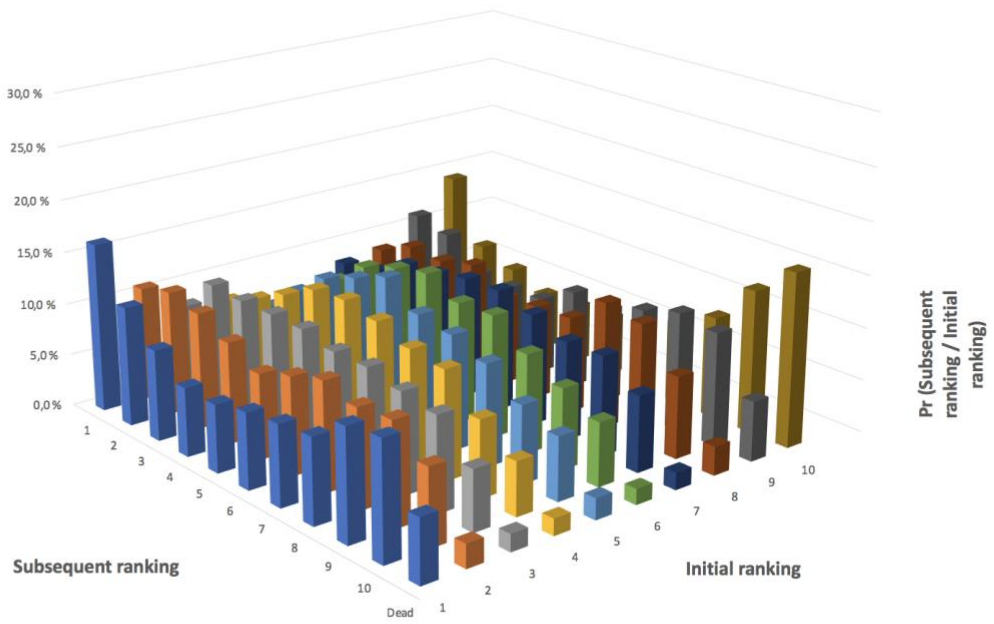
5.1 Consistency in ranking

To test the consistency in fund ranking, we create a contingency table. The contingency table is constructed to visualize the initial and subsequent ranking of the decile portfolios. Firstly, we create a contingency table based for the full time-series based on initial and subsequent ranking of one-year performance. As defined in section 3, we create the same contingency tables to specifically measure persistence in recession. Here, the initial ranking is based on one-year ranking prior to recession, and subsequent rankings are based on rankings three and six months into recession.

Full time series

Consistent with Carhart (1997), the contingency table shows that winners are somewhat more likely to remain winners, and losers show a tendency to remain losers or disappear from the sample (Figure 1, below). It is also interesting to see that there is a relatively high probability of going from the worst decile to the best decile and vice versa. Carhart (1997) attribute this as “gambling behavior” of mutual funds. Although there seems to be some signs of consistency among winners and loser, the annual turnover in ranking for the top decile is still more than 80 percent, leaving us with the conclusion that year-to-year ranking seems to be largely random.

Figure 1. Contingency table of initial and subsequent one-year performance
In each year from 1977 through 2018, funds are ranked into decile portfolios based on one-year net return. These initial decile rankings are paired with the fund´s subsequent one-year net return. Funds that do not survive the complete the subsequent year are placed in a separate category for dead funds. The bars (*j*, *i*) represents the conditional probability of achieving a subsequent ranking *j* (or dying) given an initial ranking of decile *i*.

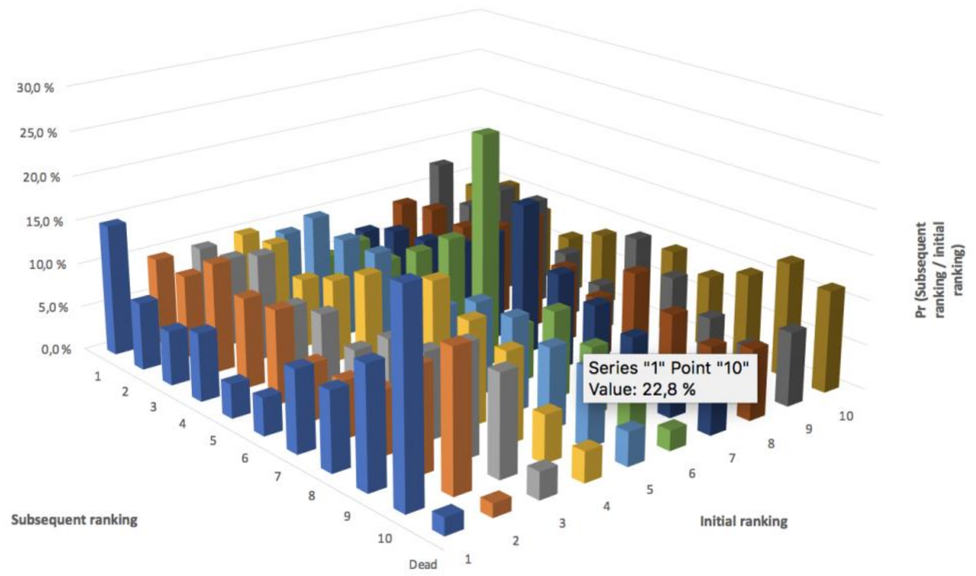


Ranking three months into recession

For the contingency table based on the subsequent ranking three-month into recession, we see from figure 2 that the subsequent ranking seems somewhat random. We find that the probability of having an initial ranking in decile 1 and a subsequent ranking in decile 10 is almost as high as the probability of going from decile 1 to decile 1 or 2, combined. The probability of ending up in any of the deciles in the subsequent ranking is evenly distributed when initially ranked in the bottom decile. The chance of having a subsequent ranking that is the same as the initial one is 11.85 percent, while the chance of dying after being ranked in any of the deciles is 4.95 percent.

