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Funds – not aging well?

An empirical evaluation of the relationship between fund age and performance in Nordic mutual funds

Karim Dassouli and Ole-Petter Røseth Lund

Supervisor: Nataliya Gerasimova

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Karim Dassouli

Ole-Petter Røseth Lund

Abstract

This study examines how fund age empirically affects the performance of Nordic mutual funds. Our research questions are motivated by a high level of investments in actively managed funds in the Nordic countries, yet we consider determinants of the abnormal returns that these funds achieve to be understudied. The data set is free of survivorship bias, and consists of 1198(net, 1138 gross) Nordic equity funds between January 2006 and February 2021. Employing multivariate panel regressions, controlling for other fund characteristics, we investigate how fund age affects performance in terms of both before- and after-fee returns on a risk-adjusted basis. Second, we research how age affects how funds are exposed to different types of risk, and whether it is affecting their investment style. Further, we investigate whether portfolios sorted by fund age are able to outperform risk-factor benchmarks. Lastly, we research persistence within age quintiles.

When controlling for fund attributes that typically affect fund performance, such as the size and expense ratio of the fund, we find the relationship to be significantly positive, i.e., that older funds perform better. We find evidence that that older funds are less exposed towards total, market and unsystematic risk. We also find that investment styles significantly differ across fund age, as older funds are more exposed to the four risk factors proposed by Fama and French (2015b). We find that long-short portfolios of young and old funds are not able to achieve risk-adjusted returns. Lastly, by employing an analysis of persistence, we find evidence that neither old or young funds continue to out- or underperform over a time period of one year.

Keywords – Mutual funds, Performance, Fund Characteristics, Persistence, Fund Age

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1 Introduction

The ongoing pandemic is influencing our consumption and saving decisions. One effect is a surge of private capital entering the financial markets. In Norway, private investors doubled their mutual fund investments in 2020 compared to 2019 (Bjørnestad, 2020).

For almost a century, private and institutional investors have been investing in open-ended mutual funds. With increasingly easier access, the fund industry has grown dramatically over the recent decades. Globally, the total mutual fund industry managed assets exceeding 63 trillion USD at the end of 2020, compared to only 6 trillion USD at the end of 1996. The US alone manages more than 29 trillion USD, constituting roughly 47% of the global AUM (assets under management), at the end of 2020. The fund industry in the Nordic countries is small in comparison. At the year-end of 2020, Sweden, Denmark, Norway, and Finland manage 518, 177, 175, and 127 billion USD, respectively, which in aggregate is a little less than 1 trillion USD. Nevertheless, since 1996, the Nordics have experienced much higher growth in AUM than the US, with almost 18.000% compared with 8.000%. Not only the industry size measured in AUM has increased rapidly, but the number of mutual funds has also risen significantly, from about 35,000 funds in 1996 to 126,000 funds globally at the end of 2020 (Investment Company Institute, 1997, 2021).

Mutual funds offer investors broad exposure to the general risk of financial markets, while requiring little knowledge about individual stocks and whether they are priced correctly. There is overwhelming evidence that actively managed mutual funds on average underperform passive benchmarks net of fees (Malkiel, 1995; Fama and French, 2010), yet private investors in Norway place 81% of their total mutual fund placement in actively managed funds (Bjørnestad, 2020). More professional investors, such as pension funds and insurance companies, place 59% in active funds.

Despite the evidence that passive index funds outperform actively managed funds on average, Kosowski (2011) find that active mutual funds significantly outperform passive during recessions. As we are in the midst of a recession due to the Covid-19 pandemic (National Bureau of Economic Researcht, 2021), investing in active funds may be a reasonable choice – if one is able to choose the right ones.

With an increased number of funds and other investment options, it is imperative that investors research how attributes of these may affect performance. To what extent an active fund is able to outperform it benchmark is found to not only depend on the fund's skill in finding investment opportunities, but also on constraints that the fund faces. One such constraint discussed in recent literature is the concept of decreasing returns to scale, that larger funds have a harder time achieving abnormal returns because of their larger size Chen et al. (2004); Ľuboš Pástor et al. (2015).

While fund size is covered in many studies, fund age often serves as a control variable. The theoretical outcomes are that performance either increases or decreases as funds age. Increased performance may be due to accumulation of skill and experience, or it may decrease due to increasing fund size (Chen et al., 2004), increased complexity of the fund, or slack. New funds may outperform when they are new because of advantages in technological knowledge, but with constant development, such effects are expected to be eradicated over time.

Studies of fund characteristics in the US are to a large extent reporting that fund age is either deteriorating performance (Ľuboš Pástor et al., 2015; Karoui and Meier, 2009), or not a determinant of performance at all (Chen et al., 2004; Ferreira et al., 2013). In larger-scale studies that include European countries, it is often found that performance is deteriorating as funds age (Otten and Bams, 2002; Ferreira et al., 2013; Filip, 2018). The academic landscape on fund characteristics in the Nordic countries is scarce, and may even refrain from including fund age in their model (Dahlquist et al., 2000).

This thesis aims to narrow what we find to be a literature gap in studies of how fund age affects fund performance in the Nordic fund industry.

The review of literature advance four hypotheses that this thesis investigates:

Hypothesis 1: *Fund age affects the performance of mutual funds*

Hypothesis 2: *Fund age affects risk-taking of mutual funds*

Hypothesis 3: *Fund age affects the investment style of mutual funds*

Hypothesis 4: *Investment strategies based on fund age outperform on a risk-adjusted basis*

We find several arguments that we believe support these hypotheses. Ľuboš Pástor et al. (2015) find that the negative age-performance turns positive after controlling for fund size and fund industry size, implying that funds learn on the job. Outside of the US, the diseconomies of scale related to increased fund size are not as evident, and with some evidence of an adverse effect of age on performance (Otten and Bams, 2002) we may expect to find the same in Nordic countries. Karoui and Meier (2009) find younger funds to exhibit higher levels of total and unsystematic risk, and Chevalier and Ellison (1997) find that younger funds tend to increase their level of risk at the end of evaluation periods when they have performed poorly. As Chevalier and Ellison (1999b) and Chan et al. (2002) explain, younger funds tend to deviate less from benchmarks because of higher higher fund-flow sensitivity. Karoui and Meier (2009) suggests that younger funds are more inclined to invest in smaller cap and less liquid stocks, exposing them to the SMB factor of Fama and French (1993). Portfolios of young funds are found to outperform older funds (Ľuboš Pástor et al., 2015; Karoui and Meier, 2009), and there is evidence that younger funds display stronger persistence (Verbeek and Huij, 2006).

To answer our hypotheses, we gather a data set free of survivorship bias that contains 1198(net, 1138 gross) Nordic equity funds, covering January 2006 to February 2021. To evaluate risk-adjusted performance, we apply the one-,three-, four- and five-factor models on both net and gross returns. First, we apply multivariate regressions where risk adjusted performance, risk-taking measures, and investment styles are our dependent variables. We regress these on fund age and other fund attributes related to performance, such as fund size, expense ratio, and the number of stocks each fund is holding at the time. Further, we apply the same factor models on a hypothetical zero-investment portfolio that is long in young funds and old funds, as and test whether these age-sorted portfolios are able to show persistent performance.

The empirical results indicate that performance increase with a higher fund age in our sample of Nordic mutual funds, which contradicts evidence from other economies(Ferreira et al., 2013). Performing robustness tests suggests that this finding is mostly based on the most recent data. Further, we find funds to reduce their risk exposure as they age. Older funds also develop strategies that expose them more towards risk factors introduced by Fama and French (2015b). However, we do not find long-short portfolios of young and old funds ti achieve risk-adjusted returns, and neither age group shows evidence of persistence.

Our study contributes to the literature in several ways. The study examines how age affects the performance of funds, and makes an effort to understand how age and other fund characteristics influence their risk propensity and investment style. Contrary to most empirical evidence that finds performance deteriorates as funds grow older (Ferreira et al., 2013), we find that fund age has a positive effect on performance of up to 10 basis points a year, depending on performance measure. The issue is of great practical importance to both investors and academics alike. First of all, investors may take the fund attribute age into account when making an investment decision. Second, fund managers may use favorable results in marketing. Third, the study will enhance the knowledge about how the attribute affects performance in academia.

The thesis proceeds as follows: In section 2, we provide a literature review of the most relevant research on the topic to place this thesis in the landscape of previous research. Section 3 presents our hypotheses. Section 4 describes our data set and the variables we employ in the study. Section 5 defines the models and techniques which we implement in the study. Section 6 present and discuss our empirical results, and section 7 presents the conclusion.

2 Litterature Review

Does the age of mutual funds matter? This section aims to place this thesis in the academic landscape surrounding research on mutual funds, and to motivate our hypotheses.

2.0.1 Why Mutual Funds?

Studies on the effect of age on fund performance is often focused on hedge funds, which are not available to most investors. Mutual funds investing, which is available to most investors, make up a larger fraction of the overall investment universe. Compared to hedge funds, mutual funds are also more strictly regulated and are required to disclose more information to the public. This transparency can avoid conflicts of interest and agency costs. Furthermore, to ensure a more homogeneous sample, we look specifically at open-ended mutual funds. As opposed to closed-end mutual funds, open-ended funds have an unlimited number of shares. Investor funds are pooled, and the returns directly follow the change in the fund's net asset value. A consequence of having to readjust the funds' holdings each day to meet investors in- and outflows is higher operational costs, impeding investors' returns. Another characteristic of open-ended funds is that they must maintain a certain cash reserve to meet sudden shareholder redemptions, which may also lead to lower returns. These drawbacks are however compensated by the flexibility and liquidity that open-ended funds offer.

Another aspect that drives our motivation to focus on open-ended funds is that each share is only priced by its underlying assets. The price of closed-ended funds are, by their nature of limited supply, affected by the supply and demand for the fund, and the price may, as a result, be discounted or get a premium. We consider these effects neither relevant nor helpful in answering our research question.

2.0.2 Measuring Performance

Funds as an investment vehicle were founded upon the idea that exposure towards the broad market returns a better risk-adjusted return than simple exposure towards idiosyncratic risks of companies. The idea was popularized by Markowitz's portfolio theory (Markowitz, 1952), which argues that only diversifiable risk should carry a risk premium, in other words, a reward. The consecutive development of the Capital Asset Pricing Model (Treynor, 1961; Sharpe, 1964; Lintner, 1965; Mossin, 1966) puts forward a model to explain how the systematic risk of an investment should affect expected returns.

As the models assume a relationship between risk and expected returns, they have evolved to become performance benchmarks. The models were by some researchers found to be less relevant after they were published, which led to the development of new and improved models covering risk factors not previously explained (Basu, 1983; Rosenberg et al., 1985; Carhart, 1997; Fama and French, 2015a).

Ever since the original CAPM model was developed, studies find that active mutual fund managers are not able to outperform the market portfolio consistently to a sufficient degree that covers the fees of the fund (Sharpe, 1964; Malkiel, 1995)). In a comprehensive study of 27 countries covering 16,313 funds, Ferreira et al. (2013) document that equity mutual funds around the world underperform by 20 basis points per quarter after fees, after adjusting for the four risk-factors of Fama and French (1993) and Carhart (1997). French (2008) finds that on average, investors would be better off by 0.7% per year by switching from active management to index funds. (Graham et al., 2019) show evidence supporting that few mutual funds, both in the US and Europe, outperform their benchmarks or justify their high fees. Studies on domestic mutual funds in Nordic countries also suggest little evidence of active mutual funds outperforming a passive benchmark (Sørensen, 2009; Christensen, 2013; Sandvall, 2000; Flam and Vestman, 2014). The overall consensus seems to be that the average active mutual fund cannot outperform the market.

Berk and van Binsbergen (2015) dissected the relationship between skill and reward in the mutual fund industry. They point to the overall conclusion of existing literature, such as Gruber (1996), that there is no clear empirical evidence of consistent stock-picking skill, yet fund managers are paid top dollar. This breach of economic principles related to assigning a high value to skill that is neither of short supply nor of value-adding nature was truly mind-boggling. Their research conclude on a tight relationship between compensation and value added, and that current compensation predicts future performance.

Despite there being much evidence that active funds underperform their benchmark on average, some do outperform. Berk and van Binsbergen (2015) found that 43% of managers were able to outperform the benchmark. Even if the average fund manager does not give reason to believe that securities markets are efficient[1], there still may be some managers that persistently do outperform. Their main findings are that skilled fund managers are able to create value, and that their efforts to a high degree end up as compensation to the managers instead of the investors.

Considering the extensive research on fund manager skill, such as the highly influential paper written by Berk and van Binsbergen (2015), it seems to be evident that the fund managers capture much (if not all) of the value created. Despite the overwhelming evidence that the fund manager collects most of the surplus they create, compared to an appropriate benchmark, they do add value in the form of implementation - the asset owner may not be able to create the benchmark themselves. However, the implementation is cheaper through index funds.

2.1 Research on Funds Characteristics

"Is there any way by which the investor can assure himself of better than average results by choosing the right funds? If not, how can he avoid choosing funds that will give him worse than average results?" - Graham (1973)

Graham (1973), author of The Intelligent Investor, demonstrates that active funds outperformed both S&P 500 and DJIA during the 1960s. Already when the book was published in 1973, smaller funds were observed to achieve higher returns. However, can investors obtain this performance without paying a premium? To uncover an investment strategy that systematically outperforms other alternative strategies signifies a market inefficiency that the observant investor can exploit.

As Graham et al. (2019, p. 17) puts it: "From a regulator's perspective, the purpose of knowing the conditions that affect the performance of funds is to evaluate the relevance of including information on these conditions in the advertising of managers". Graham et al. (2019) compare how fund characteristics affect funds performance in the US and Europe, and suggest that most characteristics have a somewhat inconclusive effect on returns. We will in the next section discuss fund age and its empirical effect on performance, followed by a presentation of literature on other related fund characteristics.

[1]Following the Efficient Market Hypothesis (Fama, 1970), stating that outperformance only signifies luck.

2.1.1 Fund Age

Choosing an active fund does, to a larger extent than when choosing a passive one, raise the attention towards the fund managers' skill. To assess the skill of a fund in any way, one would need a track record. When funds are young, they have not yet established a track record. This issue is not as relevant when investing in index funds, given that skill is not what you pay for.

The theoretical outcomes are that performance either increases or decreases as funds age. It may increase due to accumulation of skill and experience, or it may decrease due to increasing fund size (Chen et al., 2004), increased complexity of the fund, or slack. New funds may outperform when they are new because of advantages in technological knowledge, but with constant development such effects are expected to be eradicated over time.

Howell (2001) investigates how the performance of hedge funds is related to their age. The author finds a robust negative relationship between returns and the age of the fund, that there is a slow and constant erosion of performance. However, hedge funds are organized and mandated somewhat differently than mutual funds, as they are not available to every investor. Managers of hedge funds may also have a stronger incentive to deliver good results when the fund is new, as the energy put into creating a good track record is what will ensure in-flows. Hedge funds are more susceptible to attrition because of this, as almost 9% of funds die each year, which is caused by "chronic" poor performance (Bianchi and Drew, 2010), with mutual funds having half the rate.

Another argument supporting young funds outperforming old is that hedge funds are established because of opportunity to exploit a niche that is not yet correctly priced. Investigating more than 11,000 hedge funds, PerTrac (2011) report that in 13 out of the 15 years between 1996 and 2010, young funds(less than 2 years) have outperformed both mid-age(2-4 years) and tenured funds(4+ years), and young have achieved more than twice the cumulative total return over the period. In terms of size, small funds outperform in good years, but performed the worst during 2008.

The research conducted to understand the relationship between the age and returns of mutual funds is inconclusive and seemingly given less attention than other fund characteristics. To mechanically extrapolate the relationship between age and performance within the hedge fund industry to mutual funds would however not be appropriate. Webster (2002) finds no significant relationship between fund age and raw returns of American mutual funds. However, the market-adjusted return to deteriorates over time. Despite deteriorating market adjusted returns, they find indications of a positive relationship between manager tenure and performance. Filip (2018) report similar findings in a study of the polish equity fund market - age influences performance in a negative way.

In one of the first studies on how fund characteristics affect fund performance, Chevalier and Ellison (1997) find that younger funds are more risky, and that their flow-to-performance sensitivity is higher than for older funds. Chevalier and Ellison (1999a) also find that as funds age it becomes more probable to survive and Chevalier and Ellison (1999b) find that younger managers are more easily fired following poor performance, which may result in lower risk-taking and more benchmark-like investment style.

Ferreira et al. (2013) comparings performance determinants across geographical areas. Their findings indicate that there is no relation between age and performance in the US[2], but that there is a negative relationship found outside of the US. The negative effect of fund age on performance is supported by Otten and Bams (2002), covering France, Germany, the Netherlands and the United Kingdom.

Ľuboš Pástor et al. (2015) finds a negative age-performance relation that holds both within and across funds, a relationship that disappears when controlling for the industry size. They suggest that skill improves as funds grow older, but the effect is overshadowed by the performance erosion caused by the growing fund industry size and competitiveness.

Karoui and Meier (2009) find that young funds perform better, and that the outperformance lasts for up to three years. They further find young funds to exhibit higher total and unsystematic risk, and that they are more invested in smaller and less liquid stocks.

2.1.2 Fund Characteristics Related to Fund Age

Studies of fund characteristics often debate how some effects interact with each other. Research by Chen et al. (2004) and Busse et al. (2013) explain that effects of fund size

[2] The insignificant effect of fund age on performance in the US is supported by Chen et al. (2004) and Busse et al. (2013).

may be determined by the age of the fund, as young funds tend to be small. If other fund characteristics affect returns, they may affect the lifespan of funds. How, and whether, empirical evidence control for these variables affect our interpretations and expectations of how fund age affects performance. In this section, we investigate characteristics that are not fixed across a funds lifetime, but are still found to determine the performance of funds.

