Journal of
Risk and Financial Management

Article

The Performance of Hedge Funds: Are There Differences in Terms of Gender?

Francesc Naya and Nils S. Tuchschmid *

School of Management Fribourg, HES-SO—University of Applied Sciences and Arts Western Switzerland, 1700 Fribourg, Switzerland
* Correspondence: nils.tuchschmid@hefr.ch; Tel.: +41-26-429-63-50

Abstract: The hedge fund (HF) industry is known to be one of the most unequal professional fields when it comes to gender. This study quantifies and confirms this severe gender gap, which appears to be persistent or even widening in recent years. We assess whether performance and risk differences explain this gap by comparing samples of woman-managed HFs vs. man-managed HFs. Through analyzing their descriptive statistics first, examining their alphas using HF benchmark indices and a pricing model and, finally, comparing differences in wealth generation, we found no evidence of performance differences that could explain such an extreme gender gap. Furthermore, our results do not support the view that women are more risk-averse than men, or that this is translated into their investment decisions. Other sociocultural factors probably partly explain the existence and persistence of this gender gap in hedge funds.

Keywords: hedge funds; gender gap; gender equality; hedge fund performance

check for updates

Citation: 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. https://doi.org/10.3390/jrfm17110499

Academic Editor: Mika Vaihekoski

Received: 30 July 2024
Revised: 28 October 2024
Accepted: 4 November 2024
Published: 7 November 2024

1. Introduction

The financial sector and, in particular, the hedge fund (HF) industry are known to be among the most unequal professional sectors when it comes to gender representation. A large gender gap exists, in which female workers are substantially under-represented. Moreover, this gap is perceived to be exacerbated at senior levels, where decision-making responsibilities lie. Indeed, HF managers are mostly male. From an investor perspective, one might wonder whether this gap translates into reduced investment opportunities and, therefore, a decrease in the supply of solutions. If hedge funds managed by women performed better or simply differently, then capital allocators might indeed be better off if the universe were more diverse. However, despite the efforts of some organizations and associations, it is not evident whether this gender gap has tightened in recent years. Some argue that natural psychological or even neurological differences between men and women play an important role in creating this gap. For instance, some presume (see, e.g., Jianakoplos and Bernasek 1998; Dohmen et al. 2011; or Srijanani and Vijaya 2018) that women are more risk-averse than men and that this risk aversion translates into the investment decision process. Others (e.g., Fisher and Yao 2017; Bannier and Schwarz 2018; or Tinghög et al. 2021) argue that the gender gap is purely due to sociocultural aspects.

In this study, we first quantify the gender gap in HFs and analyze whether it is tightening or widening. Then, we investigate whether there are any differences in fund performance and risk, among other observable characteristics, that could explain the existence of this gap and its persistence. We conduct this analysis by exploring a unique proprietary database from Hedge Fund Research Inc. (HFR) that incorporates the gender of HF managers as a datapoint directly provided by the funds.

In the scenario that a gender gap is found, that significant differences in performance and risk exist, and that these favor man-managed funds, this phenomenon could be a rational explanation for the existence and persistence of this gap. However, if no significant differences in performance or risk are found or these favor woman-managed funds, this would suggest that sociocultural aspects are more significant in creating this gender gap.

After a brief literature review in Section 2 and a presentation of the dataset in Section 3, in Section 4, we introduce the methods employed to quantify the gender gap and test for performance differences between man-managed hedge funds (MM HFs) and woman-managed hedge funds (WM HFs). Then, in Section 5, we present the main results of these tests. Section 6 concludes the study.

2. Literature Review

While the literature on the gender gap in hedge funds and the possible reasons for its existence is not extensive, a few studies have investigated the issue. Aggarwal and Boyson (2016) used a sample of almost 10,000 HFs over the period 1994–2013. They found that only 2.6% of funds were woman-managed, while 4.6% had at least one portfolio manager who identified as a woman. They did not find any statistical evidence of differences in performance or risk profiles between MM HFs and WM HFs. Luongo (2011) examined a dataset of 2962 HFs and 4980 mutual funds. In her dataset, 4.25% of HFs and 8.72% of mutual funds were managed by women. By analyzing various performance and risk metrics at 1-year, 3-year, and 5-year horizons, the author concluded that WM funds tend to outperform MM funds, and female managers are more risk-averse than male managers. However, only the results for the mutual fund sample were statistically significant, while the ones for the HF sample were not. Klubinski et al. (2022) studied a sample of 1313 HFs for 2002–2018, of which only 4.49% were female-represented. The lowest level was for event strategy funds (2.08%), while the highest was found in arbitrage (in our sample, Relative Value) HFs (12.90%). In their study, they tested for differences in performance persistence, instead of performance only, between female- and male-managed funds. They concluded that female managers show a higher degree of persistence over short- and medium-term horizons, but this persistence is lost over long-term horizons, which was not the case in the male manager sample. More recently, Lu et al. (2024) evaluated whether HFs with heterogeneous teams (i.e., diverse educational backgrounds, academic specializations, work experiences, genders, and races) outperform homogeneous teams. By merging multiple databases, they ended up with a large sample of 12,568 HFs, of which only 5.88% were female-identified. They found that team diversity, including gender diversity, positively contributes to fund outperformance. More recently, Naya and Tuchschmid (2024) tested for performance differences in hedge fund managers in the equity hedge space. Using two pricing models appropriate for equity fund managers, they found no significant evidence of outperformance from any gender.

The same issue has been investigated in other fields of finance. Atkinson et al. (2003) examined gender differences in fixed-income mutual fund managers. In their sample of 1294 mutual funds, only 5.6% were woman-managed. They did not find significant differences in terms of performance or risk, suggesting that if differences exist, they should be attributed to investment knowledge and wealth constraints, rather than gender. However, they did find evidence that women have more difficulty in launching new funds. Gompers et al. (2022) explored gender differences in the performance of venture capital in a sample of 3483 venture capitalists, of which 6.3% were women. The number of deals made by women (5.5% of 26,328 deals) and IPOs (4.7% of 4675 IPOs) demonstrated even lower participation. They found that female venture capitalists performed 15% worse than their male counterparts, attributing this large differential to a lack of benefit from the experience and skill of colleagues within their firms, which male venture capitalists enjoy.