Figure 2. Contingency table of initial one-year and subsequent three-month performance

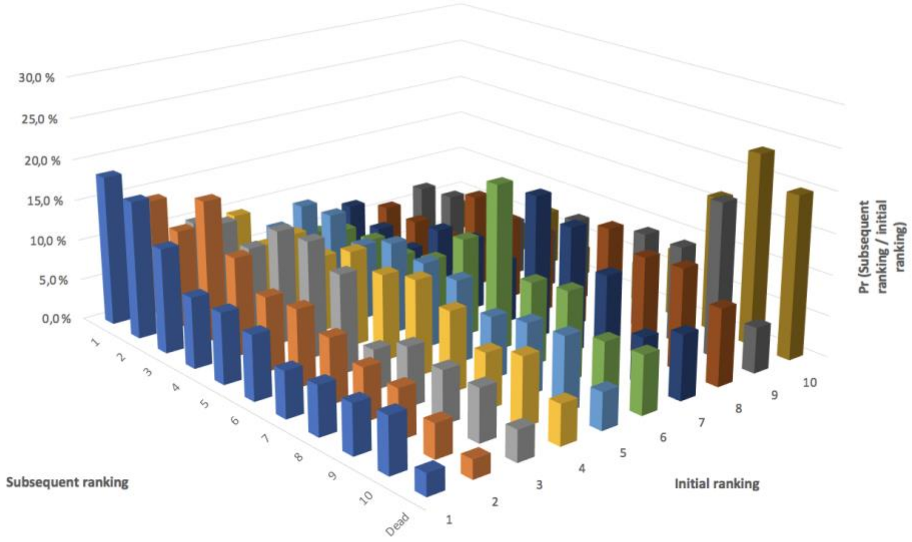
For each of the defined recession in our sample, funds are ranked into decile portfolios based on one-year net return prior to the first month of a recession. These initial decile rankings are paired with the fund´s subsequent three-month net return in recession. Funds that do not survive the complete the subsequent three months are placed in a separate category for dead funds. The bars (*j*, *i*) represents the conditional probability of achieving a subsequent ranking *j* (or dying) given an initial ranking of decile *i*.



Ranking six months into recession

Figure 3 shows the results of initial and subsequent ranking six months into recession. Being ranked in decile 1 gives you the highest probability of also being ranked in decile 1 in the subsequent period. Then there is an almost geometrically declining probability of going from the best decile to worst decile. Looking at the other end of the spectrum, we find that there is a 23.3 percent chance of staying in decile 10 if initially ranked in decile 10, but there is also a 20 percent chance of the fund being dead.

Figure 3. Contingency table of initial one-year and six-month subsequent performance
For each of the defined recession in our sample, funds are ranked into decile portfolios based on one-year net return prior to the first month of a recession. These initial decile rankings are paired with the fund´s subsequent six-month net return in recession. Funds that do not survive the complete the subsequent six months are placed in a separate category for dead funds. The bars (*j, i*) represents the conditional probability of achieving a subsequent ranking *j* (or dying) given an initial ranking of decile *i*.



Findings

Figure 2 provides an impression that the results of the initial and subsequent ranking three months into recession is largely random. However, six months into the recession the image is refined and we find clear tendencies in the data. Deciles 1 and 2 show signs of persistence with more than 40 percent probability of being ranked in the top three deciles after having an initial ranking of either 1 or 2 for the six-month ranking period. For the three-month ranking period, that probability is only about 30 percent.

The worst deciles also show the same tendencies as the top deciles but with different sign. We do not find any clear tendencies for the three-month ranking period, but the 6-month subsequent ranking shows that there is a significant probability of staying in the bottom when going from expansion to recession. E.g., the probability of having a subsequent ranking in the bottom three deciles or dying after initially being ranked in decile 10 goes increases by more than 60 percent from the three- to six-month ranking.

5.2 Bootstrap

Full time-series

In the regression of the pseudo time-series we subtract the alpha of the portfolio from the portfolio returns to achieve a zero true alpha. Since we use net returns for our analysis, we assume that a zero true alpha implies that the portfolio does not only deliver the market rate of return, but also sufficient returns to justify the cost of management, consistent with the method of Fama and French (2010).

Table 14 provides the results of the full time-series. We find that the average simulated alpha is larger than zero for all portfolios, which implies that actively managed mutual funds should on average should be able to cover the cost of management. Our finding of average positive simulated alphas for all portfolios is in line with the findings of Kosowksi et al. (2006) that nearly all mutual funds should be able to cover their expenses.

The results show that only a small fraction of the simulations is able to generate a larger alpha than the actual alpha of the top four deciles. This implies that the true alpha of these four portfolios is due to managerial skill and not due to luck. Decile 1 has a significant display of skill with only 0.22 percent of the 10,000 simulations being able to generate a higher alpha than the decile portfolio. Decile 6 through 10 all have negative true alphas, and are outperformed by the majority of the bootstrap simulations. However, decile 10 is the only portfolio which is beaten in more than 95 of the simulations, which implies that their negative performance is not due to being unlucky, but rather a display of negative skill.

The superior performance of the top four deciles is confirmed by the simulated t-statistics. The simulated t-statistics is only higher than the actual t-statistics in less than 1 percent of the simulations. This further indicates than the significance of the actual alpha is a result of skill.

Expansion

In expansion, we find that the average simulated alpha is positive for all decile portfolios which implies that all portfolios should be able to cover their costs. The simulations are only able to outperform the actual alpha of decile 1 in 0.01 percent of the simulations. Decile 2 through 4 are only outperformed by the simulations in less than 2 percent of the simulations, as can be seen in Table 15. These findings imply that the actual alphas have been attained by managerial skill, and not simply due to luck. Decile 8, 9 and 10 are outperformed in more than 98 percent of the simulations, indicating that their actual negative alphas are due to negative skill.

Decile 1 has a significant *t*-statistic which is not outperformed by any of the 10,000 simulations which proves that this performance is an example of statistically significant skill. Decile 2,3 and 4 also show clear indication of statistically significant skill, being outperformed less than 0.1 percent of the time.

Recession

Table 16 shows that in recession, we find no clear evidence of managerial skill. The average simulated alpha is negative, while six out of ten decile portfolios have positive true alphas under the 5-factor model. The portfolios that are positive are outperformed in more than five percent of the simulations which indicate that their positive alphas are not exclusively due to skill. However, the three bottom portfolios are statistically significant on a 10 percent significance level, implying that their alpha is not simply due to luck either.

Decile 8 and 10 are outperformed less than 2.50 percent of the time which indicate that the actual *t*-statistic is achieved through skill. However, since the *t*-statistic of the alphas are statistically insignificant, we cannot prove that his portfolio will outperform the benchmark during recession.

Findings

Based on the bootstrap simulations, we find no evidence of better performance in recession compared to expansion. Rather, the findings indicate that mutual fund performance is significantly better in expansion. The top four deciles show evidence of statistically significant skill during expansion, but this significance is not present during expansion. All deciles besides decile 8, 9 and 10 show that their abnormal return cannot be attributed to skill, but rather due to luck when comparing expansion to recession.

We find that the simulated bootstrapped *t*-statistics tells the same story as the simulated alphas. The top four deciles are highly statistically significant in expansions, but do not show evidence for outperformance in recessions. With the results of bootstrap simulations, we cannot conclude that mutual funds perform better in recession than in expansion.

