Essays on Hedge Fund Performance and Corporate Governance

William Joseph Klubinski

A thesis submitted for the degree of **Doctor of Philosophy in Finance** at

Essex Business School

University of Essex

2021

In the first instance, I would like to thank my parents, brother, and my fiancée for the unquantifiable support they have provided me throughout this PhD. Furthermore, I am also grateful to my dear friends Matthias and William, who have helped me maintain a healthy balance between work, studies and personal life.

Acknowledgements

The special thanks are due to Dr **Thanos Verousis** for his continuous and relentless support throughout my entire PhD. He is the most unique academic I have ever come across. His research experience, combined with a deeply rooted understanding of the financial industry, has helped me numerous times - I am <u>forever</u> grateful for your support and patience. Furthermore, I would like to express my deepest gratitude to Professor **Neil Kellard** for his timely advice, mentoring and encouragement. Finally, great thanks are also due to the Essex University Library Services and all individuals I have met and consulted throughout this PhD.

"*I can no other answer make, but, thanks, and thanks and ever thanks…*"

William Shakespeare

Abstract

The hedge fund industry aggregate is approximately US$ 3.61tn assets under management (Prequin, 2020). Despite the significance of these numbers and their potential effect on the global economic stability, the literature remains silent regarding domicile-strategic related aspects of performance, the differences in management style and performance between male and female managers, and the flow-performance relationship based on the ethnic association of the hedge fund manager.

This doctoral thesis focuses on three original topics concerning hedge fund performance and corporate governance. The first topic examines the impact of geolocation and investment strategy on the estimation of risk in performance persistence measurement dynamics. Secondly, we analyse gender differences in hedge fund performance employing risk-adjusted performance metrics and two performance persistence models. Lastly, the third topic examines whether the ethnic association of the hedge fund manager can affect the investment choice of the hedge fund investor.

This thesis reports strong performance persistence when analysing the individual domicile or strategy in line with previous findings. However, as we move to consider a combination of both domicile and the investment strategy, we can observe diminished persistence and its loss and reversal. These cross-comparison results indicate that the sole reliance on either domicile or the investment strategy clusters in isolation can be grossly misleading and lead to significant losses.

In the sphere of gender differences, the findings indicate that both male and female hedge fund managers tend to produce similar risk-adjusted returns under the umbrella of lower-order statistics. However, with the incorporation of performance measures that account for hedge funds' asymmetric returns distribution, female managers tend to produce lower returns than their male counterparts. These findings show that controlling for higher-order statistics is crucial in identifying gender differences in hedge fund performance. Further results reveal both positive and negative performance fluctuating between genders (with the dominance of statistically significant cases amongst male managers). Under the parametric approach, the performance persistence is dependent not only on managers' gender but also on the adopted time horizon. More importantly, the results underline the importance of a diverse

approach, such as the deployment of risk-adjusted metrics and non/parametric persistence methods when analysing hedge funds performance.

Lastly, the ethnic minority hedge fund managers receive significantly fewer capital inflows than their non-minority counterparts yet simultaneously deliver better (average) raw returns/performance. In addition to the regression-based approach, this part of the thesis also applies the risk-adjusted metrics to identify whether the investors' choice is statistically justified. The risk-adjusted metrics results indicate fluctuation in the level of advantage exhibited by the two groups of hedge fund managers. The presented findings provide a unique contribution to the literature concerning race/ethnicity, hedge funds, and human behaviour.

This doctoral thesis draws attention to the underdeveloped areas of the academic literature in the first place concerning hedge fund domicile and its investment strategy, managers' gender and managers' ethnicity. In all cases, it shows that the approach to the analysis requires creativity and accountability for statistical anomalies that are very often traditionally associated with hedge funds. Furthermore, it also indicates that the thorough analysis of hedge funds requires multiple approaches, often concentrating on the initial data formatting prior to the multi-layered main analysis. The results and the approaches taken in this thesis are directly relevant to both professional investors and academics.

Table of Contents

Acknowledgements ... iii

Abstract ... iv

Table of Contents ... vi

List of Tables ... viii

List of Figures ... x

Chapter 1. Introduction to the thesis ... 1

Chapter 2. Literature Review ... 6

- **2.1 Introduction** ... 6
- **2.2 On the underestimation of risk in hedge fund performance persistence: geolocation and investment strategy effects.** ... 6
  - **2.2.1 Introduction** ... 6
  - **2.2.2 Undefined Domiciles** ... 6
  - **2.2.3 Defined Domiciles** ... 9
- **2.3 Gender differences in hedge fund performance.** ... 11
  - **2.3.1 Introduction** ... 11
  - **2.3.2 Summary** ... 17
- **2.4 Hedge Fund Flows: Managers' Ethnicity.** ... 18
  - **2.4.1 Introduction** ... 18
- **2.5 Conclusion** ... 23

Chapter 3. On the underestimation of risk in hedge fund performance persistence: geolocation and investment strategy effects. ... 25

- **3.1 Introduction** ... 25
- **3.2 Data** ... 29
  - **3.2.1 Database** ... 29
  - **3.2.2 Descriptive Statistics** ... 30
- **3.3. Methods** ... 32
- **3.4 Empirical Results** ... 35
  - **3.4.1 Parametric Methods** ... 35
  - **3.4.3 Non-Parametric Methods** ... 38
- **3.5 Conclusion** ... 42
- **Tables** ... 44
- Figures ... 55

Chapter 4. Gender differences in hedge fund performance. ... 56

4.1 Introduction 56
4.2 Data 60
4.2.1 Descriptive Statistics 61
4.3 Methods 64
4.3.1 Risk-Adjusted Ratios 64
4.3.2 Performance Persistence 69
4.4 Empirical Results 72
4.4.1 Risk-Adjusted Ratios 72
4.4.2 Performance Persistence 75
4.5 Conclusion 80
Tables 82
Chapter 5. Hedge Fund Flows: Managers' Ethnicity. 99
5.1 Introduction 99
5.2 Data 104
5.2.1 General Data Overview 104
5.2.2 Descriptive Statistics 106
5.3 Methods 108
5.3.1 Regression 108
5.3.2 Risk-Adjusted Metrics 110
5.4 Empirical Results 114
5.4.1 Regression Results 114
5.4.2 Risk-Adjusted Metrics 116
5.5 Conclusion 117
Tables 119
Figures 129
Chapter 6. Conclusion of the Thesis 131
References 135

List of Tables

Table 3.1 Abbreviations……………………………………………………………………….44

Table 3.2 World's primary AIFs databases………………………………………………………45

Table 3.3: Descriptive Statistics…………………………………………………………….……46

Table 3.4. Parametric Performance Persistence [non-risk-adjusted [XR]]: Domicile/Investment Strategy…………………………………………………………………..………………47

Table 3.5: Parametric Performance Persistence [non-risk-adjusted [XR]]: Domicile Combined with the Investment Strategy………………………………………………………………………….48

Table 3.6: Parametric Performance Persistence [risk-adjusted [AXR]]: Domicile/Investment Strategy………………………………………………………………………………………..49

Table 3.7: Parametric Performance Persistence [risk-adjusted [AXR]]: Domicile Combined with the Investment Strategy……………………………………………………………………..….50

Table 3.8: Non-Parametric Performance Persistence…………………………………………….51

Table 3.9: Non-parametric Performance Persistence Statistics…………………………………..52

Table 3.10. Non-parametric Performance Persistence: Domicile Combined with the Investment Strategy……………………………………………………………………………………....53

Table 3.11: Non-parametric Performance Persistence: Domicile Combined with the Investment Strategy………………………………………………………………………………...….54

Table 4.1: Number of Hedge Funds……………………………………………………………….82

Table 4.2: Moments of Order Statistics…………………………………………………...……83

Table 4.3 Results: Risk-Adjusted Metrics…………………………………………………...……84

Table 4.4 Rank Correlation of the Risk-Adjusted Metrics for Equity HFs………………….……....85

Table 4.5 Rank Correlation of the Risk-Adjusted Metrics for All HFs……………….…………..86

Table 4.6 Non-Parametric Performance Persistence for the Equity HFs…………………………….87

Table 4.7 Non-Parametric Performance Persistence for the Equity HFs………………...………..88

Table 4.8 Non-Parametric Performance Persistence for the Universe HFs……………………….…89

Table 4.9 Non-Parametric Performance Persistence for the Universe HFs…………………....…….90

Table 4.10 The Non-Risk-Adjusted Parametric Performance Persistence for the Equity HFs……….91

Table 4.11 The Non-Risk-Adjusted Parametric Performance Persistence for the Universe HFs…......93

Table 4.12 The Risk-Adjusted Parametric Performance Persistence for the Equity HFs…………......95

Table 4.13 The Risk-Adjusted Parametric Performance Persistence for the Universe HFs…………..97

Table 5.1 The Ethnicity of HF Managers'……………………………………………………..….119

Table 5.2 Descriptive Statistics of the HF Managers with the Most Common First Names* (1999-2019)……………………………………………………………………………………..…..120

Table 5.3 Descriptive Statistics…………………………………………………………………121

Table 5.4 Variables……………………………………………………………………………..…122

Table 5.5 Variable Correlations……………………………………………………..…………123

Table 5.6 Fund Flow Regression GLS 1999-2019……………………………………………..……124

Table 5.7 Fund Flow Regression OLS 1999-2019………………………………………………….….125

Table 5.8. GLS Fund Flow Regression 2013-2019…………………………………………...…..126

Table 5.9 OLS Fund Flow Regression 2013-2019……………………………………………..…127

Table 5.10 Risk-Adjusted metrics…………………………………………………………….....128

List of Figures

CH3 Figure 1. The Number of Domicile/Strategy Hedge Funds (1995-2016)……………………….55

CH5 Figure 1. The Annual Ethnic Fluctuations of the HF Managers (1999-2019)……………..…..129

CH5 Figure 2. Top 20 Most Popular HF Manager Names (1999-2019)………………...…………..130

Chapter 1. Introduction to the thesis

In recent years, the hedge fund industry has experienced significant growth. The assets under management have grown from approx. US$1.7tn in 2009 (The Hedge Fund Journal, 2010) to US$ 3.61tn in 2020 (Prequin, 2020). To better understand the magnitude of this figure, one could compare it with Germany's GDP of US$ 3.84tn reported in 2019 (World Bank, 2020). The hedge funds are known under many definitions, although the following description will suffice for the purpose of this doctoral thesis. Hedge funds are private, pooled investments with the ability to take long/short positions across global markets. They can trade in highly illiquid assets, utilise complex trading strategies containing leverage and various exotic derivatives. In most cases, these elusive investment vehicles enjoy a relative lack of regulation. Since their inception in the 1950s, hedge funds were always looked to for their astonishing performance (Bridgewater, Soros, and Citadel), which in turn has gradually elevated their reputation to 'the money-making machines' (Rittereiser and Kochard, 2010). The industry did not thrive without controversies, and more specifically, significant defaults, for example, Amaranth Advisors, LTCM, and Tiger Management.

An accurate appraisal of hedge fund performance must recognise that the risk exposure to investment styles is constantly shifting as managers can change the fund's focus. In that respect, risk management in hedge funds is prone to systematic biases as exposure to risk factors is changing (see Bollen and Whaley, 2009). The literature related to the performance persistence of hedge funds has grown exponentially in the last two decades. Nevertheless, despite its broad coverage of all the years from approximately the late 1970s until now, utilising all major databases and various methodologies, risk management with respect to the measurement of performance persistence remains largely unexplored. One of the major examples will be the data analysis focus of the previous researchers, who were mostly focused on either the aggregation of the global hedge fund universe under one umbrella and/or the strategic division. The frequent omission or underestimation of the domicile factor has not provided a complete risk-accountability, much needed in the hedge fund environment. The only time where the literature has shown consideration for the geolocation was in the case of research focused on the Asian and Australian, Italian, and solely Australian hedge fund environments (Koh, Koh and Teo, 2003; Steri, Giorginob and Vivianib, 2009; Do, Faff & Veeraraghavan, 2010). Thus, this thesis aims to address the unexplored differences between the domicile, strategy and the combination of both to provide a unique contribution to hedge fund related literature.

Furthermore, fund performance is also largely attributed to the manager's skill and his/her approach to risk. A significant part of fund-related literature focuses on gender differences and, more specifically, the approach towards both performance and risk. The literature shows that despite the increasing amount of gender research being undertaken in financial settings, the one setting almost never examined is hedge funds (e.g., Atkinson et al. 2003; Bollen and Posavac, 2018). The early studies (for example, Johnson and Powell, 1994; Powell and Ansic, 1997) prove that the gender factor matters, especially considering the attitude to risk. The same behaviours are confirmed in the mutual fund environment by Jianakoplos and Bernasek (1998) and/or Dwyer, Gilkeson and List (2002). Nonetheless, the hedge fund literature provides no answers regarding differences in risk, performance and/or performance persistence between genders. Therefore, this thesis provides a previously unexplored contrast, making a novel contribution to the literature.