2.1.2.1 Fund Size

Chen et al. (2004) was one of the first to evaluate what they call the erosion effect, with a data set covering 1962 to 1999. They argue that many alpha opportunities lie in illiquid segments, which are harder to capture for large funds. The argument is supported by Yan (2008) and Busse et al. (2013), who also find that large funds underperform because they prefer stocks with sufficient liquidity. Consistent with such liquidity constraints, mutual fund trading is found to exert substantial price pressure in the equity markets (Edelen et al., 2007), usually referred to as diseconomies of scale. Ľuboš Pástor et al. (2015) find that performance deteriorates as the size of the fund increases, as well as when time passes because the industry grows and becomes more competitive. Thus, good investment strategies may be hard to scale, and diseconomies of scale may be a common issue.

Ferreira et al. (2013) find evidence of differences in the determinants of fund performance across economies. In the US, there is a significantly negative effect of fund size on performance, however, it is positive outside of the US. Among Nordic countries, they find that performance is negatively related to size in Denmark, while the opposite is found in Finland, Norway and Sweden(Ferreira et al., 2013). The relationship found by Chen et al. (2004) is therefore not universal. Ferreira et al. (2013) remark that US mutual funds are five times larger than non-US funds on average in their sample.

The influential article by Berk and Green (2004) establishes a relationship between the past performance of a fund and its current inflow, current size is a determinant of past performance (Berk and Green, 2004). Ferreira et al. (2013) finds similar relationship between inflow and performance, but only for funds outside of the US.

In the Swedish equity market, Dahlquist et al. (2000) find an adverse effect of fund size on performance, however, the authors do not control for fund age.

2.1.2.2 Fees - The Cost of Management

The compensation scheme of fund managers has been changing over the course of years. Today, fees are usually based on assets under management (AUM), and according to Ang (2014) they represent 85% of revenue for financial advisor firms. A peculiar effect of fees proportional to the assets under management is that managers are rewarded by general market growth. The expense ratio that a mutual fund charges for its management services consists of both direct management fees, as well as recurring expenses related to marketing and administration. Loads are also a form of compensation that either takes form as sales charge on purchase, or as deferred sales charge when the fund shares are liquidated (Ang, 2014).

Even with some evidence that higher fees does not increase investor returns (Chen et al., 2004), or rather, on the contrary, shrinks them (Carhart, 1997; Gruber, 1996; Otten and Bams, 2002), investors do not seem to react to regular expense ratios. They only react to those that visibly incur when buying the fund, such as loads and commissions (Barber et al., 2005). Moreover, Gruber (1996) also finds investors to be insensitive to fund fees and after-fee performance.

Golec (1996) find that in some cases, higher fees signify superior investment skill, which may lead to better performance. In contrast, Otten and Bams (2002) reports a negative relationship between European mutual fund performance and fees. Ferreira et al. (2013) finds that the performance of all the countries in the sample is negatively related to expense ratio, except for Finland.

Other costs that incur, but are not publicly disclosed, are related to commissions (trade frequency), bid-ask spreads (liquidity), and the market-impact effect (relative size of positions). According to Edelen et al. (2007)), these costs exceed that of the fund's expense-ratio. Carhart (1997) provide evidence that the act of trading, and therefore exposing the assets to the previously mentioned costs, indeed impacts the performance of funds in a negative way. Trading costs, therefore, are proportional to turnover. Ľuboš Pástor et al. (2017) find the opposite, and relates the positive component to funds trading in less liquid stocks and funds likely to have more skill.

In essence, fund characteristics such as the size of the fund and its costs of operation do not only display inconsistent effects on performance; they may also relate to fund flows and how fund ages.

2.2 Performance Persistence

There is a broad consensus that to assess the skill of a fund or the manager, achieving high performance is not sufficient. Following the Efficient Market Hypothesis, excess returns are due to luck, not skill (Fama, 1970). The notion that skill exists in the fund management industry must imply that funds that perform well (or poorly) continue to do so (Grinblatt and Titman, 1992). If the outperformance persists over time, however, the probability of it being due to luck decreases. Following this reasoning, persistency is often used to measure skill. The earliest literature suggests that persistence exists in the US, finding strong evidence of persistence in a one year evaluation horizon (Grinblatt and Titman, 1992; Hendricks et al., 1993; Goetzmann and Ibbotson, 1994). However, Phelps and Detzel (1997) argues that persistence disappears when considering other time horizons or other performance measures. Carhart (1997) found that the momentum factor introduced by Jegadeesh and Titman (1993), when combined with the factor model by Fama and French (1993), explain most of the persistence in fund returns. Yet, there are still some evidence that short-term persistence exists Bollen and Busse (2005).

Berk and Green (2004) developed a model that attempts to explain the common trends observed in the performance and persistence of mutual fund returns. The model assumes that investors are able to observe past abnormal performance of funds, and reward the best performers. Further, they assume that the total cost of a fund follows a positive quadratic relationship with fund size. The implication is that funds with good performance will increase in AUM, until an equilibrium between performance and expense is reached. The model explains why abnormal returns are rare, and that persistence seldom lasts long.

A more recent study by Vidal-García (2013) examines the persistence of mutual fund returns in six European countries, and finds statistically and economically significant performance persistence for time horizons for up to 36 months, however, most pronounced by the top and bottom performers. Ferreira et al. (2013) finds evidence of short-run persistence, but only for US funds. Further, Verbeek and Huij (2006) finds that younger funds display stronger persistence among both top and bottom performers.

Despite some evidence both for and against the existence of persistency in mutual funds performance, the consensus is that its existence seems to be a short-lived phenomenon (Malkiel, 1995; Otten and Bams, 2002; Bollen and Busse, 2005; Vidal-García et al., 2016)[3].

2.3 Why Nordic Countries?

Comparing mutual fund performance across different economies can indicate differences in fund manager culture or even the investor's ability to attain and act on available empirical evidence, such as the research mentioned previously.

Ferreira et al. (2013) performed a large cross-country study of determinants of performance in actively managed equity funds in 27 countries. One of their findings is that age plays no significant role in determining performance in the US, but indicates a negative impact in European countries. Further, the diminishing returns to scale that are found in the US by this study, and well as other studies (Chen et al., 2004; Ľuboš Pástor et al., 2015), does not seem to be a universal truth. They find that the scale effect in the US is related to liquidity restraints faced by funds that have to invest in small and domestic stock, by virtue of their style. They find that countries with liquid stock markets and strong legal institutions display better performance. Nordic countries may therefore yield results that differ from studies of the US fund market.

Performance studies in the Nordic countries have shown similar results as in other markets, that actively managed funds do not outperform benchmarks net of fees. Moreover, most Nordic countries show little evidence of persistence, also similar to evidence found in the US (Christensen, 2013; Sørensen, 2009; Flam and Vestman, 2014; Dahlquist et al., 2000). In a study of the Finnish mutual fund market, however, both past winners and losers were able to outperform the benchmark the subsequent period (Sandvall, 2000). In a larger scale and more comparative study, Vidal-García et al. (2016) finds Denmark to attain the highest level of performance and persistence among Nordic mutual funds, and that Sweden is the worst performer on both performance and persistence in their data set of 35 countries.

[3]Bollen and Busse (2005) also finds some evidence that persistence exists in lower liquidity sectors, which we believe that Nordic funds are more able to benefit following the fund size argument of Ferreira et al. (2013).

Investor sophistication has been investigated in the Norwegian mutual fund market by Tykhonova and Akulenka (2020). They reported that Norwegian mutual fund investors were unlikely to be sophisticated, as investors are inclined to outsource risk adjustment to Morningstar ratings. Morningstar rating outperforms all asset pricing models and market-adjusted returns in predicting the direction of fund flows. As Morningstar ratings are found to serve no predictive properties of future performance (Graham et al., 2019), these findings contradict the flow-to-skill found by Berk and Green (2004). This leads us to believe that there are inefficiencies in the Nordic mutual fund market, which fund characteristics may be able to explain.

Chan et al. (2002) claim that the choice of investment style is not only driven by maximizing portfolio returns and diversification. The fund managers' and investment companies' interests may also influence the choice of investment style. Personal career concerns, and that they usually are evaluated over short time horizons, may induce funds to play safe and avoid deviating too much from the most typical benchmarks, such as the S&P 500. By doing so, managers hope to avoid being penalized for under-performance, while sacrificing opportunities to outperform. With the same argument, Chevalier and Ellison (1999b) also find that younger funds are less likely to deviate from market benchmarks, using a sample of US. mutual funds. The Nordic countries are almost always among the highest-ranked in studies of happiness, state of democracy, political rights, gender equality and trust between citizens. More than 70% of workers in Nordic countries are covered by at least one collective bargaining agreement, compared to 11% in the US (Torp and Reiersen, 2020). These social characteristics may alleviate the career concerns of fund managers in Nordic countries.

Fund attributes are scarcely studied in the Nordic countries, and this paper serves as an attempt to fill this gap. Investigating the age of the fund, being given less attention, is also motivated by the differing empirical findings in terms of diminishing returns to scale internationally. The combination of tools we use to investigate how fund age affects fund performance is also of scarce matter. Furthermore, most studies focus on domestic funds, while we cover all available funds within the domiciles. The lack of clarity of whether the age of Nordic mutual funds provides any information on performance is a strong motivator of our study.

3 Hypothesis development

Considering the existing literature on mutual fund performance, the age of the fund is most often assigned the role of a control variable. However, the fact that fund age is included for this purpose signifies its empirical importance. As our reviewed literature suggests, the relationship between the fund's age and performance is less clear. The purpose of our study is to close what we perceive as a literature gap on a fund characteristic, and to do so within the Nordic mutual fund industry where such studies are scarce. In the next section, we will address this purpose by presenting our empirical research questions.

Hypothesis 1: Fund age affects the performance of mutual funds

Existing research on how fund age affects performance is to a high degree inconclusive. However, it is most often suggested that older funds perform worse than young funds outside the US. (Ferreira et al., 2013). Previous research that either directly assesses fund characteristics, or include them as control variables, may not take survivorship bias into account, resulting in upward an bias in the performance of especially young funds. Age and size are usually correlated - older funds tend to be larger. Increased fund size implies lower marginal costs of management but may do so at the cost of diseconomy of scale (Chen et al., 2004). Small funds are preconditioned to be more agile if market conditions change abruptly, and quickly rebalance its portfolio without being a price mover. These findings lead us to expect that there are differences between young and old mutual funds, in terms of risk-adjusted performance.

Hypothesis 2: Fund age affects risk-taking of mutual funds

The second research question we raise is that of risk-taking behavior. Following the notion that young funds tend to be more agile, they may also be less inclined to avoid volatility. We expect our findings to follow the findings posed by Chevalier and Ellison (1997) and Karoui and Meier (2009), suggesting that younger funds are incentivized to increase their risk towards year-end if they have performed poorly. We are therefore lead to expect that funds become less risky when they age.

Hypothesis 3: Fund age affects the investment style of mutual funds

New funds may be created to take advantage of a new niche, or to otherwise create value to investors by utilizing a managers' specialized knowledge about certain markets or certain risk-premia anomalies. Investment style is related to how a funds allocate its assets. Enlightened by the fact that young and old funds are inherently different in terms of characteristics, such as size - we expect to find that young and old funds also follow different investment styles.

Hypothesis 4: Investment strategies based on fund age outperform on a risk-adjusted basis

Even if age may not have causal implications on performance, we want to investigate whether it is possible for investors to consistently outperform a benchmark by trading funds based on their age. In the US, Ľuboš Pástor et al. (2015) and Karoui and Meier (2009) find that portfolios sorted on young funds outperform older funds. If a portfolio long in young funds and short in old funds outperform, this may indicate that new funds that enter the fund management industry are more skilled. With indications of a negative age-performance relation outside of the US, we expect to find similar results.

Verbeek and Huij (2006) finds stronger persistence in young funds. Further, persistence is found to be stronger in less liquid sectors (Busse et al., 2013), which Nordic funds could potentially benefit from with their smaller size compared to US funds (Ferreira et al., 2013).

4 Data

To assess the performance differences across age in the Nordic mutual fund industry, we obtain and structure a large amount of data. Our data sources and details on the sample selection will be presented in this chapter.

4.1 Data Sources and Sample Selection

We obtain monthly mutual fund data from the Morningstar Direct database. All data is obtained in USD, to be better able to compare data on an equal basis. We include both surviving and non-surviving funds in our data sample, to avoid survivorship bias. Attrition of non-surviving funds is likely to bias the sample towards better performing funds because funds that disappear tend to perform poorly prior to their dissolution (Elton et al., 1996; Brown et al., 2015). More on data biases in subsection 4.4.1.

Our study considers the mainland Nordic countries (Norway, Finland, Sweden and Denmark). This implies selecting mutual funds that are domicile to one of the Nordic countries. We include mutual funds investing within and outside their domicile country. Focusing solely on mutual funds that only invest within their home domicile is restrictive and would reduce our sample significantly. The total survivorship bias free sample available in the Morningstar Direct database for this area is 1956 funds. We are specifically looking at data between January 2006 and February of 2021. By removing all funds that are obsolete before our period of interest, our new number of funds is 1804 (net) and 1667 (gross)[4].

We use end of month observations of each funds' NAV (net asset value) to calculate returns, which we ensure by using the last observation carried forward. For example, if the 31st of January is on a Sunday, the last observation of the month would be from Friday 29th. This ensures that we do not lose any data due to inconsistency in reporting dates.

Monthly returns are included first when they have an entire month of returns, i.e., funds that start trading in the middle of a month will be attributed their first return the

[4]This sample is used for the Long-Short portfolio, as observations of fund characteristics are of less importance in portfolio studies. After balancing the panel data with last observation carried forward and omitting missing values, 1198 (net) and 1138(gross) funds remain. The process is further described in subsection 4.3.5.

following month. We calculate net returns as the monthly change in the NAV of each individual fund. This process generates more observations of net returns than of gross returns. We are not able to calculate the gross returns manually, we therefore use the data provided by Morningstar Direct.

We utilize Morningstar Direct's category search to limit our data. More specifically, we exclude all non-equity funds i.e. bond funds, money market funds, real estate funds and alternative funds. Furthermore, we exclude all funds that are index funds, according to Morningstar Direct. This allows us to compare a sample of actively managed mutual equity funds. To test for false positives not picked up by this categorization, we also remove any funds that contain the word "index" and "indeks". Additionally, we remove remaining funds that report an expense ratio that is below 0.1% per year, which active funds are highly unlikely to have.

A common practice amongst the fund managing industry is to offer the same fund (in terms of asset holdings) at different fee structures. If each subclass of a fund is treated as separate entities, the statistical significance of effects from this fund would be artificially increased (Berk and van Binsbergen, 2015). To avoid double-counting funds with multiple share classes, we keep only one share class per fund. Funds with multiple share classes are attributed with the aggregate fund family size. We choose to keep the share class with the most observations within this fund, to retain the maximum age of the fund (Ľuboš Pástor et al., 2015; Busse et al., 2013).

4.1.1 Collecting Risk Factors

To measure the abnormal returns of funds, we collect risk-factors that make up our four benchmark models. We employ CAPM (Jensen, 1968), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model and Fama and French (2015b) five-factor model. The model specifications are presented in subsection 5.1. As we are mostly interested in the aggregate effect of the funds, and not each fund specifically, we collect the international factors as provided from Kenneth French's web cite[5]. This choice is supported by the fact that the US mutual fund industry in total constitutes about 47% of the global AUM (Investment Company Institute, 2021), and that most of our funds

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

invest globally. Statista Research Department (2021) reports that as of January 2021, the US. stock market makes up almost 56% of the global equity market value, and that the three largest European equity markets (UK, France and Germany) make up in total 8.6%. With free capital flow across borders, and the observation that funds self-report what benchmark they compare against[6], we argue that use of global factors to be a reasonable choice for making aggregate comparisons. Using fund fixed effects in the multivariate analysis additionally strengthens the robustness of this choice, focusing more on the way age affects the return within funds, not in a pooled manner.

4.2 Structure of Data Sample

Several recent papers covering similar topics have used a monthly periodicity, thus our data sample contains monthly observations from January 2006 to February 2021. Most of our variables are reported monthly by Morningstar Direct, which supports the monthly periodicity, yielding higher robustness in our data set compared to annual data points.

4.3 Variables

In this section, we present the different variables that are used in our empirical methodology. First, we describe our dependent variables, which are essential to answer our hypotheses. We then present our main independent variable, followed by other fund-related control variables that are included to mitigate the risk of omitted variable bias. Finally, we present our descriptive statistics for the full data set, and a mean comparison between the youngest and oldest age-quintiles in our sample. The latter is to supplement portfolio analyses. Appendix A2.1 contains a detailed description of all the variables.

4.3.1 Dependent Variables

As suggested by Busse et al. (2013), we use both gross returns and returns net of fees, to measure the difference in returns across fund age. Gross returns are the returns funds achieve before any fee is deducted, while net returns are deducted these fund-specific fees. According to Berk and van Binsbergen (2015), gross returns are better suited to assess the

[6]As a consequence, a fund's investment objective may be conditioned to improve ex-post returns ranking (Brown and Goetzmann, 1997).

actual skill of a fund manager, while net returns are more informative for fund investors as a measure of value added. By looking at both gross- and net returns, we can better evaluate whether fees in a mutual fund implicate a difference in risk-adjusted returns, risk-taking and investment style across fund age. In all of the measures that are presented in the following section, x denotes whether the fund returns used are gross or net of fees.

To evaluate the risk-adjusted performance across fund age, we estimate four measures of fund performance. These are estimated using a 12-month rolling window[7]. Specifically, we estimate all the performance measures from *t=1* to *t=12*, then from *t=2* to *t=13*, *t=3* to *t=14* and so forth. Therefore, our first *alpha* is estimated at January of 2007, and we lack by default any estimated alphas the first year of each fund's life[8].

The first performance measure we estimate is $CAPM^x_{i,t}$, which is fund *i's alpha* at time t from the CAPM one-factor model introduced by Jensen (1968). Second, we estimate $FF3FM^x_{i,t}$, which is fund *i's alpha* at time t from the Fama and French (1993) three-factor model. Third, we estimate $CARHART^x_{i,t}$, which is the *alpha* of fund i at time t from the Carhart (1997) four-factor model. The last performance measure we estimate is $FF5FM^x_{i,t}$, which is fund *i's alpha* at time t from Fama and French (2015b) five-factor model.