6. Conclusion

In this paper, we investigate U.S. mutual fund performance during NBER recessions and expansions from January 1977 through 2018. We study the monthly net returns of 2680 actively managed mutual funds, free of survivorship bias with the purpose to determine if mutual fund managers possess the ability to protect investors during recessions. We replicate the methodology of Hendricks, Patel and Zeckhauser (1993) and Carhart (1997) by creating ten equal-weighted portfolios on lagged one-year returns. In addition to evaluating model-free performance measures, the single-factor model CAPM and multifactor models by Carhart (1997) and Fama and French (2015) to evaluate performance. Lastly, we create contingency tables for different time-periods and run bootstrap simulations to study persistence.

We do not find evidence that U.S. mutual funds on average are able to generate statistically significant alphas during NBER recessions. Rather, the results indicate that on aggregate, mutual funds perform statistically significantly better in expansion than in recession. These findings are supported by the result of the regressions performed on the synthetic decile portfolios and the individual fund regressions. 40 percent of the decile portfolios have statistically significant positive alphas in expansions compared to none in recession, and the number of individual funds with statistically significant positive alphas decreases by two thirds from expansion to recession. The number of funds that underperform also go down in recession but these funds underperform the benchmark by more than four times that of expansion. However, we do also find evidence of highly statistically significant outperformance by a small group of funds. These funds have average alphas in recession that are twice the size of those in expansion. The evidence of strong out- and underperformance by a small group of funds are further confirmed by our findings of persistence in contingency and bootstrap models.

We recommend that further research about mutual fund performance in recessions and expansions should be done on a different sub-sample which better captures the decline specific to the stock market, than the NBER Business Cycle Dates do. Secondly, we had difficulties with acquiring NAV for a large sample of funds, and therefore, we were forced to EW all of over portfolios instead of also NAV-weighting the funds in the sample.

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Appendix

Table 1: Descriptive statistics of portfolios - full time-series
The table presents descriptive statistics for the ranked decile portfolios and the EW portfolio of all funds in the sample for the full time-series from period 1977 through 2018. The second column presents the average monthly return of the portfolio in excess of the risk-free rate. The third column presents the standard deviation of the portfolio return. The fourth and fifth column presents the maximum and minimum return observed for a single month. The sixth and seventh column presents the kurtosis and skewness of the distribution.

Descriptive statistics of portfolios						
Portfolio	Monthly Excess Return	Std. Dev	Max	Min	Kurtosis	Skewness
1	1.02 %	6.47 %	26.67 %	-35.27 %	3.5036	-0.7653
2	0.66 %	4.44 %	13.51 %	-21.52 %	2.3036	-0.7390
3	0.61 %	4.24 %	11.74 %	-21.05 %	2.0947	-0.7042
4	0.60 %	4.09 %	10.81 %	-20.44 %	1.9315	-0.6817
5	0.54 %	4.02 %	11.50 %	-21.41 %	2.3252	-0.7097
6	0.50 %	4.05 %	11.58 %	-23.72 %	2.9638	-0.7842
7	0.51 %	4.04 %	11.40 %	-23.71 %	2.8973	-0.7488
8	0.48 %	4.00 %	11.73 %	-22.35 %	2.5296	-0.7062
9	0.46 %	3.98 %	13.11 %	-21.57 %	2.6721	-0.7225
10	0.34 %	3.81 %	12.08 %	-18.70 %	3.1296	-0.7282
All funds	0.56 %	4.15 %	11.31 %	-21.12 %	2.2042	-0.7464
Benchmark	0.51 %	4.08 %	13.01 %	-22.11 %	2.5146	-0.6489

Table 2: Descriptive statistics of portfolios - expansions
The table presents descriptive statistics for the ranked decile portfolios and the EW portfolio of all funds in the sample during expansions. The second column presents the average monthly return of the portfolio in excess of the risk-free rate. The third column presents the standard deviation of the portfolio return. The fourth and fifth column presents the maximum and minimum return observed for a single month. The sixth and seventh column presents the kurtosis and skewness of the distribution.

Descriptive statistics of ranked portfolios						
Portfolio	Monthly Excess Return	Std. Dev	Max	Min	Kurtosis	Skewness
1	1.37 %	5.96 %	26.67 %	-21.94 %	2.3905	-0.3315
2	0.85 %	4.13 %	13.51 %	-21.52 %	2.9745	-0.7294
3	0.80 %	3.94 %	11.74 %	-21.05 %	2.6989	-0.6996
4	0.78 %	3.79 %	8.20 %	-20.44 %	2.5745	-0.7197
5	0.73 %	3.73 %	11.50 %	-21.41 %	3.1960	-0.7558
6	0.68 %	3.76 %	6.96 %	-23.72 %	4.2316	-0.9141
7	0.69 %	3.75 %	11.40 %	-23.71 %	4.2997	-0.9078
8	0.65 %	3.71 %	10.70 %	-22.35 %	3.6864	-0.8513
9	0.64 %	3.64 %	10.41 %	-21.57 %	3.8542	-0.8726
10	0.52 %	3.37 %	10.35 %	-18.70 %	4.6156	-0.9179
All funds	0.76 %	3.82 %	11.31 %	-21.12 %	2.8405	-0.7672
Benchmark	0.70 %	3.78 %	13.01 %	-22.11 %	3.2164	-0.6643

Table 3: Descriptive statistics of portfolios - recessions

The table presents descriptive statistics for the ranked decile portfolios and the EW portfolio of all funds in the sample during recessions. The second column presents the average monthly return of the portfolio in excess of the risk-free rate. The third column presents the standard deviation of the portfolio return. The fourth and fifth column presents the maximum and minimum return observed for a single month. The sixth and seventh column presents the kurtosis and skewness of the distribution.

Descriptive statistics of portfolios						
Portfolio	Monthly Excess Return	Std. Dev	Max	Min	Kurtosis	Skewness
1	-1.80 %	9.14 %	12.77 %	-35.27 %	2.2322	-1.1694
2	-0.88 %	6.21 %	11.85 %	-16.60 %	-0.2312	-0.2980
3	-0.91 %	5.89 %	10.72 %	-16.00 %	-0.2438	-0.2418
4	-0.81 %	5.76 %	10.70 %	-15.03 %	-0.3412	-0.1237
5	-0.93 %	5.67 %	10.76 %	-15.66 %	-0.3478	-0.1079
6	-0.92 %	5.64 %	11.37 %	-15.63 %	-0.3016	0.0000
7	-0.93 %	5.68 %	11.11 %	-14.43 %	-0.4500	0.1073
8	-0.88 %	5.66 %	11.73 %	-14.49 %	-0.4012	0.0972
9	-0.96 %	5.88 %	13.11 %	-15.47 %	-0.3023	0.0980
10	-1.08 %	6.12 %	12.08 %	-15.68 %	-0.3215	0.1459
All funds	-1.00 %	5.99 %	11.05 %	-17.38 %	-0.2110	-0.1707
Benchmark	-1.05 %	5.73 %	11.67 %	-16.84 %	0.0698	-0.1036

Table 4: Sharpe-Ratio, Risk-Adjusted Returns and M^2.

