DIFFERENT MINDS, BETTER RETURNS?

INVESTIGATING DIVERSITY AND FUND PERFORMANCE IN THE SWEDISH MUTUAL FUND MARKET

CORNELIA FOGELSTRÖM

ISABEL WERNLUNDH

Bachelor Thesis

Stockholm School of Economics

2025

Different Minds, Better Returns? Investigating Diversity and Fund Performance in the Swedish Mutual Fund Market

Abstract:

Four easily observable characteristics – gender, university, academic major, and prior workplace – capture key differences in fund performance among Swedish mutual fund management teams. Using a panel dataset of Swedish actively managed equity funds, we compute team-level diversity scores and regress them on alpha and value added measures. We find that the relationship between team diversity and fund performance is dimension-specific and sensitive to model specification. Diversity in academic majors emerges as the most statistically and economically significant predictor of superior fund performance. In contrast, teams whose managers attended differentiated universities underperform their homogeneous counterparts in terms of abnormal returns. In cross-sectional analyses, we find that gender diversity is negatively associated with fund performance, while workplace diversity shows no consistent effect on financial outcomes. These findings highlight that not all dimensions of diversity contribute equally to fund performance, with implications for fund selection and team composition.

Keywords:

Swedish Mutual Funds, Team Diversity, Fund Performance, Abnormal Returns, Value Added

Authors:

Cornelia Fogelström (25588)
Isabel Wernlundh (25794)

Tutors:

Mehran Ebrahimian, Assistant Professor, Department of Finance

Examiner:

Ramin Baghai, Professor, Department of Finance

Bachelor Thesis
Bachelor Program in Business and Economics
Stockholm School of Economics

1 Introduction

This paper investigates whether diversity – in terms of gender, academic background, and prior work experience – within Swedish mutual fund management teams has a measurable impact on fund performance. We examine how these dimensions of diversity relate to fund outcomes with the aim to discover which aspects of team composition that matters the most. Specifically, we investigate the relationship between team diversity and fund performance, measured in terms of both abnormal returns and economic value added.

The composition of decision-making teams plays a crucial role in shaping financial outcomes across industries. In the asset management industry, investment decisions are the product of complex evaluation processes that rely on analysis, judgment, and strategic foresight under uncertainty. These decisions result from collaborative processes in which diverse perspectives, expertise, and qualities merge to form an investment strategy. Importantly, prior literature has shown that team-managed funds tend to outperform solo-managed funds, raising the question of what team characteristics enhance investment performance (Bär, Kempf, and Ruenzi, 2011). Understanding the factors that drive better decision-making in such teams has gained more academic and industry attention as a result of the increased competitiveness within financial markets. Among potential drivers, team diversity, defined as the distribution of attributes among team members, may impact how teams process information, evaluate risks, and allocate capital. Harrison and Klein (2007), conceptualize diversity along three types: *separation* (differences in position or opinion, such as attitude or value), *variety* (differences in kind or category, such as functional background or expertise), or *disparity* (differences in concentration of valued social assets or resources, such as pay or status). Our paper investigates whether variety diversity within Swedish mutual fund management teams has a measurable impact on fund performance. Specifically, we examine the direction and magnitude of this relationship and identify which dimensions of diversity exert the greatest influence on fund performance.

The organizational behavior literature presents contrasting evidence regarding the effects of team diversity, suggesting that diversity can be a double-edged sword. According to Sah and Stiglitz (1988), group decision-making is superior to individual decision-making because it prevents individual biases and guarantees more nuanced results. Consistent with this, Cox's (1993) value-in-diversity hypothesis posits that team diversity enhances business performance by expanding the pool of knowledge, expertise, and perspectives, thereby reducing the risk of groupthink. In particular, this theory holds for functional dimensions of diversity, as variations in team members' professional and educational background foster complementary skill sets that positively influence team performance.

However, according to Byrne's (1971) similarity-attraction paradigm, similarity between individuals increases intrapersonal attraction. People's innate propensity for homophily, which is the attachment and association with people who share similar cultural, behavioural, or genetic traits to oneself (McPherson, Smith-Lovin, and Cook, 2001), poses a challenge for creating diverse teams. In a professional context, homophily can lead to uniform teams, which can reduce the pool of perspectives and knowledge and ultimately hinder efficient decision-making. Moreover, this unconscious preference for similarity may impede collaboration and communication with individuals from diverse backgrounds, potentially diminishing the positive effects of diversity suggested by the value-in-diversity hypothesis (Cox, 1993).

Further, faultline theory posits that diversity can form subgroups within teams when multiple attributes (e.g., gender or education) align. As a result of these faultlines, in-groups and out-groups are likely to form, increasing the risk of interpersonal conflict and undermining team cohesion (Lau and Murnighan, 1998). This mechanism is consistent with the self-categorization theory, which suggests individuals reinforce subgroup distinctions by mentally classifying others and themselves into social groups (Turner, Hogg, Oakes, Reicher, and Wetherell, 1987).[1] Given that the asset management industry is considered male-dominated (Sanandaji, 2016), these dynamics may be particularly pronounced, fostering male in-groups and the exclusion of females. Even in small teams, industry dynamics might therefore make it harder to foster efficient collaboration in gender diverse teams. Building on the organizational behavior literature, we examine whether diversity-performance theories hold in a financial setting where team outcomes are objectively and economically measurable. In this context, we test the statistical and economic significance that diversity exerts on fund performance.

An extensive strand of literature investigates the impact of individual manager characteristics on financial outcomes. However, the evidence is mixed regarding the extent and direction of this impact. According to Barber and Odean (2001), male investors are more likely than female investors to be overconfident, which causes them to trade more frequently and generate lower net returns due to higher transaction costs. Chevalier and Ellison (1999) find that fund managers who attended undergraduate institutions with higher SAT scores typically provide systematically higher risk-adjusted excess returns, suggesting that a better educational background leads to higher investment skill.

Other studies highlight context-dependent or negative implications of diversity. Gompers, Mukharlyamov, Weisburst, and Xuan (2022) document that, even after controlling for fund characteristics, female venture capitalists experience structural disadvantages, such as receiving less benefit from their track records than their male counterparts, which results in lower observed performance. Additionally, Adams and Ferreira (2009) find that while the presence of female board members is associated with stronger corporate governance – through better attendance, greater degree of monitoring, and ensuring CEO accountability – the average effect on firm performance is negative. This effect appears to be driven by firms that already have strong corporate governance, where additional monitoring may be counterproductive and potentially harm performance.

In contrast, some studies find no evidence supporting such a relationship between fund manager characteristics and performance. Naya and Tuchschmid (2024), studying the hedge fund industry, find no evidence that differences in fund returns and risk-taking can be attributed to manager gender, leading the authors to conclude that gender diversity alone does not explain performance differences in the hedge fund industry. In addition to this body of research, Niessen-Ruenzi and Ruenzi (2019), studying the mutual fund industry, find no significant difference in the performance of male and female fund managers. However, they report gender-based disparities in visibility and attention: female managers are more likely to

[1]Turner et al. (1987) developed the self-categorization theory as an extension of social identity theory, which was first introduced by Tajfel (1978). Self-categorization theory pays more attention to cognitive processes when peopleclassify themselves and others into a social category, while social identity theory covers the emotional and motivational aspects of being a group member.

be assigned to smaller funds and receive less media coverage. They also provide evidence of investor gender bias, as female-managed funds receive significantly lower inflows, suggesting that structural disadvantages persist for female managers, even when performance is equal.

The existing literature has paid less attention to the implications of team diversity on financial outcomes, and the findings that do exist are often mixed and inconclusive (Lu, Naik, and Teo, 2024). In the venture capital context, Gompers, Mukharlyamov, and Xuan (2016) find supporting evidence for homophily, where venture capitalists sharing the same background characteristics are more likely to co-invest. They show that these homogeneous units underperform, suggesting that diversity in decision-making may enhance investment outcomes. Conversely, Aggarwal and Boyson (2016) find that gender diverse hedge fund teams underperform relative to all-female and all-male teams. This suggests that gender diversity may not always lead to improved outcomes and could be influenced by team dynamics. Lu et al. (2024) show a positive association between diversity and hedge fund risk-adjusted returns, whereby funds managed by diverse teams outperform their homogeneous counterparts across all diversity dimensions. Turning to the mutual fund industry, Bär, Niessen, and Ruenzi (2009) document a positive relationship between functional team diversity – in terms of manager tenure and education – and fund alpha measures. However, they observe a negative association between increased demographic diversity – in terms of gender – and performance, suggesting that different diversity dimensions may have contrasting effects. These contradicting results highlight the need for further empirical research, especially in less explored markets such as Sweden, potentially offering new contextual perspectives.

To empirically test what effect diversity within management teams has on Swedish mutual fund performance, we use a panel dataset of 538 actively managed Swedish equity funds from 2003 to 2024. Using the fund manager histories provided by Morningstar Direct, we construct a novel dataset consisting of reconstructed management teams and hand-collected background information on fund managers from LinkedIn and company websites. For each fund-team observation, we calculate a diversity score based on four diversity dimensions – gender, university, university major, and prior workplace – using Lu et al.'s (2024) network density-based methodology and diversity framework, excluding race. Each unique team receives a score reflecting its degree of homogeneity or heterogeneity across the four diversity dimensions. To measure fund performance, we employ gross alpha and value added measures following the methodology of Berk and van Binsbergen (2015) and Ibert, Kaniel, and Van Nieuwerburgh (2018). We estimate ordinary least squares (OLS) regression models at the fund-team-year level and control for unobserved heterogeneity by progressively adding fixed effects and control variables.

Our findings reveal a multifaceted and dimension-specific relationship between management team diversity and Swedish mutual fund performance. Unconditional cross-sectional comparisons suggest that teams with lower average diversity tend to underperform relative to their high-diversity counterparts. However, this relationship reverses in panel regressions, indicating that within-fund improvements in diversity contribute positively to fund performance. When decomposing average diversity into its underlying components, we find that the association depends on the specific diversity dimension studied. Notably, diversity in academic majors emerges as the most robust and consistent predictor of fund performance: teams with complete major diversity outperform their homogeneous counterparts on average by 1,065 MSEK and 2.24 percentage points in annual factor-model value added and alpha, respectively. This suggests that teams consisting of managers who have studied diverse academic fields have access to a broader pool of expertise, making them more equipped to generate better investment outcomes. In contrast, university diversity appears negatively associated with fund performance, particularly when measured by abnormal returns. Gender diversity significantly affects fund performance in cross-sectional analyses between funds, with limited evidence of a robust within-fund effect. We find limited, consistent evidence that workplace diversity significantly affects fund performance. Taken together, our findings suggest that functional diversity, in terms of educational backgrounds, plays a meaningful role in driving fund performance. Our results indicate that not all dimensions of diversity contribute equally to fund performance, stressing the need to differentiate between dimensions of diversity when evaluating their impact on investment outcomes.

This study contributes to the existing literature in three key areas. First, unlike prior studies that primarily focus on the asset management industry in the U.S., this paper explores a new contextual setting by investigating the mutual fund industry in Sweden. In contrast to the U.S., Sweden is widely recognized for its robust welfare system, access to education, gender equality, and inclusive workplace policies (Omanović, 2009; Borevi, 2013). Yet, the financial sector is characterized by homogeneity, especially in terms of gender representation (Sanandaji, 2016). This discrepancy offers a unique setting to study the impact that gender diversity has on financial outcomes while minimizing confounding factors related to broader societal discrimination. Moreover, Swedish mutual funds operate within a mature, transparent, and well-regulated market, making them particularly well-suited for empirical performance analysis (Dahlquist, Engström, and Söderlind, 2000). Further, we find that management team structures are common in the Swedish mutual fund industry, offering a suitable context for analyzing the impact of diversity on fund performance.

Second, our study broadens the concept of diversity by examining diversity across multiple dimensions, including educational background and professional experience, rather than focusing solely on gender. While much research has been made on the impact of gender diversity alone, there is still room to explore how other forms of diversity influence performance outcomes. Compared to most previous studies, our multidimensional approach allows us to capture a broader understanding of diversity within fund management. Additionally, we adopt a more innovative perspective by analyzing the composition of fund management teams rather than focusing on individual fund manager characteristics, which better reflects today's collaborative decision-making environment.