To assess how risk-taking differs across fund age, we construct three different measures of risk. All risk metrics ($Risk^x_{i,t}$) are estimated using the same 12-month rolling window. The first risk measure $FundRisk^x_{i,t}$ is given by fund *i's* standard deviation in returns at time t. $SysRisk^x_{i,t}$ is measured as the estimated factor-loading on the market portfolio from CAPM one-factor model for fund *i's* at time t (otherwise presented as βMKT). $UnsysRisk^x_{i,t}$ is the standard deviation of the residuals from the CAPM one-factor model for fund i at time t [9].

Further, to assess the investment style of funds, we estimate the factor weightings $MKT^x_{i,t}$, $SMB^x_{i,t}$ (Small Minus Big), $HML^x_{i,t}$ (High Minus Low), $RMW^x_{i,t}$ (Robust Minus Weak)

[7]Karoui and Meier (2009) use factors from months *t=1* to *t=24* (their rolling window) to estimate alpha, however they mention that they are by construction determined in-sample.

[8]Estimating time-varying alphas in accordance with Huij and Verbeek (2009) demands sacrificing a number of observations of data. The number of observations used to estimate is a decision that balances two trade-offs: loss of data and the quality of the estimates(Sørensen, 2009). Our sample of data stretches over a time period of 15 years, which constitutes at most 180 observations per fund. We consider the cost of sacrificing observations to make our analysis vulnerable, hence we decide to use less than 10% of our available observations to construct a rolling window, i.e. 12 months.

[9]Unsystematic risk is measured in accordance with the methodology of Chevalier and Ellison (1999b).

and $CMA^{x}_{i,t}$ (Conservative Minus Aggressive) from the Five-Factor Model of Fama and French (2015b). We argue that the Five-Factor Model is the most relevant to answer our hypothesis, as it is the most recent. These represent fund *i's* loading on each risk factor at time t. These are also estimated using a 12-month rolling window.

4.3.2 Main Independent Variable

Since this thesis investigates how fund age affects fund performance, we make $FundAge_{i,t}$ our main independent variable. We calculate each fund's age at each data point by counting days since the inception date. This approach requires us to have an inception date, which implies removing funds that do not report this attribute from the sample.

4.3.3 Control Variables

This section presents the different control variables related to fund characteristics that we use in our analysis.

$FundSize_{i,t}$ is the size of each fund in each month reported in USD obtained from Morningstar Direct. $Top10Holdings_{i,t}$ is a measure of how many percent each fund's total assets the ten largest asset allocations constitute. The higher the percentage, the less diversified is the fund. $NumOfStocks_{i,t}$ is the number of different stocks fund i holds at time t, which also serves as a measure of diversification. $ExpenseRatio_{i,t}$ is reported annually by Morningstar Direct, but we divide this ratio by 12 to make it fit our monthly data. We argue that this linear approach is reasonable, as the expense ratio is usually deducted and accrued on a daily basis. $Turnover_{i,t}$ is the percentage of fund *i's* stock holdings that have changed over the past year. This may indicate how actively managed a fund is.

In addition to our control variables, we want to control for time-, fund- and segment fixed effects. We create time- and geographical dummies. We extract fixed effects to isolate unobserved effects that might distort our results, such time variations, culture or regulatory conditions. These time variations could be global economic shocks like the financial crisis in 2007-2009. By including time dummies, we are able to isolate such shocks in our analysis. Economic shocks affect some geographical areas more than others, like the Euro crisis in 2011-2012. We capture these shocks with our segment dummies.

Finally, we include fund-fixed effects in our regression to capture time-invariant effects at the fund level. Fund-fixed effects are, however, captured through our panel regression model. Following this, we argue that we are able to capture some of the unobserved effects and isolate effects to have a more precise estimation of our regressions.

4.3.4 Winsorizing

Our variables contain several extreme values. We winsorize on a 1 percent level to avoid skewing of our results due to outliers in our data sample [10]. The variables we winsorize are $FundSize_{i,t}$, $ExpenseRatio_{i,t}$, $Top10Holdings_{i,t}$, $NumOfStocks_{i,t}$ and $Turnover_{i,t}$.

4.3.5 Missing Values

Most of the data that we have obtained from Morningstar Direct is reported daily or monthly. In some cases, we have odd or missing variable observations between periods with continuously reported data. In other cases, we are missing all the data on specific variables in a specific fund. Even if a common method is to omit missing values, Osbourne (2013) argues that omission could lead to severe sample selection bias and inference errors. To cope with missing values, we therefore use the method of "Last Observation Carried Forward" for the variables $FundSize_{i,t}$, $ExpenseRatio_{i,t}$, $Top10holdings_{i,t}$, $Turnover_{i,t}$ and $NumOfStocks_{i,t}$[11]. These variables are reported periodically, but we are missing data points for some months. Inspecting for robustness, we find that this method gives us many more observations, but does not skew the data when we run regressions. Our variables tend to be fixed over periods of time, and e.g. expense ratio is not expected to change drastically over time.

In the spirit of Elton et al. (2001), we exclude some of the lowest values. The presence of low values may imply some form of measurement error. According to Evans (2010), low fund sizes may also indicate that there is incubation bias present in the data set. Following the methodology of Elton et al. (2001) and Chen et al. (2004), we remove observations of the smallest funds. We remove funds with less than 2 MUSD in AUM, instead of 15 MUSD as suggested. This decision is supported by the fact that Nordic funds are smaller on average, and that a cut-off of 15 MUSD reduces the data set severely, especially among

[10] Which may also help removing implausible values, as recommended by Rohleder et al. (2010).
[11] In accordance with Berk and van Binsbergen (2015).

young funds. Further, we find it reasonable that a fund at least should report holdings of more than one stock.

4.3.6 Descriptive Statistics

The final sample includes 110 173 (net) and 103 284 (gross) fund months. The total number of funds is 1198 (net) and 1138 (gross). We present and compare the two samples in this section. Table 4.1 reports summary statistics for the variables used in our regressions, where Panel A represents observations with net returns and Panel B represents gross returns. Table 4.2 reports the difference in means in these variables between the 1st Quintile (youngest funds) and the 5th Quintile (oldest funds). We create quintiles rather than firm age intervals to create subsamples with a similar number of observations, opposed to Ľuboš Pástor et al. (2015)[12]. To further describe the two age-quintiles, we include a visualization of the age distribution in figure 4.1.

Looking at table 4.1, we observe a positive average monthly net *ExcessReturn* of 0.393% while the average monthly gross *ExcessReturn* is 0.687%[13]. Looking at the two samples' mean *FundAge*, they are similar and approximately 13 years, and the top percentile p(99) is 34 years old. Moreover, the average *NumOfStocks* held in a fund is 76 for the net sample and 77 for the gross sample, yet it varies greatly in our sample. Some funds p(1) hold only 13 stocks while other funds p(99) hold 541 stocks. The average *FundSize* is 293 MUSD (net) and 283 MUSD (gross). The bottom percentile p(1) is a little less than 3 MUSD, while the top percentile p(99) is 3200 MUSD. Furthermore, funds have approximately 43% invested in their *Top10Holdings*. The average *ExpenseRatio* is 0.131%, ranging from 0.028% to 0.276% per month. The average annual *Turnover* is 68% (Net) and 67% (Gross)[14]. Looking at the percentiles, we observe variations from 0% to 374% turnover per year.

To investigate fund portfolios based on age, we separate the data set into five groups sorted by age. We are interested in the 1st and 5th quintiles, which include the returns of

[12]The split is somehow arbitrary, but serves the purpose to distinctly separate the groups, just as Fama and French (2015b, p. 11) does with factors portfolios.

[13]By excess return, we refer to the actual returns achieved deducted the risk-free rate which is the equivalent of a one-month T-bill rate.

[14]According to Ang (2014), the average turnover of active mutual funds in the US is between 80% and 90%, which is far higher than what we find in our sample.

the 20% youngest and 20% oldest funds at each time, respectively[15]. Examining table 4.2 gives us some insight before our analysis. 1st Q. and 5th Q. show the mean values of the different characteristics for the youngest and oldest funds, respectively, for both our Net and Gross sample. The Difference column presents the difference between young and old funds. These differences are tested in a two-sided t-test to see if they are significantly different. The quintiles presented are expected to exhibit different properties[16]. This is, however, simply a comparison of means between young and older funds, and is solely used to gain presumptive insight into our data, not to draw any conclusions about causal relationships determined by belonging to different age quintiles.

Firstly, we find that older funds have higher *ExcessReturn* in both samples. The comparison also shows that younger funds have on average 17 fewer stocks. When comparing *FundSize*, we find that older funds are on average approximately three times larger than their youngest peers. Turnover significantly differs between the two groups, where younger funds turnover 75% of their portfolio and older funds only 60%, indicating that funds are more actively managed when young. Older funds' holdings are also slightly more concentrated in their *Top10Holdings*, indicating higher risk-taking and more overconfidence by the fund's management. This could be caused by investor's lower sensitivity to poor performance in older funds, as described by Chevalier and Ellison (1997). Examining the means of the different risk variables, we observe that the young funds take on more *FundRisk* (Gross) and *UnsysRisk* (Net and Gross), while the old funds take on more *SysRisk* (Net and Gross). We find that younger funds on average load more on all the risk factors (Gross). On the other hand, older funds seem to have higher *alpha* when considering *CAPM* and *FF3FM* (Gross). The difference between the remaining variables are not statistically significant at a 5% significance level.

[15]The top and bottom quintile is later used to construct the Long-Short portfolio presented in subsection 5.4.1, and in the study of persistence within these quintiles in subsection 5.4.2.

[16]Graphical representations of how our control variables vary across fund age is presented in Appendix A1.1

Table 4.1: Descriptive Statistics of Net Returns

Panel A: Net	Obs (1)	Mean (2)	Std (3)	p(1) (4)	p(99) (5)
$ExcessReturn_{i,t}$	110173	0.393	6.668	-19.759	17.0196
$FundAge_{i,t}$ (in years)	110173	12.9	7.982	1.273	34.366
$NumOfStocks_{i,t}$	110173	76.423	115.314	13	541.955
$FundSize_{i,t}$(in millions)	110173	293.636	566.223	2.896	3212.393
$Top10Holdings_{i,t}$	110173	42.83	15.817	11.49	99.392
$ExpenseRatio_{i,t}$ (per month)	110173	0.131	0.049	0.033	0.276
$Turnover_{i,t}$	110173	68.312	72.68	0	374
$FundRisk_{i,t}$	110173	5.911	2.832	1.809	15.093
$SysRisk_{i,t}$	110173	1.008	0.485	-0.638	2.056
$UnsysRisk_{i,t}$	110173	3.482	1.781	0.808	9.628
$MKT^n_{i,t}$	110173	1.001	0.645	-0.989	2.608
$SMB^n_{i,t}$	110173	-0.131	0.795	-2.292	2.045
$HML^n_{i,t}$	110173	-0.1	1.053	-3.007	3.028
$RMW^n_{i,t}$	110173	-0.119	1.456	-4.583	3.745
$CMA^n_{i,t}$	110173	-0.488	1.533	-5.562	2.746
$CAPM^n_{i,t}$	110173	-0.404	1.357	-3.763	3.552
$FF3FM^n_{i,t}$	110173	-0.537	1.554	-4.711	3.585
$CARHART^n_{i,t}$	110173	-0.496	1.557	-4.644	3.665
$FF5FM^n_{i,t}$	110173	-0.523	1.825	-5.38	4.52

Panel B: Gross	Obs (1)	Mean (2)	Std (3)	p(1) (4)	p(99) (5)
$ExcessReturn_{i,t}$	103284	0.687	6.526	-18.949	17.212
$FundAge_{i,t}$ (in years)	103284	13.010	8.037	1.312	34.685
$NumOfStocks_{i,t}$	103284	77.399	117.057	14	544.153
$FundSize_{i,t}$(in millions)	103284	283.161	538.739	2.944	2815.299
$Top10Holdings_{i,t}$	103284	42.549	15.881	11.316	99.515
$ExpenseRatio_{i,t}$ (per month)	103284	0.131	0.048	0.028	0.276
$Turnover_{i,t}$	103284	67.588	72.684	0	374
$FundRisk_{i,t}$	103284	5.793	2.833	1.702	14.942
$SysRisk_{i,t}$	103284	1.006	0.465	-0.551	2.040
$UnsysRisk_{i,t}$	103284	3.308	1.718	0.720	9.351
$MKT^g_{i,t}$	103284	1.018	0.589	-0.692	2.579
$SMB^g_{i,t}$	103284	-0.152	0.729	-2.218	1.751
$HML^g_{i,t}$	103284	-0.076	1.019	-2.884	3.015
$RMW^g_{i,t}$	103284	-0.087	1.368	-4.150	3.674
$CMA^g_{i,t}$	103284	-0.494	1.473	-5.445	2.573
$CAPM^g_{i,t}$	103284	-0.129	1.293	-3.262	3.766
$FF3FM^g_{i,t}$	103284	-0.249	1.436	-4.066	3.750
$CARHART^g_{i,t}$	103284	-0.222	1.430	-3.935	3.779
$FF5FM^g_{i,t}$	103284	-0.258	1.753	-4.912	4.667

Notes: This table presents descriptive statistics for all variables in both the sample of net returns (Panel A) and gross returns (Panel B)

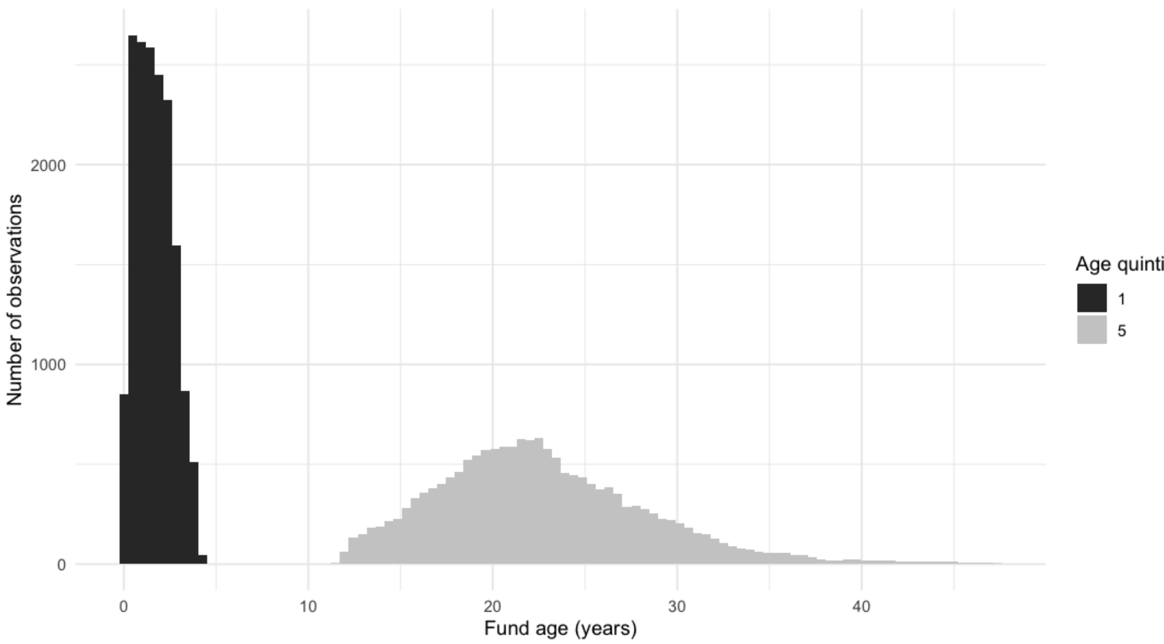
Table 4.2: Comparison of *FundAge*-Quintiles 1(young) and 5(old)

FundAge quintiles	1st Q. (Net)	5th Q. (Net)	Difference (Net)	1st Q. (Gross)	5th Q. (Gross)	Difference (Gross)
$ExcessReturn_{i,t}$	0.351	0.462	-0.111*	0.621	0.760	-0.139**
$FundAge_{i,t}$ (in years)	3.296	24.654	-21.358***	3.336	24.915	-21.579***
$NumOfStocks_{i,t}$	71.191	87.959	-16.768***	72.349	89.829	-17.480***
$FundSize_{i,t}$(in millions)	157.222	491.065	-333.843***	151.693	496.251	-344.558***
$Top10Holdings_{i,t}$	41.976	42.452	-0.476***	41.477	42.209	-0.732***
$ExpenseRatio_{i,t}$ (per month)	0.138	0.125	0.013***	0.139	0.125	0.014***
$Turnover_{i,t}$	74.631	60.353	14.278***	76.139	59.789	16.35***
$FundRisk_{i,t}$	5.841	5.833	0.008	5.777	5.683	0.094***
$SysRisk_{i,t}$	0.989	1.028	-0.039***	0.992	1.021	-0.029***
$UnsysRisk_{i,t}$	3.48	3.288	0.192***	3.345	3.097	0.248***
$MKT^x_{i,t}$	0.99	1.014	-0.024***	1.006	1.030	-0.024***
$SMB^x_{i,t}$	-0.114	-0.128	0.014*	-0.131	-0.155	0.024***
$HML^x_{i,t}$	-0.102	-0.135	0.033***	-0.074	-0.129	0.055***
$RMW^x_{i,t}$	-0.132	-0.148	0.016	-0.071	-0.109	0.038***
$CMA^x_{i,t}$	-0.487	-0.388	-0.099***	-0.513	-0.387	-0.126***
$CAPM^x_{i,t}$	-0.38	-0.392	0.012	-0.130	-0.099	-0.031**
$FF3FM^x_{i,t}$	-0.52	-0.534	0.014	-0.259	-0.231	-0.028**
$CARHART^x_{i,t}$	-0.481	-0.509	0.028*	-0.235	-0.216	-0.019
$FF5FM^x_{i,t}$	-0.519	-0.511	-0.008	-0.273	-0.241	-0.032*

*p<0.1; **p<0.05; ***p<0.01

Notes: This table compares the two age quintiles. Net and Gross returns are reported separately. The differences between the young and old quintiles are t-tested.

Figure 4.1: Age Distribution of 1st. and 5th. Age Quintile



Note: This figure showcase the age-distribution within our two age quintiles of choice.

