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Abstract

Momentum has been a persistent and robust factor in explaining excess future returns, generating great interest from investors and financial analysts. Following the financial crisis of 2008 and the Covid-19 pandemic, there have been instances of significant momentum crashes. US Equity funds are used to gain insights about the properties of momentum and its predictive ability. Momentum performance is evaluated over the period 2000 to 2023. A multifactor model is developed, using factor attribution to explain the impact on fund performance over time by factors such as risk, size, value-growth orientation and momentum. Conclusions can be made that while momentum have previously been successful in predicting future returns, particularly for growth-oriented funds, recent market situations have lead to underperformance. The multifactor model, incorporating size and value-growth orientation, suggests that momentum is not entirely responsible for the poor performance following the Covid-19 crisis.

Keywords: Equity Funds, Value, Growth, Momentum, Carhart Four-Factor Model, Multifactor Model, Momentum Crashes

Sammanfattning

Momentum har historiskt sett varit en framgångsrik faktor för att predicera framtida avkastning, vilket har skapat stort intresse från investerare och finansiella analytiker. Efter finanskrisen 2008 och Covid-19 pandemin har det skett signifikanta momentumkrascher. Amerikanska aktiefonder används för att undersöka egenskaperna hos momentum och dess prediktiva förmåga. Prestationen av momentum utvärderas under tidsperioden 2000 till 2023. En multifaktormodell utvecklas, som använder faktor-attribution för att förklara hur fonders avkastning påverkas över tid av faktorer såsom risk, marknadsvärde, värde/tillväxt-orientering och momentum. En slutsats dras att även fast momentum har presterat väl historiskt för att predicera framtida avkastning, särskilt för tillväxt-orienterade aktiefonder, så har den senaste tidens marknadsrörelser lett till underprestation. Multifaktormodellen, som innehåller marknadsvärde och värde/tillväxt-orientering, indikerar att momentum inte är en lika stor anledning till underavkastningen efter Covid-19 krisen.

Nyckelord: Aktiefonder, Värdeaktier, Tillväxtaktier, Momentum, Carhart Four-Factor Model, Multifaktormodell, Momentumkrascher

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1 Introduction

Trying to predict future returns of stocks and mutual funds is an area with great interest and implications for investors and financial advisors. Some strategies rely on fundamental analysis to find securities that are mispriced, or priced to a discount to fair value. Other strategies rely on technical analysis to find patterns in historic prices that successfully can predict future price movements. One of the most widely studied and debated investment strategies out of these is the momentum-factor. Momentum aims to capture trend-following behavior, by buying past winners and selling past losers. It is based on the idea that past winners will continue to perform well in the future, an idea that has been proven to be true in past research and therefore gained a lot interest among investment professionals.

There are different ways to define past winners, the simplest of them being to use trailing historic returns. The period for which historic returns are calculated is often referred to as the *evaluation period*, and the period for which the excess performance is evaluated the *holding period*. Previous research suggests that momentum is strongest using a 12-month evaluation period and a 3 to 6-month holding period[1] (Jegadeesh and Titman 1993).

When evaluating several time periods simultaneously, excess returns over a benchmark or average of peers can be used instead of raw returns to avoid capturing reversals and continuations in market returns. In some cases, an alternative definition of momentum is used, where last month return is deducted from the past year returns. This is to avoid capturing securities with high short-term returns, since these historically have shown price reversals in the short-term future (Jegadeesh 1990).

Historically, momentum has shown to be one of the strongest and most persistent factors to explain return patterns. Momentum explains returns that can not be attributed to other factors in multi-factor models, such as risk (beta) in the traditional Capital Asset Pricing Model (CAPM) or the size & book-to-market factors in the Fama-French model. Momentum has been persistent through bear & bull markets, compared to other factors which tend to be pro-cyclical or defensive (MSCI 2016). However, momentum has had some notable crashes, the main ones documented being in 1932 & 2009. It is therefore of great interest to study the behaviour of momentum, to gain insight into what causes crashes and how these can be avoided. One particularly interesting period to study is the stock market crash caused by the outbreak of Covid-19 pandemic in March 2020 since research of momentum in such recent events is yet to be published.

1.1 Report structure

The report is structured into five main parts. Initially, *Financial theory* relevant for the method and interpretation of results is presented. Then *Momentum* is discussed in more detail, including the main conclusions of previous studies. Steps taken to generate results are presented in the *Method*. *Results* are then presented and analysed in upcoming *Discussion*. Finally, the main conclusions are summarised.

1.2 Purpose

The purpose of the project is to explore whether the momentum-factor is significant in predicting future returns, and if so, if it is persistent across time periods and markets. By doing this, it possible to gain insight in whether this factor can be used to inform investment decisions and be used in quantitative modelling. The project is also relevant in exploring the impacts of recent events, such as the stock market crash caused by the outbreak of Covid-19 pandemic in March 2020.

The existence of momentum would also have a broader implication since this proves that historical prices can be used to predict excess future returns, thus violating the key assumption in the Efficient Market Hypothesis. Proving that there is a momentum-factor is then equivalent to concluding that the US equity fund market is not efficient.

Lastly, the project aims to explore the distribution of momentum returns to discuss previous findings by (Barroso and Santa-Clara 2014) of the negative skewness of momentum strategies. Momentum crashes are studied in order to find similarities between crashes as well as exploring common characteristics able to predict and manage momentum crashes.

[1] An evaluation period of J-months and K-month holding period is referred to as a J-month/K-month strategy (Jegadeesh and Titman 1993)

1.3 Problem definition

1. How does significance of the momentum-factor for predicting future return change in relation to time period, and restricted to different fund categories?

2. Are there any other factors, besides momentum, that are able to consistently predict future fund returns?

1.4 Scope

A total of 3381 equity funds in the US region, active during the time period 2000-2023, are included in the analysis. The US market is selected since it is the largest and among the most efficient financial markets globally. It is therefore of great interest to study market inefficiency, such as momentum, in that market.

Since funds are offered in several share classes, the data is cleaned for duplicates by only including the oldest share class, and excluding virtual classes. To avoid survivor bias (mutual funds that underperform are more likely to be liquidated) all funds that have been active within the period are included, even those that are no longer active. Funds included are those belonging to the following six Morningstar categories (Morningstar 2021)

Table 1: Selection of Morningstar Categories

Region & Size	Morningstar Category
US Large-Cap	*US Large-Cap Value Equity* *US Large-Cap Growth Equity*
US Mid-Cap	*US Mid-Cap Value Equity* *US Mid-Cap Growth Equity*
US Small-Cap	*US Small-Cap Value Equity* *US Small-Cap Growth Equity*

2 Financial theory

2.1 Mutual Funds

A mutual fund is an investment fund that pools money from investors to invest in various securities. Mutual funds often offer a more diversified portfolio and access to securities that are not available to private individuals, and use leverage from economies of scale to negotiate lower fees.

2.1.1 Type of funds

There are several type of mutual funds, some of the most common include:

1. **Equity funds**: These funds invest the majority of their assets into publicly traded stocks. Equity funds often have a strategy, which for example could dictate what size of companies they invest in (large cap, mid cap, small cap), companies located in a certain region (e.g. North America, Europe, emerging markets) or companies in the same industry (e.g. tech, basic materials, healthcare).

2. **Fixed Income**: These funds invest primarily in bonds, which are debt securities issued by companies or governments. Fixed income funds can be further categorized based on the credit quality of the bonds they hold (e.g. investment grade, high yield), the issuer (government, corporate), or the duration of the bonds they hold.

3. **Money Market Funds**: These funds invest in short-term, low-risk debt securities such as Treasury bills, commercial paper, and certificates of deposit. They can be compared to savings account, providing stable returns at a low level of risk.

4. **Balanced funds** Balanced funds invest in different securities, often a combination of stocks and bonds.

This thesis is focused on equity funds investing in a broad range of industries, restricted to a certain region and size of companies.

2.1.2 Active & passive funds

Mutual funds can be broadly be categorized into active and passive funds based on their investment strategy.

Active funds Active funds are funds managed by one or more fund managers. They will select a portfolio of stocks that they believe will outperform the market. This portfolio is then monitored and managers are working actively with finding new companies and evaluating portfolio companies in order to find the companies which in their view are currently undervalued.

There is a lot of research originating from both academics and practitioners of active management. On developed markets, few managers are able to consistently outperform the market. Sharpe (1991) claims that because of basic arithmetic, active managers will underperform their respective benchmark. This is based on the reasoning that managers on average will perform in line with the market before fees, and worse than the market net-of-fees. Since the market return is the weighted average of the returns of the securities within the market, a security overweighted by one manager has to be underweighted by another managers, resulting in that active management, on average, is unable to outperform the market.

Others have shown that fund managers have stock selection skills and are able to select stocks that on average outperform their benchmark. To generate returns greater than market average, this is not enough, since transaction costs have to be taken into account. Wermers (2000) shows that fund managers pick stocks that outperform the market by 1.3% but that 0.7% is lost in underperformance of nonstock holdings (funds hold cash for investors deposits and withdrawals) and 1.6% lost in expenses and transaction costs. All in all, this results in fund managers underperforming their benchmark by around 1%.

Passive funds Passive funds on the other hand make no active decisions when selecting investments, but instead track a specific benchmark index, such as S&P500 or OMXS30. There are passive funds tracking most of the large stock indices. These funds usually have lower management fees compared to actively managed peers.

2.1.3 Book-to-market

Another common categorisation for equity funds is to classify them based on the average book-to-market of their holdings. Often funds are classified either as growth, value or blend (mix of value & growth). Both of these are calculated on the fund's stock holdings individually and thereafter aggregated based on the weight of each holding.

