Gender differences in hedge fund performance

William Klubinski[1a], Thanos Verousis[a] and Fanis Tsoligkas

[a] Essex Business School, University of Essex, UK, [b] School of Management, University of Bath,

Abstract: This paper analyses gender differences in Hedge Fund (HF) performance using 13 risk-adjusted performance measures and two performance persistence methods. We show that both male and female HF managers tend to produce similar risk-adjusted returns using the Sharpe ratio. When incorporating performance measures that account for the asymmetric return distributions of HFs, female HF managers tend to produce lower returns than their male counterparts. Our findings show that controlling for higher-order statistics is crucial in identifying gender differences in HF performance. Furthermore, we find that the HFs led by both genders exhibit short-term negative performance persistence in the aggregated 'universe' setting. However, focusing on the largest HF strategy (Equity) reveals that male managed funds in most cases are in fact generating the positive short-term persistence, with female managed funds remaining in the negative territory.

Keywords: Hedge funds, gender, Sharpe ratio, risk, performance persistence

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[1] Corresponding author: w.klubinski@essex.ac.uk

1 Introduction

In recent decades the debate concerning gender differences in the financial investment industry has been a subject of significant attention. Interestingly, the analysis of the hedge fund (HF) industry from the gender perspective has been largely unexplored. Given the value of the assets under management in the global hedge fund industry, one can easily realise the significance of risk these investment vehicles pose for the global economy. According to Prequin (2018), hedge funds aggregate US$ 3.6tn assets under management, which is almost the equivalent to Germany's 2017 GDP of US$ 3.67tn (World Bank, 2019). Despite the relatively low profile and secrecy, the hedge fund industry has come to international prominence not only due to exorbitant profits generation but more so due to spectacular defaults and government bailouts (Jorion 2000; King and Maier 2009).

Previous research shows that male investors invest in riskier assets than their female counterparts (Barber and Odean, 2001 Marinelli et al., 2017). Similarly, others such as Powell and Ansic (1997) or Dwyer et al. (2002), find that female mutual fund investors are more risk-averse than their male counterparts. By contrast, research on mutual funds finds that little differences exist in the performance between male and female managers (Atkinson et al., 2003; Bollen and Posavac, 2018).

The Sharpe ratio (SR) is the most popular risk-adjusted performance measure used. However, the use of the SR not only implies that investors invest in just one fund but also that HF returns follow a normal distribution (see Eling and Schuhmacher, 2007). To our knowledge, the only study on risk-adjusted HF performance (Aggarwal and Boyson, 2016) relies on the estimation of the Sharpe ratio (SR) as the only risk-adjusted performance measure. However, these assumptions are unrealistic in this context given the asymmetric return distributions of HFs (see Bernard et al., 2019; Fung and Hsieh, 1999). As many authors rightly point out (Getmansky, Lo and Makarov 2004; Malkiel and Saha 2005; Eling 2006), the analysis of hedge funds requires a sophisticated approach, which extends beyond standardised appraisal methods of the first two moments and metrics such as the SR. Eling and Schuhmacher (2007) show that the choice of risk-adjusted measure does not affect the ranking of HF performance.[2] However, they still agree that the SR is inadequate in the cases of asymmetrical distribution, which is one of the key properties of alternative investment vehicles. Others such as Marinelli et al. (2017) document a "gender factor" in investment decision making and risk preferences. Therefore, we extend the investigation of HF performance beyond the first two moments of the returns' (mean and standard deviation) and incorporate the third (skewness) and fourth (kurtosis). Furthermore, our analysis includes a series of risk-adjusted metrics and the analysis of performance persistence (parametric and non-parametric).

This chapter is organised in the following way: Section 2 reviews the literature, Section 3 describes the data, Section 4 outlines the methods, while Section 5 describes the results and Section 6 concludes our findings.

[2]The size of the hedge fund industry is easily comparable with that of some of the biggest economies in the world. In 2018, hedge funds aggregated $3.67tn of assets under management (Prequin, 2018).

2 Literature Review

There exists a significant body of literature concerning gender differences and more specifically the approach towards performance and risk. A closer look at the literature, reveals that despite the increasing number of gender research being undertaken in either mutual and/or retirement funds or the simulated (universities) setting, one type of funds that are completely forgotten are hedge funds. One reason for this significant literature gap may stem from the fact that the number of females within the hedge fund universe (as well as the other types of funds) is significantly low. For example, according to Pavlenko-Lutton and Davis (2015), the number of female mutual fund (MF) managers account to approx. 9.4% - including mixed-gender teams. Whereas, the percentage of the MFs managed solely by a female, stands at merely 2.0%. In contrast, within the hedge funds universe, mixed teams account to approx. 4.6%, with sole female fund leadership at 2.6% (Aggarwal and Boyson, 2016).

The review of the pre-1980s literature by Johnson and Powell (1994), indicates that women encounter ‘glass ceilings’ within the organisations due to the perception that they are too risk-averse. Thus, being considered potentially less likely to make risky decisions, necessary for the survival and/or success of the organisation. Subsequent studies from Powell and Ansic (1997), provide further evidence, supporting the view that the gender factor affects the attitudes towards financial risk, which in turn may arise from either a difference in strategic approach or individual motivation. In similar vein Dwyer, Gilkeson, List (2002), analyses 2000 mutual fund investors, generally confirming the findings of their predecessors (e.g. Jianakoplos and Bernasek, 1998) that women as investors are in fact more risk-averse than men. Nevertheless, the research employs another complementary control, the ‘investment knowledge’ of both male and female investors. The t-test results imply a highly significant difference between both sexes (the average response score for women is 6.2, whereas men 7.7, t = -14.3). Therefore, implying that the difference cannot be solely attributed to the ‘risk preference’ but instead to the specific ‘investment knowledge’. Similarly, in order to test the financial literacy, Bucher-Koenen, Lusardi, Alessie and Van Rooij (2017) employ a sample of 5700 households across the US, Germany and Netherlands. Their findings show that females are less likely than males to provide correct answers, while they are more likely to admit they do not know what the answer is, what leads to the theory of overconfidence amongst males.