4.4 Potential Sources of Bias in the Data Sample

4.4.1 Survivorship bias

Survivorship bias arises when we exclude returns of funds that are no longer alive. Not only is the fund management industry and the number of funds growing, according to Horst et al. (2001) the relative number of funds that close or merge also increase. The bias is of high importance in performance studies. Malkiel (1995) finds that by controlling for survivorship bias in his data set covering 1982 to 1990, the average annual return decreases by 1.4%. Rohleder et al. (2010) notes that during the period between 1993 and 2006, the US domestic equity funds achieve an annual 14 basis point positive alpha if not taking into account the closed funds, while an unbiased data set achieves an annual 95 basis point negative alpha. Attrition of closed funds leads to an overestimation of fund performance, which is shown by the significant negative effect that including them has on the overall alpha. Funds are found to be more likely to die in their younger years (Chevalier and Ellison, 1999b).

Even with a complete database of all funds that have existed in the time period of interest, survivorship bias may inhibit fund performance studies. One source that may bias the results is rules proposed in the data cleaning process. Timmermann et al. (2006) require at least 60 months of returns even to include the fund in their final data set. This data selection rule is one of the issues that Fama and French (2010) addresses when comparing their results to the findings of Timmermann et al. (2006). In our data set, we do not exclude funds based on their number of observations. The attempt we make to find evidence of differences in performance between young and old funds does not coinciding with removing all funds younger than five years. This group of funds make out the full "young" quintile that we have formed, as seen in figure 4.1.

Our data set is also subject to selection bias based on data-availability. We lose observations in the process of adding variables to our model. More young funds seem to not report data on e.g. *FundSize*. Our conclusions from our performance analysis is thereby biased by what data we are able to gather.

4.4.2 Incubation Bias

Incubation bias occurs on instances where fund managers incubate a handful of funds, but do not yet publicly trade them. Those who perform well within a certain time period will be publicly available, while those who do not are closed. Incubation bias is therefore a form of selection bias that complete data set itself may be subject to. Funds in incubation are found to have nearly 10% higher returns than non-incubated funds (Evans, 2010). This outperformance is however temporary, as Evans (2010) also finds that by removing the first 3 years of records, he could mitigate 95 percent of the present incubation bias. As there are no studies on the existence of incubation bias in Nordic countries to our knowledge, we personally contacted The Norwegian Financial Supervisory Authority (Personal communication, 30.04.2021) to find if we should take this bias into account. NFSA responds that the rules covering Norwegian funds prohibit this practice. We therefore believe our data not to be strongly affected by incubation bias. Attempting to resort the potential of incubation bias, we still remove all observations where $FundAge_{i,t}$ is less than 2 MUSD, as the funds will not be large during incubation (Evans, 2010). In addition, we avoid estimating in-sample alphas during the first year, unlike what Karoui and Meier (2009) do.

5 Methodology

This section aims to describe the econometric methods applied in this thesis. To assess the objective of our thesis, we first define what constitutes performance by creating a benchmark. We then present our multivariate regression models that we use to investigate how fund age affects risk-adjusted performance, risk-propensity and investment style. Lastly, we present the setup of our long-short portfolio, and our two approaches to investigate persistence.

5.1 The Performance of Mutual Funds Across Fund Age

There are various performance measures to evaluate risk-adjusted returns of mutual funds. In this paper, we evaluate the performance of mutual funds based on fund age using four different performance measures. These models are presented below.

5.1.1 CAPM

The Capital Asset Pricing Model, known as CAPM, was developed by Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966), and later put to use as a performance measure by Jensen (1968). The CAPM introduces a relationship between risk exposure and expected return, that in aggregate an asset's covariance with the market is the only risk that explain returns as unsystematic risks are diversified away. The model measures returns generated by a fund after adjusting for market risk. We can use this to evaluate fund performances. The model is defined as

$$R^x_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \epsilon_{i,t} \quad , \tag{5.1}$$

where $\mathrm{R}^x_{\mathrm{i,t}}$ is the return of a fund in period t, where x denotes whether gross(g) or net(n) returns are used. $\mathrm{R}_{\mathrm{f,t}}$ is the risk-free rate at time t and $\mathrm{R}_{\mathrm{m,t}}$ is the return on the market portfolio at time t.

β_i is fund i's exposure to market risk (non diversifiable risk) in the market portfolio. $\varepsilon_{i,t}$ is the error term which has an expectation of zero[17] and measures unsystematic risk that is not explained by the model. The alpha α_i is the abnormal return of the fund i at time t, in excess of the market portfolio. A positive alpha indicates that the fund is outperforming the market portfolio, while a negative alpha indicates underperformance.

5.1.2 FF3FM

Several papers argue that there are other relevant risk factors that explain cross-sectional asset returns than market risk (Basu, 1983; Rosenberg et al., 1985). In the Three-Factor Model, Fama and French (1993) include two additional risk factors, the size (SMB) and value (HML) premiums.

$$R^x_{i,t} - R_{f,t} = \alpha_i + \beta_{1i}(R_{m,t} - R_{f,t}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \epsilon_{i,t} \tag{5.2}$$

Small Minus Big (SMB) is constructed as the difference in returns between the smallest and largest firms in terms of market capitalization. It represents the excess return that smaller market capitalization companies return versus larger companies. High Minus Low (HML) is constructed as the difference in returns between the high and low book-to-market firms. The factor represents value stocks outperforming growth stocks. β_1, β_2 and β_3 are fund i's estimated exposure to the risk-factors. α_i is the abnormal returns and $\varepsilon_{i,t}$ is the unsystematic risk for fund i at time t.

5.1.3 Carharts 4-factor Model

Motivated by discovering that the Fama and French 3-factor model is unable to explain cross-sectional variation in momentum-sorted portfolio returns, Carhart (1997) added a momentum factor originally proposed by Jegadeesh and Titman (1993). This factor captures the one-year momentum anomaly that was discovered to be robust over time and countries despite implying some market inefficiency (Carhart, 1997). Despite the unpredictable nature of individual stocks' performance, a portfolio of past winners

[17] An assumption necessary to estimate unbiased coefficients in an OLS-regression (Wooldridge, 2009).

outperforms a portfolio of past losers[18].

The momentum factor Up minus Down (UMD) reflects the return of a portfolio of stocks that performed well in the recent past in excess of the return on a portfolio of stocks that performed badly in the recent past. The Carhart 4-Factor model is specified as follows:

$$R^x_{i,t} - R_{f,t} = \alpha_i + \beta_{1i}(R_{m,t} - R_{f,t}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}UMD_t + \epsilon_{i,t} \quad (5.3)$$

β_1, β_2, β_3 and β_4 represents fund *i*'s corresponding exposure to each of the risk-factors. α_i is the abnormal returns and $\varepsilon_{i,t}$ is the unsystematic risk for fund *i* at time *t*.

5.1.4 FF5FM

During the last decades, the models mentioned above have become synonymous with performance evaluation. Following its broad and frequent use in both academia and by professionals, certain anomalies have been observed to manifest themselves in the market[19].

Fama and French address this issue, and attempt to increase the fit of their model, by introducing two additional factors (Fama and French, 2015b). Companies with robust profitability tend to achiever higher stock returns, which is the rationale behind the factor *RMW* (robust minus weak). The last factor is related to the rate that the companies invest to grow, *CMA* (conservative minus aggressive). The *RMW* factor is therefore constructed as the return of a portfolio of stocks with robust profitability in excess of the return on a portfolio of stocks with weak profitability. The *CMA* factor is constructed as the return of a portfolio of stocks of low investment firms (conservative) in excess of the return on a portfolio of stocks with high investment (aggressive). The Fama French 5-Factor Model is specified as follows:

$$R^x_{i,t} - R_{f,t} = \alpha_i + \beta_{1i}(R_{m,t} - R_{f,t}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \epsilon_{i,t} \quad (5.4)$$

[18] Over a time period of 5 years, however, this effect is found to be either eliminated, or even reversed. This is usually referred to as mean reversal (Bondt and Thaler, 1985).

[19] One of which is the beta anomaly, which suggests that low-beta stocks have been performing better than what the market model predicts. Common explanations cover issues such as the increased volume of investment flows into index funds and ETF's, as well as a tendency for investors to instead invest in high beta stocks than place a leveraged position in low-beta stocks. The relative price of those low-beta stocks fall, and therefore the expected return increase. These findings were made across many countries (Frazzini and Pedersen, 2014). We address market beta exposure in subsection 6.3

β_1, β_2, β_3, β_4 and β_5 represents the funds corresponding exposure to each of the risk-factors. α_i is the abnormal returns and $\varepsilon_{i,t}$ is the unsystematic risk for fund i at time t.

5.1.5 Multivariate Regression

To account for fund-specific characteristics that vary across fund age, we construct a multivariate regression:

$$\begin{aligned} Perf^{x}_{i,t} &= \beta_0 + \beta_1 FundAge_{i,t} + \beta_2 FundSize_{i,t-1} \\ &+\beta_3 Top10Holdings_{i,t-1} + \beta_4 NumOfStocks_{i,t-1} \\ &+\beta_5 ExpenseRatio_{i_t-1} + \beta_6 Turnover_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{5.5}$$

$Perf^{x}_{i,t}$ is the *alpha* of fund i at time t from one of four performance measures, $CAPM^{x}_{i,t}$, $FF3FM^{x}_{i,t}$, $CARHART^{x}_{i,t}$ or $FF5FM^{x}_{i,t}$, as described previously in subsection 4.3.1. Performance is denoted with both i and t, as we are using rolling *alphas*). And again, x denotes whether the regression is based on gross return or net return. By using $Perf^{x}_{i,t}$ as the dependent variable, we are able to control for fund characteristics that might affect abnormal returns of a fund. The $FundAge_{i,t}$ variable is the main independent variable and takes the age of fund i at time t to try to explain the *alpha*. If $FundAge_{i,t}$ shows a positive (or negative) statistically significant sign, it could indicate that young funds outperform (underperform) older funds in our sample.

The rest of our variables are control variables. We include the logarithm of $FundSize_{i,t\text{-}1}$ and $NumOfStocks_{i,t\text{-}1}$[20]. In addition, all variables are lagged one month to avoid spurious correlation and potential endogeniety problems, as discussed by Carhart (1997). Furthermore we include geographical and time dummies to capture geographical and time-specific effects. The control variables are of less interest for our research questions, but they are included in the regression to mitigate some of the risk of omitted variable bias.

Further, we assume that some funds will consistently perform at different levels. To account for and avoid autocorrelation and heteroskedasticity in the error term related to entity effects, we perform the regression with fund fixed effects and cluster our standard

[20] The distribution of these variables is left-skewed, and to accommodate this non-normality, we log-transform *FundSize* and *NumOfStocks*.

errors accordingly. In addition, fund size and fund age may propose endogeneity problems, as skill may be correlated with both these fund characteristics as well as performance(Berk and van Binsbergen, 2015). Ľuboš Pástor et al. (2015) and Berk and van Binsbergen (2015) argue that since we cannot observe skill, fund fixed effects absorb the cross-sectional variation that such omitted variable bias incur. Ultimately, fund fixed effects add to our objective of finding how age affects fund performance, and not how funds of different ages are distributed in our sample.

5.2 Risk-Taking of Mutual Funds Across Fund Age

Does fund age affect the level of risk funds take? To examine this, we run a multivariate regression that controls for fund characteristics that might affect the risk-taking of a fund:

$$\begin{aligned} Risk^x_{i,t} &= \beta_0 + \beta_1 FundAge_{i,t} + \beta_2 FundSize_{i,t-1} \\ &+\beta_3 Top10Holdings_{i,t-1} + \beta_4 NumOfStocks_{i,t-1} \\ &+\beta_5 ExpenseRatio_{i_t-1} + \beta_6 Turnover_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{5.6}$$

This regression resembles the multivariate regression from equation 5.5, but the dependent variable is now $Risk^x_{i,t}$. We include the same independent variable and control variables as in equation 5.5. $Risk^x_{i,t}$ reflects one of three risk measures for fund i at time t, $FundRisk^x_{i,t}$, $SysRisk^x_{i,t}$ or $UnsysRisk^x_{i,t}$. Whether we are using gross or net returns is again denoted by x. Our dependant variable is $FundAge^x_{i,t}$ and a statistical significant regression output would indicate that older funds take more or less risk than younger funds based on fund risk, systematic risk or unsystematic risk.

5.3 Investment Style of Mutual Funds Across Fund Age

Does fund age affect the investment style of mutual funds? We regress a funds Factor-Weightings on fund age and other fund characteristics.

$$\begin{aligned} FactorWeight^x_{i,t} &= \beta_0 + \beta_1 FundAge_{i,t} + \beta_2 FundSize_{i,t-1} \\ &+\beta_3 Top10Holdings_{i,t-1} + \beta_4 NumOfStocks_{i,t-1} \\ &+\beta_5 ExpenseRatio_{i_t-1} + \beta_6 Turnover_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{5.7}$$

Where $FactorWeight^{x}_{i,t}$ represents either $SMB^{x}_{i,t}$, $HML^{x}_{i,t}$, $UMD^{x}_{i,t}$, $RMW^{x}_{i,t}$ or $CMA^{x}_{i,t}$ for fund i, at time t. Again, x denotes whether we use gross or net returns. The main independent variable is still $FundAge^{x}_{i,t}$. Whether $FundAge^{x}_{i,t}$ has a positive or negative coefficient, indicates that age affects the investment style of funds. The same control variable from previous regressions 5.5 and 5.6 are applied.

5.4 Investment Strategies Based on Age

5.4.1 Long-Short Portfolio

To further test if young funds and older funds perform differently on a risk-adjusted basis, we create both an equal-weighted and a value-weighted portfolio. The equal-weighted portfolio is constructed by dividing the funds into five, monthly rebalanced, age quintiles (following Busse et al. (2013) and Ľuboš Pástor et al. (2015)). Fund returns in each specified month are given the same weight, for the top quintile and bottom quintile, respectively. This is then used to construct a hypothetical portfolio that is long in young funds and short in old funds[21]. The difference (Young - Old) is regressed on the one-, three-, four- and five-factor model. This allows us to interpret the *alpha* in the model, and evaluate whether risk-adjusted performance differs between young and old funds.

We repeat the process, but with returns that are weighted by the relative *FundSize* of each fund. According to Rohleder et al. (2010), the smaller non-surviving funds are affecting the measured performance downwards. Hence, a value-weighted portfolio is assumed to limit survivorship bias.

To create a value-weighted portfolio, we weight the funds according to their relative *FundSize* at time t:

$$w_{i,t} = \frac{FundSize_{i,t}}{\sum_{i=1}^{N} FundSize_{i,t}} \tag{5.8}$$

5.4.2 Performance Persistence

To test whether performance persists, and therefore investigate signs of fund managers' ability to outperform the market consistently, we follow Carhart (1997) and employ two

[21]The zero-investment Long-Short-portfolio is hypothetical, as mutual fund investors cannot short sell shares in Nordic funds. It does however more clearly highlight performance differences.

methods - the recursive portfolio approach and contingency tables. With the investor in mind, we employ the model using net returns. In January of each year, we sort funds into five equal-weighted quintile portfolios based on their lagged one-year returns[22]. The portfolios are ranked from losers to winners, i.e. portfolio 1 consists of the worst performing the prior year, and portfolio 5 consists of the best performing funds. The following year serves to evaluate whether the performance persists, however, the two methods differ in how this is executed which is described in the next sections. Our method deviates from others as we are sorting and evaluating within a sub-sample, namely the two age-quintiles in question.

5.4.2.1 Recursive Portfolio Approach

The Recursive Portfolio Approach is common in persistence studies and includes a hypothesis test of whether the portfolio formed on lagged returns outperforms the benchmark (Hendricks et al., 1993; Grinblatt and Titman, 1992; Carhart, 1997). As it has been found that the UMD factor explains most of the abnormal returns in persistence studies, we choose to not reward fund managers for exposure to this systematic anomaly by employing the 4-factor model of Carhart (1997). Following Vidal-García (2013), we use annual intervals with the argument of removing the chance of losing signals of superior performance to random noise. Persistence can be measured across different intervals of time. We argue that any time period longer than one year will limit our observations strongly in the young quintile. Berk and van Binsbergen (2015) use a minimum of 6 months of observations in their estimation window to test persistency. As a consequence, we argue that testing for one-year persistence fits the purpose of our thesis.

We form equally-weighted portfolios based on performance ranking in one period, and then evaluate the performance of these portfolios' monthly returns over the subsequent holding period. The portfolio takes into account funds that are obsolete during the evaluation period by redistributing the portfolio-weight of these funds equally to the remaining funds. The same procedure goes for funds that transfer to a new age quintile. We argue that this helps to mitigate survivorship bias[23] in the evaluation period. The portfolios formed

[22] Sørensen (2009) argues that excluding funds that do not have 12 months of returns in the formation period does not impose a survivorship bias, as investors are free to choose not to invest in funds lacking a full year of historical returns

[23] In their study of biases in persistence studies, Horst et al. (2001) argues that if there is survivorship

on lagged 1-year returns are then tested by employing Carhart (1997) 4-factor model over the holding periods. If the portfolios that previously outperformed in the ranking period continue to do so during the next holding period, there is evidence of performance persistence. Further, we create a hypothetical equal-weighted portfolio which is long past winners and short past losers (Q5-Q1), to highlight differences between the two portfolios.

We do not evaluate funds that change age-quintiles during the ranking period, as the strategy is only to hold the youngest funds.

5.4.2.2 Contingency Table

To further analyze how performance persists, we perform two consecutive performance sorts to understand further how each portfolio behave in the evaluation (subsequent) period. The use of contingency tables is of value as we want to understand how likely it is for each performance portfolio to stay in the same rank, as well as to understand the likelihood that funds either die or transfer to a new age quintile.

As with the recursive portfolio approach, we keep the data set divided into the 1st. and 5th. age-quintile to compare the persistence within these groups. The initial ranking is equal to the one employed in the recursive portfolio approach. The consecutive year we perform a similar ranking process but do, however, also categorize observations that do not have a full year of returns into two additional groups. The old quintile is only subject to being closed or merged (obsolete) during the evaluation period. All observations missing annual returns are categorized as "Dead", as they died during the evaluation period. Conversely, the young portfolio is also subject to missing values caused by funds transferring to the next age-quintile. We categorize those funds that do not have an obsolete day during the evaluation year as "Change to 2nd Q".

bias present in the evaluation period, it will cause top performing funds to display a more significant persistence.

