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Does the gender of mutual fund managers matter?

Empirical evidence of gender biases in the Nordics

Bachelor's Thesis

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Abstract

This study examines the effect of genders of single-managed equity mutual fund managers on fund flows in Iceland, Norway, Sweden, Finland, and Denmark from 2008 to 2021. Using monthly data of actively managed funds, the question is approached with a pooled OLS regression to investigate whether mutual fund investors are subject to gender discrimination.

A previous study in the U.S. suggests that individually managed funds by female fund managers have lower fund flows than male fund managers due to gender discrimination by mutual fund investors (Niessen-Ruenzi and Ruenzia 2019). In line with previous findings, the main findings of this study suggest that female fund managers have significantly lower monthly fund flows compared to male managers in an analysis conducted on samples with similar attributes.

In addition, this study aims to find potential rationale for the findings by including investment behaviour, performance, and flow-performance relationship analyses. Considering everything, the overall conclusion of this study is that Nordic female fund managers face irrational discrimination by mutual fund investors, which could provide a customer-based explanation for the low representation of female fund managers.

Keywords mutual fund, fund flow, discrimination, gender bias, investor behavior

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1 Introduction

1.1 Scope of research

Mutual fund industry has experienced an explosive growth since the 1990s. This was mainly due to rapid growth in net assets of mutual funds in the United States from USD 1.6 trillion in 1992 to 5.5 trillion in 1998 with an average annual rate of growth of 22.4 percent (Fevurly 2013). The growth has then continued strongly around the globe with an increase from $4.0 trillion in 1993 to $28.9 trillion in 2013 (Plantier 2014) with various factors driving it, including demand for professionally managed and well-diversified products that offer an efficient access to capital markets.

Since the U.S. has been at the centre of the mutual fund industry for decades, the availability of data in the U.S. is superior to other countries. Therefore, most of the previous research on mutual funds has been conducted on the U.S. data. However, mutual fund industry has also been blooming in other countries within the latest years, during which net assets of European investment funds have reached EUR 19.6 trillion and demand for equity funds has climbed to new records in 2021 (Delbecque, Tilley and Yang 2021), which has left a gap in the mutual fund literature of other countries.

Women have been highly underrepresented in the asset management industry for decades (Morningstar 2021). The data shows that the fraction of women in charge of single-managed U.S. equity funds has been around 10% over a 20-year period (Niessen-Ruenzi and Ruenzia 2019). While a range of factors can explain the low fraction of women in the mutual fund industry, such as hiring discrimination, women selecting other professions, and gender differences in career interruptions, it could also be partly due to discrimination by mutual fund investors.

The initial conjecture of this paper is that at least a fraction of mutual fund investors is subject to gender-related discrimination. If such biases exist among mutual fund investors, it could offer an explanation to the underrepresentation of female managers in the mutual fund industry, since it would be indirectly costly for funds to hire a female fund manager, as those funds would on average face lower money flows and hence generate lower profits in fees that are charged for the management of the fund.

As shown by Niessen-Ruenzi and Ruenzia (2019), female mutual fund managers face gender discrimination in the United States. To conduct a comparative examination, I include partly similar methodology in the mutual fund industry of Iceland, Norway, Sweden, Finland, and Denmark (*hereinafter "the Nordics"*) to see whether similar discrimination exists in countries, that are arguably more advanced in terms of gender equality.

Since the mutual fund industry has grown to an enormous size, and therefore plays a vital role in employment, it is important to have a comprehensive understanding of customer behaviour and the underlying reasons for the hiring decisions that fund companies make. Although the Nordic countries are different in nature, they have plenty of similarities in terms of political, geographical, and economical features, which justify connecting them as a united Nordic mutual fund industry when comparing on a global scale.

1.2 Structure of research

The empirical research begins with using the whole data from all single-managed Nordic equity mutual funds from 2008 to 2021, which shows only weak evidence of female managers facing lower inflows than male managers. To account for potential unobservable fund or managerial attributes that cannot be controlled for, I extend the main analysis by including matched samples analysis, which yields significant results for female managers experiencing lower inflows than male managers.

I approach the underlying cause of the results from matched samples analysis in two ways. Firstly, the root of cause could be rational, which is based on statistical observations that drive the investors to skew their investments towards male managers due to e.g., difference in performance, risk, or some other investment behaviour related factor. Secondly, the cause could be strictly due to irrational discrimination of female fund managers without any evidence of inferior performance or differences in other attributes.

To research for the rational cause of the lower flows of female managed funds within the matched samples, I examine whether female and male managers have differences in their investment style or behaviour, which could explain the lower fund flows. However, I did not find any evidence of differences in investment behaviour or performance that would support the view of investors rationally allocating more money to male managed funds.

Additionally, following (Ferreira et al. 2012) and others, I include flow-performance analysis, in order to examine whether the lower inflows can be explained by investors "punishing" funds of female managers more for poor performance and appreciate their good performance less. I find that measured with a risk-adjusted performance measure, female managed funds receive lower inflows following a good or poor performance than male managed funds. In the last part I discuss the potential rationale for fund companies hiring female managers despite the results in this paper as well as provide implications of this paper to research, potential limitations, and propositions to future research.

2 Theoretical background

I aim to contribute to three aspects of literature with my paper. Firstly, I relate to the general literature on gender differences in finance. Since during the past decades gender equality has faced an increasing focus in the world of business, my paper aims to fill some of the gap in literature on gender issues from the Nordic perspective, where gender equality is arguably at the most advanced level in the world. However, despite being ranked among the most gender equal countries in the world, in Finland men still occupied 95.8% of board member positions of large publicly listed companies and 65.7% of member of board positions in 2021 (Nordic Statistics 2021). This suggests that although the Nordic countries are advanced in terms of equality on a global scale, there still occur prominent differences between males and females in high quality positions.

As pointed out by Adams and Kirchmaier (2016), fraction of women working in the finance industry is low, which suggests that in comparison to other sectors, women are especially underrepresented in financial activities sectors. Evidence for gender-based discrimination is also presented by Bigelow et al. (2014), who illustrate that IPO's led by female company founders were less attractive options than those of male founders.

Although many studies in the gender equality literature find meaningful results for gender biases in finance, some researchers find little to no significance in difference between men and women. For instance, Harrison and Mason (2007) examine gender biases in venture capital industry and find that there appear to be more pronounced differences in characteristics, investment attitudes, and behaviour within the samples of women angels and men angels than between them. Even though gender biases are broadly studied in finance and business in general from various aspects, the literature focused particularly on mutual funds and their investors remains narrow.

Secondly, my paper contributes to the broad literature of the determinative factors of mutual fund flows and performance. Chevalier and Ellison (1999) examine the impact of general fund characteristics on fund flows, without focusing on the gender of the manager. They find that managers who attended higher-SAT undergraduate institutions have systematically higher risk-adjusted excess returns. Brad M. Barber, Odean, and Zheng (2005) argue that the purchase decisions of mutual fund investors are influenced by salient and attention-grabbing information about fees rather than actual operating expenses. Most of the papers that examine the determinative factors of fund flows focus on the past performance of the fund. For instance, Sirri and Tufano (1998), Berk et al. (2004), and many others investigate consumer fund purchase decisions focusing on matters such as risk-adjusted returns and flow-performance relationship.