Odean (1998) finds that the overconfident individuals are prone to trade more than rational investors, what in turns impacts upon their expected utility. Barber and Odean (2001) further explore the idea, through the acquisition of the data for 35 000 stock exchange investors over a period of six years (1991-1997) and catalogues their activities by gender. Their analysis indicates that males trade 45% more often than females and in consequence reduce their annual net returns by 2.65 percentage points (pp), whereas females by mere 1.72 pp. The same behaviour crystallises amongst men trading securities in Germany and the United States (Choi, Laibson, and Metrick, 2002; Agnew, Balduzzi, and Sundén, 2003; Dorn and Huberman 2005; Mitchell, Mottola, Utkus and Yamaguchi, 2006, Glaser and Weber, 2007) with the exception of China, where the trading volumes revolve around the same level for both genders (Feng and Seasholes, 2008). A more recent study from Bollen and Posavac (2017) combines the two aforementioned themes and analyses the impact of gender on the asset allocation between graduate business students and professional portfolio managers. In result, they identify that non-professional (students) males select riskier portfolios than females. Also, Schmidt and Traub (2002) in their analysis (at the University of Kiel) find that the female students exhibit the more frequent and larger extent of risk aversion than their male counterparts. Whereas, the professional wealth managers of both genders select the same portfolios.

The examination of the performance and risk appetite in mutual funds pursuing a fixed-income strategy shows that there are no significant differences when controlling for managers' gender (Atkinson, Boyce-Baird, Frye, 2003)[3]. The only substantial difference crystalizes at the fund flow level. Furthermore, as the authors notice the net flows of capital into the funds are particularly low for the females in their first year of management, regardless of whether they are managing it since the inception or take over from someone else. In a similar vein, the study by Niessen-Ruenzi and Ruenzi (2015) finds, that despite the adaptation of more reliable investment strategies and generation of the same returns as their male counterparts, female managers attract substantially diminished capital inflows. Interestingly, the results do not support 'rational statistical discrimination' (Phelps, 1972), but instead, imply the 'irrational' prejudice towards female fund managers (Becker, 1971).

The analysis of the European (equity only) mutual funds also confirms the results of the other studies indicating insignificant differences in performance and approach to risk between males and females (despite female managed funds often being larger and charging lower management fees) (Babalos, Caporale, Philippas, 2015). Nevertheless, the female managed funds were found to be dominated by perverse market timing, specifically with regards to Europe's Mid-Cap and Large-Cap Value investment approaches. Babalos's et al. (2015) study also identifies that female managers prefer growth strategies (versus male managers focus on Small-Cap stocks), yet they are unable to predict the movements of the growth factor. Even earlier studies (Brachinger, Schubert, Brown and Gysler, 1999) focusing on the attitudes of the Swiss undergraduate students', show that when male and female students are presented with investment or insurance scenarios, the decisions are identical (no gender differences in attitude to risk).

Drawing a direct parallel to the earlier research, one should expect higher risk aversion amongst female fund managers, while the excessive risk-taking amongst males. The same would apply to profit generation, where in some cases males would be expected to generate lower returns due to the excessive trading (e.g. Barber and Odean, 2001). Interestingly, most of the research into the fund's performance with relation to managers' gender proves, that in fact there are no differences or at most very little difference between the two genders.

We find that the modern fund (excluding hedge funds) related literature provides an extensive examination of gender differences in mutual fund's management (with a specific focus on the performance and risk appetite). While the same literature related to hedge funds is almost non-existent. The only publication concerning gender-specific differences between the hedge fund managers, reveals that on average the SR and standard deviation of the funds managed by females is marginally better than that of their male counterparts (Aggarwal and Boyson, 2016). However, due to this insignificant disparity in performance and risk, the authors' overall conclusion indicates that the differences between genders are either minimal or non-existent at all.

[3] The number of the managers in the sample stands at 269 of which 25 or 9.3% are females. Thus, reaffirming earlier estimation of approx. 9.4% by Pavlenko-Lutton and Davis (2015).

3 Data

The Morningstar's (MSD) Global Hedge Fund Universe is comprised of 4327 funds[4]. The after-cleaning sample used in our study consists of 1321 unique hedge funds. In the data cleaning process, we focus on removing funds with less than 12 months of returns, missing manager and the investment strategy details. Furthermore, in a similar fashion to Aggarwal and Jorion (2010), we also remove duplicate funds (multiple listings in various currencies and/or share classes). However, instead of removing duplicates with a correlation level of 0.99 or greater, we apply a 0.95 threshold due to increased robustness. The post-cleaning dataset consists of 20 investment strategies, which we have aggregated into 6 major groups: Equity, Arbitrage, Event, Debt, Global and Multi (Table 1). The strategy pools were organised based on the Morningstar Category Classifications (Morningstar, 2016) and the HFRI formulaic methodology (HFRI, 2019).