Our study contributes to this field of research by providing a clear, detailed picture of the severity of this gender gap. We calculate this gap not only for the HF industry as a whole, but also to determine whether it is present in every HF strategy or only in a subset. Furthermore, we show whether the gender gap in HFs has widened or tightened over the past few years, in which gender equality has been a topic of interest in many fields, including finance, and a topic of concern for international organizations, such as the United

Nations.[1] Thus, we analyze one of the most comprehensive databases (DBs) in the HF industry, the HFR database, the only DB to date that takes the information on the gender of managers as a datapoint directly provided by the funds. Another contribution of our research is the different methodology used for testing for gender differences in performance, by analyzing the funds' alphas using both HF benchmark indices and the risk-factor model from Fung and Hsieh (2004). We also examine whether differences can be detected not only in excess returns but also in the ability of managers to generate wealth for their investors. Moreover, this article contributes to the existing literature and confirms the findings of previous studies by Aggarwal and Boyson (2016) and Luongo (2011), with an updated dataset that includes the most recent decade (up to September 2023), a challenging period for HFs due to the long and steady rally of equities markets and the growth in popularity of passive, long-only investment solutions.

3. Data

This article uses the proprietary DB from HFR, one of the leaders in HF data collection and management, as well as in building, maintaining, and publishing indices for benchmarking in the HF industry (HFR indices). The data are a combination of live and graveyard datasets, the latter including all funds reported to HFR in the past but that were, for some reason, delisted from the DB. Therefore, our data are free from survivorship biases. As noted, HFR data have, among many other fund characteristics, the portfolio manager's gender as a datapoint. This information is filled in directly by the funds, making it more reliable.

In this study, only USD-denominated HFs were used. Duplicate funds (different share classes of the same fund) were eliminated, as well as funds with less than 12 monthly observations between January 2003 and September 2023, the funds of hedge funds, and funds whose main strategy was not one of the four main strategies; namely, Equity Hedge (EH), Event-Driven (ED), Macro (MA), and Relative Value (RV).[2] Funds with AuM of less than USD 1M (average monthly AuM value) were also not considered. After this data filtering process, we obtained a sample of 8641 unique HFs, of which only 126 were identified as being woman-managed.

The dataset included each fund's monthly returns and monthly assets under management (AuM), as well as many characteristics, including the fund's main strategy; the sub-strategy and investment region; the level of management fees and performance fees; the presence of high-watermark provision and a hurdle rate; the existence of a lock-up period; the length of the redemption period; whether the fund is open for investment or closed-ended; and, last but not least, the gender of the fund manager.[3]

The Fung and Hsieh (2004) factors' data were extracted from David Hsieh's data library, which is publicly available.[4] Finally, we used the US 1M T-Bill as the risk-free rate.

4. Methods

The first part of this research estimates the gender gap in HFs and analyzes whether it is persistent over time.

In the second part of this study, we tested for performance differences between MM HFs and WM HFs. We started by comparing their descriptive statistics for performance and risk. Then, we analyzed the alphas generated by regressing the funds' returns against their HFR benchmark indices and applying an 8-factor model. Finally, we estimated the funds' ability to create wealth, considering all investor withdrawals and capital allocation over the periods. These methods are explained in more detail below.

4.1. Estimating the Gender Gap

To estimate the gender gap in the HF industry, we first calculated the rate of *live* funds managed by women ($No.\ HF_t^{WM}$) over the total number of live funds ($No.\ HF_t$) at the end of each year. We began the calculation in December 2015, as this is the period when HFR started tracking manager gender for its HFR Diversity Index, and we ended it in September 2023. Therefore, the rate is equal to

$$\%HF_t^{WM} = \frac{No.\ HF_t^{WM}}{No.\ HF_t} \tag{1}$$

This ratio and the others explained below were calculated by taking the full sample of all funds available at each time step (ALL) and for the groups of funds from each main strategy: EH, ED, MA, and RV. By computing the ratio at the end of each year, it is possible to analyze the trend, if any, of this gender gap over the last 8 years.

While the previous ratio best represents the gender gap, other statistics are worth calculating. We then compared the median AuM of WM HFs vs. MM HFs.[5] Therefore, we have

$$H_t^{WM} = \frac{\eta_t^{WM}}{\eta_t^{MM}} \tag{2}$$

where η_t^{WM} corresponds to the median AuM of WM HFs at time t, and η_t^{MM} is the median AuM of MM HFs at time t.

We also computed the delisting rate, ϕ_t^i, and *new listing* rate, π_t^i:

$$\phi_t^i = 1 - \frac{No.\ HF_t^i \cap HF_{t-1}^i}{No.\ HF_{t-1}^i} \tag{3}$$

$$\pi_t^i = \frac{No.\ HF_t^i - \left(No.\ HF_t^i \cap HF_{t-1}^i\right)}{No.\ HF_{t-1}^i} \tag{4}$$

where $No.\ HF_t^i \cap HF_{t-1}^i$ corresponds to the intersection (i.e., the number of funds that are *live* at times t and $t-1$) and $i = \{WM,\ MM\}$.

Finally, to validate whether the WM HF and MM HF samples are similar, we compared all observable characteristics for the full sample (ALL) and the four main strategy groups. These are the average management fee and incentive fee, the percentage of funds with a high watermark, a hurdle rate, open for investment, a lockup period of at most 3 months, and a redemption period of at most 3 months.

4.2. Performance Differences

After quantifying the gender gap in HFs and checking for differences in all the observable characteristics from the WM and MM fund datasets, the next step was evaluating whether any differences in performance and/or risk exist between WM HFs and MM HFs that could explain, in part, the emergence and potential persistence of this gap. To homogenize the sample, only funds with "Global" or "US" investment focus were included (deleting all funds with a specific investment region focus that is not the US). To assess whether these differences exist or not, we took three different approaches, explained below.

4.2.1. Descriptive Statistics

Firstly, we compared the descriptive statistics of WM HFs vs. MM HFs. We calculated three performance (or risk-adjusted performance) measures and three risk measures. The performance measures were the annualized compounded return (μ), the Sharpe ratio (SR), and the Calmar ratio (CR). The risk measures were the annualized volatility (σ), the Conditional Value-at-Risk ($CVaR$) at 95% level, and the maximum drawdown (MDD).

To ensure a proper comparison without being restricted to too short a sample period or too few funds available, we proceeded as follows: we began by splitting all WM HFs into groups according to their main strategy (EH, MA, ED, or RV) and regional investment focus (Global or US) and restricted the analysis to the period from January 2010 to September 2023. We also excluded funds that did not have enough available data (at least 12 monthly observations). As MA is global by nature, we ended up with 7 groups of WM HFs. Table 1 shows the number of funds in each group.[6]

Table 1. Number of WM HFs in each group.

Main Strategy	Investment Focus	
	US	**Global**
EH	28	19
MA	-	11
ED	9	3
RV	13	9

In each group of WM HFs, we computed three performance measures and three risk measures for each fund, taking each fund's longest available observation period, which may be different from the remaining funds in the same group.[7] In Appendix A, an example for the US EH group is provided in Table A2 for performance measures and Table A3 for risk measures.