Thirdly, my paper contributes to the literature of behavioral finance that examines social biases, such as discrimination, gender bias, and stereotyping. The basic idea that investors of mutual funds are subject to behavioral biases is addressed by Bailey, Kumar, and Ng (2011), who find large differences in investment behaviour between experienced and well informed investors, and those that are subject to behavioral biases. Additionally, Niessen-Ruenzi and Ruenzia (2019) document significantly lower fund flows for female managers than male managers in the U.S., which indicates that mutual fund investors are subject to gender bias. Kumar, Niessen-Ruenzi, and Spalt (2015) in their paper show that name-induced stereotypes affect the investment choices of U.S. mutual fund investors. Specifically, they show that managers with foreign-sounding names have about 10% lower annual fund flows.

With this paper I aim to combine all the above-mentioned aspects by showing that stereotype-based gender bias has an influence on investment behavior of mutual fund investors and thus has an impact on fund flows. Therefore, my paper illustrates that in addition to having individual behavioral biases, investors are also subject to social biases such as gender bias, which impact their investment choices.

3 Methodology

The main variable of interest in my empirical analyses is the net inflow or outflow “Fund flow” for fund i in month t, which is defined as:

$$\text{Fund flow} = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}$$

Where $TNA_{i,t}$ is fund i’s total net assets at the end of the month t and $r_{i,t}$ is fund i’s return in month t. Essentially, fund flow is the monthly change in fund’s total net assets that cannot be explained by the internal growth of the fund.

To research the relationship between fund flows and the genders of managers, I apply a pooled regression approach for panel data and include the control variables and fixed effects as well as cluster the standard errors at the fund level. The main independent variable is the Female dummy variable, which indicates 1 if the fund month is managed individually by a female manager and 0 if it is managed by a male manager. The grouping by gender is done manually by using country-level statistics, e.g., (Statistics Norway 2022) and (Digital and Population Data Services Agency 2020).

$$\text{Fund flow}_{i,t} = \beta_0 + \beta_1 \text{Female}_{1,}\text{t} + \text{B}_2 \text{Controls}_{1,t\text{-}1} + \varepsilon_{i,t}$$

The primary set of control variables includes the natural logarithm of fund size, monthly return, fund age, standard deviation of returns, expense ratio, turnover ratio, and lagged fund flow. [1] The control variables were selected based on previous studies (Spiegel and Zhang 2013; Kumar, Niessen-Ruenzi, and Spalt 2015; Niessen-Ruenzi and Ruenzia 2019), that have proven them to have an effect on fund flows.

Additionally, for robustness, I include alternative measures for risk and performance by including another measure of fund risk, beta, alpha, and the performance rank. I also include the squared performance rank to pick up potential convexity in performance. The control variables are lagged by one month and defined in Table 1. I estimate the flow regressions by also including year, segment, region, year x segment, year x region fixed effects, which I change depending on the specification, as well as cluster the standard errors at the fund-level in every specification. [2]

4 Data

4.1 Sources of mutual fund data

The main source of my data is Morningstar Direct, which is a database containing a comprehensive coverage of open-ended mutual funds across the world. The choice is motivated by several factors. Since I am using the Nordic countries as a united combination, Morningstar Direct allows me to gather comparable data across several countries. Additionally, previous findings (Massa, Reuter, and Zitzewitz 2010; Patel and Sarkissian 2017) show that Morningstar's name data is more accurate than other sources for mutual fund name and manager data. It is also more likely to be the source of

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[1] Since some of the main control variables could not be retrieved as monthly data from Morningstar, I used the same year value for every month observation.

[2] To account for serial correlation and heteroskedasticity in the error term, the standard errors are clustered at the fund level in all specifications (1-6) in Table 2.

information that Nordic investors use when making their investing decisions based on fund managers, which makes the results more credible.

4.2 Sample selection and periodicity

In the main sample I include actively managed equity funds that invest at least 50% of their total assets in common stock and are registered in the Nordic countries from January 2008 to December 2021. To only include Nordic funds, I filter the funds by their "Domicile," which denotes the country where the fund is legally registered. Additionally, in attempt to include the majority of the funds' investors to be from the Nordic countries and reduce the amount of so-called offshore-funds, I filter the funds by using "The region of sale," which is derived from each fund's domicile and availability for sale attributes.

Although many papers researching the mutual fund industry use year or quarterly data, I use monthly data in my analyses. The choice is motivated by a study done on a British data set on monthly fund flows, that shows that monthly frequency is more accurate than a quarterly frequency, but does not yield significantly different results (Keswani and Stolin 2008). Additionally, monthly data allows to increase the sample size and thus create more accurate results, especially since the Nordic sample consists of many relatively young funds. I also exclude funds that have less than one year of data to ensure continuity.

4.3 Sample characteristics

As shown by Bär, Kempf, and Ruenzi (2011), team and single-managed funds tend to behave differently. They show that teams exhibit a lower risk level, driven by a lower level of idiosyncratic risk, as compared to single-managed funds. Additionally, Patel and Sarkissian (2017) find that team-managed funds outperform single-managed funds across various performance metrics using data from Morningstar Direct. These findings suggest that to have the observations remain comparable, I only include fund months that have been managed by a single fund manager. To determine whether fund is single, or team managed, I use the fund manager data, which includes fund manager names as well as the dates when fund managers join and leave funds. In some cases, funds use phrases such as "team managed," or "multiple managers" under their fund manager names, which I do not include in the sample.

To keep my sample survivorship bias-free, I consider both existing funds and funds that have been liquidated or merged into other funds. As shown by Elton, Gruber, and

Blake (1996), a significant survivorship bias occurs when liquidated or merged funds are ignored. This is caused by the fact that the main reason for fund stopping its operations is due to inferior performance.

To avoid including the same fund twice in the sample, I aggregate the funds by their share classes. Morningstar provides aggregated statistics by funds' share classes for all the variables that are required for the research. I verify that each fund is unique by checking that each fund has a unique Fund Id.

The separation between male-managed and female-managed fund months is made manually by identifying the gender based on the first names that Morningstar's manager history provides. If the gender of the fund manager could not be identified based on the first names that Morningstar provides, I used Morningstar Investor section, which includes data on various fund manager attributes, including gender. The actual underlying gender of the manager is not relevant, but rather the likelihood that investors link the observed first name of the manager to a certain gender.

4.4 Outliers and missing data

After the initial filtering of data, there are in total of 42 991 monthly fund observations. I remove the observations that have missing values from the main variable of interest "Fund flow," which totals in 994 (2.3%) missing values. These missing values are mostly due to some funds reporting flows only on a quarterly or yearly basis, which leaves missing values for those months that are in between the reported flows.