Third, this paper also contributes methodologically by going beyond the alpha measures that most studies focus on. Specifically, we measure fund performance using gross alpha and value added using factor-based and style-matched benchmarks (Berk and van Binsbergen, 2015; Ibert et al. 2016). This allows us to assess performance in percentage terms, but also in terms of actual economic value. This approach enables us to analyze performance from different angles, both whether diverse teams outperform their counterparts in relative terms, and how much economic value they generate in absolute SEK terms.

2 Theoretical Background

In the asset management industry, where complex decisions are made under uncertainty, the composition of fund management teams plays a crucial role in shaping investment outcomes. Empirical research has been conducted on the relationship between diversity and fund performance. However, the implications remain debated, with opposing views on whether diversity has a positive or negative impact on fund performance. This section first reviews the existing literature on diversity and fund performance, and second, outlines the rationale behind our selected metrics of diversity.

2.1 Related Works

There is a clear gap in the research made on broader dimensions of diversity, such as educational background and professional experience, within management teams and their influence on performance in regulated European markets, including Sweden. Our research fills this gap by applying an established methodology for measuring diversity and exploring its impact on a unique sample of Swedish mutual funds and manager characteristics. Several studies find that gender diversity in fund management teams can have both positive and negative effects on performance, where the market context and fund type play a crucial role. However, research on professional diversity in a team-level setting remains limited. Our paper builds on and extends the existing literature by combining multiple dimensions of diversity and applying them in a new setting: the Swedish mutual fund industry.

A central article that forms the key foundation for this paper is Lu et al. (2024), who examine the differences in performance between heterogeneous and homogeneous hedge fund teams in the U.S. asset management industry. Their study illustrates a positive relationship between team diversity and hedge fund performance, with heterogeneous teams generating stronger long-term returns compared to homogeneous teams, earning 1.96% to 5.59% more per year on a risk-adjusted basis. To measure the diversity of each team, the authors created a diversity index based on five dimensions: educational institution, college major, work experience, gender, and race. They find that heterogeneous teams outperform homogeneous teams across all diversity dimensions, as well as exhibiting more persistent performance, avoiding common behavioral biases, and exploiting a broader set of return anomalies.

While Lu et al. (2024) focus on U.S. hedge funds, this study examines whether similar effects hold in a different diversity landscape, namely the Swedish mutual fund industry. In doing so, our study introduces an institutional shift, characterized by strict regulations (e.g., EU legislations such as UCITS and MiFID II, and oversight by the Swedish FSA), and standardized investment mandates. Their methodology for measuring diversity serves as a primary method for our study, as we adapt it to the Swedish mutual fund market. This approach allows us to test whether the benefits of heterogeneous teams extend beyond U.S. hedge funds to mutual funds in Sweden, which operates in a different regulatory and diversity landscape.

Chevalier and Ellison (1999) focus on the impact of individual fund manager characteristics, including educational background and career history, on mutual fund performance. In contrast to Lu et al. (2024), who focus on team diversity, Chevalier and Ellison (1999) primarily examine the effect of individual managers on fund performance, rather than the impact of a team. Our study builds upon Chevalier and Ellison (1999) by implementing a more holistic approach to mutual fund performance, accounting for team-level diversity and its influence on fund performance, rather than individual characteristics solely. This approach provides a more comprehensive insight into how team composition impacts the performance of mutual funds.

Bär et al. (2011) examine whether investment decisions differ between solo-managed and team-managed mutual funds. When controlling for manager characteristics, they find that teams make less extreme decisions and achieve less extreme performance outcomes. However, when examining the effect of diversity within fund teams, including factors as gender, tenure, and education, they do not find a consistent or significant link between diversity and the extremity of investment outcomes. Our study extends their work by shifting focus from decision extremity to how diversity, in terms of gender, educational background, and prior work experience, directly influences the performance of Swedish funds.

Further, Evans, Prado, Rizzo, and Zambrana (2025) investigate the impact of identity-based diversity, focusing on political ideology and mutual fund performance. They document a positive relationship between ideological diversity and fund alpha, suggesting that diverse perspectives within teams could improve performance. Whereas their study investigates the impact of ideological diversity, which falls under the diversity type *separation*, we shift focus to investigating whether the diversity type *variety* has a measurable effect on fund performance (Harrison and Klein, 2007).

In contrast to previous studies, which focuses primarily on individual-level characteristics, our research emphasizes team-level diversity in a new asset management landscape, offering a new and expanded perspective of the impact that diversity has on collective decision-making. By estimating gross alpha and economic value added using both a factor-model and a style-matched benchmark (Berk and van Binsbergen, 2015), our paper contributes to the ongoing debate about the role diversity plays in the asset management industry. In particular, we investigate whether diversity within fund management teams serves as a key driver of economic value and enhances fund performance, offering new evidence from the Swedish mutual fund market.

2.2 Diversity Dimensions

To broaden our understanding of the factors influencing performance disparities, we split diversity into its various components. Previous literature demonstrates that different types of manager characteristics affect performance to different extents. The diversity metrics we analyze in this paper are selected based on support from existing literature.

One of the most widely studied diversity dimensions in finance is gender diversity. Much research has been conducted on its impact on risk preferences, decision-making, and performance outcomes. However, whether gender diversity positively or negatively influences such areas remains debated (e.g., Bär et al. 2009; Bär et al. 2011; Barber and Odean 2001; Gompers et al. 2022; Aggarwal and Boyson 2016). On this basis, we include gender diversity as one of the four dimensions in our analysis of fund team compositions and performance.

The educational background of fund managers can shape the collective expertise within a team. Different universities and academic majors provide distinct institutional training, professional networks, and exposure to varying investment strategies. For instance, managers with a background in law may approach problems through qualitative reasoning or structured argumentation, while those with a finance background may rely more on quantitative models. Managers who attended different universities may therefore contribute to a broader pool of knowledge and strategic perspectives, which can affect team decision-making and ultimately fund performance. Jalbert, Furumo, and Jalbert (2010) suggest that the university background of a CEO can have an impact on firm performance, demonstrating that where a manager is educated can influence their professional success. These results support that the educational background of managers is a relevant proxy to account for when analyzing different performance outcomes.

In addition, the prior workplace of a fund manager indicates their exposure to various organizational cultures, investment strategies, and decision-making settings. Such differences may lead managers to differ substantially in the approaches they implement in different business scenarios. According to Papageorgiou, Parwada, and Tan (2011), there is a significant relationship between fund performance and managers' prior work experience. This relationship holds both within the hedge fund sector, as well as related industries including mutual funds, prime brokers, custodian firms, and securities brokerages. Likewise, Chen, Gao, Zhang, and Zhu (2018) demonstrate that mutual fund managers' investment skill is significantly correlated with their previous work experience, suggesting that it can influence fund performance. These findings highlight the importance of accounting for workplace diversity when examining the impact of diversity on fund performance.

Taken together, these findings illustrate the importance of considering all four diversity dimensions – gender, university, university major, and prior workplace – as influential factors in the composition of teams and performance outcomes.

3 Data, Variable Construction & Methodology

This section outlines the empirical foundation and analytical framework used to investigate the impact of management team diversity and mutual fund performance. We present the construction of a novel panel dataset combining fund characteristics, team compositions, and manager backgrounds. Drawing on the mutual fund performance literature, we estimate four complementary performance measures composed of both abnormal returns and absolute economic value. To investigate the impact of diversity on fund performance, we build a series of cross-sectional and panel OLS regressions.

3.1 Data Collection

3.1.1 Mutual Fund Data

We construct an initial dataset containing Swedish open-ended mutual fund data retrieved from Morningstar Direct. Following the mutual fund literature, the dataset is restricted to actively managed equity funds (e.g., Ibert et al., 2018; Bär et al., 2011; Bär et al., 2009). Furthermore, we include dead (i.e., liquidated or merged funds) and surviving investments to mitigate survivorship bias, occurring when only currently operating funds are considered, causing inflated performance measures (Elton, Gruber, and Blake, 1996). In our universe of actively managed equity funds domiciled in Sweden, we retrieve an initial sample of 1,414 funds and a sample period from 2002 Q1 to 2024 Q4.

Morningstar Direct offers information on fund returns, fund manager histories, fund sizes, inception dates, and expense ratios, among other fund characteristics. We calculate fund age in years for each quarter using the fund's inception date. Turnover and expense ratio data are only available annually, therefore, we assume that the annual value remains constant across all quarters within a year. Furthermore, we exclude funds with a non-Swedish Krona reporting currency to ensure comparability and to circumvent distortions from exchange rate fluctuations.

Each mutual fund is assigned to a Morningstar Category, based on its actual investment style and portfolio holdings, with corresponding benchmarks matched accordingly (Morningstar Direct, 2025). In cases where a Morningstar Category Benchmark is missing or the benchmark return is nonexistent during a period, the MSCI World Index acts as a fallback benchmark. While Morningstar indexes are not in themselves directly investable, tradable proxies such as index funds and ETFs track their performance.

Table 1 presents summary statistics for the sample of mutual funds used in the main analysis. To avoid overrepresentation of funds with longer data periods, each observation corresponds to a unique fund-team combination with fund data averaged across the entire period the team managed the fund. The funds in the sample show notable variation in fund size (Mean = 6.1 billion SEK, Std = 12.7 billion SEK), suggesting considerable differences in assets under management (AUM). The average manager tenure of 4.6 years indicates a moderate turnover among fund managers, and the variation in fund age (Mean = 11.7 years, Std = 10.5 years) shows that the sample contains funds of significantly different ages.

Table 1: Summary Statistics of Fund Characteristics

	10%	**25%**	**50%**	**75%**	**90%**	**Mean**	**Std**	**N**
Fund Age (Years)	1.29	2.87	7.59	20.19	26.44	11.72	10.47	944
Fund Size (MSEK)	89.04	419.87	1 931.65	6 659.82	15 509.63	60 621.82	12 741.98	1 080
Manager Tenure (Average)	1.54	2.00	3.50	6.04	8.53	4.58	3.64	817
Turnover	2.84	20.00	35.00	80.00	149.08	65.89	92.57	750
Expense Ratio	0.76	1.29	1.46	1.71	2.28	1.52	0.52	254

Note: This table report summary statistics for key fund characteristics used in the main analysis. Each observation represent the average of a given fund characteristic during the period it was managed by a distinct team.

3.1.2 Mutual Fund Manager Data

Morningstar Direct provides the manager history of each fund, reporting the first and last names, as well as the management periods of individual managers. However, the database does not provide explicit team compositions with team members and corresponding management periods. Instead, we construct fund management teams by identifying overlapping management periods for each fund, defining a management team as consisting of at least two managers. To ensure meaningful collaboration and active contribution, excluding temporary short transition periods, we restrict the sample to managers overseeing a fund together for at least 30 consecutive days. Excluding funds managed by one person and those not fulfilling the 30-day minimum criteria, results in a sample of 902 funds, 787 teams, and 729 managers.

Building on the fund dataset described in Section 3.1.1, we merge the constructed management team data to construct a panel of fund management teams matched with fund-level information for the corresponding time period. Building on the theoretical foundation presented in Section 2.2 and following Lu et al. (2024), we collect background information for each fund manager across four dimensions: gender, educational institution, academic major, and professional experience before managing the fund. Educational institution refers to the specific university attended by the managers (e.g., Stockholm School of Economics, London Business School, etc.), and academic major refers to the specialization (e.g., finance, economics, engineering physics, etc.). Prior professional experience reflects the most recent employer prior to managing the fund (e.g., JP Morgan, Carnegie, etc.).

Background information on fund managers is collected manually from publicly available sources.[2] We primarily rely on LinkedIn to obtain managers' educational and professional history. The data is hand-collected by searching for fund managers' names on LinkedIn, matching them to the fund companies, and observing their educational background and prior workplace. We recognize the risk that the data may be biased, as managers may not provide accurate information about their backgrounds. In cases where LinkedIn information is incomplete, we supplement it with information from fund company websites. Gender information is primarily obtained from Morningstar Direct; when missing, we infer gender based on the manager's first name. In order to ensure privacy and comply with ethical standards, we exclusively use publicly available information and anonymize all personal information by assigning each team a unique team identifier. As a result, no personal details are used in the analysis following the data collection.

