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Gender differences in the Nordic mutual fund industry

Empirical evidence from Denmark, Finland, Norway and Sweden

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Preface

This thesis is written as a part of our Master of Science degree in Financial Economics at the Norwegian School of Economics (NHH). The purpose of this thesis is to investigate gender differences in the Nordic mutual fund industry, and hopefully contribute to narrow the literature gap. Our initial data sample has required both extensive programming in R, as well as structuring and sorting in Microsoft Excel. Microsoft Excel has also been used to implement certain numerical calculations, while the statistical software STATA has been applied in our empirical analysis. This thesis has been an educative process due to enhanced insights in the mutual fund industry, as well as an improved understanding of econometrics, and the methodologies used when conducting an empirical analysis in financial economics.

First and foremost, we wish to express a special gratitude to our supervisor, Professor Konrad Raff. He has given us invaluable insights and guidance, and his generous sharing of expertise has been critical for the quality of this thesis. Moreover, we would like to thank Professor Karin Thorburn, for providing us with valuable insights of empirical research and discussions. Finally, we would gratefully thank Professor Kenneth French. His advice and constructive input during the demanding process determining the proper benchmark and risk factors to use in our thesis has been valuable and much appreciated.

Bergen, 20.12.2017

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Abstract

In this thesis, we investigate gender difference across Nordic mutual fund managers. We analyse a data set free of survivorship bias, consisting of 430 Nordic single-managed mutual funds in the period January 2005 to June 2017, where we look at differences in risk-adjusted performance, risk-taking behavior and investment style caused by the managers gender. Examining previous literature, we hypothesize that female- and male mutual fund managers perform differently. Furthermore, we expect females to behave more risk-averse, and follow a different investment style than their male counterparts. By utilizing multiple methodologies to ensure robust results, we find no support for our hypotheses. Hence, we document that the mutual fund manager market in the Nordics is efficient with respect to that one cannot achieve abnormal returns by investing in funds based on the gender of the fund managers. Furthermore, our findings suggest that female- and male mutual fund managers share the same investment style and risk propensity.

Contents

Chapter 1

Introduction

Since their launch at the end of the 19th century, the mutual fund industry has experienced extraordinary growth. For instance, the global asset under management increased from 4.0 Trillion USD in 1993 to 28.9 Trillion USD in September 2013 (Plantier, 2013). The mutual fund industry also accounts for peoples savings, and according to Investment Company Institute (2013), the median mutual fund asset of mutual fund-owning households in the U.S. accounts to 125,000 USD. Given its vital role, the mutual fund industry has been a widely researched topic. Following the work of Jensen (1968), most papers have been striving to determine whether mutual fund managers achieve superior risk-adjusted returns against a benchmark portfolio.

Chevalier and Ellison (1999) were one of the first to examine a fund managers characteristics impact on fund performance, and found that fund performance is positively correlated with the managers experience and education. However, Chevalier and Ellison (1999) do not take into account whether the gender of the fund manager has an impact on fund performance. Throughout the literature review, we see some inconsistent findings concerning performance, risk-taking behavior and investment style across gender in the financial industry. If the gender of a mutual fund manager could affect the way a fund is being operated, we believe it demands further examination.

With our thesis, we aim to narrow the literature gap on gender differences in the Nordic mutual fund industry. We chose to investigate the Nordic mutual fund industry, which is mainly due to top-ranked gender equality in these countries (World Economic Forum, 2017). We argue that a top-ranked gender equality could make females in senior positions fully utilize their influence on decision making, and hence, affect the way a fund is being operated. Furthermore, by looking at Nordic countries as a whole, we are able to ensure that our data sample is relatively large, which is favorable when performing an empirical study like ours.

Studying previous literature lead us to three hypotheses, which we examine in the uncovered ground in the Nordic mutual fund industry:

H1: *Female- and male mutual fund managers perform differently on a risk-adjusted basis*
H2: *Female mutual fund managers are more risk averse than male mutual fund managers*
H3: *Female- and male mutual fund managers utilize different investment styles*

There are multiple reasons why we expect our hypotheses to hold. Barber and Odean (2001) shows that males trade more, and that such behavior could hurt fund performance. On the other hand, Gompers et al. (2014) and Green et al. (2009) documents lower performance for female venture capitalists and financial analyst, respectively. With respect to risk-taking behavior, Byrnes et al. (1999) and Jianakoplos and Bernasek (1998) documents that females are more risk-averse than males. Further, a more risk-averse behavior could lead to a different investment style. Beckmann and Menkhoff (2008) and Lewellen et al. (1977), finds that gender is a highly important factor determining an investment style.

In order to answer our hypotheses, we apply a data set free of survivorship bias, containing 430 Nordic mutual funds in the period January 2005 to June 2017. Our empirical methodology utilizes multiple approaches. First, we apply the one-, three- and four-factor model on a hypothetical portfolio that is $long$ in female managed funds, and $short$ in male managed funds. Further, we apply a multivariate regression, where our dependent variables are measures related to risk-adjusted performance, risk-taking behavior and investment style. In our multivariate regression, we control for different fund characteristics that might affect the way a fund is being operated, such as the size of the fund, age of the fund, expense ratio, number of stocks and the aggregated asset in a funds top 10 holdings, as well as fund, segment, and time dummies.

Our empirical investigation finds no support for our hypotheses regarding differences in risk-adjusted performance, risk-taking behavior and investment style between female- and male mutual fund managers in the Nordics. By robustness testing our results in several ways, we conclude that one should not use the fund managers gender as a criterion when considering which Nordic mutual fund to invest in. Hence, the superior gender equality in the Nordic countries (World Economic Forum, 2017) does not reveal an empirical difference in risk-adjusted performance, risk-taking behavior and investment style between female- and male mutual fund managers.

With our thesis, we are contributing to the extensive literature on mutual funds and sociopolitical debate on gender prejudice in the business world. Our findings regarding no differences in risk-adjusted performance are in line with Niessen-Ruenzi and Ruenzi (2015) and Atkinson et al. (2003), and suggests that there are no differences between the U.S. and the Nordic mutual fund markets regarding gender differences in performance. Furthermore, our findings concerning the insignificant differences in risk aversion across gender contradict with the majority of previous literature, which find females to be more risk averse (Byrnes et al., 1999; Barber and Odean, 2001; Jianakoplos and Bernasek, 1998). Moreover, our results support the paper from Johnson and Powell (1994), which states that in an educated managerial subpopulation, females and males tend to demonstrate a more equal risk propensity. Lewellen et al. (1977) argues that gender is one of the most important factors determining an investment style, which do not match our empirical results. In our analysis, we document that female- and male mutual fund managers share the same investment style, after controlling for fund characteristics.

The rest of our thesis is structured as follows. In Chapter 2, we present relevant literature forming a background for this thesis. Next, in Chapter 3, we present our hypotheses and elaborate around our expectations. Chapter 4, introduces our data sources, and how we have constructed our data set. In Chapter 5, we present our empirical methodology used to solve our hypotheses, while Chapter 6 presents our findings and interpretation of the results. Finally, in chapter 7, we present our conclusion of this thesis.

Chapter 2

Literature Review

Does the fund managers gender matter when investing in a mutual fund? While mutual fund performance is a widely researched topic, little research has been devoted to the impact of a fund managers gender. In our thesis, we aim to narrow the literature gap on gender differences in the Nordic mutual fund industry. Therefore, prior to our own research, we conduct a thorough review of the existing literature that is applicable to our thesis. Specifically, we examine the relevant literature on mutual fund performance, as well as evidence of gender differences in performance from other parts of the financial industry. Furthermore, we inspect the behavioral differences across gender. Hence, we present some research of interest from the social sciences and economic literature as well. Unable to present all relevant research, we will highlight the most relevant literature forming the background for our thesis.

Mutual fund performance is an extensively researched topic in the finance literature. First out was Jensen (1968), who presented the one-factor model, a model based on the Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965) and Mossin (1966). Using a data set of 115 US mutual funds, Jensen (1968) found evidence that on average, actively managed funds were not able to outperform the market when accounting for management fees. The evolution of financial theory has contributed to extended models that control for various anomalies in the stock market. The multifactor models by Fama and French (1993) and Carhart (1997), have gradually replaced the one-factor model by Jensen (1968). However, following the work of Jensen (1968), most papers have been striving to determine whether mutual fund managers achieve superior risk-adjusted returns against a benchmark portfolio.

Chevalier and Ellison (1999) were one of the first to examine the impact of manager characteristics on fund performance. After correcting for differences in factor loadings, expense ratio, risk characteristics and survivorship bias, Chevalier and Ellison (1999) find evidence that fund performance is positively correlated with the managers experience and education. However, they do not consider the gender of the fund manager in their analysis.

We have only managed to detect papers on gender differences in mutual fund performance using data from the U.S. mutual fund industry. By studying the performance of 1,366 female- and male fixed income managers, Atkinson et al. (2003) fully analyse gender differences in mutual fund management. According to their results, females and males appear to perform similarly in terms of risk-adjusted performance. Using a yearly sample of U.S. equity mutual fund returns in the period from 1992 to 2009, Niessen-Ruenzi and Ruenzi (2015) find similarly to Atkinson et al. (2003), no difference in mutual funds risk-adjusted performance across gender using a multivariate approach, where they control for fund characteristics. Furthermore, Niessen-Ruenzi and Ruenzi (2015) examine the performance using a portfolio of female- and male mutual fund managers, respectively. As a theoretical example to test the robustness of their findings, they evaluate a portfolio that is long in all funds managed by females, and short in all the male managed funds. However, they still find no statistically significant difference in risk-adjusted performance.

Contradicting the findings of Niessen-Ruenzi and Ruenzi (2015) and Atkinson et al. (2003), Bliss and Potter (2002) finds mixed support for performance differences studying U.S. mutual funds from the 1990's. Bliss and Potter (2002) find some evidence that females outperform males at domestic equity funds, but not at international funds. However, controlling for potential outside influences, they do not find any evidence of performance differences across gender in the domestic area. So far, the papers investigating gender differences in the U.S. mutual fund industry, report inconsistent results. Furthermore, we observe that it is done limited research on this topic, and there might be a gap in the literature covering gender differences in mutual fund performance, which could indicate a demand for further examination.

Looking beyond the mutual fund industry and into the hedge fund industry, there are some studies investigating gender differences. By creating the Rothstein Kass Women in Alternative Investments (WAI) index based on 82 hedge funds, the Rothstein Kass Institute (2013) claims that for six and a half year, ending in June 2013, female hedge fund managers outperformed the S&P 500 and HRF Global Hedge fund Index by 1.8- and 7.1 percentage points, respectively[1].

[1] The study conducted by Rothstein Kass Institute (2013) is only focusing on raw returns. In addition, they do not control for survivorship bias.

However, studying 9,520 hedge funds from 1994-2013, Aggarwal and Boyson (2016) find no difference in risk-adjusted performance across gender. Nevertheless, they find that team managed funds consisting of both female- and male managers underperform both female- and male single managed funds. Based on these studies from the hedge fund industry, it seems difficult to conclude that female hedge fund managers perform differently than male hedge fund managers on a risk-adjusted basis.

There have been several papers examining the gender gap in the financial sector, both from the professional- and retail perspective. By examining the performance of male- and female sell-side analyst, Green et al. (2009) find that females tend to forecast stock returns less accurately, than their male counterparts. On the other hand, they find that females are more likely to be elected by the Institutional Investor magazine as members of the All-America Research team, indicating that they outperform males from the clients perspective. Conversely, Kumar (2010) find robust evidence from 2.86 million financial forecasts that female financial analysts project a more accurate forecast than male analysts[2]. Additionally, he confirms the findings of Green et al. (2009), that female analysts are more likely to be chosen as an all-star analyst.

Gompers et al. (2014) document significant lower investment performance for female venture capitalists compared to their male counterparts. Further, they find that females have approximately 15% lower investment performance than their male colleagues. Gompers et al. (2014) argue that this is due to the lack of contribution from their male colleagues within their respective firms. On the other hand, using data on trades made by individual Finnish investors from 1995 to 2011, Lu et al. (2016) investigate whether a "holding-period-invariant" (HPI) approach will reveal a difference in performance across gender. They document a significant gain made by female investors over their male counterparts investing in Finnish stocks.