There is no consensus in the mutual fund flow literature on how to eliminate the outliers out of the data. Some studies winsorize the outliers, which is replacing the most positive (negative) observations with more reasonable maximum (minimum) observations. Additionally, some studies use trimming, which is excluding outliers from the analysis when they exceed or fall below a certain threshold (Lusk, Halperin, and Heilig 2011).

However, recent research (Schiller, Woltering, and Sebastian 2020) shows that data entry issues, which may occur due to typing errors for instance, are another potential reason for extreme outliers. In this case, winsorization could lead to biased regression results and trimming from a certain threshold would be more appropriate. I find that majority of the outliers in the data appear to be due to data entry problems, since the outliers fall exceedingly far in the tails of the distribution, after which the rest of the observations are approximately evenly distributed. Therefore, following Schiller, Woltering, and Sebastian (2020), I trim the most extreme fund flow values that occur most likely due to data entry issues and thus do not belong in the distribution. [3]

I trim the most extreme outliers until the maximum of 100% and minimum of -100% fund flow, which occur due to either data entry issues or for young funds in periods when they have just begun their operations. The latter is due to young funds still having relatively small fund size in comparison with next month's flows. In addition to excluding those observations, I exclude monthly observations when funds' sizes have been less than USD 1 million to eliminate the rest of the observations from periods when the funds have recently begun to operate. After the entire trimming process, the final sample consists of 41 754 fund month observations from total of 432 funds. However, the amount of funds varies yearly, as some funds begin their operations later within the timeframe and others get merged or liquidated. In total, the trimming procedure excluded 2.9% of total observations.

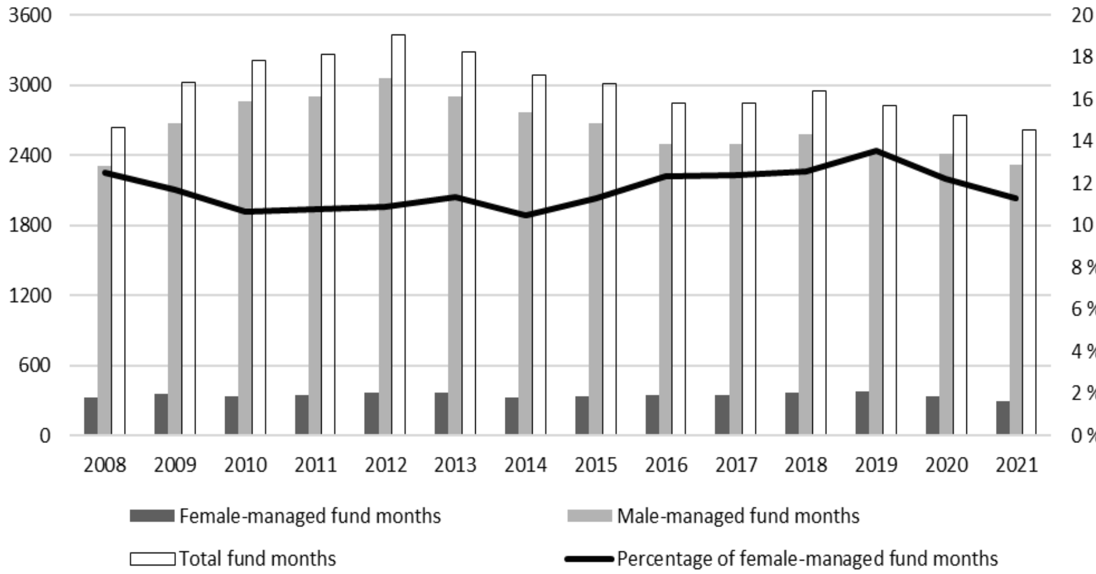

Figure 1
Distribution of yearly fund months by gender

Figure 1 illustrates yearly distribution of total female and male managed fund months in my final sample as well as the yearly percentage of female-managed funds. The ratio of individually female-managed fund months varies yearly between 10-14%, which shows a slight difference to the U.S. mutual fund market, where the ratio has been stable around 10% from 1992 to 2009 (Niessen-Ruenzi and Ruenzia 2019).

3 The main results are unaffected if I instead winsorize at the top 99% and bottom 1%.

5 Genders and fund flows

In this section, I present the variables and the first set of results. The main objective is to discover whether genders of fund managers and mutual fund flows are related. I first introduce the characteristics of male and female managed funds and then estimate flow regressions in which Fund flow is the dependent variable and the Female dummy variable is the main independent variable. The main hypothesis is that investors either consciously or subconsciously rather allocate their capital to male managed funds.

Table 1
Fund manager genders and fund characteristics

Variable	Male funds (1)	Female funds (2)	Difference (3)	t-statistic (4)
Fund attributes				
Fund flow	0.0039	-0.0002	0.0041	3.46***
Fund size	18.52	18.80	-0.28	-11.84***
Return	0.0061	0.006	0.0001	0.07
Fund age	11.60	13.36	-1.76	-12.87***
Prank	0.478	0.477	0.001	0.31
Prank^2	0.302	0.296	0.006	1.45
Sharpe ratio	0.542	0.525	0.017	0.87
Fund risk	0.43	0.436	-0.006	-2.93**
Stdev	0.189	0.192	-0.003	-2.59**
Alpha	-0.0155	-0.0158	0.0003	0.10
Beta	1.0344	1.0348	-0.0004	-0.05
Expense ratio	0.28	0.22	0.06	23.92***
Turnover ratio	0.477	0.468	0.009	0.52

The following table reports the mean fund characteristics that are sorted by the main independent variable "Female", which is a dummy variable that takes the value zero if the fund's month observation is managed by a male manager and one if it is managed by a female manager. All month observations are single-managed. The differences between the group means of male and female funds and the t-statistics are reported in Columns (3) and (4). The t-statistics are calculated using the two-tailed t-test. Fund flow is the net inflow into the fund in the current month defined as $(TNA_{i,t} - TNA_{i,t-1})/TNA_{i,t-1} - r_{i,t}$, where $TNA_{i,t}$ denotes fund i's total net assets in month t, and r_t denotes fund i's return in month t as reported in Morningstar. Fund size is the natural logarithm of the fund's month-end total net assets (TNA). Return is fund's gross return that an investor would have received had they not paid any expenses. Fund age is the fund tenure computed from the fund's start date and measured in years. Prank is the performance rank of the fund in the previous year relative to all other funds in the same Morningstar Category, where the highest and most favorable percentile rank is 1 and the lowest and least favorable percentile rank is 100, scaled to lie between zero (highest peformance) and one (lowest performance). Sharpe ratio is a risk-adjusted measure calculated by using standard deviation and excess return to determine the reward per unit of risk. Fund risk is the percentage of aggregated assets of the fund's top 10 portfolio holdings. The higher the percentage, the more concentrated the fund is in a few holdings. Stdev is the standard deviation of fund's returns, which depicts how widely the returns have varied over a year. Alpha (Jensen's alpha) measures a mutual fund manager's effectiveness by showing the difference between a fund's returns and its expected performance, given its level of risk as measured by Beta. Beta is a measure of systematic risk, that measures the sensitivity of the fund's excess return with respect to market's excess return. Expense ratio is the monthly percentage of fund assets used to pay for operating expenses and management fees. Turnover is a measure of the fund's trading activity, which is computed by taking the lesser of purchases or sales and dividing by average monthly net assets. All variables that include percentage terms are expressed in decimals.
*** 1% significance; ** 5% significance; * 10% significance

5.1 Attributes of fund managers by gender

Table 1 presents the univariate results for male and female fund characteristics. The most relevant feature of the table for this paper is that female managed funds receive 0.41 percentage points lower monthly fund flows, which is a highly significant difference from male managed funds with a t-statistic of 3.46. I also find this evidence when comparing monthly fund flows year-by-year. Figure 2 illustrates average monthly fund flows for male and female managed funds. In my sample, in 11 out of 14 years male managed funds received higher monthly fund flows on average.