The second early dimension of self-identification, right after gender, is ethnicity/racial association (Epstein, 1978). The importance of ethnic/racial research is as pivotal as gender, especially given the prevailing differences and inequalities crystallising in almost any dimension (for example, Kumar, Niessen-Ruenzi and Spalt, 2015; Politico, 2019). As previous researchers show (for example, Sirri and Tufano, 1998; Ferreira, Keswani, Miguel and Ramos, 2012; Röder and Walter, 2019), the most common relationship combination in the fund related literature is that of flows and performance. Interestingly, the studies concerning the ethnic/racial aspect with regards to capital flows, performance and risk do not exist, not in commonly examined mutual funds nor hedge funds. It is, therefore, the final aim of this thesis to address this issue and fill in the void in both hedge fund and corporate governance literature.

In summary, this doctoral thesis aims to address the aforementioned unexplored concerns regarding geo-strategic performance, gender differences in performance, and the impact of ethnicity in capital flows, to provide an original contribution within the hedge fund related literature.

Chapter 3 [1] of the thesis focuses on the empirical study concerning the risk in hedge fund performance persistence, focusing on geolocation and the investment strategy effects. The main findings of Chapter 3 indicate the presence of short-term performance persistence individually across both domicile and the investment strategy cluster. Interestingly, the fusion between the domicile and the investment strategy exhibits diminished persistence as well as its loss and reversal. Under the stricter parametric regime, yet without consideration for hedge fund specific risks, the results reveal dominant and statistically significant negative performance persistence in portfolios such as IRL and the USA. A similar occurrence takes place in the geo-strategic combinations and domiciles employing either the LSE or MLTI strategies. The incorporation of hedge fund specific risk changes the outcomes for several domiciles and the investment strategies and promotes almost all of them into the positive and statistically significant territory (except for IRL).

Chapter 4 investigates the risk-adjusted performance and performance persistence of hedge funds focusing on the gender of the fund manager. The main findings of Chapter 4 show that the performance of hedge funds managed by males and females is similar under the assumptions of metrics based on the lower-order statistics (for example, the Sharpe ratio). Furthermore, the incorporation of the third and fourth higher-order statistics reveals lower returns and higher risk amongst female hedge fund managers as compared with their male counterparts. Regarding the non-parametric performance persistence, the results indicate marginal underperformance of female managed funds. In the parametric (not yet adjusted for hedge fund risk) model, both genders struggle to maintain positive performance persistence and fluctuate between positive and negative cases depending on the time horizon. Lastly, the risk-adjusted performance persistence analysis results allow female managers to emerge in many cases into positive territory. Although, this emergence is not strong nor statistically significant enough to surpass male managed hedge funds.

Chapter 5 presents the empirical study concerning the impact of the hedge fund managers' ethnicity/race on the flows of capital. One of the main findings of Chapter 5 shows that the ethnic

[1] This chapter has been published in Zopounidis, Benkraiem and Kalaitzoglou (2021)

minority hedge fund managers receive significantly lower flows of capital into their funds despite the generation of higher raw returns. Hence, at this point, dismissing the concept of rational statistical discrimination. Nonetheless, the analysis continues to examine the performance and risk of both clusters (minority and non-minority managers). The risk-adjusted metrics based on the lower-order statistics elevate hedge funds managed by the ethnic minorities. The same cannot be said about the lower partial moment metrics, where the non-minority managers take a marginal lead. The other metrics exhibit parity between both ethnic clusters, with the ones including the third and fourth higher-order statistics (such as Modified and Conditional Sharpe Ratio) providing a marginal advantage for the minority managed funds.

Chapter 3 provides an original contribution to the literature and is directly relevant to the practical investment applications. First, it presents previously unseen contrasts in the fund related literature (between domicile, investment strategy and the combination of both). Second, it shows that the sole reliance on either domicile or the investment strategy level focused clusters can be grossly misleading and lead to undesirable consequences. Third, the results of this chapter prove that the choice of the performance persistence appraisal methods is pivotal as the omission of the risk-adjusted approach can lead to misappraisal and losses.

Chapter 4 poses an original research question that has not been previously addressed in the hedge fund literature. More specifically, this chapter's first contribution is to present the differences in risk-adjusted performance between male and female hedge fund managers. Second, it shows that controlling for higher-order statistics is pivotal in identifying the differences in performance between genders. Third, the results also draw a direct parallel to the earlier chapter and show that the choice of metrics and additionally various time horizons for the performance persistence analysis is of the utmost importance and can help the investor tailor their approach to risk and returns more accurately.

Chapter 5 makes an original contribution to the literature concerning not only hedge funds but, more importantly, ethnicity and race in the context of fund attractiveness and performance. The first major contribution of this chapter is the identification of flow levels, given the ethnic association of the hedge fund manager. Second, it further examines hedge fund managers under the scope of risk-adjusted performance metrics to identify whether performance has influenced the investors' fund selection.

Overall, this doctoral thesis raises awareness in one of the most secretive financial industries in the world, hedge funds. It draws attention to the need for a diverse approach in analysing these pooled investment vehicles. The application of methods is one area where hedge funds exhibit various properties while manipulating data points and their formulation is another. This thesis has shown that even the approaches we take for granted (such as the mere performance persistence analysis) may provide surprising results where domicile and the investment strategy converge. Furthermore, the reader can learn that gender and ethnic imbalances do exist, even in hedge funds. However, the matter may be slightly more complex than just simple and oft-quoted discrimination.

The remainder of this thesis is structured in the following way: Chapter 2 focuses on the literature review and is divided into three sub-sections, each representing an individual topic discussed in later chapters. Chapter 3 focuses on parametric and non-parametric performance persistence concerning geolocation and strategy effects. Chapter 4 provides an insight into gender differences in hedge fund performance using twelve risk-adjusted performance metrics and two performance persistence methods. Chapter 5 examines whether the racial association based on the first name of the hedge fund manager can affect hedge fund investors' investment choices. Lastly, conclusions are presented in Chapter 6.

Chapter 2. Literature Review

2.1 Introduction

The following chapter delineates the literature review, which has been divided into three parts. Each part corresponds with the empirical chapters found in the later part of this PhD thesis. Thus, "On the underestimation of risk in hedge fund performance persistence: geolocation and investment strategy effects." refers to the first empirical chapter (Chapter 3); "Gender differences in hedge fund performance." is the second (Chapter 4); and "Hedge Fund Flows: Managers' Ethnicity." is the third and last empirical chapter (Chapter 5).

2.2 On the underestimation of risk in hedge fund performance persistence: geolocation and investment strategy effects.

2.2.1 Introduction

This section discusses the literature on the performance persistence of the Alternative Investment Funds (AIFs). In general, we show that the magnitude of performance persistence amongst AIFs exhibits a high degree of variation that is conditional on the country of domicile and investment strategy. We classify papers depending on whether the country of domicile is defined or undefined. To provide more clarity on the literature around the AIFs, the data has been dissected based on the results: short and long-term persistence.

2.2.2 Undefined Domiciles

The following sub-sections aggregate all studies which do not explicitly denote the domicile of the AIFs they have analysed. Since the domicile focus is unknown/undefined, it is assumed that the entire databases (pre/post-cleaning) were collated to reflect the AIF industry.

2.2.2.1 Short-Term Persistence

Ever since their inception, the research into the performance persistence of the AIFs has rarely explored their full potential. Researchers have mostly focused on either the aggregation of the global hedge fund universe under one umbrella and/or the division based on the investment strategy. The frequent omission or underestimation of the domicile factor has not provided a complete risk-accountability, much needed in the case of the AIFs. The modern performance persistence analysis of the AIFs began with the research of Park and Staum (1998). Their research was not only one of the first to focus on performance persistence but also controlled for the survivorship bias[2]. In their results, they have shown evidence of performance persistence at annual horizons (with substantial variations from year to year) within the aggregated universe of the AIFs pursuing the CTA strategy. In the following year, Brown et al. (1999) focused again, just like their predecessors, on the aggregated universe of AIFs, this time domiciled outside of the United States, identifying performance persistence in years 1991-1993, which reversed in the next two years. Their research was one of the first to depart from a commonly adopted aggregation of the all-in-one portfolio, focusing only on non-US funds.

For approximately the same period but with significantly larger sample size, Edwards and Caglayan (2001) identified persistence with both winning and losing AIFs at both annual and bi-annual horizons, which differs significantly by the investment style. They have also indicated that the performance persistence of the AIFs can be attributed to the exploitation of market inefficiencies, which can be attained due to a relative lack of regulatory oversight. Other researchers also pointed towards interesting factors influencing performance persistence. Thus, with Liang (1999), we can learn that the performance of AIFs can be enhanced by the incentivisation of the AIFMs. At the same time, Boyson (2003) shows that young-skilled AIFMs are the driving force behind quarterly performance persistence.

Bares, Gibson and Gyger (2003) show that Relative Value and Specialist Credit focused AIFs exhibit the strongest persistence amongst all six of the analysed strategies.

[2] Survivorship bias refers to one of the most frequent and momentous weaknesses in statistical data analysis. The omission of its existence can result in erroneous investment decisions, which derive from statistically distorted data. It can be specifically responsible for overstating active hedge funds/mutual funds' performance and in effect misleading investors. In the literature, survivorship bias is depicted in a two-dimensional spectrum: as a disparity in returns between live and defunct funds and/or the disparity between live & the aggregated universe (live + defunct) (e.g., Fung and Hsieh, 1997 Ackermann, McEnally and Ravenscraft 1999; Liang 2000; Malkiel and Saha, 2005).

Others, such as Amenc, Bied and Martellini (2003), identify 8 out of 9 analysed investment strategies exhibiting performance persistence (i.e., exceeding 0.5 baselines in the Hurst Index [HI]) with Managed Futures being the only strategy below 0.5 in the HI (0.465), i.e. a mere 0.025 below the baseline.

Brown and Goetzmann (2003) further show that the performance persistence of AIFs varies significantly across investment strategies. Another approach, which continuously focuses on the aggregation of the AIF universe, comes from Capocci and Hubner (2004), who identified persistence only for the mid-range (average return portfolio) AIFs.

This result was further confirmed by Capocci, Corhay and Hübner (2005). Moreover, the authors show that Global Macro and Market Neutral were able to consistently outperform market returns. The supportive study comes from Harri and Brorsen (2004) and also shows that Market Neutral and FoHFs exhibit the strongest (short-term) persistence with Event-Driven and Global/Macro (see also Agarwal and Naik (2000a), Hentati-Kafell and Peretti (2015) and Gonzalez, Papageorgiou and Skinner (2016)). Kosowski, Naik and Teo (2007) and Joenvaara, Kosowski and Tolonen (2012) further show that some investment strategies exhibit stronger persistence (on the annual horizon); Long-Short Equity, Directional Traders, Relative Value and FoHFs. Their cluster-size focused analysis shows that the small AIFs exhibited strong annual persistence, whereas large AIFs persistence is much weaker. Moreover, they have identified that persistence amongst AIFs is sensitive to fund-specific limitations, e.g., share restrictions or the AuM.

2.2.2.2 Long-Term Persistence

In relation to long-term performance persistence, Kouwenberg (2003) has identified persistence on a three-year horizon, noting that the selection of persistently performing AIFs has been suppressed by a large number of funds disappearing from the market (see also Jagannathan, Malakhov and Novikov (2010)). While Sun, Wang and Zheng (2012) demonstrated that AIFs exhibit strong persistence within five years of their inception. The other factors influencing the performance persistence were identified by Bae and Yi (2012), who have shown that AIFs with inflow/outflow restrictions exhibit superior (winning) performance over the other funds. Finally, Ammann, Huber and Schmid (2013) showed that AIFs' characteristics (AuM and leverage ratio) impact their long-term performance persistence. Their findings reaffirmed Kouwenberg's (2003) results, indicating (Alpha) performance persistence on the horizons of up to 36 months with statistically significant over six months and substantial (yet insignificant) during 24 months for all three analysed strategies: Equity Market Neutral, Global Macro and Emerging Markets.

2.2.3 Defined Domiciles

The following sub-section aggregate all studies, which denote the domicile of the AIFs they have analysed. It is worth noting that there are no studies with defined domiciles that investigate the long-term performance persistence of AIFs.

Agarwal and Naik (2000a) were one of the first proponents to analyse AIFs based on domicile. In their research, they have identified significant quarterly performance across all ten investment strategies, which successively diminished at bi-annual and annual levels. Their other research identified quarterly persistence attributable to continuously losing rather than winning AIFs (Agarwal and Naik, 2000b). Interestingly, they have underlined that analysing performance persistence amongst AIFs is far more critical than that of mutual funds due to its impact on their longevity (i.e. default rates). Chen and Passow (2003) continued to rely on the US-based AIFs market, showing that the AIFs with lower exposure to the factors identified by Agarwal and Naik (2000b) exhibited superior performance during both adverse and advantageous market conditions. Further work by Baquero, ter Horst and Verbeek (2005) also built on Agarwal and Naik's (2000b) research and found that performance analysis can be hampered by significant attritions in databases (mainly due to a fund's liquidations or the lack of continuous reporting to the database).

In the Asian and Australian AIFs universe, Koh et al. (2003) employed single and multi-period persistence analysis, identifying performance persistence at monthly and quarterly intervals.