Based on the previously reviewed literature, we observe mixed evidence whether females or males perform differently in the financial sector. Nevertheless, there has also been an increasing focus on gender equality on the corporate side, and the benefit of diversity is documented in several studies. Studying over 3,000 companies across 40 countries, Dawson and Kersley (2014) find evidence that gender diversity benefits corporations, and other shareholders. Adjusting for industry biases, they find that companies with more than 15% females in top management, earned a Return on Equity (ROE) in 2013 of 14.7%, compared to 9.7% for corporations with

[2]Kumar (2010) argue that the inconsistency with the results from Green et al. (2009) arises due to a difference in methodological choices and the choice of control variables.

less than 10% females in top management. Another study supporting Dawson and Kersley (2014), is Manconi et al. (2017), who study diversity investing with a sample of over 40,000 top executives in the S&P 500 from 2001 to 2014. Manconi et al. (2017) show evidence that buying firms with diversity in top management and selling firms with homogeneous top management yield a statistically significant alpha.

So far, we have presented some relevant literature on mutual fund performance, as well as evidence from the financial industry regarding performance differences across gender. Overall, the presented literature gives no clear indication whether females or males outperform each other in the financial sector. As we want to examine other characteristics of female- and male mutual fund managers, we will in the following present studies on behavioral differences between females and males.

Over the last decades, there have been done a lot of research on the behavioral differences across gender. Jianakoplos and Bernasek (1998) examine U.S. household holdings of risky assets, and find that single females are more risk averse than single males. In a similar study, Barber and Odean (2001) examine the trading behavior of over 35,000 household investors, and find evidence that males trade more, take more risk, and earns a lower return than females do. They argue that males are more overconfident than females, which could lead to more trading, and thus, lower performance. Overall, they find that males trade 45% more than females, which reduce their net return by 2.65 percentage points per year. However, Jianakoplos and Bernasek (1998) and Barber and Odean (2001) all study retail investors, and thus, these findings might not necessarily apply to professionals. In a study on how the Swedish population has allocated their pension investments within the state pension system, Martenson (2008) finds that males take more risk, but the difference is less significant between males and females with a financial background. Johnson and Powell (1994) argues that findings of differences in risk-taking behavior across gender usually are obtained from populations where most individuals have no formal managerial education. Moreover, their analysis concludes that in an educated managerial sub-population, females and males display a more equal risk propensity. Examining the economic literature above, we observe clear indications that females tend to behave more risk-averse in a financial setting. We also notice that in an educated environment, females and males show a more equal risk-taking behavior.

The risk-taking behavior across gender have also been studied in the mutual fund industry. Niessen-Ruenzi and Ruenzi (2015) study risk-taking behavior for mutual fund managers on multiple levels. They study total fund risk (standard deviation), systematic risk (market risk), and unsystematic risk (firm-specific risk), and find indications that females tend to be more risk-averse. However, in their analysis, Niessen-Ruenzi and Ruenzi (2015) cannot report any statistically significant difference. Contrariwise, studying U.S. data, Bliss and Potter (2002) report that males are more risk-averse than females, both for domestic and international funds[3]. Bliss and Potter (2002) analyse risk on three different levels, by total risk (standard deviation), market risk and "bear-market rank %[4]". By every measure, Bliss and Potter (2002) find that females are taking more risk than males.

Most of the presented literature tends to find females more risk-averse than males, and a more risk-averse behavior could lead to a different investment style. In a survey of 649 fund managers from the U.S., Thailand, Germany, and Italy, Beckmann and Menkhoff (2008) reports females to be more risk-averse, and may possess a greater ability to exercise certain investment style than males. Similarly, using a sample drawn from the customer clientele for a large national retail brokerage house in 1964-1970, Lewellen et al. (1977) report that the gender is one of the most important factors determining an investment style, even surpassing characteristics like educational background and occupation.

Karagiannidis (2012) evaluate the effect of management team characteristics on investment style for mutual funds. Using yearly data of from January 1997 to January 2005, and the Carhart (1997) four-factor model, he finds that gender diversity[5] is negatively related to SMB (Small Minus Big) and UMD (Up Minus Down) style extremity. Furthermore, the study does not find any relation to the HML (High Minus Low) style extremity. Comparing Karagiannidis (2012) findings, with studies from Beckmann and Menkhoff (2008) and Lewellen et al. (1977), we notice that gender may be an important factor when determining an investment style of a fund.

In our thesis, we aim to identify differences between male- and female mutual fund managers, and the literature review conducted in this section has left us with a greater understanding of the behavioral differences between males and females. Going forward, we attempt to analyse the difference in risk-adjusted performance, risk-taking behavior and investment style between male- and female mutual fund managers.

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[3] Unfortunately, Bliss and Potter (2002) do not report any t-statistics for their results. We are therefore unable to say if the results are statistically significant.

[4] Bliss and Potter (2002) define bear-market as all months in the past five years that the S&P 500 lost more than 3%.

[5] Gender diversity is defined as a management team composition of both females and males.

Chapter 3

Hypothesis Development

As presented in the literature review, mutual fund performance is an extensively researched topic in the financial literature. However, we believe that there is an important piece of information missing in several earlier studies - gender differences. Throughout our literature review, we see some inconsistent findings concerning performance, risk-taking behavior and investment style across gender, which we believe demand further examination. To our knowledge, all previous research on the difference between male- and female mutual fund managers are done with U.S. data. With our thesis, we aim to narrow the literature gap on gender differences in the Nordic mutual fund industry. In the following, we will present our three empirical questions for this thesis, as well or rationale and expected findings based on previous literature.

H1: *Female- and male mutual fund managers perform differently on a risk-adjusted basis*

Our first empirical question relates to differences in risk-adjusted performance between female- and male mutual fund managers. Previous literature reports mixed evidence regarding performance differences across gender in the financial industry. Niessen-Ruenzi and Ruenzi (2015) and Atkinson et al. (2003) find no difference in risk-adjusted performance between female- and male mutual fund managers. However, evidence from Barber and Odean (2001) shows that males trade more than females and that such behavior could hurt fund performance. Furthermore, their studies show that overconfidence is higher for males than females. As a result, we expect female mutual fund managers to follow a more consistent investment strategy. According to the study from Brown et al. (2009), a consistent investment strategy is positively correlated with fund performance. On the other hand, Gompers et al. (2014) and Green et al.

(2009) documents lower performance for female venture capitalists and financial analysts, respectively. Based on the inconsistency in the literature, we expect female- and male mutual fund managers to perform differently on a risk-adjusted basis.

H2: *Female mutual fund managers are more risk averse than male mutual fund managers*

Our second empirical question relates to differences in risk-taking behavior between female- and male mutual fund managers. Examining previous literature, we have reason to believe that female mutual fund managers take less risk than males. Byrnes et al. (1999), are reporting highly consistent indications that females are more risk-averse than males in varying frameworks, by doing a meta-analysis of 150 studies. By studying over 35,000 households brokerage account data, Barber and Odean (2001) reports that females hold less risky assets within their stock portfolios than males. Equivalent results are documented by Jianakoplos and Bernasek (1998), who studies household holdings of risky assets. They document that single females hold significantly less risky assets than single males. However, as Johnson and Powell (1994) argues, it is important to bear in mind that these documented differences across gender are done on a sample where most of the individuals do not have a formal management education. Due to the fact that we are examining the behavior of female- and male mutual fund managers, we assume that they have a comparable professional background and work in a similar environment. Hence, our sample can be defined as a managerial sub-population. Johnson and Powell (1994) reports that in a managerial sub-population, females and males tend to demonstrate a more equal risk propensity. Based on these findings, we expect that differences in risk-aversion are less prominent, but still present in our managerial sub-population.

H3: *Female- and male mutual fund managers utilize different investment styles*

Our last empirical question is related to the difference in investment style between male- and female mutual fund managers. Investment style relates to how fund managers allocate their assets within their portfolios. As documented by Lewellen et al. (1977), gender is one of the most important factors determining an investment style. Furthermore, Beckmann and Menkhoff (2008) report that female fund managers may possess a greater ability to exercise certain investment styles than males. Barber and Odean (2001) shows that males tend to behave more overconfident, which might lead to a different investment style. Based on these findings, we expect female mutual fund managers to follow a different investment style than male mutual fund managers.

Chapter 4

Data

In order to assess the gender differences in the Nordic mutual fund industry, we have to obtain and structure a considerable amount of data. In this chapter, we are going to present our data sources, and further get into detail on the sample selection adopted. Moreover, we will discuss issues encountered during the data collection, and finally, we are going to present a summary statistics of the variables included in our regression analysis.

4.1 Data Sources and Sample Selection

Our primary data source is Morningstar Direct, where we have collected our monthly mutual fund data. Morningstar Direct is a detailed database containing statistics on mutual funds from all around the world. The database provides measures of performance, fund size, fund managers identity and other fund characteristics. All data from Morningstar Direct is obtained in USD. This approach mitigates the currency effect, and we are able to compare the data on an equal basis. When Morningstar Direct lacks necessary information, we have used the funds respective websites and reports in order to collect sufficient information, which will be explained in detail later. Our collected data covers the time period from January 2005 to June 2017[6].

In our study, we focus on actively managed mutual equity funds[7], and hence, excluding money market-, bond- and index funds. This approach allows us to focus on mutual funds that are homogeneous, and easy to compare.

[6] For lagged variables included in the regression i.e $ExpenseRatio_{i,t}$, $FundSize_{i,t}$, $NumberofStocks_{i,t}$ and $Top10Holdings_{i,t}$, we include observations from December 2004. See section 4.3.2 for description of variables.

[7] To be defined as an equity mutual fund in the Nordics, it is required to invest 75-80% in equity.

We limit our data set to mutual funds registered in Norway, Finland, Sweden and Denmark (hereinafter Nordic[8]). The Nordic selection criteria are made due to continued progress in closing the gender gap in these countries. According to World Economic Forum (2017), the Nordic countries continue to defend their top positions on the back of their strong performance on the Economic Participation and Opportunity Subindex. These measures support an argument that females in senior positions in the Nordics have a superior influence on decision-making.

Morningstar Direct provides data for mutual fund performance both solely focused on domestic equity, as well as international equity. By following an approach only focusing on mutual funds investing within their home domicile, we would reduce our sample significantly. Moreover, when addressing differences across gender, it is of interest to study the whole population of single-managed mutual funds in the Nordics. Hence, our sample contains both mutual funds investing within its home domicile, as well as outside their home domicile.

According to Rohleder et al. (2011) and Elton et al. (1996), it is important to include both surviving- and non-surviving mutual funds, to avoid the presence of survivorship bias in performance evaluation of mutual funds. Excluding funds that have been liquidated or merged with other funds, often due to poor performance, could lead to ambiguous results, by overestimating the historical returns. To eliminate the risk of survivorship bias, our sample includes both surviving- and non-surviving mutual funds.

To avoid double counting of funds with multiple share classes, we use Morningstar Directs assigned FundID[9], to ensure that we have only one monthly observation per fund. Following Carhart (1997), we choose the class with most observations when multiple classes exist for the same fund. Furthermore, Bär et al. (2011) shows that team– and single managed funds behave differently. They argue that teams take less risk than individuals, and are therefore less likely to achieve extreme investments results. Thus, we eliminate all funds where Morningstar Direct report multiple managers and concentrate our study around single managed funds. This allows us to distinguish differences across gender (male- vs. female managed funds), rather than across management structure (team- vs. single managed funds). Additionally, we eliminate all the funds that do not disclose any information about fund manager history.

The data provided by Morningstar Direct does not indicate the gender of the fund managers. However, both the full name and the start/end date of the fund manager tenure is given. Based

[8]Even though Iceland, Greenland, Faroe Islands and Åland Island is a part of the Nordic countries, we consider these countries not comparable in relation to size (mutual fund market), politics and market structure to the other Nordic countries.