In addition to flows being different for female fund managers, there are other statistically significant differences between the two groups of funds. Female managers manage larger funds than male managers in my sample, which is also a highly significant difference. This is compatible with the difference in fund age, since larger funds tend to be more established and therefore also have a higher tenure. This is also in line with the difference in the expense ratio, since as shown by Elton, Gruber, and Blake (2012), expense ratios are usually lower for large funds. Finally, both of my measurements for the riskiness of the fund are significantly larger for female managed funds. This could be e.g., due to relationship between flows and risk, which varies between large and small funds (Babalos, Mamatzakis, and Matousek 2015).

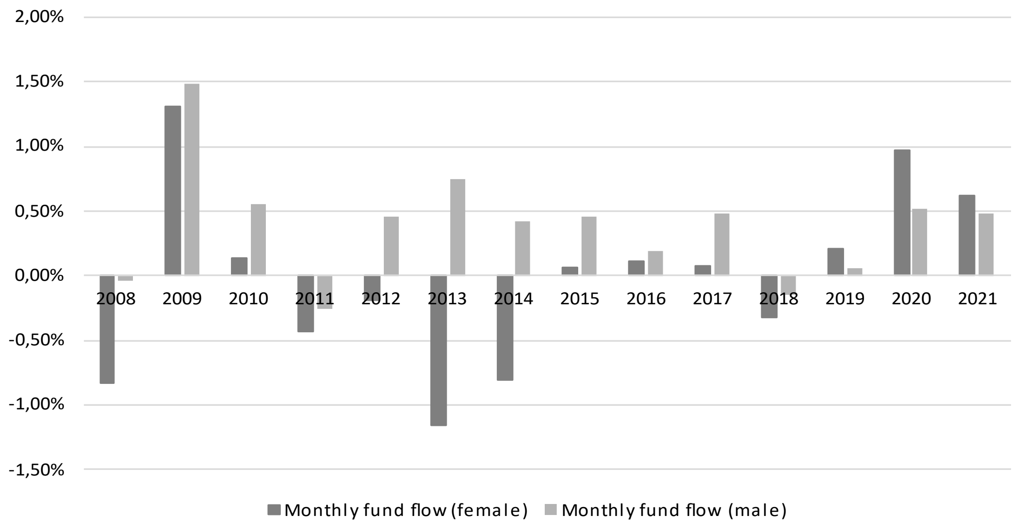

Figure 2
Average monthly fund flows, 2008 to 2021

5.2 Baseline results from flow regression

Table 2 presents the flow regression estimates. The model is estimated by pooled OLS in every column (1-6). In specification (1) I include the main set of control variables with no fixed effects. In specifications (2) I include fund and time fixed effects and in specification (3) I also add region and segment fixed effects to the regression. The specification (3) is considered as the baseline regression, as it includes all the necessary fixed effects and control variables.

Table 2
Main results
Fund flow regression estimates

	OLS	OLS	OLS	OLS	OLS	OLS
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Female $_{i,t}$	-0,0029	-0,0053	-0,0053	-0,0033	-0,0017	-0,0052
	(-1.47)	(-1.69)*	(-1.62)	(-1.74)*	(-0.75)	(-1.63)
Fund size $_{i,t-1}$	-0,0005	-0,0143	-0,0135	-0,0008	-0,0012	-0,0139
	(-1.09)	(-8.55)***	(-7.85)***	(-1.76)*	(-2.34)**	(-8.06)***
Return $_{i,t-1}$	0,0727	0,0719	0,0723	0,0635	0,0584	
	(8.22)***	(7.77)***	(7.38)***	(7.10)***	(6.24)***	
Fund age $_{i,t-1}$	-0,0005	0,0441	0,0249	-0,0005	-0,0005	0,0240
	(-6.90)***	(1.79)*	(1.84)*	(-6.87)***	(-5.80)***	(1.80)*
Stdev $_{i,t-1}$	0,0069	0,0107	0,0080	-0,0031	-0,0106	
	(1.13)	(1.14)	(0.84)	(-0.37)	(-1.05)	
Fund risk $_{i,t-1}$						-0,0204
						(-1.63)
Expense ratio $_{i,t-1}$	0,0037	-0,0061	-0,0057	0,0030	0,0019	-0,0057
	(1.52)	(-0.80)	(-0.76)	(1.24)	(0.74)	(-0.75)
Turnover ratio $_{i,t-1}$	-0,0001	-0,0003	-0,0003	-0,0001	-0,0001	-0,0003
	(-2.73)**	(-1.64)	(-1.59)	(-2.51)**	(-2.65)**	(-1.58)
Fund flow $_{i,t-1}$	0,0000	0,0000	0,0002	0,0000	0,0000	0,0002
	(-0.37)	(0.76)	(2.03)**	(-0.47)	(0.05)	(2.08)**
Prank $_{i,t-1}$						-0,0236
						(-2.55)**
Prank $^{2}_{i,t-1}$						0,0110
						(1.17)
Fixed effects						
Fund-level FE	no	yes	yes	no	no	yes
Year FE	no	yes	yes	no	no	yes
Region FE	no	no	yes	no	no	yes
Segment FE	no	no	yes	no	no	yes
Year x Region FE	no	no	no	yes	no	no
Year x Segment FE	no	no	no	no	yes	no
Adj. R^2	0.007808	0.04143	0.03736	0.01142	0.02161	0.0363
Observations	41745	41301	37607	41676	37645	37606

This table shows the estimates of percentage fund flows regressed on the Female dummy variable and various control variables. All independent variables except for the Female dummy variable are lagged by one month and have been defined in detail in Table 1. The model is estimated by pooled OLS in all columns. The t-statistics are displayed in parentheses below the coefficient estimates, and standard errors are clustered at the fund level in every specification.
*** 1% significance; ** 5% significance; * 10% significance

In addition, in specifications (4) and (5) I control for year x region and year x segment fixed effects, to see whether within the same region and year or segment and year female managers receive lower fund flows than male managers. Finally, for robustness, in specification (6) I consider alternative control variables for performance and risk to see whether the results are affected.