The same result has been achieved by Henn and Meier (2004), who also identified significant persistence on the monthly and quarterly bases, which diminished towards the annual horizon. It is important to notice that despite describing and providing statistical descriptions of specific investment strategies, their non-parametric (contingency table) persistence analysis focused solely on the aggregated universe.

Steri et al. (2009) have also analysed the European environment, focusing on their analysis of the Italian AIFs, confirming monthly persistence but demonstrating that this persistence differs on quarterly and semi-annual horizons. On an important note, the peculiarity of the Italian AIFs industry is that 95% of AIFs are FoHFs. Further results also indicate that the Italian FoHFs exhibited lower performance when contrasted with traditional asset classes, i.e. stocks/bonds/commodities.

Another study (this time solely focused on the Australian market) by Do et al. (2010), has shown that the Australian AIFs exhibit short-term monthly persistence.

Overall, the review of the literature uncovers significant limitations in terms of geolocation focus. The majority of the aforementioned research focuses on either a globally aggregated approach, i.e., all AIFs under one umbrella usually divided based on the investment strategy, or the data clusters based on the fund-specific properties, such as the AuM, returns, flows.

2.3 Gender differences in hedge fund performance.

2.3.1 Introduction

The following section discussing the literature has been divided into two parts. The first part concerns gender related-aspects in the investment fund environment. At the same time, the second part focuses on the risk-adjusted metrics and the performance persistence application in HFs.

2.3.1.1 The Gender Environment

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 (university) settings, one type of completely overlooked fund is 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 for 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 for 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 a similar vein, Dwyer et al. (2002) analyse 2000 mutual fund investors, generally confirming the findings of their predecessors (for example, Jianakoplos and Bernasek, 1998) that women as investors are more risk-averse than men. Nevertheless, the research employs another complementary control, the 'investment knowledge' of both male and female investors. The results imply a highly statistically significant difference between both sexes, with males exhibiting a higher degree of investment expertise. Therefore, implying that the difference cannot be solely attributed to the 'risk preference' but instead to the specific 'investment knowledge'. Similarly, to test 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, which leads to the theory of overconfidence amongst males. Odean (1998) finds that overconfident individuals are prone to trade more than rational investors, which in turn impacts their expected utility. Barber and Odean (2001) further explore the idea through the acquisition of the data for 35 000 stock exchange investors over six years (1991-1997) and catalogue their activities by gender. Their analysis indicates that males trade 45% more often than females and reduce their annual net returns by 2.65 percentage points (pp), whereas females by a mere 1.72 pp. Interestingly, the study by Choi, Laibson, and Metrick (2002) into the trading behaviour of young male investors in two large 401(k) corporate plans leads to a similar conclusion. A further study into 401(k) by Agnew, Balduzzi, and Sundén (2003), resonates with Barber and Odean (2001) and confirms that men indeed invest not only more than women but also with higher frequency. Their findings show that males trade 55% more often than female investors and also confirm the results of Choi et al. (2002), showing that males invest a higher portion of their portfolios in equities. Moving across the ocean, the German environment has been proven to exhibit the same qualities (Dorn and Huberman, 2005). The gender profiles of the investors correlate with the aforementioned studies (focusing on the US market), i.e., young male investors trade more aggressively and with higher frequency than females. In a peculiar turn of events, the literature shows that the same pattern does not apply to 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. As a 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 a more frequent and greater degree of risk aversion than their male counterparts. At the same time, 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 et al. 2003)[3]. The only substantial difference crystalises 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 have been managing it since its inception or taken 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. The study of Babalos et al. (2015) 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 with the earlier research, one should expect higher risk aversion amongst female fund managers while 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 excessive trading (for example, Barber and Odean, 2001). Interestingly, most of the research into the fund's

[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).

performance with relation to the manager's gender proves that 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). In contrast, 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 are 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.

2.3.1.2 Risk-Adjusted Metrics and the Performance Persistence

The academic and organisational publications offer a wealth of assessment methods with regard to the performance and risk of various investment vehicles. As we have learnt from the publications mentioned in the previous section, the most common risk-adjusted metric used in the appraisal of investments rarely goes beyond the basic SR (Sharpe, 1966). The SR is an appropriate measure for the funds exhibiting a normal distribution (Chamberlain, 1983), which may be the case with mutual funds but is rarely the case with HFs (Fung and Hsieh, 1999; Gregoriou, Sedzro and Zhu, 2005). In consequence, the SR does not allow for the accountability of the effects of higher-order moments. Furthermore, the SR does not take into account a correlation between the fund and market index, where other measures such as Jensen Alpha would be more appropriate (Jensen, 1968, Dowd, 2000; Bodie, Kane and Marcus, 2005). The inherently asymmetrical distribution of HFs has also led other researchers to the development of new risk and performance metrics (Favre and Galeano, 2002; Gregoriou and Gueyie, 2003). Nevertheless, according to Pfingsten, Wagner and Wolferink (2004) and their analysis of lower partial moments and value at risk, the choice of a particular metric does not have a significant impact on the ranking of the investment. While Pfingsten, Wagner and Wolferink (2004) employ the bank's trading book data in their analysis, Pedersen and Rudholm-Alfvin (2003) used the alternative investment market data in their risk-adjusted metrics correlation testing (noting the correlations above 60% between various metrics).

The most comprehensive study examining twelve risk-adjusted ratios[4] came from Eling and Schuhmacher (2006). Interestingly, the authors have used HF indices in their analysis, proving that since all risk-adjusted metrics (including the ones accounting for the higher-order moments) are highly correlated (more than 90% in every case), the SR is perfectly capable of describing the tradeoff between performance and risk in HFs. To further explore this avenue, only one year later Eling and Schuhmacher (2007) released a more granular study, this time focusing on individual HFs as opposed to the indices. The findings yet again indicated high correlations between the analysed metrics supporting their theory. Thus, reinforcing their initial statement that the choice of the risk-adjusted ratios does not matter even in the event of asymmetrical distributions.

The risk-adjusted ratios provide an interesting and diversified (metric-wise) insight into the risk and performance of the investment funds. However, the majority of the extant HF performance-related literature is devoted to persistence studies. The concept of performance persistence studies is to examine whether the funds will continue to generate (either positive or negative) consistent returns in the foreseeable future. A significant number of publications focuses exclusively on two approaches: the first refers to the examination of HFs in the collective context by aggregating them in portfolios based on the investment strategy, while the second, which is infrequent, diverts towards the country of domicile and/or the investment strategy. Moreover, the persistence analysis usually addresses one or two time horizons[5] at a time. The span of the extant HF persistence related literature began in the late 1990s with the research of Park and Staum (1998). This was also the first study to focus exclusively on a particular investment strategy as well as the long-term (annual) only approach to performance persistence. On the contrary, the first known research to examine the performance persistence in HFs from the geographically limited perspective came from Brown, Goetzmann and Ibbotson (1999). The angle they adopted in their data analysis was to focus on the offshore US HFs. Similar to Park and

[4] Sharpe, Omega, Sortino, Kappa 3, Upside potential, Calmar, Sterling, Burke, Excess return on VaR, Conditional Sharpe and Modified Sharpe.

[5] Time horizon refers to the monthly, bi-monthly, quarterly, etc. approach to the organisation of HF returns

Staum (1998), they have also focused on the annual persistence analysis. In parallel, the other authors introduced diversity into the time horizon of performance persistence. Thus, with the research of Edwards and Caglayan (2001), we learn that HFs exhibit persistence on both fronts (winning and losing) during the annual and bi-annual horizons. Moreover, they have found that performance persistence significantly depends on the investment style. Another piece of research that considers more than two horizons comes from Baquero, ter Horst and Verbeek (2005) and identifies positive performance persistence on a quarterly and annual basis, while the opposite is true for the bi-annual horizon. It is worth mentioning that persistence is statistically significant only on the annual horizon. Naturally, the increase in the time horizon perspective allows for more insightful analysis and thus a more educated decision on the investor's part. For example, Ammann, Huber and Schmid's (2013) enrichment of the approach provides an insight into four-time horizons (6, 12, 24 and 36 months). Interestingly, the authors decide to focus on the long-term horizons and omit periods shorter than six months due to the existence of redemption periods. The findings reveal that the performance persistence crystalises in all periods up to 36 months. However, the statistically significant persistence occurs only on a six-monthly basis. Similarly, Jagannathan, Malakhov and Novikov (2010) also focus solely on the long-term persistence within a 36-month timeframe. While their approach builds upon Getmansky et al's model (2004), the result indicates the persistence is supported on the 36-month horizon if alphas from the analysed timeframe can explain alphas from the predicted timeframe. To a lesser extent, geolocation has also been investigated under various periodical constraints. Do, Faff and Veeraraghavan (2010) examined the persistence of HFs domiciled in Australia. While their analysis employs both non-parametric and parametric methods, it focuses only on the short-term, monthly persistence. The authors find weak short-term persistence amongst Australian HFs, which mostly intensifies in funds of HFs. In the European realm, Steri, Giorgino and Viviani (2009) focused on the Italian funds of HFs, confirming persistence across all analysed periods. Although, the statistically significant persistence was only observed in monthly and quarterly horizons – excluding six-monthly periods. Interestingly, as the authors point out, the Italian HF industry is 95% comprised of funds of HFs. Last but not least, in a more geo-focused attempt, Koh, Koh and Teo (2003) confirmed the persistence on a monthly and quarterly basis in HFs domiciled in Asia and Australia. They have also found that the persistence weakens beyond the quarterly horizon (in line with the findings of Brown et al. (1999).

2.3.2 Summary

In summary, we find that the modern fund (excluding HFs) related literature provides an extensive examination of gender differences, particularly focusing on performance and risk. At the same time, the same literature related to hedge funds is almost non-existent. Furthermore, as shown previously, the analysis of the risk-adjusted metrics in HFs indicates significant correlations with SR. This in turn implies that the SR perfectly describes the risk and performance of HFs. Nevertheless, this notion has been questioned in the mainstream HF-related research, which the incorporation of the higher-order moments. The risk-adjusted ratios provide diversified (metric-wise) insight into the risk and performance of the investment funds. Nevertheless, the majority of the HF performance related literature focus on the persistence of returns. While the persistence literature seems to be saturated, only a few studies are focusing on more than one or two time horizons (short, medium and long-term). Instead, the research is usually divided into clusters focusing on the aggregate of all HFs, investment strategies, specific domiciles, or a combination of all of these, neither of which considers the gender of the HF manager. Lastly, the persistence environment utilises various methods, where the most common ones are either non-parametric, parametric or the combination of both, although that is a very rare occurrence.

2.4 Hedge Fund Flows: Managers' Ethnicity.

2.4.1 Introduction

The following literature review consists of three parts. In the first instance, we provide the reader with an insight into the socio-psychological literature concerning race and ethnicity. This part serves as a fundament of the entire chapter, allowing the reader to ascertain the intricacies of human behaviour. In particular, we draw attention to the formulation and perception of the ethnic/racial identity and the association to a particular group (demographic bias). Further, in the second part, we discuss the general fund environment and in the third part, we focus on stereotypical investor behaviours related to the fund manager's *foreign name*, *gender* and *other* factors.

2.4.1.1 Socio-Psychological (including demographic biases)

Does the race or the ethnicity of a fund manager matter to the investor? Similar questions have been asked directly and indirectly several times in the extant literature (for example, in relation to gender or the *foreignness* of a manager's name) (Kumar et al., 2015). However, before we discuss these studies, let us first try and understand the greater environment concerning human behaviour beyond mere fund management. Many would agree with Kumar et al. (2015), that whether we like it or not, upon hearing the individual's name (whether it is a conscious or a subconscious process), we assign them a multitude of attributes, which are derived from their potential association to a particular country, ethnicity, religion and so forth. The predicted performance and individual quality are systematically associated with the first name's stereotypical perception, as a study of teachers' expectations shows (Harari and McDavid, 1973). Similarly, the educational and professional aspirations amongst adolescents significantly vary across ethnic and racial lines Kao (2000). Furthermore, these aspirations are defined based on the stereotypical images attached to particular ethnic groups and extend beyond into often segregated extracurricular activities. As Kunda (1999) identifies, the name stereotyping 'may' occur in a spontaneous, almost unconscious way. However, interestingly, Bertrand and Mullainathan (2004) find that despite equal qualifications, there is discrimination in the labour market. The individuals with "white-sounding" names receive fifty per cent more interest from potential employers. Similarly, King, Mendoza, Madera, Hebl and Knight (2006) uncover the significant effects of occupational stereotyping, which go as far as “discrimination”, specifically towards Black and Hispanic individuals. Their findings were also reported to be consistent with Shih's earlier work (2002), which has identified employers common ethnic and racial stereotyping (again most pronounced against Black and Hispanic individuals).