6 Analysis

This section presents our empirical results. First, we present results from our multivariate analysis, where we compare our findings to previous research. We then examine the differences in risk-taking and investment styles of young and old funds. Furthermore, we investigate how a portfolio that is long in young funds and short in old funds performs against the four benchmark models presented in section 5.1. Finally, we investigate whether the performance of portfolios formed on fund age persists.

6.1 Does Fund Age Affect The Performance of Mutual Funds?

We run the regression presented as equation 5.5 to investigate how fund age affects performance. In this analysis, we run panel regressions of our risk-adjusted returns on different fund characteristics. The results are presented in table 6.1.

The main independent variable $FundAge_{i,t}$ is displaying the relationship between fund age and performance, after controlling for variables we believe capture much of the variance otherwise picked up by $FundAge_{i,t}$. While studies of mutual funds in the US. often find that performance deteriorates as funds becomes older (Webster, 2002; Ľuboš Pástor et al., 2015), we find the opposite in our sample. We find that the $FundAge_{i,t}$ coefficient is positive (in all specifications except CAPM on net returns), and significantly so, indicating better performance among older funds. In Panel A we find that by increasing $FundAge_{i,t}$ by 1 year, $Perf^{x}_{i,t}$ increases in the range of 4.7 to 8.8 basis points, while in Panel B we find an increase ranging between 1.1 and 9.8 basis points. The economic effect of $FundAge_{i,t}$ on $Perf^{x}_{i,t}$ is slightly stronger in the gross returns sample.

Further, we observe that the slope of $FundSize_{i,t}$ is positive, which suggests that larger funds perform better. This contradicts findings by other studies (Chen et al., 2004; Ľuboš Pástor et al., 2015). Graham et al. (2019), who compared the US and Europe, did however find that the decreasing returns to scale is not present outside of the US. The cross country study of Ferreira et al. (2013) support these findings, and argue that the deviation is caused by differing exposure towards small-cap funds, and the related liquidity premium.

The positive coefficient of expense ratio is not expected, especially considering figure A2.2 in the Appendix which demonstrate that young funds that die have significantly higher fees compared to those who survive.

Carhart (1997) claimed turnover to be a determinant to lower returns, as the activity of buying and selling assets incur higher costs. Our regression output does not coincide with his observation. On the contrary, the overall tendency is a positive effect, however, the results are not significant on a 5% significance level. As we have found previously, Nordic mutual funds have on average a lower turnover rate than US funds. This may indicate that while turnover is costly, fund managers are able to regain the costs by higher returns.

Table 6.1: Multivariate Regression

	Panel A: Net				Panel B: Gross			
	$CAPM_{i,t}$	$FF3FM_{i,t}$	$CARHART_{i,t}$	$FF5FM_{i,t}$	$CAPM_{i,t}$	$FF3FM_{i,t}$	$CARHART_{i,t}$	$FF5FM_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FundAge_{i,t}$	−0.001	0.088***	0.047***	0.073***	0.011***	0.098***	0.057***	0.088***
	t = −0.191	t = 15.949	t = 8.947	t = 12.253	t = 2.706	t = 21.583	t = 13.484	t = 16.997
$FundSize_{i,t\text{-}1}$	0.327***	0.254***	0.258***	0.224***	0.298***	0.203***	0.209***	0.165***
	t = 12.602	t = 8.509	t = 8.353	t = 6.992	t = 12.600	t = 8.467	t = 8.807	t = 5.841
$Top10Holdings_{i,t\text{-}1}$	−0.005***	−0.004*	−0.002	−0.005**	−0.004**	−0.002	−0.0001	−0.003
	t = −2.615	t = −1.648	t = −0.801	t = −2.155	t = −2.280	t = −0.841	t = −0.028	t = −1.473
$ExpenseRatio_{i,t\text{-}1}$	2.131***	2.400***	2.261***	2.557**	2.434***	2.656***	2.612***	2.848**
	t = 3.060	t = 2.714	t = 2.911	t = 2.527	t = 2.925	t = 2.588	t = 2.930	t = 2.322
$NumOfStocks_{i,t\text{-}1}$	−0.075**	0.031	0.031	0.027	−0.042	0.068*	0.065*	0.079*
	t = −2.104	t = 0.744	t = 0.808	t = 0.617	t = −1.268	t = 1.871	t = 1.930	t = 1.934
$Turnover_{i,t\text{-}1}$	0.0002	0.001*	0.0002	0.0003	0.0004	0.001*	0.0001	0.0003
	t = 0.819	t = 1.858	t = 0.726	t = 0.998	t = 1.258	t = 1.768	t = 0.513	t = 0.906
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,384	109,384	109,384	109,384	102,675	102,675	102,675	102,675
R^2	0.083	0.068	0.025	0.041	0.093	0.093	0.028	0.051
Adjusted R^2	0.073	0.058	0.014	0.030	0.083	0.082	0.017	0.040

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents a regression of $Perf^{x}_{i,t}$ as the dependent variable, where x denotes either $CAPM_{i,t}$, $FF3FM_{i,t}$, $CARHART_{i,t}$ or $FF5FM_{i,t}$. The dependent variable is the alpha estimated with a rolling regression with our four performance measures at each time t for each fund i. The regressions are estimated with the use of time, segment and fund fixed effects. All variables are defined according to the detailed description in Appendix A2.1. Panel A and Panel B displays estimations constructed with Net and Gross returns, respectively. Standard errors are clustered at the fund level.

6.2 Does Fund Age Affect Risk-Taking of Mutual Funds?

In the previous section, we found indications of fund age affecting performance. In the following section, we test the hypothesis that risk-taking varies across age. Table 6.2

reports our results. We find that an increased age leads to less risk-taking on all of our risk metrics. Our findings support Karoui and Meier (2009), who find that young funds exhibit higher total and unsystematic risk. Chevalier and Ellison (1997) report the same relationship between fund age and risk-taking, which is argued to be caused by a stronger incentive in younger funds to take risk at the end of the year if they have performed poorly.

A reduction of risk as a fund ages is often related to diversification benefits as the fund becomes larger in size. Karoui and Meier (2009) finds that the number of different stocks typically increases drastically the first year or two after inception. In our sample, we do not find this behaviour to be true, as we display in Appendix A1.1. Our sample do however support that an increased $FundSize_{i,t}$ reduce overall risk of the fund.

The positive (and sometimes significant) relationship between expense ratio and risk can indicate that higher management costs are related to more active management.

As expected, and in line with the theory of diversification, holding more stocks decreases the unsystematic risk of funds.

Table 6.2: Risk-Taking Multivariate Regression

	Panel A: Net			Panel B: Gross		
	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$FundAge_{i,t}$	-0.046^{***}	-0.049^{***}	-0.035^{***}	-0.084^{***}	-0.052^{***}	-0.067^{***}
	t = −5.104	t = −28.681	t = −5.518	t = −10.085	t = −30.836	t = −15.330
$FundSize_{i,t\text{-}1}$	-0.541^{***}	-0.028^{***}	-0.223^{***}	-0.438^{***}	-0.020^{***}	-0.127^{***}
	t = −10.504	t = −3.886	t = −5.933	t = −9.493	t = −2.892	t = −5.474
$Top10Holdings_{i,t\text{-}1}$	0.003	−0.0003	0.002	0.005	0.00002	0.003
	t = 0.512	t = −0.314	t = 0.982	t = 1.088	t = 0.019	t = 1.590
$ExpenseRatio_{i,t\text{-}1}$	2.724^{**}	0.157	1.693^{***}	1.717	0.239	0.844
	t = 2.497	t = 0.928	t = 2.601	t = 1.453	t = 1.230	t = 1.392
$NumOfStocks_{i,t\text{-}1}$	0.383^{***}	0.005	−0.081	0.369^{***}	0.001	-0.118^{***}
	t = 3.777	t = 0.383	t = −1.408	t = 3.770	t = 0.078	t = −2.631
$Turnover_{i,t\text{-}1}$	0.001^{**}	0.0001	0.001^{**}	0.001^{*}	0.0001	0.001^{**}
	t = 2.276	t = 1.123	t = 2.404	t = 1.901	t = 1.045	t = 1.987
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,384	109,384	109,384	102,675	102,675	102,675
R^2	0.222	0.116	0.252	0.251	0.142	0.318
Adjusted R^2	0.213	0.106	0.244	0.243	0.132	0.310

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: This table presents a regression of $Risk^x_{i,t}$ as the dependent variable, where x denotes either $FundRisk_{i,t}$, $SysRisk_{i,t}$ or $UnsysRisk_{i,t}$. $FundRisk_{i,t}$ captures the total risk of each fund, measured by its standard deviation at time t over the 12-month rolling window estimation. $SysRisk_{i,t}$ is the systematic risk measured by fund i's loading on the market factor from the CAPM-model at time t. $UnsysRisk_{i,t}$ is the unsystematic risk measured by the standard deviation of residuals from the CAPM-model at time t for each fund i. The regressions are estimated with the use of time, segment and fund fixed effects. All variables are defined according to the detailed description in Appendix A2.1. Panel A and Panel B displays estimations constructed with Net and Gross returns, respectively. Standard errors are clustered at the fund level.

6.3 Does Investment Styles Differ Across Fund Age?

This section investigates whether age affects the investment styles of mutual funds. The investment styles can be distinguished by each funds loading on the different risk factors. The analysis is performed using rolling betas estimated with the five-factor model of (Fama and French, 2015b). We regress the rolling factor-loadings by fund characteristics, and are able to observe how $FundAge_{i,t}$ affects each loading. The regression output is presented in Table 6.3

Our findings suggest that as funds get older they are likely to be less exposed to the overall market risk, and instead utilize other strategies. The results are indifferent to the net- or gross return samples. $FundAge_{i,t}$ significantly affects $MKT_{i,t}$ negatively and significantly positive for all the other factors. Our findings support Chevalier and Ellison (1999b), who argues that younger funds are more likely to avoid deviation from market benchmarks, as investors in young funds are more sensitive to such deviations. Our findings do not support Karoui and Meier (2009) who find young funds to invest more heavily in smaller and less liquid stocks, which constitutes the SMB-factor. A possible argument that supports this is that Nordic funds are relatively small compared to US funds, and are as a consequence not subject to the same magnitude of transaction costs that large funds incur, especially in less lliquid assets[24].

[24]Which several papers have found to be the strongest explanation for the decreasing returns to scale (Chen et al., 2004; Yan, 2008; Busse et al., 2013).

Table 6.3: Factor-Loading Multivariate Regression

	Panel A: Net					Panel B: Gross				
	$MKT_{i,t}$	$SMB_{i,t}$	$HML_{i,t}$	$RMW_{i,t}$	$CMA_{i,t}$	$MKT_{i,t}$	$SMB_{i,t}$	$HML_{i,t}$	$RMW_{i,t}$	$CMA_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$FundAge_{i,t}$	−0.060***	0.055***	0.024***	0.068***	0.081***	−0.062***	0.053***	0.024***	0.054***	0.074***
	t = −29.111	t = 20.077	t = 9.302	t = 15.790	t = 16.263	t = −32.425	t = 21.621	t = 9.678	t = 13.561	t = 15.419
$FundSize_{i,t\text{-}1}$	−0.062***	0.018	−0.107***	−0.065***	0.007	−0.053***	0.012	−0.119***	−0.036**	0.005
	t = −6.964	t = 1.488	t = −7.275	t = −3.361	t = 0.282	t = −6.829	t = 1.238	t = −8.327	t = −2.315	t = 0.234
$Top10Holdings_{i,t\text{-}1}$	0.001	−0.002	−0.001	−0.001	0.005**	0.001	−0.002*	−0.0001	−0.0004	0.004*
	t = 1.117	t = −1.591	t = −0.475	t = −0.661	t = 2.453	t = 1.193	t = −1.680	t = −0.052	t = −0.151	t = 1.943
$ExpenseRatio_{i,t\text{-}1}$	0.368*	−0.540**	−0.142	−0.676	−0.037	0.362	−0.722**	−0.017	−1.779***	0.001
	t = 1.660	t = −2.038	t = −0.411	t = −1.269	t = −0.067	t = 1.476	t = −2.550	t = −0.044	t = −3.176	t = 0.002
$NumOfStocks_{i,t\text{-}1}$	0.021	0.027	−0.012	0.118***	0.245***	0.012	0.034*	−0.022	0.061*	0.241***
	t = 1.454	t = 1.403	t = −0.531	t = 3.435	t = 6.109	t = 0.829	t = 1.831	t = −0.981	t = 1.712	t = 6.239
$Turnover_{i,t\text{-}1}$	0.00000	0.0002	0.00003	0.0003	0.0001	−0.0001	0.0003*	0.0001	0.0002	−0.0002
	t = 0.045	t = 1.454	t = 0.158	t = 1.231	t = 0.367	t = −0.488	t = 1.779	t = 0.332	t = 0.851	t = −1.040
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,384	109,384	109,384	109,384	109,384	102,675	102,675	102,675	102,675	102,675
R^2	0.086	0.088	0.026	0.016	0.038	0.103	0.084	0.033	0.014	0.037
Adjusted R^2	0.075	0.077	0.016	0.005	0.028	0.093	0.073	0.022	0.003	0.026

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents a regression of $FactorWeight^x_{i,t}$ as the dependent variable, where x denotes either $MKT_{i,t}$, $SMB_{i,t}$, $HML_{i,t}$, $RMW_{i,t}$ or $CMA_{i,t}$. The dependent variable is the factor-loading estimated with a rolling regression with the five risk-factors proposed by Fama and French (2015b) at each time t for each fund i. The regressions are estimated with the use of time, segment and fund fixed effects. All variables are defined according to the detailed description in Appendix A2.1. Panel A and Panel B displays estimations constructed with Net and Gross returns, respectively. Standard errors are clustered at the fund level.

6.4 Investment strategies

Thus far, we have investigated how fund age is affecting the performance, risk-taking and investment styles. This section examines if an investor can take advantage of these differences in performance by investing in different age portfolios.

6.4.1 Long-Short portfolio

To investigate performance differences, we first study the behaviour of our long short portfolio. We employ our four different performance measures on both Equal-Weighted and Value-Weighted portfolios. Looking at Table 6.4, Panel A represents our results from net returns, while Panel B represents gross returns.

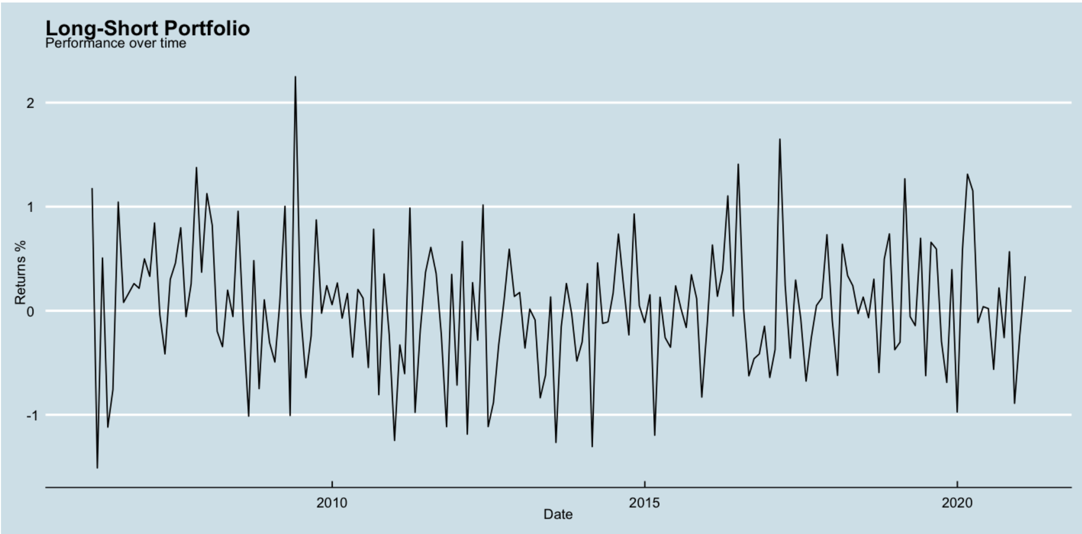
Observing Panel A, we find the long-short portfolio to outperform, however, the results are not significant. The Equal-Weighted portfolio achieves an *alpha* that ranges from 5.3 to 6.2 basis points, while the Value-Weighted portfolio achieves an *alpha* ranging between 6.0 and 7.5 basis points per month. There is an economically small increase in coefficient values as we adjust to the value-weighted portfolio, which may indicate that by giving less weight to the smallest small funds the outperformance is more distinct[25].

Panel B instead does not portray the same image. The factor weightings are comparable with that of Panel A, but the *alpha* of the portfolio is small and alternating between positive and negative values. More specifically, the value-weighted portfolio is the only one that achieves a positive *alpha*, however it is not significantly different from zero. Combined, this approach does not yield any significantly better performance in young funds compared to old. The value-weighted portfolio in Panel B has a positive coefficient for the HML factor and a negative coefficient for CMA.

To further inspect the portfolio, we display how it performs during our time-horizon in figure 6.1, constructed with an equal-weighted portfolio based on the net return sample. Most observations are within the range of one percent return per month, either negative or positive.

[25]This finding is supported by Rohleder et al. (2010), suggesting that funds performing poorly shrink in size before they die.

Figure 6.1: Long-Short Portfolio Performance Over Time



Note: This figure presents monthly returns of the long-short portfolio over the samples' time horizon. The data points are constructed with the net return sample and an equal-weighted portfolio.

Lacking a significant *alpha* in our portfolio make us reject the null hypothesis that a portfolio that is long in young funds and short in old funds achieves risk-adjusted returns, but it does however direct us toward two interpretations. First, our analysis indicate that the performance of our long-short portfolio is better when considering returns that are net of fees. One possible explanation for this is that the youngest funds charge lower fees[26]. However, this does not fit well with our observations in figure A1.1 in the Appendix. The results are, however, not significant. Secondly, we observe that in both cases, the value-weighted portfolio performs better. This observation follows the arguments of Chevalier and Ellison (1997), that younger funds are more susceptible to dissolution, caused by the higher sensitivity of outflows when performing poorly.