The table presents the Sharpe ratio, the average monthly risk-adjusted returns and the M^2-measure for the ranked decile portfolios and for the EW portfolio of all funds in the sample. Column two, three and four report the findings for the full time-series from 1977 through 2018. Column five, six and seven report the findings in expansions. The last three columns report the findings in recessions.

	Full period			*Expansion*			*Recession*		
Portfolio	Sharpe Ratio	Risk-Adjusted Return	M^2-Measure	Sharpe Ratio	Risk-Adjusted Return	M^2-Measure	Sharpe Ratio	Risk-Adjusted Return	M^2-Measure
1	15.73 %	0.73 %	0.224 %	23.00 %	0.94 %	0.232 %	-19.71 %	-0.88 %	0.161 %
2	14.84 %	0.61 %	0.097 %	20.62 %	0.78 %	0.078 %	-14.11 %	-0.80 %	0.249 %
3	14.38 %	0.58 %	0.067 %	20.29 %	0.76 %	0.054 %	-15.47 %	-0.87 %	0.172 %
4	14.65 %	0.58 %	0.068 %	20.44 %	0.75 %	0.049 %	-14.07 %	-0.83 %	0.219 %
5	13.54 %	0.54 %	0.032 %	19.55 %	0.72 %	0.020 %	-16.36 %	-0.92 %	0.128 %
6	12.36 %	0.49 %	-0.015 %	17.99 %	0.67 %	-0.035 %	-16.23 %	-0.91 %	0.140 %
7	12.55 %	0.50 %	-0.011 %	18.32 %	0.68 %	-0.024 %	-16.35 %	-0.95 %	0.093 %
8	11.93 %	0.48 %	-0.032 %	17.46 %	0.65 %	-0.057 %	-15.60 %	-0.88 %	0.163 %
9	11.49 %	0.47 %	-0.038 %	17.47 %	0.65 %	-0.053 %	-16.39 %	-0.96 %	0.081 %
10	8.90 %	0.40 %	-0.109 %	15.30 %	0.60 %	-0.104 %	-17.56 %	-1.19 %	-0.147 %
All funds	13.50 %	0.54 %	0.031 %	19.80 %	0.72 %	0.021 %	-16.74 %	-0.94 %	0.110 %

Table 5: CAPM – full time-series

Panel A presents alphas, beta coefficients and adjusted R^2 for the CAPM regression for the full time-series from 1977 through 2018. The corresponding *t*-statistic is reported in parenthesis.

Panel B reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 5A: Portfolio regressions, CAPM

Portfolio	Monthly Excess Return	α	b_{Mkt}	$A.R^2$
1	1.02 %	0.296 %	1.416	0.80
		(2.17)	(24.97)	
2	0.66 %	0.136 %	1.027	0.89
		(2.05)	(63.60)	
3	0.61 %	0.098 %	1.004	0.93
		(2.01)	(84.60)	
4	0.60 %	0.101 %	0.978	0.95
		(2.50)	(99.53)	
5	0.54 %	0.052 %	0.968	0.96
		(1.49)	(114.66)	
6	0.50 %	0.004 %	0.973	0.96
		(0.13)	(79.58)	
7	0.51 %	0.013 %	0.970	0.96
		(0.35)	(72.85)	
8	0.48 %	-0.008 %	0.954	0.94
		(-0.19)	(72.22)	
9	0.46 %	-0.019 %	0.936	0.92
		(-0.36)	(56.22)	
10	0.34 %	-0.098 %	0.857	0.84
		(-1.39)	(35.65)	
All Funds	0.56 %	0.296 %	0.997	0.96
		(1.39)	(107.67)	

Panel 5B: Individual regressions, CAPM

Sig. level	Number of funds	Average alpha
All	2263	-0.064
Pos. 5%	82	0.312
Pos. 1%	29	0.379
Neg 5%	158	-0.484
Neg 1%	44	-0.570

Table 6: CAPM - expansions

Panel A presents alphas, beta coefficients and adjusted R^2 for the CAPM regression for the full sub-sample in expansion periods within the full time-series. The corresponding *t*-statistic is reported in parenthesis.

Panel B reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 6A: Portfolio regressions, CAPM

Portfolio	Average Return	α	b_{Mkt}	$A.R^2$
1	1.37 %	0.390 %	1.392	0,78
		(2.80)	(23.64)	
2	0.85 %	0.132 %	1.023	0,88
		(1.88)	(55.96)	
3	0.80 %	0.093 %	1.004	0,93
		(1.82)	(75.74)	
4	0.78 %	0.088 %	0.977	0,95
		(2.11)	(90.24)	
5	0.73 %	0.048 %	0.967	0,96
		(1.37)	(105.38)	
6	0.68 %	-0.010 %	0.976	0,96
		(-0.27)	(103.95)	
7	0.69 %	0.004 %	0.971	0,96
		(0.10)	(64.26)	
8	0.65 %	-0.022 %	0.952	0,94
		(-0.49)	(63.40)	
9	0.64 %	-0.011 %	0.919	0,91
		(-0.20)	(47.34)	
10	0.52 %	-0.053 %	0.808	0,82
		(-0.71)	(28.84)	
All Funds	0.76 %	0.062 %	0.987	0,95
		(1.57)	(96.61)	

Panel 6B: Individual regressions, CAPM

Sig. level	Number of funds	Average alpha
All	2426	-0.066
Pos. 5%	90	0.317
Pos. 1%	27	0.310
Neg. 5%	224	-0.471
Neg. 1%	73	-0.485

Table 7: CAPM - recessions

Panel A presents alphas, beta coefficients and adjusted R^2 for the CAPM regression for the full sub-sample in recession periods within the full time-series. The corresponding *t*-statistic is reported in parenthesis.