[9]FundID is Morningstar Directs identification code of a fund.

on this information, we are able to manually identify the gender of 98.2% of all fund managers by looking at their names. In cases where we could not classify the managers gender, i.e. foreign– or ambiguous names, we used the funds prospectus, online search or career pages such as LinkedIn to identify the gender. Overall, we were able to identify the gender of all fund managers.

In order to measure fund performance by abnormal returns, we need proper risk-factors to employ the Jensen (1968) one-factor model, the Fama and French (1993) three-factor model, and the Carhart (1997) extended four-factor model[10]. Since our data sample contains funds with different domiciles and investment mandate, one could argue that the fund managers should be benchmarked against different indexes and risk-factors. This would indicate that the different factors should be estimated according to the funds investment mandate. However, according to Professor Kenneth French (Personal communication, 24.10.2017), he "do not produce factors for most individual countries (or small regions) because it does not make sense to have factors that are not well diversified". Another argument who supports this theory is the fact that capital flows freely between the countries. Hence, a share of any company would trade for the same price if listed in two different markets, there will be one and the same pricing model for the two stocks. Thus, the pricing of the risk factors should be the same. For this reason, we argue that all fund managers should be benchmarked against the world index and world risk factors. These factors were collected from Kenneth Frenchs website[11].

4.2 Structuring of Data Sample

Following arguments by Keswani and Stolin (2008), and the fact that several more recent papers covering similar topics have used a monthly periodicity, our data sample contains monthly observations from January 2005 to June 2017[12]. In addition, fund manager history is reported monthly by Morningstar Direct, which supports obtaining the data monthly. We are also able to improve the number of observations by collecting data monthly, compared to an annual approach. Hence, the robustness of our data set is increasing. In line with Bollen (2007), funds with less than 24 months existence are excluded to ensure continuity in our data set.

[10] The approach will be explained later in section 5.1.

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

[12] By obtaining monthly data from this period, we are able to capture both economic growth and downturn. I.e. the economic downturn during the financial crisis in 2007-2009.

Most funds have a determined management strategy, which implies that their fund is either managed by a team, or single managed. However, in some cases over the period from January 2005 to end of June 2017, there is a change in fund manager. Accordingly, there are some situations where it is a short overlapping period between the old and the new fund manager. In these situations, we assign the manager role to the new fund manager from the date he or she is starting to manage the fund, and it would still be treated as a single managed fund. We argue that a very short period of overlap between fund managers is unlikely to affect the new managers influence on decisions regarding the funds allocation strategy. In cases where there are longer periods with overlap, we have chosen a cut-off value of 3 months, instead of defining all these funds as team managed. Hence, we avoid eliminating funds where the majority of observations are single managed. By following this approach, we argue that we mitigate the risk of sample selection bias. In unreported results, we have robustness tested this method by deleting all funds with an overlapping period, and do not find any significant deviation in relation to our final sample.

4.3 Variables

In this section, we are going to present the different variables that are vital in our empirical methodology[13]. First, we provide a description of our dependent variables, which are essential in our analysis of gender differences in the Nordic mutual fund industry. Second, we present the fund-related control variables that are included to mitigate the risk of biased results. Third, we explain how we deal with missing values in our data set. Finally, we present our descriptive statistics, as well as a univariate mean comparison between female- and male fund managers. A detailed description of the variables is defined in Appendix 1.

4.3.1 Dependent Variables

In line with Sirri and Tufano (1998) and Wermers (2000), we obtain both gross- and net of fee returns, in order to measure the differences in stock-picking talent across gender. Gross returns relate to the returns calculated before any fee is deducted, while the net returns are calculated after deducting the fee. According to Niessen-Ruenzi and Ruenzi (2015), gross returns will better assess the actual investment talent of a fund manager, while the fund investors are ultimately

[13]See chapter 5 for a description of our empirical methodology.

interested in net returns. By doing this, we are able to evaluate whether the fee structure of a mutual fund has an implication for the difference in risk-adjusted returns, risk-taking behavior and investment style between female- and male mutual fund managers.

Furthermore, to evaluate the risk-adjusted performance across gender, we estimate three additional measures of fund performance ($Perf_{i,t}$). The different performance measures are estimated using a twelve-month rolling window. Thus, we first estimate all the performance measures from $t1$ to $t12$, then from $t2$ to $t13$, and so on. Hence, the first estimation of any $Perf_{i,t}$ will be earliest at the end of December 2005. The first performance measure is $CAPM_{i,t}$ and is fund $i's$ $alpha$ at time t from the Jensen (1968) one-factor model. Second, we estimate $FF_{i,t}$, which is the $alpha$ from the Fama and French (1993) three-factor model for fund i at time t. Third, we estimate $Car_{i,t}$, which is the $alpha$ from the Carhart (1997) four-factor model for fund i at time t.

To capture the risk-taking behavior of mutual fund managers, we construct three different measures of fund risk. All three risk metrics ($TotalRisk_{i,t}$) are estimated using a twelve-month rolling window as described above. The first risk measure is $FundRisk_{i,t}$ and is given by fund $i's$ standard deviation for the last 12 months time-series return at time t. Following Chevalier and Ellison (1999), we measure $UnsysRisk_{i,t}$ (unsystematic risk) by the standard deviation of the residuals from the Jensen (1968) single-factor model for fund i at time t. $Sysrisk_{i,t}$ (systematic risk) is measured by the factor loading on the market portfolio from the Jensen (1968) single factor model for fund i at time t.

To evaluate the investment style of a fund, we estimate three different $FactorWeigthings_{i,t}$, namely $SMB_{i,t}$ (Small Minus Big), $HML_{i,t}$ (High Minus Low), and $UMD_{i,t}$ (Up Minus Down). These $FactorWeigthings_{i,t}$ represents fund $i's$ loading on the corresponding risk-factors at time t. The factors are estimated by applying the Carhart (1997) four-factor model in an regression, using a twelve-month rolling window, as described above.

4.3.2 Control Variables

In this section, we are going to present the different control variables related to fund characteristics that are essential in our analysis. We include fund-specific control variables in order to mitigate the risk of biased results[14]. $FundSize_{i,t}$ is the size of each fund obtained from Morn-

[14] In order to get unbiased results, we rely on the zero conditional mean assumption,where $E(u|x) = 0$. This implies that our explanatory variables and the error term are uncorrelated,(Wooldridge, 2009).

ingstar Direct. We also include the $ExpenseRatio_{i,t}$ as a control variable, which is reported annually by Morningstar Direct. By dividing the expense ratio by 12, we get the ratio to fit our monthly data set. Due to the fact that the expense ratio is deducted from the funds average net assets, and accrued on a daily basis, we argue that our linear approach appears reasonable. There are some incidents where Morningstar Direct lacks information about historical expense ratios. In such cases, we manually obtain the ratios from the funds annual reports or prospectus memorandum. To ensure that this is a proper method, we cross-check old recorded ratios from Morningstar Direct, with the associated annual report or prospectus memorandum. By following this approach, we are able to ensure that the expense ratios in our sample are comparable.

The control variable $NumberofStocks_{i,t}$, is the number of different stocks each fund holds within the period. Moreover, we include $Top10Holdings_{i,t}$, which is a measure of the aggregated assets, expressed as a percentage of the funds top 10 holdings. The higher the percentage, the more concentrated the fund is in a few stocks. Being concentrated in a few number of stocks could also lead to increased exposure for fund $i's$ market fluctuations in these holdings at time t. Another control variable included is $FundAge_{i,t}$, which is measured in years. Since Morningstar Direct reports both the funds inception- and obsolete date, we are able to calculate the $FundAge_{i,t}$, based on these dates.

In order to control for time-, fund- and segment fixed effects, our sample contains time-, fund- and geographical[15] dummies. These are included due to unobserved effects that may distort our results, such as culture, regulatory conditions, and time variations. For instance, time variations could be incidents that affect the global economy like the financial crisis in 2007-2009. By including time dummies in our monthly sample from 2005 to 2017, we are able to isolate this economic shock. In addition, economic shocks that affect some geographical areas more than others, like the Euro crisis in 2011-2012, are captured by our segment dummies. Further, we include fund fixed effects in our regression in order to capture time-invariant effects at the fund level. Thus, we argue that we are able to capture some of the unobserved effects by following this approach, as well as isolate and provide a more precise estimation of our regressions.

[15] Based on the investment objective of the fund.

4.3.3 Missing Values

The data obtained from Morningstar Direct is primarily reported monthly. In some cases, we lack a few monthly observations in between periods with continuously reported data. In other cases, data is missing completely. According to Osborne (2013), a common method to use is to erase cases with missing values. Nevertheless, Osborne (2013) argues that this could lead to severe sample selection bias and inference error. Due to possible sample selection bias, we only delete funds with no independent/dependent variables reported. After this approach, there are still some cases where we lack a few monthly observations in between periods with continuously reported data. In order to complete the data set, we are either using an imputation method following a compounding growth approach[16] or "The Last Observation Carried Forward", where we use the last observed value where there is a missing observation (Pannekoek et al., 2011). For $FundSize_{i,t}$, we use the compounding monthly growth rate method, while for $NumberofStocks_{i,t}$ and $Top10Holdings_{i,t}$ we are using the "The Last Observation Carried Forward" approach. After completing the imputation method, we tested whether the technique could lead to any biases. First and foremost, incidents with missing values in between periods with continuous reported data represents less than 0.7% of our sample size of 45,040 fund months. Thus, a potential bias from our imputation method, if any, will be negligible. Moreover, we observe that all the calculated values seem like a fair estimation for the actual values, when implementing a robustness test[17].

4.3.4 Descriptive Statistics

Our final sample contains 45,040 fund months, out of which 89.23% have a male manager, while 10.77% female, which is in line with previous studies. Niessen-Ruenzi and Ruenzi (2015) find that out of a total of 13,302 fund years, 10.80% has a female manager, while 89.20% has a male manager. Bliss and Potter (2002), reports that out of 2,571 domestic fund-years, 10.50% is female-managed, and 89.50% is male-managed. Figure 1 shows the distribution of a total number of both female- and male-managed funds in our sample, as well as the percentage of female-managed funds over the whole period. These observations are from a total of 430 funds.

[16] If there is a case where the independent variable $FundSize_{i,t}$ have missing values, we may lack observations for t and $t+1$. We then calculate the compounding growth from month $t-1$ to month $t+2$, by dividing $Fundsize_{i,t+2}$ by $Fundsize_{t-1}$ to the power of fund months. $(Fundsize_{i,t+2}/Fundsize_{i,t-1})^{(1/3)}$. Following this approach, we get the compounding monthly growth rate, g. First, the missing value for month t is estimated by $Fundsize_{i,t-1} * (1+g)$, then, the missing value for month $t+1$ is estimated by $Fundsize_{i,t} * (1+g)$.

[17] When robustness testing our imputation method, we went through the data to confirm that the computed data was in line with the growth trend and values for the different funds. We did not observe any instances where our calculated values seemed unrealistically high or low.

Table 1, Panel A, reports summary statistics for the main variables presented earlier in this section, while Panel B, reports the mean difference in fund characteristics between male and female.

In the following, we will provide a short description of the patterns observed in Table 1, Panel A. For the sample as a whole, we observe a positive average monthly gross return of 0.82%, while net return average at 0.69%. Moreover, the average $FundAge_{i,t}$ is 10.5 years, where the top percentile (p99) is almost 32 years old. The average $Numberofstocks_{i,t}$ held in a fund is 80, but as Table 1 reflects, there is a huge variation between funds. The average monthly number of stocks range from 15 at the bottom percentile (p1), to 529 at the top percentile (p99). Furthermore, the average $FundSize_{i,t}$ in the sample is 234 MUSD. $Top10holdings_{i,t}$ averages at 44.17% of the total portfolio, where the patterns correspond to the observations in number of stocks in the portfolio. The top percentile (p99) of $Top10holdings_{i,t}$ is 87.21%, which is in line with the bottom (p1) $NumberofStocks_{i,t}$, equal to 13. $ExpenseRatio_{i,t}$ range from 0.02% at p(1) to 0.28% p(99) on a monthly basis, while the average $ExpenseRatio_{i,t}$ is 0.13%.