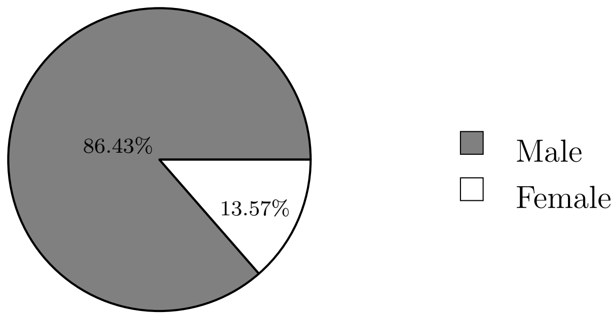
This manually constructed dataset, containing detailed information on Swedish fund manager backgrounds and time-matched team compositions linked to fund characteristics, represent, to our knowledge, a novel contribution to the literature. The panel data enables an empirical investigation of the impact that diversity has on performance in the Swedish mutual fund industry.

In line with prior literature, such as Lu et al. (2024) and Aggarwal and Boyson (2016), which document male dominance among hedge fund managers in the U.S., we find that a comparable pattern holds in the Swedish mutual fund industry. Figure 1 (a) shows that 86.43% of team mutual fund managers in our sample are male, while only 13.57% are female. However, the gender disproportion appears less prominent in the Swedish context, as Lu et al. (2024) find that only 5.88% of team-based fund managers are female in the U.S. Furthermore, Figure 1 (b) reports that teams consisting of only female managers are scarce, representing only 2.72% of the teams in our final sample.

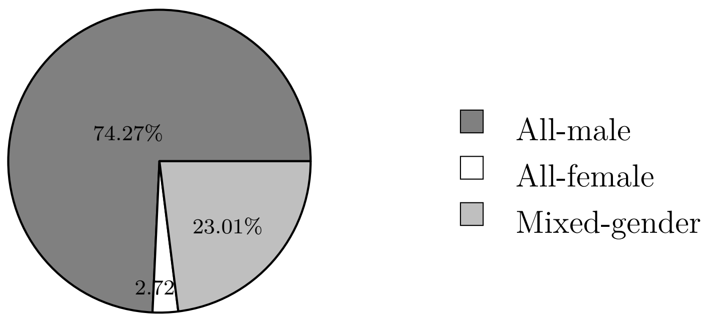
Table 2 presents the ten most common universities, majors, and previous workplaces among the managers in our sample. The most represented universities include the Stockholm School of Economics, followed by Stockholm University. The most common majors are economics and finance, and the most common previous workplaces are the biggest banks in Sweden. This indicates that a large portion of managers in our sample possess a financial

[2]LinkedIn explicitly prohibits the use of automated scraping tools under its Terms and Conditions, requiring manual data collection.

background, both in terms of education and professional experience.



(a) Gender distribution of unique managers (n=501)



(b) Gender distribution of teams (n=478)

Figure 1: Gender distribution among managers and teams

3.2 Variable Construction

3.2.1 Diversity Measure

To measure the diversity of each fund management team, we follow the approach used by Lu et al. (2024), in which team diversity is calculated as one minus the team's network density. The concept of network density originates from FM 3-24/MCWP 3-33.5, a field manual by the United States Department of the Army (2014), which defines it as "the proportion of links in a network relative to the total number of links possible". In our application, the network consists of the fund manager within the team, and a link exists when two or more managers share a background characteristic, following Lu et al. (2024). Therefore, network density measures the degree of shared connections, in which a higher network density corresponds to more homogeneity.

Team-level diversity scores are computed across the four dimensions of diversity: gender, educational institution, university major, and former workplace. For every team, a diversity score is calculated for each diversity dimension by applying the network density formula proposed by Lu et al. (2024). Let N denote the number of team members with valid data for a given dimension, and C_i the number of other team members sharing the same background characteristic (e.g., same gender or educational institution) as the member i. Consequently, the maximum number of shared connections any team member can have is

Table 2: Table 2: Summary Statistics of Fund Manager Educational and Professional Background

Panel A: Top Universities			
Rank	University	# Managers	% Managers
1	Stockholm School of Economics	81	16.14
2	Stockholm University	67	13.35
3	Uppsala University	50	9.96
4	Lund University	40	7.97
5	University of Gothenburg	38	7.57
6	Linköping University	24	4.78
7	Kungliga Tekniska Högskolan	17	3.39
8	Copenhagen Business School	7	1.39
9	Umeå University	6	1.20
10	University of Copenhagen	6	1.20
Panel B: Top Majors			
Rank	University Major Normalized	# Managers	% Managers
1	Economics	111	22.11
2	Finance	94	18.73
3	Business Administration	26	5.18
4	Finance & Accounting	24	4.78
5	Business & Economics	23	4.58
6	Industrial Engineering & Mgmt	14	2.79
7	Business Admin & Economics	9	1.79
8	Accounting	8	1.59
9	Financial Economics	8	1.59
10	Engineering Physics	6	1.20
Panel C: Top Workplaces			
Rank	Former Workplace	# Managers	% Managers
1	Svenska Enskilda Banken (SEB)	35	6.97
2	Handelsbanken	33	6.57
3	Nordea	29	5.78
4	Swedbank	25	4.98
5	Carnegie Investment Bank	14	2.79
6	Danske Bank	13	2.59
7	Skandia	10	1.99
8	Alfred Berg	10	1.99
9	DNB	9	1.79
10	Brummer & Partners	6	1.20

Note: Panel A-C present the top 10 most frequently observed universities, academic majors and prior workplaces among fund managers in our final sample. The final columns report the number and percentage of managers sharing a given background characteristic.

equal $N-1$. Network density and diversity score are computed using the following formulas (Lu et al., 2024):

$$Network\ Density = \frac{1}{N}\sum_{i=1}^{N}\frac{C_i}{N-1} \tag{1}$$

$$Diversity\ Score = 1 - Network\ Density \tag{2}$$

To illustrate the calculation in practice, we consider two examples. First, consider a four-member fund team consisting of three male managers and one female manager. Each manager has three possible connections ($N-1=3$). The female fund manager does not share gender with anyone ($C=0$), while the three male fund managers share gender with two others ($C=2$), resulting in a gender-based network density of $\left(\frac{0}{3}+\frac{2}{3}+\frac{2}{3}+\frac{2}{3}\right)\div 4 = 0.5$. This yields a diversity score of $1-0.5=0.5$.

Secondly, consider a team of five fund managers in which four managers graduated from the Stockholm School of Economics (SSE) and one from the University of Gothenburg. Each of the SSE alumni shares a university background with three others ($C=3$), while the University of Gothenburg alumnus shares with none ($C=0$). This implies an educational institution-based network density of $\left(\frac{3}{4}+\frac{3}{4}+\frac{3}{4}+\frac{3}{4}+\frac{0}{4}\right)\div 5 = 0.6$, resulting in a diversity score of $1-0.6=0.4$.

This measure reflects the proportion of unique characteristics within a team. The diversity score can take any value from 0 to 1, with 0 implying complete homogeneity, i.e., all members within the team share the same background characteristics, and 1 implying complete heterogeneity, i.e., a team with no shared characteristics among team members. After calculating a separate diversity score for each metric, we compute an average diversity score per team by summing the diversity scores of the available metrics and dividing by the number of valid metrics for that team.

To ensure the robustness of our results, we exclude some teams due to missing data. For the individual metrics, we do not compute a diversity score if a team consists of only two or fewer members with valid data for that metric. At the team level, we exclude any team for which fewer than three out of the four diversity metrics can be computed. These thresholds are chosen to ensure that the results remain meaningful and reliable, as calculating an average diversity score based on highly incomplete data risks misrepresenting the true variation in team composition. After cleaning the data, our final dataset consists of 538 funds and a sample period from 2003 Q1 to 2024 Q4. During this period, we observed 472 unique team structures involving 502 fund managers.

Table 3 provides summary statistics of diversity scores and team size for the mutual fund management teams included in our analysis. Team sizes are generally small, with a median of 2.00 and a mean of 2.43, indicating that most team-managed funds are only managed by two managers. Consequently, the diversity measures are by definition constrained to binary outcomes (0 or 1) for many teams, since diversity in a two-person team simply reflects whether two individuals differ on a given diversity dimension. This constraint results in a skewed distribution across diversity scores, with clusters around 1 and 0, as seen in Table 3. We recognize that this skewness represents a limitation in the variability of the diversity data, which should be considered when interpreting the results. However, the U-shaped distribution accurately reflects the composition of mutual fund management teams and therefore represents an inherent characteristic of the Swedish asset management sector. Consequently, excluding two-person teams would not accurately reflect the nature of this industry. We note that teams on average achieve high diversity scores across university, major, and workplace diversity, with means exceeding 0.8, indicating that a considerable number of managers differ along the educational and professional dimensions. In contrast, the gender diversity remains low, with a median of 0 and a mean of 0.195, suggesting a low proportion of mixed-gender teams, which can be attributed to the large number of male managers in our sample.

Table 3: Distribution of Diversity Score and Team Size

	10%	**25%**	**50%**	**75%**	**90%**	**Mean**	**Std**	**N**
Gender Diversity	0.00	0.00	0.00	0.00	1.00	0.20	0.37	472
University Diversity	0.00	1.00	1.00	1.00	1.00	0.85	0.34	470
Major Diversity	0.00	1.00	1.00	1.00	1.00	0.83	0.35	410
Workplace Diversity	0.67	1.00	1.00	1.00	1.00	0.89	0.29	468
Average Diversity	0.50	0.58	0.75	0.75	0.91	0.68	0.17	472
Team Size	2.00	2.00	2.00	3.00	3.00	2.43	0.79	478

Note: This table presents percentiles, mean, standard deviation and number of observations for each diversity score and team size. Diversity score ranges form 0 to 1, where a higher score indicates greater heterogeneity. Min and Max for team size are 2 and 7, respectively.

3.2.2 Fund Performance Measures

We evaluate fund performance using both benchmark-adjusted abnormal returns and absolute economic value performance measures. Specifically, we estimate gross alphas and value added measures based on (i) factor-model benchmark proposed by Berk and van Binsbergen (2015) and (ii) style-matched benchmark consistent with Ibert et al. (2018). Across all specifications, we use gross return to isolate managerial skill, thereby removing confounding effects of expense ratios and ensuring comparability among funds (see e.g., Berk and van Binsbergen 2015). To attribute performance to a specific management team and reduce short-term volatility, we calculate performance measures at the fund-team-year unit. For each unique combination of fund, management team, and calendar year, a single performance metric is computed. The measures are based on quarterly return data and subsequently annualized, requiring a minimum of four observations within each calendar year.

Berk and van Binsbergen (2015) argue that alpha alone does not adequately measure management skill. Alpha measures ignore that fund managers face diminishing returns to scale as fund size grows, failing to capture the absolute value created by managers. Berk and van Binsbergen (2015) propose that managerial skill should be measured as the absolute value a fund extracts from financial markets. The value added measure reflects the absolute economic contribution to investors by accounting for assets under management (AUM) to control for the diminishing returns associated with increasing fund size.

First, we follow Berk and van Binsbergen (2015) and construct a time-varying benchmark based on each fund-team's factor exposure. We estimate factor loadings by regressing fund-team excess gross return on the Carhart (1997) four-factor loadings over the full sample period. We collect monthly data on European factor returns and risk-free rate from Kenneth French's data library, and average them to a quarterly level. The regression model is specified as:

$$r_{i,t}^{G} - r_{f,t} = \alpha_{i,t} + \beta_{m,i}(MKT_t - r_{f,t}) + \beta_{s,i}SMB_t + \beta_{h,i}HML_t + \beta_{mom,i}WML_t + \epsilon_{i,t} \quad (3)$$

where $r_{i,t}^{G}$ is the gross return for the fund-team combination i in the quarter t, $r_{f,t}$ the risk-free rate, and $MKT_t - r_{f,t}$, SMB_t, HML_t, WML_t are the market excess return, size factor, value factor, and momentum factor returns, respectively. The coefficients $\beta_{m,i}$, $\beta_{s,i}$, $\beta_{h,i}$, and $\beta_{mom,i}$ represent the estimated factor loadings.