[26]Ľuboš Pástor et al. (2015) finds smaller differences when measuring with net returns, and suggests that younger funds charge higher fees to capture a portion of their higher skill.

Table 6.4: Long Short Portfolio

Panel A: Net Return

	Equal-Weighted				Value-Weighted			
	$CAPM_t^{y-o}$	$FF3FM_t^{y-o}$	$CARHART_t^{y-o}$	$FF5FM_t^{y-o}$	$CAPM_t^{y-o}$	$FF3FM_t^{y-o}$	$CARHART_t^{y-o}$	$FF5FM_t^{y-o}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Alpha_t$	0.062	0.053	0.053	0.056	0.060	0.075	0.074	0.068
	t = 1.362	t = 1.132	t = 1.138	t = 1.176	t = 0.844	t = 1.032	t = 1.017	t = 0.911
MKT_t	−0.038***	−0.033***	−0.034***	−0.035***	−0.063***	−0.066***	−0.059***	−0.068***
	t = −3.777	t = −2.917	t = −2.971	t = −3.011	t = −4.080	t = −3.794	t = −3.297	t = −3.717
SMB_t		−0.009	−0.009	−0.006		−0.014	−0.012	−0.002
		t = −0.427	t = −0.456	t = −0.279		t = −0.442	t = −0.375	t = −0.059
HML_t		−0.017	−0.021	−0.005		0.033	0.048	0.051
		t = −0.978	t = −1.138	t = −0.231		t = 1.221	t = 1.648	t = 1.620
UMD_t			−0.007				0.024	
			t = −0.619				t = 1.362	
CMA_t				−0.042				−0.064
				t = −1.159				t = −1.136
RMW_t				0.014				0.066
				t = 0.466				t = 1.393
Observations	180	180	180	180	180	180	180	180
R^2	0.074	0.082	0.084	0.090	0.086	0.093	0.103	0.110
Adjusted R^2	0.069	0.066	0.063	0.064	0.080	0.078	0.082	0.084

Panel B: Gross Return

	Equal-Weighted				Value-Weighted			
	$CAPM_t^{y-o}$	$FF3FM_t^{y-o}$	$CARHART_t^{y-o}$	$FF5FM_t^{y-o}$	$CAPM_t^{y-o}$	$FF3FM_t^{y-o}$	$CARHART_t^{y-o}$	$FF5FM_t^{y-o}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Alpha_t$	−0.017	−0.024	−0.024	−0.019	−0.009	0.009	0.008	0.011
	t = −0.379	t = −0.515	t = −0.507	t = −0.394	t = −0.131	t = 0.123	t = 0.104	t = 0.144
MKT_t	−0.022**	−0.018	−0.020*	−0.021*	−0.047***	−0.052***	−0.044**	−0.058***
	t = −2.170	t = −1.598	t = −1.683	t = −1.818	t = −3.005	t = −2.947	t = −2.448	t = −3.191
SMB_t		−0.007	−0.008	−0.004		−0.011	−0.008	0.003
		t = −0.352	t = −0.378	t = −0.200		t = −0.340	t = −0.268	t = 0.088
HML_t		−0.012	−0.015	0.003		0.039	0.056*	0.075**
		t = −0.665	t = −0.821	t = 0.165		t = 1.453	t = 1.914	t = 2.388
UMD_t			−0.006				0.027	
			t = −0.547				t = 1.490	
CMA_t				−0.051				−0.122**
				t = −1.408				t = −2.200
RMW_t				0.015				0.073
				t = 0.481				t = 1.546
Observations	180	180	180	180	180	180	180	180
R^2	0.026	0.030	0.032	0.042	0.048	0.060	0.071	0.097
Adjusted R^2	0.020	0.013	0.009	0.014	0.043	0.044	0.050	0.071

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents a regression of an equal- and value-weighted portfolio that is long in young funds and short in old funds (y-o). The portfolio returns are used as the dependent variable. $Alpha_t$ represents the abnormal returns of the long-short strategy. Panel A and Panel B displays estimations constructed with Net and Gross returns, respectively. Each panel displays results of portfolios formed on Equal-Weighted and Value-Weighted returns separately.

6.4.2 Persistence

So far, our analysis does not yield any clear indications for investors in terms of investment decisions. We have found the young portfolio to slightly, but not significantly, outperform the old portfolio. To investigate whether the performance that our age quintiles in question display is not a result of luck and high risk-taking, we test for persistence.

We measure the performance persistence of portfolios that are ranked on lagged one-year returns. We analyze persistence within the young and old quintiles to capture how these groups behave separately, with two complementary approaches; the Recursive Portfolio Approach and Contingency tables.

6.4.3 Recursive Portfolio Approach

First, we assess the young quintile. The regression output presented in table 6.5 implies that none of the portfolios outperform the four-factor model of Carhart (1997), as all portfolios display significantly negative coefficients. In our sample, we argue that persistence does not necessitate a positive alpha for previous top-performers[27], but they should at least perform better than the other quintiles. Our findings indicate the opposite. The 5th quintile, which is formed on the prior top -erformers, does not show evidence of better performance compared to the other quintiles. Conversely, it seems to show worse performance than most other quintiles, only slightly outperforming 4th Q. The same is found for the old quintile, i.e. no evidence of persistence in either age quintiles. Model 6, which is a portfolio long in past winners and short in past losers, support our evidence of persistence. The young quintile (Panel A) indicates that the long-short strategy returns a negative 17.1 basis points *alpha* per month, which is not significant. The same result is found in the old quintile (Panel B), however a somewhat smaller economic effect of only a negative 8.6 basis points *alpha* per month.

[27]While a sample of domestic funds and a benchmark created on domestic stocks, this argument does not hold if some funds are found to outperform in the ranking period

Table 6.5: Persistency

	Panel A: Young quintile					
	1st Q	2nd Q	3rd Q	4th Q	5th Q	5th-1st Q
	(1)	(2)	(3)	(4)	(5)	(6)
$Alpha_t$	-0.865^{***}	-0.519^{**}	-0.954^{***}	-1.110^{***}	-1.036^{***}	-0.171
	t = −3.226	t = −2.519	t = −3.717	t = −3.977	t = −4.297	t = −0.638
MKT_t	1.038^{***}	0.989^{***}	1.178^{***}	1.257^{***}	1.237^{***}	0.199^{***}
	t = 16.361	t = 20.289	t = 19.399	t = 19.038	t = 21.680	t = 3.130
SMB_t	-0.104	-0.044	-0.170	-0.195	-0.215^{**}	-0.111
	t = −0.898	t = −0.492	t = −1.537	t = −1.626	t = −2.072	t = −0.965
HML_t	-0.174^{*}	-0.116	-0.224^{**}	-0.295^{***}	-0.219^{**}	-0.045
	t = −1.693	t = −1.469	t = −2.270	t = −2.755	t = −2.366	t = −0.435
UMD_t	-0.399^{***}	-0.200^{***}	-0.132^{**}	-0.146^{**}	-0.062	0.338^{***}
	t = −6.264	t = −4.089	t = −2.167	t = −2.207	t = −1.076	t = 5.298
Observations	156	156	156	156	156	156
R^2	0.763	0.809	0.768	0.759	0.795	0.210
Adjusted R^2	0.756	0.804	0.762	0.753	0.790	0.189

	Panel B: Old quintile					
	1st Q	2nd Q	3rd Q	4th Q	5th Q	5th-1st Q
	(1)	(2)	(3)	(4)	(5)	(6)
$Alpha_t$	-0.699^{***}	-0.558^{***}	-0.696^{***}	-0.786^{***}	-0.785^{***}	-0.086
	t = −2.918	t = −2.710	t = −3.185	t = −3.180	t = −3.296	t = −0.417
MKT_t	1.110^{***}	1.091^{***}	1.183^{***}	1.224^{***}	1.222^{***}	0.112^{**}
	t = 19.584	t = 22.403	t = 22.880	t = 20.926	t = 21.687	t = 2.299
SMB_t	-0.098	-0.121	-0.116	-0.099	-0.113	-0.015
	t = −0.951	t = −1.360	t = −1.230	t = −0.928	t = −1.102	t = −0.169
HML_t	-0.146	-0.168^{**}	-0.201^{**}	-0.277^{***}	-0.277^{***}	-0.131
	t = −1.591	t = −2.132	t = −2.395	t = −2.916	t = −3.030	t = −1.650
UMD_t	-0.277^{***}	-0.241^{***}	-0.168^{***}	-0.099^{*}	0.009	0.286^{***}
	t = −4.860	t = −4.923	t = −3.241	t = −1.686	t = 0.159	t = 5.823
Observations	156	156	156	156	156	156
R^2	0.802	0.835	0.829	0.792	0.792	0.268
Adjusted R^2	0.796	0.830	0.825	0.787	0.786	0.249

*p<0.1; **p<0.05; ***p<0.01

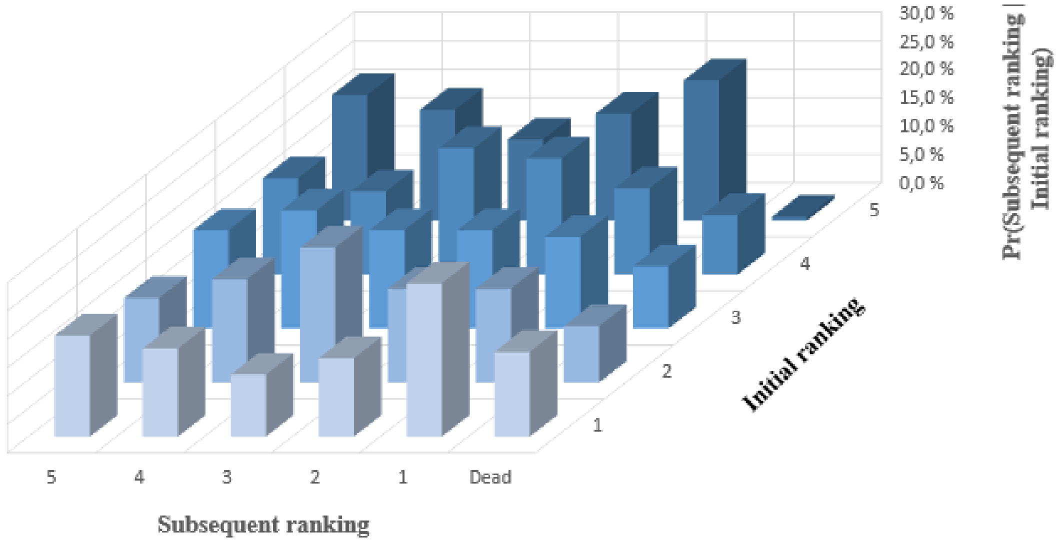
Notes: This table presents a regression of $R^x_{i,t}$ - $R_{f,t}$ (excess return) as the dependent variable, where x denotes the portfolio of which is benchmarked. Models (1)-(5) are regressions of portfolios formed on sorted lagged one-year returns, while model (6) is a hypothetical long-short portfolio going long in previous winners and short in previous losers. $CARHART_{i,t}$ is the *alpha* we measure, according to formula 5.3. The regressions are estimated with the use of time, segment and fund fixed effects. All variables are defined according to the detailed description in Appendix A2.1. Panel A and Panel B displays estimations constructed with Net and Gross returns, respectively.

6.4.4 Contingency Table

The contingency tables are presented below, the young portfolio in table 6.2 and the old portfolio in table 6.3.

The graph measures *Pr(Subsequent Ranking | Initial Ranking)*, i.e. the conditional probability that funds from each of the initial sorts end up in either of the subsequent ranking portfolios, becomes obsolete(or transfer to the next age-quintile[28]).

Figure 6.2: Persistence in The Young Quintile



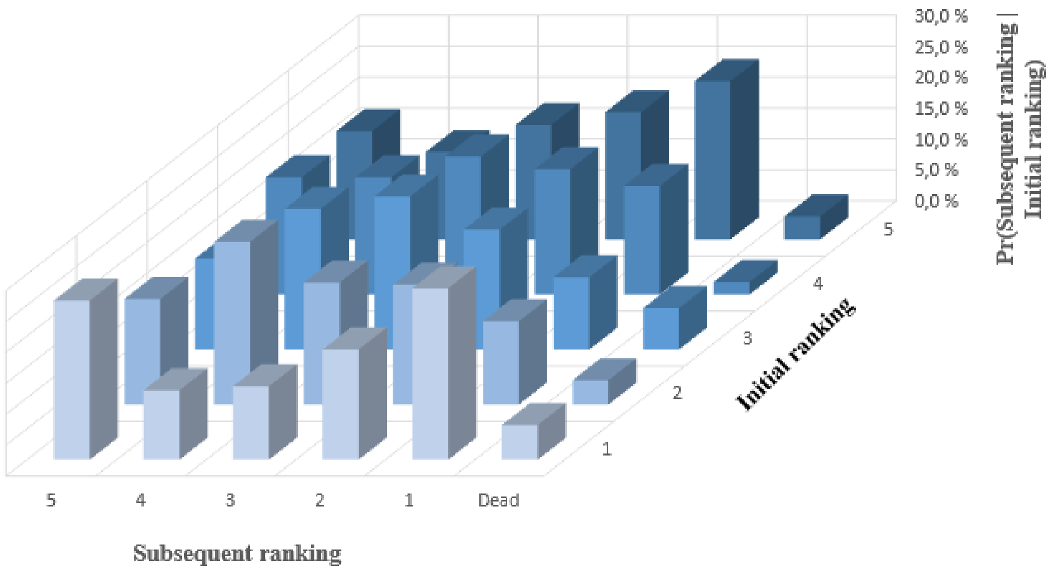
Note: This figure presents how young funds behave in the period after their initial ranking. The z-axis represents the conditional probability of funds being ranked in each subsequent performance quintile or dies. This figure does not include funds that change from 1st to 2nd age-quintile during the evaluation period, for the purpose of comparison. In the Appendix A1.2, the figure includes those funds that change age-quintile.

About 25% of the young (1st age quintile) funds do, independent of its initial ranking, transfer to the 2nd. age quintile during the subsequent holding period, and are therefore not assigned a new rank. This transfer is expected, as the average age of funds in this quintile is about 3 years[29]. For the purpose of comparing the young and old groups, we only display observations of those who do not change age-quintile.

Observing the young funds in figure 6.2, we find that the worst and best performing funds are highly likely to perform poorly the following year. However, the previously strong performers do, almost never (0.5% of the funds) die/close the subsequent year, whereas

[28]In the Appendix A1.2, the figure includes those funds that change age-quintile.
[29]The distribution of observations in each age quintile is presented in figure 4.1.

Figure 6.3: Persistence in The Old Quintile



Note: This figure presents how old funds behave in the period after their initial ranking. The z-axis represents the conditional probability of funds being ranked in each subsequent performance quintile or dies.

11% of poor performers do.

The old funds are less likely to become obsolete, compared to the young funds. This observation is more obvious when comparing the worst-performing portfolios of young and old funds, thus, older funds seem to be less sensitive to recent poor performance than young funds. The funds in the third and worst-performing quintiles are the least likely to switch quintiles, with 24.7% and 27.7% probability of staying, respectively.

The young and old quintiles seem to embody a common trait. The extreme performers tend to continue achieving extreme performance. In both age-groups, the top-performers in one year are most likely to be the worst performers the following year. 24.7% of the young and 25.6% of the old top-performing portfolios transitions to become worst performers. While top-performing matured funds making this transition is not a common finding, young funds have found to behave in this manner (Karoui and Meier, 2009). Further, 22.1% and 17.5% stay within the top-performing group, respectively. Among the initial worst-performing group of both age groups, the same is true - they are also most likely to stay in the worst-performing group the following year. 27% of the young and 27.7% of the old bottom performers stay worst performers. This indicates persistence in poor performance in both groups, but we cannot draw any statistical conclusion from this test.

From the contingency table, we derive at a certain narrative. There is no evidence of persistence among top-performers in either age group, however there are slight indications that poor performance is persistent, in line with Carhart (1997). The initial superior performance followed by sudden poor performance suggests that good performance is due to risk taking rather than skill. We do not find support for the findings of Verbeek and Huij (2006), that young funds exhibit higher levels of persistence. The death of young funds are more correlated with their performance last year, which fits the arguments of Chevalier and Ellison (1999a) stating that the probability of young funds being taken down is more sensitive to prior performance.

6.5 Robustness

The estimation window of rolling window alphas, used to perform our multivariate regression, is only 12 months[30]. Under other circumstances, a longer estimation window is preferable to a shorter. However, with our data set we found the number of observations to be of higher importance as we want to investigate the age of the funds. By increasing the estimation window we sacrifice most of the first observations we have of each fund.

We investigate how survivorship of funds affect our studies in Table A2.4 in the Appendix. Survivorship bias occurs as the performance of funds that die is not taken into account. A high fund age is itself a consequence of good performance in the past. We want to inspect how the performance of funds in our sample is explained by the fund dying within our sample period. Is there any difference across age? We regress our performance measures on *FundAge*, a dummy indicating that the fund dies and an interaction term. A significant interaction term indicates that age of dead funds significantly affect performance. When not controlling for any other variables, we find that the interaction term is significant in explaining $CAPM^{n}_{i,t}$ at a 5% significant level, at a low economic value of negative 0.3 basis points, that older funds that die affect performance more significantly downwards. Survivorship bias is usually related to young funds being measured to achieve higher risk-adjusted returns. Our findings indicate that an increased age yields higher

[30] There is no exact answer to how many data points to use in a rolling regression. However, a study on the use of multi-factor models in performance studies suggests using 36 months (Huij and Verbeek, 2009), a suggestion often followed in academia.

returns, contradicting to what is expected with survivorship bias present. If there still is survivorship present, we therefore argue that our findings would be more significant.