For each WM HF, we found, in the sample of MM HFs, all funds with the same main strategy, investment focus, and sub-strategy (as indicated in Table A2) and with data available for the full period from the start to the end of the respective WM HF (also indicated in Table A2 for the US EH subsample). For instance, for the US EH group, the number of MM HFs for each WM HF compared with is indicated in the column N_{FS}^{MM}.

The next step was calculating the same performance and risk metrics of these MM HFs using the same sample periods, and calculating the percentile corresponding to each of the coefficients from the WM fund with respect to its comparable MM fund subsample. For each metric, this percentile appears in the right column of each coefficient in Tables A2 and A3 for the US EH example.

We repeated the same process but restricted the sample of MM HFs to only those that had similar average AuM to their respective WM HFs (in groups of up to USD 100 M, USD 100–500 M, USD 500 M–1 B, and more than USD 1 B) and similar inception dates (at most, 5 years older or younger than the respective WM HF).

In the Section 5, we summarize the findings for all seven groups, taking the average percentiles in each for the six performance and risk metrics (for instance, the values in the last row of Tables A2 and A3 for the US EH group). The results with the "restricted sample" in terms of AuM and inception dates are the ones labeled RS (as opposed to FS, "full sample").

4.2.2. Alpha Coefficients

Secondly, we estimated the alpha (α) coefficients that resulted from regressing the funds' returns against their respective HFR index benchmark and then applying an 8-factor model.[8]

The α using the HFR benchmarks was found by regressing a fund's excess returns against the excess returns of the benchmark index from its main strategy, applying the following regression:

$$\mathrm{R}_t^i - \mathrm{R}_t^F = \alpha^i + \beta^B \left(\mathrm{R}_t^B - \mathrm{R}_t^F\right) + \epsilon_t \tag{5}$$

where R_t^i is the monthly return of fund i at time t, R_t^F is the risk-free rate prevailing at the beginning of the month t, and R_t^B is the monthly return of the HFR benchmark index: B = {HFR Equity Hedge Index, HFR Macro Index, HFR Event Driven Index, HFR Relative Value Index}.

An appropriate risk factor model for evaluating abnormal HF performance was introduced by Fung and Hsieh (2004). They initially proposed using seven risk factors, namely, equity market (EQ), size (SIZE), bond market (BO), and credit spread (CREDIT) plus three trends following factors for bonds (BOTF), currencies (FXTF), and commodities (COTF).

Recently, they added the equity emerging market (EQEM) risk factor. The alpha is derived as follows:

$$R_t^i - R_t^F = \alpha^i + \beta^{BOTF} R_t^{BOTF} + \beta^{FXTF} R_t^{FXTF} + \beta^{COTF} R_t^{COTF} + \beta^{EQ}\left(R_t^{EQ} - R_t^F\right) + \beta^{SIZE} R_t^{SIZE} + \beta^{BO}\left(R_t^{BO} - R_t^F\right) + \beta^{CREDIT} R_t^{CREDIT} + \beta^{EQEM}\left(R_t^{EQEM} - R_t^F\right) + \epsilon_t \quad (6)$$

To compare the α between WM HFs and MM HFs that resulted from Equations (5) and (6), we proceeded as follows.

For the WM HFs, we grouped them by the main strategy (EH, ED, MA, or RV) and investment region (US or GL), just as we did to calculate the descriptive statistics. For each group, we regressed the excess funds' returns using Equations (5) and (6), taking each fund's longest observable period between January 2010 and September 2023. Then, we counted the number of positive (+) and negative (−) statistically significant α coefficients at 95% significance level that appeared in the group.

In contrast, the process was slightly different for MM HFs. We started from the same FS, as well as the RS subsamples from the previous sub-section of descriptive statistics.[9] Then, for each group (a combination of strategy and investment period), we randomly selected one fund for each corresponding WM HF. Therefore, for each group, we ended up with a MM HF subsample that was equivalent to the WM HFs in terms of main strategies, sub-strategies, investment regions, and investment periods. We regressed these MM HFs using Equations (5) and (6) and counted the number of positive and negative significant α coefficients. We repeated this process 25 times, building 25 equivalent subsamples of MM HFs for each group, whose individual components (for each subsample) were randomly selected from the MM HFs in the FS and RS. In short, for each WM HF, we calculated 25 α coefficients from equivalent MM HFs. Similarly, for each group (a combination of strategy and investment period) we performed 25 counts of positive and negative significant α coefficients. Finally, we computed the average of these 25 counts (the average number of positive and negative α coefficients in the 25 MM HF subsamples).[10]

For illustrative purposes, we also calculated the average α coefficients.

4.2.3. Wealth Generation

As a final assessment, we compared the wealth generated by the funds relative to their AuM. Consider the following example. A fund is up 20% in the first month on USD 10 million in assets under management. This impressive performance results in a net inflow of USD 38 million from new investors. However, the fund is down 5% the following month. Over two months, this translates into a net loss of USD 500,000, even though the fund is up 14%. Thus, the rationale here is to compare the real economic value that has been generated, as opposed to returns, which does not consider the different AuM at different periods. For that, we compute the following ratio:

$$\theta_i = \frac{\sum_1^{T_i} CF_t^i}{\sum_1^{T_i} \frac{AuM_t^i}{T_i}} \quad (7)$$

where the denominator is simply the time-average AuM of fund i, and the numerator is the sum of all cash flows (in USD) generated during the period, calculated as follows:

$$CF_t^i = AuM_{t-1}^i R_t^i \quad (8)$$

5. Results

5.1. Estimating the Gender Gap

The gender gap was estimated annually from December 2015 to September 2023, the end of our sample period. We began in December 2015, as this is the period when HFR began to track manager gender to build the HFR Diversity Index. Due to the low number of WM HFs, we confirmed, one by one, that these funds were indeed WM and deleted or corrected the period whenever necessary (e.g., if a manager began her role after December 2015). Table 2 presents the results from Equations (1) and (2).

Table 2. Percentage (%) of WM HFs and the ratio of median AuM of WM HFs vs. MM HFs.

Date	EH		MA		ED		RV		ALL	
	$\%HF_t^{WM}$	H_t^{WM}	$\%HF_t^{WM}$	H_t^{WM}	$\%HF_t^{WM}$	H_t^{WM}	$\%HF_t^{WM}$	H_t^{WM}	$\%HF_t^{WM}$	H_t^{WM}
2015	3.03%	1.48	2.30%	0.78	3.01%	1.98	3.32%	2.12	2.92%	1.25
2016	3.34%	1.71	2.50%	0.80	3.77%	1.54	2.87%	3.32	3.12%	1.65
2017	3.60%	1.71	2.69%	0.86	4.29%	1.58	3.31%	2.51	3.42%	1.71
2018	3.56%	1.75	2.35%	0.47	4.60%	1.24	3.59%	2.34	3.41%	1.89
2019	3.39%	2.24	2.24%	0.92	4.64%	1.36	3.63%	2.82	3.32%	2.02
2020	3.04%	2.81	2.01%	1.47	4.27%	1.36	3.71%	2.67	3.08%	2.15
2021	2.83%	3.02	1.73%	1.56	3.85%	1.33	3.20%	2.83	2.80%	2.39
2022	2.64%	2.52	1.71%	2.26	4.11%	1.20	3.04%	2.92	2.71%	2.18
2023	2.40%	2.27	2.07%	4.15	4.23%	1.43	3.46%	3.06	2.74%	2.60
Avg.	3.09%	2.17	2.18%	1.47	4.08%	1.45	3.35%	2.73	3.06%	1.98

$\%HF_t^{WM}$ refers to the percentage of funds managed by women (Equation (1)). H_t^{WM} refers to the ratio of the median AuM from WM HFs vs. MM HFs (Equation (2)).

