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Mutual Fund Flows and Gender Biases in Scandinavia

Empirical evidence from the mutual fund industry in Norway, Sweden and Denmark

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Abstract

My empirical analyses are conducted based on a monthly survivorship-bias free sample of all single-managed equity mutual funds in Norway, Sweden and Denmark from 2005 to 2014. Using a pooled regression approach, I investigate whether Scandinavian investors chase past returns, and further whether flows are sensitive to the fund manager's gender. To address the concern that it is impossible to empirically observe and control for all potential drivers of fund flows, the empirical analysis in the second part of my study is supplemented with an experimental investment task conducted on students at NHH. The experiment attempts to capture the effect of the fund manager's gender on investment decisions in a "real life" setting, controlling for any confounding real world factors that might influence flows.

My findings suggest that Scandinavian investors chase past performance, which is similar to findings from the U.S. They do not, however, tend to disproportionately flock around top performing funds, implying that the convexity of the flow-performance relationship, suggested by the literature, is not present in Scandinavia. This finding deviates from several studies on mutual fund flows conducted on U.S. data. However, it is in line with a worldwide study of fund flows by Ferreira, Keswani, Miguel and Ramos (2012), suggesting significant differences in the flow-performance relationship between countries.

Furthermore, I find neither empirical, nor experimental, evidence of Scandinavian investors preferring male fund managers to female fund managers. Whereas a similar study from the U.S. by Niessen and Niessen-Ruenzi (2013) suggest that investment decisions are affected by gender biases, my results indicate that Scandinavian investors behave differently, and that they do not disproportionally allocate money to male-managed funds.

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Preface

With this thesis I conclude my Master of Science degree in Economics and Business Administration at the Norwegian School of Economics (NHH). Majoring in Financial Economics, I have found it very interesting to take a deep dive into one of the most successful financial innovations, namely the mutual fund industry. Although the global mutual fund industry has flourished over the past decades, the literature beyond the U.S. is scant. Being able to contribute in narrowing a literature gap has been a motivation in itself throughout this study.

The data material, and also the foundation for this thesis, is mainly obtained from Morningstar Direct. Excel has been used in the initial sorting and structuring of my data set, as well as to conduct certain numerical analyses, while the statistical tool STATA has been used to conduct all my empirical analyses. I have also carried out a classroom investment experiment in a finance course at the master's level at NHH.

Working on this study has been challenging as well as educative and exciting. It has largely enhanced my knowledge of the mutual fund industry, but also my competence in econometrics and in the methodology used when conducting empirical analyses in finance.

First and foremost, I wish to express my gratitude towards my supervisor, Professor Karin Thorburn. She has given me invaluable counseling and feedback, and has generously shared of her profound experience and expertise. Furthermore, I would like to thank Jens Nielsen in Morningstar Inc. for sharing essential knowledge and information of the user interface of Morningstar Direct, enabling me to obtain crucial data for my analysis. Moreover, I would like to thank Professor Thore Johnsen at NHH for providing me with valuable insights of empirical research, as well as Svein Lamvik at the IT department for quickly helping me gain access to the Morningstar Direct database through NHH. Finally, I wish to thank Professor Michael Kisser and Professor Konrad Raff at NHH for allowing me to conduct my investment experiment in their finance classes.

Bergen, June 19th, 2015

Tiril Flognfeldt Rieker

1. Introduction

Globally, the mutual fund industry has experienced a tremendous growth during the past two decades. In 1993 total worldwide assets were $4.0 trillion, while in 2013 the number was $28.9 trillion, more than seven times greater. In particular, the growth can be attributed to increasing demand for professionally managed and well-diversified products in order to gain access to capital markets, high return on capital market securities as well as countries' general economic development (Plantier, 2014).

The majority of the research on mutual funds has been conducted on U.S. data. As the industry has been influential in the U.S. financial markets for several years, data availability through the Center for Research in Security Prices (CRSP) has been superior compared to other countries. However, several countries around the world have experienced flourishing mutual fund industries during the later years, and the growth has been particularly strong in the more developed economies (Khorana, Servaes, & Tufano, 2005). This development urges the need and interest of addressing mutual fund industries beyond the U.S.

In this paper I examine the aggregated mutual fund flows for the three Scandinavian countries, Norway, Sweden and Denmark. Although three different countries today, they have historically been closely linked together, resulting in striking similarities in terms of political, economical and social structure, at least seen from a global perspective. Hence, it seems reasonable to treat the mutual funds in each of these countries as belonging to a united Scandinavian mutual fund industry. Moreover, by looking at Scandinavia as a whole, I ensure a relatively large data sample, which is preferable when conducting empirical analysis like mine.

Two main questions are addressed in my paper: i) Do Scandinavian investors chase past returns? and ii) Do they care about the manager's gender when making investment decisions? The first question relates to the well-documented literature of the relationship between mutual fund flows and past performance. The second matter, however, relates to social and behavioral biases in investment decisions, highlighting the concern of gender prejudice among mutual fund investors.

Very few previous studies examine fund flows in the Scandinavian mutual fund market. Although some papers address other characteristics of Scandinavian mutual funds, the work on flows in particular is scant.[1] As for the second question of my analysis, the previous literature is particularly inadequate. As far as I know, the study conducted by Niessen and Niessen-Ruenzi (2013) is the only previous paper addressing the specific matter of gender prejudice among mutual fund investors. However, to my knowledge there are no similar studies beyond the U.S.

Therefore, by answering my two main questions I attempt to narrow a relatively wide gap in the mutual fund literature seen from a Scandinavian perspective. Moreover, my study contributes to the large established literature on mutual fund performance and flows developed in the U.S. (e.g. Hendricks et al. (1994), Chevalier and Ellison (1995), Sirri and Tufano (1998)). When addressing social biases in investment behavior, my study is also a contribution to the sociopolitical debate on stereotyping and gender prejudice in the business world (e.g. Adams and Funk (2011), Graham et al. (2012) and Kumar et al. (2015)).

In particular, I apply two different approaches when answering my main questions. First and foremost, I conduct empirical analyses based on my survivorship-bias free sample of 421 single-managed Scandinavian equity funds observed over the ten-year period from 2005 to 2014. However, the number of funds has not been stable throughout my period of analysis, as new funds have been started up, while other funds have “died”. Overall, the main trend has been a growing number of funds, which is in accordance with the global development of the mutual fund industry over the past decades (see Figure 1). Due to the characteristics of my data sample,[2] my empirical approach consists of several pooled OLS regressions. The regressions include various model specifications in order to explore the robustness of my results. With net fund flows as the dependent variable, I investigate whether Scandinavian investors chase past returns, and further whether flows are sensitive to the fund manager’s gender.

In order to investigate my second question in greater detail, I conduct a classroom investment experiment attempting to capture the effect of the manager’s gender on

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[1] See literature review: Hansen and Steffensen (2013), who investigate capital inflows and outflows of Norwegian mutual funds listed at Oslo Stock Exchange.

[2] My sample consists of cross sectional time series data, often referred to as panel data, longitudinal data or pooled data.

investment decisions in a “real life” setting. As opposed to my empirical analysis, this experiment controls for any confounding real world factors that might influence flows.[3]

My paper is structured as follows. In section 2, I present related literature that has formed a basis for the topics investigated in my study. Next, in section 3, I present the formal hypotheses, on which I aim to answer with my analyses. In section 4, I present my data collection and structuring process along with a discussion of certain limitations to my data sample. In this section, I also include a description of the most salient variables in my empirical analyses. Section 5 outlines the empirical methodologies and procedures applied in my analyses, as well as addressing some econometric pitfalls, while section 6 presents the results from the empirical analyses. In section 7, I describe the methodology behind the experimental investment task along with the results from the experiment. Finally, in section 8, I present my main conclusions as well as a final discussion of the impact of my results.

[3] Niessen and Niessen-Ruenzi (2013) as well as Choi, Laibson and Madrian (2010) have conducted similar experiments in order to reveal differences in investment decisions among groups.

2. Litterature Review

The broad literature on mutual fund flows in the U.S. provides overwhelming evidence that investors tend to chase past performance. Earlier studies have documented a general positive flow-performance relationship, while more recent studies have focused on the non-linearity of the relation between past performance and fund flows. These studies in particular find that fund inflows seem disproportionately larger for top performing funds, than for funds located at the bottom performance quintiles. Thus, these papers suggest a convex flow-performance relationship. Unable to present all the important findings from past literature, I will highlight some interesting results forming the background of my particular study.

Smith (1978) documents a positive linear flow-performance relationship when studying 74 funds over a ten-year period from 1966 to 1975. He shows that the positive relation is present both when using traditional performance measures as well as when applying more advanced risk-adjusted procedures. Ippolito (1992) further documents the positive linear relation when studying 143 open-end equity funds between 1965 and 1984. Hendricks, Patel and Zeckhauser (1994) study 96 open-end no-load equity funds over the period from 1975 to 1982, and document a positive linear relationship between annual flows and past raw returns. In addition they find that also fund size and past flows are significantly related to a fund's annual growth. The list of papers addressing the flow-performance relationship in the U.S. continues. Overall, the investors' tendency to chase past returns is salient.

However, several studies from the recent years have drawn attention to the convexity of the flow-performance relationship. Chevalier and Ellison (1995) find a significant non-linear flow-performance relationship by analyzing 449 funds observed between 1982 and 1992. Sirri and Tufano (1998) verify the convexity of the flow-performance relation, stating that consumers of equity funds tend to *"disproportionately flock to high performing funds, while failing to flee lower performing funds at the same rate"*. Further, Sirri and Tufano (1998) find some evidence that both fees and fund risk affect consumers when shopping for mutual funds. Barber, Odean and Zheng (2005), analyzing mutual funds over 30 years from 1970 to 1999, also confirm the well-documented non-linear relation between flows and past performance. Moreover, they highlight the impact of fees on investment decisions, and suggest that investors have gradually become more aware and averse to mutual fund fees.

The studies presented above address the U.S. mutual fund market. The literature on flows chasing returns is still relatively scant beyond the U.S. However, there are some papers from recent years addressing different characteristics of mutual funds in other countries.

Dahlquist, Engström and Söderlind (2000) study the performance and characteristics of Swedish mutual funds over a five-year period from end of 1992 to end of 1997. In addition to his main findings related to fund attributes' influence on fund performance, he also confirms that past performance has a positive effect on current flows. Sørensen (2009) examines the performance and persistence of Norwegian equity mutual fund listed at the Oslo Stock Exchange between 1982 and 2008, and outlines several important aspects of mutual fund analysis, in addition to his main findings related to performance persistence.

I have only managed to detect one paper from Scandinavia examining mutual fund flows specifically. In their master thesis, Hansen and Steffensen (2013) investigate monthly inflows and outflows of Norwegian equity funds listed at Oslo Stock Exchange over the period from 2006 and 2012. They report that individual equity inflows are positively related to past returns, hence supporting the findings from the U.S. mutual fund market.

Another recent paper by Jank (2011) analyzes flows in the German mutual fund market. In addition to confirming the positive flow-performance relationship, he also shows the convexity of the relation. Moreover, he suggests three different approaches of measuring fund performance, namely by raw returns, Jensen's Alpha and Sharpe Ratio.

Keswani and Stolin (2008) use monthly data from 1992 to 2000 to analyze British mutual funds. Observing exact inflows and outflows, they confirm that U.K. investors also chase past returns. Furthermore, they compare their monthly results with results based on a less frequent periodicity commonly applied by similar studies from the U.S. They find that results are fairly similar regardless of the periodicity adopted, however they also suggest that the use of monthly data can improve the accuracy of the results to some extent.

Another interesting study addressing the use of monthly data when analyzing fund flows, is Cashman, Deli, Nardari and Villupuram (2007). They study the gross flows of mutual funds and suggest that investors base at least some of their investment decision on returns on the monthly interval. These results are highly interesting because it implies that by concentrating solely on annual data, important information regarding investor behavior may be lost.

Compared to previous studies on mutual fund flows, which mainly focus on annual data, this study argues that using monthly data when analyzing fund flows is the superior choice.

Ferreira, Keswani, Miguel and Ramos (2012) contribute to the mutual fund literature with a very interesting study. In order to address the potential differences in the flow-performance relationship around the world, they use a worldwide sample of mutual funds from 28 countries. Their sample includes more than 16,000 open-end and actively managed equity funds over the period from 2001 to 2007. They find that there are significant differences in the flow-performance relationship across countries, suggesting that the recent findings of a convex relation from the U.S. do not apply universally. Moreover, they suggest that the flow-performance relationship's convexity is likely to decline as countries develop due to higher investor sophistication and lower participation costs. These findings are of particular interest when studying the mutual fund industry in Scandinavia. Norway, Sweden and Denmark are all largely developed countries where high levels of education and information transparency are leading to increased investor sophistication, as well as lowering the cost of participating in the mutual fund industry.

So far, I have presented literature addressing the flow-performance relationship, as well as other important aspects of mutual fund analysis. As I am extending my analysis of fund flows to also assess the impact of the fund manager's gender, I will in the following present literature focusing on individual investor characteristics and gender differences in a professional context.

During the past decades there has been an increasing focus on gender equality in the business world, not only for governance priorities, but also to benefit the shareholders, the companies as well as other stakeholders (Dawson & Kersley, 2014). The benefits of diversity within companies have been documented in different studies. An example is Dawson and Kersley (2014) studying diversity in more than 3000 companies across 40 different countries. They find that in companies where more than 15% of senior management is female, ROEs in 2013 were 14.7% compared to 9.7% in companies where the female fraction is less than 10%. Moreover, they show that, since 2005, companies with at least one female director have performed 3.7% better than their male-only counterparts.

If female participation is economically beneficial, why are there so few women in executive positions? This phenomenon applies worldwide, even in the most developed countries where gender equality has been in focus for many years. Norway is an example of a country where gender equality has come far, and where the number of female leaders is increasing. However, men still occupy 75 percent of the top executive positions in Norway in 2013 (Statistics Norway, 2015). The U.S. literature suggests several different explanations for the low fraction of female leaders. Goldin and Rouse (2000) propose hiring discrimination against women, while Niessen and Niessen-Ruenzi (2013) suggest customer-based discrimination as an alternative explanation for the phenomenon. The latter type of discrimination involves segregation of workforce to match potential customer demands, based on the notion that customers discriminate (Becker, 1971).

Several other studies have shown that gender differences are important factors in the business world. Graham, Harvey and Puri (2013) provides striking evidence that psychological traits such as a manager's risk aversion, optimism and past career experience correlate with corporate decision making. Moreover they reveal that certain types of firms attract managers with specific psychological profiles, or with the "right" personality traits. Translating these findings to the mutual fund industry, where the fraction of female managers is continuously decreasing (Financial Times, 2015), it is not unlikely that females either self-select away from mutual fund companies, or that companies do not hire female managers due to lack of company "fit".

Adams and Funk (2011) compare differences between highly educated Swedish female and male directors, and suggest that values between the genders differ. More interestingly, they find that the women making it into the board of companies are a very select sample with a high taste for stimulation and a low need for security. In other words, females in top positions tend to have more male-like characteristics than the average female. In light of this study, there is reason to believe that women who are recruited as mutual fund managers, possess the "right" psychological profile and personality needed to "fit" into these companies. Thus, the small fraction of female managers consists of females with similar attributes as their male counterparts. If this is indeed the case, there is no rational reason why inflows to female- and male-managed funds should differ. Niessen and Niessen-Ruenzi (2013) further elaborates on this particular question, and claim to be the first study to show that social biases, such as gender prejudice among investors, have significant impact on investment decisions.

Kumar, Niessen-Ruenzi and Spalt (2015) investigate whether foreign-sounding names have an impact on mutual fund flows. They find that name-induced stereotypes affect investment decisions of U.S. mutual fund investors, and that managers with a foreign-sounding name receive about 10% lower annual flows than other U.S. managers. Hence, they confirm the existence of social biases among mutual fund investors.

In my paper, I attempt to address similar concerns as proposed by Niessen and Niessen-Ruenzi (2013). Particularly, by analyzing whether net flows into female-managed funds significantly differs from those of male-managed funds.

3. Hypothesis

As presented in the literature review, the majority of all previous papers on fund flows study the U.S. mutual fund market. Although some recent papers are focusing on the mutual fund industry in other countries, there is still relatively scant work on mutual fund flows beyond the U.S. With the hypotheses presented below, I aim to fill some of this gap by investigating different characteristics of the Scandinavian mutual fund market. The basis for my hypotheses is the previous studies and results presented in the literature review. My objective is to examine whether empirical findings from other countries, specifically from the U.S., are also observable in the Scandinavian mutual fund market.