The empirical investigation is conducted based on monthly returns for the period of 377 months (October 1978 - December 2018)[5]. Out of 1321 funds, 60 are managed solely by female managers and 1261 by a male. The percentage of funds per investment strategy managed by female managers ranges from 2.1% to 12.9%. In the analysis, we focus on the Equity strategy which is the most populated strategy by both male and female managers and accounts for 25.3% ($914bn) of the HF market (Preqin, 2018). The monthly risk-free rate of 0.209 has been computed from 10-year US Treasury Bonds[6], which as of April 2019 stands at 2.51%.

Insert Table 1

3.1 Descriptive Statistics

This section provides insight into the descriptive statistics of the Equity HFs (Table 2). The average and median return across the strategy is marginally higher for female managers and stands at 0.82 versus 0.72 for males. The same cannot be said about the median monthly standard deviations, which are lower in female managed funds - this finding is also consistent with the literature on other types of funds i.e. mutual and retirement. Nevertheless, despite increased volatility male managed funds exhibit more attractive levels of skewness and kurtosis. The Ljung-Box test for the autocorrelation of returns rejects the null hypothesis of no autocorrelation and the Jarque-Bera test for the higher-order statistics rejects the null hypothesis of a normal return distribution, for both male and female HF managers' returns.

Insert Table 2

[4] The size of the hedge fund industry is easily comparable with that of some of the biggest economies in the world. In 2018, hedge funds aggregated $3.67tn of assets under management (Prequin, 2018).

[5] For robustness, we also use a smaller sample of HFs from 2002 to 2018 where the presence of female HF managers is more prominent. The results remain qualitatively similar (available upon request).

[6] www.treasury.gov

4 Methods

The investigation of the risk-adjusted performance considers the classical risk-adjusted metrics (*Sharpe, Jensen Alpha,* and *Treynor*), as well as the ones based on the lower partial moments (*Omega*, *Sortino, Kappa 3* and the *Upside Potential*), drawdowns (*Calmar*, *Sterling,* and *Burke*) and Value at Risk (*Excess return on VaR*, *Conditional Sharpe* and *Modified Sharpe*). The VaR approach concentrates on the return properties of analysed hedge funds. As previously identified (Getmansky, Lo and Makarov 2004; Malkiel and Saha 2005; Eling 2006), the analysis of hedge funds r2equires a sophisticated approach, which extends beyond standardised appraisal methods of the first two moments. Thus, this part focuses on the Sharpe ratio (*SR*) and Value at Risk (*VaR*) and their modifications incorporating the higher moments of return distribution (skewness (*S*) and kurtosis (*K*)): The *Modified SR* and *VaR* (*MSR* / *MVaR*).

In a subsequent step, the analysis focuses on the two forms of performance persistence. The first form is non-parametric contingency table of the winners and losers, while the second form adopts a parametric, regression approach.

4.1 Risk-Adjusted Ratios

4.1.1 Classic Ratios

1) Sharpe Ratio

The Sharpe ratio (1) measures the excess return per unit of total risk (Sharpe, 1966). The metric is also referred to as the reward to variability ratio and in principle assumes that the returns of the analysed vehicle are normally distributed.

$$SR = \frac{r_i^p - r_f}{\sigma^p} \tag{1}$$

2) Jensen Alpha

The Jensen Alpha (2) measures the excess return above the return predicted by the Capital Asset Pricing Model. The metric reports in a percentage format, which indicates the over/underperformance as contrasted with the market.

$$Jensen = \left(r_i^d - r_f\right) - (r_{rp}^d - r_f)\beta \tag{2}$$

3) Treynor

The Treynor ratio (3) measures the risk of a portfolio through the incorporation of systematic risk, represented by Beta (β_i). Thus, very often referred to as the return to volatility ratio.

$$Treynor_i = \frac{r_i^d - r_f}{\beta_i} \tag{3}$$

4.1.2 Lower Partial Moment Ratios

1) Omega

The Omega ratio (4) refers to the excess return over minimum accepted return and the lower partial moment of the first order (LPM_1). Furthermore, as can be seen, Omega is similar to the Sharpe ratio and referred by Kazemi, Schneeweis, and Gupta (2004) as the Omega-Sharpe.

$$Omega = \frac{r_i^d - \tau}{LPM_{1(\tau)}} + 1 \quad (4)$$

2) Sortino

The Sortino ratio (5) refers to the excess return over the minimum target return and the LPM. Its physiology is similar to Shape's ratio, which σ is replaced with downside deviation. While, the order of the LPM (seen previously in Omega) is increased to 2, which reflects a concave utility function (Kaplan and Knowles, 2004).

$$Sortino_i(\tau) = \frac{r_i^d - \tau}{\sqrt[2]{LPM_2(\tau)}} \quad (5)$$

3) Kappa 3

The Kappa 3 ratio (6), refers to the excess return over minimum accepted return and the lower partial moment of the first order (LPM_3). Same as the Omega and Sortino, this metric does not assume that the returns follow a normal distribution.

$$Kappa_i(\tau) = \frac{r_i^d - \tau}{\sqrt[3]{LPM_3(\tau)}} \quad (6)$$

4) Upside Potential

The Upside Potential ratio (7) is one of the metrics combining both lower (LPM) and higher (HPM) partial moments (Sortino, van der Meer, and Plantinga, 1999). The ratio measures the attractiveness of investment through an increased weighting to the negative deviations below minimum acceptable return.

$$UP_i = \frac{HPM_{li}(\tau)}{\sqrt[2]{LPM_2(\tau)}} \quad (7)$$

4.1.3 Drawdown Ratios

1) Calmar

The Calmar ratio (8) measures the fund's performance through the return versus drawdown risk (Young, 1991). The Calmar ratio is in an essence smoothed version of the Sterling ratio as it employs smoothed values for both numerator and denominator.