The time-invariant estimated factor loadings are then used to construct a time-varying benchmark in each period, combining the factor exposures with the realized factor returns:

$$r_{b,t}^{FM} = \beta_{m,i}(MKT_t - r_{f,t}) + \beta_{s,i}SMB_t + \beta_{h,i}HML_t + \beta_{mom,i}WML_t \quad (4)$$

where $r_{b,t}^{FM}$ represent the return of the factor-model benchmark for fund-team combination i in quarter t, calculated by using the fund's estimated factor loadings ($\beta_{m,i}$, $\beta_{s,i}$, $\beta_{h,i}$, and $\beta_{mom,i}$) with the returns of the factor mimicking portfolios ($MKT_t - R_{f,t}$, SMB_t, HML_t, and WML_t). This benchmark represents the return the fund would be expected to realize based on its factor exposure.

The factor-model gross alpha is defined as the fund's excess gross return after deducting the proportion of its return attributable to systematic risk exposure, as captured by the factor-model constructed benchmark return:

$$\alpha_{i,t}^{FM} = r_{i,t}^{G} - r_{f,t} - r_{b,t}^{FM} \quad (5)$$

where $\alpha_{i,t}^{FM}$ is the factor-model gross alpha for fund-team combination i, in quarter t. $r_{i,t}^{G}$ is the gross return, $r_{f,t}$ is the risk-free rate, and $r_{b,t}^{FM}$ is the return of the factor-model benchmark.

Finally, to account for the economic significance of our alpha measure and the diminishing returns to scale, we compute by multiplying the factor-model gross alpha by fund size:

$$VA_{i,t}^{FM} = \alpha_{i,t}^{FM} \times AUM_{i,t-1} \quad (6)$$

where $VA_{i,t}^{FM}$ denote value added under the factor-model benchmark for fund-team combination i in quarter t, and $AUM_{i,t-1}$ correspond to the fund's asset under management lagged by one period. This factor-modeled value added reflects the economic contribution generated by the management team, beyond what is explained by its exposure to the systematic risk factors.

Second, we follow Ibert et al. (2018), who define the benchmark as the fund's prospectus stated benchmark, departing from Berk and van Binsbergen (2015). Similarly, we define the benchmark for each fund using the fund's assigned Morningstar Category Benchmark. Assigning benchmarks in this manner ensures performance is evaluated relative to a style-matched index. This approach aligns performance evaluation closely to the benchmark investors would intuitively use when assessing fund performance. With this specification, style-matched gross alpha is calculated as:

$$\alpha_{i,t}^{MS} = r_{i,t}^{G} - r_{b,t}^{MS} \tag{7}$$

where $\alpha_{i,t}^{MS}$ represents the style-matched gross alpha of fund-team combination i in period t, computed by deducting the fund's assigned Morningstar Category Benchmark $r_{b,t}^{MS}$ from the fund's gross return, $r_{i,t}^{G}$. This style-matched alpha reflects the fund's performance in excess of its Morningstar Category index, reflecting how well the fund performs relative to a benchmark following the same investment style and holding similar assets.

Consistent with Berk and van Binsbergen (2015), the value added is calculated by scaling the benchmark-adjusted abnormal return by the fund's size:

$$VA_{i,t}^{MS} = \alpha_{i,t}^{MS} \times AUM_{i,t-1} \tag{8}$$

where $VA_{i,t}^{MS}$ corresponds to style-matched value added for fund-team combination i in quarter t, $\alpha_{i,t}^{MS}$ is the style-matched alpha and $AUM_{i,t-1}$ is the fund's lagged assets under management. This measure reflects the absolute value that the fund management team is able to extract, after controlling for the investment style.

By employing both the factor-model derived benchmark and the style-matched benchmark, we obtain two complementary measures of performance. Following Berk and van Binsbergen (2015), the factor model approach controls for return attributable to factor loadings and assesses whether a team generates excess returns given its exposure to systematic risk factors. However, this approach relies on historical factor exposures and risks not fully reflecting the fund's current investment style. In contrast, the style-matched approach, consistent with Ibert et al. (2018), compares fund performance to the opportunity set investors face and use to intuitively assess performance. Benchmarking against an index aligned with the fund's investment style captures mandate-specific constraints, such as sector or market-cap limits. Combining both approaches mitigates benchmark bias and strengthens the robustness of the performance evaluation by integrating both statistical and mandate-aligned methods.

In addition to using two complementary benchmark methods, we employ both the alpha and value added measures in our analysis to capture two distinct dimensions of performance. Alpha captures relative performance, the extent to which a fund generates return in excess of its benchmark, and serves as a proxy for security selection skill. However, as Berk and van Binsbergen (2015) emphasize, alpha alone is not sufficient to evaluate managerial skill since it overlooks the diminishing returns to scale managers face as fund size grows. Small funds generating high alphas may also contribute small absolute amounts. Therefore, relying solely on alpha risks failing to proxy economic significance and welfare impacts. In conclusion, this multifaceted method provides a comprehensive and robust framework to investigate how team diversity relates to both abnormal performance and economic value creation.

3.3 Methodology

3.3.1 Control Variables and Fixed Effect Dummies

Following the econometric literature (e.g., Angrist and Pischke, 2008), we limit the inclusion of control variables in our regression models to avoid including "bad controls". Bad controls refer to variables that are themselves affected by fund performance or managerial decisions. For example, skilled managers demonstrating strong performance attract more capital, resulting in fund size becoming an endogenously determined variable. While prior studies in this area have included controls such as turnover, fund size, and past performance (e.g., lagged alpha), we depart from this since these variables are likely to be endogenous outcomes of fund success. Including them introduces a risk of post-treatment bias (Angrist and Pischke, 2008), since these variables may be influenced by earlier fund performance or team diversity.

Instead, in some specifications we include only fund age and average manager tenure as control variables, since these represent exogenous characteristics not affected by previous performance. We include fund age as a control to account for lifecycle effects, as older funds may systematically differ from younger firms (e.g., Berk and Green, 2004; Aggarwal and Jorion, 2010). As a proxy for manager quality and experience, we use the average manager tenure of each fund. Managers with longer tenure may have developed accumulated knowledge, built stronger relations with investors, both of which may partially explain return outcomes.

Furthermore, we include fund-fixed effects and year-fixed effects to account for unobserved heterogeneity. Fund-fixed effects control for time-fixed characteristics specific to each fund, isolating the effects of team diversity on fund performance over time and allowing us to examine the effect of within-fund diversity variations. Year-fixed effects control for macroeconomic conditions and market trends within a given year that affect the full sample of funds. Including fund- and year-fixed effects helps mitigate omitted variable bias by accounting for unobserved factors that influence fund returns, thereby isolating the effects of team diversity on performance.

3.3.2 Model Specifications

We estimate OLS regression models at the fund-team-year level, using the panel dataset described in Section 3.1. The dependent variable in each regression corresponds to a specific performance measure, as defined in Eqs. (5), (6), (7), and (8): factor-model alpha, factor-model value added, style-matched alpha, and style-matched value added, respectively. We specify four individual regression models progressively adding more controls, and estimate them separately for each diversity metric, following the approach by Lu et al (2024). To mitigate potential endogeneity concerns, all diversity metrics are lagged, reflecting the teams' diversity composition in the year prior to performance measurement.

The baseline specification estimates separate regressions for each of the fund-team's lagged diversity scores: gender, university, university major, and prior workplace diversity. This approach captures the four distinct dimensions of heterogeneity within the management team. The baseline model is specified as:

$$Perf_{i,t} = \beta_0 + \beta_1 Div_{i,t-1} + \epsilon_{i,t} \tag{9}$$

where $Perf_{i,t}$ denotes one of the four performance metrics of the fund-team combination i in year t. $Div_{i,t-1}$ refers to the diversity score for one of the four metrics – gender, university, university major, or prior workplace – lagged by one year. The estimated coefficient β_1 reflects the relationship between the degree of diversity along a particular dimension and fund performance.

To control for unobserved heterogeneity and potential confounding factors, we estimate four increasingly more controlled specifications. Model 1, as specified in Eq. (9), includes only the lagged diversity metric. Model 2 introduces year-fixed effects to control for macroeconomic events and time-varying conditions. Model 3 adds fund-fixed effects to account for time-fixed characteristics specific to each fund. Finally, Model 4 includes fund age and average manager tenure in order to control for fund lifecycle effects and managerial skill. Model 4 is defined as:

$$\begin{aligned} Perf_{i,t} = \beta_0 + \beta_1 Div_{i,t-1} + \beta_2 FundAge_{i,t-1} + \beta_3 AvgTenure_{i,t-1} \\ + \sum_k \beta_4^k YearFE_t^k + \sum_m \beta_5^m \ FundFE_i^m + \epsilon_{i,t} \end{aligned} \tag{10}$$

where $Perf_{i,t}$ denotes one of the four performance measures of fund-team combination i in year t and $Div_{i,t-1}$ corresponds to the lagged diversity score. $YearFE_t$ and $FundFE_i$ represent year- and fund-fixed effects. Control variables are lagged, including fund age and average manager tenure, denoted as $FundAge_{i,t-1}$ and $AvgTenure_{i,t-1}$, respectively.

The complete set of regression equations, including Model 2 and Model 3 specifications, is presented in Appendix C. All regressions are estimated using heteroskedasticity robust standard errors, and missing observations are excluded within each model.

By estimating four increasingly controlled models, we evaluate the robustness of the relationship between team diversity and mutual fund performance. The sequential inclusion of controls, as well as employing multiple performance metrics, allows us to investigate whether observed effects hold under alternate specifications, reinforcing the validity of our results. This approach enables us to account for both time-invariant and time-varying differences, as well as reducing omitted variable bias, potentially affecting both fund performance and diversity measures. By comparing results across specifications, we assess the extent to which the relationship between team diversity and fund performance is sensitive to alternative model assumptions, offering a detailed investigation of the results.

4 Empirical Results and Discussion

This section outlines the empirical findings on the relationship between management team diversity and Swedish mutual fund performance. First, we present unconditional comparisons between high- and low-diversity teams using descriptive fund performance statistics. Second, we estimate OLS regression models to examine the relationship between average diversity score and fund performance. Third, we decompose average diversity into its underlying components – gender, university, major, and prior workplace diversity – to assess their individual effects. Finally, we interpret these results in the context of the Swedish mutual fund industry and situate them within the existing literature.

4.1 Descriptive Statistics by Diversity Category

Table 4 presents descriptive summary statistics across five panels, each corresponding to a lagged diversity metric: gender, workplace, university, major, as well as a compound average diversity measure. For each metric, teams are categorized into "high" or "low" diversity groups based on the median split of the lagged diversity score. The high-diversity group corresponds to teams with values greater than or equal to the median, while those classified into the low-diversity group have a value below the median. All results use unadjusted Welch t-tests and omit controls for fund characteristics to compare mean differences across groups. In the upcoming section, we will go through each panel to discover any differences or similarities in fund characteristics between the four diversity metrics and discuss their implications.

4.1.1 Panel A: Average Diversity

Panel A comprises the average diversity of fund outcomes. This measure is an aggregate index combining the four diversity metrics: gender, university, major, and workplace diversity. In total, there is a sample of 3,467 fund-team-year observations, where 1,807 make up the high average-diversity group, while the remaining 1,660 accounts for the low average-diversity group, based on a median split of the composite diversity score.

We find statistically significant differences in several performance and fund characteristics between the two groups. The gross alpha measures show opposing results. The factor-model based gross alpha shows that low average-diversity teams, on average, generate higher returns (2.14% vs. 1.62%) than high average-diversity teams, with a difference of –0.52 percentage points ($p < 0.001$). Conversely, the style-matched gross alpha suggests that high average-diversity teams, on average, outperform low average-diversity teams (0.58% vs. 0.41%), although the difference is small and only marginally significant ($p < 0.1$). The value added results are also mixed, with the factor-model-based measure demonstrating that low average-diversity teams perform better than high average-diversity teams (diff: –205.18, $p < 0.001$), while the teams do not show any statistically significant result. These results show an inconclusive relationship between average diversity and fund performance, and may therefore vary depending on the performance measure used.