In my analysis, I attempt to answer the following hypotheses:

1) *Do Scandinavian investors chase past returns when making investment decisions?*
2) *Are top performers chased more rapidly than poorly performing mutual funds? I.e. is the convex flow-performance relationship present in Scandinavia?*
3) *Do Scandinavian investors care about the manager's gender when allocating money between mutual funds?*

The first two hypotheses address topics that are well documented in particularly the U.S. literature, and it is therefore of interest to explore whether these hypotheses also hold in Scandinavia. The third hypothesis, however, address an area that is still relatively unexplored, especially beyond the U.S. Inspired by Niessen and Niessen-Ruenzi (2013), who examine gender prejudice in the U.S. mutual fund industry, I aim to reveal potential differences between female- and male-managed funds in Scandinavia.

My paper proceeds as follows. Section 4 provides a description of my data sources, the sample selection process along with some concerns regarding my data sample. Moreover, section 4 includes a presentation of the most salient variables used in my analyses. In section 5, I present the empirical methods I use to analyze my hypotheses, as well as outlining some potential econometric pitfalls. In section 6, I elaborate on the results of my empirical analyses, focusing on all three hypotheses, while in section 7, I specifically address the impact of hypothesis number three in light of results from the investment experiment. Finally, section 8 concludes and discusses.

4. Data

In order to evaluate the flow-performance relationship and gender differences in the Scandinavian mutual fund market, a considerable amount of data has to be collected and structured. In this section, I will first present my data sources, and then present the sample selection criteria adopted. Further, I describe my data sample in greater detail, as well as address possible issues and concerns. Lastly, I will present the primary variables included in my regression analyses.

4.1 Data Sources

Primarily, I have obtained all my data from Morningstar Direct, a database containing detailed statistics on mutual funds from all over the world. When looking at the Scandinavian market as a whole, Morningstar Direct appears as a superior alternative compared to alternative domestic databases as Morningstar Direct provides comparable figures for mutual funds across countries. In addition to providing measures of performance, fund flows, size, etc., Morningstar Direct also collects detailed manager information, such as manager history and identity.

Where Morningstar Direct lacks sufficient information, I have used the respective fund's websites and reports to collect necessary information.[4] Further, I have used the numbers obtained from Morningstar Direct to compute additional variables, which will be explained in detail later.

4.2 Sample Selection

The sample consists of actively managed open end equity funds registered in Norway, Sweden or Denmark (hereinafter Scandinavia), and hence, index funds as well as bond and money market funds are excluded. This selection criterion is made in order to focus on a

[4] This procedure was only carried out for the variable Expense Ratio, as Morningstar Direct lacked historical numbers of expense ratios for a considerable fraction of funds in my data sample.

similar group of funds where performance easily can be compared. In the Scandinavian countries, equity funds invest between 75%-80% of their assets in equity securities.[5]

A representative data sample should include both surviving and "dead" funds. Ignoring funds that closed down during the period of analysis can produce inaccurate results due to the overestimation of surviving fund performance (Rohleder, Scholz, & Wilkens, 2007). Moreover, Elton, Gruber and Blake (1996) show that there is significant survivorship-bias when "dead" funds are ignored, as the main reason for closing a fund lies in inferior performance. To ensure a survivorship-bias free sample, I include funds that have ceased operations or have merged with other funds during my sample period.

To avoid double counting of funds, I eliminate multiple share classes of the same fund and use Morningstar Direct aggregate statistics on all measures.[6] The initial sample includes 1,194 unique funds (both active and dead) in the period from 2005 to 2014. Similar to Niessen and Niessen-Ruenzi (2013), the sample includes both funds primarily investing in stocks within its own country domicile, and funds investing primarily in stocks outside the country domicile.[7] I exclude 96 unique funds registered in Scandinavia, but offered in a foreign base currency (such as Euro, Dollar etc.), so called offshore-funds.[8] As these funds are primarily aiming at attracting foreign capital (DNB v/ Gehrken, Espen, 2015), the possibility of money inflows from Scandinavian investors is reduced.

I use monthly data (see section 4.3.1) for all variables in the study, and 93 funds with less than 12 months of data (TNA,[9] return and fund flows) are excluded to ensure sufficient continuity in data on the fund level.

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[5] By definition, a mutual fund in Norway and Denmark invests minimum 80% of its total assets in equity securities, while in Sweden the corresponding limit is 75%.

[6] Morningstar Direct provides a unique Fund ID for all funds, meaning that the different share classes of a fund is identified with the same Fund ID. Hence, it is easy to avoid double counting by only including unique Fund IDs in my sample.

[7] Many studies from the U.S. focus on funds investing in domestic equity only. However, as the Scandinavian mutual fund market is significantly smaller than in the U.S., excluding funds investing in international equity would reduce my sample from 31,971 fund months to 7,812 fund months. In addition, when addressing differences in fund flows between female and male-managed funds, it is of interest to look at the whole population of single-managed funds in Scandinavia.

[8] By unique, I mean offshore-funds with a unique Fund ID in Morningstar Direct. Several funds in my sample have multiple share classes where some of these classes may be offered in foreign currencies. However, as opposed to unique offshore-funds, these share classes are all identified with the same Fund ID.

[9] TNA = Total Net Assets measured at the end of each month.

Following Niessen and Niessen-Ruenzi (2013), I eliminate all team-managed funds (see section 4.3.3 for a more detailed description).[10] According to Baer, Kempf, and Ruenzi (2011), team and single managed funds behave differently. Specifically, they argue that teams make less extreme decisions than individuals because extreme opinions of members in a team are averaged out (Baer et al., 2011). This finding suggests concentrating on single managed funds in order to capture the effect of a mutual fund manager's individual decisions, as they directly impact the fund's performance.

Morningstar Direct reports manager history for each fund, including manager name, start-date and end-date. First, I exclude 87 funds without any recorded manager history. For the remaining funds, I can identify 497 team-managed funds where Morningstar Direct lists multiple manager names over the same period of time. Restricting the sample to single-managed funds only, reduces the sample to 421 funds.

In order to separate male-managed fund months from female-managed months, I identify the gender of the fund managers based on the first names listed in Morningstar's manager history. In those very few cases where I could not clearly classify a name as male or female, i.e. foreign names or ambiguous names, I was able to identify them all by searching online on fund companies' websites etc. [11]

My final sample contains 421 single-managed funds over a total of 31,971 fund months. Out of these monthly observations, 28,590 have a male manager and 3,381 have a female manager. This corresponds to ratios of 89.42% and 10.58%, respectively. The low female ratio of around 10% in Scandinavian mutual funds shows a very similar patter as Niessen and Niessen-Ruenzi (2013) find for the U.S. mutual fund market.[12] Figure 2 illustrates the distribution of male- and female-managed fund months per year over my sample period from 2005 to 2014, as well as the fraction of female-managed fund months over the period. As the figure shows, the proportion of female-managed fund months is fairly stable around the 10% level over my sample period.

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[10] After thoroughly going through the manager history for all funds, I chose a cut-off value of 85% for a fund to be defined as "Single-Managed". I.e. the fund has been managed by one person in 85% of reported months within my time period.

[11] Career and recruiting websites, such as LinkedIn proved useful in this process, as it is possible to see people's past career experience and employers.

[12] Niessen and Niessen-Ruenzi (2013) find that out of a total of 16,509 fund years 14,804 (89.67%) has a male manager, while the same number is only 1,705 (10.33%) for female-managed fund years.

4.3 Structuring of Data Sample

In this section, I will elaborate on how I have structured and gathered the data in greater detail. I will also address possible implications for and biases in my final data sample.

4.3.1 Periodicity

In my analyses I use monthly data for the period from January 2005 to December 2014. Most papers studying the mutual fund industry use quarterly or yearly data, including Niessen and Niessen-Ruenzi (2013), who specifically investigate gender prejudice in the mutual fund industry. Although some would argue that using similar periodicity would be advantageous in order to compare results with previous studies in this field, I have chosen to use monthly data for my base analyses following suggestions by some recent studies.

Cashman et al. (2007) use a large sample of monthly fund flows from 1997 to 2003 to examine investor behavior in the mutual fund industry. They uncover several undocumented regularities in investor behavior. Particularly, they find that net flows respond contemporaneously to monthly fund performance, and suggests that although yearly performance measures may be important, investors also respond to past performance over much shorter time periods than previous papers have assessed.

Furthermore, Keswani and Stolin (2008) compare the use of monthly and quarterly fund flows in the U.S. and U.K. mutual fund market, and argue that using data at a higher frequency reduce the loss in accuracy that occur when using net flows over longer periods of time.[13] However, they also find that although monthly data yields higher precision, the results are not significantly different when using data at a lower frequency.

Moreover, as Keswani and Stolin (2008) also mention, previous studies are mainly from the U.S., where monthly flow data for mutual funds from CRSP has only been available since 1991, and hence the choice of periodicity in early studies may be due to lack of data at a higher frequency.

[13] Most studies evaluating mutual fund flows, including this one, use implied net fund flows calculated as $(TNA_t - TNA_{t-1} \cdot (1 + r_t))/TNA_{t-1}$ instead of actual inflows and outflows.

Several other studies of the mutual fund industry from later years use monthly data. Examples are Sørensen (2009), who studies the mutual fund performance at Oslo Stock Exchange, Deaves (2004) analyzing performance, persistence and flows in the Canadian equity fund market, and Phillips, Pukthuanthong and Rau (2014) looking at fund performance, flows and fees in the U.S.

Based on the arguments by Cashman et al. (2007) and Keswani and Stolin (2008), and the fact that several more recent papers covering similar topics have used a monthly periodicity, I am confident that also my analysis is a relevant contribution to the large literature of mutual fund performance and flows. However, for both robustness and comparison purposes, I have conducted the analyses based on yearly data for the same time period.

4.3.2 Missing Values

Kocher, Osborne and Tillman (as cited in Osborne 2013, pp. 108) study highly regarded journals from the American Psychological Association, and find that as much as 61% of the authors fail to report anything relating to missing data in their articles. Further, Osborne (2013) argues that if this finding is representative for qualitative studies across different sciences, there is a cause for concern. Based on own experience from reading empirical studies in finance, there are surprisingly few that address problems regarding missing values. Although some authors quickly state the variables they are eliminating, they rarely describe in greater detail how they proceed in the elimination process. This is a problem because then these empirical analyses could hardly be replicated. Based on arguments by Osborne (2013) and own experience, I find it valuable to devote some space in my study to describe how I handle the issue of missing values in my data sample.

Morningstar Direct reports monthly flows for most funds in my sample from their inception date and onwards. However, for some funds TNA is not reported for earlier periods, and hence the corresponding flows are not calculated. A simple and commonly used approach to deal with this is to include only cases with complete data in the analysis (Osborne, 2013). According to Sørensen (2009), Schafer and Graham (2002), Osborne (2013) and others, merely deletion of cases with incomplete data could impose severe sample selection biases and increase the probability of inference error. Deleting cases with missing data can further lead a researcher to misestimate the population parameters, and hence making replication more difficult (Osborne, 2013). Following Ferreira et al. (2012), Sørensen (2009) and others, I only eliminate fund-months without any recorded TNA in my base model. This means that although a fund's inception date was before 2005, it is not necessarily the case that data for all 120 months (10 years) are included in my analysis.[14] In my base sample, I have included a total of 421 funds and 31,971 fund months.

Keeping funds with incomplete data yields the advantage of a dataset free of sample selection bias. However, there might be a drawback of including funds with few observations as the regression could be imprecisely estimated (Sørensen, 2009). To test whether this might be a problem in my analysis, I perform robustness tests with a sample consisting only of funds where data is reported for the complete period from 2005 to 2014, or for the complete period of the fund's lifespan.[15] Excluding funds with incomplete data leaves 259 funds with 21,271 fund months.

Although removing fund months without recorded TNA for certain periods solves the issue of missing values to a great extent, it does not completely eliminate the problem.[16] My sample still contains a few instances where there are intermittent missing fund months in between periods with continuously recorded data. To ensure a complete time series for all the funds in my sample, I chose to implement a single imputation technique to fill in TNA for the missing fund months. By doing so, I can use equation (1) (see section 4.4.1) to calculate the corresponding net fund flows.

In general, multiple imputation methods[17] are viewed as superior to single imputation as they provide more robust results where variance estimates are unbiased (Schafer & Graham, 2002). However, according to Schafer and Graham (2002), Osborne (2013) and others,

[14] I use 119 months (February 2005 to December 2012), as one month is removed in order to calculate the net fund flows for January 2005.

[15] Some funds in my sample start operations after 2005, or cease operations before 2014.

[16] The elimination of fund months without recorded TNA only includes periods until when data is reported on a continuous basis. For funds that are still active today, this means that only the earlier periods of the fund's lifespan have been removed, while for funds that ceased operations between 2005 and 2014, also later parts of the fund's lifespan might have been removed when TNA is not recorded for these periods. However, intermittent missing values may still exist for both active and dead funds.

[17] Multiple imputation (MI) represents one of many techniques applied when dealing with missing values in data sets. When using single imputation techniques, a single value is filled in for each missing value, whereas the MI procedure produces a set of plausible values for each missing value, creating multiple datasets. Each of these data sets is then analyzed by the same statistical procedure, and finally, the results from the analyses are pooled together (Schafer & Graham, 2002).

single imputation can in some instances be an efficient method as the observed data contains useful information for predicting the missing values. There exists numerous imputation methods, and the answer to which one is the best is heavily dependent on the data sample as well as to which degree data is missing (Osborne, 2013).

My intention is not to dig too deep into the literature of missing values, but to describe and defend the use of single imputation in my particular case. TNA is fairly stable as it is (on average) growing or being reduced by a very small portion of its total value every month,[18] as opposed to net fund flows, which is a variable that can potentially fluctuate a lot from month to month.[19] Therefore, single imputation of TNA based on already existing observations is likely to induce less estimation errors than imputation of net fund flows.

In longitudinal studies a common method of single imputation is "*The Last Observation Carried Forward"*, where simply the last observed value is imputed where there is a missing observation (Pannekoek, Scholtus, & Waal, 2011). I base my imputation on this method, but to also account for the growth trend often observed for the TNA variable, I use the average of the month before and after the period with the missing observation. This method yields an estimate of the missing value in time t based on the linear growth in TNA between month t-1 and t+1. Similarly, in the few incidents where data for two or three months are missing in a row, I calculate the linear monthly growth rate over the period of missing values, and impute the corresponding values for each missing month.[20] Hence, my choice of imputation is based on somewhat discretionary judgment of my particular sample, as opposed to documented empirical studies on imputation techniques.[21] However, there are several reasons why I believe my method is viable. The first, and also most important, reason is that the instances with intermittent missing fund months in my sample constitute less than 0.5% of my 31,971 observations. Hence, the potential bias, if any, from my chosen imputation technique will be

[18] In my data sample, TNA grows by 0.5% per month on average.

[19] Because Net Fund Flows is calculated as an implied value, as shown in equation (1), this value can fluctuate a lot depending heavily on both the amount of inflows/outflows and the fund's performance.

[20] I.e. if two months, $\boldsymbol{t}$ and $\boldsymbol{t+1}$, have missing values for TNA, I calculate the linear growth rate from month $\boldsymbol{t-1}$ to month $\boldsymbol{t+2}$. This growh rate is divided by 3 to get the linear monthly growth rate, $\boldsymbol{g}$. First, the missing value for month $\boldsymbol{t}$ is estimated by $\boldsymbol{TNA_{t-1} \cdot (1+g)}$, and then, the missing value for month $\boldsymbol{t+1}$ is estimated by $\boldsymbol{TNA_{t} \cdot (1+g)}$.

[21] Most empirical studies addressing missing values and imputation techniques suggest using advanced techniques such as multiple imputation to ensure robust results with unbiased variance estimates. However, these studies often deal with missing observations in survey data, and not with longitudinal time series and cross sectional data in particular.

minor. Second, with a monthly periodicity the effect of wrongly estimating the actual TNA for one missing fund month is small, as opposed to the effect with i.e. yearly data. Third, since I also conduct the analysis with yearly data as robustness, where no intermittent missing values are present,[22] I formally test whether the imputation technique applied induce biases on my results. In my case, all imputed estimates of TNA seem like a fair approximation for the real values, which also the robustness tests indicate. [23]

4.3.3 Single vs. Team Management

Investigating whether female-managed funds experience lower inflow than male-managed funds restricts the sample to consist of single managed funds only. As previously mentioned, the main reason for this requirement is to capture the effect of managers' individual decisions on fund performance. Moreover, when also distinguishing between the managers' gender, the single-managed restriction seems even more obvious.