Table 2 shows that the gender gap exists, is severe, and has persisted over time. If anything, the trend is negative, exacerbating this gap over the last 6 years since 2017. The percentage of WM HFs fluctuates at around 3% when considering all strategies combined. On average, the value is 3.06%, and the most recent value (2023) is as low as 2.74%.

Despite differences between the groups classified by their main strategy, the gender gap is always present: the lowest value can be found in the MA funds, with a low 2.18% representation of WM HFs (time average), while the highest percentage can be found in the ED funds, with an average of 4.08% of WM HFs.

When comparing the median AuM of WM HFs vs. MM HFs, an unexpected outcome emerges. In our sample, the median AuM of the WM HFs is almost twice as large as the one from MM HFs. In fact, the time average of the ratio is 1.98 for the full sample (the ALL group). Moreover, this value shows an upward trend, with its minimum at the beginning of the period (ratio of 1.25) and its maximum at the end (2.60). However, these values can be largely impacted by the very small number of WM HFs in the sample at each time step. For instance, the MA group comprises only six WM HFs in 2023. The sample also comprises many MM HFs with very small AuM.

Despite this surprising result, the gender gap in the HF industry is present, extreme, and persistent. The larger AuM does not compensate for the low value of 3.06% female representation in terms of the number of funds.

Table 3 illustrates the delisting rate. On average, the radiation rate is 10.35% for WM HFs, but it is slightly higher and equal to 11.85% for MM HFs. The annual delisting rates for WM strategy groups are very volatile owing to the very low number of funds that these groups are made of. There are no substantial differences between the groups in their average delisting rates except for the ED group, whose low average of 5.29% is due to no funds being delisted between 2015 and 2018.

Table 4 shows the data for new listing rates (i.e., the percentage of new funds that were not part of the sample in the previous period). On average, this rate is only 3.11% for WM HFs, whereas it is 5.35% for MM HFs, almost double. Moreover, the new listing rate is lower for WM funds with respect to their MM counterparts in all four groups when classified by their main strategy, except for the ED strategy. Combined with the previous delisting rate, this suggests that the low number of women managers, which appears to be dropping in relative terms, is due to a lack of new WM fund launches rather than the accelerated disappearance of existing WM funds.

Table 3. Delisting rate (%).

Date	EH		MA		ED		RV		ALL	
	WM	MM	WM	MM	WM	MM	WM	MM	WM	MM
2015	15.22	11.78	11.76	14.04	0.00	13.14	10.00	15.12	12.09	13.04
2016	4.44	10.92	0.00	11.44	0.00	9.66	16.67	11.45	5.75	11.00
2017	2.08	9.30	0.00	13.00	0.00	9.61	0.00	12.03	1.11	10.65
2018	7.84	12.17	18.75	13.67	0.00	11.57	5.88	11.27	8.33	12.26
2019	10.64	11.39	15.38	15.74	8.33	13.65	5.56	14.67	10.00	13.16
2020	16.67	11.69	18.18	15.59	18.18	7.08	11.76	18.85	16.05	13.41
2021	11.43	9.85	22.22	13.67	10.00	6.25	20.00	11.05	14.49	10.47
2022	16.13	11.84	14.29	17.38	0.00	11.56	16.67	14.88	13.56	13.42
2023	15.38	8.14	0.00	11.05	11.11	7.62	10.00	11.60	11.76	9.23
Avg.	11.09	10.79	11.18	13.95	5.29	10.01	10.73	13.44	10.35	11.85

Table 4. New listing rate (%).

Date	EH		MA		ED		RV		ALL	
	WM	MM	WM	MM	WM	MM	WM	MM	WM	MM
2015	13.04	8.03	0.00	7.31	12.50	6.09	0.00	8.36	7.69	7.73
2016	11.11	7.37	6.67	9.09	22.22	6.55	0.00	8.21	9.20	7.82
2017	8.33	7.64	0.00	5.78	9.09	4.98	13.33	10.06	7.78	7.40
2018	0.00	5.50	0.00	7.09	0.00	4.48	11.76	8.65	2.08	6.32
2019	0.00	5.50	0.00	4.81	0.00	4.42	0.00	7.85	0.00	5.70
2020	0.00	4.92	0.00	6.86	9.09	6.19	0.00	5.10	1.23	5.48
2021	0.00	5.10	0.00	4.10	0.00	6.70	0.00	4.37	0.00	4.93
2022	0.00	1.88	0.00	4.03	0.00	4.89	0.00	2.75	0.00	2.78
2023	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Avg.	3.61	5.11	0.74	5.45	5.88	4.92	2.79	6.15	3.11	5.35

To finalize the first part of this study, we compared all the observable relevant characteristics available in the database. These characteristics are provided as static variables. As it can be observed in Table 5, none of the characteristics show a substantial enough difference to explain the large gender gap.

Table 5. HF characteristics.

Date	EH		MA		ED		RV		ALL	
	WM	MM	WM	MM	WM	MM	WM	MM	WM	MM
No. HFs	67	4043	20	1936	14	853	25	1683	126	8515
Man. Fee (%)	1.43	1.43	1.73	1.56	1.70	1.53	1.36	1.42	1.49	1.47
Inc. Fee (%)	16.52	17.72	17.45	17.94	17.86	18.49	14.27	16.76	16.39	17.66
% w/High WM	92.54	89.24	95.00	88.33	92.86	92.97	84.00	83.01	91.27	88.17
% w/Hurdle Rate	8.96	12.59	5.00	9.50	21.43	8.56	20.00	14.85	11.90	11.93
% Open for Inv.	95.52	92.46	100.0	92.25	100.0	92.03	100.0	90.37	97.62	91.96
% Lockup $\leq$ 3M	76.12	67.08	85.00	89.88	50.00	58.85	64.00	68.03	72.22	71.63
% Redem. $\leq$ 3M	97.01	95.62	100.0	99.07	92.86	90.39	100.0	96.08	97.62	95.97

No. HFs refers to the number of funds in each group; Man. Fee (%) to the average management fee reported; Inc. Fee (%) to the average incentive fee; % w/High WM to the percentage of funds with a high watermark; % w/Hurdle Rate to the percentage of funds with a hurdle rate; % Open for Inv. to the percentage of funds that are open for investment; % Lockup $\leq$ 3M to the percentage of funds with a reported lockup period of less than or equal to 3 months; and % Redem. $\leq$ 3M to the percentage of funds with a reported redemption period of less than or equal to 3 months.