Regarding the fund characteristics included in the table, we observe that low average-diversity teams manage larger assets under management (AUM) (6,000.67 MSEK vs. 5,009.19 MSEK, diff: –991.48 MSEK, $p < 0.01$) and manage their fund during a shorter time (11.03 years vs. 12.90 years, diff: 1.86 years, $p < 0.001$) compared to high average-diversity teams.

4.1.2 Panel B: Gender Diversity

In Panel B, we observe a large proportional difference between the size of low versus high gender-diversity teams, with low gender-diversity teams constituting the larger group (N = 2,805 versus N = 662). This distribution, where the majority of teams are all-male, creates

Table 4: Descriptive Statistics by Diversity Dimension - High vs. Low Diversity Teams

Metric	Mean (All)	Mean (High)	Mean (Low)	Mean (Diff)	Median (All)	Median (High)	Median (Low)	Median (Diff)
Panel A: Average Diversity								
Number of Observations	3467	1807	1660					
Gross Alpha Factor-Model (%)	1.86	1.62	2.14	-0.52***	1.74	1.60	1.96	-0.36
Gross Alpha Style-Matched (%)	0.50	0.58	0.41	0.17°	0.54	0.53	0.60	-0.07
Value Added Factor-Model (MSEK)	316.25	220.91	426.10	-205.18***	113.69	122.05	108.69	13.36
Value Added Style-Matched (MSEK)	128.87	153.73	100.38	53.35	21.40	23.27	15.42	7.85
Fund Size (MSEK)	5467.03	5009.19	6000.67	-991.48**	2661.81	2572.82	3082.42	-509.60
Fund Age (Years)	12.04	12.90	11.03	1.86***	9.85	10.87	7.74	3.13
Panel B: Gender Diversity								
Number of Observations	3467	662	2805					
Gross Alpha Factor-Model (%)	1.86	1.25	1.98	-0.74***	1.72	0.98	1.83	-0.84
Gross Alpha Style-Matched (%)	0.50	0.31	0.55	-0.24°	0.54	0.26	0.67	-0.41
Value Added Factor-Model (MSEK)	316.25	1.77	374.74	-372.96***	113.69	115.70	113.69	2.01
Value Added Style-Matched (MSEK)	128.87	57.73	143.80	-86.08*	21.40	0.74	29.04	-20.30
Fund Size (MSEK)	5467.03	4743.16	5615.99	-872.82**	2661.81	2769.10	2549.47	219.63
Fund Age (Years)	12.04	14.90	11.45	3.45***	9.85	12.88	9.23	3.65
Panel C: University Diversity								
Number of Observations	3449	2797	652					
Gross Alpha Factor-Model (%)	1.84	1.66	2.72	-1.06***	1.73	1.60	2.24	-0.64
Gross Alpha Style-Matched (%)	0.49	0.46	0.63	-0.17	0.54	0.53	0.60	-0.07
Value Added Factor-Model (MSEK)	317.39	311.73	345.27	-33.54	113.69	114.13	113.69	0.44
Value Added Style-Matched (MSEK)	126.34	114.80	195.49	-80.70	21.83	24.38	2.67	21.70
Fund Size (MSEK)	5499.62	5668.39	4663.59	1004.80*	2677.55	2768.84	2334.43	434.41
Fund Age (Years)	12.00	12.15	11.22	0.94*	9.65	9.85	8.50	1.35
Panel D: Major Diversity								
Number of Observations	3031	2199	832					
Gross Alpha Factor-Model (%)	1.81	1.86	1.66	0.20	1.65	1.73	1.44	0.29
Gross Alpha Style-Matched (%)	0.47	0.64	0.03	0.60***	0.48	0.62	0.24	0.38
Value Added Factor-Model (MSEK)	303.15	316.31	267.25	49.06*	116.52	112.17	130.49	-18.33
Value Added Style-Matched (MSEK)	133.29	170.44	33.37	137.07***	19.67	20.64	9.88	10.76
Fund Size (MSEK)	5343.64	5079.68	6055.23	-975.55**	2768.84	2441.25	4772.64	-2331.39
Fund Age (Years)	11.41	10.98	12.57	-1.60***	8.88	8.87	9.50	-0.63
Panel E: Workplace Diversity								
Number of Observations	3403	2749	654					
Gross Alpha Factor-Model (%)	1.89	1.90	1.80	0.10	1.77	1.77	2.11	-0.34
Gross Alpha Style-Matched (%)	0.50	0.50	0.50	-0.00	0.58	0.45	1.03	-0.59
Value Added Factor-Model (MSEK)	322.68	298.14	445.05	-146.91*	117.16	111.94	204.76	-92.82
Value Added Style-Matched (MSEK)	132.26	138.62	103.92	34.70	23.32	18.19	54.17	-32.98
Fund Size (MSEK)	5544.83	5166.38	7366.59	-2200.21***	2734.76	2443.03	4131.34	-1688.31
Fund Age (Years)	12.03	12.60	9.24	3.36***	9.85	10.96	6.71	4.25

Note: This table reports mean, median and Welch's t-test for differences in fund performance and characteristics across high and low diversity teams. Teams are divided into high and two diversity groups using a median split. All observations are at the fund-team-year level. Significance: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, ° $p \leq 0.10$.

a binary and skewed nature of this metric, leading to a median value of 0. As a result, any team with at least one female and one male manager is classified as a "high" gender-diversity team, indicating a lagged gender-diversity score greater than zero (gender diversity score > 0). In contrast, teams consisting only of managers of the same gender are classified as a "low" gender-diversity team, with a lagged gender-diversity score equal to 0.

We find evidence suggesting there is a statistically and economically significant difference in performance between the two groups. The results from the two alpha measures demonstrate that low gender-diversity teams, on average, generate higher annual returns (factor-based: 1.98%, style-matched: 0.55%) compared to high gender-diversity teams (factor-based: 1.25%, style-matched: 0.31%), with significant differences of –0.74 percentage points ($p < 0.001$) and –0.24 percentage points ($p < 0.1$), respectively. The same relationship holds in absolute terms, as shown by the value added measures. There is a difference in value added (factor-model) of –372.96 MSEK ($p < 0.001$) and in value added (style-matched) of –86.08 MSEK ($p < 0.05$). These results suggest that low gender-diversity teams generate higher returns on average.

However, since we do not control for any risk factors or fund characteristics, these results could be caused by other differences between the groups, such as the funds they manage, the risks they take, or the way teams are formed.

Moreover, looking at the fund size and fund age results, we find that gender-homogeneous teams tend to manage larger AUM (5,615.99 MSEK vs. 4,743.16 MSEK, $p < 0.01$), but for fewer years (11.45 years vs. 14.90 years, $p < 0.001$) compared to heterogeneous teams.

4.1.3 Panel C: University Diversity

Panel C represents the impact of diversity, in terms of university background, on fund performance. We classify each of the 3,449 fund-team-year observations based on whether the team members graduated from different universities (N = 2,797) or from the same university (N = 652). This skewed distribution indicates that the majority of teams are composed of members with different university backgrounds.

We find significant results when using the gross alpha (factor-model) measure, with low university-diversity teams performing better, on average, than high university-diversity teams (2.72% vs. 1.66%), showing a statistically significant difference of –1.06 percentage points at the 0.1% level. The other three performance measures also suggest that homogeneous teams outperform heterogeneous ones; however, these results are not statistically significant, meaning we cannot draw conclusions with high confidence.

Interestingly, high university-diversity teams manage, on average, larger funds (5,668.39 MSEK vs. 4,663.59 MSEK, $p < 0.05$) and for longer time periods (12.15 years vs. 11.22 years, $p < 0.05$) compared to low diversity teams.

4.1.4 Panel D: Major Diversity

Panel D examines the impact of diversity in terms of university majors on fund outcomes. Of the 3,031 fund-team-year observations, 2,199 fall into the "high" major-diversity group (i.e., teams with managers who studied different academic fields), while 832 are included in the "low" major-diversity group (i.e., teams with managers who studied the same academic field). This variable is also skewed toward maximum diversity, resulting in a small number of low-diversity groups and limited statistical power.

The results show a statistically significant gross alpha (style-matched) between the two groups, with high major-diversity teams, on average, generating higher returns than low major-diversity teams (0.64% vs. 0.03%, diff: 0.60, $p < 0.001$). In contrast, we find no statistically significant difference between the two groups when looking at the gross alpha based on the factor-model (1.86% vs. 1.66%, diff: 0.20). This could indicate that when adjusting for investment style, diverse academic backgrounds may be related to better fund performance.

The two value added results support a similar interpretation. Highly major-diverse teams generate more value added according to both the factor-model (diff: 49.06 MSEK, $p < 0.05$) and style-matched measure (diff: 137.07 MSEK, $p < 0.001$), with the latter being more statistically significant.

In terms of fund size, we observe that low major-diversity teams manage larger funds on average (6,055.23 MSEK vs. 5,079.68 MSEK, $p < 0.01$) and for longer time periods (12.57 years vs. 10.98 years, $p < 0.001$) compared to high major-diversity teams.

4.1.5 Panel E: Workplace Diversity

Panel C splits 3,403 fund-team-year combinations based on workplace diversity, yielding 2,749 observations in the "high" group (i.e., teams with members from different prior employers), versus 654 observations in the "low" group (i.e., teams with members from the same prior employer). Similar to the other diversity metrics, the distribution is skewed toward high diversity, resulting in a smaller low-diversity group.

Observing the alpha results, we find no statistically significant difference between the two groups. The same applies to value added (style-matched). However, the value added (factor-model) shows a statistically significant difference between the two groups (diff: −146.91 MSEK, $p < 0.05$), with the low workplace-diversity teams generating the highest value added (445.05 MSEK vs. 298.14 MSEK) compared to high workplace-diversity teams. These mixed results, with both insignificant and weakly significant findings, suggest that the relationship between workplace diversity and fund performance is vague and potentially influenced by other factors not controlled for.

Furthermore, there is a strong, statistically significant difference between low and high workplace-diversity groups in terms of fund size (diff: –2,200.21 MSEK, $p < 0.001$) and fund age (diff: 3.36 years, $p < 0.001$). This demonstrates that, on average, low workplace-diversity teams manage larger AUM (7,366.59 MSEK vs. 5,166.38 MSEK, $p < 0.001$), but high workplace-diversity teams manage their funds for a longer period (12.60 years vs. 9.24 years, $p < 0.001$). In general, we find no strong evidence supporting that workplace diversity improves alpha, and the higher value added observed among low diversity teams may be driven by differences in fund size and age rather than diversity itself.

In general, the summary statistic from Table 4 offers mixed evidence on the relationship between the different diversity metrics and fund performance. Much of the results across the panels suggest that low-diversity teams outperform high-diversity teams, although in some cases, the differences are not statistically significant or only marginally significant. Furthermore, these comparisons do not control for other fund-level characteristics or risk exposures, making it difficult to draw meaningful and accurate conclusions. Therefore, in the upcoming section, we will run OLS regressions to formally test the relationship between diversity and fund performance while controlling for other factors that may impact the results.

4.2 Regression Analysis on Average Diversity and Fund Performance

Unconditional comparisons in Table 4 provide some evidence that high-diversity teams, on average, underperform relative to low-diversity teams. We further investigate the relationship between diversity and fund performance by estimating OLS regression models progressively introducing fixed-effects and control variables, as outlined in Section 4.3.1. Table 5 presents the association between a fund's average team diversity score and each performance measure across these model specifications. Model (1) is univariate; Models (2) to (4) sequentially add year-fixed effects, fund-fixed effects, and control variables.

In the cross-sectional Models (1) and (2), higher diversity is negatively and significantly associated with both factor-model and style-matched alpha. Specifically, in the cross-section fully homogeneous team achieve, on average, 1-1.3 percentage point higher alpha than their heterogeneous counterparts. However, once time-invariant fund-fixed effects are introduced in Model (3), the coefficient turns positive, indicating that within a given fund, improvements in diversity score are positively associated with a 2.36 percentage point increase in factor-model alpha ($p < 0.01$). Adding controls for fund age and manager tenure weakens this effect but does not eliminate the positive association between within-fund improvements in team diversity and performance measured by alpha.