Most fund companies tend to have defined management strategies, which implies that their funds are either managed by teams or by individuals. However, there are several funds that switch between team and single management over the sample. For this reason, a clear definition of single management is important.

As I have spent a considerable amount of time in the process of sorting out single managed funds from my initial sample, I believe a short description of the process is appropriate as well as informative. For a large portion of the funds in my sample, there have been one or more manager changes over the period from 2005 to 2014. Naturally, these changes sometimes cause a couple of months overlap between two managers. Where there are overlapping periods, I assign the manager role to the new person from the date Morningstar reports as his or hers starting date. Funds falling under the category described above are treated as single managed. This can be justified by the fact that a very short period of overlap

[22] There are no intermitting missing fund years in the yearly data sample, as all TNA as of December 31st each year are recorded for all funds in the sample.

[23] When proceeding with this technique, I went carefully through my data set to ensure that the imputed values seemed in line with the growth trend of TNA for the different funds. There were no incidents where the imputed values appeared unrealistically high or low.

between managers is unlikely to affect the individual manager's decision-making, nor investors.[24]

For other funds, with longer periods of more than one manager, the reason for periodical team management is difficult to depict. Instead of defining all these funds as team managed, I have chosen a cut-off value of 15%. For a fund with 120 recorded months in my sample, this means a limit of up to 18 months with team management. Hence, I avoid elimination of unreasonable many funds where the majority of fund months are single-managed.

There are also incidents where Morningstar Direct report certain manager periods as "Not Disclosed". For a number of funds in my data sample, this is the case in the first 12-24 months. In these situations, I remove the data without any recorded manager history, similar to how I treat missing values for TNA (see section 4.3.2).

I run robustness tests to ensure that the discretionary sorting of single-managed funds does not bias my results. The robustness sample is the same described in section 4.3.2, and includes only funds with complete series of data, both for manager history and TNA.

4.4 Variables

In the following sections, I will describe the primary variables included in my analyses. First I devote some space to describe fund flows and different performance measures, as these variables constitute the foundation of my analysis. Further, I elaborate on variables used to capture the mutual fund flows' sensitivity to female-managed funds, representing the second part of my study. Next, I introduce some control variables that are important for my study in particular. Finally, I briefly present descriptive statistics of the main variables introduced in section 4.4. A detailed overview of all variables, including definitions and calculations, is included in Appendix A.

[24] Changes in manager style may off course occur when there is a manager change, and further affect investor's decision. But a very short period of two managers itself, is not likely to be reflected in the market.

4.4.1 Fund Flows

Following Sirri and Tufano (1998), Niessen and Niessen-Ruenzi (2013) and others, fund flows are defined as the growth in total net assets (TNA) beyond capital gains and dividends. Morningstar Inc (2011) uses the same methodology, and defines fund flows as follows:

”The cash flow estimate for a month (C) is simply the difference in beginning and ending total net assets (TNA) that cannot be explained by the monthly total return (r).”

Hence, net fund flows (FundFlow) is defined as the net growth in TNA beyond capital gains and dividends, and can be calculated as follows:

$$FundFlow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \cdot \left(1 + FundReturn_{i,t}\right)}{TNA_{i,t-1}}, \tag{1}$$

where $TNA_{i,t}$ is the total net assets of fund *i* at the end of month *t,* and $FundReturn_{i,t}$ denotes fund *i*’s return in month *t*.[25] [26]

Highly unusual flows can occur for very young funds, in periods where a fund is about to cease operations or where mergers take place. To avoid that such extreme values drive my results, I eliminate observations with fund flows above the 99th percentile and below the 1st percentile,[27] following the approach of Keswani and Stolin (2008) and Ferreira et al. (2012). This method is called “winsorizing”, and is a commonly used approach to avoid impact of extreme outliers in empirical studies.

When running robustness tests, as an alternative measure of the dependent variable, I replace $FundFlow_{i,t}$ with its absolute number measured in million NOK. $AbsFundFlow_{i,t}$ is obtained from Morningstar Direct and represents the numerator in equation (1), in line with the Morningstar definition mentioned above.

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[25] All numbers obtained from Morningstar Direct are presented in the same currency, NOK. The conversion to NOK is done through Morningstar Directs database.

[26] This measure is assuming that flows occur at the end of each month. However, Sirri and Tufano (1998) show that this assumption does not affect the results.

[27] Results do not change significantly when instead winsorizing at the 0.1% and 99.9% level.

4.4.2 Performance Measures

Measuring fund performance can be done in several ways, and the literature uses various measures when documenting the flow-performance relationship. However, according to Sirri and Tufano (1998) it is unclear which particular measures of performance and risk that are most salient to consumers investing in mutual funds. Historically, consumers have always had easy access to performance measures such as historical returns and return rankings relative to other funds with similar investment style or objective. Similarly, a measure of total risk readily available for consumers is the standard deviation of historical returns (Sirri & Tufano, 1998). Although the more advanced risk-adjusted returns, such as Jensen's Alpha and Sharpe Ratio, may be more appropriate measures of return in financial theory, they are not necessarily the measures that investors rely on when allocating money between funds. (Hendricks et al., 1994). Following both Hendricks et al. (1994), Sirri and Tufano (1998) and Niessen-Ruenzi and Ruenzi (2013), I use the fund's raw monthly returns, $FundReturn_{i,t}$ in my base regression model, and supplement these results with alternative performance measures to explore the robustness of the results to alternative specifications.

Following Niessen and Niessen-Ruenzi (2013), Jank (2011) and others, I apply Sharpe Ratio as an alternative performance measure, as it is the most widely used method for calculating risk-adjusted return. Sharpe Ratio measures the average excess return per unit of risk in a certain evaluation period (Sharpe, 1994). Morningstar Direct provides Sharpe Ratios for all funds in my data sample on an annual basis.[28] The Morningstar annualized Sharpe Ratio is calculated as follows:

$$Sharpe\ Ratio_A = \frac{\overline{R_i - R_f}}{\sigma_A^e}, \tag{2}$$

where $\overline{R_i - R_f}$ is the average annualized excess return based on the past 36-month period, and σ_A^e its annualized standard deviation. R_f represents a risk free benchmark suitable to the particular fund (Morningstar, Inc, 2005). [29]

[28] From Morningstar Direct, I extract 10 different Sharpe Ratios, calculated for each of the years in my data sample. The first is calculated from 1.1.2005 to 31.12.05 and the last one from 1.1.2014 to 31.12.2014.

[29] Morningstar chooses a risk free benchmark based on the fund's domicile.

Further, following Sirri and Tufano (1998), Niessen and Niessen-Ruenzi, Jank (2011) and others, I also use Jensen's Alpha (also known as one-factor alpha), a performance measure based on the CAPM.[30] Michael Jensen introduced alpha as a proposed performance measure for actively managed funds in 1970, arguing that a manager should not receive credit for achieving above-market performance by taking on systematic risk measured by beta (Morningstar, Inc, 2009). Alpha measures a fund's average excess return above what can be obtained from holding a position in the market portfolio, and is calculated as follows:

$$Jensen's\ Alpha_A = \alpha_i = R_i - (R_f + \beta_i(R_m - R_f)), \tag{3}$$

where R_i is the return of fund i, and R_f is the appropriate risk free benchmark. R_m is the return of the market benchmark portfolio and β_i measures the fund's sensitivity to movements in this market portfolio. The yearly alphas I obtain from Morningstar Direct are based on least squares regressions of monthly fund return over the appropriate market portfolio and the fund's benchmark index. Hence, the calculated alphas in my data sample are based on numerous different benchmarks depending on the primary location of their investments (Morningstar, Inc, 2015).

At no (or negligible) cost, all three performance measures used in my study are easily available to all investors through different online information services, such as Yahoo! Finance, Google Finance, Norwegian Netfonds etc., in addition to Morningstar.[31] Hence, when investigating whether Scandinavian investors adjust their flows according to the theory of flows chasing returns, I believe the availability of these performance measures make them superior to, or at least equally good as, other existing measures.

Risk is closely related to performance as financial theory suggests that that higher risk yields higher expected return. In other words, on the upside investors are rewarded for taking on greater risk, but they are also exposed to a greater downside. Hence, risk is an important measure to include when analyzing mutual fund flows. To measure a fund's riskiness, I

[30] The Capital Asset Pricing Model is defined as: $R_i - (R_f + \beta_i(R_m - R_f)$.

[31] Morningstar has separate web pages for all three Scandinavian Countries; Morningstar.dk, Morningstar.no and Morningstar.se.

calculate the standard deviation of monthly returns,[32] which is in line with similar analyses conducted by Sirri and Tufano (1998), Niessen-Ruenzi and others. Like the performance measures, a fund's standard deviation is readily available for all investors and is widely used in evaluating the volatility, and hence riskiness, of desired investments.

To quickly summarize, three measures of performance are included in my analysis. In my base model I use lagged fund return, $FundReturn_{i,t-1}$, to capture the influence of past performance on flows. Further, in order to consider alternative performance measures, I run yearly regressions with the two risk-adjusted performance measures Sharpe Ratio and Jensen's Alpha. As robustness, these analyses both capture alternative measures as well as an alternative time horizon, as suggested by Sirri and Tufano (1998). Sharpe Ratio and Jensen's Alpha are also included in lagged terms, for the same reason as before. The same applies for the fund riskiness, and hence $FundRisk_{i,t-1}$ is included in the model.

4.4.3 Capturing Flow Sensitivity to Female-Managed Funds

With the intention of finding an answer to the hypothesis of whether female-managed funds attract lower inflows than male-managed fund in Scandinavia, I follow Niessen and Niessen-Ruenzi (2013), and include a dummy variable $Female_{i,t}$ in my regression. This dummy variable equals one if the manager of fund i at time t is female, and zero otherwise. Regressing this dummy variable on the dependent variable $FundFlows_{i,t}$ enables analysis of flows' sensitivity to female-managed funds. This means, that if observing a significant negative coefficient of $Female_{i,t}$ the implications could be that female-managed funds on average receive lower inflows than male-managed funds.

Although the coefficient of $Female_{i,t}$ can say something about the average inflow into female-managed funds relative to male-managed fund, it does not say anything about the female-managed funds sensitivity to past performance. This measure is also of interest because it measures to which degree a female-managed fund profits from good past performance relative to male-managed funds. Hence, do flows chase returns of female-managed funds to the same extent as for male-managed funds? A variable capturing this

[32] In my yearly data set used for robustness purposes, I have annualized the monthly return in year *t*. Standard deviation of monthly returns are calculated in line with the method used by Morningstar, and is hence comparable to the two yearly performance measures extracted from Morningstar Direct (Sharpe Ratio and Jensen's Alpha).

relationship is made by interacting the dummy variable $Female_{i,t}$ with lagged fund return $FundReturn_{t-1}$: $FemaleXFundReturn_{t-1} = Female_{i,t} * FundReturn_{t-1}$.

4.4.4 Control Variables

The literature on mutual fund flows shows that not only performance-related variables can explain flows' sensitivity to past performance. There are a number of other variables that also have proven influence investors when "shopping for funds". Sirri and Tufano (1998) find that funds with higher total fees tend to grow more slowly than funds with lower fees. Barber et al. (2005) investigate fees and fund flows specifically, and suggest that investors have become gradually more aware and averse to mutual fund costs. Other studies have also shown significant impact of a fund's age and size on fund flows, such as Chevalier and Ellison (1997), Sirri and Tufano (1998) and Niessen and Niessen-Ruenzi (2013).

Following the literature, I include several non-performance related control variables in my analyses. First, the fund's expense ratios are collected from Morningstar Direct. These are recorded on a yearly basis, and hence I divide them by 12 to fit my monthly data set. However, Morningstar Direct lacks sufficient information on this variable, as historical ratios are completely missing or only partly available for several funds in my sample. For the funds with incomplete history of expense ratio, I collect the ratios from the fund's annual reports, usually found on the fund company's website.[33] Although time consuming, the method results in a complete sample of expense ratios, for surviving as well as for dead funds. I include the lagged expense ratio, $ExpRatio_{i,t-1}$, in my regressions to capture the possible effects of a fund's previous expense ratio on fund flows.

Second, in measuring the size of a fund, I apply the natural logarithm of the fund's total net assets plus one, which is similar to the method used by Sirri and Tufano (1998) and Niessen and Niessen-Ruenzi (2013): $FundSize_{i,t} = \ln{(TNA_{i,t} + 1)}$. In order to capture flows sensitivity to past size of a fund, I include the lagged fund size, $FundSize_{i,t-1}$.

[33] The expense ratios obtained from the fund's annual reports are cross-checked with the ratios recorded by Morningstar Direct, in order to make sure that all expense ratios in my sample are comparable.

As a third control variable, I include the age of the fund in months based on the fund's inception date, i.e. when the fund was first offered.[34] A fund's inception date is readily available from Morningstar Direct's database. Similar to the fund size, the age is calculated as the natural logarithm of the fund's age in months plus one: $FundAge_{i,t} = \ln{(Age_{i,t} + 1)}$. And for the same reason as for fees and size, I include lagged fund age, $FundAge_{i,t-1}$, in my analyses.

I also include the dependent variable lagged by one month, $FundFlow_{i,t-1}$, as fund flows show a pattern of autocorrelation. Moreover, Cashman et al. (2007) find that while returns, by themselves, can explain the variation in net fund flows to a great extent, they add little incremental value in explaining net flows when the analysis also includes lagged net flows. Hence, they suggest that any research considering the determinants of monthly fund flows, should take prior fund flows into account.

In addition to the variables mentioned above, I include several other control variables when running various robustness tests. These controls are all calculated based on the variables presented above, and include different lagged performance interaction terms; $LowXFemale_{i,t-1}$, $MidXFemale_{i,t-1}$, $HighXFemale_{i,t-1}$, $AlphaXFemale_{i,t-1}$ and $SharpeXFemale_{i,t-1}$, as well as lagged squared/cubed terms of fund size to capture the possible non-linear impact of size on flows; $FundSize^2_{i,t-1}$ and $FundSize^3_{i,t-1}$. All variables included in my regression analyses are presented in Appendix A, and hence, I will not elaborate on these additional control variables in further detail here.

4.4.5 Descriptive Statistics

Table 1 reports summary statistics for the main variables presented earlier in section 4.4, both for the monthly sample (panel A) and yearly sample (panel B). Panel C reports differences in fund characteristics between female- and male-managed funds in the monthly sample. In the following, I briefly highlight some observed patterns in Table 1 that can potentially influence the impending regression analyses.

[34] In my yearly data set, age is measured in years from the fund's inception date.

Panel A and B show a positive mean $FundFlow_{i,t}$ for both samples, indicating an average monthly growth of 0.5%, while on the yearly basis, the average fund grows by 10.5%. Further, the mean monthly return of the funds in my sample is 0.8%, while the mean yearly return is 11.2%. The sizes of the funds in my monthly sample range from 11.5 million NOK at the bottom percentile (p1) to 12.75 billion NOK at the top percentile (p99), while the average fund has a TNA of 1.66 billion NOK. A similar pattern is naturally reflected in the yearly sample. In my monthly sample, the average fund's risk is 4.5%, while in the yearly sample, the average fund has an annualized risk of 15.7%. The average expense ratio is 1.5% on an annual basis, corresponding to an average of 0.125% per month. Finally, $FunAge_{i,t}$ shows that the average fund in my sample is 12 years. The oldest fund is 34 years, and as previously mentioned, funds with less than 12 months of data are excluded from the samples.

When examining panel C, some interesting differences between female- and male-managed funds are observed. Column 1 and 2 present the mean characteristics for the female- and male-managed funds, respectively. Note first that the average female-managed fund grows by 0.07% per month, while the average male-managed fund grows by 0.52%. This corresponds to a difference of 0.46 percentage points, which is particularly interesting to formally test in the regression analyses. A similar pattern is naturally observed for absolute fund flows. Moreover, the table shows that the average female-managed fund is 187.25 million NOK smaller than the average male-managed fund, and further that the average female-managed fund is about 18 months older the average male-managed fund. For the remaining variables, $FundReturn_{i,t}$, $FundRisk_{i,t}$ and $ExpRatio_{i,t}$, the differences presented in the table are non-existing or negligible.

5. Empirical Methodology

In order to capture the flow-performance relationship, and to investigate the sensitivity of flows to female-managed funds, I run several pooled OLS regressions with different specifications and with the presence of various control variables.[35] In all regressions standard errors are clustered at the fund level, in order to account for serial correlation and heteroskedasticity in the error term (Hoechle, 2007). In addition, time and fund fixed effects are included to control for time and fund variations in flows.