5.2. Performance Differences

We observed a severe gender gap in HFs and noticed that there were no substantial differences in any of the observable characteristics that could explain its existence. Thus, this section focuses on performance and risk differences. If female managers systematically underperform in comparison to male managers because of their distinct investment styles or degrees of risk aversion, this large gender gap can be explained. Otherwise, if there are no noticeable systematic differences—or there are but in favor of WM HFs—the gender gap must be explained by other external factors, such as sociocultural aspects.

5.2.1. Descriptive Statistics

First, we compared the respective descriptive statistics. For each of the three performance measures and three risk measures, Table 6 shows the average percentile at which each coefficient found in the WM HFs falls within their respective MM HF subsamples.[11] We show the results for the seven groups (combinations of main strategy and investment region) for both the "full sample" and the "restricted sample" cases (as a reminder, RS restricts the selection of MM HFs to those with similar AuM and inception dates as the respective WM HFs). The percentiles are ranked from "best" (e.g., the highest return or lowest volatility) to "worst" (e.g., the lowest return or highest volatility), such that a value of 0.0% would imply that no MM HFs outperformed the WM HFs and a value of 100% that all MM HFs outperformed the WM HFs.

Table 6. Average percentile of WM HF coefficients with corresponding MM HF subsamples.

Strategy	Inv. Region	MM Sample	μ-pct	SR-pct	CR-pct	σ-pct	$CVaR$-pct	MDD-pct
EH	US	FS	62.66	67.20	65.34	52.45	56.47	57.99
		RS	66.63	74.01	71.44	55.60	59.60	62.07
	GL	FS	62.95	62.93	65.22	52.68	50.11	56.34
		RS	53.64	58.06	65.31	48.48	43.43	53.72
MA	GL	FS	58.11	63.92	64.66	42.12	55.42	58.89
		RS	60.65	68.52	78.70	56.17	49.85	77.16
ED	US	FS	53.50	55.35	53.44	58.98	52.32	51.42
		RS	53.12	58.33	57.29	63.54	54.17	52.08
	GL	FS	24.01	33.80	33.80	64.85	52.12	62.42
RV	US	FS	77.78	60.14	64.72	52.36	54.44	49.86
		RS	60.16	61.96	60.92	58.93	56.56	58.51
	GL	FS	62.66	67.20	65.34	52.45	56.47	57.99
Total Average			57.99	60.95	62.18	54.88	53.41	58.20

μ-pct refers to the average percentile at which WM HFs rank in terms of annual return with their respective MM HF subsamples. Similarly, SR-pct, CR-pct, σ-pct, $CVaR$-pct, and MDD-pct are the percentiles at which the WM HFs rank in terms of the Sharpe ratio, the Calmar ratio, annualized volatility, Conditional Value-at-Risk (95% level), and the maximum drawdown, from peak to trough. The 1st percentile represents the "best" 1% (the highest return, SR, or CR or lowest volatility, CVaR, or maximum drawdown, the latter two in absolute terms).

In terms of annual returns, the total average percentile is of 57.99, meaning that slightly more than half of the MM HFs tend to outperform their respective WM funds with the same strategy or sub-strategy and for the same sample period. This value is above the 50th-percentile threshold on the three performance measures (annual return, Sharpe ratio, and Calmar ratio) for all groups and samples analyzed, except for the ED GL FS. Notably, the EH strategy englobes about 50% of all funds in the sample, so its results alone represent half of the HF industry.

Regarding risk, we did not notice less risk-taking from WM HFs, as would be expected only from empirical evidence from finance and sociological and psychological studies (see, for instance, Eckel and Grossman 2008). In fact, the global average is slightly above the 50th percentile in all metrics: volatility, CVaR, and maximum drawdown. Even in the few cases where the values are smaller (EH GL RS for the volatility and CVaR metrics, for example), these are still very close to the median.

The results indicate slight but consistent performance differences across all groups and subsamples analyzed.

5.2.2. Alpha Coefficients

The regressions in Equation (5) (HFR indices) and Equation (6) (eight-factor model) are shown in Table 7. For WM HFs, the values represent the number of positive or negative significant alphas, at 95% confidence level. For MM HFs, the values are the average number of significant positive and negative alphas over multiple subsamples (25 for FS and 10 for RS).

Table 7. Number of positive (+) and negative (−) statistically significant α coefficients.

Strategy	Inv. Region	MM Sample	HFR Indices				8-Factor Model			
			+		−		+		−	
			WM	MM	WM	MM	WM	MM	WM	MM
EH	US	FS	3	6.00	3	0.76	2	4.80	3	1.72
		RS	2	5.60		0.50	1	3.00		1
	GL	FS	2	3.52	0	0.52	1	3.48	0	0.64
		RS	1	2.30		0.80		2.10		0.50
MA	GL	FS	3	0.80	2	0	0	0.72	1	0.12
		RS						0.90		0.20
ED	US	FS	2	2.08	2	0.24	3	2.64	1	0.12
		RS		1.80		0.20	2	1.70		0
	GL	FS	2	0.82	0	0	2	1.12	0	0
RV	US	FS	1	2.52	3	1.40	6	7.16	0	0
		RS		2.10	2	0.50	4	6.30		
	GL	FS	0	0.68	2	0.84	5	4.88	0	0

Summary of significant positive (+) and negative (−) alpha coefficients from the regressions in Equation (5) (HFR indices) and Equation (6) (8-factor model). The WM values are the number of significant alphas. The MM values are the average number of significant alphas over multiple subsamples of randomly selected comparable MM funds (same strategy, sub-strategy, or period, plus similar AuM and inception dates for the RS case). Whenever the number of significant alphas is the same for the FS and RS subsamples in the same group, only one value is shown in the middle.

By focusing on the number of alphas using the HFR benchmark indices, we can see that there is only one group in which WM HFs seem to underperform. In the US EH group, WM HFs show three (FS) and two (RS) positive alphas and three negative ones (FS and RS). Conversely, MM HFs show, on average, 6.00 and 5.60 positive coefficients and only 0.76 and 0.50 negative ones. For the remaining groups, there is no clear evidence of outperformance or underperformance in the WM HFs vs. MM HFs.