Examining panel B gives some interesting indications for further regression analysis. Column (1) and (2) present the mean of the different characteristics for female- and male managed funds, respectively. Column (3) presents the difference between female- and male managed funds. The univariate comparison in Panel B shows that female managers are responsible for 18.8 MUSD smaller funds, than funds managed by males. Further, females are managing funds that are 0.5 years older than males. Funds with female managers have on average 11.1 fewer stocks in their portfolio. Moreover, we find an interesting difference in $Top10holdings_{i,t}$. Female fund managers tend to hold a more concentrated portfolio, where the percentage of $Top10holdings_{i,t}$ is 1.68 percentage points higher than male fund managers. Concentrated portfolios could indicate higher risk and a more overconfident fund manager. These findings contradict with the findings of Barber and Odean (2001), who reports a significant difference across gender in terms of overconfidence. Examining the mean of the different risk variables, we observe that females take on more unsystematic- and fund risk than males. The difference in systematic risk seems to be the opposite, where females take slightly less risk than males. In relation to investment style, we observe that females load significantly less on $HML_{i,t}$, while they load significantly more on the momentum factor $UMD_{i,t}$. Finally, we observe that females achieve a higher $alpha_{i,t}$ than males both in term of gross- and net returns adjusting for different risk-factors. The difference in the remaining variables, $SMB_{i,t}$, $ExpenseRatio_{i,t}$, $GrossReturn_{i,t}$

and $NetReturn_{i,t}$, is negligible. Moreover, we stress that this is just a mean-comparison test between gender, but it would be interesting to investigate in further detail.

Chapter 5

Empirical Methodology

In this chapter, we present the empirical framework we will use to analyse the difference in risk-adjusted performance, risk-taking behavior and investment style between female- and male mutual fund managers. In order to study the difference, we need appropriate models related to our hypothesis presented in chapter 3. The chapter will be structured according to our hypotheses, namely hypothesis 1, hypothesis 2 and then hypothesis 3. We will also discuss our econometric approach, as well as potential pitfalls of using our selected models.

5.1 The Performance of Female- and Male Mutual Fund Managers

Over time, various performance measures have been developed to evaluate risk-adjusted returns of mutual funds. To achieve robust results, we will evaluate the performance across gender utilizing multiple performance measures presented below.

5.1.1 One-Factor Model

The one-factor model developed by Jensen (1968) was rooted in the CAPM theory developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The model measures the abnormal returns generated by a fund after adjusting for market risk, and can be used to evaluate fund managers selectivity skills. The one-factor model can be expressed as:

$$R^x_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \epsilon_{i,t} \tag{1}$$

Where $R^x_{i,t}$ is the return of a fund in period t and x denotes whether we use gross (g) or net (n) return[18]. Further, $R_{f,t}$ is the risk-free rate at time t, $R_{m,t}$ is the return on the market portfolio at the period t. The coefficient β_i is the funds exposure to the non-diversifiable risk (market risk) in the market portfolio. The error term $\epsilon_{i,t}$ has an expectation of zero and measures the unsystematic risk that cannot be explained by the model. The alpha α_i is the abnormal return of the fund i at time t, in excess of the market portfolio. A positive alpha indicates outperformance of the market portfolio. Conversely, a negative alpha indicates underperformance. It is important to notice that the one-factor model of Jensen (1968) is based on the assumptions that, (1) all investors are risk-averse and seeks to maximize their wealth, (2) all investor have identical decision horizon and comparable expectations concerning investment opportunities, (3) all investors are rational and choose portfolios based on expected return and risk, (4) transaction cost and taxes are zero, and (5) all assets have separable shares.

5.1.2 Three-Factor Model

Fama and French (1993) present evidence in their paper that market risk is not the only relevant risk factor explaining cross-sectional asset returns. In their model, Fama and French (1993) include two additional risk factors, the size– (SMB) and value (HML) premiums.

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

The SMB (Small Minus Big) reflects the return of a portfolio that is long in small-cap stocks, and short in large-cap stocks. The HML (High Minus Low) reflects the return of a portfolio that is long in stocks with high book-to-market, and short in stocks with low book-to-market. Where the β_1, β_2 and β_3 are the funds corresponding exposure to the risk-factors. α_i is the abnormal returns and $\epsilon_{i,t}$ is the unsystematic risk for fund i at time t.

5.1.3 Four-Factor Model

The Carhart (1997) four-factor model is an extension from the Fama and French (1993) three-factor model. In addition to the market, size and value factors, Carhart (1997) added the momentum (UMD) risk-factor. The momentum factor was originally identified by Jegadeesh and Titman (1993). The UMD factor reflects the average return on the two high prior return

[18] Or rationale behind including gross- and net return are explained in section 4.3.1

portfolios, subtracted by the average return on the two low prior return portfolios from six value-weighted portfolios formed on size and prior returns the last 12 months. The Carhart (1997) four-factor model can be specified as follows:

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

Where the β_1, β_2, β_3, β_4 represents the funds corresponding exposure to the risk-factors. α_i is the abnormal returns and $\epsilon_{i,t}$ is the unsystematic risk for fund i in period t.

To examine hypothesis 1, that female- and male mutual fund managers perform differently on a risk-adjusted basis, we create a value– and equal-weighted portfolio. The value-weighted portfolio is constructed as a fund $i's\ FundSize$, divided by the total $FundSize$ for female- and male managers at time t, respectively. Furthermore, the equal-weighted portfolio is constructed by giving funds that operate in a specified month the same weight, for female- and male fund managers, respectively. In addition, we compute a hypothetical portfolio that is long in female-managed funds (F) and short in male-managed funds (M)[19]. The difference (F-M) is regressed in an OLS model on the one-factor, three-factor, and four-factor model for both the value– and equal-weighted portfolio, respectively. This allows us to interpret the $alpha_t$ in the model, and evaluate whether risk-adjusted performance differs between female- and male mutual fund managers.

5.1.4 Multivariate Regression

The previously discussed methodology does not account for fund-individual characteristics that vary between male- and female fund managers, as presented in Table 1, Panel B. To account for fund characteristics that might affect performance for both female- and male managed funds, we extend our analysis into a multivariate regression:

$$\begin{aligned} Perf_{i,t}^{x} &= \beta_0 + \beta_1 Female_{i,t} + \beta_2 ExpenseRatio_{i,t-1} \\ &+ \beta_3 Top10Holdings_{i,t-1} + \beta_4 NumberofStocks_{i,t-1} \\ &+ \beta_5 FundSize_{i,t-1} + \beta_6 FundAge_{i,t-1} + \epsilon_{i,t} \end{aligned} \quad (4)$$

Where $Perf_{i,t}^{x}$ is the performance of fund i at time t. $Perf_{i,t}^{x}$ reflects one of three performance measures for fund i at time t, namely $CAPM_{i,t}^{x}$, $FF_{i,t}^{x}$ or $Car_{i,t}^{x}$, as described in section

[19] There is not possible to go short in a mutual fund (to our knowledge), hence, this is a highly hypothetical example.

4.3.1. Further, x denotes whether the regression is based on gross return (g) or net return (n). By applying the $Perf_{i,t}^{x}$ on the left-hand side in the regression equation, we are able to control for fund characteristics that might affect the abnormal returns of a fund. The $Female_{i,t}$ takes the value one if a female is the mutual fund manager in the twelve-month period, and conversely zero if a male is the fund manager. In cases where there is a mix of females and males over the twelve-month rolling period, we do not assign $Perf_{i,t}^{x}$ to any gender.

As of control variables[20], we include the lagged natural logarithm of $FundSize_{i,t-1}$ and $FundAge_{i,t-1}$, $NumberofStocks_{i,t-1}$, $Top10Holdings_{i,t-1}$ and $ExpenseRatio_{i,t-1}$[21]. Furthermore, we include fund, segment, and time dummies to capture fund, segment, and time-specific effects. The important coefficient will be $Female_{i,t}$. If $Female_{i,t}$ shows a positive (or negative) statistical significant sign, it could indicate that female outperform (underperform) male fund managers in our sample. The control variables are of less interest for our research questions, and are primarily included in the multivariate regression to mitigate the risk of omitted variable bias. The model will be estimated using a pooled OLS regression.

5.2 The Risk-Taking Behavior of Female- and Male Mutual Fund Managers

To examine hypothesis 2, that female mutual fund managers are more risk-averse than male fund managers, we will run a multivariate regression, which controls for fund characteristics that might affect the fund managers risk-taking behavior:

$$\begin{aligned} TotalRisk_{i,t}^{x} &= \beta_0 + \beta_1 Female_{i,t} + \beta_2 ExpenseRatio_{i,t-1} \\ &+ \beta_3 Top10Holdings_{i,t-1} + \beta_4 NumberofStocks_{i,t-1} \\ &+ \beta_5 FundSize_{i,t-1} + \beta_6 FundAge_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{5}$$

Where $TotalRisk_{i,t}^{x}$ is regressed on the $Female_{i,t}$ and other relevant control variables, as in equation (4). $TotalRisk_{i,t}^{x}$ reflects one of three risk measures for fund i at time t, namely $FundRisk_{i,t}^{x}$, $SysRisk_{i,t}^{x}$ or $UnsysRisk_{i,t}^{x}$ as described in section 4.3.1. Further, x denotes whether the regression is based on gross return (g) or net return (n). To examine our second hypothesis, the coefficient of interest will be the $Female_{i,t}$. A statistical significant

[20] The control variables are explained in section 4.3.2.

[21] We lag the control variables to mitigate potential endogeneity problems.

$Female_{i,t}$ could indicate that female take more (less) risk than male fund managers based on our risk metrics. We include the same control variables as in equation (4), namely natural logarithm of $FundSize_{i,t-1}$ and $FundAge_{i,t-1}$, $NumberofStocks_{i,t-1}$, $Top10Holdings_{i,t-1}$ and $ExpenseRatio_{i,t-1}$, as well as fund, segment, and time dummies to capture fund, segment, and time-specific effects.

5.3 The Investment Style of Female- and Male Mutual Fund Managers

To examine female- and male mutual fund managers investment style, we will deploy two different models. Our first model emphasises the same approach as discussed under section 5.1, where we use both a value- and equal-weighted approach in the Carhart (1997) four-factor model (equation 3). Instead of focusing on the alpha in this model, the important coefficients will be the different factor-loadings, namely SMB_t, HML_t and UMD_t. The different coefficients will reveal if there are any statistical differences between female- and male fund managers, in our equal- and value-weighted portfolio. A difference in the factor loadings could indicate that investment style vary across gender, since they load differently on the risk-factors created by Fama and French (1993) and Carhart (1997).

As a second approach, we directly regress a funds $FactorWeightings_{i,t}$ on $Female_{i,t}$, and any other relevant fund characteristics:

$$\begin{aligned} FactorWeightings^x_{i,t} = \beta_0 &+ \beta_1 Female_{i,t} + \beta_2 ExpenseRatio_{i,t-1} \\ &+ \beta_3 Top10Holdings_{i,t-1} + \beta_4 NumberofStocks_{i,t-1} \\ &+ \beta_5 FundSize_{i,t-1} + \beta_6 FundAge_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{6}$$

Where $FactorWeightings_{i,t}$ denotes either $SMB^x_{i,t}$, $HML^x_{i,t}$ and $UMD^x_{i,t}$ for fund i, at time t, as described in section 4.3.1. Further, x denotes whether the regression is based on gross return (g) or net return (n). The important coefficient is as in equation (4) and (5), the $Female_{i,t}$. Whether $Female_{i,t}$ shows a positive (or negative) sign, indicate that males and females manage their funds differently. We include the same control variables as in equation (4) and (5), namely the natural logarithm of $FundSize_{i,t-1}$ and $FundAge_{i,t-1}$, $NumberofStocks_{i,t-1}$, $Top10Holdings_{i,t-1}$ and $ExpenseRatio_{i,t-1}$, as well as fund, segment, and time dummies to capture fund, segment, and time-specific effects.