In this section, I elaborate on the methods applied as well as address potential econometric pitfalls that may be apparent in my sample. Empirical results are presented in section 6.

5.1 Flow-Performance Relationship

A general positive flow-performance relationship has been well documented in the extant literature. Early studies, such as Hendricks et al. (1994) report a positive linear relationship between flows and performance of individual funds. However, there are several papers on mutual fund flows arguing that the flow-performance relationship is non-linear. In accordance with these findings, I begin by analyzing the linear flow-performance relationship as my base model. To test for non-linearity, I apply a second approach and run a piecewise-linear regression following Sirri and Tufano (1998).

As already mentioned in section 4.4.2, it is unclear whether the average investor focus on raw performance measures or risk adjusted measures when allocating investments between funds. Hendricks et al. (1994) argue that the more complex risk adjusted performance measures have marginal explanatory power for relative flows to mutual funds, as these measures are more difficult to obtain by the average investor, and hence rarely used in investment decisions. However, as there is reason to believe that investor sophistication has increased since 1994,[36] one should expect that today's investors apply these measures to a

[35] Pooled data combines time series for several cross-sections and consists of repeated observations (in my case months) on the same cross section (in my case funds) for several periods (Cameron & Trivedi, 2005). Other commonly used names of pooled time series cross sectional analysis (TSCS) are panel analysis or analysis of longitudinal data. The different names can be confusing, especially since panel analysis often refers to panel research in survey studies (Podestà, 2002).

[36] Barber et al. (2005) argue that in conjunction with the rapid growth in mutual fund investing over the past three decades, investors have had the opportunity to learn more about mutual funds. Hence, over time investors have accordingly adjusted the way in which they make investment decisions.

greater extent when making investment decisions. Hence, in order to explore the robustness of my monthly analyses with raw returns, I report alternative regressions using two additional performance measures on a yearly data sample. This way I am also able to test whether my results are consistent on a yearly basis. Moreover, it makes my results directly comparable to earlier papers using yearly data.

Base regression

First, following suggestions by Hendricks et al. (1994) and also the approach adopted by Niessen and Niessen-Ruenzi (2013), I begin my analysis estimating the monthly regression model with raw return as performance measure, in addition to several control variables. The model investigates the linear relationship between fund flows and past performance, and is specified as follows:

$$FundFlow_{i,t} = \beta_0 + \beta_1 FundReturn_{i,t-1} + \beta_2 Controls_{i,t-1} + \varepsilon_{it}\ , \tag{4}$$

where i refers to the cross-sectional unit (fund) and t refers to the time period (month). Hence $FundFlow_{i,t}$ is the flow of fund *i* at time *t*, and $FundReturn_{i,t-1}$ is fund i's return in the previous month. The control variables include lagged fund flow, lagged fund size, lagged age, lagged fees, and lagged volatility. Table 2, column 2 shows this base regression model.

Piecewise-linear regression

Running a piecewise-linear regression enables separate flow-performance sensitivities at different levels of performance. Based on past month's return, funds are ranked within their equity segment on a monthly basis, similar to the approach of Sirri and Tufano (1998).[37] This way of ranking funds' performance forms a basis for comparison that is not affected by cyclicality or special events that is out of the individual fund's control, nor is it affected by differences in equity segments which are likely to entail differences in performance.

By normalizing the ranks, so that they are evenly distributed between zero and one, the poorest performing fund and the best performing fund within the same month and equity segment, are assigned the rank zero and one, respectively. Funds are then categorized into

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[37] In order to sort funds according to their equity segment, I use the widely applied Morningstar Equity Style box. Based on a fund's market capitalization, Morningstar classifies a fund as Small, Medium or Large, while as for a fund's value-growth orientation, Morningstar differentiates between value, blend and growth funds. In total these yields nine categories of funds, where risk and return levels should be fairly comparable within the groups. Equity segments for all funds in my sample are obtained from Morningstar Direct.

quintiles, allowing for estimation of a distinct coefficient for each quintile. I categorize funds' fractional performance ranks in the bottom quintile (Low), the middle three quintiles (Mid) and the upper quintile (High). The three variables are created as follows:

$$
\begin{aligned}
Low_{i,t} &= Min(Rank_{i,t}, 0.20) \\
Mid_{i,t} &= Min(Rank_{i,t} - Low_{i,t}, 0.60) \qquad (5) \\
High_{i,t} &= Min(Rank_{i,t} - Mid_{i,t} - Low_{i,t})
\end{aligned}
$$

The three coefficients Low, Mid and High represent the piecewise decomposition of the fractional ranks, $Rank_{i,t}$, and can be interpreted as the slope of performance-growth relationship within the performance range (Sirri & Tufano, 1998). To capture the effect of past performance, I include the lagged term of these three variables in my regression. The model can thus be specified as follows:

$$
\begin{aligned}
FundFlow_{i,t} = \beta_0 + \beta_1 Low_{i,t-1} + \beta_2 Mid_{i,t-1} + \beta_3 High_{i,t-1} \\
+ \beta_4 Controls_{i,t-1} + \varepsilon_{i,t} \, , \qquad (6)
\end{aligned}
$$

where $FundFlow_{i,t}$ represent the flow of fund *i* in month *t*. The regression includes the same control variables as described for the base regression (4). A detailed overview of the piecewise-linear regression is presented in Table 2, column 3.

Alternative model specifications

In order to ensure that the results from my monthly models are consistent, I apply two alternatives to my base model (4), where performance is measured on a yearly basis by Jensen's Alpha and Sharpe Ratio, respectively. Table 3 presents an overview of all yearly regression models.

Essentially, there are two reasons why I have chosen to run yearly regressions when testing for alternative performance measures. Firstly, by applying the same periodicity, as well as similar model specifications as previous papers, comparison is easier as results are directly transferable. Particularly to this study, comparing results with Niessen and Niessen-Ruenzi (2013) is of interest, as they are also investigating fund flow sensitivity to female-managed funds, and has been the main inspiration for writing this paper. Secondly, accurately estimated risk-adjusted performance measures of all funds in my sample were available from

Morningstar Direct on a yearly basis,[38] and hence enabling estimation of alternative regression models with Sharpe Ratio and Jensen's Alpha. Morningstar Direct uses advanced tools in order to calculate precise risk-adjusted performance measures for each fund. As these measures are more advanced than simple raw returns and volatility, my belief is that an average researcher (like myself) is unlikely to estimate more accurate measures than a highly reputable service existing for the purpose of providing such numbers. At best, I would have obtained the exact same numbers from doing the calculations myself.

5.2 The Relationship Between Fund Flows and Female Managers

To answer my second hypothesis whether there exists a negative relationship between fund flows and female managers, I expand model (4) and (5) described in section 5.1 with additional variables intended to describe this particular relation. Specifically, I include the dummy variable $Female_{i,t}$ and the interaction term $FemaleXFundReturn_{t-1}$, as presented in section 4.4.3. Similar to the analyses of the flow-performance relationship, lagged fund return is included in the regressions. Moreover, I also apply the two additional performance measures, Sharpe Ratio and Jensen's Alpha, when estimating flow sensitivity to female managers on the yearly basis. Furthermore, the same empirical methods apply when analyzing this relationship, as when analyzing the fund-performance relationship described in section 5.1, and for further details about regression models I refer to this section. Monthly regressions are presented in Table 4 and 5, while yearly regressions are presented in Table 6.

5.3 Econometric Pitfalls

When running Ordinary Least Square regressions (OLS) on pooled or longitudinal data, there are particularly three problems that could potentially lead to biased, inefficient and/or inconsistent estimators. As pooled data consist of both cross sections and time series data, typical problems that generally affect each of the data characteristics should be addressed (Garba, Oyejola, & Yahya, 2013). Presence of autocorrelation is typically observed in time series data as an observation in time t is likely to be closely linked to the previous

[38] Morningstar Direct's calculations of the risk-adjusted performance measures are cross-checked by doing estimations (not reported) for a small group of randomly selected funds. The results were very similar.

observation, t-1. When this is the case, the error terms are not independent of each other. Further, when jointly analyzing several cross-sections (i.e. funds), the volatility of the observed variables for each unit are likely to vary, as the units can have very different characteristics. Hence, heteroscedasticity is a common problem for cross-sectional data, meaning that the variance of the error terms is not constant.[39]

However, modern statistical tools, such as STATA, provide commands that ensure robust standard errors in the regression. As mentioned in the beginning of section 5, I use the cluster command to provide standard errors that are robust to both heteroscedasticity and autocorrelation. Hence, an estimation of the models described in section 5.1 and 5.2 should not be affected by the potential existence of these two conditions.

In the following, I will describe the nature of the third econometric pitfall, why it might be a problem in pooled regression analysis, and how to formally test for its existence.

If two or more explanatory variables are strongly correlated, so that one of the variables can be expressed as a linear function of at least one of the other variables, multicollinearity is present (Garba et al., 2013). Highly correlated explanatory variables are likely to describe the same variability in the dependent variable. This might be a concern as it typically leads to larger standard errors, hence resulting in unreliable estimates of coefficients (Garba et al., 2013). However, the presence of multicollinearity does not lead to biased or inconsistent estimates of the coefficients, but significance might be harder to establish when the correlated variables are jointly included in the analysis (Friendly & Kwan, 2009).

To formally test for the existence of multicollinearity, I conduct a post-estimation Variation Inflation Factor (VIF) test. This test calculates the variance inflation factors and tolerances corresponding to each of the explanatory variables in the regression model. As a rule of thumb, multicollinearity is present if the values of VIF are greater than 10 (Friendly & Kwan, 2009). The tables on the next page report results for the monthly and yearly base regressions.

[39] For OLS to be optimal, it is necessary that all the errors have the same variance (homoscedasticity) and that all of the errors are independent of each other. However, in most real life situations, these conditions are almost always violated to some extent. Although difficult to avoid, by being aware of the pitfalls and by handling them in the right way, the OLS estimates can still be consistent (Garba et al., 2013).

Variable	VIF	Tolerance (1/VIF)
$FundSize_{i,t-1}$	1.15	0.8674
$FundAge_{i,t-1}$	1.15	0.8687
$FundReturn_{i,t-1}$	1.15	0.8715
$FundReturnXFemale_{i,t-1}$	1.14	0.8807
$FundFlow_{i,t-1}$	1.05	0.9546
$ExpRatio_{i,t-1}$	1.04	0.9612
$FundRisk_{i,t-1}$	1.03	0.9728
$Female_{i,t-1}$	1.02	0.9775
Mean VIF/Tolerance	**1.09**	**0.9193**

Table i: VIF test for monthly base regression.

Variable	VIF	Tolerance (1/VIF)
$FundReturn_{i,t-1}$	1.23	0.8114
$FundReturnXFemale_{i,t-1}$	1.21	0.8287
$FundAge_{i,t-1}$	1.18	0.8458
$FundSize_{i,t-1}$	1.16	0.8651
$FundFlow_{i,t-1}$	1.12	0.8894
$Female_{i,t-1}$	1.11	0.8999
$FundRisk_{i,t-1}$	1.10	0.9111
$ExpRatio_{i,t-1}$	1.04	0.9644
Mean VIF/Tolerance	**1.14**	**0.8770**

Table ii: VIF test for yearly base regression.

As one would expect, the VIF tests for the monthly and yearly models show very similar results. For the monthly model the mean (max) VIF is 1.09 (1.15), and a mean (min) tolerance of 0.87 (0.92). If no sign of multicollinearity, both the VIF and the tolerance would be equal to one. And according to the rule of thumb, one should be concerned when values rise above 10. Hence, a mean VIF of 1.13 indicates weak multicollinearity, and there should not be any problems by running regressions with the variables presented.[40]

[40] Unreported VIF tests for the piecewise-linear regression approach, for robustness tests, as well as for yearly regressions with alternative performance measures show similar results. In all regressions mean (max) VIF is below 1.3 (1.7).

6. Empirical Results

6.1 Do Scandinavian Investors Chase Past Returns?

The presence of a general positive flow-performance relationship

I start the empirical analysis by applying my base model, as presented in equation (4). Here, relative net inflow to a fund, $FundFlow_{i,t}$, is regressed on the lagged performance measure $FundReturn_{i,t-1}$. As control variables, I include lagged fund flows, $FundFlow_{i,t-1}$, lagged fund size $FundSize_{i,t-1}$, lagged fund age $FundAge_{i,t-1}$, lagged fund risk, $FundRisk_{i,t-1}$, as well as a fund's lagged expense ratio, $ExpRatio_{i,t-1}$. The model is as follows:

$$\begin{aligned} FundFlow_{i,t} &= \beta_0 + \beta_1 FundReturn_{i,t-1} + \beta_2 FundFlow_{i,t-1} + \beta_3 FundSize_{i,t-1} \\ &+ \beta_4 FundAge_{i,t-1} + \beta_5 FundRisk_{i,t-1} + \beta_6 ExpRatio_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

My results presented in Table 2, column 2, show a highly significant (at 0.1% level) coefficient of past returns. Hence, my evidence confirms that Scandinavian mutual funds are also sensitive to past performance. The coefficient of 0.155 is also economically meaningful, and implies that by one percentage point increase in fund return, the average fund grows by 15.5% per month. The lagged dependent variable is statistically significant at 0.1% level, and also economically meaningful. A one percentage point increase in flows, yield on average additional growth of 16.6% the next month. If excluding the lagged dependent variable (column 1), I find increased coefficients for lagged return, as well as somewhat decreased explanatory power. This is in line with findings by Cashman et al. (2007).

Further, I find that fund age and size significantly affect flows. The negative coefficient of $FundAge_{i,t-1}$, indicates that on average, older funds tend to grow more slowly than younger funds. Similarly, the coefficient of $FundSize_{i,t-1}$, implies that larger funds on average experience less inflows than smaller funds. These findings are consistent with Chevalier and Ellison (1997) and Sirri and Tufano (1998). However, the control variable, $FundRisk_{i,t-1}$, is only significant at the 10% level (5% when the lagged dependent variable is excluded). Although only marginally significant, the coefficient indicates that investors tend to allocate their money to funds with higher risk. The last control variable, $ExpRatio_{i,t-1}$ is not significant, implying that sensitivity of flows to a fund's fees is negligible.

Capturing the non-linear flow-performance relationship in Scandinavia

Applying the model presented by equation (5) in section 5.1, I attempt to capture a non-linear relationship between fund flows and past performance. In this regression, net fund flows is related to funds' performance through three different levels, $Low_{i,t-1}$, $Mid_{i,t-1}$ and $High_{i,t-1}$. In order to determine whether a convex flow-performance relationship exists, I compare the slope of the flow-performance relationship in the High region with the slope in the Low region. The control variables included are the same as in my base regression, resulting in the following model.

$$\begin{aligned} FundFlow_{i,t} = \beta_0 &+ \beta_1 Low_{i,t-1} + \beta_1 Mid_{i,t-1} + \beta_1 High_{i,t-1} + \beta_2 FundFlow_{i,t-1} \\ &+ \beta_3 FundSize_{i,t-1} + \beta_4 FundAge_{i,t-1} + \beta_5 FundRisk_{i,t-1} \\ &+ \beta_6 ExpRatio_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{8}$$

The results are presented in Table 2, column 4. Note first that the coefficients of the lower, middle and higher performance quintiles are all positive and highly statistically significant at 0.1% (Mid and High) and 1% (Low) level. This confirms the presence of a general positive flow-performance relationship I found in my base model.

Moreover, the coefficients weakly indicate a convex flow-performance relationship, where top performing funds on average experience a growth of 0.9 percentage points above the lowest performing funds. However, compared to studies from the U.S., the flow-performance relationship seems different for Scandinavian funds. Sirri and Tufano (1998), among others, show that the flow-performance sensitivity for the top performing funds in the U.S. is much more extreme than for the lower quintiles. My results from the Scandinavian mutual fund market show that the flow-performance relationship is performance sensitive at the bottom, ($\beta_{Low} = 0.032$), flat in the middle, ($\beta_{Mid} = 0.009$), and slightly more sensitive at the top, ($\beta_{High} = 0.041$).

The flow-performance sensitivity for the top performers in Scandinavia is apparently not as strong as for the U.S. top performing funds. This is in line with findings by Ferreira et al. (2012) who study worldwide convexity among 28 countries. They find that the flow-performance relationship differs significantly from country to country, and particularly, by graphing the relationships, they show that all three Scandinavian countries have flow-performance relationships that are sensitive at the top and bottom, but with no sign of an extreme sensitive flow-performance relationship for the top performers. Regarding the middle region, all three Scandinavian countries stand out compared to the remaining 25 countries in the sample, with almost with flat slopes (Ferreira et al., pp. 1766-1768).