Conflicted with the main conjecture that mutual fund investors are subject to gender bias in their investment decisions, I find that although still negative, the Female dummy variable is not significantly negatively related to fund flows at the 5% significance level or below in any of the specifications. Although in specifications (2) and (4) the Female dummy variables are significantly negative at the 10% significance level, which could indicate weak evidence against the null hypothesis, they are generally not considered low enough to justify the rejection. Additionally, these two specifications do not include segment fixed effects, which indicates that the results are likely to be influenced by some unobservable factor that is varying at the segment level.

5.3 Matched sample flow regression estimates

One of the main concerns regarding the baseline flow regression results is that there may be unobservable fund or managerial attributes that may influence the fund flows and therefore my regressions might compare very dissimilar funds in those unobservable attributes.

As shown in Table 1, there are differences in the observable attributes of female and male managed funds. To reduce the effect of possible unobservable attributes, I divide the funds to matched samples of funds, for which the baseline regressions are re-estimated. Since the funds within the matched samples are more similar in the attributes that are observed, the possible unobservable attributes are also likely to be more similar.

To conduct the matched samples analysis, a set of matching attributes must firstly be identified for funds. I select the attributes according to the largest differences between the fund groups as according to Table 1, which illustrates differences in the observable attributes between male and female managed funds in the main sample. Based on Table 1, the main concerns are fund size, age, and fund riskiness.[4] Additionally, following Kumar, Niessen-Ruenzi, and Spalt (2015), I also match funds based on time, performance and segment. First, I divide the funds to the 10-90 percentile ranges by size, performance, and risk. Then, for each year, I include every male managed fund that

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[4] Although the expense ratio is also significantly negative between the two groups, I assume it to vary mainly due to the difference in fund size.

match the attributes of female managed funds in that year. Only these male managed funds are kept in the new sample, and other observations are dropped. The aim of this selection process is to only pick funds in the sample that match with the selected criteria. For robustness, I include in total of five samples with different attributes.

For the sample (1) I match the funds based on segment and size within the same year. In the sample (2) I require the funds to have similar yearly gross return and additionally include the standard deviation of returns as a risk criterion in the sample (3). In specification (4) I include the fund age criteria and drop the segment criteria.

Table 3 presents the fund flow regressions results for five alternative samples. The baseline regression (Table 2, specification 3) is used for every matched sample. As opposed to the results in Table 2, the matched sample regressions have significantly negative coefficient for the female dummy variable at the 5% significance level except for the sample (4), which is in line with the observation from Table 2 that there may be unobservable attributes at the segment level that influence the results. The sample (5) is equivalent to sample (4), except for the added segment attribute, which yields negatively significant results. The monthly difference varies between 0.66 – 0.77 percentage points, which equals to approximately 8-9 percentage points difference in annual fund flows.

Although I lose over a quarter of the observations in most of the specifications, the results become more significant. Overall, based on the flow regression estimates in Table 3, fund flows are significantly lower for female fund managers than male fund managers.

Table 3
Matched samples analysis

	Baseline regression (Table 2, specification 3)			
Matching attributes	Coefficient	t-statistic	Observations	Funds
(1) Year, segment, size	-0.00687	(-1.97)**	30696	351
(2) Year, segment, size and performance	-0.00765	(-2.19)**	28978	340
(3) Year, segment, size, performance and riskiness	-0.00763	(-2.18)**	28176	329
(4) Year, fund age, riskiness	-0.00527	(-1.51)	23425	352
(5) Year, segment, fund age, riskiness	-0.00661	(-2.03)**	19836	269

This table shows flow regression results for five ways of performing the matched samples. Only the coefficients and corresponding t-statistics of the female dummy variable and total observations within the matched samples are reported. The results are based on the specification 3 of the baseline regressions from Table 2. The matched fund samples are constructed by matching each female managed fund with only the set of male managed funds that have the same set of matching criteria in a given year. The following matching attributes are used: fund segment, natural logarithm of the fund size, fund performance as raw returns, riskiness as the standard deviation of returns, and fund age. All specifications are estimated with robust standard errors clustered at the fund level. T-statistics are in parenthesis and indicate *** 1% significance; ** 5% significance; * 10% significance.

6 Gender discrimination or rational statistical discrimination

The evidence from the matched samples analysis suggests that Nordic mutual fund investors prefer male managed funds over female managed funds. I propose that gender bias is one of the possible explaining factors in this phenomenon. However, the findings could also be caused by rational statistical discrimination instead of gender bias.

Following methods from other similar papers (Niessen-Ruenzi and Ruenzia 2019; Kumar, Niessen-Ruenzi, and Spalt 2015), I aim to clarify whether the results are driven by rational statistical discrimination rather than irrational gender discrimination. Therefore, I examine whether there is any evidence of differences in investment behaviour or performance between female and male fund managers that could influence the investment decisions of mutual fund investors.

As shown in Table 1, there are differences in the attributes between male and female-managed funds in the main sample, when the comparison is made with a univariate two-tailed t-test. To further examine this, I investigate whether there are differences within the matched samples using various measures, as well as control variables, fixed effects, and standard error clustering.

To measure fund risk and performance, it is essential to choose the measures of risk and performance that are likely to be commonly observed and taken into consideration by investors. Since only the matched samples (1), (2), (3), and (5) yielded significant results in the previous section, in this section I use samples (3) and (5), which together include all the matching attributes, and therefore I assume they can represent all the matched samples in further analyses.

6.1 Investment style

To examine investment style differences between male and female fund managers, I focus on risk-taking behaviour and trading activity. To measure fund i‘s risk in month t, I use one of the following three risk measures as the dependent variable: standard deviation of fund i’s gross return in month t ($Stdev_{i,t}$), measure of investment diversification ($Fund\ risk_{i,t}$), or systematic risk ($Beta_{i,t}$). I also include Turnover ratio as measure of trading activity, all as defined in Table 1.

Table 4
Investment style analysis
Panel A: Sample 3

Variable	*Stdev* $_{i,t}$	*Fund risk* $_{i,t}$	*Beta* $_{i,t}$	*Turnover ratio* $_{i,t}$
Female $_{i,t}$	-0.009	0.0111	-0.0493	0.0203
	(-1.48)	(0.87)	(-1.45)	(1.35)
Fund size $_{i,t-1}$	-0.0025	-0.0137	0.0043	-0.0093
	(-0.97)	(-3.11)***	(0.32)	(-1.44)
Return $_{i,t-1}$	0.0284	0.001	0.0909	-0.0747
	(6.18)***	(0.14)	(4.72)***	(-0.71)
Fund age $_{i,t-1}$	0.0004	0.0437	0.0757	-0.0204
	(0.03)	(1.03)	(0.49)	(-1.81)*
Expense ratio $_{i,t-1}$	0.0133	0.002	0.0138	0.0594
	(1.10)	(0.11)	(0.22)	(1.39)
Adj. R^2	0.64	0.74	0.69	0.038
Observations	28180	28180	28180	28180