5.4 Econometric Pitfalls

In our regressions, we will deal with both time-series and panel data. When we are using our portfolio approach (equation 1-3), with both an equal- and value-weighted portfolio, we have one observation for each time period (time-series) and apply the OLS model. By applying the OLS model on our sample, problems with biased or inconsistent estimators may lead to spurious results. In order to control for potential problems with autocorrelation and heteroskedasticity, we have clustered our standard errors at the fund level, to ensure that they are robust.

In our multivariate regressions (equation 4-6), we deal with panel data, which both contain time series, as well as cross-sectional data. A possible bias with panel data is an unbalanced panel, which in our case should indicate that we do not have all months for all units of observations. Due to the fact that we mitigate the risk of survivorship bias by including both surviving- and non-surviving mutual funds, our panel is unbalanced. However, we have to distinguish between randomly missing data and non-randomly missing data (Wooldridge, 2009). In our case, we argue that the missing data is non-random, and the reason for the unbalanced panel lies in the presence of newly established funds, as well as those that are liquidated or merged for our period from January 2005 to June 2017.

Our panel data allows us to account for variation over time, between cross-sections and control for time-invariant effects (Wooldridge, 2009). In our pooled OLS regression we follow the same approach as above. Hence, we cluster our standard errors at the fund level to ensure that our standard errors are robust to possible heterogeneity and autocorrelation problems. Further, panel data require strict exogeneity, with no correlation between the explanatory variables and the unobserved error term. As we discussed in section 4.3.2, we include both fund, segment, and time dummies in our regressions, to capture fund, segment, and time-specific effects, to mitigate the risk of omitted variable bias.

Further, another assumption that may be violated both in the OLS- and pooled OLS approach, is the assumption of no perfect multicollinearity between variables. In order to formally test for multicollinearity, we conduct a VIF test[22]. The VIF test calculates the variance inflation factors, corresponding to every explanatory variable in our regression. Usually, the value 10

[22] Post-estimation Variation Inflation Factor.

is chosen as a cutoff value to test whether multicollinearity is a problem for estimating the coefficient β (Wooldridge, 2009). In Appendix 2, we present a VIF-test, as well as a correlation matrix in Appendix 3 for the variables used in our multivariate regression. The mean VIF value is 1.19, and the maximum value is 1.51. Hence, we conclude that we do not deal with multicollinearity problems.

Chapter 6

Empirical Results

In this chapter, we present our analysis of the hypotheses developed in chapter 3. Our main focus will be on the variable related to gender differences, but we will also discuss the control variables, and compare our results to previous research when appropriate. Lastly, we assess the robustness of our results.

6.1 Do Female- and Male Mutual Fund Managers Perform Differently?

We start our empirical analysis by applying the one-, three- and four-factor model on our equal- and value-weighted portfolio, respectively. Table 2, Panel A, presents the result of our portfolio approach using gross return. Our results reveal that female fund managers obtain a higher alpha (α_i) than male fund managers, in both our value- and equal-weighted portfolio. However, the results are not delivering any statistically significant abnormal returns. The results do not differ whether we focus on the Jensen (1968) one-factor Alpha, Fama and French (1993) three-factor Alpha, or the Carhart (1997) four-factor Alpha. Furthermore, Panel B, presents the same approach using net return. The net return approach yields similar results, irrespective of portfolio choice or factor model deployed to estimate the abnormal returns. Based on our portfolio approach, we find no evidence that female- and male mutual fund managers perform differently on a risk-adjusted basis.

Our portfolio approach does not take into account fund specific characteristics. To investigate whether fund characteristics could affect performance, we run equation (4). Our results are presented in Table 3, Panel A and B, for gross- and net return, respectively. The $Female_{i,t}$ coefficient is positive, indicating better performance after adjusting for fund characteristics. However, the results are not statistically significant from zero. Even though our univariate comparison between male- and female fund managers in Table 1, Panel B, shows significant differences in alphas, we cannot say that this is true after controlling for fund characteristics. These results are in line with the research reported byNiessen-Ruenzi and Ruenzi (2015). Niessen-Ruenzi and Ruenzi (2015) uses both a portfolio- and multivariate approach, and find no statistically significant difference in performance across gender.

Furthermore, we find that our control variable $FundSize_{i,t-1}$ is negatively related to fund performance, indicating that larger funds tend to perform worse than smaller funds[23]. $FundAge_{i,t-1}$ is statistically negative related to fund performance for the one-factor model, but not in three- and four-factor models. The rest of our control variables are not statistically significant, and has a negligible effect on fund performance[24].

Our results indicate that the market for mutual fund managers is efficient with respect to that it is not possible to achieve abnormal returns by investing in funds based on the fund managers gender. Another explanation of our insignificant results may be that the fund managers are restricted by investment policies. Investment policy constraints is a common feature of a contract between mutual fund managers and investors (Almazan et al., 2004). According to Almazan et al. (2004), these restrictions may appear in a variety of forms, i.e. constraints against short sale, borrowing, holding of illiquid assets and use of derivatives. If the fund manager is restricted by policies, this could potentially bias our results. However, Almazan et al. (2004) documents no economically or statistically difference between high- and low constraint funds applying several approaches.

6.2 Are Female Mutual Fund Managers More Risk Averse?

In the previous section, we presented evidence that there is no difference between female- and male mutual fund managers in risk-adjusted performance. Next, we are going to elaborate around our second hypothesis, that female mutual fund managers are more risk averse than

[23] Niessen-Ruenzi and Ruenzi (2015) also finds that fund size is negatively related to performance. Further, Carhart (1997), reports an insignificant negative relationship between fund size and performance.

[24] Even if the variables are not significant, excluding these variables could potentially lead to omitted variable bias, and we might end up with spurious results.

male mutual fund managers. As reported in Table 1, Panel B, the univariate comparison gives mixed results. On average, female fund managers take more risk in our $FundRisk_{i,t}$, and $UnsysRisk_{i,t}$ measures, but less risk than male fund managers in $SysRisk_{i,t}$. Nevertheless, we stress that this is only a univariate comparison.

To investigate this further, we run equation (5), for all of the different risk metrics. Table 4, Panel A, presents the results of the different fund risk metrics, using gross return. $Female_{i,t}$ is negative for all of the different risk metrics, indicating that female fund managers take less risk on all levels. However, our results are not statistically significantly different from zero. This contradicts with the majority previous literature, which finds females to be significantly more risk averse (Byrnes et al., 1999; Barber and Odean, 2001; Jianakoplos and Bernasek, 1998). Table 3, Panel B, reports our findings based on net return, which yields the same results as gross return. Our results support the paper from Johnson and Powell (1994), which states that in an educated managerial subpopulation, females and males tend to demonstrate a more equal risk propensity.

With respect to our control variables, we find that $NumberStocks_{i,t-1}$ have a negative relationship with $UnsysRisk_{i,t}$. This is in line with the theory of diversification developed by Markowitz (1952), meaning that you can diversify away your unsystematic risk ($UnsysRisk_{i,t}$), but not the systematic risk ($SysRisk_{i,t}$). Hence, if you increase your number of stocks, it is more likely that you can be able to diversify away from the unsystematic risk. Furthermore, our results show that the size of the fund ($FundSize_{i,t-1}$) has a statistically significant negative relationship with $UnsysRisk_{i,t}$ as well. This may be due to the increased ability to invest in several stocks when a fund increases their size[25]. The fund size coefficient also reveals a negative impact on a firms systematic risk on the 10% significance level. Nevertheless, our control variable $FundAge_{i,t-1}$ has a negative relationship with $FundRisk_{i,t}$ and $UnsysRisk_{i,t}$, which is similar to Chevalier and Ellison (1997) findings. Lastly, we observe that $ExpenseRatio_{i,t-1}$ has a positive relationship with $FundRisk_{i,t}$ and $UnsysRisk_{i,t}$.

[25] As we can see from the correlation matrix in Appendix 3, there is a relatively high correlation between $FundSize_{i,t-1}$ and $NumberofStocks_{i,t-1}$, at 0.47.

6.3 Do Female- and Male Mutual Fund Managers Follow Different Investment Styles?

In this section, we are going to analyse our last hypothesis, that female- and male mutual fund managers follow different investment styles. Our first analysis elaborates around the value- and equal-weighted portfolios presented earlier. The results in Table 2, shows that female fund managers tend to load less on the HML_t factor than male fund managers in the value-weighted portfolio. This is an indication that they invest less in the HML value portfolio created by Fama and French (1993). Hence, females tend to load more on growth stocks compared to value stocks according to our portfolio approach. Furthermore, there is weak evidence in the value-weighted portfolio that female fund managers load more on the SMB_t factor than male fund managers do. Examining the equal-weighted portfolio, we find a positive statistical significant UMD_t factor, which could indicate that female fund managers bet more on past years winners than male fund managers.[26] These findings are supported by our univariate comparison in Table 1, Panel B, which find that females on average load more on growth stocks, thus the negative load on the HML_t factor, and a positive load on the UMD_t factor, in comparison with their male counterparts. These results could indicate that female- and male mutual fund managers manage their fund differently.

However, our portfolio approach and univariate comparison do not take into account fund-specific characteristics that could affect a funds investment style. By including the fund-specific characteristics, we mitigate the risk of endogenous regressors. To be able to confirm that female- and male mutual fund managers have different investment style, we run equation (6). The results are presented in Table 5, and show the female fund managers impact on the different $FactorWeightings_{i,t}$. Examining Table 5, we find a negative relationship between $Female_{i,t}$ and the factors $SMB_{i,t}$ and $HML_{i,t}$, indicating that female fund managers load less on these factors. Conversely, they load positive on the $UMD_{i,t}$ factor. However, our results are not statistically significant from zero. Further, we document a positive relationship between $ExpenseRatio_{i,t-1}$ and $SMB_{i,t}$ factor. $FundSize_{i,t-1}$ has a negative relationship with the $HML_{i,t}$. Finally, we report that an increase in $Top10Holdings_{i,t-1}$ leads to a decrease in the weighting on the $UMD_{i,t}$ factor.

[26] Our findings regarding the factors HML_t and UMD_t is in line with Niessen-Ruenzi and Ruenzi (2015), who also documents that females tend to have significantly lower (higher) loadings on the HML_t (UMD_t) factor. However, they do not find any statistically significant difference in SMB_t loading.

Our two different approaches measuring investment style provides us with mixed results. Our portfolio approach indicates a difference in investment style, while on the other hand, our multivariate regression shows no significant difference. Given that our portfolio approach does not take into account fund specific characteristics, which could greatly affect the investment style of a fund, we do not find it reasonable to conclude that there is any difference in investment style between female- and male mutual fund managers. Hence, our empirical results do not support Lewellen et al. (1977), which argues that gender is one of the most important factors determining an investment style.

6.4 Robustness

In this section, we discuss the robustness of our results. First, we investigate whether there is any difference if we estimate our regressions in a different time interval. Second, we explore if there is any difference between the Nordic countries. Third, we discuss if there should be an additional overlapping period after a change of fund manager in our multivariate regressions. Lastly, we discuss possible issues with external validity for our Nordic sample selection criteria.

We set the new time interval to January 2005 - June 2011 and July 2011 - June 2017. The results are presented in Table 6, panel A, B, C, for equation (4), (5), and (6), respectively[27]. We only report the coefficient estimate for the impact of the $Female_{i,t}$, but we have used the same control variables as in the original equations. By examining Table 6, we do not find any additional evidence towards a statistically significant difference in risk-adjusted performance, risk-taking behavior or investment style between female- and male mutual fund managers. In unreported results, we also test the new time interval on our portfolio approach, and find no significant difference. Thus, we conclude that our results are not sensitive to the specific time period we are analysing.

To address concerns that there is a difference between the country of domicile, we estimate equation (4), (5) and (6) for all the Nordic countries, respectively. The results[28] are presented in Table 7[29], where column 1-3 represents equation (4), column 4-6 equation (5), and column 7-9 equation (6). Furthermore, Panel A represents Denmark, Panel B Finland, Panel C Norway

[27] We only present results based on gross return. In unreported results we find that regression on net return yielded similar results.