An objective observer may notice a continuous pattern of repetitive behaviour, which according to evolutionary psychologists, may occur due to humans being tribal species (Van Vugt and Park, 2009). For that, we need to acknowledge humans make impulsive in/out-group categorisations and have the tendency to favour ‘in’ rather than ‘out’ group associates (Tajfel and Turner, 1979). This type of social categorisation (or mere perception of association to a particular group) is sufficient to provoke intergroup competitiveness, bias and in the extreme forms discrimination as it has been proven in many studies; Doise, Csepeli, Dann, Gouge, Larsen and Ostell (1972) show that when the competitive interaction between groups is anticipated, the level of discrimination is stronger; Hatch and Schultz (2004) further show that the out-group perceptions are generally negative, while Zizzo (2011) finds that sharing a common fate with the in-group but not the out-group members' influences how the economic agents approach economic transactions (independent of strategic incentives).

As Jenkins (2014) argues, the primary human identification is his/her race and/or ethnicity. There is an ongoing debate as to whether the ethnicity is primordial (and therefore unchanging) or situational (and therefore floating) (Jenkins, 2008). Nevertheless, ethnic (including racial) identification is often considered an early dimension of self-identification, although not as early as gender. The learning process during which the individuals ascertain frameworks for classifying their (and others) racial and ethnic association usually occurs during childhood. If associated with emotion and affect, such classification may become significantly embedded in selfhood (Epstein, 1978). That in turn, leads adult individuals to readily identify themselves (regardless of the group size and the composition, which may often include unfamiliar subjects) with a particular in-group and to display their loyalty and association, often at a high personal cost (Zdaniuk and Levine, 2001; Van Vugt and Hart, 2004). These findings support and confirm the hypothesis posed by Charness, Rigotti and Rustichini (2007), which states that the individuals, by default, consider stipulations of the group membership as a guide in the social environment. Moreover, according to Hewstone, Rubin and Willis (2002), people tend to adopt favourable opinions about their in-group members while remaining indifferent or even disparaging in their perception towards the out-group. It is worth noting, as explained by Fehr and Gachter (2002), that in the in-group scenario, the individual member's selfishness and disloyalty, as well as defection, is severely punished. Thus, making it difficult for in-group members to change their perceptions and behaviour towards the out-group.

2.4.1.2 Fund Flows

There have been numerous studies investigating the determinants of fund flows. In most cases, the subjects of these publications are mutual funds, while the most common relationship is that between performance and capital flows. We see an example of this in the research of Sirri and Tufano (1998), who find that US mutual fund investors are mostly concerned with previous (yet most recent) highest returns (which in turn drives flows). A similar analysis is performed by Ferreira, Keswani, Miguel and Ramos (2012) regarding flows and past performance in mutual funds across 28 countries. Their findings reveal that due to the sophistication of the investors in more developed countries, their reactions to the top (bottom) performers are more restrained (pro-active) than in less developed countries. Further, the funds with higher flow-performance relationships take on more risk as the increased risk-taking may increase the likelihood of winning. As Berk and Green (2004) indicate, the relation between flows and past performance has implications for future fund performance persistence. Other researchers such as Ippolito (1992) or Gruber (1996), also confirm this kind of asymmetric performance-flow relationship where the high (low) performing funds receive large (small) inflows (outflows) of capital. As Röder and Walter (2019) find, the dependence between investment flows and past performance is also similar in the socially traded portfolios issued as structured products. Despite the common use of the performance-flow relationship, the literature also employs other classical fund characteristics such as age, volatility (Huang, Wei and Yan, 2007), fees (Greene, Hodges and Rakowski 2007), advertising and media mentions (Jain and Wu 2000; Solomon, Soltes, and Sosyura 2014), or even the association of the fund with large umbrella funds (Nanda, Wang, and Zheng, 2004). Interestingly, mutual fund name changes reflecting their investment style generate abnormal flows despite there being no changes in the fund's performance (Cooper, Gulen, and Rau, 2005)

In a more specified, sociocultural setting this time, Kumar et al. (2015) examines the stereotypes associated with the manager's name and whether or not it exhibits influence over the investor's perception. As the authors' note, the mutual fund setting with its widely available performance measures is a perfect environment for the identification and examination of social biases. Therefore, it should not come as a surprise (given our earlier socio-psychological literature insight) that the managers with a foreign-sounding name experience 10% per cent less annual capital inflows despite their overall funds' performance being on par with other funds, where the name of the fund manager is typically American (Kumar et al., 2015). Similar investor behaviour, which often lacks rational explanation, is more profoundly documented in gender studies concerning fund management. For instance, the analysis of performance and risk appetite in fixed-income funds show similarities between both genders (Atkinson, Baird and Frye, 2003). Nevertheless, the difference, as it was in the case of Kumar et al. (2015), also occurs at the fund flow level. The authors note that the net flows of capital into female managed funds are particularly low in the first year of their management - that is, regardless of whether the female becomes a manager at the inception of the fund or simply takes over from someone else. Interestingly, the case investigated by Niessen-Ruenzi and Ruenzi (2015) is even more profound as it finds female managers attract substantially lower capital inflows despite the adaptation of more reliable strategies and generation of the same returns as their male counterparts (Schmidt and Traub, 2002). Once again, the results do not support rational statistical discrimination (Phelps, 1972), but instead demonstrate an irrational prejudice towards female mutual fund managers (Becker, 1971). In both cases, the minorities, be it a mutual fund manager with a foreign-sounding name or a female manager, suffer from a direct and/or in-direct preconceived perception that is not based on reason or experience.

2.4.1.3 Socio-Psychological Fund Environment

Previously mentioned authors (e.g., Kunda 1999; Bertrand and Mullainathan, 2004) claim that prejudicial behaviour may occur in a spontaneous, almost unconscious way. However, that would contradict another of Kumar *et al's*. (2015) findings, which shows that before changes in the law governing the disclosure of individual names of fund managers, the fund management companies were more likely to allocate a manager with a foreign-sounding name to the team. The practice, combined with the favourable law, prevented the investors from knowing that the managers with foreign-sounding names were effectively managing their capital. Furthermore, speaking of teams, Patel and Sarkissian (2017) find that 'team (collective) management' has a positive (55 bps per year higher) impact on funds' performance as juxtaposed against single managed mutual funds. Thus, indirectly indicating that the presence of a manager with a potentially foreign-sounding name amongst other team members certainly is not detrimental to the fund's performance. In a combined context of ethnicity and gender (outside of fund management), both Honara (2002) and Swanson, Cunningham and Spencer (2003) acknowledge that males representing the ethnic minority are subject to more negative treatment as compared to females of the same ethnicity. This, in turn, suggests, like Jung, Kumar, Lim and Yoo (2019) note, that having an 'unfavourable' surname may be more damaging to male analysts. Their research concerning surname favourability also finds that the investors' judgement is biased as they constantly seek consistency between the analyst's surname perception and the quality of their forecast. This behaviour construct, where the individual (in their case the investor) endorses a favourable conclusion, is known in the cognitive science literature as motivated reasoning. Interestingly, Jung et al. (2019) note that the combination of the surname favourability and the foreignness (mentioned in Kumar's et al. (2015) work) elevates the market's response to forecast revisions. Thus, suggesting the in-group bias against the foreign-sounding name is very closely associated with the surname favourability.[6]

Focusing further on fund management, we learn that the investors are not only sensitive to a manager's name or gender but also, as Kostovetsky (2015) shows, to the general changes in fund management

[6] This brief socio-psychological review, regardless of the conclusions we may reach, should serve as a good indication of human behaviour (regarding collective associations and the perception of race/ethnicity) as it is not always driven by the individual but more than likely a collective in-group perception.

and/or ownership. Importantly, he also finds that the change in either ownership or management has no detrimental effect on the fund's performance. Nevertheless, the portion of investors (particularly those with a high expense ratio) seem to value the trust they have in the old management and thus are more likely to withdraw their capital. This behaviour has been already observed in other types of investments, such as retirement funds (Cohen, 2009). Once again, the authors observe the same in-group association or favouritism, which we have already seen in ethnic, racial, and gender-related studies. In a slight yet still relevant deviation from the personified (name/surname/gender) approach of the previous authors, Xing, Anderson and Hu (2016) have found that a ticker symbol also influences the investors. This 'name' likeability has been found to influence stock acquisitions significantly.

2.5 Conclusion

Summarising, this literature review has highlighted several gaps, which in turn inform the subsequent chapters. In the first instance, we learn that the granularity of studies concerning performance persistence of hedge funds rarely go beyond an examination of the collective database (all hedge funds in one portfolio and/or divided based on the investment strategy, or any other type of cluster). Only less than a handful of studies have focused on a domicile, be it the USA, Asia and/or Australia. The literature has never provided a direct contrast between the persistence crystallising in various domiciles, investment strategies and the combination of both. Thus, these findings become the primary motivators in the third chapter of this thesis: "On the underestimation of risk in hedge fund performance persistence: geolocation and investment strategy effects." The second part of the literature investigated the gender aspect, exclusively within the fund related environment. The general literature concerning gender is very rich, although one will almost immediately notice that when looking at funds in this context, there are only a handful of publications. Most of them focus on mutual funds with only one in/directly related publication in hedge funds. The hedge fund literature remains silent regarding performance persistence and performance (with accountability for the effects of the higher-order moments). Thus, being the main motivator for the development of the fourth chapter: "Gender differences in hedge fund performance." Lastly, the final part of the literature review has focused on a cross-disciplinary approach investigating socio-psychological connection to demographics and separately reviewing fund flow-related studies. This investigation indicated no studies are examining the perception of the ethnic/racial association of the hedge fund manager by the investor and whether it has an impact on the capital flows. Thus, motivating the last chapter of this thesis: "Hedge Fund Flows Managers' Ethnicity."

Chapter 3. On the underestimation of risk in hedge fund performance persistence: geolocation and investment strategy effects.

3.1 Introduction

The last three decades have seen a gradual but significant increase in interest in the AIFs. The extreme expansion of the industry has seen its value increase from approximately US$118.2bn in 1997 to US$3.55tn in November 2017 (Prequin, 2018). This chapter investigates the impact of geolocation and investment strategy effects on the estimation of risk in performance persistence measurement dynamics.[7]

An accurate appraisal of AIF performance must recognise that AIFs' risk exposure to investment styles is constantly shifting as managers are able to change the fund's focus. In that respect, risk management in AIFs is prone to systematic biases as exposure to risk factors is changing (see Bollen and Whaley, 2009). Further, AIFs' strategies expose investors to high correlation risk (see Buraschi et al., 2014). Since their inception in the 1950s, AIFs were always looked to for their astonishing performance (Bridgewater, Soros, and Citadel)[8] , which in turn has gradually elevated their reputation to 'the money-making machines' (Rittereiser and Kochard, 2010). The industry did not thrive without controversies, and more specifically, significant exposure to left-tail risk (see Agarwal and Naik, 2004) and defaults (Amaranth Advisors, LTCM, and Tiger Management)[9].

The literature related to the performance persistence of AIFs has grown exponentially in the last two decades. Nevertheless, despite its wide coverage of all the years from approximately the late 1977s until 2018, utilisation of all major databases and variety of methodologies, risk management with respect to the measurement of performance persistence remains largely unexplored. One of the areas where AIF

[7] This chapter has been published in Zopounidis, Benkraiem and Kalaitzoglou (2021)
[8] Bridgewater: (net gains) approx. $50bn since 75', Soros: approx. $42 (73'), Citadel: approx. $25bn (90')

[9] Amaranth Advisors losses = approx. $6.5bn, LTCM = approx. $4.6bn, Tiger Management = approx. $2bn

risk management is crucial is geolocation, as the majority of academic research focuses on one (or a combination of) of the following approaches in data analysis: The globally aggregated approach (all AIFs in one portfolio), the investment strategies (all AIFs aggregated in portfolios based on their primary investment strategy), or the data clusters (some of which are based on the fund-specific properties, e.g., low, medium or high return portfolios). The only studies that we have come across that disrupted the aforementioned pattern focused on the Asian and Australian (Koh, Koh and Teo, 2003), Italian (Steri, Giorginob and Vivianib, 2009) and solely Australian (Do, Faff & Veeraraghavan, 2010) AIF universes.

Therefore, in this chapter, we are going to assess the performance persistence of AIFs in the sphere of geolocation and identify whether the country of domicile and the investment strategy impact their risk dynamics. In particular, this chapter will answer the following questions. What is the performance persistence of hedge funds located in the world's most saturated domiciles, employing the most popular investment strategies, and whether the combination of domicile and the investment strategy changes the attractiveness of hedge funds? The focus on geolocation should not come as surprise, given different tax regimes and legal requirements in the most popular hedge fund havens. Moreover, we also focus on the importance of the most often employed investment strategies and their varying risk profiles. The additional side objective of this investigation is to contribute to the scarce literature concerning the previously noted non-US AIFs domiciles (Koh et al., 2003; Steri et al., 2009; Do et al., 2010).