Panel B reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 7A: Portfolio regressions, CAPM

Portfolio	Average Return	α	b_{Mkt}	$A.R^2$
1	-1.80 %	-0.269 %	1.467	0.84
		(-0.60)	(11.07)	
2	-0.88 %	0.217 %	1.046	0.93
		(1.01)	(23.18)	
3	-0.91 %	0.138 %	1.004	0.95
		(0.81)	(30.41)	
4	-0.81 %	0.219 %	0.985	0.96
		(1.48)	(34.62)	
5	-0.93 %	0.089 %	0.972	0.97
		(0.63)	(43.88)	
6	-0.92 %	0.097 %	0.968	0.97
		(0.69)	(40.28)	
7	-0.93 %	0.086 %	0.972	0.96
		(0.56)	(33.74)	
8	-0.88 %	0.126 %	0.966	0.96
		(0.80)	(33.55)	
9	-0.96 %	0.078 %	0.997	0.94
		(0.40)	(25.86)	
10	-1.08 %	-0.006 %	1.023	0.92
		(-0.02)	(21.89)	
All Funds	-1.00 %	0.073 %	1.029	0.97
		(0.50)	(37.88)	

Panel 7B: Individual regressions, CAPM

Sig. level	Number of funds	Average alpha
All	1821	0.085
Pos. 5%	44	1.040
Pos. 1%	11	1.592
Neg. 5%	25	-1.280
Neg. 1%	3	-1.780

Table 8: Carhart 4-factor model - full time-series

Panel A presents alphas, beta coefficients and adjusted R^2 for the Carhart 4-factor regression for the full time-series from 1977 through 2018. The corresponding *t*-statistic is reported in parenthesis.

Panel B presents the descriptive statistics for the factors in the used in the Carhart 4-factor model throughout the full period. Two first columns present the average return and standard deviation for each of the factors. On the left side we present the correlation matrix of the factors.

Panel C reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 8A: Portfolio regressions, Carhart 4 –factor model

Portfolio	Average Return	α	b_{Mkt}	s_{SMB}	h_{HML}	m_{Pr1YR}	$A.R^2$
1	1.02 %	0.114 %	1.380	0.513	-0.038	0.156	0.86
		(0.84)	(22.32)	(8.76)	(-0.69)	(3.55)	
2	0.66 %	0.022 %	0.997	0.280	-0.100	0.145	0.95
		(0.42)	(57.69)	(11.82)	(-3.47)	(7.85)	
3	0.61 %	0.016 %	0.984	0.198	-0.060	0.099	0.96
		(0.40)	(72.11)	(11.91)	(-3.20)	(6.99)	
4	0.60 %	0.050 %	0.961	0.160	-0.043	0.055	0.97
		(1.43)	(78.97)	(9.93)	(-2.98)	(4.24)	
5	0.54 %	0.029 %	0.954	0.133	-0.030	0.015	0.97
		(0.95)	(101.34)	(8.67)	(-2.33)	(1.26)	
6	0.50 %	0.000 %	0.958	0.132	-0.028	-0.012	0.97
		(-0.01)	(91.25)	(8.86)	(-1.89)	(-0.96)	
7	0.51 %	0.024 %	0.956	0.121	-0.024	-0.033	0.97
		(0.68)	(77.50)	(6.46)	(-1.42)	(-2.48)	
8	0.48 %	0.025 %	0.939	0.099	-0.027	-0.059	0.95
		(0.60)	(72.05)	(3.71)	(-1.05)	(-3.68)	
9	0.46 %	0.035 %	0.919	0.096	-0.035	-0.084	0.93
		(0.71)	(57.81)	(3.06)	(-1.08)	(-4.38)	
10	0.34 %	0.029 %	0.829	0.087	-0.079	-0.166	0.86
		(0.47)	(38.80)	(2.35)	(-1.78)	(-6.98)	
All Funds	0.56 %	0.032 %	0.976	0.179	-0.045	0.008	0.98
		(1.04)	(89.49)	(12.50)	(-3-29)	(0.68)	

Panel 8B: Factor returns, standard deviations and correlations, full sample

Factor Portfolio	Average *Return*	Standard Deviation	Correlations MKT	SMB	HML	MOM
MKT	0.51 %	4.08 %	1			
SMB	0.21 %	2.89 %	0.107	1		
HML	0.25 %	2.86 %	-0.230	-0.131	1	
MOM	0.67 %	3.34 %	-0.064	0.091	-0.212	1

Panel 8C: Individual regressions, Carhart 4

Sig. level	Number of funds	Average alpha
All	2454	-0.081
Pos. 5%	72	0.260
Pos. 1%	18	0.285
Neg. 5%	156	-0.496
Neg. 1%	70	-0.598

Table 9: Carhart 4-factor model - expansions

Panel A presents alphas, beta coefficients and adjusted R^2 for the Carhart 4-factor regression for the expansion cycles. The corresponding *t*-statistic is reported in parenthesis.

Panel B presents the descriptive statistics for the factors in the used in the Carhart 4-factor model throughout the expansion periods. Two first columns present the average return and standard deviation for each of the factors. On the left side we present the correlation matrix of the factors.

Panel C, reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 9A: Portfolio regressions, Expansion, Carhart 4 –factor model

Portfolio	Average Return	α	b_{Mkt}	s_{SMB}	h_{HML}	m_{Pr1YR}	$A.R^2$
1	1.37 %	0.197 %	1.365	0.526	-0.022	0.169	0.852
		(1.33)	(19.85)	(8.51)	(-0.39)	(3.58)	
2	0.85 %	0.030 %	0.990	0.274	-0.100	0.146	0.931
		(0.54)	(46.87)	(10.70)	(-2.89)	(7.32)	
3	0.80 %	0.019 %	0.984	0.190	-0.059	0.099	0.956
		(0.45)	(58.60)	(10.71)	(-2.66)	(6.42)	
4	0.78 %	0.034 %	0.963	0.152	-0.035	0.063	0.965
		(0.94)	(65.30)	(9.19)	(-2.06)	(4.84)	
5	0.73 %	0.012 %	0.959	0.127	-0.013	0.028	0.972
		(0.40)	(88.23)	(8.25)	(-0.88)	(2.30)	
6	0.68 %	-0.039 %	0.971	0.132	0.000	0.006	0.970
		(-1.23)	(88.80)	(8.93)	(0.03)	(0.52)	
7	0.69 %	-0.008 %	0.967	0.117	0.001	-0.017	0.964
		(-0.22)	(74.57)	(6.22)	(0.07)	(-1.16)	
8	0.65 %	-0.016 %	0.949	0.098	0.004	-0.042	0.945
		(-0.38)	(67.63)	(3.56)	(0.12)	(-2.32)	
9	0.64 %	0.014 %	0.914	0.087	-0.005	-0.063	0.914
		(0.27)	(49.89)	(2.67)	(-0.14)	(-2.78)	
10	0.52 %	0.041 %	0.793	0.074	-0.060	-0.136	0.821
		(0.63)	(30.97)	(1.86)	(-1.11)	(-4.74)	
All Funds	0.76 %	0.027%	0.974	0.175	-0.029	0.021	0.974
		(0.85)	(75.77)	(11.94)	(-1.94)	(1.74)	