Growth Growth stocks are stocks that have high book-to-market, a high valuation compared to current earnings or book value. These companies are expected to grow faster than the overall market and thus generate larger cash-flows in the future. Usually these companies are in industries such as technology and healthcare. Growth funds often have higher volatility and risk as they invest in companies that have a higher potential for growth but also are highly subject to market fluctuations.

Value Value funds on the other hand invest in companies that have a lower valuation compared to book value/current earnings. These companies are typically found in sectors such as energy, financials, and utilities. Value funds tend to have lower volatility but also lower growth potential.

Comparing the historic return of these two categories, it is not clear which one of these strategies that generates the highest return. From 2000 to 2010, value stocks outperformed growth, but from 2010 to 2020 growth stocks outperformed value (Weng and Butler 2022). This is largely determined by the overall market conditions where growth stocks tend to underperform with rising interest rates since they tend to have higher debt and cash-flows further into the future.

2.1.4 Share Classes

In some cases a mutual fund can be offered in several share classes. All share classes invest in the same portfolio of securities but the different classes can have different fees, expenses or currencies. Often share classes are made for different client segments, such as creating one class for retail and another for institutional clients or clients that fulfill higher capital requirements.

2.2 Developed & emerging markets

Global financial markets can broadly be divided into two groups, developed & emerging markets. Developed markets are characterized by high-standard of living, well-functioning stock markets and financial system, free trade and regulatory bodies. Emerging markets, in contrast are missing one, or several of these. Emerging markets are for this reason associated with higher market and geopolitical risks.

MSCI, a global stock-index provider has developed a framework when determining which markets they include in their *MSCI Emerging Markets Index*. The framework is based on three dimensions of a country's market (MSCI 2012):

- **Economic development** uses Gross National Income (GNI) per capita as published by the World Bank.

- **Size and liquidity of its equity markets** consistent cross country comparison for 77 markets.
- **Accessibility for foreign investors** uses 18 distinct measures such as foreign ownership limits or capital flow restrictions.

2.3 Efficient Market Hypothesis

Efficient market hypothesis (EMH) states that financial markets are efficient, meaning that all current information is reflected in a security's price. This implies that securities always are priced at fair value and that it is impossible for investors to consistently outperform the market (E. Fama 1970). This hypothesis is widely discussed and research has been published both to support and to disprove this hypothesis (Malkiel 2003).

There are three forms of EMH: the weak form, semi-strong form and strong form (Malkiel 1989).

Weak form All historical prices is currently priced into the security and therefore it is impossible to consistently outperform the market by using historical data. This implies that technical analysis (studying past price movements to predict future movements) is ineffective. This means that the conditional expectation of a security's excess future return ε_i is independent of previous returns (due to the Markov Property). The expected excess return is zero since no fund should be able to consistently outperform the market if markets are efficient.

$$\mathbb{E}[\varepsilon_{i,t}|\varepsilon_{i,t-1}, \varepsilon_{i,t-2}, \ldots, \varepsilon_{i,t-n}] = \mathbb{E}[\varepsilon_{i,t}] = 0 \tag{1}$$

Semi-strong form In addition to historical prices considered in the weak form, semi-strong EMH also assumes that all publicly available information, such as financial reports, news and macro events are also reflected in a security's price. This implies that fundamental analysis is not effective in trying to achieve superior returns.

Strong form In the strong form, all information, including insider information, is always reflected in a security's price. This means that even insider trading cannot provide an investor with superior returns. Strong form EMH is considered the strongest form of the hypothesis and implies that no one can consistently outperform the market.

EMH states that the total expected return (R_t) of a security is only a function of it's risk premium.

$$\mathbb{E}[R_t \mid I_t] = (1 + r_t) \tag{2}$$

where I_t denotes available information (price history, publicly available information or all available information depending on type of EMH) and r_t denotes the risk premium.

2.4 Mean reversion

Mean reversion is a financial theory that states that assets return and volatility eventually will return to its historic average. Assets which price deviate from its mean past performance will eventually revert back to its mean. "Value Investing" is a common example, where managers try to buy undervalued assets and wait for them to eventually revert to their long-term average growth (M. Poterba and Summers 1988).

2.5 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) describes a relationship between the systematic risk of a security and its expected return. The expected return $\mathbb{E}[R_s]$ of a security is given by (Sharpe 1964):

$$\mathbb{E}[R_s] = R_f + \beta_s(\mathbb{E}[R_m] - R_f) \tag{3}$$

where R_f is the risk-free rate (typically treasury bill rate), β_s the beta of security and $\mathbb{E}[R_m]$ the expected market return.

The beta of a security measures the volatility of a single asset compared to the systematic risk of the entire market, and is defined as:

$$\beta_s = \frac{\mathrm{Cov}(R_s, R_m)}{\mathrm{Var}(R_m)} \tag{4}$$

where R_s is the return of an individual security and R_m the return of the market.

CAPM is widely used to value assets and companies, since it captures the trade-off between risk and return. Many of the multi-factor models that have been developed since are based on CAPM.

2.6 Factor attribution

Factor attribution is a method used to decompose a security's returns into contributions from different factors. A factor is any characteristic that helps to

explain the long-term performance of a security.
For mutual funds consisting of a portfolio of individual securities, these attributes could represent both the portfolio composition and returns such as holding concentration, momentum etc., measures related to the management such as management history & experience. Common factors are also measures aggregated from holdings such as average market cap, book-to-market etc.

The residuals that can't be explained by attributions from factors are fund-specific returns. The expected value of this residual can be interpreted as a fund manager's stock selection skills.

2.6.1 Fama-French three-factor Model

E. F. Fama and French (1993) is an extension of the traditional CAPM by including two additional factors, Small-minus-big (SMB) and High-minus-low (HML). Fama-French is defined as:

$$\mathbb{E}[R_s] = R_f + \beta_1(\mathbb{E}[R_m] - R_f) + \beta_2(SMB) + \beta_3(HML) \tag{5}$$

using the same notation as in (3).

Small-minus-big (SMB) The SMB factor measures the excess return of small-cap stocks over large-cap stocks. According to Fama-French, smaller companies carry higher risk because of them being less established and having lower liquidity. Small-cap stocks should therefore outperform large-cap stocks in the long run. Excess returns generated are captured by this factor.

High-minus-low (HML) The HML factor captures the value effect, which is that value stocks tend to outperform growth stocks over a longer period of time. It compares returns between companies with high book-to-market value (value stocks) with those having low book-to-market value (growth stocks).

2.6.2 Carhart Four-Factor Model

Carhart four-factor model is a further extension of Fama-French model, including a fourth factor, the Monthly Momentum Factor (MOM) (Carhart 1997). The expected return is then given by:

$$\begin{aligned}\mathbb{E}[R_s] = R_f + \beta_1(\mathbb{E}[R_m] - R_f) + \beta_2(SMB) +\\ \beta_3(HML) + \ \beta_4(MOM)\end{aligned} \tag{6}$$

Monthly Momentum (MOM) The monthly momentum factor can be calculated by subtracting the equal weighted average of the lowest performing stocks from the highest performing stocks, lagged by one month.

2.6.3 Fee

Fee is an important factor when looking at mutual fund returns. The fee charged by managers is meant to cover costs related to research, where higher fees represent more effort and time being devoted to equity research that will generate excess returns. Previously, research have suggested that managers may not live up to that promise (see e.g. (Gil-Bazo and Ruiz-Verdú 2009)).

All other things equal, the fee is deducted directly from a fund's return and investors should therefore choose funds with low fees. However, it is also possible for funds with higher fees to outperform given that the extra effort in equity research can produce enough excess returns to cover the costs.

2.6.4 Morningstar factors

Morningstar is a US-based financial services firm, providing data and research insights on financial data, including mutual fund data. Their factor profile is comprised of 7 factors that offers investors insights in analysing an equity portfolio's exposure to key investment factors. The factors are:

- **Style** Describes value/growth orientation.
- **Yield** Describes dividend and buyback yield.
- **Momentum** Describes how much a stock's price has risen recently.
- **Quality** Describes profitability and financial leverage
- **Volatility** Describes variability of long-term returns.
- **Liquidity** Describes trading frequency of a company.
- **Size** Describes market cap.

3 Momentum

Momentum is a factor that captures trend-following behavior, a continuation of (relative) performance into the future. The strategy is based on the idea that past winners will continue to outperform in the future. One common momentum-strategy is a decile-based strategy of buying a portfolio of past winners and sell a portfolio of past losers. Past winners are selected based on the past J months (relative) return. Then, the portfolio is held for K months and compared to the overall market for the same time period. This, known as a J-month/K-month-strategy was first presented by Jegadeesh and Titman (1993).

Momentum in Efficient Markets The Efficient Market Hypothesis directly contradicts the existence of momentum. Momentum violates one of the key ideas in EMH, the assumption that the historic price of a security has no influence on future performance. According to EMH, even in its weakest form, it would be impossible to predict future returns using only historical price patterns. To support the efficiency theory, researchers have suggested that the profitability of momentum can be explained by an increase in risk for past winners (Conrad 1998) which would then suggest that past winners are actually fairly priced even though they have higher conditional returns. Other research show that momentum is an anomaly not captured by any other factor, and Carhart (1997) famously includes the Monthly Momentum Factor (MOM) in the Carhart Four-Factor model.

Momentum & Mean Reversion Mean reversion does not need to be in contrast with the relative strength strategy of momentum. It is possible, as shown in (Jegadeesh and Titman 1993) that assets experiences periods of momentum strength followed by periods of mean reversion. Jegadeesh and Titman (ibid.) concludes that stocks with high momentum outperform their peers in the coming year but then under-performs the year after that. If this was not true, the momentum strategy would find stocks that consistently outperforms market rather than finding stocks that will outperform in the short future.