To provide an adequate perspective for the analysis of performance persistence, we have employed both non-parametric contingency tables and parametric regressions. The analysed sample of AIFs in this study comes from the EurekaHedge database. The sample data aggregates 5619 AIFs (post-processing) and spans January 1995 to October 2016. Interestingly, the period covered in our analysis consists of two major economic events (the Russian financial crisis of 1998 (combined with the LTCM's collapse) and the sub-prime mortgage crisis of 2007), which may be of interest, particularly to the potential AIF investors. In our analysis, we have focused on the world's four most saturated domiciles (USA, CAYI, LUX and IRL) and the four most commonly employed strategies (LSE, CTA, FIX and MLTI).[10]

We have several findings to report. We show that metrics based on the individual domiciles and (separately) the investment strategies indicate the existence of short-term performance persistence. However, as we move to consider a combination of both domicile and the investment strategy, we can observe diminished persistence as well as its loss and reversal. Interestingly, one can draw a parallel between the geo-strategic combinations exhibiting high risk and the positive level of persistence. To provide greater depth into our analysis, we have further employed a two-step parametric regression method. In the first instance, we have computed the performance persistence on raw data without consideration for risks crystallising in the AIFs. The results reveal dominant and statistically significant negative performance persistence in portfolios such as IRL and the USA (a result previously unseen under the non-parametric approach). The same goes for the geo-strategic combinations and domiciles employing either the LSE or MLTI strategies. In the second instance, we have enhanced our parametric method to account for the risks materialising in the AIFs. The accountability for risk has completely changed the outcomes for some of the individual domiciles and the investment strategies, as they have all moved into a positive and statistically sig. territory (except for IRL). As to the cross combinations, we no longer observe any negative performance persistence across domiciles practising the LSE approach. A similar reversal and, in effect, a dominance of the positive β_p coefficients occur at the MLTI level.

The results of our analysis for both the non-parametric and parametric approaches uncovered differences in performance persistence between the general overview of the domicile, investment strategy and a combination of two. Furthermore, we prove that the sole reliance on either the general domicile or on the investment strategy level focused clusters can be grossly misleading and lead to undesirable consequences.

[10] Table 3.1 provides a list of abbreviations.

The definition of risk propagated by the participants in the AIFs industry very often varies. Therefore, the results of this study are specifically relevant to AIF investors. Primarily, the performance persistence of the AIFs is far more important than in mutual funds, as it has a bigger impact on the fund's survival (Agarwal and Naik, 2000a). Secondarily, the results of our study allow potential investors for more educated investment decisions. We clearly show that the sole reliance on either the general domicile or on the investment strategy level focused clusters can be grossly misleading and lead to undesirable consequences.

The rest of the chapter is organised in the following way: Section 3.2 analyses the database and provides descriptive statistics; Section 3.3 discusses the methodology, and Section 3.4 provides the interpretations of the results; Section 3.5 concludes. Lastly, the literature review has been explored in Chapter 2 (sub-section 2.1).

Insert Table 3.1

3.2 Data

3.2.1 Database

The AIF data used in this research comes from the EurekaHedge[11] database. EurekaHedge is the world's largest alternative investment data provider and consists of more than 28500 investment vehicles (as of January 2017), according to Capocci (2013). Additionally, EurekaHedge provides a much more comprehensive reflection of the contemporaneously reporting hedge funds universe than (for example) Lipper, HFR or MorningStar, as noted by Joenvaara et al. (2012). Currently, the largest AIFs data providers on the market are EurekaHedge, Lipper, HFR, Morningstar, Barclays Hedge, and CISDM (see Table 3.2). Thus, from the perspective of a single data source, this research utilises the dataset with the highest saturation of contemporaneously reporting AIFs in the world.

Insert Table 3.2

The research timeframe covers the period from January 1995 to October 2016. In order to minimise their tax liabilities, hedge funds have a tendency to domicile themselves in tax havens. Due to this, the majority of the hedge funds in the database are located in a few specific domiciles. After the examination of the database, we have determined that the only domiciles and strategies with the meaningful number of hedge funds are the United States, Cayman Islands, Luxembourg and Ireland. We have further limited our dataset by selecting the four most prominent investment strategies within each domicile: Long-Short-Equity (LSE), Fixed-Income (FIX), Commodity-Trading-Advisors (CTA), and Multi-Strategy (MLTI). This way, we have reduced the initial dataset from 16678 AIFs to 11197[12]. Further reductions occurred due to missing/not-disclosed observations in sections such as management and performance fees, assets under management (AuM) and lockup and redemption periods.

[11] For more detailed description, please visit www.eurekahedge.com

[12] The null hypothesis of the unit root is uniformly rejected. The results are available upon request.

Another important aspect of the data cleaning process is the potential existence of duplicate funds, previously identified by Aggarwal and Jorion (2010) and Bali, Brown and Caglayan (2011), whose analysis eliminated duplicate fund classes and all other funds of which correlation was either equal to or exceeded 0.99. Therefore, we investigated our database and removed all duplicate classes and all AIFs where the correlation was either equal to or greater than 0.99. For the robustness check, we have also analysed the data where the correlation threshold has been set at 0.95 and subsequently at 0.90. This operation (0.99), as well as the removal of all funds with a lifespan equal to or shorter than six months, limited our collective data set to 5619 AIFs across four domiciles (USA (United States of America) 2302, CAYI (Cayman Islands) 2034, LUX (Luxembourg) 853, IRL (Ireland) 430) or four investment strategies (CTA 1212, FIX 912, LSE 2928, MLTI 567) (Figure 1).

Insert Figure 1

3.2.2 Descriptive Statistics

In this section, we are looking at the descriptive statistics of the aforementioned domiciles and their associated investment strategies. Table 3.3 comprises the USA (Panel A) and CAYI (Panel B), LUX (Panel C) and IRL (Panel D). Furthermore, each domicile has been divided into four most commonly employed strategies (within the EurekaHedge database). The data gathered in this table aggregates 5619 AIFs. A significant proportion of the AIFs domiciled in the USA and CAYI can be classed as defunct as they did not report any returns in October 2016. The case of the other two domiciles is much less severe, nevertheless in almost all cases across IRL (except CTA) and LUX, more than 50% of the AIFs are classed as defunct. Furthermore, the negative skew of the returns dominates all domiciles and strategies apart from the CTA (all domiciles) and LSE (USA, CAYI and IRL) strategies. In addition, the kurtosis has exhibited non-normal properties across all domiciles and strategies. With regards to the average returns, the USA and its strategies dominate all other cases, with LUX and IRL generating the lowest returns.

Insert Table 3.3

3.3. Methods

In order to maximise the reach and the ability to provide in/direct contrast to previous literature concerning performance persistence, we rely on a dual-layered (non-risk and risk-adjusted) regression (parametric) approach as well as the “industry standard” contingency tables (non-parametric). The determination to employ these methods stems from their frequent use in hedge fund literature and thus the ability to in/directly compare the results of this chapter with the results presented by other authors. We undertook all our tests at monthly intervals for the timeframe between January 1995 and October 2016.

The parametric approach employs the XR (3.1) (Excess Returns) to identify performance persistence. Unlike Do et al. (2010), our XR calculation measures the XR of an individual AIF in contrast to the median (and not the average) return of all AIFs within the same domicile and strategy. The reason for this change lies within the predominantly skewed return distributions of the analysed AIFs (see Table 3.3). The XR approach is then further enhanced into AXR (3.2) to account for the risks associated with the AIFs investments. The AXR (Adjusted Excess Returns) measures the XR of an individual AIF in contrast to the median (and not the average) return of all AIFs within the same domicile and strategy. It is further divided by the residual standard deviation from a linear regression of the AIF’s return on median returns from AIFs within the same domicile and strategy.

$$XR_{it} = a_n D_n + a_p D_p + \beta_{i,n} D_n XR_{i,t-1} + \beta_{i,p} D_p XR_{i,t-1} + \varepsilon_{it} \tag{3.1}$$

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

$$AXR_{it} = a_n D_n + a_p D_p + \beta_{i,n} D_n AXR_{i,t-1} + \beta_{i,p} D_p AXR_{i,t-1} + \varepsilon_{it} \tag{3.2}$$

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

With regards to the dummies of D_n and D_p, they stand for negative (lose) and positive (win) returns. While the $\beta_{i,n}$ and $\beta_{i,p}$ identify the level of return autocorrelation of the AIFs amongst the negative and positive cases, respectively.[13]

The non-parametric method consists of widely utilised contingency tables (see Brown and Goetzmann 1995; Agarwal and Naik 2000a; Eling 2009, Do et al. 2010). The anchor value which serves as a performance benchmark is the median return of all funds across all four domiciles and specific investment strategies. Thus, the fund which exceeds (is below) the median return is considered a winner (loser) and denoted as WW (LL). Whereas the winner (in the first period) transforms into a loser (in the second period) as WL or LW if the opposite is true. This non-parametric measure uses three different metrics: cross-product ratio (CPR), Z-statistic (Z) and Chi-square (X^2). The CPR defines the odds ratio of the funds, which exhibit performance persistence as opposed to those that do not. Its fundamental null hypothesis is $CPR = 1$, implying no persistence (when WW=25%, LL=25%, WL=25%, LW=25%). Carpenter and Lynch (1999) conclude that the X^2 test based on the number of winners and losers is well specified, powerful and more robust to the presence of biases compared to other non-parametric methodologies. The CPR (3.3) can be denoted as:

$$CPR = \frac{(WWxLL)}{(WLxLW)} \tag{3.3}$$

The statistical significance of the CPR has been measured through the application of the standard error of the natural logarithm ($\alpha_{\ln(CPR)}$) what results in a Z-statistic, which is the ratio of $\alpha_{\ln(CPR)}$ to the standard error of the $\ln x \equiv log_e\, x$. Thus, in parallel to Z ~ N $(0,1^2)$ → Z, whenever the value of 1.96 or 2.58 (for 5% and 1% confidence interval respectively) is exceeded, significant performance persistence occurs. The Z-statistic (3.4) can be denoted as:

---

[13] E.g., the $\beta_{i,n}$ with a significant positive figure implies the existence of the autocorrelation or persistence of the negative (lose) cases. On the contrary, the $\beta_{i,p}$ implies the autocorrelation or persistence amongst positive (win) cases.

$$Z = \frac{\ln(CPR)}{a_{ln_{(CPR)}}} = \frac{\ln{(CPR)}}{\sqrt{\frac{1}{WW}+\frac{1}{WL}+\frac{1}{LW}+\frac{1}{LL}}} \quad (3.4)$$

The chi-square (X^2) compares the observed frequency distribution of all four denominations with the expected frequency distribution. Thus, if the value of X^2 for one d.f. exceeds 3.84 or 6.64 (for 5% and 1% confidence interval respectively), we can observe a significant performance persistence. The chi-square (3.5) can be denoted as (where n is the number of funds in a given period):

$$X^2 = \frac{\left(WW - (\frac{(WW+WL)(WW+LW)}{n})\right)^2}{\frac{(WW+WL)(WW+LW)}{n}} + \frac{\left(WL - (\frac{(WW+WL)(WL+LL)}{n})\right)^2}{\frac{(WW+WL)(WL+LL)}{n}} + \frac{\left(LW - (\frac{(LW+LL)(WW+LW)}{n})\right)^2}{\frac{(LW+LL)(WW+LW)}{n})} + \frac{\left(LL - (\frac{(LW+LL)(WL+LL)}{n})\right)^2}{\frac{(LW+LL)(WL+LL)}{n}} \quad (3.5)$$

Furthermore, we have computed the percentage of repeating winners (PRW) (3.6).

$$PRW = \frac{WW}{WW+WL} \quad (3.6)$$

Lastly, we also provide additional numbers concerning the winner (loser) gone WG (LG), which refers to the HFs, that are no longer reporting to the database (not necessarily defunct) (see Table 3.4). To complete the picture, the reverse is also provided. Thus, the new entrant winner (loser) is denoted as NEW (NEL) and refers to the fund, which has generated a higher (lower) return as contrasted with the median return of all funds in the same category in the first reported period.

3.4 Empirical Results

3.4.1 Parametric Methods

3.4.1.1 Non-Risk Adjusted

3.4.1.2 The Domicile and Investment Strategies

In this section, we analyse the results of a non-risk-adjusted parametric performance persistence test for the individual domiciles (Panel A) and investment strategies (Panel B) presented in Table 3.4. Panel A shows that the majority of the AIFs across LUX and CAYI dominate with positive $\beta_{i,p}$ and statistically sig. (at 5%) cases over the number of $\beta_{i,n}$ coefficients. The exception to this is the USA and IRL, where the number of positive and statistically sig. $\beta_{i,n}$ cases dominate $\beta_{i,p}$. Despite no signs in our non-parametric analysis, in this case, the USA and IRL exhibit negative performance persistence. In terms of the investment strategies (Panel B), the only approach where the $\beta_{i,n}$ cases dominate is MLTI – the difference between the significant cases is minimal and stands at 316/315 cases.