We observe that the same pattern holds under factor-model value added. In the cross-section, team diversity is negatively associated with value added. Similarly, when accounting for time-invariant characteristics of funds, this relationship is reversed. A one-unit increase in diversity score, moving from complete homogeneity to complete heterogeneity, is associated with an average improvement of 2,337 MSEK (Model (4),$p < 0.001$) in annual factor-model value added. The coefficient of 2,337 MSEK should be interpreted against the fund size distribution presented in Table 1. This value represents 3.9% of the average fund (mean AUM = 60,622 MSEK), making the effect both statistically and economically meaningful. While baseline models exhibit low R2, we observe a substantial improvement when incorporating more controls, with the fully specified model explaining up to 71.3% of the variations in performance.

In conclusion, the panel regressions reveal a different story compared to simple cross-sectional models. Once fund-specific characteristics are fixed, we observe a positive relationship between improvements within a given fund's management team and both abnormal returns and economic value creation. The obvious next question concerns which dimensions of diversity affect performance and the magnitude of their contribution. The following section addresses this by decomposing the average diversity into its core components: gender, university, university major, and workplace diversity.

Table 5: Ordinary Least Squares Regressions on Gross Alpha and Value Added

AverageDiversity_lag Across All Models	**Gross Alpha Factor-Model (%)**				**Gross Alpha Style-Matched (%)**				**Value Added Factor-Model (MSEK)**				**Value Added Style-Matched (MSEK)**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversity Metric																
AverageDiversity_lag	-1.07**	-1.31***	2.36**	1.67°	-0.99***	-1.03***	-1.00	-1.14	-549.30***	-525.50***	1645.00***	2337.00***	117.90	131.00	-125.00	24.54
	(0.40)	(0.31)	(0.90)	(0.95)	(0.30)	(0.28)	(0.82)	(1.00)	(171.00)	(163.00)	(472.00)	(622.00)	(131.00)	(130.00)	(404.00)	(541.00)
Fixed effects																
Time FE		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓
Fund FE			✓	✓			✓	✓			✓	✓			✓	✓
Control Variables																
AvgTenure_lag				-0.49***				-0.04				-129.50*				-5.58
				(0.09)				(0.10)				(58.20)				(53.10)
FundAge_lag				0.08				0.30*				45.33				42.03
				(0.13)				(0.15)				(85.50)				(81.60)
R^2	0.003	0.404	0.683	0.713	0.004	0.211	0.450	0.465	0.005	0.132	0.537	0.372	0.000	0.049	0.275	0.253
No. obs.	2 267	2 267	2 267	1 777	2 724	2 724	2 724	2 153	2 267	2 267	2 267	1 777	2 724	2 724	2 724	2 153

Note: This table reports the coefficient estimate from cross-sectional and panel OLS regressions. The dependent variable is one of the performance measures, and the independent variables of interest is the lagged average diversity score. Performance measures are annualized and include: factor-model alpha, style-matched alpha, factor-model value added and style-matched value added. Each diversity metric is studied in a separate regression. Column (1) includes only the lagged diversity metric, (2) adds year-fixed effects (3) adds fund-fixed effects, and (4) adds controls for average manager tenure and fund age. All observations are at the fund-team-year level. Standard errors in parenthesis. Significance: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, ° $p \leq 0.10$.

4.3 Regression Analysis on Diversity Dimensions and Fund Performance

4.3.1 Effects on Gross Alpha

Table 6 presents the relationship between the different diversity metrics and alpha measures across the regression models, progressively adding fixed-effects and control variables. For each diversity dimension and performance measure, four separate regressions are estimated. Panel A reports the coefficients for the lagged diversity metrics for factor-model alpha, whereas Panel B reports the results for style-matched alpha.

In the cross-sectional regressions (1) and (2), both factor-model and style-matched alpha exhibit a negative and statistically significant relationship with gender diversity. For example, in Model (2), the coefficient for gender diversity is –0.53% ($p < 0.001$) for factor-model alpha and –0.85% ($p < 0.001$) for style-matched alpha. Similar to the coefficient for average diversity in Table 5, the effect of gender diversity reverses once fund-fixed effects are introduced. Economically, this suggests that within a given fund, moving from fully gender-homogeneous teams (diversity score = 0) to full gender diversity (diversity score = 1) is associated with an average increase of 1.11 percentage points ($p < 0.01$) in abnormal returns relative to its factor-model benchmark (Panel A, Model 3). However, when additional controls are introduced in specification (4), the effect loses statistical significance, indicating that the relationship between gender diversity and abnormal performance is sensitive to model specification. In Panel B, the negative association observed in the cross-section becomes insignificant when introducing fund-fixed effects, but reappears marginally significant in Model (4), weakly suggesting a positive relationship between within-fund gender diversity and style-matched alpha.

Panel A shows a consistent negative and statistically robust relationship between university diversity and factor-model alpha across both cross-sectional and panel regressions. In the final model specification (4), a one-unit within-fund increase in university diversity is associated with a 1.43 percentage point decrease in factor-model alpha ($p < 0.001$). Panel B reveals a similar, albeit smaller, effect, where a one-unit within-fund increase in university diversity is associated with a 0.70 percentage point ($p < 0.1$) decrease in style-matched alpha. While the effect on style-matched alpha is weaker and only marginally significant, the consistent negative coefficients once introducing fund-fixed effects suggest the effect persists within funds and cannot be fully explained by time-invariant fund characteristics, cultures, or investment mandates.

We find evidence that the opposite relationship holds for university major diversity and abnormal performance. While Panel A initially shows no significant association between major diversity and factor-modeled alpha, this relationship becomes strongly significant and positive once fund-fixed effects are introduced. Specifically, in the full specification (Model 4), a one-unit within-fund increase in major diversity is, on average, associated with a 2.24 percentage point improvement in annual factor-model alpha ($p < 0.001$). This suggests that diversity in managers' field of study improves abnormal performance beyond what can be explained by the fund's exposure to systematic risk factors. Although Panel B reports a negative coefficient for major diversity on style-matched alpha in specification (4), this effect is marginally significant, inconsistent, and weaker. Given the strong significance of the factor-model results and positive effect on value added (Table 7), we place greater weight on the robust positive association observed in Panel A.

With respect to prior workplace diversity, we find some evidence that workplace diversity positively influences abnormal fund performance. Panel A indicates a positive and significant relationship between workplace diversity and factor-model alpha in Model specifications (3) and (4), with coefficients of 1.07% ($p < 0.05$) and 0.88% ($p < 0.05$), respectively. We find the effect has a similar magnitude in Panel B Model (4), where a one-unit increase in workplace diversity is associated with a 0.82 percentage point ($p < 0.05$) increase in style-matched alpha.

Taken together, Table 6 reveals that the association between diversity and abnormal performance is highly dimension-specific. The effect of gender diversity primarily holds in the cross-section, largely diminishing when accounting for time-invariant fund characteristics. In contrast, university major consistently exhibits a negative association with abnormal performance across cross-sectional and panel regressions, especially for factor-model alpha. Conversely, university major appears positively associated with fund performance across specifications. Similarly, workplace diversity shows a positive association, though the statistical significance is weaker compared to that of major diversity.

4.3.2 Effects on Value Added

Table 7 reveals that a similar pattern holds for the relationship between the different diversity metrics and value added as observed for alpha measures in Table 6. Panel A shows regression results on value added using the factor-based benchmark, and Panel B shows regression results of value added based on the style-matched benchmark.

Panel A shows a significantly negative relationship between gender diversity and factor-model value added in the cross-sectional Models (1) and (2). Specifically, when comparing across different funds, fully gender-diverse teams, on average, underperform by –428.70 MSEK (Model (2), $p < 0.001$) in annual economic value added, compared to their homogeneous counterparts. This effect diminishes once accounting for fund-fixed effects, meaning that within a given fund, changes in gender compositions are not significantly associated with performance. In Panel B, we find no significant evidence of an association between gender diversity and performance.

Turning to university diversity, we observe a negative and statistically significant effect on style-matched value added only in Panel B, Models (1) and (2), with coefficients of –146 MSEK ($p < 0.05$) and –166.8 MSEK ($p < 0.01$), respectively. In line with the results presented in Table 6, we find a statistically significant positive relationship between university major diversity and factor-model value added once fund-fixed effects are incorporated. Specifically, a one-unit within-fund increase in major diversity score is associated with an average increase of 1,065 MSEK ($p < 0.001$) in annual factor-model value added (Panel A, Model (4)). Given the magnitude of this effect, the relationship observed in Table 6 appears not only statistically but also economically meaningful. However, in Panel B, the positive relationship is only present in the cross-sectional models and not when fund-fixed effects are added in Model (3). Notably, the weak statistical evidence of negative performance observed in Table 6 has diminished in the value added results. We find no evidence that workplace diversity significantly influences either value added specification.

Table 6: Ordinary Least Squares Regressions on Gross Alpha

Panel A: Gross Alpha Factor-Model (%)	**Gender**				**University**				**Major**				**Workplace**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversity Metrics																
GenderDiv_lag	-0.41*	-0.53***	1.11**	0.86												
	(0.19)	(0.15)	(0.42)	(0.55)												
UniversityDiv_lag					-0.83***	-0.74***	-0.87*	-1.43***								
					(0.19)	(0.15)	(0.37)	(0.33)								
MajorDiv_lag									0.12	0.08	1.26***	2.24***				
									(0.17)	(0.14)	(0.34)	(0.32)				
WorkplaceDiv_lag													0.13	-0.10	1.07*	0.88*
													(0.20)	(0.16)	(0.43)	(0.38)
Fixed effects																
Time FE		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓
Fund FE			✓	✓			✓	✓			✓	✓			✓	✓
Control Variables																
AvgTenure_lag				-0.44***				-0.41***				-0.55***				-0.46***
				(0.09)				(0.09)				(0.09)				(0.09)
FundAge_lag				0.07				0.07				0.08				0.06
				(0.13)				(0.13)				(0.14)				(0.13)
R^2	0.002	0.403	0.683	0.713	0.009	0.403	0.680	0.712	0.000	0.363	0.670	0.715	0.000	0.398	0.677	0.705
No. obs.	2 267	2 267	2 267	1 777	2 253	2 253	2 253	1 763	1 964	1 964	1 964	1 558	2 218	2 218	2 218	1 728

Panel B: Gross Alpha Style-Matched (%)	**Gender**				**University**				**Major**				**Workplace**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversity Metrics																
GenderDiv_lag	-0.74***	-0.85***	0.11	0.68°												
	(0.14)	(0.13)	(0.31)	(0.38)												
UniversityDiv_lag					-0.27°	-0.41**	-0.53	-0.70°								
					(0.14)	(0.13)	(0.37)	(0.36)								
MajorDiv_lag									0.30*	0.39***	-0.53°	-0.60*				
									(0.13)	(0.11)	(0.29)	(0.30)				
WorkplaceDiv_lag													-0.08	-0.04	0.35	0.82*
													(0.15)	(0.13)	(0.37)	(0.40)
Fixed effects																
Time FE		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓
Fund FE			✓	✓			✓	✓			✓	✓			✓	✓
Control Variables																
AvgTenure_lag				-0.04				-0.04				-0.05				-0.06
				(0.10)				(0.10)				(0.10)				(0.10)
FundAge_lag				0.29°				0.29°				0.32				0.30*
				(0.15)				(0.15)				(0.16)				(0.15)
R^2	0.010	0.220	0.450	0.466	0.001	0.208	0.450	0.465	0.002	0.214	0.467	0.486	0.000	0.212	0.458	0.469
No. obs.	2 724	2 724	2 724	2 153	2 710	2 710	2 710	2 139	2 398	2 398	2 398	1 917	2 675	2 675	2 675	2 104

Note: This table reports the coefficient estimate from cross-sectional and panel OLS regressions. The dependent variable is annual gross alpha and the independent variables of interest are the lagged diversity scores. Panel A reports factor-model gross alpha and Panel B shows style-matched gross alpha. All observations are at the fund-team-year level. Each diversity metric is studied examined in a separate regression. Column (1) includes only the lagged diversity metric, (2) adds year-fixed effects (3) adds fund-fixed effects, and (4) adds controls for average manager tenure and fund age. Standard errors in parenthesis. Significance levels: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, ° $p \leq 0.10$.