$$Calmar_i = \frac{r_i^d - \tau}{-MD_1} \quad (8)$$

2) Sterling

The Sterling ratio (9) (unlike Sharpe with its σ) measures risks through the application of the average drawdown (Lhabitant, 2004, p.84). Furthermore, due to the employment of the smallest drawdowns within a fixed period of time (as a risk metric), it is more sensitive to the outliers than the Calmar ratio.

$$Sterling_i = \frac{r_i^d - r_f}{\frac{1}{N}\sum_{j=1}^{N} -MD_j} \quad (9)$$

3) Burke

The Burke ratio (10) is another metric similar to the Sharpe ratio, which also measures the adjusted risk. Unlike the Sharpe ratio, Burke's denominator consists of a square root of the sum of squares of the smallest drawdowns (Burke, 1994).

$$Burke_i = \frac{r_i^d - r_f}{\sqrt{\sum_{j=1}^{N} MD_j^2}} \quad (10)$$

4.1.4 Ratios Based on the Value at Risk

1) Excess Return on Value at Risk

The Excess Return on value at Risk (11) measures the excess risk over the Value at Risk (VaR) (Dowd, 2002).

$$ErVaR_i = \frac{r_i^d - r_f}{VaR_i} \tag{11}$$

2) Conditional Sharpe Ratio

Conditional SR (12) measures the expected loss only considering the values, which exceed VaR (Albrecht and Koryciorz, 2003).

$$CSR_i = \frac{r_i^d - r_f}{CVaR_i} \tag{12}$$

3) Modified Sharpe Ratio

The Modified SR (13) measures the excess return over the portfolio's Modified VaR (MVaR). The metric incorporates the effects of the higher moments of the return distribution.

$$MSR_i = \frac{r_i^d - r_f}{MVaR_i} \tag{13}$$

4.2 Accountability for Higher-Order statistics

4.2.2 Data Analysis and Integration

In the first instance, we analyse the risk and return employing standard metrics such as the mean return (14), the annualised standard deviation (15), and Sharpe Ratio (1).

$$r_i^p = \frac{r_{i1} + \cdots r_{in}}{n} \tag{14}$$

$$\sigma_{mA} = \sqrt{\frac{\sum(x-\bar{x})^2}{n}} / \sqrt{12} \tag{15}$$

However, given the previous literature (Getmansky, Lo and Makarov 2004; Malkiel and Saha 2005; Eling 2006), we know that under Markowitz's (Markowitz, 1952) Modern Portfolio Theory (i.e. mean-variance analysis (the first two moments)), we cannot account for the existence of the autocorrelation, survivorship and selection biases as well as the higher moments of return distribution. Thus, we test for the autocorrelation (16) at lag 1. The autocorrelation in hedge funds is a by-product of erroneous investment valuations. The errors in valuation arise due to the illiquidity of specific investment instruments, e.g. sub-prime (distressed) RMBS's (Residential Mortgage-Backed Securities) (Kat, 2002).

$$\mathrm{AC}_{k=1}\; AC_1 = \frac{\sum_{t=k+1}^{AC}(Y_t-\bar{Y})(Y_{t-k}-\bar{Y})}{\sum_{t=1}^{AC}(Y_t-\bar{Y})^2} \tag{16}$$

The significance of the autocorrelation is tested with Ljung-Box (17) (Ljung and Box, 1978) statistic;

$$LB = T(T+2)\sum_{j=1}^{k}\frac{T_j^2}{T-J} \tag{17}$$

Subsequently, we assess the higher moments of the return distribution, such as skewness (18) and kurtosis (19). The asymmetrical distribution of hedge funds is their widely known property, which is a result of the investment in derivatives.

$$S = \frac{1}{N}\sum_{i=1}^{N}(\frac{y_i - \bar{y}}{\hat{\sigma}})^3 \quad (18)$$

$$K = \frac{1}{N}\sum_{i=1}^{N}(\frac{y_i - \bar{y}}{\hat{\sigma}})^4 \quad (19)$$

To test the significance of the *S* and *K*, we employ the Jarque-Bera (20) distribution test for both 0.05 and 0.01 confidence.

$$JB = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \quad (20)$$

In order to get a better insight into the risk approach of both male and female hedge fund managers, we calculate standard VaR (21), where $Z_a = -2.33$ $(0.99\ CI)$ and $w = US\$1$. Jorion (2001, p. xxii) describes VaR in the following way: "VaR measures the worst expected loss over a given horizon under normal market conditions at a given level of confidence."

$$VaR = -\left(Z_a \sigma_{Am} + r_i^p\right)w \quad (21)$$

To integrate the deviations of higher moments of return distributions (*S* and *K*), we apply Favre and Galeano's (2002) Modified VaR (22), in which the alpha value of the standard VaR has been replaced with Cornish-Fisher expansion (23).

$$MVaR = -\left(Z_{CF} \sigma_{Am} + r_i^d\right)w \quad (22)$$

$$Z_{CF} = Z_a + \frac{1}{6}(Z_a^2 - 1)S_i + \frac{1}{24}(Z_a^3 - 3Z_a)K_i - \frac{1}{36}(2Z_a^3 - 5Z_a)S_i^2 \quad (23)$$

To complement the change in MVaR, we use the modification employed by Eling and Schuhmacher (2007) and replace the σ_{Am} in the SR formula with the MVaR. Thus, our new metric, the Modified SR (MSR) (24) incorporates the effects of the *S* and *K*.