Insert Table 3.4

3.4.1.3 Domicile Combined with Investment Strategy

Continuing with our more in-depth perspective, we turn to Table 3.5, which aggregates the combination of domiciles and the investment strategies. Table 3.5, Panel A (LSE) shows that the number of funds exhibiting positive $\beta_{i,p}$ amongst those domiciled in the USA, stands at 792 out of 1159 with 654 sig. at 5% level, while for CAYI, it stands at 937 out of 1275 with 783 statistically sig. Concerning the other two domiciles, LUX exhibits positive $\beta_{i,p}$ at 197/276 with 178 sig. at 5% and IRL at 137/218 with 118 sig. at 5%. The contrarian, negative $\beta_{i,n}$ coefficient implies that 579 (USA), 730 (CAYI), 130 (LUX), and 120 (IRL) AIFs exhibit significant (at 5%) losing performance persistence. Again, the exception is the IRL domicile, which, when combined with the LSE strategy, continues to minimally exhibit dominant losing properties. Overall, the XR performance persistence method's application indicates some short-term persistence, specifically of a positive magnitude (except IRL).

Table 3.5, Panel B represents the second most populated investment strategy in our analysis, namely the CTA with 1212 total AIFs: USA (787), CAYI (262), LUX (106) and IRL (57). In this case, Panel B shows that the number of positive $\beta_{i,p}$ coefficients (sig. at 5%) dominates over the negative ones in all cases, which correlates with the results from Table 3.4 (Panel B). Furthermore, Panel C aggregates 912 AIFs employing the FIX strategy: USA (187), CAYI (230), LUX (371) and IRL (124). Panel C shows that the number of funds exhibiting positive (at 5%) $\beta_{i,p}$ ($\beta_{i,n}$) in the USA stands at 94 (88), LUX at 228 (189), while on the contrary, negative cases (losers) dominance can be seen in CAYI at 117 (129) and IRL at 61 (73).

Lastly, in Table 3.5, Panel D gathers the lowest number of the AIFs in our dataset, pursuing the MLTI strategy with the total number of 567 funds: USA (169), CAYI (267), LUX (100) and IRL (31). Focusing on panel D, we can observe that the number of positive $\beta_{i,p}$ ($\beta_{i,n}$) (at 5%) coefficients for the USA stands at 89 (97), IRL at 15 (17), while LUX at 64 (60) and CAYI 147 (142). Simultaneously, making CAYI the only domicile, which is capable of delivering positive performance persistence while employing the MLTI investment strategy.

Insert Table 3.5

3.4.2.1 Risk-Adjusted

3.4.2.1 The Domicile and Investment Strategies

Further to the previous non-risk-adjusted parametric approach, we provide here risk-adjusted analysis (AXR). In the domicile only scenario (Panel A of Table 3.6), the IRL is no longer dominated by the negative values and instead regains its positive dominance with 230 cases for $\beta_{i,p}$ (sig. at 5%) versus 197 for $\beta_{i,n}$. This reversal implies that the AIFs located in IRL regain their positive performance persistence after being adjusted for risk. Another peculiar case refers to the LUX domicile, which in this environment begins to underperform and generates 427 negative versus 417 positive cases.

In the realm of investment strategies only (Panel B of Table 3.6), there is no more dominance of negative persistence as was the case in the XR analysis (MLTI strategy). Despite the positive performance persistence, the number of statistically significant cases that exhibit persistence is much lower than in the non-risk-adjusted analysis (e.g., CTA down from 706 to 578, LUX 1733 to 1464, LSE 500 to 470 and MLTI 315 to 283).

Insert Table 3.6

3.4.2.2 Domicile Combined with Investment Strategy

In this sub-section, we provide the risk-adjusted (AXR) analysis of domiciles combined with the investment strategies. Table 3.7, Panel A indicates that all domiciles employing the LSE strategy exhibit performance persistence. In Table 3.7, Panel B (CTA), we can observe that the CTA strategy's persistence trend in LUX and CAYI reverses in the post-risk-adjustment case. Thus, the LUX is dominated by negative values in 56 ($\beta_{i,p}$) to 41 ($\beta_{i,n}$) and CAYI 123 to 129. The FIX strategy (Panel C) exhibits trend reversal in performance persistence when comparing non-risk-adjusted and risk-adjusted approaches. The domiciles CAYI and IRL where positive performance persists in XR reverses into negative territory in AXR. While the same reversal occurs in the USA and LUX, which no longer generate positive persistence in the post-risk-adjusted scenario. Lastly, Panel D shows that the MLTI strategy for LUX domiciled funds has been dominated by the AIFs exhibiting losing performance persistence.

Insert Table 3.7

In summary, from the autoregressive perspective, we have found performance persistence amongst all strategies. Furthermore, in certain instances, we have observed trend reversals between the XR and AXR parametric approaches. Our results vary and cannot unilaterally confirm Do et al. (2010) nor Agarwal and Naik's (2000b) outcomes, which held that the majority of the persistence is on the negative side. Lastly, the applicability of the risk-adjusted testing proves that the simple approach (excluding risk) of the XR can be misleading in assessing the performance persistence of the AIFs.

3.4.3 Non-Parametric Methods

The following sub-sections outline the results of the two approaches. The first individually examines domiciles and investment strategies, while the second deals with the combination of both. The results unequivocally confirm the existence of short-term performance persistence across all of the examined universes, regardless of whether it is the individual domicile/strategy or a combination. However, when we increase granularity and begin to focus on smaller clusters, we observe the equal number of persistent cases (WW versus LL) in the USA (CTA & FIX), CAYI_FIX and IRL (LSE & FIX) registered funds, as well as the loss and reversal of persistence in places such as LUX (all strategies) and IRL_MLTI.

3.4.3.1 Domiciles and Investment Strategies

Tables 3.8 and 3.9 present results of the non-parametric method with regards to the mean and total number of the AIFs exhibiting winning (WW) and losing (LL) cases of persistence (section 4.0). Tables 3.8 and 3.9 each consists of two panels that reflect the domicile (Panel A) and separately the strategy (Panel B) of the analysed AIFs. On the contrary, Tables 3.10 and 3.11 consist of 4 different panels (A: USA, B: CAYI, C: LUX and D: IRL) reflecting the domiciles combined with the investment strategies, which are directly associated with Tables 3.8 and 3.9 and provide the statistics for the non-parametric test. The timeframe for this data is January 1995 through to October 2016 (262 months) and aggregates 5619 AIFs.

Insert Table 3.8

The initial examination of Table 3.8 shows us that in all cases, regardless of whether we are considering the domicile or the investment strategy alone, the number of funds denoted as WW dominates all other instances (i.e., LL, WL or LW). Such an outcome implies positive performance persistence at the very start of our analysis; as such, we examine further the statistical results of the CPR, X^2, Z-statistics and the PRW.

The domicile focused analysis (Table 3.8, Panel A) indicates that the CPR and X^2 show statistical significance at 5% (1%) in 126 (112) and 181 (159) out of 262 months for the USA domiciled AIFs. The PRW is greater than 50% in 165 out of 262 cases (or 63%). The average (total) CPR of all USA based AIFs is 1.79 (1.30), rejecting the null hypothesis of no persistence in 196/262 cases. At the same time, the total (average) X^2 for the entire sample is 26.96 (1.64), which reaffirms that the AIFs domiciled in the USA exhibit short-term (monthly) performance persistence.

Similarly, the funds domiciled in the CAYI exhibit the CPR and X^2 in 123 (102) and 160 (135) out of 262 months, respectively. Their mean and total CPR stands at 1.95 and 1.49, implying performance persistence in 196 out of 262 months. The mean and total X^2 exceed the value of 1.96 for the sig. at 5%, further demonstrating persistence. The PRW, in this case, is much higher (than in the USA) and is equal to 195 (or 74%).

The number of months where LUX based AIFs exhibit significance at 5% (1%) for CPR and X^2 stands at 79 (66) and 127 (99). The mean (2.68) and total (1.27) CPR differ from the value of 1 and, as it can be seen with Z-stat (13.91), exhibit persistence.

Lastly, the CPR and X^2 of the IRL domiciled funds show statistical significance at 5% (1%) in 63 (39) and 109 (64) out of 262 months. With the mean (total) CPR of 3.27 (1.20) and the Z-stat of 7.59, they do exhibit performance but to a lesser magnitude than the other domiciles.

In Table 3.8, Panel B, we can observe the same number of AIFs (5619). However, this time they have been dissected based on their investment approach: LSE, CTA, FIX and MIRL. All strategies defy the null hypothesis of the CPR and report more than 190 out of 262 months (in every case), representing the existence of performance persistence. The total Z-stats is significant in all cases. Furthermore, as was the case with domiciles, every single type of strategy generates PRW >50%.

Insert Table 3.9

3.4.3.2 Domiciles Combined with Investment Strategy

The combination of domiciles and investment strategies allowed us to provide significantly greater granularity. The initial assessment of Table 3.10 already reveals that all LUX strategies and IRL_MLTI are dominated by losing (LL) cases of performance persistence. The panels A-D of Table 3.11 correspond to the following domiciles, each with four specific strategies (LSE, CTA, FIX and MLTI): the USA, CAYI, LUX and IRL. The total X^2 and Z-stats of all strategies in the USA (Panel A) is highly significant at 5%. Moreover, the percentage of repeating winners above 50% dominates across all strategies. The trends in CAYI (Panel B) are similar to the USA across all strategies except CTA. The CTA's total CPR stands at 1.07, which confirms the default null hypothesis of no persistence. While the total Z-stats stands at 2.31, which is approximately ten times lower than the other strategies (such as FIX and LSE) within this domicile. The Z-stat at 5% shows only 44 out of 262 months of persistence. Therefore, this particular strategy (CTA in CAYI) exhibits weak performance persistence.

Insert Table 3.10

In contrast to previously described domiciles, the results for the European ones, LUX (Panel C of Table 3.11) and IRL (Panel D), differ significantly. Immediately apparent are the LUX_CTA and IRL_CTA, which generate the total CPR that is in line with the null hypothesis of no persistence. Neither LUX nor IRL CTA strategy exhibits significance at 5% for either the Z-stat or the X^2. Therefore, they do not exhibit significant performance persistence. Moreover, the PRW in LUX is below the 50% threshold for both LSE and CTA strategies. Similarly, the IRL's CTA and FIX strategies are at PRW 40 and 42, respectively, with the remaining two at 53 (LSE) and 55 (MLTI) per cent.

Insert Table 3.11

We have evaluated performance persistence through the idea of comparing 'winning' and 'losing' alternative investment funds returns in each period over 262 months. Moreover, this comparison has been enhanced with statistical measures of the CPR, X^2 and Z-statistic at both 1 and 5 per cent significance. We have seen that the analysis based individually on either the domicile or the investment strategy of the AIFs does not provide a full overview of the risks lurking for potential investors. After expanding the scope of the analysis, we have shown that the individual strategies *combined* within domiciles such as IRL and LUX tend to underperform and do not maintain significant performance persistence.

3.5 Conclusion

The value of the AIF industry has increased from approximately US$118.2bn in 1997 to US$3.55tn in November 2017. Equally, there is a large increase in the number of studies focusing on the performance persistence of AIFs. However, to our knowledge, the area of risk management concerning the measurement of performance persistence remains largely unexplored. In this paper, we have analysed four of the world's most saturated AIFs domiciles and four of the most commonly employed investment strategies for the period between January 1995 and October 2016. We employ parametric and non-parametric analysis. Our objective was to investigate the impact of geolocation and investment strategy effects on the estimation of risk in performance persistence measurement dynamics. More specifically, we have posed to answer what is the performance persistence of hedge funds located in the world's most saturated domiciles such as the USA (USA), Cayman Islands (CAYI), Luxembourg (LUX) and Ireland (IRL), employing the most popular investment strategies such as Long-Short-Equity (LSE), Fixed-Income (FIX), Commodity-Trading-Advisors (CTA), and Multi-Strategy (MLTI). Furthermore, we have also focused on whether the combination of domicile and the investment strategy changes the attractiveness of hedge funds. Our focus on geolocation underlines the importance of different tax regimes and legal requirements guarding the most popular hedge fund havens. Furthermore, we also explored the risk and returns of the most popular investment strategies and their varying risk profiles.

The results of the non-parametric approach unequivocally confirm the existence of short-term performance persistence across all the examined combinations. However, despite most of them representing potentially attractive investments, we show that some domicile/strategy combinations are quite the opposite. For instance, the number of winner/loser cases is equal across USA_CTA, USA_FIX, CAYI_FIX, IRL_LSE and IRL_FIX. Interestingly, we find negative performance persistence across all strategies in the LUX domicile and MLTI in IRL.

The results of the non-risk-adjusted parametric performance persistence test for the individual domiciles shows that the majority of funds domiciled in LUX and CAYI dominate with positive $\beta_{i,p}$ and statistically significant cases. On the contrary, the USA and IRL are dominated with statistically sig yet (negative) $\beta_{i,n}$ cases - this result has not been discovered by the industry-standard contingency tables analysis. Regarding the investment strategies, the only approach where the $\beta_{i,n}$ cases dominate is the MLTI – although the difference between the significant cases is minimal and stands at 316/315 cases.

The contrasts between domiciles, investment strategies and the combination of both undertaken in this chapter have not been addressed previously in the hedge fund related literature. Thus, providing a new and more insightful view into one of the most secretive financial vehicles known to man. Furthermore, we show that the results between non-parametric, parametric (risk and non-risk adjusted) metrics can lead to erroneous investment decisions and the potential loss of the investment capital. Moreover, the same happens when we look at domicile or/and the investment strategies in isolation. The results of this study are primarily relevant to hedge fund investors and researchers. We clearly show that the sole reliance on either the general domicile or on the investment strategy level focused clusters can be grossly misleading and lead to undesirable consequences.