Panel 9B: Factor returns, standard deviations and correlations, Sub-Sample expansion

Factor Portfolio	Average *Return*	Standard Deviation	Correlations MKT	SMB	HML	MOM
MKT	0.70 %	3.78 %	1			
SMB	0.22 %	2.89 %	0.054	1		
HML	0.25 %	2.75 %	-0.288	-0.161	1	
MOM	0.67 %	3.17 %	0.004	0.147	-0.285	1

Panel 9C: Individual regressions, Carhart 4, Expansion

Sig. level	Number of funds	Average alpha
All	2426	-0.082
Pos. 5%	67	0.309
Pos. 1%	22	0.356
Neg. 5%	263	-0.417
Neg. 1%	89	-0.450

Table 10: Carhart 4-factor model - recessions

Panel A presents alphas, beta coefficients and adjusted R^2 for the Carhart 4-factor regression for the recession cycles. The corresponding *t*-statistic is reported in parenthesis.

Panel B presents the descriptive statistics for the factors in the used in the Carhart 4-factor model throughout the recession periods. Two first columns present the average return and standard deviation for each of the factors. On the left side we present the correlation matrix of the factors.

Panel C, reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 10A: Portfolio regressions Recession, Carhart 4 –factor model

Portfolio	Average Return	α	b_{Mkt}	s_{SMB}	h_{HML}	m_{Pr1YR}	$A.R^2$
1	-1.80 %	-0.475 %	1.423	0.374	-0.100	0.131	0.850
		(-1.12)	(49.88)	(2.63)	(-0.58)	(1.22)	
2	-0.88 %	0.011 %	1.020	0.321	-0.120	0.161	0.961
		(0.06)	(10.51)	(4.75)	(-2.53)	(4.38)	
3	-0.91 %	-0.022 %	0.977	0.264	-0.073	0.112	0.971
		(-0.17)	(40.64)	(5.38)	(-2.06)	(3.74)	
4	-0.81 %	0.128 %	0.950	0.225	-0.075	0.043	0.973
		(0.96)	(49.03)	(4.55)	(-2.55)	(1.33)	
5	-0.93 %	0.058 %	0.932	0.185	-0.082	-0.015	0.976
		(0.48)	(52.39)	(3.91)	(-3.17)	(-0.58)	
6	-0.92 %	0.122 %	0.924	0.148	-0.105	-0.063	0.979
		(1.11)	(60.18)	(3.46)	(-3.77)	(-2.52)	
7	-0.93 %	0.109 %	0.920	0.174	-0.097	-0.074	0.973
		(0.89)	(59.96)	(3.78)	(-2.88)	(-2.88)	
8	-0.88 %	0.191 %	0.920	0.121	-0.121	-0.095	0.971
		(1.48)	(40.18)	(2.63)	(-3.36)	(-3.49)	
9	-0.96 %	0.148 %	0.940	0.158	-0.154	-0.109	0.963
		(0.93)	(38.32)	(2.58)	(-3.50)	(-3.56)	
10	-1.08 %	0.172 %	0.959	0.087	-0.190	-0.203	0.953
		(0.89)	(27.85)	(1.21)	(-3.66)	(-5.79)	
All Funds	-1.00 %	0.042 %	0.986	0.201	-0.105	-0.015	0.981
		(0.37)	(24.54)	(4.32)	(-3.20)	(-0.65)	

Panel 10B: Factor returns, standard deviations and correlations, Sub-Sample Recession

Factor Portfolio	Average *Return*	Standard Deviation	Correlations MKT	SMB	HML	MOM
MKT	-1.05 %	5.73 %	1			
SMB	0.14 %	2.94 %	0.384	1		
HML	0.26 %	3.60 %	-0.007	0.043	1	
MOM	1.03 %	4.45 %	-0.297	-0.214	0.106	1

Panel 10C: Individual regressions, Carhart 4, Recession

Sig. level	Number of funds	Average alpha
All	1821	-0.010
Pos. 5%	38	0.891
Pos. 1%	9	0.740
Neg. 1%	42	-1.278
Neg. 1%	6	-1.797

Table 11: Fama-French 5-factor model - full time-series

Panel A presents alphas, beta coefficients and adjusted R^2 for the Fama-French 5-factor regression for the full time-series from 1977 through 2018. The corresponding *t*-statistic is reported in parenthesis.

Panel B presents the descriptive statistics for the factors in the used in the Fama-French 5-factor model throughout the full period. Two first columns present the average return and standard deviation for each of the factors. On the left side we present the correlation matrix of the factors.

Panel C reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 11A: Portfolio regressions, Fama-French 5 factors

Deciles	Average *Return*	α	b_{Mkt}	s_{SMB}	h_{HML}	r_{RMW}	c_{CMA}	$A.R^2$
1	1.02 %	0.359 %	1.336	0.446	-0.034	-0.275	-0.044	0.862
		(2.86)	(22.97)	(8.53)	(-0.45)	(-3.83)	(-0.43)	
2	0.66 %	0.160 %	0.973	0,287	-0.098	-0.026	-0.085	0.937
		(2.73)	(57.53)	(9.14)	(-3.69)	(-0.53)	(-1.77)	
3	0.61 %	0.101 %	0.967	0.214	-0.047	0.018	-0.092	0.960
		(2.42)	(73.35)	(10.18)	(-2.28)	(0.56)	(-2.54)	
4	0.60 %	0.104 %	0.948	0.173	-0.013	0.020	-0.105	0.969
		(2.87)	(80.44)	(10.43)	(-0.74)	(0.88)	(-3.51)	
5	0.54 %	0.045 %	0.946	0.145	0.004	0.029	-0.091	0.974
		(1.44)	(104.28)	(10.81)	(0.27)	(1.61)	(-3.38)	
6	0.50 %	-0.006 %	0.955	0.141	0.008	0.028	-0.080	0.972
		(-0.18)	(92.34)	(10.76)	(0.45)	(1.60)	(-3.19)	
7	0.51 %	0.000 %	0.953	0.134	0.029	0.045	-0.108	0.967
		(-0.01)	(82.04)	(8.78)	(1.40)	(2.08)	(-3.54)	
8	0.48 %	-0.026 %	0.940	0.118	0.038	0.070	-0.125	0.952
		(-0.62)	(77.24)	(5.77)	(1.39)	(2.09)	(-3.27)	
9	0.46 %	-0.034 %	0.919	0.118	0.055	0.085	-0.168	0.928
		(-0.67)	(60.71)	(4.65)	(1.74)	(1.95)	(-3.46)	
10	0.34 %	-0.051 %	0.822	0.082	0.085	0.009	-0.269	0.854
		(-0.76)	(60.71)	(2.28)	(2.09)	(0.13)	(-3.99)	
All funds	0.56 %	0.064 %	0.964	0.180	0.007	-0.008	-0.119	0.977
		(2.07)	(93.25)	(13.48)	(0.42)	(-0.47)	(-4.63)	

Panel 11B: Factor returns, standard deviations and correlations.