$$MSR = \frac{r_i^p - r_f}{MVaR_i} \quad (24)$$

4.3 Performance Persistence

Given the differences in approach towards the risk between male and female managers, as described in the literature review, we provide additional insight into the performance persistence. We compare the HFs based on gender and categorise them in either Equity strategy-based funds or the Universe (which includes multiple strategies). The analysis concerns the period between October 1978 - December 2018. We are using four performance benchmark medians, each of them corresponds with the number of analysed HFs and their strategic focus. The fund exceeding (receding) the median return equals a winner (loser) and is denoted as WW (LL). While the winner (in the initial period), transforming into a loser (secondary period) as WL and vice versa LW. The contingency tables approach is structured in the following way: cross-product ratio (CPR), Z-statistic (Z) and Chi-square (X^2).

The cross-product ratio indicates whether or not the HF exhibits performance persistence. The null hypothesis of the CPR is 1 (25), suggesting no persistence at all.

$$CPR = \frac{(WWxLL)}{(WLxLW)} \tag{25}$$

The statistical significance of the CPR results is measured with Z-statistic (26). Thus, if the Z-stat value of 1.96 (5%) or 2.58 (1%) is exceeded, we can observe the significant performance persistence.

$$Z = \frac{\ln(CPR)}{a_{ln_{(CPR)}}} = \frac{\ln(CPR)}{\sqrt{\frac{1}{WW}+\frac{1}{WL}+\frac{1}{LW}+\frac{1}{LL}}} \tag{26}$$

The chi-square (27) compares the observed frequency distribution with the expected frequency distribution. Therefore, if the X^2 exceeds 3.84 (5%) or 6.64 (1%) we can further confirm the existence of significant performance persistence.

$$X^2 = \frac{\left(WW-\left(\frac{(WW+WL)(WW+LW)}{n}\right)\right)^2}{\frac{(WW+WL)(WW+LW)}{n}} + \frac{\left(WL-\left(\frac{(WW+WL)(WL+LL)}{n}\right)\right)^2}{\frac{(WW+WL)(WL+LL)}{n}} + \frac{\left(LW-\left(\frac{(LW+LL)(WW+LW)}{n}\right)\right)^2}{\frac{(LW+LL)(WW+LW)}{n}} + \frac{\left(LL-\left(\frac{(LW+LL)(WL+LL)}{n}\right)\right)^2}{\frac{(LW+LL)(WL+LL)}{n}} \tag{27}$$

We also provide an additional metric of the percentage of repeating winners (PRW) (28).

$$PRW = \frac{WW}{WW+WL} \tag{28}$$

In terms of the parametric approach, we use two types of regressions, the XR and AXR. Both regressions are similar to what Do et al. (2010), used in their research, although with one notable difference, our benchmark variables are medians and not average returns of the aggregated HF groups. The XR regression measures the HF returns with respect to the median return of all HFs in a particular group (i.e. Equity and the Universe). Whereas, the AXR approach accounts for the risks associated with HFs. Thus, the AXR regression works in the same way as the XR, although the results are further divided by the residual standard deviation of the XR.

$$XR_{it} = a_n D_n + a_p D_p + \beta_{i,n} D_n XR_{i,t-1} + \beta_{i,p} D_p XR_{i,t-1} + \varepsilon_{it} \quad (29)$$

$$D_n = 1 \; where \; XR_{i,t-1} < 0 \; and \; D_p = 1 \; where \; XR_{i,t-1} > 0$$

$$AXR_{it} = a_n D_n + a_p D_p + \beta_{i,n} D_n AXR_{i,t-1} + \beta_{i,p} D_p AXR_{i,t-1} + \varepsilon_{it} \quad (30)$$

$$D_n = 1 \; where \; AXR_{i,t-1} < 0 \; and \; D_p = 1 \; where \; AXR_{i,t-1} > 0$$

The dummy variables D_n and D_p, refer to the negative (losing) and positive (winning) returns. Similarly, the $\beta_{i,n}$ and $\beta_{i,p}$ refer to the negative and positive level of returns' autocorrelation. The significant positive $\beta_{i,n}$ indicates the presence of the autocorrelation and negative (losing) HFs, while the $\beta_{i,p}$ stands for the exact opposite.

5 Empirical results

5.1 Risk-Adjusted Ratios

Table 3 presents the results of the performance measures between male and female HF managers. Table 3, Panel A, presents the estimation results for the Sharpe ratio, Jensen's alpha and the Treynor measure. The average Sharpe ratio is 0.11 for both male and female HF managers. Equally, both female and male HF managers outperform the market, on average, by one basis point. Given that Jensen's alpha is sensitive to leverage effects, we also estimate the Treynor ratio that adjusts performance to the level of systematic risk in a portfolio. The Treynor measure for male and female HF managers is 0.05 and 0.24, respectively. When accounting for the level of systematic risk, female HF managers outperform male HF managers by 19 basis points.

Classic ratios consider risk as negative and positive deviations of returns from expected returns. In contrast, LPM ratios consider only negative deviations of returns from a minimum acceptable return. Whilst these measures produce similar results when the return distributions are normal, they produce different results when return distributions are lognormal (Price et al., 1982). Table 3, Panel B presents the results for the Omega, Sortino, Kappa 3 and Upside Potential Ratios. Three of four LPM ratios show that male HF managers outperform female HF managers when accounting for negative deviations from the minimum acceptable return. Given the differences in skewness between male and female HF managers (Table 3), the above results are not surprising: Female (male) HF returns tend to exhibit negative (positive) skewness and LPM ratios penalize negatively skewed returns relative to positively skewed returns.