Tables

Table 3.1 Abbreviations	
Abbreviation	**Explanation**
AIF/s	Alternative Investment Fund/s
AIFM/s	Alternative Investment Fund Manager/s
AuM	Assets under Management
CTA	Commodity Trading Advisors are primarily AIFs trading futures contracts
FIX	Fixed-Income
FOHFs	Funds of Hedge Funds
HFR	Hedge Fund Research
LSE	Long-Short-Equity
MLTI	Multi-Strategy

Table 3.2 World's primary AIFs databases		
Database	**# of live AIFs**	**# of defunct AIFs**
EurekaHedge	9 722	12 138
Lipper	7 500	11 000
HFR	7 200	16 000
MorningStar	7 000	12 000
Barclays Hedge	6 366	17 965
CISDM	5 000	11 000
Note: The figures refer to the total number of contemporaneously reporting AIFs (as of January 2017).		

Table 3.3: Descriptive Statistics

Panel A																
United States	**CTA [Obs.787]**				**FIX [Obs.187]**				**LSE [Obs.1159]**				**MLTI [Obs.169]**			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max		S.D.	Min	Max	Mean	S.D.	Min	Max
Dead/Alive	0.70	0.46	0.00	1.00	0.63	0.49	0.00	1.00	0.72	0.45	0.00	1.00	0.75	0.43	0.00	1.00
Negative Skew %	0.40	0.49	0.00	1.00	0.52	0.50	0.00	1.00	0.49	0.50	0.00	1.00	0.57	0.50	0.00	1.00
Skewness	0.18	1.23	-5.86	5.63	-0.14	1.76	-7.98	6.26	0.06	0.98	-4.40	6.42	-0.26	1.39	-6.35	5.28
Kurtosis	3.30	5.32	-1.64	48.70	5.92	9.00	-0.97	69.61	2.69	4.54	-1.52	72.08	4.79	6.62	-1.15	52.90
Std. Dev. of r	5.33	4.71	0.29	73.90	1.98	1.57	0.07	12.06	4.39	4.18	0.36	107.54	3.37	2.69	0.31	19.67
AVG r	0.77	1.29	-3.47	15.01	0.73	0.60	-1.26	5.62	0.74	1.58	-46.22	5.17	0.70	0.66	-2.69	3.38
Age [yrs]	7.02	5.23	1.10	21.90	6.35	4.30	1.20	21.90	7.34	5.01	1.10	21.90	7.74	5.31	1.30	21.90
AVG AuM	35.86	132.65	0.10	2203.50	338.78	2208.07	0.10	29776.90	75.54	355.35	0.10	9437.80	212.81	561.79	0.20	5843.00
MED AuM	29.52	114.50	0.00	1788.00	336.81	2218.79	0.00	29903.00	64.36	285.23	0.00	7710.00	190.22	506.22	0.00	5262.00
Panel B																
Cayman Islands	**CTA [Obs.262]**				**FIX [Obs.230]**				**LSE [Obs.1275]**				**MLTI [Obs.267]**			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Dead/Alive	0.73	0.45	0	1	0.65	0.48	0.00	1.00	0.76	0.42	0.00	1.00	0.78	0.42	0.00	1.00
Negative Skew %	0.41	0.50	0	1	0.60	0.49	0.00	1.00	0.56	0.50	0.00	1.00	0.52	0.50	0.00	1.00
Skewness	0.13	1.00	-5.90	4.753	-0.44	2.00	-8.15	6.93	-0.01	0.94	-3.50	6.73	-0.08	1.51	-7.27	6.81
Kurtosis	2.14	4.25	-1.40	37.557	7.73	11.98	-0.93	86.99	2.47	4.19	-1.20	70.36	4.63	8.19	-1.20	72.80
Std. Dev. of r	4.45	3.09	0.67	22.3	2.84	5.26	0.04	73.32	4.02	2.84	0.40	36.09	3.94	4.09	0.44	47.95
AVG r	0.44	1.22	-3.99	9.319	0.62	1.24	-3.97	14.71	0.53	0.83	-9.35	7.15	0.48	0.93	-3.54	5.60
Age [yrs]	6.54	4.67	1.2	21.9	5.95	3.87	1.20	19.40	6.35	4.08	1.20	21.90	6.43	4.12	1.20	19.70
AVG AuM	113	553.46	0.5	7734.4	165.91	252.11	0.30	1821.20	95.40	178.58	0.10	2127.50	204.32	456.28	0.30	3870.60
MED AuM	102.1	521.35	0	7659	159.28	260.76	0.00	1863.00	84.31	166.83	0.00	2024.00	176.78	400.11	0.00	3471.00
Panel C																
Luxembourg	**CTA [Obs.106]**				**FIX [Obs.371]**				**LSE [Obs.276]**				**MLTI [Obs.100]**			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Dead/Alive	0.58	0.50	0.00	1.00	0.26	0.44	0.00	1.00	0.46	0.50	0.00	1.00	0.50	0.50	0.00	1.00
Negative Skew %	0.48	0.50	0.00	1.00	0.69	0.46	0.00	1.00	0.63	0.48	0.00	1.00	0.73	0.45	0.00	1.00
Skewness	0.01	0.68	-1.57	4.82	-0.44	0.99	-4.39	3.42	-0.20	0.92	-8.97	3.96	-0.35	0.88	-4.64	2.81
Kurtosis	1.09	3.92	-0.92	37.90	2.77	4.28	-0.90	35.15	1.86	6.22	-1.08	92.48	1.82	4.49	-1.14	29.62
Std. Dev.	3.83	2.37	0.56	11.94	1.30	0.83	0.03	5.66	2.79	1.87	0.62	11.45	1.67	1.49	0.26	11.66
AVG r	-0.08	0.62	-2.84	1.62	0.15	0.35	-0.66	3.40	0.26	0.54	-1.91	2.55	0.12	0.26	-0.85	1.02
Age [yrs]	5.54	4.14	1.10	21.90	5.91	3.85	1.20	22.70	4.75	2.88	1.10	16.30	4.68	2.41	1.10	16.80
AVG AuM	104.83	201.97	1.00	1454.70	1138.01	2000.87	1.00	8770.60	201.14	292.38	1.00	1696.80	1006.92	2686.33	1.00	16200.90
MED AuM	93.91	172.58	0.00	1414.00	1137.01	1999.38	1.00	8806.50	168.17	246.94	1.00	2048.50	987.94	2660.18	1.00	16018.00
Panel D																
Ireland	**CTA [Obs.57]**				**FIX [Obs.124]**				**LSE [Obs.218]**				**MLTI [Obs.31]**			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Dead/Alive	0.42	0.50	0.00	1.00	0.73	0.45	0.00	1.00	0.53	0.50	0.00	1.00	0.52	0.51	0.00	1.00
Negative Skew %	0.40	0.49	0.00	1.00	0.66	0.48	0.00	1.00	0.63	0.48	0.00	1.00	0.71	0.46	0.00	1.00
Skewness	0.20	0.99	-2.28	4.02	-0.29	0.77	-2.67	2.97	-0.17	0.93	-3.61	6.57	-0.31	0.69	-2.06	1.32
Kurtosis	1.67	3.86	-1.09	21.54	2.13	3.84	-0.65	27.19	2.00	5.00	-1.11	58.17	1.18	1.76	-0.83	7.36
Std. Dev. of r	3.24	1.51	0.74	6.45	1.54	0.91	0.03	4.70	3.17	2.09	0.44	17.66	2.02	1.82	0.30	8.64
AVG r	0.24	0.54	-1.23	1.68	0.28	0.34	-0.80	2.57	0.29	0.52	-2.12	1.49	0.01	0.49	-1.64	1.05
Age [yrs]	5.22	4.61	1.10	20.60	4.95	2.55	1.20	13.50	5.23	3.75	1.10	21.90	3.40	2.79	1.20	13.10
AVG AuM	90.81	141.88	1.00	832.46	455.24	675.74	1.00	3122.68	152.77	315.38	1.00	3728.08	166.26	290.07	1.00	1587.41
MED AuM	75.92	127.69	0.00	826.00	446.48	662.16	0.00	3340.00	145.50	314.94	0.00	3623.00	154.90	282.49	0.00	1563.00

Note: The Dead/Alive: denotes the percentage of AIFs, which have not reported any results in Oct 2016. The Negative Skew %: percentage of AIFs with negative skewness. Skewness and Kurtosis: the average skew/kurt value for a given strategy. Std. Dev. of r: standard deviation of the returns. The AVG r: average returns. The Age [yrs]: the average age of AIFs for a given strategy. While the AVG and MED AuM: average and median assets under management in $US millions.

Table 3.4. Parametric Performance Persistence [non-risk-adjusted [XR]]: Domicile/Investment Strategy

Panel A

XRDomicile	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**CAYI**	**LUX**	**IRL**
Mean	-2.228	-1.616	-1.923	-1.823	3.520	1.500	2.978	2.090	0.079	0.273	0.191	0.250	0.176	0.299	0.223	0.153	0.474	0.439	0.401	0.413
Sigma	2.637	1.659	2.121	1.572	3.335	1.508	2.646	1.587	1.297	0.961	0.455	0.653	0.444	0.588	0.454	0.673	0.155	0.163	0.200	0.215
Max	29.432	5.794	4.385	3.131	59.368	9.708	47.553	8.358	3.695	11.786	6.634	4.827	3.806	2.612	4.313	5.391	0.996	0.996	0.985	0.962
Min	-27.820	-10.925	-18.056	-11.405	-17.032	-2.404	-5.586	-2.927	-50.693	-9.922	-2.078	-5.449	-8.119	-2.704	-3.232	-2.763	-0.502	-1.097	-0.719	-0.776
Positive	168	51	190	18	2280	811	2015	405	1378	563	1387	294	1599	619	1484	268				
Sig @ 0.05									1183	440	1156	240	1284	537	1204	229				
Negative	2134	802	1844	412	22	42	19	25	924	290	647	136	703	234	550	162				
Sig @ 0.05									858	269	603	124	681	225	534	156				

Panel B

XRInvStra	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	CTA	**FIX**	**LSE**	**MLTI**	**CTA**	**FIX**	**LSE**	**MLTI**	**CTA**	**FIX**	**LSE**	**MLTI**	**CTA**	**FIX**	**LSE**	**MLTI**	**CTA**	**LSE**	**FIX**	**MLTI**
Mean	-2.702	-2.134	-0.895	-1.523	3.902	3.074	1.312	2.492	0.118	0.145	0.271	0.169	0.201	0.185	0.312	0.193	0.471	0.430	0.445	0.418
Sigma	2.925	2.014	1.746	1.844	3.849	2.237	2.158	3.018	1.521	0.460	1.344	0.608	0.480	0.444	0.624	0.514	0.163	0.204	0.161	0.189
Max	28.085	4.385	29.432	5.794	59.368	26.817	47.553	39.250	3.695	6.634	11.786	2.750	3.796	5.391	4.554	3.063	0.992	0.996	0.959	0.961
Min	-27.820	-22.413	-16.007	-14.149	-17.032	-5.586	-2.927	-2.109	-50.693	-9.922	-30.356	-6.445	-8.119	-3.088	-2.704	-3.232	-0.324	-0.336	-0.776	-1.097
Positive	47	172	142	66	1198	2901	864	548	780	1840	630	372	853	2063	663	391				
Sig @ 0.05									665	1559	479	316	706	1733	500	315				
Negative	1165	2756	770	501	14	27	48	19	432	1088	282	195	359	865	249	176				
Sig @ 0.05									402	1019	256	177	342	840	242	172				

Note: This table provides the parametric (XR) test results for a collective sample of 5619 AIFs from January 1995 to October 2016 [monthly intervals]. The first two 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 n) implies the auto-correlation or persistence amongst positive (winning) cases, the last column provides the adjusted r-squared figures.