Regarding the alphas derived for the eight-factor model, it is also in the US EH funds that WM HFs show fewer positive alphas (2 for FS and 1 for RS vs. 4.80 and 3.00 for the MM funds, respectively) and more negative alphas (3 in both the FS and RS subsamples vs. 1.72 and 1, respectively, in the MM HFs). The other strategies, namely, MA, ED, RV, and even EH GL show more mixed results. There is no clear evidence of outperformance from either side.

Table 8 below reports the average α coefficients for the same groups. Differences are most noticeable in the US EH group, both for the full and restricted samples (FS and RS), which is consistent with the results from Table 7. For the remaining groups, there are no large differences.[12] The differences in average α values between the FS and RS samples in the WM HFs groups stem from the fact that there are some WM HFs with comparable MM funds in FS but not in RS. These funds were not taken into account when calculating the average α in RS.

Table 8. Average annualized α coefficients (%).

Strategy	Inv. Region	MM Sample	HFR Indices		8-Factor Model	
			WM	MM	WM	MM
EH	US	FS	0.67	3.37	−1.32	2.42
		RS	0.18	3.26	−1.91	2.12
	GL	FS	2.17	3.30	1.82	3.66
		RS	2.07	1.87	1.80	2.42
MA	GL	FS	−0.23	1.87	1.69	1.02
		RS	0.49	2.82	2.75	1.96
ED	US	FS	0.14	1.12	2.61	3.33
		RS	−0.15	1.22	2.15	2.65
	GL	FS	2.16	1.43	4.39	2.71
RV	US	FS	0.07	−0.14	3.20	3.81
		RS	1.30	0.57	4.58	3.30
	GL	FS	−1.77	−0.12	4.16	4.46

Average annualized alpha coefficients (%) from the regressions in Equation (5) (HFR indices) and Equation (6) (8-factor model). Whenever the median value is the same for the FS and RS subsamples in the same group, only one value is shown in the middle.

5.2.3. Wealth Generation

Lastly, we compared the results for the wealth generation, or cash flow generation, relative to the fund's average AuM, presented in Table 9. Notably, the cash flow generation percentiles from WM HFs are generally similar to the percentiles from the annualized compounded returns, with a few exceptions: the percentile is higher (worse) in the ED strategy (US and Global) and the RV GL group, while it is lower in the EH US (FS), MA GL (RS), and RV US groups. Overall, the WM HFs tend to be close to the median (θ-pct of 50). These results cannot provide evidence of clear over- or underperformance in terms of wealth generated by investment funds, whether managed by women or men.

Table 9. Average percentile of WM HF cash flow generation ratio.

Strategy	Inv. Region	MM Sample	θ-pct
EH	US	FS	62.69
		RS	58.11
	GL	FS	66.48
		RS	52.77
MA	GL	FS	54.89
		RS	48.96
ED	US	FS	62.41
		RS	55.19
	GL	FS	40.74
RV	US	FS	51.73
		RS	44.22
	GL	FS	71.80
	Total Average		55.83

θ-pct refers to the average percentile at which WM HFs rank in terms of cash flow generation (relative to AuM) with their respective MM HF subsamples; this is the 1st percentile, that is, the "best" 1%. See Equations (7) and (8) for details on the cash flow generation calculation.

6. Discussion

The HF industry is one of the most unequal professional fields with regard to gender. In its first sections, this study confirms that this is the case and quantifies this severe gender gap by comparing the number of funds and AuM between woman-managed funds and man-managed funds. In our sample, only 3% of HFs are managed by women. The gender gap is present among all hedge fund strategies. Moreover, this extremely low representation of women managers is not only persistent over time but appears to have been exacerbated in the last 8 years, reaching a low of 2.74% in September 2023, the end of our sample period. The findings from the delisting and new listing rates suggest that a lack of new WM HFs is responsible for widening this gender gap, not a higher delisting rate.

If there were differences in performance or risk between MM HFs and WM HFs favoring man-managed funds, this phenomenon could at least partially offer a rational explanation for the existence and persistence of the gender gap. However, the performance evaluation shows that female managers are not more risk-averse than male managers. While the initial performance statistics could indicate some degree of underperformance from WM HFs in terms of annualized returns or risk-adjusted returns, the alpha analyses cannot statistically or consistently prove that this is indeed the case. Perhaps the only group with a sign of outperformance from the MM HFs is the US EH group. Finally, the wealth generation results also cannot conclusively support the hypothesis of outperformance from MM HFs vs. WM HFs.

These results cannot demonstrate an outperformance of HFs based on gender, implying that there must be other factors that explain the gender gap—probably more related to sociocultural aspects. This can at least partially explain the severity and persistence of this significant gender gap in the HF sector. Further research should be conducted on the sociocultural barriers that prevent women from creating new funds or achieving senior positions in the hedge fund industry, if the aim is to develop appropriate policies that encourage more women to join the financial sector and seek management positions or start their own businesses.

Our results should be considered in light of certain limitations. First, the very limited number of female managers in our sample implies that the results could be affected by adding or deleting a small number of funds. Along the same lines, it should be remembered that some alphas may appear positive or negative due to luck (or lack thereof) rather than the true skill of a manager (see e.g., Barras et al. 2010). Moreover, even if the funds declare the gender of the manager to HFR and this information has been verified, it remains possible that this declaration was not made correctly by some funds and, therefore, that they are not part of our sample. However, we believe that the impact of this bias, if it is present, is marginal given the large number of portfolio management funds included in the sample.

Author Contributions: Conceptualization, F.N. and N.S.T.; methodology, F.N. and N.S.T.; formal analysis, F.N. and N.S.T.; investigation, F.N. and N.S.T.; data curation, F.N. and N.S.T.; writing—original draft preparation, F.N. and N.S.T.; writing—review and editing, F.N. and N.S.T.; project administration, N.S.T.; funding acquisition, N.S.T. All authors have read and agreed to the published version of the manuscript.

Funding: The authors received funding from the *Fonds de recherche interne* (AGP 128123) of the School of Management Fribourg, Switzerland.

Data Availability Statement: The data used in this study are a proprietary dataset from Hedge Fund Research Inc. (HFR Inc.) and are not publicly available.

Acknowledgments: The authors would like to thank the *Fonds de recherche* from School of Management Fribourg, Switzerland for financial support. They are also grateful to the five anonymous reviewers and the editor whose comments and suggestions greatly contributed to improving this article.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Appendix A

Table A1. Hedge fund groups' descriptive statistics.