Based on my results as well as findings from previous literature, it is unlikely that the well-documented convex flow-performance relationship in the U.S. is universally transferable to other countries. Hence, I formally test for convexity in Scandinavia by running a Wald test, checking for equality between the Low and High region, similar to Ferreira et al. (2012). The p-value is presented at the bottom of column 3 in Table 2. The test reports a F-statistic of 0.48, with the corresponding p-value of 0.4886, and hence the null hypothesis stating equality between the Low and High region cannot be rejected. This means that there is no significant difference between the High segment and the Low segment, further indicating that convexity is not present in Scandinavia. This is in line with the results reported on Scandinavian countries by Ferreira et al. (2012), and a reasonable explanation might be that as Scandinavian countries are among the highest developed countries in the world, investors are more sophisticated and tend not to chase winners to the same extent as in other countries. In addition, as information about mutual funds is transparent and readily available in the Scandinavian countries, participation costs are low for the average investor. According to Ferreira et al. (2012), countries with low participation costs are expected to have lower convexity than countries where these costs are high.

Altogether, the results from the piecewise-linear regression suggest that convexity is not present in Scandinavia. However, as coefficients for Low, Mid and High are all positive and highly significant, the general positive relationship between mutual fund flows and performance is also found in Scandinavia, although to a lesser extent than what is reported for the U.S. In my analyses below, I therefore continue to expand my base model, depicting the linear flow-performance relationship.

Alternative performance measures and periodicity

In this section, I explore the robustness of my results to different performance measures as well as for a different time interval. Results are presented in Table 3. First, I conduct the same analysis as presented in equation (7), except now *t* represents years instead of months. The results are presented in column 2. The coefficient on fund return is positive and highly significant at the 0.1% level, indicating a positive flow-performance relationship. Moreover, it is consistent with the results from my monthly sample reported above.

However, in the yearly model, the lagged dependent variable changes from being significant at the 0.1% level in the monthly sample, to not being significant. The coefficient is still positive, but I cannot reject the null hypothesis that it is equal to zero. This indicates that net flows' response to lagged flows is diminishing over time in the Scandinavian market. Results from the regression in column 1 indicate the same, as the explanatory power only marginally decreases when removing lagged fund flows from the analysis.

Regarding the other control variables, only $FundSize_{i,t-1}$, is highly significant at the 0.1% level. The coefficient of $FundAge_{i,t-1}$ is still negative, but only statistically significant at the 10% level. The coefficient of $FundRisk_{i,t-1}$ has changed from positive to negative, however it is still not significant, and hence the null hypothesis the coefficient being equal to zero cannot be rejected.

Overall, when concentrating on the flow-performance relationship, the results from the yearly regressions do not seem to deviate significantly from the results obtained from the monthly regressions.

Next, I run my base regression with $FundReturn_{i,t-1}$ replaced by Jensen's Alpha and Sharpe Ratio. Hence, I use the following alternative specifications of model (7).

$$\begin{aligned} FundFlow_{i,t} &= \beta_0 + \beta_1 Alpha_{i,t-1} + \beta_2 FundFlow_{i,t-1} + \beta_3 FundSize_{i,t-1} \\ &\quad + \beta_4 FundAge_{i,t-1} + \beta_5 FundRisk_{i,t-1} + \beta_6 ExpRatio_{i,t-1} + \varepsilon_{i,t} \,, \end{aligned} \tag{9}$$

$$\begin{aligned} FundFlow_{i,t} &= \beta_0 + \beta_1 SharpeRatio_{i,t-1} + \beta_2 FundFlow_{i,t-1} + \beta_3 FundSize_{i,t-1} \\ &\quad + \beta_4 FundAge_{i,t-1} + \beta_5 FundRisk_{i,t-1} + \beta_6 ExpRatio_{i,t-1} + \varepsilon_{i,t} \,, \end{aligned} \tag{10}$$

Results from regression (9) are presented in column 3. The coefficient of $Alpha_{i,t-1}$is positive, but only significant at the 10% level, indicating that the one factor alpha may not be a particularly common used measure by investors shopping for mutual funds. However, the remaining control variables are very similar to those obtained in column 2.

When using Sharpe Ratio as an alternative performance measure, results are very similar to results from column 2 with raw returns. Results are shown in column 4. The coefficient of $SharpeRatio_{i,t-1}$ is positive and highly significant at 0.1% level. In addition, the explanatory power of the model has been marginally enhanced. However, the rest of the variables remain largely unchanged.

To summarize, all four alternative models essentially allow for the same conclusion as from the monthly regressions: Scandinavian investors tend to chase past returns. However the evidence is weaker when using Jensen's Alpha as performance measure. Moreover, there is evidence of a diminishing effect of lagged flows on fund flows, as $FundFlow_{i,t-1}$ goes from being highly significant with monthly periodicity to becoming insignificant when using the yearly sample.

6.2 Do Scandinavian Investors Care About the Manager's Gender ? – Empirical Evidence

So far, I have presented evidence suggesting that Scandinavian investors chase past returns, although to a lesser extent than seems to be the case in the U.S. Next, I am going to elaborate on my second hypothesis, namely whether Scandinavian investors allocate less money to female-managed funds than to male-managed funds.

I start my analysis by expanding the base model presented by equation (7), adding the dummy variable $Female_{i,t}$:

$$\begin{aligned} FundFlow_{i,t} = \beta_0 &+ \beta_1 Female_{i,t} + \beta_2 FundReturn_{i,t-1} + \beta_3 FundFlow_{i,t-1} \\ &+ \beta_4 FundSize_{i,t-1} + \beta_5 FundAge_{i,t-1} + \beta_6 FundRisk_{i,t-1} \\ &+ \beta_7 ExpRatio_{i,t-1} + \varepsilon_{i,t} \,, \end{aligned} \tag{11}$$

where the female dummy captures average growth of a female-managed fund compared to a male-managed fund. The results are presented in column 2 in Table 4. My main finding from this first regression is a slightly negative but insignificant coefficient of the female dummy variable. Hence, unlike Niessen and Niessen-Ruenzi (2013), who find a highly significant and negative impact of the female dummy variable in the U.S., there seems to be no difference in fund flows between female and male-managed funds in Scandinavia. Before discussing the impact of this finding in more detail, I will in short present the various regressions I run in order to make sure the findings from model (11) are not sensitive to changes in the model specification. All estimation results are presented in Table 4.

In column 1, I run a regression without the lagged dependent variable. For the same reasons as mentioned in section 6.1, removal of $FundReturn_{i,t-1}$, reduces the explanatory power somewhat as well as increases the size of the coefficient on past performance.

In column 3, I include the interaction term between lagged fund returns and the female dummy variable. I do this in order to capture potential differences in the flow-performance relationship between female and male-managers. Although slightly negative, the coefficient of the interaction term is not significantly different from zero, and hence suggests that flows to female-managed funds in general are equally performance sensitive as flows to male-managed funds. This shows a similar pattern as my initial finding, suggesting on average no difference between flows to female-managed and male-managed funds. However, my conclusion again differs from Niessen and Niessen-Ruenzi (2013), who finds that flows to female-managed funds in the U.S are generally less performance sensitive.
Regarding the other variables, both the female dummy and the controls remain unchanged.

Although my earlier regressions failed to find any convex flow-performance relationship in Scandinavia (see section 6.1), I include piece-wise linear regressions to test the robustness of the female dummy to such changes in the model specification. The results are presented in column 4 and 5, where column 5 includes interaction terms with the female dummy and each of the three regions, Low, Mid and High. In both column 4 and 5, all results remain similar to the results presented above. Although the female dummy variable in column 5 changes from slightly negative to slightly positive when including the interaction term, it remains insignificant, and does not change the initial conclusion.

In all previous regressions, $FundSize_{i,t-1}$ had highly significant coefficients, hence indicating that a fund's size explain some of the variation in dependent variable. However, I only considered a linear relationship between flows and fund size. This may affect the estimation of my coefficients, as I observe relatively large differences in the size of female- and male-managed funds (see Table 1, panel B). This is in line with findings by Niessen and Niessen-Ruenzi (2013). They suggest that both differences in size between female and male-managed funds, as well as the possibility of a non-linear influence of fund size on flows should be addressed. Hence, in column 6, I repeat the base regression from column 2 and include fund size to the power of two and three as additional explanatory variables. The results show that the coefficient of $FundSize_{i,t-1}$ decrease from -0.014 to -0.062, and is still significant at the 1% level. Moreover the coefficient of the two new explanatory variables, ${FundSize^2}_{i,t-1}$ and ${FundSize^3}_{i,t-1}$, are statistically significant at 5% level, but have however minor impact on fund flows. Similar to Niessen and Niessen-Ruenzi (2013), there are negligible changes to my main result when accounting for the non-linearity of fund size.

Following Niessen and Niessen-Ruenzi (2013), in column 7 I, again repeat the regression from column 2, but with standard errors clustered at the monthly level instead of at the fund level. The impact of the female dummy remains unchanged, and the same holds for all the control variables.

So far, I have compared funds across different segments of investment. As mentioned in section 4.2, my sample includes funds investing in domestic as well as international equity, which implies that there might be a natural difference in performance between funds. In order to address the concerns of including funds that may not be easily comparable, in column 8, I focus on a more homogenous subgroup of my sample investing only in Scandinavian equity. This sample consists of about one fourth of my base sample, and some variability in the coefficients is expected. The results show that the coefficient of lagged fund return is now significant at the 5% level, as opposed to the 0.1% level in the previous regressions. The same pattern applies for lagged fund age. Despite some minor changes to the model, the coefficient of the female dummy remains insignificant and of about the same magnitude as before, although it has faced a negligible change from -0.002 to 0.002. Thus, the initial conclusion also holds for funds investing exclusively in Scandinavian equity.

Regardless of changes in model specification and inclusion of additional explanatory variables, my findings show that flows into female-managed funds do not significantly differ from flows into male-managed funds. The impact of the female dummy variable remains insignificant in all my eight model specifications, and varies only in the small interval between -0.002 and 0.002. Hence, my results so far suggest that investors in Scandinavia do not care about the manager’s gender when making mutual fund purchase decisions.

Compared to Niessen and Niessen-Ruenzi (2013) who study a similar phenomenon, my results are completely different. They conclude that female-managed funds experience significantly less inflow than male-managed funds, and their results are also uniform across different model specifications. However, the difference in conclusions for the Scandinavian and U.S. market is in line with findings by Ferreira et al. (2012), who show that characteristics of the mutual fund market revealed in the U.S., cannot be mapped directly onto other countries. Moreover, based on the fact that the Scandinavian countries are in the forefront when it comes to gender equality in the business world, my results are not very surprising.

Robustness

Although my results so far suggest no difference in flows between female- and male-managed funds, it is important to explore the robustness of my results to further variation in my base regression model (column 2 in Table 4). In addition to testing the robustness of my results to more drastic changes in my sample, I run my base regression using yearly observations. The results are presented in Table 5 and Table 6, respectively, and I will in the following elaborate on my findings in more detail.

Monthly robustness – Table 5

In column 1 and 2, instead of net fund flows, I include absolute fund flows, $AbsFundFlow_{i,t}$, measured in million NOK as the dependent variable. I also replace lagged net fund flows with lagged absolute flows, $AbsFundFlow_{i,t-1}$. In column 2, I have in addition added the performance interaction between lagged fund return and the female dummy variable. In both cases, I find that the coefficient of the female dummy variable is insignificant. Overall the results remain similar as my initial results from Table 4, column 2.

In column 3 and 4, I address the temporal stability of my results by running regressions on two different time periods. In column 3, I assess the five latest years, from 2010 to 2014, while in column 4, I assess the first five years, from 2005 to 2009. The results show that in both cases, the impact of the female dummy variable is insignificant. As for the remaining variables, results are similar to those received before, and there do not seem to be any notable differences between the two time periods.

In column 5, I include a sample of complete observation series only. As discussed in section 4.3.2, this sample includes 259 funds for which complete data series are reported in Morningstar Direct.[41] This enables me to explore the robustness of my results to my sample selection criteria. Again, results do not drastically deviate from my initial findings, and the impact of the female dummy remains insignificant.

Finally, to address the concern that there might be individual differences between the three Scandinavian countries, I repeat the base regression from Table 4, column 2 for each of the three countries. The number of single-managed mutual fund months in Sweden (13,280) is

[41] By complete, I mean funds where all data is reported for the time interval of my analyses. The panel is still unbalanced, due to the presence of newly started as well as funds that ceased operations during the period from 2005 to 2014.

almost twice as big as in Norway (7,721), with Denmark falling in the middle (10,549). While the fraction of female-managed fund months over the period is 13.5% in Sweden, the equivalent ratios for Norway and Denmark are only 8.67% and 8.27%, respectively. The results presented in column 6 to 8 indicate a couple of minor differences across countries. First, the impact of the female dummy variable in Denmark is negative and significant at a 10% level. However, the statistical significance is weak, and hence it does not seem reasonable to conclude that Denmark differs significantly from Norway and Sweden, where the impact of the female dummy variable remains insignificant. Second, lagged fund risk is significant at 1% level for Norway, but has no impact on flows in the two other countries. Third, In Denmark lagged expense ratio is significant at the 5% level, but remains insignificant in Norway and Sweden. Apart from this, there are no major differences among the three countries. The variables in all individual regressions show the same pattern as in the aggregate models, with a highly significant positive linear flow-performance relationship, as well as significant impact of past flows (positive), size and age (negative).

Yearly robustness – Table 6

Similar to the yearly regressions run in section 6.1, I estimate equation (7), (9) and (10) on a yearly basis and expand them by adding the female dummy variable as well as performance interaction variables. The results with raw return as performance measure are presented in column 1 and 2. The findings are similar to my yearly robustness results in section 6.1, and more importantly the impact of the female dummy variable remains insignificant, confirming the initial results from Table 4, column 2. In column 3 and 4, I use Jensen's Alpha and Sharpe Ratio as alternative performance measures, as well as the corresponding performance interaction variables. Again, results are similar to my findings from section 6.1, with a weak significant impact of past alpha at the 10% level, and a highly significant impact of past Sharpe Ratio at the 0.1% level. Furthermore, the female dummy variable remains insignificant in both regressions. In sum, also the yearly results confirm the insignificant impact of the female dummy variable.

After further exploration of the robustness of the initial results, my findings still suggest that Scandinavian investors do not care about the manager's gender when allocating their money between mutual funds.

7. Investment Experiment

7.1 Do Scandinavian Investors Care About the Manager's Gender? – Experimental Evidence

Although all my empirical analyses point in the same direction, and suggest that Scandinavian investors do not prefer male-managed funds to female-managed funds, it is impossible to empirically observe and control for all potential drivers of fund flows. Therefore, as a supplement to my empirical analyses, I conduct a controlled investment experiment, similar to Niessen and Niessen-Ruenzi (2013). Moreover, by running a similar experiment as one previously run in the U.S., I am able to directly compare and assess potential behavioral differences between continents. With this experiment, I aim to shed further light on Scandinavian investors' attitude towards female fund managers, by analyzing the impact of the manager's gender through a fictional investment decision.

Investment experiment – Discription and methodology

I start by creating a simple investment task where responding subjects have to split 100 NOK between two fictive OSEBX Index Funds.[42] As also referred to in Niessen and Niessen-Ruenzi (2013), Choi, Laibson and Madrian (2010) suggest using index funds when analyzing specific variables' impact on investment decisions as index funds barely differ from each other. Moreover, due to the homogenity of index funds, the optimal choice is always to allocate the total investment to the lowest-cost fund (Choi et al., 2010). This feature makes it possible to examine whether respondents make rational decisions when exposed to a fictional investment task in a closed laboratory.