Historically, momentum has shown to be one of the most persistent and significant factors for future return. Momentum is in contrast with other common factors not as sensitive to bull & bear markets (MSCI 2016).

Momentum & Fama-French model The Fama-French three-factor model (E. F. Fama and French 1993) is a well-established model that capture two of the known anomalies in CAPM. To confirm the existence and profitability of momentum it is therefore often useful to compare returns to this model. Past research have found that momentum can not be explained by the well-known factors of the Fama-French three-factor model, hence the extension of momentum in the Carhart four-factor model (Carhart 1997).

When evaluating momentum in relation to the Fama-French Model it is also interesting to note momentum's correlation with the others factors included in the model. Momentum have time-varying exposure to the three Fama French equity risk factors (Oord and Martens 2014) with the average long-term correlation to the growth factor (low book-to-market) being positive (Prentice and Wroblewski 2022). Asness, Tobias J. Moskowitz, and Pedersen (2013) also confirms by showing that the value factor (high book-to-market) have a negative correlation with the momentum factor.

3.1 Momentum definitions

Historic Returns There are a multiple ways to define momentum, the simplest of them being to use trailing historic returns for a set period of time, i.e. 3-months, 6-months, 1-year, etc. Denoting the price of the security at time t as P_t, the historic return R_t during one time period is defined as

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{P_t}{P_{t-1}} - 1. \tag{7}$$

The time period used to compute historical returns vary between different articles. In section 5.1, the correlation between historic returns and future returns for various time periods is examined.

Short-term reversal effect As shown by Jegadeesh (1990) stocks show negative first-order serial correlation in monthly returns. Low-performing stocks in the month outperform in the coming month and vice versa.

Because of this effect, one definition of momentum (used by Morningstar (Strauts 2019)) excludes the last month return from the previous 12-month return to find securities with high momentum but lower exposure to the short-term reversal effect. The last month performance is essentially disregarded from last year performance.

$$\text{Momentum} = \ln(r_{12}) - \ln(r_1). \tag{8}$$

3.2 Momentum crashes

Momentum has shown to be one of the most consistent factors for outperformance across markets, time periods and asset classes. It has outperformed other factors in most observed time periods, both in bull & bear markets. Although momentum has provided the highest sharpe ratio of the market, style and size factors, it has also had the worst crashes. For that reason, momentum is unappealing to investors who dislike negative skew - risk for large crashes. (Barroso and Santa-Clara 2014).

Stock returns are not normally distributed, but instead show leptokurtosis properties with greater downside risk than what would be expected from a normal distribution. Biglova et al. (2019) shows that these properties are inherited to momentum-strategies and the profits from such strategies are therefore largely effected by properties of stock returns.

Momentum crashes are infrequent but somewhat predictable, occurring when market volatility is high following market declines. 14 out of the 15 worst momentum returns occur when the past 2-year market return is negative. All occur in months of quick and unexpected rebounds. The worst-performing months are clustered with 5 of them being in 1931-1933, 3 months being in 2009, 3 months in 2001 and 2 months in 1938-1939 (Tobias J Moskowitz and Daniel 2016).

Barroso and Santa-Clara (2014) shows that by scaling momentum using an estimate of momentum risk it is possible to drastically decrease left skew and double the sharpe ratio of the strategy. The variance forecast is:

$$\hat{\sigma}^2_{\text{WML},t} = 21 \sum_{j=0}^{1} 25 r^2_{\text{WML},d_{t-1}-j}/126. \tag{9}$$

The forecasted variance is thereafter used to scale the returns:

$$r_{\text{WML}^*,t} = \frac{\sigma_{\text{target}}}{\hat{\sigma}_t} r_{\text{WML},t}, \tag{10}$$

where $r_{\text{WML},t}$ is the unscaled momentum, $r_{\text{WML}^*,t}$ the scaled momentum, and σ_{target} is a constant corresponding to a target level of volatility. The target volatility level is set to 12% by (ibid.).

Using this scaled momentum, the annualized mean return is increased from 14.46% to 16.50% but most importantly the standard deviation decreases from 27.53 to 16.95 and skewness from -2.47 to -0.42. This results in the sharpe ratio nearly doubling to 0.97 from 0.53 (ibid.).

3.3 Momentum for Equity Funds

Most past research on momentum is conducted on stocks. While there are some similarities that can be translated to equity funds, there are also some notable differences between single stocks and the portfolio of stocks held by equity funds. Hendricks, Patel, and Zeckhauser (1993) shows that momentum in equity funds can be achieved in one of two ways:

- **By following a momentum strategy** The fund actively follows a momentum strategy by trading stocks to maintain a portfolio of high-momentum stocks. By this strategy however, most of the excess return generated by momentum is lost in transaction costs since the turnover-rate to maintain a high-momentum portfolio is considerable.

- **By "luck", referred to as "hot hands"** The fund follows a different strategy and has a more static portfolio of stocks. Occasionally, several of the stocks in the portfolio have high momentum, thus giving the fund high momentum. This is funds with the "right" portfolio at a certain point in time.

It is not only true that the latter holds, but as shown in their article, most of mutual funds excess return can be explained by the "hot hands"-phenomena. Carhart (1997) is later able to relate most of this excess return to the monthly momentum factor in the Carhart Four-factor model, thus showing that momentum exists in equity funds as well.

Grinblatt, Titman, and Wemers (1995) provide a similar finding where they conclude that funds following a momentum strategy of buying past winners realized a significant better average performance. They find that as many as 77% of funds included in their analysis follows a momentum strategy of buying past winners. They also find that the funds did not sell past losers to the same extent.

3.4 Sources of momentum

Momentum shows up for different type of assets (equities, commodities, fixed income) (Kolanovic and Z. Wei 2015) and across multiple regions (U.S., Europe etc.). One notable exception is Japan where momentum strategies does not generate statistically significant profits (Asness, Tobias J. Moskowitz, and Pedersen 2013) (Chui, Titman, and J. K. Wei 2010). A lot of research have been done to untangle the sources of momentum, and explain why momentum is so consistent over time across asset classes and regions. Some refer to behavioral tendencies of investors, while others have been able to relate momentum to industries or macroeconomic factors.

3.4.1 Behavioral Models

Since traditional models can't explain momentum, as it violates efficient markets, researchers have opened up for the possibility that markets are not as rational as assumed and that momentum can be explained by cognitive biases of investors. One explanation is that overconfidence about the precision of private information causes price reversals in the long-term. In the short-term biased self-attribution causing price continuations when investors attribute the positive outcomes to their own skill (Daniel, Hirshleifer, and Subrahmanyam 1998).

Hong and Stein (1999) divides market actors into *newswatchers* and *momentum traders*. Newswatchers make forecasts based on public information and causes a stock's price to rise when receiving positive news about a company's future earning potential. However, this is not instant since information spreads slowly through the newswatcher population, causing a short-term underreaction. Momentum traders on the other hand only condition future returns on historic price patterns. When prices start to raise as a consequence of newswatcher's forecasts, momentum traders buy that stock which causes the price to raise further. This not only compensates for the underreaction but actually creates a short-term overreaction to the news released. When the stocks become overvalued, newswatchers sell causing the stock to return to its fair value - mean reversion.

3.4.2 Industry momentum

Tobias J. Moskowitz and Grinblatt (2002) show that momentum in industry components of stock returns can explain a significant part of momentum effects. This also addresses a key question of whether momentum is an arbitrage-free opportunity. If an investor could buy past winners and short past losers a portfolio with zero factor risk could be created. But because most of individual stock momentum is explained by industry momentum, such a portfolio would carry industry risk and since stocks in same industry generally are highly correlated, a momentum strategy is not well diversified.

3.4.3 Macroeconomic factors

Lewellen (2002) creates size and book-to-market (B/M) portfolios and finds strong momentum between these portfolios. The portfolios are well-diversified in terms of number of stocks and industries and there must therefore be alternative sources of momentum other than industry and firm-specific momentum.

3.4.4 Momentum decomposition

A framework for decomposition of momentum is developed by Lo (1990). The framework is based on a proportional-based strategy where securities are bought in proportion to momentum (defined as excess past returns). The weight for each security in month t is:

$$w_{i,t} = \frac{1}{N} r_{e,i,t-1} \tag{11}$$

where N is the total number of securities and $r_{e,i,t-1}$ the excess return of security i in month $t-1$. Based on that framework, momentum returns for equity funds can be divided into autocorrelation and cross-serial correlation of returns. Returns have unconditional mean $\mu = \mathbb{E}[r_t]$ and autocovariance matrix $\Omega = \mathbb{E}[(r_{t-1}-\mu)(r_t-\mu)']$. The portfolio return in month t equals:

$$\begin{aligned} \pi_t = \sum_i w_{i,t} r_{i,t} &= \frac{1}{N}\sum_i r_{e,i,t-1}\cdot r_{i,t} \\ &= \frac{1}{N}\sum_i (r_{i,t-1} - r_{m,t-1}) r_{i,t} \end{aligned} \tag{12}$$

Then, the expected profit becomes

$$\begin{aligned} \mathbb{E}\left[\pi_t\right] &= \frac{1}{N}\mathbb{E}\left[\sum_i r_{i,t-1} r_{i,t}\right] - \frac{1}{N}\mathbb{E}\left[r_{m,t-1}\sum_i r_{i,t}\right] \\ &= \frac{1}{N}\sum_i \left(\rho_i + \mu_i^2\right) - \left(\rho_m + \mu_m^2\right) \end{aligned} \tag{13}$$

where ρ_i is the autocovariances of asset i and ρ_m the autocovariances of equal-weighted average index.