Strat.	Inv. Region	μ (%)		*SR*		*CR*		σ (%)		*CVaR* (%)		*MDD* (%)	
		WM	MM	WM	MM	WM	MM	WM	MM	WM	MM	WM	MM
EH	US	5.80	7.84	0.38	0.82	0.27	1.00	13.48	9.75	−8.30	−5.34	−24.12	−10.45
	GL	6.49	7.75	0.60	0.51	2.69	0.36	12.46	15.18	−6.91	−7.95	−25.81	−27.09
MA	GL	1.35	3.70	−0.21	0.25	0.06	0.18	10.35	13.58	−6.31	−7.66	−21.96	−24.50
ED	US	6.04	5.89	0.65	0.50	0.55	0.26	9.86	11.92	−5.52	−7.96	−16.62	−23.97
	GL	6.81	5.54	0.91	0.77	0.53	0.55	9.85	7.17	−6.55	−4.59	−23.20	−11.59
RV	US	4.54	7.84	0.60	0.64	0.28	0.42	7.73	12.30	−4.74	−6.60	−19.57	−19.58
	GL	5.31	7.61	0.60	0.83	0.34	0.71	8.98	12.69	−6.22	−7.40	−20.14	−17.75

For each performance and risk metric, the coefficients represent the average values of each hedge fund group, classified by strategy and investment region. The performance metrics are μ (annualized return), SR (Sharpe ratio), and CR (Calmar ratio). The risk measures are σ (volatility), $CVaR$ (Conditional Value-at-Risk at 95% level), and MDD (maximum drawdown). The sample period begins on January 2010 and ends on September 2023, but each fund can have a later start date and/or an earlier end date.

Table A2. Performance statistics for EH HFs with a US investment focus.

WMHF ID	Start	End	Sub-strat.	N_{FS}^{MM}	μ	μ-pct	*SR*	*SR*-pct	*CR*	*CR*-pct
ID1	01/10	11/13	EMN	42	−1.89%	97.62	−0.49	97.62	−0.19	95.24
ID2	04/11	09/18	EMN	25	2.56%	84.00	0.34	84.00	0.26	76.00
ID3	12/11	09/23	EMN	15	7.91%	46.67	1.12	13.33	0.84	0.00
ID4	07/15	09/23	EMN	19	5.76%	36.84	1.12	0.00	0.95	0.00
ID5	01/10	09/23	FG	33	3.85%	81.82	0.30	81.82	0.11	81.82
ID6	01/10	06/12	FG	92	−2.70%	88.04	−0.32	90.22	−0.15	90.22
ID7	09/10	11/14	FG	75	8.09%	56.00	0.81	48.00	0.88	32.00
ID8	08/11	12/18	FG	61	5.60%	47.54	0.40	55.74	0.16	72.13
ID9	01/12	11/15	FG	85	3.90%	72.94	0.34	81.18	0.23	81.18
ID10	01/10	05/20	FG	44	6.52%	45.45	0.48	54.55	0.30	47.73
ID11	05/13	09/23	FG	41	10.93%	14.63	0.65	29.27	0.33	39.02
ID12	10/17	09/20	FG	74	2.68%	72.97	0.14	72.97	0.09	77.03
ID13	07/14	07/22	FG	53	10.74%	16.98	0.57	35.85	0.34	35.85
ID14	01/10	09/23	FV	59	7.19%	55.93	0.40	81.36	0.24	62.71
ID15	01/10	06/21	FV	82	4.50%	92.68	0.34	93.90	0.17	91.46
ID16	01/10	07/17	FV	142	1.91%	97.18	0.21	97.89	0.11	97.18
ID17	01/10	03/13	FV	221	18.44%	11.31	0.97	29.41	0.79	37.56
ID18	03/10	09/23	FV	59	12.03%	27.12	0.57	50.85	0.30	50.85
ID19	07/12	06/18	FV	158	5.72%	81.65	0.59	85.44	0.46	70.89
ID20	02/16	09/23	FV	94	2.26%	93.62	0.15	96.81	0.08	95.74
ID21	10/10	12/17	FV	142	2.08%	97.18	0.20	98.59	0.10	97.89
ID22	01/10	09/23	FV	59	11.07%	28.81	0.63	44.07	0.48	15.25
ID23	02/16	09/23	FV	94	−0.12%	97.87	−0.03	100.0	−0.01	100.0
ID24	04/17	07/19	FV	183	−6.26%	93.99	−1.07	98.91	−0.49	99.45
ID25	02/16	09/20	FV	144	2.27%	79.17	0.17	80.56	0.09	80.56
ID26	01/10	10/21	QD	11	11.60%	36.36	0.67	72.73	0.43	81.82
ID27	01/10	09/23	Sec-Health.	5	12.76%	80.00	0.76	60.00	0.34	60.00
ID28	01/16	02/20	Sec-Tech.	15	12.95%	20.00	0.85	46.67	0.56	60.00
Avg. pct.						62.66		67.20		65.34

Start and End are each WM HF's start and end dates (for funds with data before Jan 2010, Start was set at Jan 2010). Sub-strat. refers to the fund's sub-strategy: Equity Market Neutral (EMN), Fundamental Growth (FG), Fundamental Value (FV), Quantitative Directional (QD), Sectorial—Healthcare (Sec-Health.), and Sectorial—Technology (Sec-Tech.). N_{FS}^{MM} is the number of MM HFs with the same sub-strategy and data available for the same period as the respective WM HF (the FS stands for "full sample", as opposed to RS, "restricted sample", in which only MM HFs with similar AuM and inception dates are considered). μ is the WM HF's annualized return, SR its Sharpe ratio, and CR its Calmar ratio. The -pct columns following each metric represent the percentile of the WM HF's coefficient with respect to its MM HF subsample: the 1st percentile, that is, the "best" 1% (highest return, SR or CR).

Table A3. Risk statistics for EH HFs with a US investment focus.

WMHF ID	σ	σ-pct	*CVaR*	*CVaR*-pct	*MDD*	*MDD*-pct
ID1	3.86%	21.43	−2.29%	40.48	−9.89%	71.43
ID2	7.46%	48.00	−3.66%	40.00	−9.71%	40.00
ID3	6.33%	26.67	−3.02%	20.00	−8.45%	26.67
ID4	4.14%	10.53	−2.06%	5.26	−4.87%	5.26
ID5	13.85%	54.55	−8.88%	54.55	−36.82%	78.79
ID6	7.90%	17.39	−4.79%	25.00	−16.46%	55.43
ID7	10.23%	40.00	−4.88%	32.00	−9.35%	21.33
ID8	16.26%	85.25	−8.95%	67.21	−39.46%	88.52
ID9	14.49%	81.18	−9.04%	91.76	−20.91%	82.35
ID10	14.15%	56.82	−9.23%	65.91	−23.05%	54.55
ID11	16.97%	65.85	−10.15%	65.85	−33.14%	63.41
ID12	12.31%	31.08	−9.75%	52.70	−18.81%	54.05
ID13	20.38%	83.02	−12.73%	83.02	−34.21%	69.81
ID14	21.80%	77.97	−12.88%	84.75	−35.54%	52.54
ID15	15.07%	42.68	−10.83%	60.98	−29.10%	47.56
ID16	12.11%	51.41	−7.45%	63.38	−22.97%	72.54
ID17	19.46%	81.45	−9.51%	72.40	−23.82%	79.64
ID18	23.98%	89.83	−14.05%	88.14	−46.05%	83.05
ID19	9.83%	46.84	−6.05%	64.56	−12.59%	44.30
ID20	12.17%	25.53	−7.62%	30.85	−24.51%	35.11
ID21	17.35%	87.32	−11.21%	92.25	−34.03%	90.14
ID22	18.33%	66.10	−10.32%	49.15	−23.97%	32.20
ID23	13.15%	29.79	−9.21%	40.43	−36.04%	57.45
ID24	7.09%	9.84	−6.01%	33.33	−15.52%	54.64
ID25	9.30%	13.89	−7.87%	26.39	−17.71%	27.78
ID26	18.06%	90.91	−10.36%	90.91	−28.28%	81.82
ID27	17.03%	40.00	−9.69%	40.00	−38.28%	60.00
ID28	14.34%	93.33	−9.86%	100.0	−21.85%	93.33
Avg. pct.		52.45		56.47		57.99