Students studying finance can be assumed to have the appropriate knowledge needed in order to make optimal investment decisions, while students studying topics entirely unrelated to finance, may be less sophisticated in this area. Therefore, the investment experiment was conducted at Norwegian School of Economics (NHH) in a finance course at the master's level, where enrolled students were divided in two groups in order to make each

[42] Alexandra Niessen-Ruenzi emailed me one of the investment tasks used in their experiment, and I got permission to use it as inspiration to my own experiment. As my experiment is conducted among students in Norway, I chose to create a fictive example of Norwegian index funds as Norwegian students are likely to be more familiar with the Norwegian Stock Exchange than with the Swedish or Danish one. Further, by conducting the study on primarily Norwegian students, I am assuming their representativeness to Scandinavia as a whole.

class smaller. One group was taught on Mondays (X), while the other was taught on Tuesdays (Y). By examining two groups of students taking the same finance course, I ensure comparable respondents, as the individuals in each group are likely to be relatively similar. Moreover, since I conducted the experiment within the same week, I obtained two groups, X and Y, of mutually exclusive respondents.[43]

At the beginning of the investment experiment, the subjects were presented with information about the two index funds, one cheaper than the other. In addition, one of the funds had a female manager, while the other had a male manager. The funds were not presented by names, instead they were labeled Fund A and Fund B. The respondents were then asked to allocate the complete amount of 100 NOK between the two funds, based on the presented information. Each of the two groups was presented with the same information on the same two funds. However, while keeping everything else constant, I switched gender of the fund manager between the two groups. Group X observed a female fund manager for fund A (higher cost) and a male manager for Fund B (lower cost), while group Y observed a male manager for fund A (higher cost) and a female manager for fund B (lower cost). Hence, group X and Y observed different gender of the manager for the cheapest fund, i.e. the fund being the optimal investment decision. Figure 3 shows the information presented to each of the two groups. As can be seen from the figure, the only difference between the information provided to each group of students is the name of the fund manager.[44] When the fund manager's gender is the only information that differs between group X and Y, any differences in investment behavior between the two groups can be attributed solely to the gender of the fund manager.

The total number of students participating in my experiment was 75. However, Although NHH initially divided the finance course in two groups of equal size, students showed up at the class that fitted best according to their individual time schedule, resulting in one group being smaller than the other.[45] Group X consisted of 57 students, while the number of

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[43] The finance course was taught on both Mondays and Tuesdays, covering the same topics both days in a given week. NHH divided the course in two groups (X and Y), aiming at smaller groups of students per class. Hence, as students are highly unlikely to attend two classes covering the exact same topic, the two groups X and Y are mutually exclusive when conducting the experiment for both groups within the same week.

[44] Similar to Niessen and Niessen-Ruenzi (2013), I use common Norwegian first and last names to ensure that the respondents perceive these names as common for each gender group.

[45] According to the two professors teaching the course, many of the students who originally belonged to the Tuesday class at 8am, often attend the class on Mondays class at 10 am. There may be several reasons why students were prevented from attending the 8am class on Tuesdays. However, the professors believed that students just preferred to sleep longer.

students in group Y were 18. Although the experiment was done in a finance class, students with other majors than finance could attend the course. Hence, prior to making the investment decision, the subjects were asked to provide individual characteristics. Specifically they were asked about their gender, age, nationality and main field of study. Table 7, panel A presents an overview of the demographic characteristics of the subjects participating in the experiment. The largest group of students, 45%, indicated Finance as their main field of study, while the remaining 55% of the students were distributed on master profiles such as Economics, International Business, Strategy and Management or Other.[46] The gender distribution was fairly balanced, with 40% female and 60% male students. Of subjects participating in my experiment, 81% indicated Scandinavian nationality, and the mean age of students was 24.2 years.

In spite of different size of group X and Y, the demographic characteristics proved to be fairly similar also on the group level. An overview is provided in Table 7, panel B. In the biggest group, X, the female-to-male ratio was 35% to 65%, while in the smaller group, Y, female students outnumbered male students, with a ratio of 56% to 44%. Each of the groups, X and Y, consisted of 81% and 83% Scandinavian students, respectively.[47] Moreover, the fraction of finance students was similar in both groups, with 46% in group X and 44% in group Y. Finally, the average student in group X was 24.0 years old, while the equivalent number for group Y was 24.8 years.

Investment experiment – Results

The main objective of the investment task is to assess differences in investment decisions between group X and Y, and specifically to isolate the effect that the gender of a fund manager has on a Scandinavian investor's investment decision. Similar to Niessen and Niessen-Ruenzi (2013), I therefore compare the differences in the amount invested in fund A between group X and Y.[48] The results from the investment task are presented in Table 8.

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[46] NHH offer several different master profiles, and regardless of which profile is a student's major, he/she is eligible for two elective courses. This explains the relatively large fraction of students from other profiles than Finance. However, the objective is to capture the fraction of finance students, and confirm that these students are highly represented in the sample.

[47] In this experiment, I am aiming to capture the investment behavior of the Scandinavian investor, and hence it is important that most of the students in the experiment is from Scandinavia. Above 80% in each group is a decent fraction.

[48] I conduct the experiment in one round only. In the very similar experiment conducted by Niessen and Niessen-Ruenzi (2013), investment decisions are carried out over several rounds. However, as they also point out them selves, only the first round of investment decisions like this can be considered completely independent. This supports my choice of only carrying out the investment task once.

In panel A, results based on all subjects are presented.[49] It shows that both groups invest a considerably smaller fraction of their money in fund A than in fund B. The fact that fund A is the more expensive fund, would seem like a plausible explanation for this behavior. However, as subjects are choosing between two index funds, the only rational investment decision is to allocate 100% of the 100 NOK to the cheaper fund. With subjects in both groups allocating above 30% to the most expensive fund, irrational behavior is observed among the students. These results are in line with similar studies conducted by Niessen and Niessen-Ruenzi (2013), and Choi et al. (2011).

More interestingly, Niessen and Niessen-Ruenzi (2013) find that subjects invest significantly less in fund A if it is managed by a female than they invest in Fund A if it is managed by a male. Trying to detect a similar pattern for Scandinavian investors, I formally test the significance of the difference between group X's investment in fund A and group Y's investment in fund A.[50] The result is presented in panel A, column 3. Although the difference is negative, indicating a similar pattern as found in the U.S. experiment, the difference is not significant, and I fail to reject the null hypothesis of equal proportions.

In panel B, I compare investment decisions by gender within the two groups in order to capture possible differences in investment behavior among female and male subjects. As opposed to Niessen and Niessen-Ruenzi (2013), who find that male students invest significantly less in in fund A if managed by a woman, I find no significant difference between female and male students.[51]

In panel C and D, I conduct similar analyses as in panel B, but splitting observations by field of study and nationality, respectively. The results in panel C show that independent of the field of study, there is no significant difference in the fraction of money allocated between female- and male-managed funds. The same results apply in panel D, where Scandinavian students and students with other nationalities are analyzed separately. My findings from panel B, C and D suggest no difference in investment behavior between the subject

[49] In Table 8, only the investments in fund A is compared between funds. Meaning that column 1 report investments in fund A by subjects in group X, while column 2 reports investments in fund A by subjects in group Y. Hence, the fractions presented in column 1 and 2 do not add up to 100. However, the conclusion would have remained the same if instead comparing investments in fund B.

[50] I conduct a two-sample z-test for comparing two sample proportions.

[51] Although the differences presented in panel B, column 3 seem large in magnitude, when the sample is small, the p-value is above the significance level even for greater differences.

characteristics. Moreover, they support the main finding from panel A, namely that the fraction invested in fund A does not significantly differ between group X and Y.

Overall, my experimental evidence confirms the empirical evidence presented in section 6.2. As opposed to Niessen and Niessen-Ruenzi (2013), who finds evidence in both the empirical and experimental analysis supporting their presumption that investors prefer male-managed funds, I fail to reject equality in both analyses. However, as the subjects in my experiment represent only a small fraction of the Scandinavian population, as well as group X and Y being of different size, I cannot make any broader inference based on my results. Nevertheless, the observed pattern from the investment task indicates that Scandinavian investors are less sensitive to the fund manager's gender when making investment decisions. Based on this, in addition to my findings from the empirical analysis, I conclude that there exist differences between the U.S. and the Scandinavian mutual fund market; While investors in the U.S. presumably prefer male-managers, the Scandinavian investor do not seem to have the same aversion against female managers. In light of the previously discussed findings by Ferreira et al. (2012), it seems plausible that Scandinavian investors behave differently than U.S. investors.

8. Conclusions and Final Discussion

In this study, I examine two different aspects of the mutual fund industry. My first two hypotheses relate to the well-documented flow-performance relationship, while my third hypothesis relates to a relatively unexplored field of social biases in investment decisions. In this final section, I answer my three hypotheses and present some related findings. Finally, I briefly address the impact of my findings in a broader context. I specifically discuss the second part of my study, as this phenomenon is subject to confounding explanations.

Hypothesis 1 & 2: *Scandinavian investors chase past returns, but the relationship is not convex.*

While my findings clearly support the presence of a general positive linear relationship between mutual fund flows and past performance, I find no evidence of a non-linear relationship in Scandinavia. This indicates that Scandinavian investors do not disproportionately flock around top performing funds. My findings are in line with Ferreira et al. (2012), and suggest that there are differences in the flow-performance relationship between the U.S. and Scandinavian markets. If convexity declines for countries with high education levels and well informed investors, these differences are likely to be explained by the high level of investor sophistication and low participation costs in Scandinavia.

Hypothesis 3: *Scandinavian investors do not seem to care about the fund manager's gender.*

As opposed to the study addressing differences in flows between female and male-managed funds in the U.S., I find no significant evidence that mutual fund investors prefer male managers. This empirical finding is robust to a range of model specifications. Again my conclusion implies a major difference between Scandinavia and the U.S., this time regarding differences in investor behavior. Since the Scandinavian countries are at the forefront of gender equality compared to other countries, these results are not surprising.

The results from my experimental analysis confirm my empirical evidence. There is no significant difference in the fraction of money invested in female- and male-managed funds between the two groups of students. Neither do I observe differences in investment behavior between various subject characteristics, such as gender, field of study and nationality. Hence, I find no evidence of gender bias when subjects participating in my experiment are making investment decisions. These findings differ significantly from a similar experiment conducted by Niessen and Niessen-Ruenzi (2013) on U.S. students, which documents strong gender bias among participants, particularly among males.

Overall, my results from both the empirical and the experimental analysis suggest that Scandinavian investors are insensitive to the fund manager's gender when "shopping" for mutual funds.

As my literature review points out, female participation in the business world is proven to be beneficial for companies, investors as well as other stakeholders. However, women are still outnumbered by men in management positions – even in the countries where gender equality has made most progress. This phenomenon has captured the attention of many researchers attempting to find solutions to the low female participation. As mentioned earlier, the literature proposes several reasons for why there are so few women in certain industries. Niessen and Niessen-Ruenzi (2013) in particular suggest that it is due to customer-based discrimination, and propose that their study provide a possible new explanation for the low fraction of female mutual fund managers. With my study, I aim to shed light on social biases and gender prejudice in the mutual fund industry in Scandinavia. As opposed to Niessen and Niessen-Ruenzi (2013), I find no evidence of gender bias among the Scandinavian investors. Hence, the low fraction of female fund managers in Scandinavia does not seem to be directly caused by differences in inflow between female- and male-managed funds.

So what is the reason why we observe so few female mutual fund managers in Scandinavia? Do fund companies discriminate against women when hiring new managers? Or do women self-select away from this profession? A third phenomenon proposed in the U.S. literature is that the female gender in general lack certain psychological and personality traits that are seen as essential factors to succeed in some businesses. Do these explanations hold for countries beyond the U.S.? This may be the case, but fundamental differences between the world's nations seem evident. For further research on gender biases in the Scandinavian mutual fund industry, it would be interesting to investigate these questions in more detail.

Overall, my study reveals prominent characteristics of the Scandinavian mutual fund industry that significantly differs from what is documented in the U.S. literature. Considering the apparently major differences between countries, both when it comes to mutual fund investment behavior in general and regarding the attitude towards female managers in particular, I believe country-specific research on mutual funds should receive more attention.

9. Appendix

Appendix A: Variable Definitions and Data Sources

This table presents an overview of all variables used in the empirical analyses, both in the monthly and yearly regressions. The variable name is reported in column 1, followed by a brief description of the monthly (yearly) variable in column 2. Column 3 presents the data sources of the variable. My main data source is Morningstar Direct, but I also estimate some variables based on the data obtained from Morningstar Direct. Moreover, I use fund companies' websites to obtain the fund's expense ratios when these are missing in Morningstar Direct. Panel A presents the measures of fund flows. Net fund flows is used as dependent variable in all the base regression models, while absolute fund flows is used as an alternative measure of flows in two of the monthly robustness tests. Panel B reports the various performance measures used as explanatory variables in the different model specifications. In panel C, I present the rest of the independent variables used in my regression models, both those used in the base regressions and those added to explore the robustness of my initial results.

Variable Name (1)	Description (2)	Source (3)
Panel A: Measures of Fund Flows – The Dependent Variable		
$FundFlow_{i,t}$	Net fund flows is computed as $FundFlows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \cdot (1+FundReturn_{i,t})}{TNA_{i,t-1}}$, where TNA is fund *i*'s total net assets at the end of month (year) *t*, and FundReturn denotes fund *i*'s raw return in month (year) *t*.	Morningstar Direct, Estimated
$AbsFundFlow_{i,t}$	Absolute fund flows is computed as $AbsFundFlow_{i,t} = TNA_{i,t} - TNA_{i,t-1} \cdot \left(1 + FundReturn_{i,t}\right)$, and is measured in million NOK.	Morningstar Direct, Estimated
Panel B: Measures of Fund Performance – Explanatory Variable		
$FundReturn_{i,t}$	Fund return is fund *i*'s monthly (yearly) return	Morningstar Direct
$Alpha_{i,t}$	Calculation of Jensen's Alpha (one-factor alpha, $\alpha_{i,t}$) in year *t* is based on least square regression of fund *i*'s monthly return over the appropriate market portfolio, R_m as well as fund *i*'s benchmark index, R_f. $Jensen's\ Alpha_A = \alpha_{i,t} = R_i - \left(R_f + \beta_i(R_m - R_f)\right)$.	Morningstar Direct
$Sharpe_{i,t}$	The Sharpe Ratio in year *t* is calculated as the average annualized excess return of fund *i* based the past 36-month period over fund *i*'s annualized standard deviation: $Sharpe\ Ratio_A = Sharpe_{i,t} = \frac{R_i - R_f}{\sigma_A^e}$. R_f represents the risk free benchmark suitable to fund *i*.	Morningstar Direct
$Low_{i,t}$	The bottom quintile in the piecewise-linear regression (PLR), estimated as $Low_{i,t} = Min(Rank_{i,t}, 0.20)$, where $Rank_{i,t}$ denotes fund *i*'s fractional rank in month *t* among the funds in the same equity segment.	Morningstar Direct, Estimated
$Mid_{i,t}$	The three middle quintiles in the piecewise-linear regression, estimated as $Mid_{i,t} = Min(Rank_{i,t} - Low_{i,t}, 0.60)$, where $Rank_{i,t}$ denotes fund *i*'s fractional rank in month *t* among the funds in the same equity segment.	Morningstar Direct, Estimated
$High_{i,t}$	The upper quintile in the piecewise-linear regression, estimated as $High_{i,t} = Min(Rank_{i,t} - Mid_{i,t} - Low_{i,t})$, where $Rank_{i,t}$ denotes fund *i*'s fractional rank in month *t* among the funds in the same equity segment.	Morningstar Direct, Estimated