The average autocovariance equals $\operatorname{tr}(\Omega)/N$ and the autocovariance of the market portfolio equals $i'\Omega i/N^2$ where i is a vector of ones.

$$\begin{aligned}\mathbb{E}[\pi_t] &= \frac{1}{N}\operatorname{tr}(\Omega) - \frac{1}{N^2}i'\Omega i + \sigma_\mu^2 \\ &= \frac{N-1}{N^2}\operatorname{tr}(\Omega) - \frac{1}{N^2}[i'\Omega i - \operatorname{tr}(\Omega)] + \sigma_\mu^2\end{aligned} \tag{14}$$

From equation 14 we can conclude that there are three main ways that momentum can arise, one or several of these must be true (Lewellen 2002). These are:

1. Asset returns are auto-correlated ($\operatorname{tr}(\Omega) > 0$), meaning that future returns correlate with past-returns.

2. Cross-serial correlations are negative ($[i'\Omega i - \operatorname{tr}(\Omega)] < 0$), suggesting lead-lag relations (assets with high returns predicts that other assets will have low returns in the future).

3. Momentum assets have higher unconditional means ($\sigma_\mu^2 > 0$).

3.5 Contrarian strategies

An opposite strategy of momentum is the contrarian strategy that relies on price reversal, i.e. that previous winners will under-perform. Contrarian strategies are common among practitioners, and some common examples are mean-reversion and value-investing.

Momentum & contrarian are opposite strategies, making it seem that only one of them can be profitable. However, as shown by Conrad (1998), both strategies generate statistically significant profits but on different time horizons. Momentum on medium-term (3 to 12-months) and contrarian on short-term (weekly, monthly) and longer time horizons (3 to 5-years, or longer). They tested 36 strategies on different time periods and subsets of NYSE/AMEX stocks from 1926-1989 and found that 21 out of 36 strategies produced a statistically significant profit. Out of these strategies, 11 were contrarian and 10 momentum-based, showing that neither one of them were dominant. But looking at the investment horizons a clear pattern emerges, all the 10 momentum strategies were profitable on medium-term (3 to 12-month) and all contrarian strategies were profitable on longer time horizons (>1 year).

4 Method

In order to analyze the impact of the momentum-factor for predicting future excess returns, quantitative methods based on regression analysis are used.

4.1 Implementation

Analytics Lab by Morningstar is an open-source tool in the form of a coding environment that allows for customized quantitative analysis with access to the platform data. Implementation is done using Python, including libraries such as Numpy, Pandas, Matplotlib and Statsmodels.

4.2 Data Collection

Data for all 3381 mutual funds was downloaded using the built-in Morningstar library. Each data point was saved to CSV-files in order to optimize execution times of the computations. Data was downloaded for each of the 6 categories, at the end of each month during the time period starting from 2000-01-31 up until 2023-03-31. Data points downloaded were:

- **Net Asset Value** (NAV) The price of the underlying mutual fund, also referred to as daily price. NAV is defined as

  $$\text{NAV} = \frac{\text{Assets} - \text{Liabilities}}{\text{Total number of outstanding shares}}$$

  As NAV is often unavailable on a daily basis, the last known NAV is used in place, going back a maximum of 5 days. If there is no known NAV for the last 5 days of the month, the fund is omitted that month.

- **Management Fee** Active funds that are managed by an investment manager charge a management fee as compensation. This fee varies between funds, but is generally between 0.4% – 2.5%.

- **Size Score** Each fund is given a size score based on the average market size of holdings. This score is rescaled from -100 to 400 where -100 represent micro-cap and 400 the largest market cap possible. (Morningstar 2023)

- **Value-Growth Score** Each fund is given a value-growth score based on the average exposure to growth stocks. A low value-growth score indicates exposure to value-oriented stocks, while a high score indicates high exposure to growth-stocks (Morningstar 2023).

The equity funds included in each category are determined by the Morningstar categories, as seen in table 1. Since multiple share classes and currencies of each fund is available, a selection needs to be made in order to filter out a single share class per fund. Additionally, survivorship bias is avoided by including funds that have been active during the period but are currently closed. Categorization is summarized as:

- Morningstar Category is selected
- Non-surviving investments are included
- Only oldest share class is included
- Virtual classes are excluded (original currency)

Table 2: Number of funds in each category

Category	**Unique funds**	**Month Avg**
Large-Cap Growth	1038	408
Large-Cap Value	813	327
Mid-Cap Growth	487	184
Mid-Cap Value	243	98
Small-Cap Growth	499	197
Small-Cap Value	301	118
Total	**3381**	**1332**

4.2.1 Number of included funds

Number of active funds each period is defined as the amount of funds containing values for each of the variables in the full factor model. Data points for NAV, size, value-growth and excess market return need to be available in order to compute the multifactor model regressions.

Amount of currently surviving funds vary over time, due to funds entering the market or being closed. After the financial crisis of 2008, many funds were closed due to poor performance, as evident by figure 1. By including funds that have already been liquidated or merged, a *reverse survivorship bias* arises. The bias can lead to an overestimation of the true level of persistence in mutual fund performance, as compared to only including surviving funds (Linnainmaa 2013).

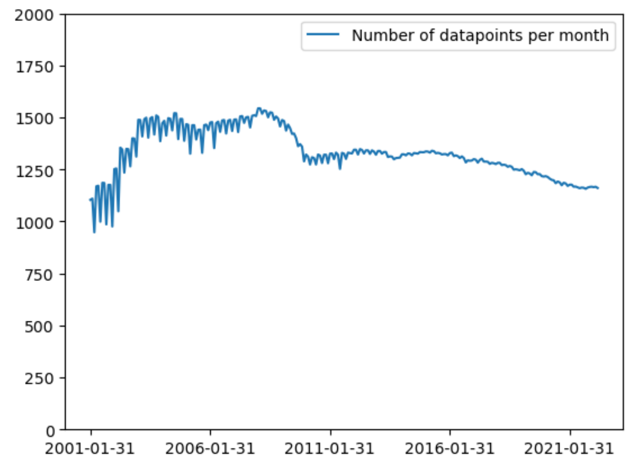

Figure 1: Number of active funds each month

4.3 Definitions

Excess Returns In most cases, finding the funds that outperform its peers in a specific category is of interest, as opposed to absolute returns since they are highly correlated with the aggregated category return. In order to identify the best performing funds in a certain category, the excess return is utilized as the response variable for regressions. Defined as

$$R_{i,excess} = R_i - R_{mkt}$$

where R_i is the absolute return of the security i, and R_{mkt} the average return of the category.

Momentum There are many definitions of momentum, including different time periods and adjustments for recent returns. In our implementation, excess historic returns during a time period is used as the definition of momentum. This approach adjusts for differences in absolute returns between categories. Since the short-term reversal effect is a time-series finding rather than a cross-sectional one (Jegadeesh 1990), no adjustment for last-month returns are made when calculating momentum.

Correlation Measure of the relation between two variables. It captures the strength and sign of their relationship. The mathematical definition is

$$\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

where $\text{Cov}(X, Y) = \mathbb{E}[(X - \mu_X)(Y - \mu_Y)]$ and σ is the standard deviation.

4.4 Correlation Matrix

Determining the time period for which to compute momentum depends on a variety of factors, including the time horizon for predicting excess returns. By looking at the correlation between different periods of past and future returns, both for absolute and excess returns, a deeper insight into the predictive ability is gained.

4.5 Single-factor Model

To examine how the impact of momentum has changed over time across different categories, a linear regression is conducted on a monthly basis. Excess past returns (momentum) is used as regressor, with the response variable as excess future returns. By using excess return, instead of absolute returns, the data is essentially centered around the mean. This improves the interpretation of the slope coefficient, which explains the impact of momentum.

The coefficient corresponding to the momentum regressor is plotted against time, for each category. To evaluate the effect momentum has on different categories, the mean, standard deviation, and skew of the coefficients are analysed.

Since independent regressions are made on each category, and the funds within each category have holdings of same size & style, the SMB and HML-factors are somewhat captured within the model.

4.6 Multifactor Model

The multifactor model used is an extension of the Carhart-four model. It includes the factors MKT, SMB, HML, MOM and FEE. A multiple linear regression is performed each month to compute the coefficients. The coefficients are subsequently plotted over time, to provide insights into the development of sources of mutual fund performance over time. The model is defined as

$$\begin{aligned} R_{excess} = &\alpha + \beta_1(\mathbb{E}[R_{mkt}] - R_f) + \beta_2(SMB) + \\ &\beta_3(HML) + \beta_4(MOM) + \beta_5(FEE) \end{aligned}$$

The regression is also performed on the total time period 2000-2023 with the purpose of identifying overall impact of each factor. Furthermore, it allows for analysis of outliers, multicollinearity, significance of the parameters, and F-tests.

4.6.1 Intercept, α

The model intercept, alpha (α), represents the overperformance of the underlying financial asset compared to the market. A positive, and statistically significant alpha indicates fund-specific excess returns not attributable to any of the factors. In essence, it represents the fund manager's skill of creating excess returns.

4.6.2 Market Risk Premium, MKT

This factor is originating from CAPM, capturing the volatility of a mutual fund in relation to the overall market. The market risk premium, or excess market return, is defined as the expected market return R_{mkt}, less the risk-free rate R_f.

$$MKT = \mathbb{E}[R_{mkt}] - R_f$$

The market return is represented by the *MSCI US Index*, which is a broad-based index covering both value and growth, containing approximately 85% of the US market capitalization (MSCI 2023). The underlying financial asset used as proxy for risk-free rate is the *US 3-month treasury bill.* The asset is backed by the US government, and is considered free of default risk.

4.6.3 High Minus Low, HML

The HML-factor captures the returns resulting from differences in book-to-market value, which is defined as the ratio of book value of equity to market cap. High book-to-market investments essentially represent value-based funds, while low book-to-market represent growth-based funds. High-minus-low is a quantifiable measure of an equity fund's value-growth orientation.