Incubation bias occurs when the fund family employs an incubation strategy. Incubation is in its essence that several funds are created, but only the best performers are actually registered and is offered to the public. This form of bias is mostly know to affect data on hedge funds, but is argued also to be affecting mutual fund data bases(Evans, 2010). However, by our personal contact with The Norwegian Financial Supervisory Authority (Personal communication, 30.04.2021), we believe this not to be a problem in our data set. If incubation bias is an issue, however, we would have to discard observations of funds the first few years that they are alive and defy the purpose of our research. By removing the first three years of returns, Evans (2010) report that all incubation bias is eliminated. Following Ľuboš Pástor et al. (2015) and Karoui and Meier (2009), we perform a supplementing Long-Short portfolio which is long in the 2nd quantile instead of the 1st, however still short the 5th quintile. The positive, but insignificant, result we find using the youngest quintile is eradicated. Our results are reported in Appendix A3.6.

We perform robustness on all our multivariate regressions, in which we split the data set into two time periods, where the first part is from January 2006 to June 2013, and the second is from July 2013 to January 2021. We find the coefficient of *FundAge* to be negative in the first period, which may indicate that the positive effect that fund age has in our full sample is recent. We have more observations in our late sample, which may explain why the aggregate effect in the full sample still is significantly positive.

Persistence studies usually include several time horizons. Adjusting the interval of the ranking period and the following evaluation period may lead to different results, as Hendricks et al. (1993) has found that most persistence is eradicated after one year, while some find it to stay for as long as five years Grinblatt and Titman (1992). Phelps and Detzel (1997) show evidence that the horizon and performance measure greatly affect the results.

Brown et al. (2015) argues that persistence in poor fund performance potentially can be explained with persistence in fund fees. To investigate how the expense ratio is related to the probability that young funds die, we have created a table which is further discussed in Appendix A2.2. We find that on average, the funds who die had higher expense ratios than those that survive. For funds that are 4 and 5 years old, the difference in the expense ratio of those who survive and those who die is significant a 1% level, which may support the notion that young funds performing consistently poorly do so to some degree because they charge high fees.

6.5.1 Look-Ahead Bias

Our proposed research question regarding persistence is challenged by yet another source of bias. The nature of young and old funds and their probability of being dissolved or merged differ (Chevalier and Ellison, 1997). A consequence of this difference is that old funds to a lesser degree are subject to survivorship bias, following their higher probability of surviving. Studies of persistence in mutual fund performance have historically not adjusted for what Horst et al. (2001) call a look-ahead bias, which is a form of ex-post conditioning. When measuring persistency, it is common to distinguish two different periods - one that is used to rank the performance of the funds, and another that evaluates the persistency of their performance. The bias occurs, however, as the evaluation of portfolio performance is only determined for the funds that survived the both period (Brown et al., 2015). In effect, only those that survive are contributing to the evaluation period, and risky funds more often die because they achieve more extreme results (in both directions). They do find significant bias of the kind they describe, but when they use the technique on performance studies similar to Carhart (1997), Horst et al. (2001) conclude that look-ahead bias is of minor importance given results that closely correspond to the unadjusted findings of Carhart. As we create rebalancing equal-weighted portfolios on all available fund returns, not only those who survive for the whole evaluation period, we believe that we mitigate some of the problem they warn against. Look-ahead bias is further investigated in table A2.2 in the Appendix.

6.5.2 Econometric Pitfalls

In our multivariate study, we include several variables that we have explained to be related to similar effects. *NumOfStocks* and *Top10Holdings* are, in our view, both determinants of diversification. Our OLS model may be subject to violation of the assumption of no perfect multicollinearity, thus, returning instability in the estimated regression coefficients. For the purpose of formally testing for multicollinearity, we perform a VIF-test. Test values exceeding 10 indicate that multicollinearity is a problem according to Wooldridge (2009). The test results from our VIF-test are presented in Appendix A3.1, alongside a correlation matrix in Appendix A3.2. With a VIF-test value of only 1.15 on average, we conclude on not having issues regarding multicollinearity in our econometric models.

6.5.3 Limitations

Our research is based on models to make statements about performance, which are assuming efficient markets. Efficient market theory suggests that market participants respond to information such that the market reflects all this information. The assumption is being scrutinized by many researchers, as there are evidence of both slow and premature reactions to new information in the market. Furthermore, "friday earnings" and fact that weather and sports events affect prices implies market inefficiency (Hirshleifer and Shumway, 2003). These apparently unexplainable effects which result in abnormal returns may be attributable to risk premiums that we are still unaware of, or might indicate that the markets are inefficient, or even that the model is incorrect. The notion of inefficient markets depends on a model to even be evaluated. Given that the model assumes efficient markets we have not yet been able to affirm any of the two. The alpha and the benchmark are simultaneously determined. This issue is often referred to as the joint hypothesis problem (Jarrow and Larsson, 2012). The EMH is not falsifiable, but as alternatives are lacking, we are forced to endure any weakness that such assumptions imply.

In addition, there is evidence that higher exposure to the market risk factor is not necessarily correlated with higher returns (Frazzini and Pedersen, 2014). Empirical evidence supports the notion that low beta securities, combined with leverage, will outperform high beta securities. According to Fama and French (2015a), such beta anomaly is accounted for by introducing new factors. The uncertainty of the usability of such benchmark models is still disputed. Even when the five-factor model was first introduced Fama and French (2015b), it was described as an incomplete description of expected returns, with a GRS statistic by Shanken et al. (1989) that was less than 5 percent.

Fama and French (1993) guide the reader in how to interpret the model they develop. While one interpretation is that the factors serve as available alternative investment portfolios, they argue that one cannot form such portfolios and rebalance them often enough without incurring transaction costs. Their interpretation is that these factors only serve as means of explaining the returns, not serve as zero-investment portfolios. The same goes for the UMD-factor, which to an even larger degree demands rebalancing.

The degree to which factor models are able to explain security returns does vary across sample periods and markets. (Ferreira et al., 2013) finds that the SMB factor is not significant in European countries. In their discussion of model application, Fama and French (2015b) point out that they find the HML factor to be redundant, after the addition of the profitability and investment factors. They do, however, suggest that this result may be specific to their sample.

Lastly, as we have discussed in subsection 4.1.1, we use international factors to assess risk-adjusted performance. Sørensen (2009) argues that using risk-factors constructed within each funds' investment mandate more accurately measures risk-adjusted performance, and directly assesses skill rather than allocation decisions. We argue that capital flows freely across borders, that some funds self-report what benchmark they measure against ex-post, and that large economies such as the US make most of the global equities. For these reasons, we argue that on aggregate, the world index is reasonable to benchmark Nordic mutual funds.

7 Conclusion

In this thesis, we have studied how the age of Nordic funds is related to performance, risk-taking and investment style. Our data sets are free of survivorship bias, and contain 1198(net, 1138 gross) Nordic equity funds in the period of January 2006 to February 2021. In our literature review we find inconsistent evidence regarding how risk-adjusted performance, risk-taking and investment style is affected by fund age in the mutual fund industry. Based on this literature, we made the following hypotheses:

Hypothesis 1: *Fund age affects the performance of mutual funds*
Hypothesis 2: *Fund age affects risk-taking of mutual funds*
Hypothesis 3: *Fund age affects the investment style of mutual funds*
Hypothesis 4: *Investment strategies based on fund age outperform on a risk-adjusted basis*

To evaluate risk-adjusted performance, we apply the one-,three-, four- and five-factor models on both net and gross returns. When controlling for other fund characteristics that may affect performance, our findings are clear. The Nordic mutual fund market is not efficient considering that it is possible to achieve superior returns by looking at a funds age. These findings do not follow that of previous research, where fund age typically is found to have a deteriorating effect on performance (Webster, 2002; Ferreira et al., 2013).

Secondly, we find that an increased age leads to less risk-taking on all our risk metrics when controlling for fund characteristics. These findings are in line with prior research, which argues that this can be caused by a more substantial incentive in younger funds to take on risk at the end of the year if they have performed poorly(Chevalier and Ellison, 1997; Karoui and Meier, 2009).

Furthermore, we find that as fund age increases, funds are less likely to be exposed towards overall market risk, but inherit a style of investing that is more exposed towards other risk factors. Our results does not support Karoui and Meier (2009) who found younger funds to be more exposed towards small and less liquid stocks, captured by the SMB-factor. These findings are, however, in line with research that argues that younger funds are more likely to avoid deviation from market benchmarks (Chevalier and Ellison, 1999b) as they are more sensitive to fund out-flow.

Moreover, when testing investment strategies based on fund age, we do not find evidence of any difference in performance between young and old funds in a hypothetical long-short portfolio. Our findings contradict the existing literature finding such portfolios to outperform (Ľuboš Pástor et al., 2015; Karoui and Meier, 2009).

Lastly, neither age-quintile demonstrates persistence, as we do not find evidence that investors are able to outperform the benchmark with strategies based on previous performance. Hence, it seems hard to find an ex-ante criterion based on fund age that will outperform the market.

Contrary to what previous studies on funds in the US and Europe suggest, our research suggests that funds actually do age well in the Nordic countries.

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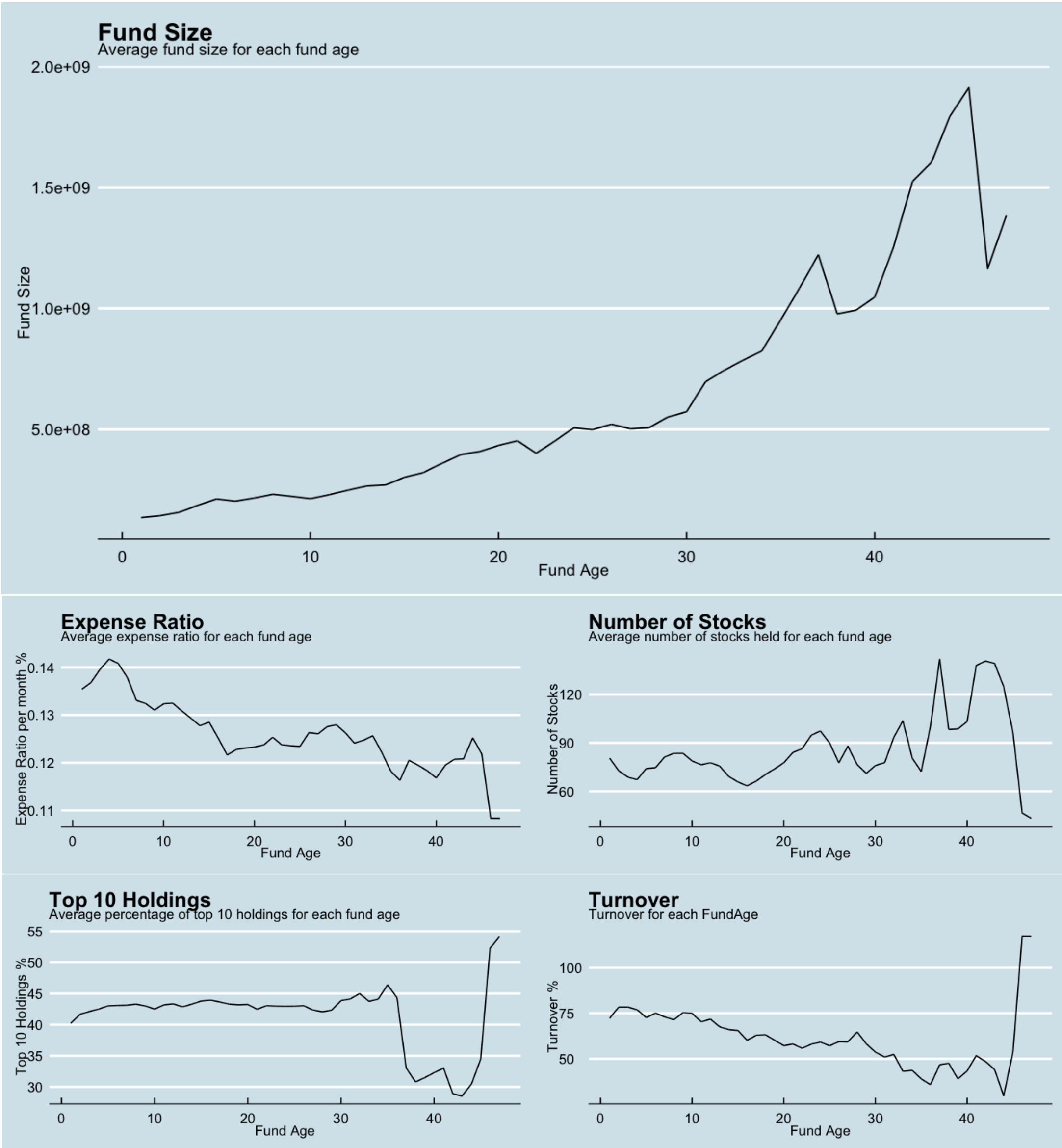
Appendix

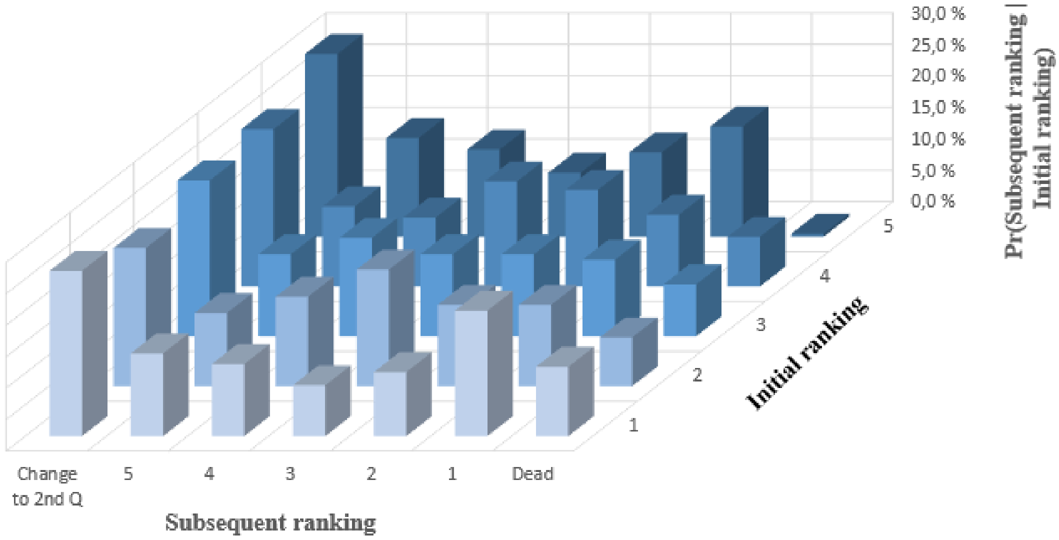
A1 Figures

Figure A1.1: Average Values of Control Variables Against Fund Age



Note: At high ages (>35), we have very few observations, which makes the graph returns values representative only for a few funds. Top percentile p(99) of the fund age variable is 34 years.

Figure A1.2: Persistence in The Young Quintile, Including Transistions to 2nd Quintile



Note: This figure presents how young funds behave in the period after their initial ranking. The z-axis represents the conditional probability of funds being ranked in each subsequent performance quintile or dies. In addition, the figure includes funds that change from 1st quintile to 2nd quintile during the evaluation period.

A2 Tables

Table A2.1: Description of Variables

Variable (1)	Description (2)	Source (3)
$R^x_{i,t}$	Fund *i's* monthly return where x denotes whether net returns (n) or gross returns fee (g) are used.	Morningstar Direct
$R_{f,t}$	Risk free rate at time t.	Kenneth French
$FundAge_{i,t}$	Fund *i's* years since their inception date at time t.	Morningstar Direct, Estimated
$FundSize_{i,t}$	Logarithm of Fund *i's* total assets at time t, ln(FundSize).	Morningstar Direct, Estimated
$Top10Holdings_{i,t}$	Fund *i's* exposure to their top 10 holdings in period t, measured in percent.	Morningstar Direct
$NumOfStocks_{i,t}$	Fund *i's* number of stock holdings in period t	Morningstar Direct
$ExpenseRatio_{i,t}$	Fund *i's* monthly expense ratio at time t. Measured in percent.	Morningstar Direct
$Turnover_{i,t}$	Fund *i's* yearly turnover, in percent	Morningstar Direct
$FundRisk^x_{i,t}$	Fund *i's* standard deviation at time t based on a 12 month rolling period. The x denotes whether net or gross returns are used.	Morningstar Direct, Estimated
$SysRisk^x_{i,t}$	Fund *i's* loading on the market portfolio from CAPM at time t based on a 12-month rolling regression.The x denotes whether net or gross returns are used.	Morningstar Direct, Kenneth French, Estimated
$UnsysRisk^x_{i,t}$	Fund *i's* standard deviation of the residual from CAPM model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used.	Morningstar Direct Kenneth French Estimated
$MKT^x_{i,t}$	Fund *i's* loading on the MKT-factor from the FF5F five-factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used.	Morningstar Direct, Kenneth French, Estimated

Variable (1)	**Description (2)**	**Source (3)**
$SMB^{x}_{i,t}$	Fund *i's* loading on the SMB-factor from the FF5F five-factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used.	Morningstar Direct, Kenneth French, Estimated
$HML^{x}_{i,t}$	Fund *i's* loading on the HML-factor from the FF5F five-factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used.	Morningstar Direct, Kenneth French, Estimated
$RMW^{x}_{i,t}$	Fund *i's* loading on the RMW-factor from the FF5F five-factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used.	Morningstar Direct, Kenneth French, Estimated
$CMA^{x}_{i,t}$	Fund *i's* loading on the CMA factor from the FF5F five-factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used.	Morningstar Direct, Kenneth French, Estimated
$CAPM^{x}_{i,t}$	Fund *i's* abnormal return using CAPM one-factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used. Measured in percent.	Morningstar Direct, Kenneth French, Estimated
$FF3FM^{x}_{i,t}$	Fund *i's* abnormal return using FF3F three-factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used. Measured in percent.	Morningstar Direct, Kenneth French, Estimated
$CARHART^{x}_{i,t}$	Fund *i's* abnormal return using CARHART four-factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used. Measured in percent.	Morningstar Direct, Kenneth French, Estimated
$FF5FM^{x}_{i,t}$	Fund *i's* abnormal return using FF5F five factor model at time t based on a 12 month rolling regression. The x denotes whether net or gross returns are used. Measured in percent.	Morningstar Direct, Kenneth French, Estimated
$DeadDummy_i$	Dummy that returns 1 if the fund i has an obsolete date that is within our data sample.	Morningstar Direct, Estimated

Table A2.2: Look Ahead Bias

Age		**Living**	**Died**	**Total / Difference**
1	Frequency (return)	969	26	995
	Avg return %	0,73	-0,36	1,08***
	Frequency (expense)	703	10	713
	Avg expense ratio %	0,132	0,142	-0,009
2	Frequency (return)	905	53	958
	Avg return %	0,58	-0,03	0,61***
	Frequency (expense)	729	37	766
	Avg expense ratio %	0,133	0,147	-0,014
3	Frequency (return)	859	53	912
	Avg return %	0,48	-0,26	0,75***
	Frequency (expense)	733	42	775
	Avg expense ratio %	0,136	0,138	-0,002
4	Frequency (return)	795	50	845
	Avg return %	0,42	0,13	0,30***
	Frequency (expense)	717	43	760
	Avg expense ratio %	0,136	0,150	-0,015***
5	Frequency (return)	718	68	786
	Avg return %	0,46	-0,02	0,48***
	Frequency (expense)	663	61	724
	Avg expense ratio %	0,136	0,162	-0,026***

*p<0.1; **p<0.05; ***p<0.01

Notes: We consider all observations of funds that are of age one through five years, which we find to be representative of young funds. We characterize each fund as either "Living" and "Died", that is, if a fund dies when its age is between one and two full years, it will be regarded as "Died" at Age 1. For each fund i, we calculate the average return it achieved the full year prior to the present age. In this case, those who died at age 1 performed with an average of negative 0.36% per month it was less than one year old. To compare those surviving and those who do not in terms of their prior performance, we want to perform a formal test in which we hypothesise the two groups to have a mean difference of zero. The formal test is often a regular t-test. As we deal with small populations, may suffer from some shortcomings. We perform Shapiro Wilkinson tests, in which the null hypothesis is that the variable is normally distributed. We are not able to reject the null hypothesis, and must therefore use a Wilcox rank test instead, which is non-parametric. The p-value of each test is represented with (*), as described below the table.