Panel C: Other Explanatory Variables

$Female_{i,t}$	$Female_{i,t}$ is a dummy variable that equals one if the manager of fund *i* in month (year) *t* is a woman, and zero otherwise.	Morningstar Direct, Estimated
$FundReturnXFemale_{i,t}$	This variable is an interaction term between lagged fund return and the female dummy variable, and is calculated as $FundReturn_{i,t} \cdot Female_{i,t}$.	Morningstar Direct, Estimated
$FundAge_{i,t}$	Fund age is estimated by taking the natural logarithm of fund i's age in months (years) pluss one: $FundAge_{i,t} = \ln{(Age_{i,t} + 1)}$	Morningstar Direct, Estimated
$FundSize_{i,t}$	Fund size is estimated by taking the natural logarithm of fund *i*'s TNA in month (year) *t*: $FundSize_{i,t} = \ln{(TNA_{i,t} + 1)}$. The variable is measured in million NOK.	Morningstar Direct, Estimated
$ExpRatio_{i,t}$	A fund's expense ratio is obtained from Morningstar Direct as well as from Fund Companies' Annual Reports on an annual basis. In the monthly sample, fund i's expense ratio in year *t* is divided by 12.	Morningstar Direct, Fund Annual Reports
$FundRisk_{i,t}$	Monthly fund risk is measured as fund *i*'s monthly return standard deviation, while yearly fund risk is measured by the annualized monthly return standard deviation of fund *i* in year *t*.	Morningstar Direct, Estimated
$LowXFemale_{i,t}$	This variable is an interaction term between the PLR variable Low and the female dummy variable for fund *i* in month *t*, and is calculated as $Low_{i,t} \cdot Female_{i,t}$.	Morningstar Direct, Estimated
$MidXFemale_{i,t}$	This variable is an interaction term between the PLR variable Mid and the female dummy variable for fund *i* in month *t*, and is calculated as $Mid_{i,t} \cdot Female_{i,t}$.	Morningstar Direct, Estimated
$HighXFemale_{i,t}$	This variable is an interaction term between the PLR variable High and the female dummy variable for fund *i* in month *t*, and is calculated as $High_{i,t} \cdot Female_{i,t}$.	Morningstar Direct, Estimated
$AlphaXFemale_{i,t}$	This variable is an interaction term between the risk adjusted performance measure Jensen's Alpha and the female dummy variable for fund *i* in year *t*, and is calculated as $Alpha_{i,t} \cdot Female_{i,t}$.	Morningstar Direct, Estimated
$SharpeXFemale_{i,t}$	This variable is an interaction term between the risk adjusted performance measure Sharpe Ratio and the female dummy variable for fund *i* in year *t*, and is calculated as $Sharpe_{i,t} \cdot Female_{i,t}$.	Morningstar Direct, Estimated
$FundSize^2_{i,t}$	Squared fund size is estimated by taking the natural logarithm of fund i's TNA in month *t* to the power of two: $FundSize^2_{i,t-1} = (\ln(TNA_{i,t} + 1))^2$.	Morningstar Direct, Estimated
$FundSize^3_{i,t}$	Cubed fund size is estimated by taking the natural logarithm of fund *i*'s TNA in month *t* to the power of three: $FundSize^3_{i,t-1} = (\ln(TNA_{i,t} + 1))^3$.	Morningstar Direct, Estimated

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Table 1: Descriptive Statistics

	Panel A		**Monthly Sample**				**Panel B**		**Yearly Sample**			
	Mean	Median	SD	p1	p99	N	Mean	Median	SD	p1	p99	N
	(1)	**(2)**	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(2)**	**(3)**	**(4)**	**(5)**
$FundFlow_{i,t}$	0.005	-0.001	0.062	-0.212	0.336	31971	0.105	-0.021	0.536	-0.749	3.062	2645
$Female_{i,t}$	0.106	0.000	0.308	0.000	1.000	31971	0.104	0.000	0.305	0.000	1.000	2645
$AbsFundFlow_{i,t}$	2.51	-0.27	170.68	-278.58	321.15	31971	23.02	-5.90	659.86	-1675.47	1944.15	2645
$FundReturn_{i,t}$	0.008	0.011	0.052	-0.145	0.133	31971	0.112	0.136	0.254	-0.539	0.707	2645
$FundSize_{i,t}$	1659.2	584.8	5671.2	11.513	12751.6	31971	1787.4	631.8	6510.7	13.471	13365.4	2645
$FundRisk_{i,t}$	0.045	0.040	0.020	0.016	0.110	31971	0.157	0.140	0.071	0.054	0.384	2645
$ExpRatio_{i,t}$	0.001	0.001	0.000	0.000	0.002	31971	0.015	0.015	0.006	0.002	0.029	2645
$FundAge_{i,t}$	140.484	129.000	95.288	4.000	407.000	31971	11.949	11.000	7.786	1.000	34.000	2645
$Alpha_{i,t}$							-0.002	-0.002	0.077	-0.216	0.224	2645
$Sharpe_{i,t}$							0.453	0.680	1.232	-2.170	2.970	2645

Table 1: continued

Panel C	**Monthly Sample**		
	Female	Male	Difference
	(1)	**(2)**	**(3)**
$FundFlow_{i,t}$	0.0007	0.0052	-0.0046
$AbsFundFlow_{i,t}$	-2.665	3.119	-5.784
$FundReturn_{i,t}$	0.007	0.008	-0.0005
$FundSize_{i,t}$	1491.78	1679.03	-187.25
$FundRisk_{i,t}$	0.045	0.045	0.000
$ExpRatio_{i,t}$	0.001	0.001	0.000
$FundAge_{i,t}$	156.302	138.613	17.688

This table presents summary statistics of the different fund characteristics used in my analyses. A more detailed description of the variables are presented in Appendix A. Column 1-5 in panel A and B report means, medians, standard deviations (SD), bottom percentile (p1), upper percentile (p99) and the number of observations (N). The variables are based on my sample of single-managed Scandinavian equity funds form January 2005 to December 2014. In panel C, column 1 and 2, the mean of all characteristics are presented for female- and male-managed funds respectively. Column 3 shows the difference between the average characteristics in column 1 and 2.

Table 2: Flow-Performance Relationship (monthly sample)

	No lagged DV	Include lagged DV	Performance Quintiles
	(1)	(2)	(3)
$FundReturn_{i,t-1}$	0.181***	0.155***	
	(9.70)	(9.54)	
$FundFlow_{i,t-1}$		0.166***	0.166***
		(9.31)	(9.26)
$Low_{i,t-1}$			0.032**
			(3.16)
$Mid_{i,t-1}$			0.009***
			(4.70)
$High_{i,t-1}$			0.041***
			(4.46)
$FundAge_{i,t-1}$	-0.023***	-0.017***	-0.017***
	(-8.36)	(-7.62)	(-7.51)
$FundSize_{i,t-1}$	-0.013***	-0.014***	-0.014***
	(-7.86)	(-9.42)	(-9.41)
$ExpRatio_{i,t-1}$	-3.276	-3.025	-3.097
	(-1.41)	(-1.53)	(-1.59)
$FundRisk_{i,t-1}$	0.107*	0.081+	0.071
	(2.00)	(1.78)	(1.60)
$Constant_{i,t}$	0.202***	0.179***	0.175***
	(10.50)	(11.11)	(10.76)
Fund fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Adjusted R-squared	0.113	0.139	0.138
Number of observations	31550	31550	31243
Wald test High = Low, p-value			0.4886

Table 2: continued

This table presents the results of three panel regressions where net fund flows, $FundFlow_{i,t}$, is regressed on lagged performance and various other fund characteristics as controls, using a monthly sample of single-managed Scandinavian equity funds. Pooled OLS regression is used to estimate the coefficients of the independent variables. The dependent variable, $FundFlow_{i,t}$, is defined as $\frac{TNA_{i,t}-TNA_{i,t-1}\cdot(1+FundReturn_{i,t})}{TNA_{i,t-1}}$, where $TNA_{i,t}$ is fund i's total net assets at time *t*. $FundReturn_{i,t-1}$ denotes fund i's lagged raw return. $FundFlow_{i,t-1}$ represents fund i's previous month's net fund flow. $FundAge_{i,t-1}$ is the lagged natural logarithm of fund i's age in months, and $FundSize_{i,t-1}$ is the lagged natural logarithm of a fund's size in million NOK. $ExpRatio_{i,t-1}$ is fund i's lagged expense ratio, and finally $FundRisk_{i,t-1}$ is the lagged return standard deviation of fund i. Column 1 reports results with the lagged dependent variable excluded from the regression, while column 2 presents my base regression including lagged net fund flow. In column 3 I apply a piecewise linear regression in order to investigate the non-linearity of the flow-performance relationship, where three different linear segments in the flow-performance relationship are defined. In each month, by equity segment, each fund is assigned a fractional performance rank, ranging from zero to one, based on the funds' raw return in the preceding month. The performance ranks are divided into three segments, represented by the three variables $Low_{i,t-1}$, $Mid_{i,t-1}$ and $High_{i,t-1}$. The performance segment (Low) represents the lowest performance quintile and is defined as $Min(Rank_{i,t-1}, 0.20)$, the combined group of the middle three performance quintiles (Mid) is defined as $Min(Rank_i - Low_{i-t}, 0.60)$, while the third segment (High) represents the upper performance quintile and is defined as $Min(Rank_i - Mid_{i-1} - Low_{i-1})$. All regressions are estimated with robust standard errors clustered at the fund level, as well as with time and fund fixed effects. In column 3, the last row reports the p-value from a Wald test of equality between the coefficients of the top and bottom performance quintile in the regression. t-statistics are in parenthesis, and +, *, **, *** indicate significance level 10%, 5%, 1% and 0.1% respectively.

Table 3: Flow-Performance Relationship (yearly sample)

	No lagged DV	Include lagged DV	Alpha	Sharpe Ratio
	(1)	(2)	(3)	(4)
$FundReturn_{i,t-1}$	0.288***	0.271***		
	(4.06)	(3.80)		
$FundFlow_{i,t-1}$		0.042	0.050	0.036
		(1.09)	(1.42)	(0.92)
$Alpha_{i,t-1}$			0.208+	
			(1.79)	
$Sharpe_{i,t-1}$				0.093***
				(4.65)
$FundAge_{i,t-1}$	-0.203*	-0.168+	-0.166*	-0.179*
	(-2.40)	(-1.93)	(-2.06)	(-2.06)
$FundSize_{i,t-1}$	-0.351***	-0.361***	-0.350***	-0.366***
	(-8.48)	(-8.58)	(-9.18)	(-8.66)
$ExpRatio_{i,t-1}$	0.862	0.961	0.651	1.014
	(0.25)	(0.26)	(0.18)	(0.28)
$FundRisk_{i,t-1}$	-0.084	-0.134	-0.229	-0.136
	(-0.29)	(-0.44)	(-0.83)	(-0.45)
$Constant_{i,t}$	2.796***	2.780***	2.680***	2.796***
	(7.59)	(7.70)	(8.77)	(7.75)
Fund fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.286	0.287	0.281	0.294
Number of observations	2231	2231	2231	2231

This table reports the results of four regressions on a yearly sample of single-managed Scandinavian equity funds, conducted in order to explore the robustness of my monthly base regression in Table 2 column 2. The yearly regressions have similar specification as the monthly baseline specification in Table 2 column 2, except that raw return is being replaced by alternative performance measures in column 3 and 4. Column 1 reports yearly results with the lagged dependent variable excluded from the regression, while column 2 presents my yearly base regression including lagged net fund flow. In column 3, lagged fund return is replaced by the lagged one factor Alpha, $Alpha_{i,t-1}$, measuring a fund's average excess return above what can be obtained from holding a position in the market portfolio. In column 4, I replace lagged raw return with lagged Sharpe Ratio, which measures the average excess return per unit of risk based on the past 36 months period. All regressions are estimated with robust standard errors clustered at the fund level, as well as with time and fund fixed effects. t-statistics are in parenthesis, and +, *, **, *** indicate significance level 10%, 5%, 1% and 0.1% respectively.

Table 4: Fund Flows and Manager Gender (monthly sample)

	Exclude lagged DV (1)	Include lagged DV (2)	Performance Interaction (3)	Performance Quintiles (4)	Performance Quintiles & PI (5)	Size (6)	Month Cluster (7)	Scandinavian Equity (8)
$Female_{i,t}$	-0.002	-0.002	-0.002	-0.002	0.001	-0.002	-0.002	0.002
	(-1.01)	(-1.06)	(-1.06)	(-1.06)	(0.12)	(-0.96)	(-1.44)	(0.78)
$FundFlow_{i,t-1}$		0.166***	0.166***	0.166***	0.166***	0.165***	0.166***	0.117*
		(9.31)	(9.31)	(9.26)	(9.27)	(9.27)	(11.35)	(2.32)
$FundReturn_{i,t-1}$	0.181***	0.155***	0.155***			0.155***	0.155***	0.181***
	(9.71)	(9.54)	(9.40)			(9.52)	(6.88)	(5.17)
$Low_{i,t-1}$				0.032**	0.033**			
				(3.16)	(3.02)			
$Mid_{i,t-1}$				0.009***	0.010***			
				(4.69)	(4.67)			
$High_{i,t-1}$				0.041***	0.040***			
				(4.46)	(4.02)			
$FundAge_{i,t-1}$	-0.023***	-0.017***	-0.017***	-0.017***	-0.017***	-0.016***	-0.017***	-0.013*
	(-8.35)	(-7.61)	(-7.61)	(-7.50)	(-7.50)	(-7.51)	(-10.57)	(-2.20)
$FundSize_{i,t-1}$	-0.013***	-0.014***	-0.014***	-0.014***	-0.014***	-0.062***	-0.014***	-0.015***
	(-7.86)	(-9.42)	(-9.43)	(-9.42)	(-9.42)	(-3.77)	(-12.66)	(-4.81)
$ExpRatio_{i,t-1}$	-3.209	-2.963	-2.961	-3.035	-3.016	-3.422+	-2.963+	5.406
	(-1.38)	(-1.50)	(-1.49)	(-1.55)	(-1.54)	(-1.75)	(-1.66)	(0.45)
$FundRisk_{i,t-1}$	0.107*	0.082+	0.082+	0.071	0.071	0.083+	0.082	0.057
	(2.00)	(1.79)	(1.79)	(1.60)	(1.60)	(1.85)	(1.56)	(0.63)
$FundReturnXFemale_{i,t-1}$			-0.001					
			(-0.06)					
$LowXFemale_{i,t-1}$					-0.006			
					(-0.27)			
$MidXFemale_{i,t-1}$					-0.006			
					(-1.12)			
$HighXFemale_{i,t-1}$					0.012			
					(0.49)			
$FundSize^2_{i,t-1}$						0.007*		
						(2.55)		
$FundSize^3_{i,t-1}$						-0.000*		
						(-2.10)		
$Constant_{i,t}$	0.178***	0.179***	0.179***	0.175***	0.175***	0.274***	0.179***	0.148***
	(10.50)	(11.10)	(11.11)	(10.76)	(10.75)	(8.06)	(16.21)	(3.73)
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.113	0.139	0.139	0.138	0.138	0.140	0.139	0.101
Number of observations	31550	31550	31550	31243	31244	31550	31550	7812
Wald test High = Low, p-value				0.4880	0.6300			

Table 4: continued

This table presents the coefficient estimates of net fund flows, $FundFlow_{i,t}$, regressed on a female manager dummy, $Female_{i,t}$, as well as past performance and various other fund characteristics as controls. The regressions in column 1-3 and 6-8 are expanded versions of my base regression in Table 2, column 2, while regressions in column 4 and 5 are based on the piecewise-linear regression approach, similar to the regression in Table 2, column 3. As in Table 2, the models presented in this table are conducted using pooled OLS regressions on a monthly sample of single-managed Scandinavian equity funds, with equivalent definitions of $FundFlow_{i,t}$, $FundReturn_{i,t-1}$, $FundFlow_{i,t-1}$, $FundAge_{i,t-1}$, $FundSize_{i,t-1}$, $ExpRatio_{i,t-1}$ and $FundRisk_{i,t-1}$. $Female_{i,t}$ is a dummy variable that equals one if fund *i* is managed by a female manager in month *t,* and zero otherwise. Column 1 reports results with the lagged dependent variable excluded from the regression, while column 2 presents results including lagged net fund flow. In column 3, I interact the female dummy variable with lagged fund return. Column 4 and 5 show the piecewise-linear regression approach, where the three variables $Low_{i,t-1}$ ($\mathrm{Min(Rank_{i,t-1}, 0.20)}$), $Mid_{i,t-1}$ ($\mathrm{Min(Rank_{i} - Low_{i-t}, 0.60)}$) and $High_{i,t-1}$ ($\mathrm{Min(Rank_{i} - Mid_{i-1} - Low_{i-1})}$) represent three different linear segments in the flow-performance relationship, as described in Table 2. In column 5, I interact the female dummy variable with each of the three performance segments. In column 9, I include fund size to the power of two and three to control for a possible non-linear impact of size. In column 7, standard errors are clustered on the month level instead of at the fund level. Finally, column 8 presents results from a subsample of funds investing in Scandinavian equities only. All regressions (except in column 7) are estimated with standard errors clustered at the fund level. Time and fund fixed effects are included in all models. In column 4 and 5, the very last row presents the p-values from Wald tests of equality between the coefficients of the top and bottom performance quintile in the regressions. t-statistics are in parenthesis, and +, *, **, *** indicate significance level 10%, 5%, 1% and 0.1% respectively.