σ is the WM HF's annualized volatility, *CVaR* its monthly Conditional Value-at-Risk (95% level), and *MDD* its maximum drawdown from peak to trough. The -pct columns following each metric represent the percentile of the WM HF's coefficient with respect to its MM HF subsample: the 1st percentile, that is, the "best" 1% (lowest volatility, CvaR, or maximum drawdown, the latter two in absolute terms).

Notes

1. The United Nations has developed 17 Sustainable Development Goals (SDGs), with SDG 5 being "Gender Equality".
2. EH funds take both long and short positions in stocks and other equity-related instruments, aiming to profit from upward and downward movements in the equity markets. ED hedge funds focus on investing in the debt or equity of companies undergoing significant corporate events, such as mergers, restructurings, or bankruptcies. MA hedge funds allocate capital across various asset classes (equities, foreign exchange, fixed income, commodities, etc.) by capitalizing on large-scale economic or geopolitical shifts. RV strategies, often referred to as "arbitrage" strategies, seek to take advantage of pricing inefficiencies between related assets.
3. Note that the HFR DB includes many other variables that are not considered for this study.
4. David Hsieh's data library is available at: https://people.duke.edu/~dah7/HFRFData.htm (accessed on 21 March 2024).
5. The average AuM would not be appropriate in this case because the funds' AuM distribution is highly skewed.
6. Note that there are 92 WM HFs, fewer than the 126 funds used to estimate the gender gap. The difference comprises all WM HFs whose investment regions are not the US or Global.
7. Table A1 in Appendix A exhibits the average values of these three performance and three risk metrics for the groups by strategy and investment region.
8. The Newey and West (1987) method is used to control for possible autocorrelation issues in the returns' series.
9. As a reminder, FS is the "full sample" of MM HFs, i.e., all those man-managed funds with the same main strategy, sub-strategy, and investment universe as each corresponding woman-managed fund and that have data available at least for the same period as this corresponding WM HF. The RS further restricts the sample of MM HFs to those with similar AuM and inception dates as the corresponding WM HF.
10. Given the very limited number of MM HFs available in the RS, only 10 subsamples are created.

11 For instance, the values of the EH US FS in the first row of Table 1 are the same values of the last rows (Avg. pct) of Tables A2 and A3 in Appendix A.

12 Note that the average α was calculated taking the α from all funds, even if these are not statistically significant at the 95% level.

References

Aggarwal, Rajesh, and Nicole M. Boyson. 2016. The performance of female hedge fund managers. *Review of Financial Economics* 29: 23–36. [CrossRef]

Atkinson, Stanley M., Samantha B. Baird, and Melissa B. Frye. 2003. Do female mutual fund managers manage differently? *Journal of Financial Research* 26: 1–18. [CrossRef]

Bannier, Christina E., and Milena Schwarz. 2018. Gender- and education-related effects of financial literacy and confidence on financial wealth. *Journal of Economic Psychology* 67: 66–86. [CrossRef]

Barras, Laurent, Olivier Scaillet, and Russ Wermers. 2010. False discoveries in mutual fund performance: Measuring luck in estimated alphas. *The Journal of Finance* 65: 179–216. [CrossRef]

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner. 2011. Individual risk attitudes: Measurement, determinants and behavioral consequences. *Journal of the European Economic Association* 9: 522–50. [CrossRef]

Eckel, Catherine C., and Philip J. Grossman. 2008. Men, Women and Risk Aversion: Experimental Evidence. In *The Handbook of Experimental Economics*. Edited by C. Plott and V. Smith. New York: Elsevier, vol. 1, chp. 113. pp. 1061–73.

Fisher, Patti J., and Rui Yao. 2017. Gender differences in financial risk tolerance. *Journal of Economic Psychology* 61: 191–202. [CrossRef]

Fung, William, and David A. Hsieh. 2004. Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal* 60: 65–80. [CrossRef]

Gompers, Paul A., Vladimir Mukharlyamov, Emily Weisburst, and Yuhai Xuan. 2022. Gender gaps in venture capital performance. *Journal of Financial and Quantitative Analysis* 57: 485–513. [CrossRef]

Jianakoplos, Nancy A., and Alexandra Bernasek. 1998. Are women more risk averse? *Economic Inquiry* 36: 620–30. [CrossRef]

Klubinski, William J., Thanos Verousis, and Fanis Tsoligkas. 2022. Gender Differences in Hedge Fund Performance Persistence. *SSRN*. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4064765 (accessed on 9 April 2024).

Lu, Yan, Narayan Y. Naik, and Melvyn Teo. 2024. Diverse hedge funds. *The Review of Financial Studies* 37: 639–83. [CrossRef]

Luongo, Angela. 2011. Fund-management gender composition: The impact on risk and performance of mutual funds and hedge funds. *Fordham Business Student Research Journal* 1: 7.

Naya, Francesc, and Nils S. Tuchschmid. 2024. Gender disparities among financial entrepreneurs: The case of hedge funds. *Journal of the International Council for Small Business*, 1–9. [CrossRef]

Newey, Whitney. K., and Kenneth D. West. 1987. Hypothesis testing with efficient method of moments estimation. *International Economic Review* 28: 777–87. [CrossRef]

Srijanani, D., and T. Vijaya. 2018. A study on impact of gender in investment decisions. *Journal of Management Research and Analysis* 5: 161–65.

Tinghög, Gustav, Ali Ahmed, Kinga Barrafrem, Thérèse Lind, Kenny Skagerlund, and Daniel Västfjäll. 2021. Gender differences in financial literacy: The role of stereotype threat. *Journal of Economic Behavior & Organization* 192: 405–16.