Table 3, Panel C, presents the results for the Drawdown-based performance measures: Calmar, Sterling and Burke ratios. In contrast to Classic and LPM ratios, Drawdown-based measures use the maximum possible loss over a period of time as a measure of risk. Two of the three Drawdown-based measures show no differences between male and female HF managers. The Calmar ratio shows that male HF managers tend to underperform female HF managers when accounting for drawdown risk.

Table 3, Panel D, reports risk-adjusted performance metrics on the basis of VaR. We estimate the Excess return on value at risk (ErVaR), Conditional SR and Modified SR measures. VaR performance-based measures utilise the possible maximum loss of an investment with a given probability over a given period and are therefore similar to the LPM-based measures. Two of three measures show that HFs managed by male managers produce better risk-adjusted returns than their female colleagues when accounting for the expected VaR. This result is consistent with the findings on the LPM-based measures and reflective of the negative skewness of HFs managed by females (see Table 3).

Insert Table 3

5.2 Performance Persistence

5.2.1 Non-Parametric

The following section examines non-parametric performance persistence based on the HF managers gender. As mentioned earlier, the analysis focuses on the Equity HFs, nonetheless, we also provide the figures for the aggregated HF Universe for comparison. The Equity strategy (HF Universe) aggregates 36 (60) HFs managed by females and 779 (1261) managed by a male. The results of the analysis (for both genders) undoubtedly confirms the existence of short-term performance persistence, which on average (CPR) is more pronounced amongst the female managed HFs.

Insert Table 4

Panel A and B of Table 4 present the results of the non-parametric performance persistence analysis between the male and female equity HFs mangers. In both cases, the average number of losing (LL) periods dominates over the winning (WW) ones. Although, in case of the female managed HFs the difference between the number of LL and WW periods is merely 1.05%, while for male managed funds this number stands at 5.35%. The average CPR stands at 2.34 for male and 2.53 for female managers. Thus, violating the null hypothesis of no persistence (i.e. CPR=1) in 296 (male) and 222 (female) out of 375 analysed months. The statistically significant persistence crystallises in male managed HFs in 132/375 months for the X^2 @1% and 36/375 @5%, while the same metric for the females' reports 10/375 months @1% and 14/375 @5%. The Z-Stat for males exhibits significance @1% for 93/375 months and @5% for 23/375 versus the female managed HFs with 6 @1% and 5 @5%. Lastly, despite the average PRW being higher for female managers (0.60 vs 0.58), the number of months where the PRW is greater than 50% is much higher amongst male managed funds with 63.4% versus 45.4% for females.

Turning our attention to the panels C and D (HF Universe), we observe that the gap between the number of WW and LL periods has significantly widened for the female managed HFs (Δ of 19.49%) and contracted for the males (Δ of 2.45%). Nevertheless, the number of LL periods still dominates in both cases. The CPR levels are comparable for male managed funds (Equity vs Universe i.e. Δ of 2.82%) but increase in line with the number of LL periods for female managed HFs (Δ of 19.27%). Furthermore, CPR $\neq$ 1 in 306/375 (243) months for male (female) HF managers (the CPR boundaries were set at 20% i.e. 0.8-1.2 (instead of

CPR=1.0) to account for minor variability). The statistical significance of the X^2 (Z-Stat) can be observed @1% in 24 (15) monthly periods for the female managed HFs, while for their counterparts, in 165 (122) of 375 months. The figures @5% confidence interval have also increased for the HF Universe and for female managers, they stand at 40 (21) monthly periods for the X^2 (Z-Stat), and at 37 (26) for the males. The PRW greater than 50% is almost identical between both genders with male managers at 66.14% and female at 67.30%.

5.2.2 Parametric

Panel A (Table 5) indicates that 26 of 30 (or 87%) female managed equity HFs have a positive Beta n coefficient with 7 being statistically significant (@5%). While the male managed funds achieve positive values in 69% of cases (i.e. 539 of 779 HFs) of which 104 are statistically sig. When we take into account the aggregated universe of female managers, the number of positive Beta n values stands at 65% (39 of 60) with 16 statistically sig. Similarly, the positive cases for the male managers circulate around 67% (839 of 1261) with 210 being statistically sig. Further, Panel A (Beta p) shows that 21 of 30 female managed equity HFs have a positive Beta p coefficient (with 6 statistically sig.). In the male equity HFs, we have 511 of 779 HFs with positive Beta p and 107 statistically sig. For the aggregated universes females stand at 35/60 (9 sig.) and males at 797/1261 (174 sig.). Therefore, the overall results suggest a significant short-term losing persistence in all cases except male managed Equity HFs (MAL-EQU), where the number of statistically sig. positive Beta p cases are 107 (against 104 negatives (Beta n)). Thus, the male managed equity HFs represent a significant short-term winning persistence.

Panel B (Table 5), which concerns the AXR (risk-adjusted) shows that despite the number of Beta n and Beta p cases slightly changing from our earlier XR assessment (Panel A), the male managed equity HFs still dominate with short term winning persistence.

Insert Table 5

6 Conclusion

Despite the surge in academic studies that investigate the role of gender in risk-taking and investment performance, the literature is in general silent about the risk-adjusted performance of female fund managers versus their male counterparts. Furthermore, the avenue of performance persistence also remains unexplored. In this paper, we use 13 performance measurement ratios to compare the risk-adjusted performance of male and female HF managers, as well as the non/parametric methods of performance persistence.