Table 5: Robustness (monthly sample)

	Absolute Fund Flows	Absolute Fund Flows & PI	From Year 2010 to 2014	From Year 2005 to 2009	Complete Series of Data	Norway	Sweden	Denmark
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Female_{i,t}$	-1.170	-1.120	-0.001	0.003	-0.003	-0.007	-0.001	-0.012+
	(-0.56)	(-0.54)	(-0.49)	(0.88)	(-0.91)	(-1.26)	(-0.25)	(-1.71)
$AbsFundFlow_{i,t-1}$	0.175***	0.175***						
	(6.18)	(6.18)						
$FundFlow_{i,t-1}$			0.145***	0.148***	0.187***	0.122*	0.145***	0.219***
			(8.49)	(4.62)	(7.72)	(2.62)	(7.28)	(11.27)
$FundReturn_{i,t-1}$	163.422***	164.165***	0.201***	0.114***	0.138***	0.125***	0.277***	0.062***
	(8.21)	(8.14)	(8.38)	(6.08)	(7.11)	(3.67)	(10.03)	(3.59)
$FundAge_{i,t-1}$	-0.556	-0.558	-0.017***	-0.019***	-0.017***	-0.023***	-0.022***	-0.010***
	(-0.25)	(-0.25)	(-4.20)	(-4.75)	(-7.06)	(-3.54)	(-4.01)	(-4.80)
$FundSize_{i,t-1}$	-3.528**	-3.527**	-0.018***	-0.025***	-0.015***	-0.019***	-0.015***	-0.009***
	(-2.83)	(-2.83)	(-7.45)	(-7.41)	(-8.13)	(-5.67)	(-5.73)	(-5.07)
$ExpRatio_{i,t-1}$	-4710.782**	-4699.153**	-2.505	-7.880	-1.161	-1.553	-2.499	-9.115*
	(-2.80)	(-2.79)	(-0.83)	(-1.61)	(-0.34)	(-0.60)	(-0.59)	(-2.02)
$FundRisk_{i,t-1}$	87.502+	87.290+	0.025	0.068	0.121*	0.233**	0.138	-0.039
	(1.92)	(1.92)	(0.30)	(1.03)	(2.11)	(2.73)	(1.47)	(-0.50)
$FundReturnXFemale_{i,t-1}$		-7.924	0.016	-0.010	0.008	0.004	-0.011	0.007
		(-0.31)	(0.60)	(-0.31)	(0.23)	(0.08)	(-0.31)	(0.16)
$Constant_{i,t}$	26.095+	26.081+	0.204***	0.270***	0.182***	0.218***	0.219***	0.117***
	(1.80)	(1.80)	(9.17)	(9.18)	(9.54)	(6.28)	(5.65)	(6.22)
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.116	0.116	0.133	0.185	0.155	0.152	0.135	0.187
Number of observations	31550	31550	19582	11968	21012	7721	13280	10549
Female-managed fund months	10.58 %	10.58 %	9.81 %	11.80 %	10.34 %	8.67 %	13.50 %	8.27 %

Table 5: continued

In this table, all coefficients are estimated using the similar regression approach as well as the same base specifications as in Table 4, column 2. In column 1 and 2, the dependent variable net flow is replaced by the absolute fund flows from the preceding month, $AbsFundFlow_{i,t}$, measured in million NOK. Moreover, the lagged dependent variable, $AbsFundFlow_{i,t-1}$, is also included in absolute terms. In column 2, I include the interaction term of the female dummy variable and lagged returns. Results in column 3 and 4 are based on subsamples of funds, where in column 3, the five most recent years from 2010 to 2014 are included, while results from the first five years, from 2005 to 2009, are presented in column 4. Column 5 presents results based on a subsample of funds with complete data series only. Finally, in order to control for potential individual differences between the Scandinavian countries, column 6-8 present results for Norwegian, Swedish and Danish funds respectively. All regressions have standard errors clustered at the fund level, as well as fund and time fixed effects. The last row of column 3-8 show the fraction of female managed fund months in each of the subsamples analyzed. In column 1 and 2, this fraction represents the female managed fund months for the full sample. t-statistics are in parenthesis, and +, *, **, *** indicate significance level 10%, 5%, 1% and 0.1% respectively.

Table 6: Fund Flows and Manager Gender (yearly sample)

	Raw Return (1)	Raw Return & PI (2)	Alpha & PI (3)	Sharpe & PI (4)
$Female_{i,t}$	-0.025	-0.028	-0.033	-0.022
	(-0.48)	(-0.50)	(-0.63)	(-0.41)
$FundFlow_{i,t-1}$	0.042	0.042	0.050	0.036
	(1.09)	(1.09)	(1.29)	(0.92)
$FundReturn_{i,t-1}$	0.270***	0.268***		
	(3.79)	(3.76)		
$Alpha_{i,t-1}$			0.207+	
			(1.73)	
$Sharpe_{i,t-1}$				0.092***
				(4.61)
$FundAge_{i,t-1}$	-0.169+	-0.168+	-0.166+	-0.179*
	(-1.93)	(-1.93)	(-1.88)	(-2.05)
$FundSize_{i,t-1}$	-0.361***	-0.361***	-0.350***	-0.366***
	(-8.57)	(-8.55)	(-8.32)	(-8.63)
$ExpRatio_{i,t-1}$	0.861	0.822	0.523	0.902
	(0.24)	(0.23)	(0.13)	(0.25)
$FundRisk_{i,t-1}$	-0.133	-0.13	-0.228	-0.134
	(-0.44)	(-0.42)	(-0.75)	(-0.44)
$FundReturnXFemale_{i,t-1}$		0.041		
		(0.32)		
$AlphaXFemale_{i,t-1}$			0.024	
			(0.06)	
$SharpeXFemale_{i,t-1}$				0.008
				(0.34)
$Constant_{i,t}$	2.785***	2.785***	2.802***	2.800***
	(7.66)	(7.66)	(7.60)	(7.72)
Fund fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.287	0.287	0.281	0.293
Number of observations	2231	2231	2231	2231

This table provides yearly regression results conducted in order to explore the robustness of my monthly regression in Table 4, column 2. All yearly regressions use similar specification as the monthly baseline specification in Table 4 column 2, except that raw return is being replaced by alternative performance measures in column 3 and 4. Column 1 and 2 reports yearly results with raw return as performance measure. In column 2, I have included the interaction term of the female dummy variable and past return. In column 3, lagged fund return is replaced by the lagged one factor Alpha, $Alpha_{i,t-1}$, while in column 4, I use Sharpe Ratio, $Sharpe_{i,t-1}$ as performance measure. In both column 3 and 4, I interact the female dummy variable with the performance measure. All regressions are estimated with robust standard errors clustered at the fund level, as well as with time and fund fixed effects. t-statistics are in parenthesis, and +, *, **, *** indicate significance level 10%, 5%, 1% and 0.1% respectively.

Table 7: Demographic Characteristics of Subjects

Panel A: All participating students		Number	Percentage
i) Gender	Female	30	40 %
	Male	45	60 %
ii) Age	≤21	3	4 %
	22	6	8 %
	23	20	26 %
	24	25	33 %
	25	9	12 %
	26	6	8 %
	≥ 27	6	8 %
	Average age	24.2	
iii) Nationality	NOR/SWE/DAN	61	81 %
	Other	14	19 %
iv) Field of study	Finance	34	45 %
	Other	27	55 %
Total subjects		75	100 %

Panel B: Group level characteristics		Group X		Group Y	
		N	*%*	*N*	*%*
i) Gender	Female	20	35 %	10	56 %
	Male	37	65 %	8	44 %
ii) Age	< 21	3	5 %	0	0 %
	22	4	7 %	2	11 %
	23	16	28 %	4	22 %
	24	20	35 %	5	28 %
	25	7	12 %	2	11 %
	26	4	7 %	2	11 %
	> 27	3	5 %	3	17 %
	Average age	24.0		24.8	
iii) Nationality	NOR/SWE/DAN	46	81 %	15	83 %
	Other	11	19 %	3	17 %
iv) Field of study	Finance	26	46 %	8	44 %
	Other	31	54 %	10	56 %
Total subjects		57	100 %	18	100 %

This table presents an overview of the demographic characteristics of the students participating in the investment experiment. Panel A shows characteristics for all subjects all together, while panel B displays characteristics for group X and Y separately. In each panel, field *i* to *iv* present the number and percentages of subjects in the different categories within the four characteristics; gender, age, nationality and field of study. The "other" category in field *iv* include Economics, International Business, Strategy and Management or other master profiles offered at NHH (see figure 3). Both panels also include the total subjects and the mean age.

Table 8: Investment Decisions

	Group X: Female Manager of fund A	Group Y: Male Manager of Fund A	Difference (1) - (2)	Observations	
	% Invested into fund A			*Group X*	*Group Y*
	(1)	(2)	(3)	(4)	(5)
Panel A: All Subjects	31.88	34.17	-2.29	57	18
			(-0.2)		
Panel B: Gender					
Females	48.5	20.50	28.00	20	10
			(1.5)		
Males	22.89	51.25	-28.36	37	8
			(-1.6)		
Panel C: Field of Study					
Finance	28.73	31.88	-3.14	26	8
			(-0.2)		
Other	34.52	36.00	-1.48	31	10
			(-0.1)		
Panel D: Nationality					
Scandinavian	28.15	30.33	-2.18	46	11
(NOR/SWE/DAN)			(-0.1)		
Other	47.45	53.33	-5.88	15	3
			(-0.2)		

This table displays the fraction of money invested in fund A by group X (column 1) and group Y (column 2) in my investment experiment. Since group X observed a female manager for fund A, while group Y observed a male manager for fund A, column 1 represent the fraction that group X invested in the female-managed fund, and column 2 represent the fraction that group Y invested in the male-managed fund. The difference between the amount invested in the female- and male- managed fund is presented in column 3. In column 4 and 5 the number of observations in each group are presented. Panel B report results comparing investments by gender in each group. Panel C shows investments by students having finance as their main field of study compared to students with other main fields of study. Finally, panel D compare investments of Scandinavian students and students with other nationalities. z-statistics are in parentheses (column 3), and +, *, **, *** indicate significance level 10%, 5%, 1% and 0.1% respectively. (But none of the differences are significant.)

Figure 1: Number of Funds per Year by Manager Gender

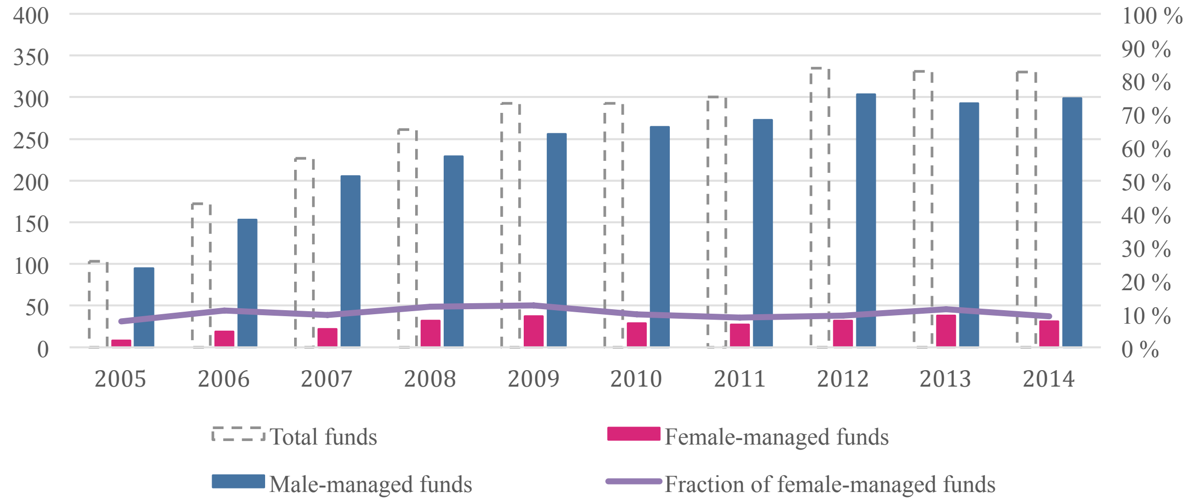

Figure 1 presents the total number of female-managed funds (pink bars) and male-managed funds (blue bars) per year over my sample period from January 2005 to December 2014. The dotted grey bars illustrate the number of funds per year in total, while the purple line shows the fraction of female managed funds over the period. The sample consists of both surviving and closed funds.

Figure 2: Fund Months per Year by Manager Gender

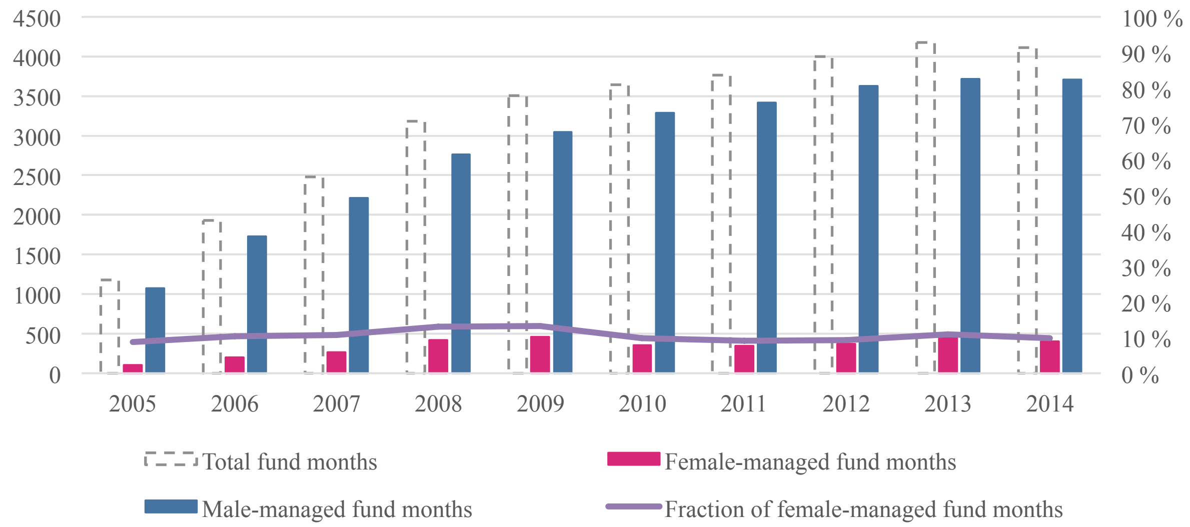

Figure 2 presents the total number of female-managed fund months (pink bars) and male-managed fund months (blue bars) per year over my sample period from January 2005 to December 2014. The dotted grey bars illustrate the number of fund months per year in total, while the purple line shows the fraction of female managed fund months over the period. The sample consists of both surviving and closed funds.

Figure 3: Investment Experiment - Information Provided to The Students

Panel A: Group X

	Fund A	Fund B
Fund Segment **Fund Manager**	OSEBX Index Fund Lise Nilsen	OSEBX Index Fund Kristian Olsen
About the Fund		
Size	NOK 196.9 Million	NOK 200.2 Million
Inception Date	18.11.99	14.12.96
Annual Expense Ratio	0.62 %	0.58 %
Trading Activity (Annual Turnover Ratio)	3.05 %	2.96 %
Fund Facts	The investment seeks to replicate the total return of the Oslo Stock Exchange, before fees and expenses. The fund invests primarily in common stocks issued by companies that are listed on the Oslo Stock Exchange.	The investment seeks to replicate the total return of the Oslo Stock Exchange, before fees and expenses. The fund invests primarily in common stocks issued by companies that are listed on the Oslo Stock Exchange.
Top Five Stock Holdings		
1	Statoil	Statoil
2	Norsk Hydro	Norsk Hydro
3	Telenor	Telenor
4	DNB	DNB
5	Marine Harvest	Marine Harvest

Panel B: Group Y

	Fund A	Fund B
Fund Segment **Fund Manager**	OSEBX Index Fund Kristian Olsen	OSEBX Index Fund Lise Nilsen
About the Fund		
Size	NOK 196.9 Million	NOK 200.2 Million
Inception Date	18.11.99	14.12.96
Annual Expense Ratio	0.62 %	0.58 %
Trading Activity (Annual Turnover Ratio)	3.05 %	2.96 %
Fund Facts	The investment seeks to replicate the total return of the Oslo Stock Exchange, before fees and expenses. The fund invests primarily in common stocks issued by companies that are listed on the Oslo Stock Exchange.	The investment seeks to replicate the total return of the Oslo Stock Exchange, before fees and expenses. The fund invests primarily in common stocks issued by companies that are listed on the Oslo Stock Exchange.
Top Five Stock Holdings		
1	Statoil	Statoil
2	Norsk Hydro	Norsk Hydro
3	Telenor	Telenor
4	DNB	DNB
5	Marine Harvest	Marine Harvest

This figure shows the information provided to each of the two groups in my investment experiment. Panel A and B present the information provided to group X and Y respectively. Both panels include the exact same information, except that group A observe a female manager for fund A and a male manager for fund B, while group Y observe the opposite.