[28] We only report the coefficient estimate for the impact on $Female_{i,t}$, but we have used the same control variables as in the original equations.

[29] We only present results based on gross return. In unreported results we find that regression on net return yielded similar results.

and Panel D Sweden. The results presented in Table 7 indicate a couple of minor differences across the Nordic countries. First, in Panel A, all the $Female_{i,t}$ coefficients are insignificant, except column (4), which reveals a negative and significant $FundRisk_{i,t}$. This indicates that female fund managers in Denmark take more risk at the fund level than their male counterparts. Furthermore, Panel C, column (5), reveals a positive and significant effect on the $SysRisk_{i,t}$ for the $Female_{i,t}$ coefficient, indicating that female fund managers in Norway take more systematic risk than male fund managers. However, the statistical significance is only at the 10% level, and it do not seem reasonable to conclude that female fund managers from Denmark and Norway deviate from the other countries where the $Female_{i,t}$ coefficients are still insignificant on all the other measures.

Furthermore, in our multivariate equations (equation (4), (5), and (6)), there could be an argument that when there is a change in fund manager (from female to male, or reversely), it could take some time for the new fund manager to be in full control of the assets. In our results, we have assigned the proper variable to the fund managers when they have had 12 months of previous return historic[30]. We explore the robustness of our method in unreported results, where we included a time-lag of 1, 3 and 6 months without assigning the $Perf^{x}_{i,t}$, $TotalRisk^{x}_{i,t}$ and $FactorWeightings^{x}_{i,t}$ to any fund manager. The unreported results do not reveal any deviation from our main analysis in the previous sections.

So far, we have discussed possible issues with different time intervals, differences across the Nordic countries, and if there should be an additional overlapping period after a change in fund manager. The last concern we want to address, is problems with external validity for our Nordic sample. Although we are including Nordic mutual funds investing inside their home domicile, as well as those investing in foreign equity, we could experience problems with external validity. The external validity elaborates around whether the Nordic mutual fund industry could be used to draw conclusions for a sample outside the Nordics. We argue that the Nordic mutual fund industry is strongly regulated and mature, reflecting similar traits as the global mutual fund industry. On the other hand, the top-ranked gender equality in the Nordic countries (World Economic Forum, 2017) might raise issues with external validity for our sample. A superior equality across gender in the Nordics could be argued as a potential drawback of our sample, because it may not be representative for the global mutual fund industry as a whole. In countries with a wider gender gap, females in senior positions may experience an

[30] See section 4.3.1 for a more detailed explanation.

unequal work environment, where they encounter discrimination and boundaries for how they should behave. In such cases, their influence on decisions may be limited, and highly different from the Nordic countries. However, we argue that in order to report unbiased results, we should examine a sample where we are able to capture the actual difference across gender, and mitigate the risk of being affected by potential biases like discrimination and behavioral constraints by the fund.

6.5 Critical Assessment

As discussed earlier in this paper, we control for multiple risk-factors[31] to comprehensively evaluate risk-adjusted performance, risk-taking behavior and investment style female- and male mutual fund managers. However, it could be argued that we should have used factors and benchmarks according to the investment mandate of the fund in this process. Soerensen (2009) argues that by not omitting funds with international mandates, it would be hard to gauge whether performance reflects skills or allocation decisions, which is unrelated to stock picking skills. Furthermore, he argues that restricting the sample to funds that primarily invest in domestic equities, would lead to more accurate measures of risk-adjusted performance. On the other hand, estimating these factors in Nordic countries would contradict with arguments from Kenneth French (Personal communication, 24.10.2017), where he argues that producing factors for most individual countries (or small regions) would not makes sense, because they are not well diversified. We have used a considerable amount of time discussing this topic, due to the fact that unless proper benchmarks are used, it can lead to erroneous conclusions regarding our hypotheses. Our final conclusion is that we believe capital flows freely between countries. Thus, a share of any company would trade for the same price if listed in two different markets, and there will be one and the same pricing model for the two stocks. Hence, the pricing of the risk factors should be the same. For this reason, we argue that all fund managers should be benchmarked against the world index and world risk factors.

[31] The market factor (MKT), size factor (SMB), value factor (HML) and momentum factor (UMD).

Chapter 7

Conclusion

In this thesis, we examine the differences in risk-adjusted performance, risk-taking behavior and investment style between male- and female mutual fund managers. Our data set is free of survivorship bias, and contains 430 Nordic mutual funds in the period January 2005 to June 2017. Throughout the literature review, we reveal inconsistent findings regarding differences in risk-adjusted performance, risk-taking behavior and investment style across gender in the financial industry. Based on the previous literature, and expected findings, we made the following hypotheses:

H1: *Female- and male mutual fund managers perform differently on a risk-adjusted basis*
H2: *Female mutual fund managers are more risk averse than male mutual fund managers*
H3: *Female- and male mutual fund managers utilize different investment styles*

To comprehensively evaluate risk-adjusted performance, we apply multiple performance measures. By applying the one-, three- and four-factor model on both gross- and net returns, we document that one cannot achieve abnormal returns following a hypothetical strategy that is long in females, and short in males. Furthermore, controlling for fund characteristics that could affect a funds performance, our evidence is consistent. This indicates that the market for fund managers are efficient with respect to that it is not possible to achieve superior returns by looking at the fund managers gender.

The economic literature in recent years suggests that female investors are more risk-averse than males. By reviewing three different risk metrics, and controlling for fund characteristics, we cannot document any evidence towards a significant difference in risk-taking behavior across gender in our sample.

Furthermore, using a portfolio approach, we find some evidence that female- and male mutual fund managers load differently on our the SMB_t-, HML_t- and UMD_t risk-factors. However, controlling for fund characteristics, our findings become statistically insignificant. Since fund characteristics could greatly affect the way a fund manager is running his fund, we conclude that the investment style of a mutual fund does not seem to be directly caused by the gender of the fund manager.

Overall, examining differences across gender in the Nordic mutual fund industry, we cannot report any empirical difference. By robustness testing these results in several ways, we conclude that one should not use gender as criteria when considering which Nordic mutual fund to invest in. Our findings regarding risk-adjusted performance are in line with Niessen-Ruenzi and Ruenzi (2015) and Atkinson et al. (2003), indicating that there are no differences between the U.S. and the Nordic mutual fund market regarding gender differences. Our findings concerning the insignificant differences in risk aversion across gender, contradict with previous literature, which finds females to be more risk averse (Byrnes et al., 1999; Barber and Odean, 2001; Jianakoplos and Bernasek, 1998). However, our results support the paper from Johnson and Powell (1994), which states that in an educated managerial sub-population, females and males tend to demonstrate a more equal risk propensity. Finally, Lewellen et al. (1977) argues that gender is one of the most important factors determining an investment style, which do not match our empirical analysis. In our sample, we document that female- and male mutual fund managers share the same investment style, after controlling for fund characteristics. Hence, the superior gender equality in the Nordic countries (World Economic Forum, 2017) does not reveal an empirical difference in risk-adjusted performance, risk-taking behavior or investment style between female- and male mutual fund managers.

Appendix

Appendix 1 - Variable Definitions

This table presents our variables used in the empirical analysis. The variable name is presented in colunm (1). Column (2) provides a descirption of the variable, while column (3) presents the data source for the variable. The data sources are: Morningstar Direct, Kenneth French Data Library, Fund Annual Reports or Estimated by the authors.

Variable (1)	**Description** (2)	**Source** (3)
$GrossReturn_{i,t}$	Fund $i's$ monthly return before any fee has been deducted. Measured in percent.	Morningstar Direct
$NetReturn_{i,t}$	Fund $i's$ monthly return after fee has been deducted. Measured in percent.	Morningstar Direct
$Female_{i,t}$	Dummy variable that takes the value 1 if the fund manager is a female, and value 0 if the fund manager is a male.	Morningstar Direct, Estimated
$FundAge_{i,t}$	Logarithm of Fund $i's$ years since their inception date, ln(Age + 1).	Morningstar Direct, Estimated
$NumberofStocks_{i,t}$	Fund $i's$ number of stock holdings in period t.	Morningstar Direct
$FundSize_{i,t}$	Logarithm of Fund $i's$ total assets, ln(FundSize + 1).	Morningstar Direct, Estimated
$Top10Holdings_{i,t}$	Fund $i's$ aggregated assets, expressed as a percentage of the funds top 10 holdings. Measured in percent.	Morningstar Direct
$ExpenseRatio_{i,t}$	Funds $i's$ monthly expense ratio at time t. Measured in percent.	Morningstar Direct, Fund Annual Reports
$FundRisk^{x}_{i,t}$	Fund $i's$ standard deviation at time t based on time series return for a 12 month period. The x denotes whether it is estimated using gross (g) or net (n) return. Measured in percent.	Morningstar Direct, Estimated

Variable (1)	Description (2)	Source (3)
$SysRisk^{x}_{i,t}$	Fund $i's$ loading on the market portfolio from the Jensen (1968) one-factor model at time t based on a 12 month horizon. The x denotes whether it is estimated using gross (g) or net (n) return.	Morningstar Direct, Kenneth French, Estimated
$UnsysRisk^{x}_{i,t}$	Fund $i's$ standard deviation of the residual from the Jensen (1968) one-factor model at time t based on a 12 month horizon. The x denotes whether it is estimated using gross (g) or net (n) return.	Morningstar Direct, Kenneth French, Estimated
$SMB^{x}_{i,t}$	Fund $i's$ loading on the SMB-factor from the Carhart (1997) four-factor model at time t based on a 12 month horizon. The x denotes whether it is estimated using gross (g) or net (n) return.	Morningstar Direct, Kenneth French, Estimated
$HML^{x}_{i,t}$	Fund $i's$ loading on the HML-factor from the Carhart (1997) four-factor model at time t based on a 12 month horizon. The x denotes whether it is estimated using gross (g) or net (n) return.	Morningstar Direct, Kenneth French, Estimated
$UMD^{x}_{i,t}$	Fund $i's$ loading on the UMD-factor from the Carhart (1997) four-factor model at time t based on a 12 month horizon. The x denotes whether it is estimated using gross (g) or net (n) return.	Morningstar Direct, Kenneth French, Estimated
$CAPM^{x}_{i,t}$	Fund $i's$ abnormal return using the Jensen (1968) one-factor model at time t based on a 12 month horizon. The x denotes whether it is estimated using (g) or net (n) return. Measured in percent.	Morningstar Direct, Kenneth French, Estimated
$FF^{x}_{i,t}$	Fund $i's$ abnormal return using the Fama and French (1993) three-factor model at time t based on a 12 month horizon. The x denotes whether it is estimated using gross (g) or net (n) return. Measured in percent.	Morningstar Direct, Kenneth French, Estimated
$Car^{x}_{i,t}$	Fund $i's$ abnormal return using the Carhart (1997) three-factor model at time t based on a 12 month horizon. The x denotes whether it is estimated using gross (g) or net (n) return. Measured in percent.	Morningstar Direct, Kenneth French, Estimated

Appendix 2 - VIF Test

VIF Test

Variable	VIF	Tolerance 1/VIF
$Female_{i,t}$	1.01	0.9862
$ExpenseRatio_{i,t-1}$	1.05	0.9550
$Top10Holdings_{i,t-1}$	1.20	0.8354
$NumberofStocks_{i,t-1}$	1.51	0.6639
$FundSize_{i,t-1}$	1.32	0.7551
$FundAge_{i,t-1}$	1.03	0.9663
Mean VIF	1.19	

$Notes$: This table presents the VIF test. The VIF test calculates the variance inflation factors, and tolerances for each of the control variables in our regression model. $Female_{i,t}$ takes on the value 1 if the fund manager is a female, and 0 if the fund manager is a male. $ExpenseRatio_{i,t-1}$ is the monthly expense ratio measured in percent of a fund. $Top10Holdings_{i,t-1}$ is a measure of the aggregated assets, expressed as a percentage of the funds top 10 holdings. $NumberofStocks_{i,t-1}$ is the number of different stocks each fund holds. $FundSize_{i,t-1}$ is the natural logarithm of the fund size MUSD. $FundAge_{i,t-1}$ is the natural logarithm of the fund $i's$ age. All variables are defined in Appendix 1.