Table A2.3: Dead funds - Quintile 1 and 5

	Panel A: Young				Panel B: Old			
	$CAPM^n_{i,t}$	$FF3FM^n_{i,t}$	$CARHART^n_{i,t}$	$FF5FM^n_{i,t}$	$CAPM^n_{i,t}$	$FF3FM^n_{i,t}$	$CARHART^n_{i,t}$	$FF5FM^n_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.159***	0.0003	−0.102***	0.022	−0.054	−0.865***	−0.911***	−0.738***
	t = 4.886	t = 0.008	t = −2.827	t = 0.514	t = −1.236	t = −16.743	t = −17.584	t = −12.363
$FundAge_{i,t}$	−0.135***	−0.096***	−0.055***	−0.101***	−0.012***	0.016***	0.019***	0.012***
	t = −14.825	t = −9.570	t = −5.390	t = −8.493	t = −6.904	t = 8.175	t = 9.606	t = 5.098
$DeadDummy_i$	0.012	−0.199***	−0.250***	−0.093	−0.107	0.096	−0.359***	0.173
	t = 0.239	t = −3.485	t = −4.313	t = −1.375	t = −1.048	t = 0.795	t = −2.969	t = 1.245
FundAge x *DeadDummy*	−0.074***	−0.093***	−0.072***	−0.128***	−0.004	−0.017***	0.002	−0.019***
	t = −5.042	t = −5.777	t = −4.425	t = −6.683	t = −0.883	t = −3.423	t = 0.413	t = −3.270
Observations	22,101	22,101	22,101	22,101	21,974	21,974	21,974	21,974
R^2	0.030	0.038	0.028	0.031	0.007	0.013	0.015	0.007
Adjusted R^2	0.030	0.038	0.028	0.031	0.006	0.013	0.015	0.007

*p<0.1; **p<0.05; ***p<0.01

Notes: We consider all observations of funds that are of age one through five years, which we find to be representative of young funds. We characterize each fund as either "Living" and "Died", that is, if a fund dies when its age is between one and two full years, it will be regarded as "Died" at Age 1. For each fund i, we calculate the average return it achieved the full year.

Table A2.4: Dead funds - Full sample

	Panel A: Complete data set			
	$CAPM^n_{i,t}$	$FF3FM^n_{i,t}$	$CARHART^n_{i,t}$	$FF5FM^n_{i,t}$
	(1)	(2)	(3)	(4)
Constant	−0.279***	−0.398***	−0.373***	−0.354***
	t = −28.467	t = −35.549	t = −33.316	t = −26.929
$FundAge_{i,t}$	−0.006***	−0.001**	−0.001	−0.004***
	t = −9.304	t = −2.080	t = −0.764	t = −4.711
$DeadDummy_i$	−0.123***	−0.328***	−0.340***	−0.334***
	t = −7.523	t = −17.555	t = −18.158	t = −15.196
FundAge x *DeadDummy*	−0.003**	−0.002*	0.0002	−0.001
	t = −2.275	t = −1.707	t = 0.178	t = −0.889
Observations	110,173	110,173	110,173	110,173
R^2	0.004	0.011	0.010	0.008
Adjusted R^2	0.004	0.011	0.010	0.008

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: We consider all observations of funds that are of age one through five years, which we find to be representative of young funds. We characterize each fund as either "Living" and "Died", that is, if a fund dies when its age is between one and two full years, it will be regarded as "Died" at Age 1. For each fund i, we calculate the average return it achieved the full year.

A3 Robustness

Table A3.1: VIF-test

Variable	VIF	Tolerance
$FundAge_{i,t}$	1.08	0.93
$FundSize_{i,t}$	1.17	0.86
$Top10Holdings_{i,t}$	1.21	0.82
$ExpenseRatio_{i,t}$	1.10	0.91
$NumOfStocks_{i,t}$	1.29	0.78
$Turnover_{i,t}$	1.03	0.97
Mean VIF	1.15	

Notes: This table presents the VIF-test.

Table A3.2: Correlation Matrix

	$FundAge_{i,t}$	$FundSize_{i,t}$	$Top10Holdings_{i,t}$	$ExpenseRatio_{i,t}$	$NumOfStocks_{i,t}$	$Turnover_{i,t}$
$FundAge_{i,t}$	1					
$FundSize_{i,t}$	0.25	1				
$Top10Holdings_{i,t}$	0.02	-0.12	1			
$ExpenseRatio_{i,t}$	-0.09	-0.19	0.17	1		
$NumOfStocks_{i,t}$	0.02	0.25	-0.41	-0.21	1	
$Turnover_{i,t}$	-0.09	-0.11	-0.01	0.13	-0.01	1

Notes: This table presents a correlation matrix for control variables used in the multivariate regression. .

Table A3.3: Robustness - Different Time Horizon - Fund Return

Panel A: Net Returns

	January 2006 - June 2013				July 2013 - February 2021			
	$CAPM^n_{i,t}$	$FF3FM^n_{i,t}$	$CARHART^n_{i,t}$	$FF5FM^n_{i,t}$	$CAPM^n_{i,t}$	$FF3FM^n_{i,t}$	$CARHART^n_{i,t}$	$FF5FM^n_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FundAge_{i,t}$	-0.313^{***}	-0.402^{***}	-0.073^{***}	-0.234^{***}	0.021^{***}	0.143^{***}	0.124^{***}	0.214^{***}
	t = −21.181	t = −23.515	t = −3.928	t = −13.161	t = 2.800	t = 15.597	t = 13.738	t = 19.310
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,157	48,157	48,157	48,157	60,538	60,538	60,538	60,538
R^2	0.199	0.154	0.039	0.055	0.021	0.057	0.039	0.084
Adjusted R^2	0.183	0.138	0.021	0.037	0.004	0.042	0.024	0.068

Panel B: Gross Return

	January 2006 - June 2013				July 2013 - February 2021			
	$CAPM^g_{i,t}$	$FF3FM^g_{i,t}$	$CARHART^g_{i,t}$	$FF5FM^g_{i,t}$	$CAPM^g_{i,t}$	$FF3FM^g_{i,t}$	$CARHART^g_{i,t}$	$FF5FM^g_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FundAge_{i,t}$	-0.297^{***}	-0.395^{***}	-0.077^{***}	-0.215^{***}	0.030^{***}	0.151^{***}	0.129^{***}	0.227^{***}
	t = −19.334	t = −22.631	t = −4.325	t = −11.943	t = 4.442	t = 19.002	t = 16.847	t = 22.583
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,985	43,985	43,985	43,985	58,043	58,043	58,043	58,043
R^2	0.219	0.193	0.042	0.065	0.016	0.066	0.041	0.098
Adjusted R^2	0.204	0.177	0.023	0.046	0.0004	0.051	0.026	0.084

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents results based on the analysis found in table 6.1. This table presents a regression of an equal- and value-weighted portfolio that is long in funds of the 2nd quintile and short in funds of 5th quintile (Q2-Q5). The portfolio returns are used as the dependent variable. $Alpha_t$ represents the abnormal returns of the long-short strategy. Panel A and Panel B displays estimations constructed with Net and Gross returns, respectively. Each panel displays results of portfolios formed on Equal-Weighted and Value-Weighted returns separately.

Table A3.4: Robustness - Different Time Horizon - Fund Risk

Panel A: Net Returns

	January 2006 - June 2013			July 2013 - February 2021		
	$FundRisk^n_{i,t}$	$SysRisk^n_{i,t}$	$UnsysRisk^n_{i,t}$	$FundRisk^n_{i,t}$	$SysRisk^n_{i,t}$	$UnsysRisk^n_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$FundAge_{i,t}$	0.450***	0.077***	−0.113***	0.409***	−0.016***	0.027***
	t = 16.570	t = 20.098	t = −8.055	t = 39.845	t = −8.118	t = 3.324
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,157	48,157	48,157	60,538	60,538	60,538
R^2	0.226	0.087	0.307	0.217	0.009	0.028
Adjusted R^2	0.211	0.070	0.294	0.204	−0.007	0.012

Panel B: Gross Returns

	January 2006 - June 2013			July 2013 - February 2021		
	$FundRisk^g_{i,t}$	$SysRisk^g_{i,t}$	$UnsysRisk^g_{i,t}$	$FundRisk^g_{i,t}$	$SysRisk^g_{i,t}$	$UnsysRisk^g_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$FundAge_{i,t}$	0.306***	0.067***	−0.183***	0.377***	−0.017***	−0.007
	t = 10.857	t = 16.610	t = −13.241	t = 40.587	t = −9.262	t = −1.343
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,985	43,985	43,985	58,043	58,043	58,043
R^2	0.239	0.069	0.344	0.203	0.012	0.008
Adjusted R^2	0.224	0.050	0.331	0.190	−0.004	−0.008

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents results based on the analysis found in table 6.2. The table presents the coefficient and t-statistic on $FundAge_{i,t}$. All control variables used in our analysis are included in the regression, but unreported in the table. The sample is split into two sub samples based on time, the first presents evidence from January of 2006 to June of 2013, and the second presents evidence from July of 2013 to February of 2021. All standard errors are clustered at the fund level.

Table A3.5: Robustness - Different Time Horizon - Factor Loadings

Panel A: Net Returns

	January 2006 - June 2013					July 2013 - February 2021				
	$MKT^n_{i,t}$	$SMB^n_{i,t}$	$HML^n_{i,t}$	$RMW^n_{i,t}$	$CMA^n_{i,t}$	$MKT^n_{i,t}$	$SMB^n_{i,t}$	$HML^n_{i,t}$	$RMW^n_{i,t}$	$CMA^n_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$FundAge_{i,t}$	0.033^{***}	-0.195^{***}	-0.079^{***}	-0.143^{***}	0.226^{***}	-0.062^{***}	0.083^{***}	-0.001	0.002	0.209^{***}
	t = 5.446	t = −22.401	t = −7.264	t = −9.894	t = 18.015	t = −22.944	t = 18.760	t = −0.290	t = 0.326	t = 21.543
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,157	48,157	48,157	48,157	48,157	60,538	60,538	60,538	60,538	60,538
R^2	0.081	0.164	0.018	0.019	0.051	0.048	0.062	0.006	0.003	0.087
Adjusted R^2	0.063	0.148	−0.001	0.0002	0.033	0.032	0.046	−0.011	−0.014	0.072

*p<0.1; **p<0.05;

Panel B: Gross Returns

	January 2006 - June 2013					July 2013 - February 2021				
	$MKT^g_{i,t}$	$SMB^g_{i,t}$	$HML^g_{i,t}$	$RMW^g_{i,t}$	$CMA^g_{i,t}$	$MKT^g_{i,t}$	$SMB^g_{i,t}$	$HML^g_{i,t}$	$RMW^g_{i,t}$	$CMA^g_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$FundAge_{i,t}$	0.038^{***}	-0.221^{***}	-0.054^{***}	-0.168^{***}	0.248^{***}	-0.069^{***}	0.089^{***}	-0.010^{**}	-0.016^{**}	0.198^{***}
	t = 6.158	t = −26.700	t = −4.946	t = −11.935	t = 20.227	t = −29.167	t = 25.811	t = −2.308	t = −2.481	t = 20.570
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	43,985	43,985	43,985	43,985	43,985	58,043	58,043	58,043	58,043	58,043
R^2	0.072	0.168	0.020	0.027	0.058	0.074	0.085	0.010	0.003	0.086
Adjusted R^2	0.053	0.152	0.0001	0.008	0.039	0.059	0.070	−0.006	−0.013	0.071

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents results based on the analysis found in table 6.3. The table presents the coefficient and t-statistic on $FundAge_{i,t}$. All control variables used in our analysis are included in the regression, but unreported in the table. The sample is split into two sub samples based on time, the first presents evidence from January of 2006 to June of 2013, and the second presents evidence from July of 2013 to February of 2021. All standard errors are clustered at the fund level.

Table A3.6: Robustness - Long 2nd Q Short 5th Q Net Returns

Panel A: Net Return

	Equal-Weighted				Value-Weighted			
	$CAPM_t^{2Q-5Q}$	$FF3FM_t^{2Q-5Q}$	$CARHART_t^{2Q-5Q}$	$FF5FM_t^{2Q-5Q}$	$CAPM_t^{2Q-5Q}$	$FF3FM_t^{2Q-5Q}$	$CARHART_t^{2Q-5Q}$	$FF5FM_t^{2Q-5Q}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Alpha_t$	−0.056	−0.052	−0.050	−0.039	0.006	0.012	0.013	0.007
	t = −1.164	t = −1.058	t = −1.041	t = −0.789	t = 0.082	t = 0.157	t = 0.160	t = 0.093
MKT_t	−0.031***	−0.028**	−0.036***	−0.036***	−0.036**	−0.033*	−0.034*	−0.039**
	t = −2.947	t = −2.425	t = −3.019	t = −2.958	t = −2.164	t = −1.752	t = −1.757	t = −2.011
SMB_t		−0.020	−0.022	−0.016		−0.028	−0.029	−0.008
		t = −0.946	t = −1.077	t = −0.728		t = −0.833	t = −0.843	t = −0.234
HML_t		0.013	−0.004	0.043**		0.019	0.016	0.060*
		t = 0.733	t = −0.228	t = 2.049		t = 0.656	t = 0.502	t = 1.816
UMD_t			−0.029**				−0.005	
			t = −2.423				t = −0.274	
CMA_t				−0.101***				−0.143**
				t = −2.717				t = −2.430
RMW_t				0.021				0.110**
				t = 0.658				t = 2.193
Observations	180	180	180	180	180	180	180	180
R^2	0.047	0.053	0.083	0.093	0.026	0.031	0.031	0.086
Adjusted R^2	0.041	0.036	0.062	0.067	0.020	0.014	0.009	0.060

Panel B: Gross Return

	Equal-Weighted				Value-Weighted			
	$CAPM_t^{2Q-5Q}$	$FF3FM_t^{2Q-5Q}$	$CARHART_t^{2Q-5Q}$	$FF5FM_t^{2Q-5Q}$	$CAPM_t^{2Q-5Q}$	$FF3FM_t^{2Q-5Q}$	$CARHART_t^{2Q-5Q}$	$FF5FM_t^{2Q-5Q}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Alpha_t$	−0.086*	−0.075	−0.074	−0.060	−0.051	−0.038	−0.037	−0.028
	t = −1.797	t = −1.556	t = −1.549	t = −1.218	t = −0.655	t = −0.475	t = −0.461	t = −0.343
MKT_t	−0.019*	−0.017	−0.026**	−0.025**	−0.025	−0.022	−0.028	−0.031
	t = −1.820	t = −1.484	t = −2.191	t = −2.050	t = −1.457	t = −1.145	t = −1.393	t = −1.563
SMB_t		−0.029	−0.031	−0.027		−0.041	−0.043	−0.029
		t = −1.362	t = −1.520	t = −1.261		t = −1.178	t = −1.230	t = −0.832
HML_t		0.028	0.009	0.055***		0.037	0.024	0.080**
		t = 1.579	t = 0.454	t = 2.651		t = 1.262	t = 0.762	t = 2.341
UMD_t			−0.032***				−0.021	
			t = −2.735				t = −1.077	
CMA_t				−0.091**				−0.147**
				t = −2.467				t = −2.416
RMW_t				0.005				0.059
				t = 0.161				t = 1.148
Observations	180	180	180	180	180	180	180	180
R^2	0.018	0.037	0.077	0.070	0.012	0.025	0.031	0.063
Adjusted R^2	0.013	0.021	0.055	0.043	0.006	0.008	0.009	0.036

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents a regression of $R^x_{i,t}$ - $R_{f,t}$ (excess return) as the dependent variable, where x denotes the portfolio of which is risk-adjusted. The dependent variable is the factor-loading estimated with a rolling regression with the five risk-factors proposed by Fama and French (2015b) at each time t for each fund i. The regressions are estimated with the use of time, segment and fund fixed effects. All variables are defined according to the detailed description in Appendix A2.1. Panel A and Panel B displays estimations constructed with Net and Gross returns, respectively. Each panel displays results of portfolios formed on Equal-Weighted and Value-Weighted returns separately. Standard errors are clustered at the fund level.