Panel B: Sample 5

Variable	*Stdev* $_{i,t}$	*Fund risk* $_{i,t}$	*Beta* $_{i,t}$	*Turnover ratio* $_{i,t}$
Female $_{i,t}$	-0.004	0.006	-0.049	0.022
	(-0.68)	(0.63)	(-1.29)	(1.26)
Fund size $_{i,t-1}$	-0.004	-0.013	-0.016	-0.01
	(-1.2)	(-2.56)**	(-0.99)	(-1.00)
Return $_{i,t-1}$	0.030	-0.006	0.094	-0.112
	(5.45)***	(-0.79)	(4.21)***	(-0.74)
Fund age $_{i,t-1}$	-0.012	-0.02	0.193	-0.013
	(-0.61)	(-1.18)	(0.99)	(-1.02)
Expense ratio $_{i,t-1}$	0.024	-0.009	0.039	0.004
	(1.87)*	(-0.49)	(0.65)	(0.14)
Adj. R^2	0.62	0.75	0.69	0.036
Observations	19839	19839	19839	19839
Fixed effects				
Fund-level FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Region FE	yes	yes	yes	yes
Segment FE	yes	yes	yes	yes

In panel A and B are the results of the investment style analysis conducted on the sample 3 and 5 respectively. The dependent variable is one of the following: Stdev, which is fund i's standard deviation of returns. Fund risk, which is the aggregate assets of the fund i's top 10 portfolio holdings. The higher the percentage, the more concentrated the fund is in a few holdings. Beta, which is a measure of systematic risk, that measures the sensitivity of the fund's excess return with respect to market's excess return. Turnover ratio, which is a measure of the fund's trading activity, which is computed by taking the lesser of purchases or sales and dividing by average monthly net assets. The main independent variable is the Female dummy variable that takes on the value 1 if fund i is managed by a female manager in month t and 0 otherwise. All other variables are defined in Table 1. All regressions include fund, year, segment and region fixed effects. The t-statistics are in parentheses and based on robust standard errors clustered at the fund level.
*** 1% significance; ** 5% significance; * 10% significance

In addition to the female dummy variable, I include lagged fund size, the expense ratio, fund age and return as the control variables, as well as fund, segment, year, and region fixed effects. Standard errors are clustered at the fund level.

Contrary to the univariate results in Table 1, but consistent with the literature regarding risk-taking behaviour between female and men (Sundén and Surette 1998) the results of Table 4 suggest that female-managed funds are more risk-averse, which shows as negative coefficients in two of the three risk-related regressions in both of the matched samples. I also find that women seem to trade more, which is inconsistent with the risk-taking literature, as high turnover ratio is considered as having more overconfidence (B M Barber and Odean 2001). However, these results are not statistically significant, and therefore differences with respect to the investment style between female and male fund managers cannot completely explain the results of the previous section regarding the investment decisions of mutual fund investors.

6.2 Fund performance analysis

I now examine whether the results of section 4 are caused by the performance of funds, which could explain the results as rational discrimination rather than gender discrimination. According to Sirri and Tufano (1998) it is not clear which measures of performance are the most prominently used by mutual fund investors. To measure fund i's performance in month t, I follow a common approach in other studies (e.g., Massa, Reuter, and Zitzewitz 2010; Kumar, Niessen-Ruenzi, and Spalt 2015) and regress various fund performance variables on a set of controls.

Specifically, for robustness, I relate in total of four different measures of fund performance as well as the expense ratio to the fund manager's gender including control variables, fixed effects, and clustering standard errors at the fund-level. I use one of the following performance measures for fund i in month t: $Return_{i,t}$, $Alpha_{i,t}$[5] (Jensen 1972), $Prank_{i,t}$, $Sharpe\ ratio_{i,t}$[6] (Sharpe 1994), and $Expense\ ratio_{i,t}$. The performance measures are defined in Table 1. Although there are more advanced risk-adjusted measures of returns that would be more appropriate according to the finance theory, they may not be the measures that investors commonly observe and use when allocating money between funds.

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[5] Jensen's alpha, which is a performance measure based on the CAPM, was introduced by William Jensen in 1970. Jensen's alpha is computed as:
$\alpha = R_P-(R_f+\beta(R_M-R_f))$, where R_P is return of the portfolio, R_f is the risk-free rate, β is the beta measuring systematic risk, and R_M is the market return.

[6] Sharpe ratio measures the average excess return per unit of risk, and is a common method for measuring risk-afjusted reutrn. Sharpe ratio is measured as:
Sharpe ratio = $(R_p-R_f) / \sigma_p$, where R_p is the return of portfolio, R_f is the risk-free rate, and σ_p is the standard deviation of the portfolio's excess return.

Table 5
Performance analysis
Panel A: Sample 3

Variable	*Return* $_{i,t}$	*Alpha* $_{i,t}$	*Prank* $_{i,t}$	*Sharpe ratio* $_{i,t}$	*Expense ratio* $_{i,t}$
Female $_{i,t}$	-0.00251	0.0018	0.00054	0.008322	0.001119
	(-2.14)**	(1.82)*	(0.20)	(1.44)	(0.59)
Fund size $_{i,t-1}$	-0.00617	0.00021	0.001713	0.002921	0.000922
	(-9.54)***	(0.47)	(1.68)*	(1.04)	(0.99)
Performance $_{i,t-1}$	0.00181	0.92345	0.92057	0.92355	0.8712
	(0.32)	(338.59)***	(428.22)***	(303.47)***	(115.12)***
Risk $_{i,t-1}$	0.02228	-0.00024	-0.003627	0.005088	0.000864
	(5.47)***	(-0.30)	(-0.47)	(0.29)***	(0.13)
Fund age $_{i,t-1}$	-0.00525	-0.00184	-0.001903	0.013719	-0.0233
	(-0.69)	(-0.53)	(-0.12)	(0.47)*	(-2.50)**
Turnover ratio $_{i,t-1}$	-0.00017	-0.00004	-0.000122	-0.000004	-0.000029
	(-2.48)**	(0.80)	(-2.71)**	(-0.03)	(-0.70)
Adj. R^2	0.082	0.93	0.8494	0.96	0.84
Observations	28179	28179	28179	28179	28179

Panel B: Sample 5

Variable	*Return* $_{i,t}$	*Alpha* $_{i,t}$	*Prank* $_{i,t}$	*Sharpe ratio* $_{i,t}$	*Expense ratio* $_{i,t}$
Female $_{i,t}$	-0.002	0.00111	0.00158	0.00724	0.00134
	(-1.63)	(1.03)	(-1.23)	(1.05)	(0.78)
Fund size $_{i,t-1}$	-0.0066	0.00049	0.00031	0.00407	0.00202
	(-7.66)***	(0.81)	(-3.61)***	(1.06)	(1.60)
Performance $_{i,t-1}$	0.0041	0.9186	0.91697	0.9163	0.85386
	(0.59)	(272.35)***	(374.14)***	(223.2)***	(86.27)***
Risk $_{i,t-1}$	0.0258	-0.00106	-0.02142	0.00195	0.01272
	(4.70)***	(-0.97)	(-0.52)	(0.07)	(1.62)
Fund age $_{i,t-1}$	-0.0061	0.00726	0.02566	-0.29758	-0.00474
	(-0.78)	(0.71)	(-0.82)	(-2.23)**	(-0.50)
Turnover ratio $_{i,t-1}$	-0.00014	-0.00002	-0.00014	0.00005	-0.00006
	(-1.99)*	(-0.34)	(-5.53)***	(0.25)	(-2.48)**
Adj. R^2	0.083	0.92	0.845	0.94	0.83
Observations	19838	19838	19838	19838	19838