In conclusion, the analysis reveals an association between diversity and fund performance that is highly-dimension specific. For gender diversity, the effect is on alpha and value added is negative in the cross-section but disappears once fund-fixed effects are introduced, providing limited robust evidence that gender proportions explain within-fund variations. Similarly, workplace diversity offers suggestive results of a positive effect on performance, as the statistical significance is weak across performance measures. University diversity provides more robust evidence of a negative within-fund association on performance, as the negative relationship on factor alpha measures remains highly significant when introducing fund-fixed effects and controls. This suggests that managers who have attended different educational institutions may face coordination challenges affecting abnormal performance measures, even if it does not significantly affect absolute value creation. Notably, university major diversity emerges as the most robust and consistent predictor of fund performance, as reflected in both alpha and value added measures. This result suggests that fund management teams composed of managers with diverse fields of study are, on average, better positioned to generate abnormal returns and create greater economic value.

4.4 Discussion

The results presented reveal a dimension-specific association between management team diversity and mutual fund performance in Sweden. In this section, we will interpret the empirical findings, situates within the existing literature and investigate their broader implications.

We find evidence supporting the value-in-diversity hypothesis, as suggested by Cox (1993). Functional diversity, proxied by managers' academic majors, appears to have a positive effect on performance when measuring performance, both in terms of alpha and value added. This suggests that diversity in academic majors may expand a management team's knowledge base, enabling varying perspectives, strategies, and skill sets. Under the right conditions, managers are better positioned to leverage this diverse pool of knowledge and effectively enhance investment outcomes. For example, a team consisting of a manager who has majored in engineering and another in finance are able to combine different analytical skills, allowing them to make robust financial decisions. Specifically, a within-fund shift to a fully major-diverse team from a fully major-homogeneous team will, on average, increase annual factor-model alpha and value added by 2.24% (Table 6, Panel A, Model (4), $p < 0.001$) and 1,065 MSEK (Table 7, Panel A, Model (4), $p < 0.001$), respectively.

We observe that the opposite pattern holds for university diversity in the alpha dimension. Highly diverse teams along this dimension achieve a lower annual factor-model alpha in the fully specified model; this translates to a coefficient of −1.43% (Table 6, Panel A, Model (4), $p < 0.05$). However, we do not find statistical evidence that this abnormal underperformance has economic significance when introducing fund-fixed effects (Table 7).

The observed phenomena can be explained by university affiliation being more closely linked to manager identity than academic major. Attending the same university may contribute to managers' social identity, causing the formation of in-groups and out-groups consistent with faultline theory (Lau and Murnighan, 1998). These group dynamics on the industry level may spill over to even small teams, causing coordination and communication conflicts, effectively hindering managers ability to make efficient investment decisions.

Table 7: Ordinary Least Squares Regressions on Value Added

Panel A: Value Added Factor-Model (MSEK)

	Gender				University				Major				Workplace			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversity Metrics																
GenderDiv_lag	-448.20***	-428.70***	-110.30	-294.50												
	(82.90)	(79.80)	(221.00)	(364.00)												
UniversityDiv_lag					-57.22	-36.75	-123.40	-357.00								
					(81.50)	(77.40)	(195.00)	(221)								
MajorDiv_lag									99.32	93.06	984.20***	1 065.00***				
									(72.10)	(68.70)	(167.00)	(202.00)				
WorkplaceDiv_lag													-156.90°	-176.00*	-256.40	-316.20
													(89.00)	(85.70)	(226.00)	(253.00)
Fixed effects																
Time FE		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓
Fund FE			✓	✓			✓	✓			✓	✓			✓	✓
Control Variables																
AvgTenure_lag				-93.07				-87.74				-126.30*				-85.23
				(57.70)				(58.20)				(59.50)				(58.60)
FundAge_lag				38.87				35.67				29.69				37.16
				(85.90)				(86.50)				(86.10)				(88.10)
R^2	0.013	0.139	0.534	0.367	0.000	0.128	0.535	0.368	0.001	0.118	0.577	0.390	0.001	0.131	0.535	0.367
No. obs.	2 267	2 267	2 267	1 777	2 253	2 253	2 253	1 763	1 964	1 964	1 964	1 558	2 218	2 218	2 218	1 728

Panel B: Value Added Style-Matched (MSEK)

	Gender				University				Major				Workplace			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversity Metrics																
GenderDiv_lag	-89.20	-90.79	-17.01	52.38												
	(60.80)	(60.80)	(153.00)	(207.00)												
UniversityDiv_lag					-146.00*	-166.80**	-10.93	31.10								
					(61.20)	(60.70)	(181.00)	(198.00)								
MajorDiv_lag									187.10***	203.10***	46.96	31.98				
									(53.10)	(52.20)	(139.00)	(154.00)				
WorkplaceDiv_lag													72.14	83.15	-237.70	-215.80
													(63.90)	(63.80)	(186.00)	(218.00)
Fixed effects																
Time FE		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓
Fund FE			✓	✓			✓	✓			✓	✓			✓	✓
Control Variables																
AvgTenure_lag				-4.27				-5.91				-6.65				-0.57
				(52.80)				(53.10)				(51.20)				(53.10)
FundAge_lag				41.69				41.49				49.21				42.96
				(81.60)				(82.10)				(80.40)				(83.40)
R^2	0.001	0.049	0.275	0.253	0.002	0.051	0.275	0.253	0.005	0.065	0.327	0.310	0.000	0.049	0.276	0.254
No. obs.	2 724	2 724	2 724	2 153	2 710	2 710	2 710	2 139	2 398	2 398	2 398	1 917	2 675	2 675	2 675	2 104

Note: This table reports the coefficient estimate from cross-sectional and panel OLS regression. The dependent variable is annual value added and the independent variables of interest are the lagged diversity scores. Panel A reports factor-model value added and Panel B shows style-matched value added. Each diversity metric is included examined in a separate regression. Column (1) includes only the lagged diversity metric, (2) adds year-fixed effects (3) adds fund-fixed effects, and (4) adds controls for average manager tenure and fund age. All observations are at the fund-team-year level. Standard errors in parenthesis. Significance levels: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, ° $p \leq 0.10$.

The dynamics of the Swedish mutual fund industry can be expected to influence our observed relationship between management team diversity and fund performance. First, compared to the U.S. educational market, there are a considerably smaller number of universities in Sweden. In our sample, a large majority of managers have attended a small number of Swedish universities (Table 2), potentially reinforcing the in-group formations based on social identity. This context may further explain the identified negative relationship between university diversity and alpha measures.

Second, although Sweden is recognized as a gender-equal country, we find that less than 3% are female fund managers in our sample (Figure 1), resulting in a small number of gender diverse teams. Consequently, there is a limited within-fund gender diversity, reducing the statistical power to detect a robust effect of within-fund gender diversity on performance, which may explain why significant results primarily appear in the cross-sectional analyses.

Third, the Swedish asset management industry is substantially smaller than its U.S. counterpart, resulting in lower job mobility for fund managers and a limited number of employers. This is identified in Table 2, where a large number of managers have professional backgrounds from one of Sweden's biggest banks. Although we report a relatively high average diversity score for workplace diversity (Table 3), we recognize that, given the industry's small size, a higher diversity score does not necessarily mean heterogeneous industry knowledge or networks. The innate homogeneity of the asset management industry could therefore explain the limited evidence on a relationship between fund performance and workplace diversity.

Finally, the Swedish mutual fund sector is characterized by small management teams, with a mean of 2.43 and a median of 2.00 managers (Table 3). This is an important limitation of our study, as two-person teams are constrained to binary diversity scores; the team either shares or differs for a given characteristic. The U-shaped distribution limits the statistical variability and reduces the granularity of diversity scores. Further, the manual data collection acts as a limitation due to (i) the risk of human error such as mistakenly identifying managers with identical names, and (ii) potentially biased information provided by the managers themselves.

Our findings partially align with the existing strand of team-diversity asset management literature. Consistent with Lu et al. 2024 and Bär et al. (2009) we find support for a positive association between major diversity and fund alpha. We extend their analysis by incorporating value added as a performance measure, and find evidence that major diverse teams on average generate superior economic contributions, not only higher alpha. In contrast to these papers, we find support for a negative relationship between fund alpha and university diversity. Our partially contradicting results indicate that the findings of Lu et al. (2024) and Bär et al. (2009) in the U.S. may not be directly transferable to a Scandinavian setting, due to significant structural differences, as previously explained. In addition, Lu et al. (2024) focus their analysis on hedge funds, a setting where managers have increased flexibility to pursue unconventional strategies. In contrast, mutual funds operate with standardized and predetermined investment strategies, putting management teams in a less favorable position to fully capitalize on the gains of a diversity.

Our research offers insights into the Swedish asset management industry but also to the broader debate regarding team composition and performance. We find evidence that fund companies may improve performance by fostering some functional diversity within management teams. Specifically, constructing teams consisting of teams coming from diverse academic majors may improve that team's ability to generate economic value and abnormal returns. Further, our findings are relevant for investors, who may benefit from considering the different dimensions of team-diversity as potential indicators of future fund performance.

5 Conclusion

Our paper explores whether team-level diversity measured across four diversity dimensions – gender, university, academic major, and prior workplace – has any impact on the performance of Swedish mutual funds. We find support that teams with a high average diversity score tend to underperform in the cross-section, however, when accounting for time-invariant fund characteristics this relationship reverses. This indicates that within a given fund, increases in team diversity are positively associated with performance, measured both by gross alpha and value added.

When decomposing average diversity into its core components, we gain further insight into the drivers behind these performance differences. In the cross-section, gender diversity shows a negative association to performance, but this effect diminishes once accounting for fund-fixed effects, possibly reflecting the low within-fund variation in gender diversity. We find some evidence that university diversity is associated with underperformance, especially when measuring performance using alpha. Notably, the most robust predictor of fund performance is diversity in academic majors, where diverse teams along this dimension consistently outperform their homogeneous counterparts. We find no uniform pattern of workplace diversity being related to performance. In conclusion, our findings highlight that the impact of diversity in the Swedish mutual fund industry is highly dimension-specific, underscoring the need to understand how different management team compositions affect performance outcomes.

6 References

Published Papers:

Adams, Renée B., and Daniel Ferreira, 2009, Women in the boardroom and their impact on governance and performance, Journal of Financial Economics 94, 291–309.

Aggarwal, Rajesh K., and Nicole M. Boyson, 2016, The Performance of Female Hedge Fund Managers, Review of Financial Economics 29, 23–36.

Aggarwal, Rajesh K., and Philippe Jorion, 2010, The Performance of Emerging Hedge Fund Managers, Journal of Financial Economics 96, 238–256.

Barber, Brad M., and Terrance Odean, 2001, Boys will be Boys: Gender, Overconfidence, and Common Stock Investment, The Quarterly Journal of Economics 116, 261–292.

Berk, Jonathan B., and Jules H. van Binsbergen, 2015, Measuring skill in the mutual fund industry, Journal of Financial Economics 118, 1–20.

Berk, Jonathan B., and Richard C. Green, 2004, Mutual fund flows and performance in rational markets, Journal of Political Economy 112, 1269–1295.

Bär, Michaela, Alexander Kempf, and Stefan Ruenzi, 2011, Is a Team Different from the Sum of its Parts? Evidence from Mutual Fund Managers, Review of Finance 15, 359–396.

Carhart, Mark M., 1997, On persistence in mutual fund performance, The Journal of Finance 52, 57–82.

Chen, Rui, Zhennan Gao, Xueyong Zhang, and Min Zhu, 2018, Mutual Fund Managers' Prior Work Experience and Their Investment Skill, Financial Management 47, 3–24.

Chevalier, Judith, and Glenn Ellison, 1999, Are Some Mutual Fund Managers Better than Others? Cross-Sectional Patterns in Behavior and Performance, The Journal of Finance 54, 875–899.

Dahlquist, Magnus, Stefan Engström, and Peter Söderlind, 2000, Performance and Characteristics of Swedish Mutual Funds, The Journal of Financial and Quantitative Analysis 35, 409–423.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 1996, Survivorship Bias and Mutual Fund Performance, The Review of Financial Studies 9, 1097–1120.

Evans, Richard B., Melissa Porras Prado, Antonino Emanuele Rizzo, and Rafael Zambrana, 2025, Identity, Diversity, and Team Performance: Evidence from U.S. Mutual Funds, Management Science 71, 3026–3051.