Factor Portfolio	Average *Return*	Standard Deviation	Correlations MKT	SMB	HML	RMW	CMA
MKT	0.51 %	4.08 %	1				
SMB	0.21 %	2.89 %	0.107	1			
HML	0.25 %	2.86 %	-0.230	-0.131	1		
RMW	0.34 %	2.30 %	-0.222	-0.405	0.204	1	
CMA	0.26 %	1.95 %	-0.337	-0.069	0.692	0.111	1

Panel 11C: Individual regressions, Fama-French 5, Full sample

Sig. level	Number of funds	Average alpha
All	2263	-0.056
Pos. 5%	180	0.376
Pos. 1%	85	0.430
Neg. 5%	205	-0.402
Neg. 1%	76	-0.434

Table 12: Fama-French 5-factor model - expansions

Panel A presents alphas, beta coefficients and adjusted R^2 for the Fama-French 5-factor regression for the expansion cycles. The corresponding *t*-statistic is reported in parenthesis.
Panel B presents the descriptive statistics for the factors in the used in the Fama-French 5-factor model throughout the expansion periods. Two first columns present the average return and standard deviation for each of the factors. On the left side we present the correlation matrix of the factors.
Panel C, reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 12A: Portfolio regressions, Fama-French 5 factors

Deciles	Average *Return*	α	b_{Mkt}	s_{SMB}	h_{HML}	r_{RMW}	c_{CMA}	$A.R^2$
1	1.37 %	0.422 %	1.332	0.466	-0.027	-0.252	-0.045	0.859
		(3,19)	(20.96)	(8.04)	(-0.41)	(-3.37)	(-0.44)	
2	0.85 %	0.177 %	0.968	0.280	-0.080	-0.053	-0.133	0.933
		(2.96)	(51.35)	(8.04)	(-2.65)	(-1.02)	(-2.45)	
3	0.80 %	0.111 %	0.969	0.209	-0.031	0.002	-0.129	0.958
		(2.64)	(66.15)	(9.14)	(-1.32)	(0.05)	(-3.14)	
4	0.78 %	0.099 %	0.951	0.167	0.006	0.004	-0.131	0.967
		(2.73)	(73.39)	(9.60)	(0.33)	(0.18)	(-4.21)	
5	0.73 %	0.044 %	0.952	0.140	0.027	0.015	-0.106	0.973
		(1.40)	(96.17)	(10.39)	(1.49)	(0.79)	(-3.75)	
6	0.68 %	-0.027 %	0.967	0.143	0.038	0.018	-0.089	0.971
		(-0.87)	(91.87)	(11.19)	(2.01)	(1.03)	(-3.53)	
7	0.69 %	-0.017 %	0.964	0.131	0.053	0.034	-0.105	0.966
		(-0.47)	(80.83)	(8.52)	(2.43)	(1.54)	(-3.31)	
8	0.65 %	-0.055 %	0.950	0.124	0.071	0.075	-0.130	0.949
		(-1.29)	(78.19)	(5.94)	(2.43)	(2.23)	(-3.13)	
9	0.64 %	-0.043 %	0.916	0.119	0.083	0.094	-0.163	0.920
		(-0.83)	(57.33)	(4.43)	(2.42)	(2.12)	(-2.99)	
10	0.52 %	-0.035 %	0.792	0.080	0.091	0.032	-0.228	0.829
		(-0.51)	(33.06)	(2.09)	(1.95)	(0.48)	(-2.93)	
All funds	0.76 %	0.066 %	0.964	0.180	0.026	-0.010	-0.126	0.976
		(2.11)	(83.96)	(13.20)	(1.44)	(-0.62)	(-4.61)	

Panel 12B: Factor returns, standard deviations and correlations.

Factor Portfolio	Average *Return*	Standard Deviation	Correlations MKT	SMB	HML	RMW	CMA
MKT	0.70 %	3.78 %	1				
SMB	0.22 %	2.88 %	0.05	1			
HML	0.25 %	2.75 %	-0.29	-0.16	1		
RMW	0.29 %	2.32 %	-0.18	-0.43	0.24	1	
CMA	0.24 %	1.89 %	-0.31	-0.04	0.72	0.10	1

Panel 12C: Individual regressions, Fama-French 5, Expansion

Sig. level	Number of funds	Average alpha
All	2426	-0.043
Pos. 5%	187	0.406
Pos. 1%	99	0.472
Neg. 5%	264	-0.387
Neg. 1%	104	-0.404

Table 13: Fama-French 5-factor model - recessions

Panel A presents alphas, beta coefficients and adjusted R^2 for the Fama-French 5-factor regression for the recession cycles. The corresponding *t*-statistic is reported in parenthesis. Panel B presents the descriptive statistics for the factors in the used in the Fama-French 5-factor model throughout the recession periods. Two first columns present the average return and standard deviation for each of the factors. On the left side we present the correlation matrix of the factors.

Panel C, reports the average alpha of all funds and the statistically significant positive and negative average alpha based in the individual fund regressions.