In panel A (and B) are the results of performance analysis conducted on the sample 3 (and 5). The dependent variable is one of the following: Return, which is fund i's return in month t, measured by its monthly gross return; Alpha (Jensen's alpha) measures a mutual fund manager's effectiveness by showing the difference between a fund's returns and its expected performance, given its level of risk as measured by Beta; PRank is the performance rank of the fund in the previous year relative to all other funds in the same Morningstar category, scaled to lie between zero (highest performance) and one (lowest performance); Sharpe ratio, which is a risk-adjusted measure calculated by using standard deviation and excess return to determing reward per unit of risk; Expense ratio, which is the monthly percentage of fund assets used to pay for operating expenses and management fees. The main independent variable is the Female dummy variable that takes on the value 1 if fund i is managed by a female manager in month t and 0 otherwise. For every measure except for Jensen's alpha (also known as one factor alpha), for which I use "Beta", I use the standard deviation of returns as the control variable for risk. Additionally, the lagged performance control variable is the lagged dependent variable in every unique specification. All other variables are defined in Table 1. All independent variables except for the Female dummy are lagged by one month. All regressions include fund, year, segment, region fixed effects. The t-statistics are in parentheses and based on robust standard errors clustered at the fund level. *** 1% significance; ** 5% significance; * 10% significance

Table 5 presents the results of fund performance analysis. I find that in Panel A the regression with $Return_{i,t}$ as the independent variable yields negatively significant female dummy variable coefficient at the 5% level. However, $Alpha_{i,t}$ is positively and significantly related to the female dummy variable at the 10% level in the same sample. The other regressions in Panel A as well as none of the regressions in Panel B yield a significantly negative coefficient for the female dummy variable.

These findings give contradictory results, which suggest that in the sample (3) female managers have performed worse than male managers if measured with gross returns, but better if measured with Jensen's alpha, which is a risk-adjusted performance. It could be argued that since gross returns are the returns that investors would have had they not paid any taxes, they are more likely to observe and give value to gross returns rather than a more advanced risk-adjusted return such as Jensen's alpha. Only if this was proven, these observations would give some validation for the lower fund flows of female managers and offer a rational rather than irrational explanation to the results in the matched samples analysis.

However, since gross returns and Jensen's alpha are both likely to be common measures of performance among mutual fund investors and considering that none of the regressions in Panel B (sample 5) has significant results, the results in this section do not support the idea of investors rationally avoiding female fund managers due to differences in performance.

6.3 Gender and flow-performance relationship

My results so far suggest that fund flows are lower for female fund managers than male fund managers, and differences in performance or investment behaviour between female and male managers cannot explain the differences in fund flows. In this section, I research whether female fund managers get "punished" more or "rewarded" less in terms of decrease or increase of fund flows after their performance. This is motivated by the observation, that investors seem to react more to extreme positive and negative performance than to average performance (J. A. Chevalier and Ellison 1995).

To assess whether there are differences in the flow-performance relationship between male and female managed funds, I re-estimate the baseline flow regression (see Table 2) and add interactions between the female dummy variable and various measures of past performance. In addition to the performance measures used in

Table 5, I also include the squared performance rank (*Prank*^{2}) to capture potential nonlinearity in performance. In this section, in addition to samples (3) and (5) I include the main sample, since although the main sample did not yield significant results for difference in fund flows, the difference in flow-performance relationship may still occur.

The flow-performance relationship regression results are presented in Table 6. I find negative coefficient for the interaction term for every performance measure in every sample, except for the interaction between lagged gross return and female dummy variable, which is slightly positive. However, the only significant interaction term is in Column (2), in which the coefficient of the interaction between lagged Jensen's alpha and female dummy variable is negatively significant at the 10% level in the main sample and at the 5% level in the sample 3. The other measures of performances do not have significant interaction effects.

These estimates indicate that flows to the female-managed funds are less performance sensitive following a good performance, and more sensitive following a poor performance measured in Jensen's alpha. This finding together with the results in Table 5, in which in the sample (3) female managers had significantly greater performance measured in Jensen's alpha, indicate that investors do not give appreciation for this comparatively greater performance to female managed funds. Particularly, investors value the risk-adjusted performance measured with Jensen's alpha in a more optimistic way if a male manager individually manages the fund. The results in this section show similar pattern as my main findings that suggests that female managed funds receive lower fund flows but amplify that they get punished more and rewarded less in terms of lower fund flows after their performance.

Table 6
Flow-performance regression analysis

	Column (1)			Column (2)			Column (3)			Column (4)			Column (5)		
	Return			Alpha			Prank			Prank2			Sharpe ratio		
Variable	(Main)	(3)	(5)	(Main)	(3)	(5)	(Main)	(3)	(5)	(Main)	(3)	(5)	(Main)	(3)	(5)
Female $_{i,t}$	-0.0054	-0.0078	-0.0067	-0.0056	-0.0079	-0.0066	-0.0018	-0.0045	-0.002	-0.0028	-0.0055	-0.0041	-0.0044	-0.0067	-0.0063
	(-1.66)*	(-2.25)**	(-2.08)**	(-1.71)*	(-2.23)**	(-2.46)***	(-0.56)	(-1.33)	(-0.50)	(-0.97)	(-1.87)*	(-1.23)	(-1.25)	(-1.80)*	(-1.79)*
Return $_{i,t-1}$	0.07	0.0546	0.0611												
	(6.91)***	(5.30)***	(4.56)***												
Alpha $_{i,t-1}$				0.0199	0.0216	0.005									
				(3.91)***	(3.77)***	(0.87)									
Prank $_{i,t-1}$							-0.012	-0.012	-0.0058						
							(-4.81)***	(-4.14)***	(-1.70)*						
Prank $^{2}_{i,t-1}$										-0.011	-0.0114	-0.0066			
										(-4.34)***	(-3.77)***	(-1.80)*			
Sharpe ratio $_{i,t-1}$													0.0025	0.0025	0.0009
													(2.64)***	(2.28)**	(0.69)
Female $_{i,t}$ *X Return* $_{i,t-1}$	0.0183	0.0306	0.0257												
	(0.56)	(0.93)	(0.75)												
Female $_{i,t}$ *X Alpha* $_{i,t-1}$				-0.0145	-0.0172	-0.0103									
				(-1.76)*	(-2.23)**	(-1.27)									
Female $_{i,t}$ *X Prank* $_{i,t-1}$							-0.007	-0.0064	-0.0099						
							(-1.14)	(-0.95)	(-1.46)						
Female $_{i,t}$ *X Prank* $^{2}_{i,t-1}$										-0.0075	-0.0069	-0.0087			
										(-1.19)	(-0.98)	(-1.26)			
Female $_{i,t}$ *X Sharpe ratio* $_{i,t-1}$													0.0017	-0.0018	-0.0007
													(-1.07)	(-1.11)	(-0.40)
Adj. R^2	0.037	0.038	0.045	0.035	0.036	0.042	0.036	0.037	0.043	0.036	0.037	0.043	0.035	0.036	0.042
Observations	37606	28176	19835	37606	28176	19835	37606	28176	19835	37606	28176	19835	37606	28176	19835