Gompers, Paul A., Vladimir Mukharlyamov, Emiliy Weisburst, and Yuhai Xuan, 2022, Gender Gaps in Venture Capital Performance, Journal of Financial and Quantitative Analysis 57, 485–513.

Gompers, Paul A., Vladimir Mukharlyamov, and Yahai Xuan, 2016, The cost of friendship. Journal of Financial Economics 119, 626–644.

Harrison, David A., and Katherine J. Klein, 2007, What's the difference? Diversity constructs as separation, variety, or disparity in organizations, Academy of Management Review 32, 1199–1228.

Ibert, Markus, Ron Kaniel, Stijn Van Nieuwerburgh, and Ronie Vestman, 2018, Are Mutual Fund Managers Paid for Investment Skill?, The Review of Financial Studies 31, 715–772.

Jalbert, Terrance, Kimberly Furumo, and Mercedes Jalbert, 2011, Does Educational Background Affect CEO Compensation And Firm Performance?, The Journal of Applied Business Research 27, 15–39.

Lau, Dora C., and J. Keith J. Murnighan, 1998, Demographic Diversity and Faultlines: The Compositional Dynamics of Organizational Groups, The Academy of Management Review 23, 325–340.

Lu, Yan, Narayan Y. Naik, and Melvyn Teo, 2024, Diverse Hedge Funds, The Review of Financial Studies 37, 639–683.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook, 2001, Birds of a Feather: Homophily in Social Networks, Annual Review of Sociology 27, 415–444.

Naya, Francesc, and Nils S. Tuchschmid, 2024, The Performance of Hedge Funds: Are There Differences in Terms of Gender?, Journal of Risk and Financial Management 17, 499.

Niessen-Ruenzi, Alexandra, and Stefan Ruenzi, 2019, Sex Matters: Gender Bias in the Mutual Fund Industry, Management Science 65, 3001–3025.

Omanović, Vedran, 2009, Diversity and its management as a dialectical process: Encountering Sweden and the U.S., Scandinavian Journal of Management 25, 352–362.

Sah, Raaj Kumar, and Joseph E. Stiglitz, 1988, Committees, Hierarchies and Polyarchies, The Economic Journal 98, 451–470.

Unpublished Papers:

Bär, Michaela, Alexandra Niessen, and Stefan Ruenzi, 2009, The Impact of Team Diversity on Mutual Fund Performance, Working Paper, University of Mannheim.

Papageorgiou, Nicolas A., Jerry T. Parwada, and Kian M. Tan, 2011, Where Do Hedge Fund Managers Come from? Past Employment Experience and Managerial Performance, Working Paper.

Government Documents:

United States Department of the Army, 2014, FM 3-24 MCWP 3-33.5: Insurgencies and Countering Insurgencies, Department of the Army, Washington, DC.

Books:

Angrist, Joshua D., and Jörn-Steffen Pischke, 2009, Mostly harmless econometrics: An empiricist's companion, Princeton University Press, Princeton, NJ.

Borevi, Karin, 2013, Understanding Swedish Multiculturalism, in Peter Kivisto and Östen Wahlbeck, eds., Debating Multiculturalism in the Nordic Welfare States, Palgrave Macmillan, London, UK.

Byrne, Donn Erwin, 1971, The attraction paradigm, Academic Press, New York, NY.

Cox, Taylor H., 1993, Cultural diversity in organizations: Theory, research and practice, Berrett-Koehler Publishers.

Sanandaji, Nima, 2016, The Nordic Gender Equality Paradox: How Nordic welfare states are not only empowering women, but also (un)intentionally holding them back, Timbro, Stockholm.

Tajfel, Henri, 1978, Differentiation between social groups: Studies in the social psychology of intergroup relations, Academic Press, London, UK.

Turner, John C., Michael A. Hogg, Penelope J. Oakes, Stephen D. Reicher, and Margaret S. Wetherell, 1987, Rediscovering the social group: A self-categorization theory, Blackwell, Oxford, UK.

Websites:

Morningstar, 2025, Morningstar Category, Morningstar UK. Available at: `https://www.morningstar.co.uk/uk/glossary/98381/morningstar-category.aspx`

7 Appendix

Appendix A

Table 8: List of Morningstar Category Benchmarks used in Analysis

Benchmark Name
Cat 50%MSCI Wld/CD NR & 50%MSCI Wld/CS NR
Cat 50%MSCI WldFree NR & 50%MSCI Sweden NR
MSCI Frontier Markets NR
MSCI Nordic Countries Small Cap NR
MSCI Russia NR
MSCI Sweden Small Cap NR
Morningstar APAC TME NR
Morningstar Asia xJpn TME NR
Morningstar BIC TME NR
Morningstar Brazil TME NR
Morningstar China TME NR
Morningstar DM Eur Real Est NR
Morningstar DM Eur TME NR
Morningstar Dev Eur Sml TME NR
Morningstar Dev Europe Grt TME NR
Morningstar Dev Ezn TME NR
Morningstar EM Americas TME NR
Morningstar EM Eur TME NR
Morningstar EM TME NR
Morningstar Finland TME NR
Morningstar Gbl Fin Svc TME NR
Morningstar Gbl Gold NR
Morningstar Gbl Growth TME NR
Morningstar Gbl Health TME NR
Morningstar Gbl High Div Yld NR
Morningstar Gbl Renew Enrg NR
Morningstar Gbl SMID NR
Morningstar Gbl Tech TME NR
Morningstar Gbl Upstm Nat Res NR
Morningstar Gbl Val TME NR
Morningstar Global All Cap TME NR
Morningstar Global Enrg TME NR
Morningstar Global TME NR
Morningstar Japan TME NR
Morningstar Nordic TME NR
Morningstar Norway NR
Morningstar Sweden TME NR
Morningstar Switzerland TME NR
Morningstar US LM Brd Growth NR
Morningstar US Large-Mid NR
Morningstar US Mid NR
Morningstar US Small Extended NR
Red Rocks Gbl Listed Private Eqty TR
S&P Global Infrastructure TR
S&P Pan Africa TR

Appendix B

Table 9: Correlation Matrix Between Diversity Scores

	Gender	University	Major	Workplace	Average
Gender Diversity	1.000	0.022	0.035	-0.133	0.546
University Diversity	0.022	1.000	0.127	-0.073	0.553
Major Diversity	0.035	0.127	1.000	-0.070	0.577
Workplace Diversity	-0.133	-0.073	-0.070	1.000	0.296
Average Diversity	0.546	0.553	0.577	0.296	1.000

Appendix C

Regression Model Specifications

Regression Model (1):

$$Perf_{i,t} = \beta_0 + \beta_1 GenderDiv_{i,t-1} + \epsilon_{i,t} \tag{11}$$

$$Perf_{i,t} = \beta_0 + \beta_1 UniversityDiv_{i,t-1} + \epsilon_{i,t} \tag{12}$$

$$Perf_{i,t} = \beta_0 + \beta_1 MajorDiv_{i,t-1} + \epsilon_{i,t} \tag{13}$$

$$Perf_{i,t} = \beta_0 + \beta_1 WorkplaceDiv_{i,t-1} + \epsilon_{i,t} \tag{14}$$

Regression Model (2):

$$Perf_{i,t} = \beta_0 + \beta_1 GenderDiv_{i,t-1} + \sum_k \beta_2^k YearFE_t^k + \epsilon_{i,t} \tag{15}$$

$$Perf_{i,t} = \beta_0 + \beta_1 UniversityDiv_{i,t-1} + \sum_k \beta_2^k YearFE_t^k + \epsilon_{i,t} \tag{16}$$

$$Perf_{i,t} = \beta_0 + \beta_1 MajorDiv_{i,t-1} + \sum_k \beta_2^k YearFE_t^k + \epsilon_{i,t} \tag{17}$$

$$Perf_{i,t} = \beta_0 + \beta_1 WorkplaceDiv_{i,t-1} + \sum_k \beta_2^k YearFE_t^k + \epsilon_{i,t} \tag{18}$$

Regression Model (3):

$$Perf_{i,t} = \beta_0 + \beta_1 GenderDiv_{i,t-1} + \sum_k \beta_2^k YearFE_t^k + \sum_m \beta_3^m FundFE_i^m + \epsilon_{i,t} \tag{19}$$

$$Perf_{i,t} = \beta_0 + \beta_1 UniversityDiv_{i,t-1} + \sum_k \beta_2^k YearFE_t^k + \sum_m \beta_3^m FundFE_i^m + \epsilon_{i,t} \tag{20}$$

$$Perf_{i,t} = \beta_0 + \beta_1 MajorDiv_{i,t-1} + \sum_k \beta_2^k YearFE_t^k + \sum_m \beta_3^m FundFE_i^m + \epsilon_{i,t} \tag{21}$$

$$Perf_{i,t} = \beta_0 + \beta_1 WorkplaceDiv_{i,t-1} + \sum_k \beta_2^k YearFE_t^k + \sum_m \beta_3^m FundFE_i^m + \epsilon_{i,t} \tag{22}$$

Regression Model (4):

$$\begin{aligned} Perf_{i,t} = \beta_0 + \beta_1 GenderDiv_{i,t-1} + \beta_2 FundAge_{i,t-1} + \beta_3 AvgTenure_{i,t-1} \\ + \sum_k \beta_4^k YearFE_t^k + \sum_m \beta_5^m FundFE_i^m + \epsilon_{i,t} \end{aligned} \tag{23}$$

$$\begin{aligned} Perf_{i,t} = \beta_0 + \beta_1 UniversityDiv_{i,t-1} + \beta_2 FundAge_{i,t-1} + \beta_3 AvgTenure_{i,t-1} \\ + \sum_k \beta_4^k YearFE_t^k + \sum_m \beta_5^m FundFE_i^m + \epsilon_{i,t} \end{aligned} \tag{24}$$

$$\begin{aligned} Perf_{i,t} = \beta_0 + \beta_1 MajorDiv_{i,t-1} + \beta_2 FundAge_{i,t-1} + \beta_3 AvgTenure_{i,t-1} \\ + \sum_k \beta_4^k YearFE_t^k + \sum_m \beta_5^m FundFE_i^m + \epsilon_{i,t} \end{aligned} \tag{25}$$

$$\begin{aligned} Perf_{i,t} = \beta_0 + \beta_1 WorkplaceDiv_{i,t-1} + \beta_2 FundAge_{i,t-1} + \beta_3 AvgTenure_{i,t-1} \\ + \sum_k \beta_4^k YearFE_t^k + \sum_m \beta_5^m FundFE_i^m + \epsilon_{i,t} \end{aligned} \tag{26}$$

Appendix D

Table 10: Diversity Metrics

Variable	Description
Gender Diversity	Computed based on the degree of gender heterogeneity among managers (Higher = more diverse).
University Diversity	Computed based on the degree of universities affiliation heterogeneity among managers (Higher = more diverse).
Major Diversity	Computed based on the degree of academic major heterogeneity among managers (Higher = more diverse).
Workplace Diversity	Computed based on the degree of prior workplace heterogeneity among managers (Higher = more diverse).
Average Diversity	Mean of the four diversity scores, representing overall diversity in teams.

Table 11: Fund Performance Metrics

Variable	Description
Factor-Model Gross Alpha)	Annualized abnormal return calculated by subtracting the factor-model benchmark from fund gross return. Factor-model benchmark is computed by regressing fund gross return on Carhart's four risk factors.
Style-Matched Gross Alpha	Annualized abnormal return calculated by subtracting the Morningstar Category Benchmark return from fund gross return. Morningstar Category Benchmarks are assigned to funds based on their investment style.
Factor-Model Value Added	Factor-model gross alpha multiplied by lagged fund size (AUM). Aggregated annually. Fund size is lagged by one quarter.
Value Added (Style-Matched)	Style-matched gross alpha multiplied by lagged fund size (AUM). Fund size is lagged by one quarter.

Table 12: Control and Other Variables

Variable	Description
Fund Age	Calculated in years using the fund's inception date.
Average Manager Tenure	Average number of years fund managers have managed a fund.
Fund Size	Total assets managed by a fund across share classes.

Appendix E

This paper has used generative AI tools for language purposes to enhance the formality and readability of the text, as well as for minor code improvement. Specifically, AI was employed for advanced grammar checks to ensure high quality throughout the paper and to improve document formatting in LaTeX.