Panel 13A: Portfolio regressions, Fama-French 5 factors

Deciles	Average *Return*	α	b_{Mkt}	s_{SMB}	h_{HML}	r_{RMW}	c_{CMA}	$A.R^2$
1	-1.80 %	-0.111 %	1.326	0.349	-0.066	-0.382	-0.073	0.850
		(-0.27)	(8.32)	(2.35)	(-0.28)	(-1.42)	(-0.26)	
2	-0.88 %	-0.013 %	1.044	0.298	-0.140	0.214	0.127	0.953
		(-0.07)	(24.70)	(4.09)	(-2.31)	(1.77)	(1.17)	
3	-0.91 %	-0.033 %	0.989	0.246	-0.077	0.145	0.060	0.966
		(-0.21)	(29.60)	(4.67)	(-1.81)	(1.40)	(0.73)	
4	-0.81 %	0.094 %	0.957	0.215	-0.063	0.107	-0.010	0.972
		(0.66)	(34.94)	(4.31)	(-1.99)	(1.32)	(-0.12)	
5	-0.93 %	-0.010 %	0.939	0.182	-0.055	0.100	-0.068	0.977
		(-0.09)	(45.68)	(3.88)	(-1.88)	(1.57)	(-0.88)	
6	-0.92 %	0.056 %	0.923	0.149	-0.064	0.047	-0.125	0.978
		(0.47)	(39.53)	(3.37)	(-2.04)	(0.73)	(-1.68)	
7	-0.93 %	0.029 %	0.913	0.172	-0.032	0.070	-0.192	0.973
		(0.22)	(33.26)	(3.52)	(-0.84)	(1.06)	(-2.56)	
8	-0.88 %	0.175 %	0.902	0.127	-0.075	-0.064	-0.159	0.967
		(1.24)	(31.09)	(2.65)	(-1.65)	(-0.97)	(-1.87)	
9	-0.96 %	0.156 %	0.913	0.166	-0.103	-0.113	-0.179	0.960
		(0.95)	(22.06)	(2.86)	(-1.74)	(-1.68)	(-1.85)	
10	-1.08 %	0.228 %	0.902	0.105	-0.107	-0.279	-0.309	0.946
		(1.17)	(22.81)	(1.51)	(-1.75)	(-3.54)	(-2.79)	
All funds	-1.00 %	0.063 %	0.967	0.197	-0.068	-0.030	-0.103	0.981
		(0.51)	(37.84)	(4.22)	(-1.92)	(-0.42)	(-1.53)	

Panel 13B: Factor returns, standard deviations and correlations.

Factor Portfolio	Average *Return*	Standard Deviation	Correlations MKT	SMB	HML	RMW	CMA
MKT	-1.05 %	5.73 %	1				
SMB	0.14 %	2.94 %	0.38	1			
HML	0.26 %	3.60 %	-0.01	0.04	1		
RMW	0.81 %	2.07 %	-0.43	-0.15	-0.05	1	
CMA	0.39 %	2.41 %	-0.44	-0.22	0.57	0.17	1

Panel 13C: Individual regressions, Fama-French 5, Recession

Sig. level	Number of funds	Average alpha
All	1821	-0.067
Pos. 5%	47	0.959
Pos. 1%	10	0.916
Neg. 5%	72	-1.629
Neg. 1%	9	-2.199

Table 14: Bootstrap simulation - full time-series

The table presents the bootstrapped results for our full sample period 1977-2018. The first three columns in the table shows the actual alpha for our performance based deciles, the average simulated alpha and the fraction of simulations that supersedes the actual alpha. The last three columns presents the actual t-statistics, simulated t-statistics and the fraction of simulated t-statistics that supersedes the actual t-statistic.

	Alphas			t-Statistics		
Portfolios	Act	Sim	%(Sim>Act)	Act	Sim	%(Sim>Act)
1	0.3594 %	0.0932 %	0.22 %	2.858	0.638	0.03 %
2	0.1602 %	0.0284 %	0.28 %	2.731	0.410	0.06 %
3	0.1013 %	0.0218 %	1.20 %	2.424	0.412	0.14 %
4	0.1041 %	0.0147 %	0.22 %	2.866	0.329	0.01 %
5	0.0453 %	0.0147 %	12.25 %	1.443	0.312	5.39 %
6	-0.0059 %	0.0151 %	74.84 %	-0.185	0.357	76.94 %
7	-0.0003 %	0.0159 %	70.44 %	-0.009	0.346	70.57 %
8	-0.0265 %	0.0248 %	90.73 %	-0.619	0.452	93.43 %
9	-0.0340 %	0.0347 %	94.27 %	-0.670	0.524	96.43 %
10	-0.0511 %	0.0577 %	96.96 %	-0.759	0.649	98.49 %

Table 15: Bootstrap simulation - expansions

The table presents the bootstrapped results for our sub-sample containing the expansion periods. The first three columns in the table shows the actual alpha for our performance based deciles, the average simulated alpha and the fraction of simulations that supersedes the actual alpha. The last three columns presents the actual t-statistics, simulated t-statistics and the fraction of simulated t-statistics that supersedes the actual t-statistic.

	Alphas			t-Statistics		
Portfolios	Act	Sim	%(sim>Act)	Act	Sim	%(sim>Act)
1	0.4223 %	0.1324 %	0.01 %	3.186	0.917	0.00 %
2	0.1774 %	0.0441 %	0.19 %	2.965	0.627	0.04 %
3	0.1109 %	0.0288 %	1.41 %	2.637	0.536	0.08 %
4	0.0988 %	0.0219 %	0.69 %	2.729	0.483	0.04 %
5	0.0436 %	0.0219 %	17.55 %	1.404	0.446	8.17 %
6	-0.0270 %	0.0198 %	94.44 %	-0.869	0.465	97.47 %
7	-0.0167 %	0.0234 %	89.71 %	-0.473	0.504	92.26 %
8	-0.0549 %	0.0353 %	99.08 %	-1.294	0.630	99.73 %
9	-0.0425 %	0.0532 %	98.12 %	-0.827	0.781	99.16 %
10	-0.0346 %	0.0921 %	98.55 %	-0.514	1.019	99.29 %

Table 16: Bootstrap simulation - recessions

The table presents the bootstrapped results for our sub-sample containing the recession periods. The first three columns in the table shows the actual alpha for our performance based deciles, the average simulated alpha and the fraction of simulations that supersedes the actual alpha. The last three columns presents the actual t-statistics, simulated t-statistics and the fraction of simulated t-statistics that supersedes the actual t-statistic.

	Alphas			t-Statistics		
Portfolios	Act	Sim	%(sim>Act)	Act	Sim	%(sim>Act)
1	-0.1110 %	-0.2263 %	37.48 %	-0,269	-0.382	43.71 %
2	-0.0134 %	-0.0355 %	44.62 %	-0,067	-0.148	45.48 %
3	-0.0333 %	-0.0258 %	52.69 %	-0,209	-0.122	55.03 %
4	0.0943 %	-0.0239 %	16.65 %	0,663	-0.132	12.54 %
5	-0.0104 %	-0.0239 %	48.19 %	-0,085	-0.104	49.32 %
6	0.0562 %	-0.0191 %	24.35 %	0,465	-0.130	20.01 %
7	0.0285 %	-0.0214 %	33.56 %	0,221	-0.134	30.69 %
8	0.1752 %	-0.0296 %	5.74 %	1,239	-0.167	2.25 %
9	0.1556 %	-0.0338 %	9.99 %	0,954	-0.159	5.17 %
10	0.2277 %	-0.0598 %	5.12 %	1,168	-0.233	2.08 %