4.6.4 Small Minus Big, SMB

The SMB-factor captures the difference in returns between small cap and large cap companies. Small-minus-big is a quantifiable measure of an equity fund's market cap orientation.

For the factors HML and SMB, data is only available on a quarterly basis. To perform monthly regressions, the values are linearly interpolated to obtain monthly data. Let $t-3$ denote the previous quarter and t the current quarter. The size & value-growth exposure in month $t-2$ and $t-1$ are then calculated as

$$
\begin{aligned}
x_{i,t-2} &= \frac{2}{3}x_{i,t-3} + \frac{1}{3}x_{i,t} \\
x_{i,t-1} &= \frac{1}{3}x_{i,t-3} + \frac{2}{3}x_{i,t}
\end{aligned} \tag{15}
$$

where $x_{i,t}$ denotes the exposure to factor x (size or value-growth) by fund i in month t.

4.6.5 Momentum, MOM

Momentum captures the difference in returns between mutual funds that are high- and low-performing. The definition of momentum is the same as previously, using excess past returns for a period of 12 months. In the Carhart four factor model, this is also referred to as "Up-minus-down" (UMD).

4.6.6 Management Fee, FEE

Finally, management fee is included as a regressor in the model. There has been lots of research on whether management fee has a positive impact on performance. Excess returns attributable to high-fee active equity funds will be captured by the factor. As time-series of current fees are unavailable, the last-known fee of each fund is used in place.

5 Results

Results are structured to test which of the three sources of momentum (as presented in section 3.4.4) that is most significant. Therefore a correlation matrix is first created to look at auto-correlation in individual fund returns.

Thereafter, a regression is performed with excess return to test for lead-lag relations between funds. This is done both as a single-factor model only with momentum, but also in a multifactor model (a variant of Carhart Four-Factor model) to test whether other factors can have an impact on momentum performance.

Lastly, different holding periods are tested to test whether momentum chooses funds with higher unconditional mean or whether the performance of momentum is short-lived.

5.1 Correlation Matrix

For all funds, past & future returns are calculated for 1-month up to 5-years, starting in January 2005 and ending in March 2018. The time period is shortened, since 5-years of data towards each end is needed to compute the correlations.

5.1.1 Absolute returns

To test for auto-correlation in fund returns, a correlation matrix is created, calculating the correlation between the funds' past return & future return.

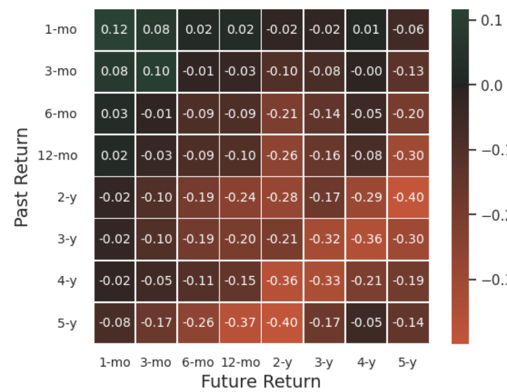

Figure 2: Correlation Matrix Absolute Returns

Using figure 2, a conclusion can be made that there is a positive autocorrelation for shorter time-periods (1 to 3-months) but a negative for longer time-periods (especially 2 to 4-years).

However, this not only captures the time-series component of individual fund returns but also the time-series component of the market as a whole. The correlation matrix in figure 2 is of more interest examining the strengths and lengths of market cycles rather than momentum in fund-specific returns.

5.1.2 Excess returns

To examine the auto-correlation of fund-specific returns, the market return must be adjusted for. As by section 4.3, the category average is used as a proxy for market return. Therefore excess returns are used instead of absolute returns to see how individual fund returns contribute to auto-correlation. This is also a result more comparable to that of decile-based strategies (such as (Jegadeesh and Titman 1993)) since those capture cross-serial correlation rather than individual auto-correlation.

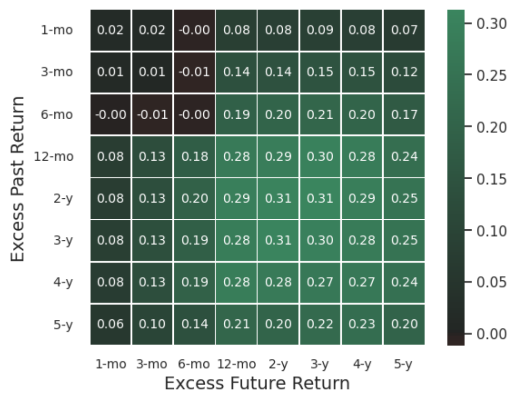

Figure 3: Correlation Matrix Excess Returns

Figure 3 indicates that most of the auto-correlation in the shorter time-span is explained by market auto-correlation but that there is a positive correlation between excess past and future returns in the 1 to 4 year time frame. Biglova et al. (2019) also shows that momentum strategies using excess returns are more profitable than those using raw returns.

5.2 Single-factor model

Based on the findings from figure 3, auto-correlation between excess past and excess future returns is strongest using a evaluation and holding period of 1-4 years. The correlation is not considerably stronger past the one-year holding period suggesting that most of the auto-correlation lies in the first year. Previous research suggests that momentum is strongest using a 3 to 12-month evaluation period. Based on this, a model using an evaluation period of 12-month and holding period of 12-month (12/12-month strategy) is used. The regressor used in the simple linear regression is the excess past 12-month return with the response variable being excess future 12-month return.

The data set used in the regression is from January 2001 to March 2022, to enable computing one-year past returns and one-year future returns for all funds included.

5.2.1 Distribution of variables

If returns are normal distributed, $R_i \sim N(\mu, \sigma)$, the mean return will be μ, and excess returns $R_e \sim N(0, \sigma)$ due to standardization. It holds that $\mathbb{E}[R_e] = 0$, and to test whether R_e are normally distributed, a Jarque-Bera test is conducted both on the regressor (past 12-month excess returns) and response variable (future 12-month excess returns). Given the sample size (150.000+ data points) it is likely that distribution of returns will be close to its true value over the examined time period. Both tests give a p-value of almost 0, resulting in rejecting the null hypothesis that they are normally distributed. The conclusion can also be drawn from the distribution of regressors as illustrated in figure 5.

5.2.2 Full regression

Firstly, a regression is performed for each category, where the model is of the form $y = \alpha + \beta x + \varepsilon$ with y being the excess 12-month future return, β the momentum-coefficient, x the excess 12-month past return and ε the error-term.

Table 3: Summary of Single-factor Model

Regressor	**Coeff**	**p-value**	**[0.025**	**0.975]**
Large Growth	0.200	0.000	0.192	0.208
Large Value	0.115	0.000	0.107	0.123
Mid Growth	0.163	0.000	0.151	0.174
Mid Value	0.105	0.000	0.088	0.122
Small Growth	0.167	0.000	0.156	0.179
Small Value	0.091	0.000	0.064	0.118

While the explanatory power of this model is low (Adjusted R-squared ranges from 0.009 to 0.043), the momentum-coefficient is significant in all categories. This means that only a fraction of a funds future excess returns is explained by momentum, but that momentum at the same time is statistically significant in the period.

5.2.3 Outlier Detection

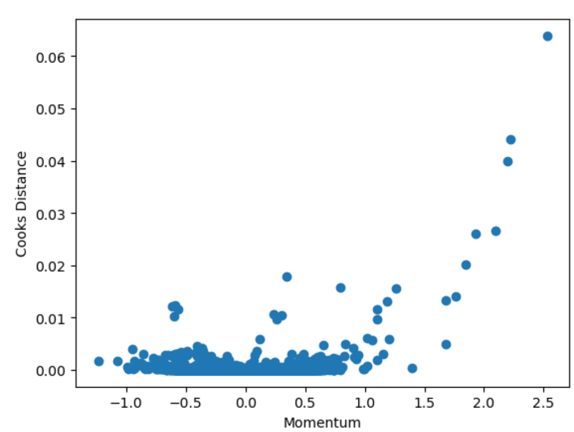

Figure 4: Cook's distance

To check for outliers, the Cook's distance is calculated to find data points which have a significant impact. From figure 4 it is clear that high momentum funds have a significant impact on the regression. A value of 1.0 for momentum is equivalent to a fund having a monthly return of 100 percentage points above its category average. It it therefore reasonable to be careful when interpreting results with these values included.

5.2.4 Residual Analysis

To check if the normality assumption holds, a Normal QQ-Plot is created comparing the standardized residuals to the theoretical quantiles.

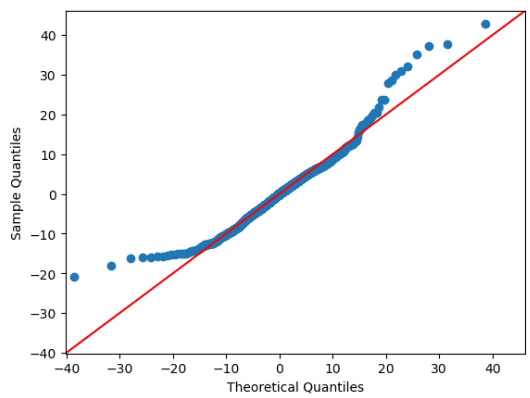

Figure 5: Normal QQ-Plot

It is evident that the residuals are not normally distributed, as a left skew is present. To examine the differences and low adj. R2 of the full model, regressions are instead conducted monthly, per category.