We show that when using the SR as a measure of investment performance, male and female HF managers produce similar results, in line with prior literature. However, the assumptions of SRs are unrealistic in this setting. We show that, when using a more realistic set of performance measures that account for higher-order statistics, female HF managers tend to produce lower returns than their male counterparts. Returns of HFs managed by female managers are on, average, negatively skewed and performance measures that capture the negative deviations of returns only penalize negatively skewed funds relative to those managed by males, which are positively skewed. Our findings clearly show that controlling for higher-order statistics is crucial in identifying gender differences in HF performance.

The results of our non-parametric performance persistence analysis show that the HFs managed by both genders are marginally dominated with losing (LL) instances. The further investigation from the parametric perspective reveals both male and female managed HFs tend to exhibit short-term losing persistence. The only exception to this are male managed equity HFs, which exhibit weak short-term winning persistence.

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Table 1: Number of Hedge Funds

Investment strategy	Total	Male	Female	% Female
Equity	815	779	36	4.40%
Arbitrage	31	27	4	12.90%
Event	48	47	1	2.10%
Debt	130	122	8	6.20%
Global	125	118	7	5.60%
Multi	172	168	4	2.30%
Total	1321	1261	60	4.50%

Note: This table presents the total number of hedge funds considered in the analysis across various strategies and genders.

Table 2: Moments of order statistics

Equity	Male				Female			
	r_p	σ_m	S	$K_{(ex)}$	r_p	σ_m	S	$K_{(ex)}$
Average	0.72	5.06	0.01	2.15	0.82	5.00	-0.1	1.79
Min	-5.35	0.02	-8.48	-2.97	-0.42	0.10	-6.90	-2.87
Max	7.25	34.98	7.37	98.89	1.77	13.29	2.07	53.23
Median	0.65	3.70	-0.12	1.10	0.72	3.52	-0.29	1.09
Jarque-Bera (J-B)	331.97**				124.41**			
Ljung-Box (L-B)	0.32**				0.25**			
# of obs.	779				36			

Note: This table contains the descriptive statistics dissected based on the manager's gender. The columns (from left) in each section consist of the mean return, standard deviation, skewness and kurtosis. The significance at 0.01 is denoted with *, while for the 0.05 with **.

Table 3 Results: Risk-Adjusted Metrics

	Male	Female
Panel A: Classic Ratios		
Sharpe Ratio	0.11	0.11
Jensen Alpha	0.01	0.01
Treynor (S&P500)	0.05	0.24
Panel B: Lower Partial Moment Ratios		
Omega Ratio	1.68	1.45
Sortino Ratio	0.18	0.17
Kappa 3	0.06	0.02
Upside Potential Ratio	0.19	0.19
Panel C: Drawdown Ratios		
Calmar Ratio	-0.59	-0.57
Sterling Ratio	0.05	0.05
Burke Ratio	0.01	0.01
Panel D: Ratios Based on the Value at Risk		
ErVaR	0.06	0.06
CSR	1.84	0.47
MSR	0.07	0.05

Note: This table provides the results of four types of risk-adjusted performance measures (Panel A: Classic Ratios, Panel B: Lower Partial Moment Ratios, Panel C: Drawdown Ratios, Panel D: Ratios Based on the Value at Risk).

Table 4 Non-Parametric Performance Persistence													
Panel A													
Male HF - Equity		WW	LL	WL	LW	WG	LG	NHFW	NHFL	CPR	X^2	Z-Stat	PRW
Monthly - short term performance persistence 779 HFS	Mean <>0	66.05	69.59	61.53	62.21	2.24	2.07	8.82	8.68	2.34	10.431	1.105	0.580
	STDEV.P <>0	67.28	67.86	61.95	61.95	1.62	1.60	47.53	46.51	2.90	18.610	3.070	0.157
	Maximum	248	251	218	212	10	11	324	324	25	138.407	11.286	0.83
	Minimum	1	1	1	1	1	1	1	1	0.16	0.008	-9.220	0.293
	Total	24307	24356	21350	21337	399	383	397	408	296	132*	93*	240$^{\#}$
											36**	23**	0.633$^{\#\#}$
Panel B													
Female HF - Equity		WW	LL	WL	LW	WG	LG	NHFW	NHFL	CPR	X^2	Z-Stat	PRW
Monthly - short term performance persistence 36 HFS	Mean <>0	4.74	4.79	4.44	4.45	1.04	1.17	2.88	2.88	2.53	1.708	0.248	0.598
	STDEV.P <>0	2.89	2.72	2.67	2.66	0.20	0.37	4.96	4.59	3.48	1.980	1.191	0.197
	Maximum	13	13	11	11	2	2	16	15	30	12.500	3.238	0.86
	Minimum	1	1	1	1	1	1	1	1	0.0625	0.029	-2.587	0.200
	Total	1385	1227	1168	1167	24	14	23	23	222	10*	6*	171$^{\#}$
											14**	5**	0.454$^{\#\#}$
Panel C													
Male HF - All		WW	LL	WL	LW	WG	LG	NHFW	NHFL	CPR	X^2	Z-Stat	PRW
Monthly - short term performance persistence 1261 HFS	Mean <>0	110.30	113.00	96.33	96.10	2.83	2.53	10.65	10.79	2.28	14.905	1.547	0.559
	STDEV.P <>0	109.16	110.43	97.70	97.68	2.04	1.96	69.34	69.89	3.40	24.349	3.550	0.125
	Maximum	370	368	357	358	12	11	552	552	49	174.343	12.783	0.88
	Minimum	1	1	1	1	1	1	1	1	0.03	0.011	-11.229	0.167
	Total	40811	41132	35065	35075	678	601	660	658	306	165*	122*	252$^{\#}$
											37**	26**	0.661$^{\#\#}$
Panel D													
Female HF - ALL		WW	LL	WL	LW	WG	LG	NHFW	NHFL	CPR	X^2	Z-Stat	PRW
Monthly - short term performance persistence 60 HFS	Mean <>0	6.49	7.76	6.54	6.56	1.03	1.04	7.75	9.67	3.02	2.439	0.509	0.671
	STDEV.P <>0	5.43	5.19	4.62	4.60	0.18	0.19	11.69	12.26	4.31	2.725	1.370	0.228
	Maximum	20	19	17	18	2	2	28	27	30	13.520	3.481	0.86
	Minimum	1	1	1	1	1	1	1	1	0.0625	0.014	-3.255	0.200
	Total	2305	2118	1824	1824	31	28	31	29	243	24*	15*	247$^{\#}$
											40**	21**	0.673$^{\#\#}$