Appendix 3 - Correlation Matrix

Correlation Matrix

	$Female_{i,t}$	$FundAge_{i,t}$	$ExpenseRatio_{i,t}$	$Top10Holdings_{i,t}$	$NumberofStocks_{i,t}$	$FundSize_{i,t}$
$Female_{i,t}$	1					
$FundAge_{i,t}$	0.001	1				
$ExpenseRatio_{i,t}$	0.114	-0.0200	1			
$Top10Holdings_{i,t}$	0.037	-0.004	0.095	1		
$NumberofStocks_{i,t}$	-0.023	0.072	-0.171	-0.402	1	
$FundSize_{i,t}$	-0.011	0.182	-0.127	-0.168	0.470	1

$Notes$: This table presents a correlation matrix for the control variables used in the multivariate regression. $Female_{i,t}$ takes on the value 1 if the fund manager is a female, and 0 if the fund manager is a male. $ExpenseRatio_{i,t-1}$ is the monthly expense ratio measured in percent of a fund. $Top10Holdings_{i,t-1}$ is a measure of the aggregated assets, expressed as a percentage of the funds top 10 holdings. $NumberofStocks_{i,t-1}$ is the number of different stocks each fund holds. $FundSize_{i,t-1}$ is the natural logarithm of the fund size MUSD. $FundAge_{i,t-1}$ is the natural logarithm of the fund $i's$ age. All variables are defined in Appendix 1.

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Table 1: Descriptive Statistics

Panel A	Obs (1)	Mean (2)	Std (3)	p(1) (4)	p(99) (5)
$GrossReturn_{i,t}$	45 040	0.821	6.733	-19.70	17.84
$NetReturn_{i,t}$	45 040	0.687	6.724	-19.81	17.66
$Female_{i,t}$	45 040	0.108	0.310	0.000	1.000
$FundAge_{i,t}$ (in years)	45 040	10.46	7.594	0.210	32.11
$NumberofStocks_{i,t}$	45 040	80.36	139.0	15.00	529.0
$FundSize_{i,t}$ (in millions)	45 040	234.0	536.0	201.0	2070
$Top10Holdings_{i,t}$	45 040	44.17	15.40	12.99	87.27
$ExpenseRatio_{i,t}$	45 040	0.130	0.051	0.017	0.275
$FundRisk_{i,t}$	39 054	6.073	2.957	2.023	15.56
$SysRisk_{i,t}$	39 054	1.256	0.412	0.298	2.444
$UnsysRisk_{i,t}$	39 054	2.816	1.553	0.591	8.140
$SMB^n_{i,t}$	39 054	0.165	0.847	-1.909	2.624
$SMB^g_{i,t}$	39 054	0.165	0.849	-1.857	2.628
$HML^n_{i,t}$	39 054	-0.008	1.089	-2.660	3.268
$HML^g_{i,t}$	39 054	-0.008	1.090	-2.665	3.275
$UMD^n_{i,t}$	39 054	-0.020	0.692	-1.657	2.106
$UMD^g_{i,t}$	39 054	-0.020	0.693	-1.659	2.108
$Car^n_{i,t}$	39 054	-0.266	1.235	-3.863	2.954
$Car^g_{i,t}$	39 054	-0.133	1.236	-3.685	3.122
$FF^n_{i,t}$	39 054	-0.189	1.217	-3.552	3.162
$FF^g_{i,t}$	39 054	-0.056	1.219	-3.391	3.347
$CAPM^n_{i,t}$	39 054	-0.102	1.134	-3.214	3.113
$CAPM^g_{i,t}$	39 054	0.031	1.137	-3.040	3.304

Table 1: Continued

Panel B	Female (1)	Male (2)	Difference (3)
$GrossReturn_{i,t}$	0.829	0.820	0.008
$NetReturn_{i,t}$	0.675	0.688	-0.013
$FundAge_{i,t}$	10.91	10.41	0.496***
$NumberofStocks_{i,t}$	70.45	81.56	-11.108***
$FundSize_{i,t}$	217.0	235.8	-18.80***
$Top10Holdings_{i,t}$	45.66	43.99	1.675***
$ExpenseRatio_{i,t}$	0.147	0.127	0.019***
$FundRisk^n_{i,t}$	6.235	6.045	0.190***
$FundRisk^g_{i,t}$	6.245	6.053	0.192***
$SysRisk^n_{i,t}$	1.227	1.258	-0.031***
$SysRisk^g_{i,t}$	1.229	1.249	-0.030***
$UnsysRisk^n_{i,t}$	3.095	2.781	0.314***
$UnsysRisk^g_{i,t}$	3.100	2.785	0.315***
$SMB^n_{i,t}$	0.158	0.165	-0.007
$SMB^g_{i,t}$	0.158	0.165	-0.007
$HML^n_{i,t}$	-0.066	-0.001	-0.065***
$HML^g_{i,t}$	-0.066	-0.001	-0.065***
$UMD^n_{i,t}$	0.004	-0.023	0.026**
$UMD^g_{i,t}$	0.004	-0.023	0.026**
$Car^n_{i,t}$	-0.231	-0.270	0.039**
$Car^g_{i,t}$	-0.078	-0.140	0.06195***
$FF^n_{i,t}$	-0.148	-0.194	0.046***
$FF^g_{i,t}$	0.006	-0.063	0.069***
$CAPM^n_{i,t}$	-0.066	-0.106	0.040**
$CAPM^g_{i,t}$	0.088	0.025	0.063***

$Notes$: This table presents the summary statistics of the different fund characteristics of all fund used in our analysis. Appendix 1 shows a detailed description of all the variables. Panel A, column (1-5) presents number of observations (Obs.), mean, standard deviation (SD), bottom percentile (p1) and upper percentile (p99). Panel B, column (1-2) presents the average of the characteristics for female- and male-managed funds. Column (3) presents the difference between the averages. The significance in column (3) is calculated using a two-sided t-test. ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 2: Gender and Performance - Portfolio Evidence

Panel A: Gross Return

	Equal-Weighted			Value-Weighted		
	$CAPM_t^{f-m}$	FF_t^{f-m}	Car_t^{f-m}	$CAPM_t^{f-m}$	FF_t^{f-m}	Car_t^{f-m}
	(1)	(2)	(3)	(4)	(5)	(6)
$Alpha_t$	0.089	0.084	0.053	0.074	0.07	0.055
	(1.22)	(1.18)	(0.73)	(0.94)	(0.99)	(0.75)
MKT_t	-0.027	-0.026	-0.014	0.031	0.041*	0.047**
	(-1.36)	(-1.35)	(-0.76)	(1.24)	(1.88)	(2.03)
SMB_t		0.079	0.076		0.095*	0.093*
		(1.42)	(1.36)		(1.85)	(1.81)
HML_t		-0.046	-0.008		-0.190***	-0.171***
		(-0.99)	(-0.18)		(-3.69)	(-3.21)
UMD_t			0.057*			0.029
			(1.83)			(1.16)
Observations	150	150	150	150	150	150
Adj. R^2	0.018	0.041	0.080	0.022	0.158	0.168

Panel B: Net Return

	Equal-Weighted			Value-Weighted		
	$CAPM_t^{f-m}$	FF_t^{f-m}	Car_t^{f-m}	$CAPM_t^{f-m}$	FF_t^{f-m}	Car_t^{f-m}
	(1)	(2)	(3)	(4)	(5)	(6)
$Alpha_t$	0.049	0.045	0.014	0.054	0.051	0.034
	(0.68)	(0.63)	(0.19)	(0.68)	(0.71)	(0.47)
MKT_t	-0.027	-0.027	-0.014	0.031	0.041*	0.048**
	(-1.35)	(-1.34)	(-0.75)	(1.25)	(1.89)	(2.05)
SMB_t		0.078	0.075		0.094*	0.092*
		(1.42)	(1.35)		(1.85)	(1.80)
HML_t		-0.048	-0.009		-0.191***	-0.172***
		(-1.02)	(-0.20)		(-3.71)	(-3.23)
UMD_t			0.058*			0.029
			(1.85)			(1.21)
Observations	150	150	150	150	150	150
Adj. R^2	0.019	0.041	0.082	0.023	0.160	0.170

$Notes$: This table reports the regression of a equal- and value-weighted portfolio that is long in funds managed by females , and short in funds managed by males (F-M) as the dependent variable. The independent variables are the the market factor MKT_t, the size factor SMB_t, the value factor HML_t, and the momentum factor UMD_t. The $alpha_t$ measures the abnormal returns of the long-short strategy. Panel A shows results based on gross return, while Panel B shows results based on net return. T-statistics are presented in the parentheses, and ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 3: Gender and Performance - Multivariate Evidence

	Panel A: Gross			Panel B: Net		
	$Car_{i,t}$	$FF_{i,t}$	$CAPM_{i,t}$	$Car_{i,t}$	$FF_{i,t}$	$CAPM_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_{i,t}$	0.079	0.057	0.045	0.073	0.0523	0.041
	(1.10)	(0.86)	(0.73)	(1.03)	(0.79)	(0.66)
$ExpenseRatio_{i,t-1}$	-0.182	0.395	0.318	-0.816	-0.401	-0.486
	(-0.03)	(0.56)	(0.44)	(-1.13)	(-0.55)	(-0.66)
$Top10Holdings_{i,t-1}$	-0.001	-0.002	-0.002	-0.001	-0.002	-0.002
	(-0.27)	(-0.77)	(-1.06)	(-0.34)	(-0.85)	(-1.15)
$NumberofStocks_{i,t-1}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.41)	(-0.44)	(-0.74)	(-0.30)	(-0.33)	(-0.93)
$FundSize_{i,t-1}$	-0.037***	-0.037***	-0.009**	-0.034***	-0.034***	-0.007**
	(-3.05)	(-3.01)	(-2.11)	(-2.90)	(-2.85)	(-2.04)
$FundAge_{i,t-1}$	0.014	0.004	-0.045**	0.015	0.005	-0.044**
	(0.61)	(0.16)	(-2.05)	(0.65)	(0.21)	(-2.01)
$cons_{i,t-1}$	0.804***	0.806***	0.296	0.770***	0.772***	0.262
	(4.34)	(3.96)	(1.47)	(4.16)	(3.79)	(1.31)
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39054	39054	39054	39054	39054	39054
Adj. R^2	0.141	0.222	0.240	0.144	0.224	0.241

$Notes$: This table presents the regression where $Perf_{i,t}$ is the dependent variable. $Perf_{i,t}$ is one of the following: $Car_{i,t}$ is the funds alpha from the four-factor model. $FF_{i,t}$ is the funds alpha from the three-factor model. $CAPM_{i,t}$ is the funds alpha from the one-factor model. $Female_{i,t}$ takes on the value 1 if the fund manager is a female, and 0 if the fund manager is a male. $ExpenseRatio_{i,t-1}$ is the monthly expense ratio measured in percent of a fund. $Top10Holdings_{i,t-1}$ is a measure of the aggregated assets, expressed as a percentage of the funds top 10 holdings. $NumberofStocks_{i,t-1}$ is the number of different stocks each fund holds. $FundSize_{i,t-1}$ is the natural logarithm of the fund size MUSD. $FundAge_{i,t-1}$ is the natural logarithm of the fund $i's$ age. All variables are defined in Appendix 1. Panel A shows results based on gross return, while Panel B shows results based on net return. All standard errors are clustered at the fund fund level. T-statistics are presented in the parentheses, and ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 4: Gender and Risk Taking - Multivariate Evidence