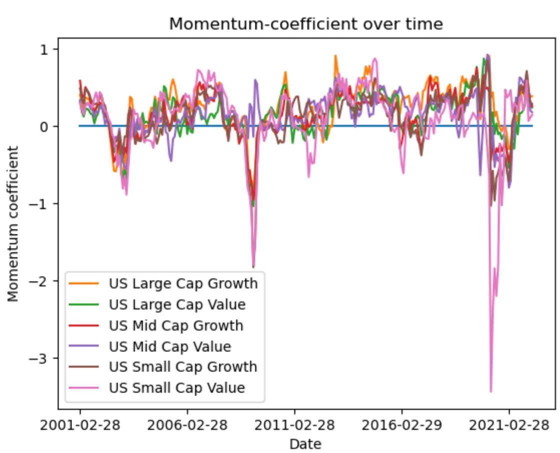

Figure 6: Momentum-coefficient over time

5.2.5 Monthly regressions

A total of 1530 simple linear regressions are made (one for each of the 6 categories in each of the 255 months included in the data set). The momentum-coefficient for each month is then plotted in figure 6 and table 4.

Table 4: Summary of momentum-skew, per category

Category	**Skew** γ
US Large Cap Growth	-0.89
US Large Cap Value	-0.84
US Mid Cap Growth	-0.72
US Mid Cap Value	-0.61
US Small Cap Growth	-1.70
US Small Cap Value	-2.89

Firstly, a conclusion is made that momentum is stronger within growth-oriented categories, showing higher average momentum-coefficients. They also show a similar or lower standard deviation than their respective value-oriented category of same size. Momentum-strategies in growth-categories are therefore more profitable but at the same time also carry less risk (seen by less negative skew). Grinblatt, Titman, and Wemers (1995) also finds that growth-funds more closely follows a momentum-strategy and that those funds have higher realized returns.

5.2.6 Momentum crashes

All categories still have a negative skew, suggesting that there is a risk for negative momentum-coefficients. The negative skew is explained by some notable crashes in figure 6, both in 2008-2009 but also in 2020, following the stock crash caused by the outbreak of the Covid-19 pandemic. Next, we examine the lowest overall momentum-coefficients obtained.

Table 5: Lowest average momentum-coefficients

Date	**Average coefficient**
Feb 2009	-1.09
Mar 2020	-0.80
Mar 2009	-0.72
Jan 2009	-0.70
May 2020	-0.63
Dec 2008	-0.59
Nov 2008	-0.58

Five of these months are consecutive, November 2008 to March 2009. This is the period directly following the stock crash of 2008, confirming previous research

((Tobias J Moskowitz and Daniel 2016), (Barroso and Santa-Clara 2014)) that have found momentum-crashes in the same period.

Most interestingly is the momentum-crash of 2020, where March and May 2020 are among the worst performing months of momentum and several other months during 2020 showing negative momentum-coefficients on average. This is a period that has not yet been researched in detail and these results suggest that a momentum-crash, similar, or more severe than 2008-2009 occurred in this period. There also seems to be a difference between different categories, with *US Small Cap Value* performing the worst, while other categories performed better compared to the crash of 2008-2009. To gain deeper understanding into what caused this crash and what other factors had an impact, a multifactor regression (a variant of Carhart Four-Factor model) is performed.

5.3 Multifactor Model

For the multifactor model, a total of five factors are included in the regression: Market risk premium, Momentum, Value-Growth, Size & Management Fee. Since market risk premium is now part of the regression, the response variable is now raw returns instead of excess returns since market risk premium captures the average return of the market. Since size & value-growth factors are now quantified in the regression all categories are included as a whole. The differences between them are captured in those variables.

5.3.1 Distribution of variables

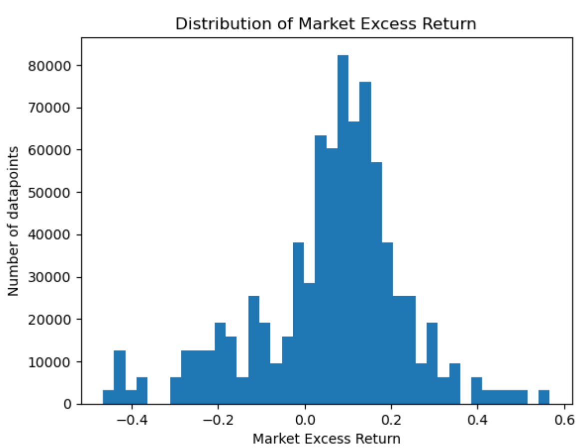

Figure 7: Distribution of Market Excess Return

Market Excess Return This measure captures the excess return of the market (*MSCI US Index*) over the risk-free rate (*US 3-month treasury bill*), on average it is 4.7% but it varies between months, as illustrated by figure 7.

The coefficient for this factor corresponds is often referred to as β, and represents the volatility of a certain fund in relation to the market. A value of one indicates that the price of the equity funds move with the market, which also coincides with the mean of the data. Some deviations are present due to different numbers of active funds.

Momentum Since momentum is defined as *excess* past returns, the variable is centered around zero. Computing the excess is effectively has the same impact as shifting the mean to zero. Note that excess return is still computed in relation to the category average, to avoid distortions that result from using a too broad index as reference. Different number of active funds in each category causes some small deviations. Overall, the data seems to closely follow a normal distribution as seen in Figure 8.

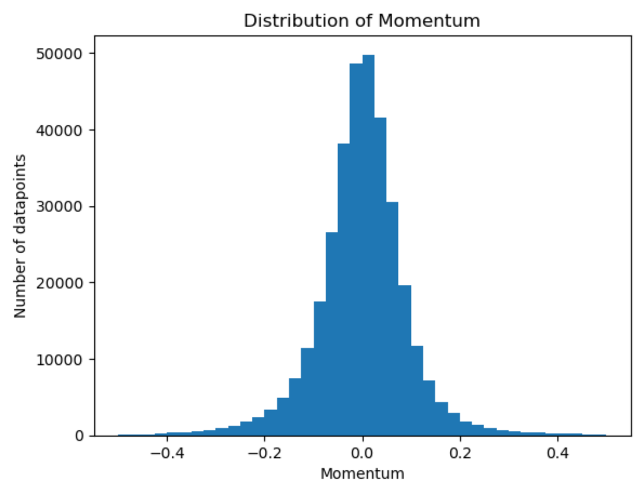

Figure 8: Distribution of Momentum

Size & Value-Growth Distribution of factors size and value-growth are shown in figures 9 and 10. As a consequence of the categories pertaining to a certain size, or value-growth orientation, the data is normally distributed within each category. But, the aggregate data will not follow a normal distribution. While this may have some impact on the resulting coefficients, it is determined to be insignificant.

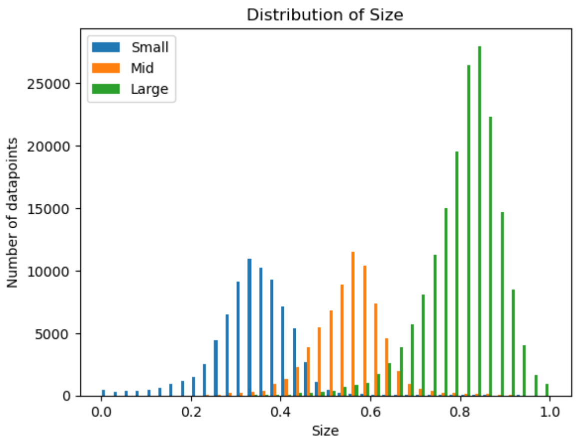

Figure 9: Distribution of Size

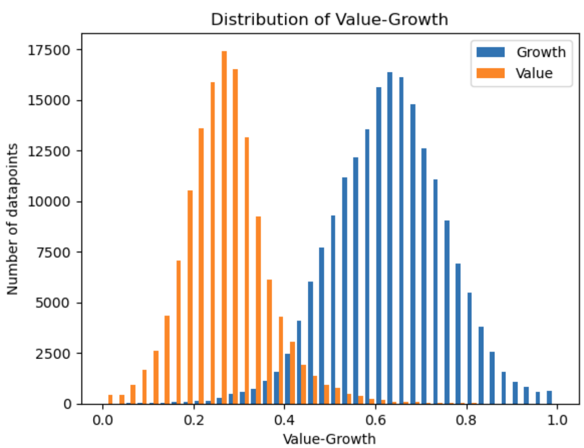

Figure 10: Distribution of Value-Growth

Management Fee Fees differ between funds and across categories. Growth-categories as well as small-cap categories exhibit slightly higher average fees than the other categories. In total, 95% of fees lie between 0.40% to 2.50%.

Table 6: Average Fees for each category

Category	Avg Fee
US Large Cap Growth	1.15%
US Large Cap Value	1.04%
US Mid Cap Growth	1.32%
US Mid Cap Value	1.09%
US Small Cap Growth	1.35%
US Small Cap Value	1.17%

The distribution of fees in the data set is as illustrated by figure 11.

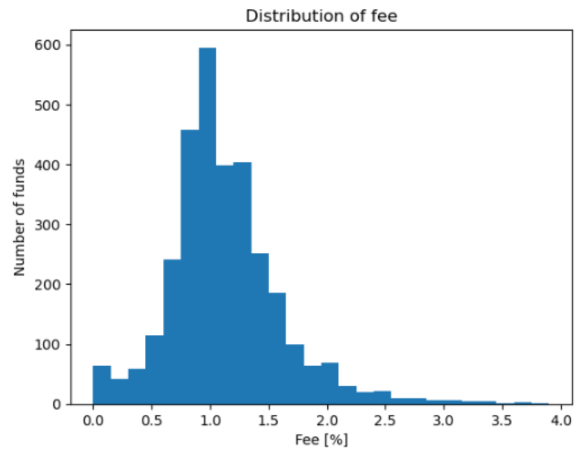

Figure 11: Distribution of Management Fees

Some fees are higher than what is determined to be reasonable and have a significant impact on the standardisation. For that reason, all funds with a fee higher than 5% are excluded from the data set.