In this table are the results of the flow-performance analysis conducted on the main sample, sample 3 and sample 5. Each column include unique measures of performance which are used to estimate flow-performance relationships in the three samples. All of the regressions are estimates of percentage fund flows regressed on the Female dummy variable that is interacted with various lagged performance indicators. The performance measures used as the interaction variables are mentioned below column numbers. The same specifications are used as in Table 2 specification 3, except that the lagged gross return control variable is replaced by the alternative lagged performance measure. Additionally, in column (2) the lagged Beta is used as the control variable for risk (see Table 5). All control variables are lagged by one year and are defined in Table 1. All regressions include fund, year, segment and region fixed effects. The t-statistics are in parentheses and based on robust standard errors clustered at the fund level.
*** 1% significance; ** 5% significance; * 10% significance

7 Discussion and conclusion

In this paper I examine whether social biases caused by a fund manager's gender influence the investment choices of Nordic mutual fund investors. Specifically, I research whether Nordic mutual fund investors are more likely to allocate their funds in mutual funds managed by males rather than females.

My key finding is that within matched samples that consist of similar funds in various attributes, funds of female managers experience lower monthly fund flows, which cannot be explained by dissimilarities in investment behaviour or performance of the fund managers. Although the baseline regressions on the main sample do not yield any significant results, there could be many unobserved attributes within the main sample of funds. Therefore, it is safe to assume that the matched samples analysis resulted in more robust results. Additionally, funds of female managers experience inferior appreciation in fund flows following good performance measured by the Jensen's Alpha.

In this section, I discuss the consequences that the observed results may have in the mutual fund industry, as well as rationale behind employing female managers. I finish the paper with concluding thoughts, potential limitations of research, and propositions to future research.

7.1 Consequence of gender bias

Overall, my findings show that evidence of gender bias exists among investors in countries that are known to be advanced in terms of gender equality. This is relevant, since it can provide customer-based justification for the fact that women are clearly outnumbered by men in fund manager positions.

As shown in Figure 1, this still occurs in modern times in the Nordic mutual fund industry, as despite various goals towards more equal representation of women and men in financial activity sector positions, the fraction of representation of female fund managers remains low. Therefore, the results in this paper can provide some explanation for fund companies not being able to hire as many female managers as male managers, as it would indirectly be costly in terms of lower profits in fees due to gender discrimination by investors. This is relevant since it could shift some of the responsibility of hiring low fraction of female managers towards investors from fund companies.

7.2 Rationality of employing female fund managers

Considering everything, these results imply that social biases such as in-group bias, discrimination, and stereotyping influence the investment choices of Nordic mutual fund investors. Consequently, as discussed by (Niessen-Ruenzi and Ruenzia 2019; Kumar, Niessen-Ruenzi, and Spalt 2015), these results raise an equilibrium question as to why do fund companies employ female managers, if the funds under their management generate lower flows.

One potential reason that fund companies employ managers that on average receive lower fund flows could simply be the fact that they are not aware of the social bias. However, I observe in my data sample that the fraction of all fund months that are individually managed by a female manager out of all the months that include a female manager is noticeably small (below 5%), which suggests that fund companies may be aware of the social bias, and thus "hide" female managers in teams to fulfill their diversity requirements. Therefore, the second potential reason could be that e.g., institutional investors or other companies that the fund companies do business with may have diversity policies, which the fund companies want to meet to gain numerous benefits. This would suggest that although female managers attract lower inflows on average, their presence in the fund company would lead to other positive effects that the fund companies want to benefit from.

Third possible reason is that fund companies act strategically and offer female managed funds to a minority of investors who are not biased against female fund managers or may even invest more in them, as shown by Niessen-Ruenzi and Ruenzia (2019). Therefore, it may be beneficial to hire female fund managers to attract these groups of investors.

7.3 Conclusions

Taken together, my findings add a new dimension to the growing literature of discrimination from a Nordic perspective, which is distinguishable from various other geographical locations for the advanced level of gender equality. The results show that despite growing public awareness, in a judgement free environment such as the mutual fund market, investors are still subject to gender discrimination that cannot be explained by rational reasons.

However, the methodology used in this paper has some limitations. As inevitably there are numerous unobservable factors that influence fund flows, the selection of control variables and fixed effects has a significant impact on the results. Additionally, there are numeral other ways to measure the investment behaviour and performance of fund managers than the method covered in this paper, which could potentially show different results.

In future work, it would be interesting to see whether experimental methods on Nordic investors would yield equivalent results as this paper. Furthermore, research on other roles such as hedge fund managers or CEOs should also receive more attention from the discrimination perspective in the Nordic countries.

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Appendix

The following table defines the main variables used in the empirical analyses.

Panel A: Main dependent variable

Variable name	Description	Source
Fund flow	The net inflow into the fund in the current month defined as $(TNA_{i,t} - TNA_{i,t-1})/TNA_{i,t-1} - r_{i,t}$, where $TNA_{i,t}$ denotes fund i's total net assets in month t, and r_t denotes fund i's return in month t	Morningstar Direct, Estimated

Panel B: Main independent variable

Variable name	Description	Source
Female	Dummy variable that takes the value zero if the fund's month observation is managed by a male manager and one if it is managed by a female manager.	Morningstar Direct, Morningstar Investor

Panel C: Other variables

Variable name	Description	Source
Fund size	The natural logarithm of the fund's month-end total net assets (TNA).	Morningstar Direct
Return	Montly gross return that an investor would have received had they not paid any expenses.	Morningstar Direct
Fund age	Fund tenure computed from the fund's start date and measured in years.	Morningstar Direct
Prank	The performance rank of the fund in the previous year relative to all other funds in the same Morningstar Category.	Morningstar Direct
Sharpe ratio	Risk-adjusted measure calculated by using standard deviation and excess return to determine the reward per unit of risk.	Morningstar Direct
Fund risk	The percentage of aggregated assets of the fund's top 10 portfolio holdings.	Morningstar Direct
Stdev	Standard deviation of fund's returns, which depicts how widely the returns have varied over a year.	Morningstar Direct
Alpha	Measures a mutual fund manager's effectiveness by showing the difference between a fund's returns and its expected performance.	Morningstar Direct
Beta	Measure of systematic risk, that measures the sensitivity of the fund's excess return with respect to market's excess return.	Morningstar Direct
Expense ratio	The monthly percentage of fund assets used to pay for operating expenses and management fees.	Morningstar Direct
Turnover ratio	Measure of the fund's trading activity, which is computed by taking the lesser of purchases or sales and dividing by average monthly net assets.	Morningstar Direct