	Panel A: Gross			Panel B: Net		
	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_{i,t}$	-0.183	-0.038	-0.051	-0.183	-0.038	-0.050
	(-1.04)	(-1.05)	(-0.46)	(-1.04)	(-1.05)	(-0.45)
$ExpenseRatio_{i,t-1}$	2.674**	0.136	3.089***	2.608**	0.123	3.053***
	(2.39)	(0.59)	(3.79)	(2.33)	(0.53)	(3.75)
$Top10Holdings_{i,t-1}$	0.021***	0.002**	0.022***	0.021***	0.002	0.022***
	(5.33)	(2.25)	(6.48)	(5.32)	(2.25)	(6.49)
$NumberofStocks_{i,t-1}$	-0.000	-0.000	-0.001***	-0.000	-0.000	-0.001***
	(-1.07)	(-0.75)	(-2.92)	(-1.07)	(-0.75)	(-2.93)
$FundSize_{i,t-1}$	0.0623	0.016	-0.005**	0.0623	0.0155	-0.005**
	(1.43)	(1.54)	(-2.09)	(1.43)	(1.54)	(-2.09)
$FundAge_{i,t-1}$	-0.089*	-0.003	-0.093**	-0.089*	-0.003	-0.092**
	(-1.77)	(-0.43)	(-2.16)	(-1.76)	(-0.43)	(-2.16)
$cons_{i,t-1}$	0.660**	0.687***	0.774***	0.669***	0.688***	0.777***
	(2.01)	(7.76)	(3.37)	(2.04)	(7.78)	(3.39)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Segment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39054	39054	39054	39054	39054	39054
Adj. R^2	0.761	0.266	0.543	0.761	0.266	0.543

$Notes$: This table presents the regression where $TotalRisk_{i,t}$ is the dependent variable. $TotalRisk_{i,t}$ is one of the following: $FundRisk_{i,t}$ is the funds total risk measured by its standard deviation at time t. $SysRisk_{i,t}$ is the funds systematic risk measured by its loading on the market factor from the one-factor model at time t. $UnsysRisk_{i,t}$ is the funds unsystematic risk measured by the standard deviation of the residual from the one-factor model at time t. $Female_{i,t}$ takes on the value 1 if the fund manager is a female, and 0 if the fund manager is a male. The regressions are estimated using time, segment and fund fixed effects. All the other control variables are as defined in previous table, and a detailed description is presented in Appendix 1. Panel A shows results based on gross return, while Panel B shows results based on net return. All standard errors are clustered at the fund fund level. T-statistics are presented in the parentheses, and ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 5: Gender and Investment Style - Multivariate Evidence

	Panel A: Gross			Panel B: Net		
	$SMB_{i,t}$	$HML_{i,t}$	$UMD_{i,t}$	$SMB_{i,t}$	$HML_{i,t}$	$UMD_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_{i,t}$	-0.031	-0.047	0.006	-0.030	-0.047	0.005
	(-0.73)	(-0.97)	(0.17)	(-0.72)	(-0.97)	(0.17)
$ExpenseRatio_{i,t-1}$	0.720**	-0.023	0.040	0.714**	-0.017	0.041
	(2.35)	(-0.07)	(0.21)	(2.34)	(-0.05)	(0.22)
$Top10Holdings_{i,t-1}$	0.001	0.001	-0.002***	0.001	0.001	-0.002***
	(0.53)	(0.44)	(-2.84)	(0.53)	(0.45)	(-2.83)
$NumberofStocks_{i,t-1}$	-0.000	0.000	0.000	0.000*	0.000	0.000
	(-1.49)	(0.82)	(0.73)	(1.49)	(0.83)	(0.74)
$FundSize_{i,t-1}$	0.011	-0.021*	-0.011	0.011	-0.021*	-0.011
	(0.96)	(-1.87)	(-1.53)	(0.97)	(-1.87)	(-1.53)
$FundAge_{i,t-1}$	-0.037	-0.004	0.006	-0.037	-0.004	0.006
	(-1.59)	(-0.15)	(0.50)	(-1.59)	(-0.15)	(0.50)
$cons_{i,t-1}$	-0.275	-0.134	0.398***	-0.274**	-0.136	0.398***
	(-2.42)	(-1.44)	(5.35)	(-2.43)	(-1.46)	(5.34)
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Segment Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39054	39054	39054	39054	39054	39054
Adj. R^2	0.152	0.181	0.268	0.152	0.181	0.268

$Notes$: This table presents the regression where $FactorWeightings_{i,t}$ is the dependent variable. $FactorWeightings_{i,t}$ is one of the following: $SMB_{i,t}$ is the funds loading on the size factor at time t. $HML_{i,t}$ is the funds loading on the value factor at time t. $UMD_{i,t}$ is the funds loading on the momentum factor at time t. $Female_{i,t}$ takes on the value 1 if the fund manager is a female, and 0 if the fund manager is a male. All the other control variables are as defined in previous tables, and a detailed description is presented in Appendix 1. Panel A shows results based on gross return, while Panel B shows results based on net return. All standard errors are clustered at the fund fund level. T-statistics are presented in the parentheses, and ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 6: Robustness - Different Time Horizon

Panel A: Fund Return

	Jan 2005 - June 2011			July 2011 - June 2017		
	$Car_{i,t}$	$FF_{i,t}$	$CAPM_{i,t}$	$Car_{i,t}$	$FF_{i,t}$	$CAPM_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_{i,t}$	0.001	-0.039	-0.024	0.182	0.203	0.174
	(0.01)	(-0.41)	(-0.28)	(1.33)	(1.27)	(1.01)
Observations	18500	18500	18500	20554	20554	20554
Adj. R^2	0.133	0.206	0.218	0.153	0.176	0.155

Panel B: Fund Risk

	Jan 2005 - June 2011			July 2011 - June 2017		
	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnSysRisk_{i,t}$	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnSysRisk_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_{i,t}$	-0.118	-0.043	0.065	-0.208	-0.026	-0.146
	(-0.53)	(-0.93)	(0.45)	(-1.06)	(-0.57)	(-1.06)
Observations	18500	18500	18500	20554	20554	20554
Adj. R^2	0.780	0.297	0.549	0.667	0.237	0.507

Panel C: Factor loadings

	Jan 2005 - June 2011			July 2011 - June 2017		
	$SMB_{i,t}$	$HML_{i,t}$	$UMD_{i,t}$	$SMB_{i,t}$	$HML_{i,t}$	$UMD_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_{i,t}$	-0.0525	-0.110	-0.012	-0.025	0.008	0.0512
	(-0.71)	(-1.41)	(-0.30)	(-0.54)	(0.17)	(1.15)
Observations	18500	18500	18500	20554	20554	20554
Adj. R^2	0.167	0.205	0.340	0.198	0.232	0.154

$Notes$: This table presents the regressions used in Table 3, Table 4 and Table 5 using different time periods. The table presents the coefficient and t-statistic on $Female_{i,t}$ in regressions done as in Table 3, Table 4 and Table 5. All relevant control variables are included, but unreported. Panel A presents evidence from Jan 2005 to June 2011. Panel B presents evidence from July 2011 to June 2017. All standard errors are clustered at the fund fund level. T-statistics are presented in the parentheses, and ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

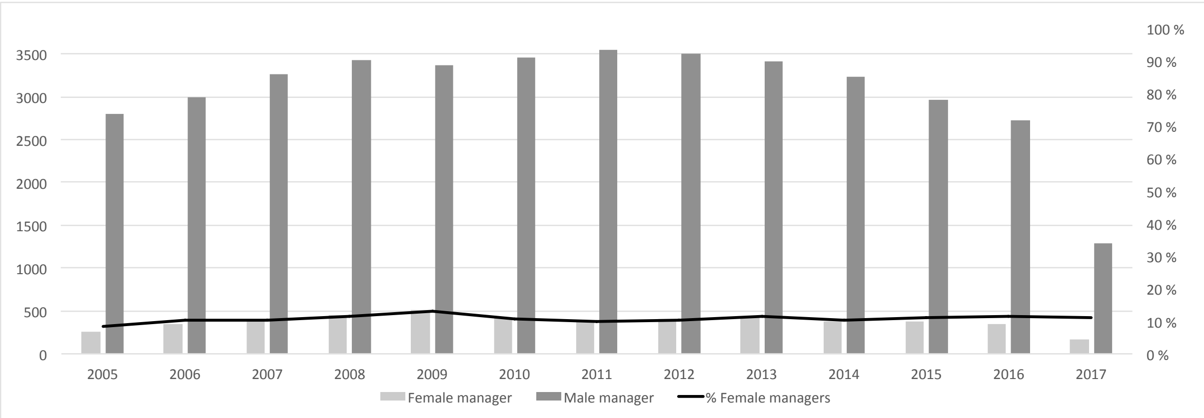
Table 7: Robustness - Different Country of Domicile

Panel A: Denmark	$Car_{i,t}$	$FF_{i,t}$	$CAPM_{i,t}$	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$	$SMB_{i,t}$	$HML_{i,t}$	$UMD_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Female_{i,t}$	0.241	0.206	0.183	-0.682*	-0.013	-0.004	0.092	-0.142	0.024
	(1.59)	(1.45)	(1.51)	(-1.77)	(-0.19)	(-0.13)	(1.27)	(-1.29)	(0.36)
Observations	7919	7919	7919	7919	7919	7919	7919	7919	7919
Adj. $R2$	0.107	0.156	0.181	0.765	0.124	0.603	0.157	0.154	0.174
Panel B: Finland	$Car_{i,t}$	$FF_{i,t}$	$CAPM_{i,t}$	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$	$SMB_{i,t}$	$HML_{i,t}$	$UMD_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Female_{i,t}$	0.021	-0.079	-0.103	0.125	0.035	-0.066	-0.077	-0.018	0.010
	(0.11)	(-0.43)	(-0.54)	(0.32)	(0.44)	(-0.23)	(-0.80)	(-0.18)	(0.13)
Observations	10140	10140	10140	10140	10140	10140	10140	10140	10140
Adj. R^2	0.124	0.205	0.227	0.711	0.179	0.541	0.169	0.163	0.231
Panel C: Norway	$Car_{i,t}$	$FF_{i,t}$	$CAPM_{i,t}$	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$	$SMB_{i,t}$	$HML_{i,t}$	$UMD_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Female_{i,t}$	0.123	0.075	-0.009	0.324	0.074*	-0.179	-0.077	-0.061	-0.077
	(1.01)	(0.61)	(-0.08)	(1.11)	(1.73)	(-1.24)	(-0.66)	(-0.58)	(-0.69)
Observations	6432	6432	6432	6432	6432	6432	6432	6432	6432
Adj. R^2	0.325	0.422	0.433	0.872	0.521	0.675	0.414	0.448	0.473
Panel D: Sweden	$Car_{i,t}$	$FF_{i,t}$	$CAPM_{i,t}$	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$	$SMB_{i,t}$	$HML_{i,t}$	$UMD_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Female_{i,t}$	0.049	0.075	0.063	-0.089	-0.023	-0.026	-0.084	-0.002	0.055
	(0.53)	(0.87)	(0.81)	(-0.32)	(-0.40)	(-0.15)	(-1.54)	(-0.02)	(1.47)
Observations	14563	14563	14563	14563	14563	14563	14563	14563	14563
Adj. R^2	0.222	0.284	0.278	0.801	0.305	0.541	0.210	0.203	0.367

Table 7: Continued

$Notes$: This table presents the regressions used in Table 3, Table 4 and Table 5 for each of the Nordic countries. The table presents the coefficient and t-statistic on $Female_{i,t}$ in regressions done as in Table 3, Table 4 and Table 5. All relevant control variables are included, but unreported. Panel A presents evidence from Denmark. Panel B presents evidence from Finland. Panel C presents evidence from Norway. Panel D presents evidence from Sweden. All standard errors are clustered at the fund fund level. T-statistics are presented in the parentheses, and ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Figure 1: Distribution of Female- and Male Mutual Fund Managers



$Notes$: This figure present a sample of all female- and male fund managers satisfying our requirements for the data sample of mutual funds in the Nordics from January 2005 to end of June 2017. The bars display the total number of female- and male managed funds, while the line is the fraction of female managed funds.