Max-min standardization To allow for comparisons of the magnitude of regression coefficients, the data is standardized. It ensures that the coefficients are of the same scale, which allows for easier comparison. Max-min standardization preserves the original distribution of the data, but maps the values to the interval $[0, 1]$.

$$\bar{x} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

5.3.2 Full regression

Regression is performed for all 3381 mutual funds included in the data set, over the period January 2001 to March 2022. Resulting coefficients are presented in the following table.

Table 7: Summary of Full Model Regression

Regressor	Coeff	p-value	[0.025	0.975]
Intercept	-0.059	0.000	-0.063	-0.056
Market risk	1.012	0.000	1.008	1.015
Momentum	0.162	0.000	0.155	0.168
Value-Growth	0.055	0.000	0.053	0.058
Size	-0.002	0.149	-0.005	0.001
Fee	0.077	0.000	0.070	0.084

Furthermore, the full regression has an Adjusted R2 of 0.706. The F-statistic is $7.13 \cdot 10^4$ with corresponding p-value of 0.000. This model performs significantly better than the single factor model. This is to be expected since the model now captures raw returns instead of excess returns, and the market average is a large portion of that. Additionally, an F-test still confirms that the regression is statistically significant.

5.3.3 Residual Analysis

By plotting the observed residuals against the fitted values inconsistencies can be detected, including unequal error variances, non-linearity and outliers. The points are contained within a horizontal band, indicating that the residuals are independent of the fitted values and have finite variance, homoscedasticity. A few outliers are present in the data set, which coincide with periods of momentum crashes.

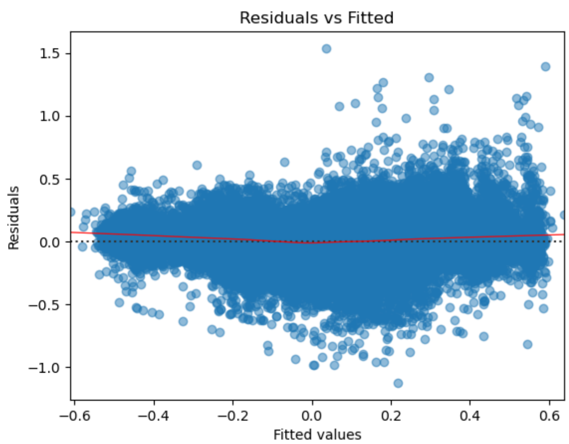

Figure 12: Residuals vs. fitted values

5.3.4 Multicollinearity

If two or more variables are dependent, i.e. there exists a linear or near-linear relationship between them, the interpretation of coefficients is difficult since they are sensitive to small changes in data. The variance inflation factor (VIF) is used to measure linear relationship between regressors. VIF for regressors in the model is presented as below.

Table 8: VIF for full model

Regressor	**VIF**
Market Excess Return	1.005
Momentum	1.000
Value-Growth Score	1.055
Size Score	1.101
Fee	1.102

It is clear that there are no significant correlations between variables. The correlation between growth and momentum have been previously studied and although there is a long-term correlation between the two, it is not static but rather time-varying (Prentice and Wroblewski 2022). This makes both variables relevant to include when conducting regressions analysis on different time-spans.

5.3.5 Monthly regressions

To examine the development of factor attribution over time, a regression of the full model is performed on a monthly basis, resulting in a total of 255 regressions. The factor-coefficients for the monthly regressions are plotted in figure 13. Market risk premium is omitted due to being highly volatile when performing monthly regressions.

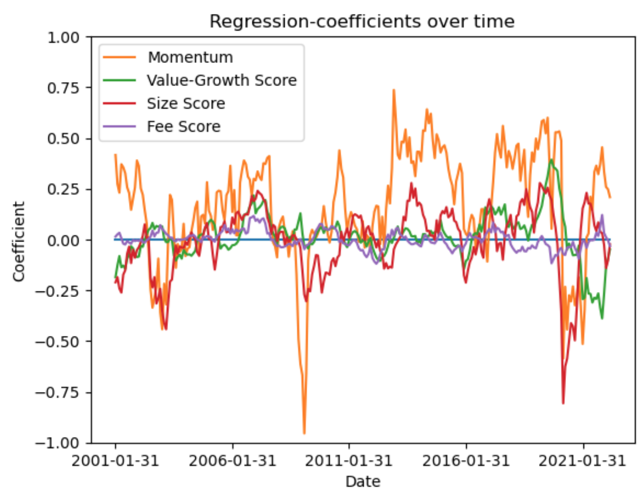

Figure 13: Factor-coefficients multifactor model

Table 9: Average Skew of Coefficients

Regressor	**Skew** γ
Momentum	-0.89
Value-Growth Score	-0.13
Size Score	-1.23
Fee Score	0.10

It is clear that all factors vary with regards to time, but for size and value-growth factors, periods of negative coefficients are followed by periods of positive coefficients. This is in line with previous literature (MSCI 2016) showing that both of them are highly cyclical. We also conclude that momentum has larger magnitude than other coefficients.

Carhart (1997) shows in his Four-Factor model that value stocks outperforms growth stocks and that small-sized companies outperform large-sized. For the equity funds included in this paper, during the period from January 2001 to March 2022 the coefficients for size and value/growth are not significant. On average, the size-factor is 0.00 and the value-growth factor 0.03. However, we can see that, even when accounting for other factors in Carhart Four-Factor model, that momentum funds continue to outperform.

5.3.6 Momentum crashes

As for the simple linear regression, there are crashes for the momentum-coefficient at the approximately same times suggesting that these crashes can't be explained by other factors. The worst months for the momentum-coefficient in the multi-factor model are the following.

Table 10: Lowest average momentum-coefficients

Date	Average coefficient
Feb 2009	-0.96
Jan 2009	-0.67
Mar 2009	-0.66
Dec 2008	-0.61
Mar 2020	-0.59
Jan 2021	-0.51
Nov 2008	-0.49

November 2008 to March 2009 are the worst months for momentum in a multifactor-model as well. We can see that the coefficient are slightly smaller compared to single-factor model as presented by table 5, suggesting that some part of the crash can be explained by other factors.

We can also see from the monthly regressions that the momentum-crash in 2020 was less severe when accounting for additional factors. A shift in the size factor explains part of the crash and a shift from a positive value-growth factor (growth-orientation) to negative (value-orientation) is also apparent in the period 2019 to 2022. This aligns with the change in interest rates that benefited value-stocks which traditionally are less sensitive to higher interest rates. Figure 14 provides a closer look at the recent years and shows that momentum had a notable crash in 2020 and thereafter a year of negative coefficients before rebounding during the latest year.

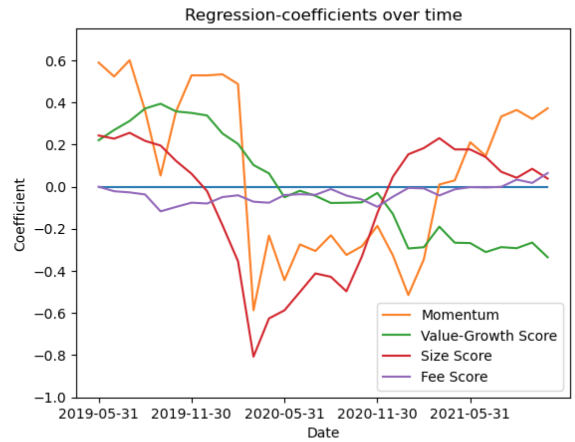

Figure 14: Factor-coefficients multifactor model

5.4 Unconditional mean

To test whether high momentum funds have higher unconditional mean or whether the outperformance is just in short-term, funds are sorted monthly within their category based on momentum (excess past 1-year return) and put into decile portfolios. The deciles are then aggregated to contain funds within the same decile for all categories. Funds in the 9th decile will be the top 10% of funds with highest momentum in each category. The average next 1-year return is then calculated monthly for each of the deciles and the performance for the period January 2001 to March 2018 (this is for results to be comparable to figure 16 where 5 years of future returns are needed). The average monthly returns for each of the deciles are summarized as follows.

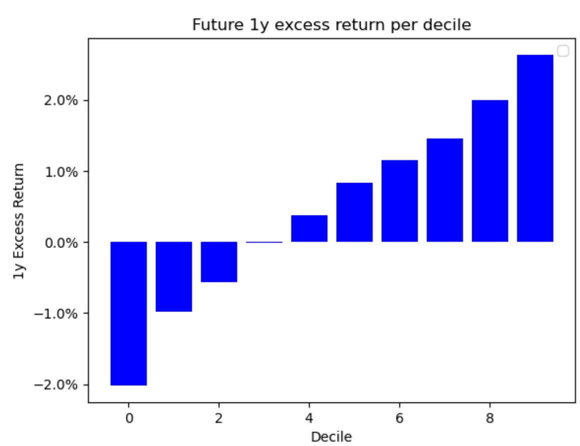

Figure 15: Average Excess Return per decile

The results are not surprising, given that deciles where formed based on the regressor (excess past 1-year return) used in the linear regression and plotted against the response (excess future 1-year return). Since the momentum-coefficient was positive in the regression this implies that higher deciles on average will outperform lower ones, as confirmed in figure 15.

To see whether high momentum funds have higher unconditional means, the average excess return of each decile is calculated past the 1-year holding period used in the regression.