Note: This table provides the results of the non-parametric test for two gender-focused strategy groups. Panel A and B examine the Equity strategy HFs, while C and D focus on the entire HF Universe. The table presents the statistics for the mean, standard deviation, max and min values, as well as totals. The denominators in columns stand for W-winning, L-Losing, G-Gone, NHF-New Hedge Fund, CPR – Cross Product Ratio, X^2 – Chi-Square, Z-Stat – Z-Statistic, PRW – Percentage of Returning Winners. While the * (**) denotes 99% (95%) confidence interval and $^{\#}$ ($^{\#\#}$) the number of months where PRW >50% (percentage of months were the count of PRW's >50% is divided by the count of total periods (375) minus periods where the PRW = 0 (no data)).

Table 5 Parametric Performance Persistence

Panel A Non-Risk-Adjusted Persistence

XR	Alpha n				Alpha p				Beta n				Beta p				Adj R2			
	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL
Mean	-3.674	-3.528	-2.84	-3.112	3.544	3.697	2.83	3.110	0.194	0.174	4.59	0.313	0.038	0.125	0.06	0.127	0.543	0.548	0.563	0.549
Sigma	1.919	1.988	2.83	2.833	1.823	2.130	1.88	2.209	0.336	0.378	32.56	3.915	0.248	0.291	0.27	0.351	0.063	0.120	0.116	0.120
Max	-0.673	-0.097	12.22	0.690	9.635	22.817	9.64	22.817	1.171	4.147	248.24	136.71	0.556	1.732	0.96	2.786	0.653	0.999	0.977	0.999
Min	-10.852	-21.51	-10.85	-70.123	0.627	0.110	-0.05	-1.777	-0.302	-0.856	-0.46	-6.266	-0.881	-1.036	-0.88	-1.816	0.378	-0.307	0.257	-0.307
Pos	0	0	2	4	36	776	59	1249	26	539	39	839	21	511	35	797				
Sig @ 0.05	0	2	4	24	35	756	57	1203	7	104	16	210	6	107	9	174				
Neg	36	777	55	1233	0	0	1	9	10	239	18	398	15	268	25	464				
Sig @ 0.05	35	732	53	1143	0	0	0	6	0	13	0	26	0	28	0	46				

Panel B Risk-Adjusted Persistence

AXR	Alpha n				Alpha p				Beta n				Beta p				Adj R2			
	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL	FEM-EQU	MAL-EQ	FEM-ALL	MAL-ALL
Mean	0.004	0.001	0.021	-0.149	0.429	0.510	0.519	0.573	0.014	0.021	1.071	-0.003	-0.007	0.010	-0.009	0.005	0.068	0.123	0.116	0.125
Sigma	0.580	1.027	1.322	1.035	0.350	0.480	0.404	0.550	0.158	0.451	7.926	0.626	0.040	0.099	0.046	0.115	0.077	0.198	0.185	0.199
Max	2.012	23.754	8.534	23.754	1.411	3.453	1.411	6.340	0.880	11.785	60.379	11.785	0.088	1.143	0.088	1.401	0.343	0.999	0.977	0.999
Min	-1.240	-2.532	-1.729	-9.735	-0.002	-0.752	-0.054	-1.591	-0.289	-1.273	-0.289	-16.210	-0.129	-0.524	-0.232	-1.527	-0.027	-1.156	-0.260	-1.156
Pos	14	295	20	403	35	728	57	1166	20	396	30	623	17	407	30	642				
Sig @ 0.05	2	51	8	100	17	399	32	698	2	36	7	71	0	45	1	67				
Neg	22	482	37	833	1	49	3	93	16	382	27	615	19	371	30	618				
Sig @ 0.05	8	101	18	255	0	3	0	3	0	31	0	50	5	30	6	44				

Note: This table provides the results for the parametric performance persistence test (non-risk adjusted XR and risk-adjusted AXR). The data has been divided into four clusters FEM-EQU/MAL-EQU (Female/Male Equity Only HFs) and FEM-ALL/MAL-ALL (Female/Male All Strategies HFs). The first two main columns refer to the dummy variables which separate negative (Alpha n) and positive (Alpha p) cases, the third column (Beta n) implies the existence of the auto-correlation or persistence of the negative (losing) cases, while the fourth column (Beta p) implies the auto-correlation or persistence amongst positive (winning) cases, the last column provides the adjusted r-squared figures.