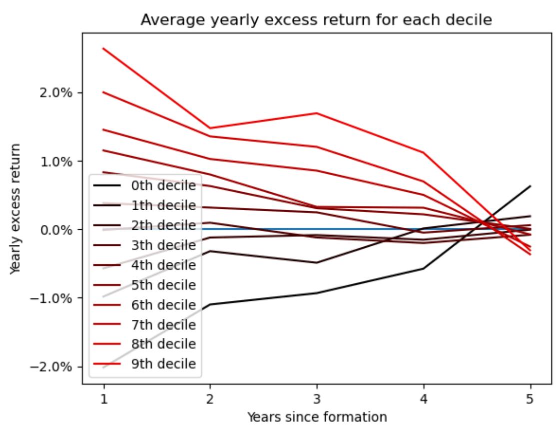

Figure 16: Average Excess Return for each decile

In the first year following the formation, past winners (funds in the 9th decile) clearly outperforms past losers (funds in the 0th decile). This effect then decreases, and in year 5 the funds in the 0th decile instead outperforms those in the 9th decile. This result confirms previous research that the profitability of momentum is not a result of selecting securities with higher unconditional means but rather securities that will outperform in the near future (Jegadeesh and Titman 1993). Instead, securities show signs of mean reversion in the 3 to 5-year holding period, as previously shown by (Conrad 1998) [2].

6 Discussion

Absolute returns are negatively auto-correlated except for the short-term horizon (1 to 3-months) and momentum strategies using absolute returns would therefore not be profitable. However, using excess returns we find a positive auto-correlation and momentum strategies using excess returns or decile-based strategies (*buying winners, selling losers*) can therefore be profitable.

6.1 Single-factor Model

A single-factor model with momentum as regressor have low predictive ability on the excess future return. However, in this model we can conclude that momentum is significant and have a positive effect on excess future 12-month returns in all six categories included. From the single-factor model we can also conclude that momentum has negative skew, which is also clear from the residual analysis as well as from monthly regressions. Much of the negative skew is attributable to a few notable crashes, primarily in 2008-2009 as observed in previous research (Barroso and Santa-Clara 2014). In the single-factor model we can also observe negative momentum-coefficients in 2020. In contrast to 2008-2009 they are not negative for all categories, where growth-categories are showing positive coefficients in the same period. This indicates that there are alternative explanations behind the poor performance of momentum in 2020 and this period is therefore of more interest in the multifactor model.

This paper also confirms findings regarding the longevity of momentum returns as shown by (Carhart 1997) with the excess return reverting back to zero within a couple of years after portfolio formation. This is to show that high-momentum funds are not funds with higher unconditional mean but rather funds that experience periods of excess returns, followed by periods of mean reversion. This aligns with some of the psychological explanations that has been provided to explain momentum. For stocks, momentum has shown to generate excess returns in the medium-term future (3 to 12-months) (Jegadeesh and Titman 1993). Momentum in equity funds can in comparison generate excess returns further into the future (up to 3 to 5-years) after portfolio formation, although most of the excess return is generated in the first year after portfolio formation.

6.2 Multifactor Model

In the multifactor model, a variant of Carhart Four-Factor model is used (Carhart 1997) but with fee as an additional factor. This improves the explanatory

[2]Conrad (1998) uses a J-year/J-year strategy with the formation period being the same as the holding period while these results are based on a static formation period of 1-year for all holding periods

power of the model and shows that value-growth orientation and size are important factors to consider when predicting excess fund returns. No factor shows significant correlation with another even though previous research has suggested a time-varying correlation between growth/value & momentum. When accounting for other factors, it is still clear that momentum is the strongest and most persistent factor for predicting excess future performance.

When taking other factors into consideration, the momentum-crash of 2008-2009 is still clear but momentum's poor performance during 2020 is partly explained by shifts in other factors such as a shift from large cap to small cap as well as a shift from growth-oriented funds during 2020 to value-oriented funds in 2021 and forward.

6.3 Additional research

Based on the findings from this paper as well as previous research, some areas which could be of interest to research further could include, but is not limited to:

Risk-managed momentum Momentum crashes are somewhat predictable, and by using realized variance of returns, Barroso and Santa-Clara (2014) has shown that it is possible to scale momentum to maintain a set variance. This consequently decreases the risk of momentum, especially the left skewness (risk of crashes). It is therefore of great interest to examine the characteristics of momentum crashes and some common factors prior to the crashes.

Different regions This paper focuses on US equity funds but previous research has suggested that momentum is strong in other regions as well, such as UK, Europe etc. It is therefore of interest to test the same models on other regions and compare the strength of momentum across regions (and possible asset classes).

Behavioral Finance Psychological influences can affect the market sentiment, especially in regards to momentum. Biases can cause overconfidence in momentum strategies, which in turn is a self-reinforcing prophecy of increasing prices. Conversely, the disposition effect, the tendency for investors to sell assets that have increased in value and keep assets that have decreased in value, can have the opposite effect.

Industry Momentum Instead of restricting the scope by market cap and value-growth orientation, momentum in different industries can be examined. Industry momentum investment strategies that invests in past winning industries and sells stocks from past losing industries have been shown to be profitable by Tobias J. Moskowitz and Grinblatt (2002).

7 References

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen (2013). "Value and Momentum Everywhere". In: *The Journal of Finance* 68.3, pp. 929–985.

Barroso, Pedro and Pedro Santa-Clara (2014). "Momentum has its moments". In: *Journal of Financial Economics* 116.1, pp. 111–120.

Biglova, Almira et al. (2019). "Profitability of momentum strategies: Application of Novel Risk/return Ratio Stock Selection Criteria". In: *Investment Management and Financial Innovations* 4, pp. 48–62.

Carhart, M. Mark (1997). "On Persistence in Mutual Fund Performance". In: *Journal of Finance* 52.1, pp. 57–82.

Chui, Andy C.W., Sheridan Titman, and John K.C. Wei (2010). "Individualism and Momentum around the World". In: *The Journal of Finance* 65.1, pp. 361–392.

Conrad Jennifer & Kaul, Gautam (1998). "An Anatomy of Trading Strategies". In: *The Review of Financial Studies* 11.3, pp. 489–519.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam (1998). "Investor Psychology and Security Market under- and Overreactions". In: *The Journal of Finance* 53.6, pp. 1839–1885.

Fama, Eugene F. and Kenneth R. French (1993). "Common risk factors in the returns on stocks and bonds". In: *Journal of Financial Economics* 33.1, pp. 3–56.

Fama, Eugene.F. (1970). "Efficient Capital Markets: A Review of Theory and Empirical Work". In: *The Journal of Finance* 25.2, pp. 383–417.

Gil-Bazo, Javier and Pablo Ruiz-Verdú (2009). "The Relation between Price and Performance in the Mutual Fund Industry". In: *The Journal of Finance* 64.5, pp. 2153–2183.

Grinblatt, Mark, Sheridan Titman, and Russ Wemers (1995). "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior". In: *The American Economic Review* 85.5, pp. 1088–1105.

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser (1993). "Hot Hands in Mutual Funds: Short-Run Persistence of Relative Performance". In: *Journal of Finance* 48.1, pp. 93–130.

Hong, Harrison and Jeremy C. Stein (1999). "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets". In: *The Journal of Finance* 54.6, pp. 2143–2184.

Jegadeesh, Narasimhan (1990). "Evidence of Predictable Behavior of Security Returns". In: *The Journal of Finance* 45.3, pp. 881–898.

Jegadeesh, Narasimhan and Sheridan Titman (1993). "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency". In: *Journal of Finance* 48.1, pp. 65–91.

Kolanovic, Marko and Zhen Wei (2015). *Momentum Strategies Across Asset Classes*. Accessed: 25-04-2023.

Lewellen, Jonathan (2002). "Momentum and Autocorrelation in Stock Returns". In: *Review of Financial Studies* 15.2, pp. 533–564.

Linnainmaa, Juhani T. (2013). "Reverse Survivorship Bias". In: *The Journal of Finance* 68.3, pp. 789–813.

Lo Andrew W. & MacKinlay, Craig (1990). "When are Contrarian Profits Due to Stock Market Overreaction?" In: *Review of Financial Studies* 3.2, pp. 175–205.

M. Poterba, James and Lawrence H. Summers (1988). "Mean reversion in stock prices: Evidence and Implications". In: *Journal of Financial Economics* 22, pp. 27–59.

Malkiel, Burton G. (1989). "Efficient Market Hypothesis". In: *In: Eatwell, J., Milgate, M., Newman, P. (eds) Finance*, pp. 127–134.

— (2003). "The Efficient Market Hypothesis and Its Critics". In: *The Journal of Economic Perspectives* 17.1, pp. 59–82.

Morningstar (2021). *Morningstar Global Category Classifications*. Accessed: 25-04-2023.

— (2023). *Morningstar Style Score*. Accessed: 25-04-2023.

Moskowitz, Tobias J and Kent Daniel (2016). "Momentum crashes". In: *Journal of Finance* 122.3, pp. 221–247.

Moskowitz, Tobias J. and Mark Grinblatt (2002). "Do Industries Explain Momentum?" In: *The Journal of Finance* 54.4, pp. 1249–1290.

MSCI (2012). *Emerging vs. Developed Markets Classification*. Accessed: 25-04-2023.

— (2016). *Focus: Momentum*. Accessed: 25-04-2023.

— (2023). *MSCI Index Factsheet*. Accessed: 25-04-2023.

Oord, Arco van and Martin Martens (2014). "Hedging the time-varying risk exposures of momentum returns". In: *Journal of Empirical Finance* 28, pp. 78–89.

Prentice, Travis and David Wroblewski (2022). "Momentum Is Not Growth". In.

Sharpe, William F. (1964). "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of risk". In: *The Journal of Finance* 3.-, pp. 425–442.

— (1991). "The Arithmetic of Active Management". In: *Financial Analysts Journal* 47.1, pp. 7–9.

Strauts, Timothy (2019). *Morningstar Factor Profile User Guide*. Accessed: 25-04-2023.

Weng, Joyce and Ian Butler (2022). *Value vs. Growth investing: Value returns with a vengeance*. Accessed: 25-04-2023.

Wermers, Russ (2000). "Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses". In: *The Journal of Finance* 552.4, pp. 1655–1695.