Table 3.5: Parametric Performance Persistence [non-risk-adjusted [XR]]: Domicile Combined with the Investment Strategy

Panel A

XRLSE	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**CAYI**	**LUX**	**IRL**
Mean	-2.230	-2.237	-1.993	-2.317	3.412	2.153	3.032	2.683	0.101	0.052	0.196	0.200	0.141	0.226	0.229	0.112	0.4663	0.4243	0.4547	0.4451
Sigma	2.106	1.722	2.030	1.678	2.380	1.636	2.246	1.536	0.352	0.755	0.439	0.537	0.385	0.395	0.461	0.623	0.1459	0.1497	0.1989	0.2217
Max	3.830	0.175	4.385	0.461	25.387	9.708	26.817	8.358	3.003	1.867	6.634	4.827	3.806	1.568	4.313	5.391	0.9592	0.9207	0.9159	0.9135
Min	-22.413	-9.583	-18.056	-11.405	-2.584	-0.988	-5.586	-0.135	-1.763	-9.922	-1.359	-0.974	-3.088	-0.846	-2.191	-2.763	-0.5019	-0.3477	-0.7193	-0.7762
Positive	60	3	103	6	1152	273	1260	216	675	149	870	146	792	197	937	137				
Sig @ 0.05									579	130	730	120	654	178	783	118				
Negative	1099	273	1172	212	7	3	15	2	484	127	405	72	367	79	338	81				
Sig @ 0.05									450	115	387	67	358	77	329	76				

Panel B

XRCTA	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**CAYI**	**LUX**	**IRL**
Mean	-2.824	-2.556	-2.589	-1.805	4.353	2.563	3.474	2.122	0.055	0.328	0.204	0.201	0.171	0.357	0.206	0.296	0.4885	0.4616	0.4051	0.3998
Sigma	3.205	2.267	2.448	1.364	4.359	2.107	2.635	1.512	1.856	0.535	0.377	0.517	0.499	0.572	0.372	0.399	0.1497	0.1613	0.2040	0.1979
Max	28.085	0.385	4.368	0.251	59.368	9.692	15.960	5.425	3.695	1.780	1.642	1.848	3.796	2.523	1.687	1.140	0.992	0.9741	0.8993	0.9616
Min	-27.820	-10.925	-17.694	-6.836	-17.032	-2.404	0.040	-2.281	-50.693	-1.511	-0.858	-1.208	-8.119	-0.694	-0.980	-0.536	-0.3235	-0.1266	-0.2523	-0.1783
Positive	25	7	11	4	780	102	262	54	485	81	178	36	542	80	187	44				
Sig @ 0.05									419	61	155	30	447	67	157	35				
Negative	762	99	251	53	7	4	0	3	302	25	84	21	245	26	75	13				
Sig @ 0.05									279	24	80	19	233	25	71	13				

Panel C

XRFIX	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**CAYI**	**LUX**	**IRL**
Mean	-0.485	-0.983	-1.006	-1.042	1.390	0.829	2.073	1.228	0.007	0.438	0.217	0.269	0.379	0.345	0.275	0.181	0.5036	0.4940	0.3718	0.3767
Sigma	2.539	1.050	2.107	0.916	1.540	0.737	3.734	1.178	2.296	1.118	0.613	0.837	0.482	0.688	0.470	0.813	0.2130	0.1917	0.1927	0.1696
Max	29.432	3.720	1.397	3.131	13.919	4.268	47.553	6.311	2.248	11.786	4.381	2.077	2.282	2.612	1.962	4.554	0.9964	0.9961	0.9845	0.816
Min	-9.374	-5.487	-16.007	-3.962	-0.906	-0.701	-1.053	-2.927	-30.356	-3.965	-1.390	-5.449	-1.081	-2.704	-1.728	-2.168	0.0364	0.0281	-0.3359	-0.2714
Positive	56	37	44	5	183	343	227	111	111	266	166	87	151	272	170	70				
Sig @ 0.05									88	189	129	73	94	228	117	61				
Negative	131	334	186	119	4	28	3	13	76	105	64	37	36	99	60	54				
Sig @ 0.05									71	99	53	33	36	93	60	53				

Panel D

XRMTLI	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**CAYI**	**LUX**	**IRL**
Mean	-1.371	-1.253	-1.722	-1.508	2.731	1.063	3.013	1.314	0.120	0.212	0.132	0.618	0.215	0.265	0.166	0.072	0.4885	0.4616	0.4051	0.3998
Sigma	1.895	1.459	1.916	1.859	3.545	1.030	3.077	1.599	0.405	1.054	0.435	0.651	0.445	0.621	0.471	0.743	0.1497	0.1613	0.2040	0.1979
Max	1.966	5.794	0.723	0.897	39.250	5.000	33.105	7.424	2.117	2.750	2.232	1.834	3.063	1.749	2.284	2.952	0.939	0.9223	0.8825	0.9612
Min	-14.149	-7.224	-11.945	-8.067	-2.109	-1.960	-0.178	-1.112	-1.382	-6.445	-2.078	-0.626	-1.166	-2.686	-3.232	-1.227	0.0762	-1.0972	-0.2233	-0.2513
Positive	27	4	32	3	165	93	266	24	107	67	173	25	114	70	190	17				
Sig @ 0.05									97	60	142	17	89	64	147	15				
Negative	142	96	235	28	4	7	1	7	62	33	94	6	55	30	77	14				
Sig @ 0.05									58	31	83	5	54	30	74	14				

Note: This table provides the parametric (XR) test results for a collective sample of 5619 AIFs from January 1995 to October 2016 [monthly intervals]. The first two 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 n) implies the auto-correlation or persistence amongst positive (winning) cases, the last column provides the adjusted r-squared figures.

Table 3.6: Parametric Performance Persistence [risk-adjusted [AXR]]: Domicile/Investment Strategy

Panel A

AXRDomicile	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**LUX**	**CAYI**	**IRL**	**USA**	**CAYI**	**LUX**	**IRL**
Mean	-2.328	-1.654	-1.916	-1.819	3.691	3.027	3.097	2.252	0.006	0.015	0.007	0.037	0.008	8.532	-0.006	0.056	0.456	0.415	0.365	0.387
Sigma	2.478	1.577	2.319	1.539	4.266	45.113	2.658	2.175	0.451	0.321	0.405	0.929	0.829	249.296	0.369	0.606	0.169	0.178	0.218	0.226
Max	7.325	3.184	35.118	1.617	132.712	1317.945	51.408	30.967	7.586	4.587	13.641	18.300	27.972	7285.249	3.173	9.722	0.995	0.999	0.981	0.884
Min	-32.997	-9.999	-28.547	-9.176	-6.409	-48.429	-4.704	-5.236	-8.467	-3.180	-3.004	-2.741	-22.605	-4.105	-9.992	-1.638	-1.139	-0.910	-1.032	-0.934
Positive	191	60	205	26	2295	832	2018	413	1172	450	1034	205	1217	441	1060	238				
Sig @ 0.05									1114	427	980	197	1145	417	1003	230				
Negative	2111	793	1829	404	7	21	16	17	1130	403	1000	225	1085	412	974	192				
Sig @ 0.05									1084	378	969	210	1029	395	922	183				

Panel B

AXRInvStra	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	CTA	**FIX**	**LSE**	**MLTI**	**CTA**	**FIX**	**LSE**	**MLTI**	**CTA**	**FIX**	**LSE**	**MLTI**	**CTA**	**FIX**	**LSE**	**MLTI**	**CTA**	**LSE**	**FIX**	**MLTI**
Mean	-2.820	-2.149	-0.929	-1.572	4.111	3.187	1.408	4.845	0.008	0.010	0.010	0.017	-0.024	0.014	-0.007	12.879	0.454	0.386	0.425	0.394
Sigma	2.675	2.167	1.516	1.897	5.418	2.297	2.899	55.255	0.709	0.406	0.376	0.272	0.783	0.349	0.241	305.683	0.176	0.220	0.179	0.190
Max	1.296	35.118	7.325	2.022	132.712	30.967	51.408	1317.945	18.300	13.641	4.587	3.197	3.254	9.722	2.542	7285.249	0.979	0.999	0.989	0.942
Min	-32.997	-23.006	-28.547	-15.357	-1.856	-5.236	-48.429	-6.409	-5.316	-4.511	-8.467	-2.741	-22.605	-2.968	-4.105	-9.992	-0.856	-0.480	-1.139	-1.032
Positive	46	186	174	76	1200	2905	897	556	597	1496	480	288	619	1543	495	299				
Sig @ 0.05									568	1419	456	275	578	1464	470	283				
Negative	1166	2742	738	491	12	23	15	11	615	1432	432	279	593	1385	417	268				
Sig @ 0.05									593	1378	402	268	555	1326	399	249				

Note: This table provides the parametric (AXR) test results for a collective sample of 5619 AIFs from January 1995 to October 2016 [monthly intervals]. The first two 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 n) implies the auto-correlation or persistence amongst positive (winning) cases, the last column provides the adjusted r-squared figures.

Table 3.7: Parametric Performance Persistence [risk-adjusted [AXR]]: Domicile Combined with the Investment Strategy

Panel A

AXRLSE	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL
Mean	-2.289	-2.251	-1.979	-2.270	3.517	2.233	3.150	2.859	0.013	0.021	0.008	-0.015	0.010	-0.004	0.000	0.131	0.4480	0.4009	0.4329	0.4361
Sigma	2.184	1.724	2.307	1.595	2.345	1.672	2.244	2.606	0.339	0.332	0.482	0.319	0.246	0.300	0.295	0.819	0.1648	0.1720	0.2100	0.2262
Max	2.480	3.184	35.118	0.599	24.691	9.893	28.275	30.967	4.585	1.377	13.641	2.052	2.152	2.814	3.173	9.722	0.9757	0.9893	0.8102	0.8476
Min	-23.006	-9.811	-14.825	-9.176	-0.492	-0.163	-4.704	-5.236	-4.511	-3.026	-3.004	-2.240	-2.968	-2.595	-2.418	-1.385	-1.1393	-0.9098	-0.67	-0.9338
Positive	71	3	105	7	1156	275	1262	212	606	138	653	99	610	154	660	119				
Sig @ 0.05									576	132	615	96	582	148	622	112				
Negative	1088	273	1170	211	3	1	13	6	553	138	622	119	549	122	615	99				
Sig @ 0.05									530	130	606	112	528	115	586	97				

Panel B

AXRCTA	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	CAYI	LUX	IRL
Mean	-3.004	-2.514	-2.596	-1.878	4.642	2.627	3.483	2.420	-0.003	-0.037	-0.015	0.344	-0.031	-0.027	-0.013	0.021	0.4778	0.433	0.3762	0.3588
Sigma	2.871	2.166	2.358	1.522	6.435	2.107	2.523	1.498	0.544	0.409	0.280	2.408	0.955	0.231	0.243	0.289	0.1598	0.1824	0.2015	0.2200
Max	1.296	0.739	1.015	0.249	132.712	9.926	17.438	6.104	7.586	0.543	1.913	18.300	3.254	0.671	0.930	0.837	0.979	0.9099	0.8594	0.7965
Min	-32.997	-9.999	-19.167	-8.246	-1.856	-0.925	-0.380	-0.178	-5.316	-3.180	-1.675	-0.819	-22.605	-1.052	-1.911	-1.638	-0.856	-0.3238	-0.3438	-0.4089
Positive	24	6	12	4	784	99	261	56	373	60	131	33	411	45	129	34				
Sig @ 0.05									350	56	129	33	381	41	123	33				
Negative	763	100	250	53	3	7	1	1	414	46	131	24	376	61	133	23				
Sig @ 0.05									400	42	127	24	344	60	130	21				

Panel C

AXRFIX	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL
Mean	-0.525	-1.041	-0.999	-1.076	1.731	0.696	2.343	1.318	-0.033	0.027	0.019	0.009	0.006	-0.013	0.005	-0.028	0.4629	0.4608	0.3210	0.3282
Sigma	1.254	0.943	2.410	0.887	1.565	2.894	3.940	0.983	0.670	0.314	0.146	0.154	0.092	0.314	0.227	0.144	0.2267	0.2042	0.2093	0.1854
Max	7.325	1.717	0.860	0.246	15.336	6.969	51.408	5.604	2.866	4.587	0.989	0.630	0.469	2.542	0.677	0.451	0.9945	0.9986	0.9809	0.8626
Min	-5.234	-5.591	-28.547	-4.123	0.170	-48.429	0.244	-0.903	-8.467	-1.113	-0.477	-0.878	-0.361	-4.105	-2.740	-0.988	-0.1544	-0.0015	-0.4795	-0.3878
Positive	64	45	53	12	187	358	230	122	107	199	114	60	102	189	132	72				
Sig @ 0.05									105	187	108	56	95	177	126	72				
Negative	123	326	177	112	0	13	0	2	80	172	116	64	85	182	98	52				
Sig @ 0.05									74	162	109	57	83	176	90	50				

Panel D

AXRMLTI	α_n				α_p				β_n				β_p				$Adj\ R^2$			
	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL	USA	LUX	CAYI	IRL
Mean	-1.446	-1.367	-1.735	-1.507	2.625	14.290	3.110	1.416	0.043	0.008	0.012	-0.051	0.171	72.868	-0.042	-0.075	0.3996	0.4243	0.3278	0.3214
Sigma	2.078	1.226	1.963	1.949	2.206	131.025	3.082	1.739	0.324	0.164	0.211	0.545	2.155	724.872	0.720	0.242	0.1508	0.1689	0.2347	0.2953
Max	2.022	0.230	0.604	1.617	18.490	1317.945	30.573	7.901	3.197	0.541	2.065	0.907	27.972	7285.249	2.165	0.213	0.9395	0.942	0.7758	0.8841
Min	-15.048	-7.140	-15.357	-8.425	-6.409	0.030	-0.328	-0.402	-1.137	-0.803	-0.570	-2.741	-1.249	-0.415	-9.992	-1.255	-0.2138	-0.4795	-1.0316	-0.3697
Positive	32	6	35	3	168	100	265	23	86	53	136	13	94	53	139	13				
Sig @ 0.05									83	52	128	12	87	51	132	13				
Negative	137	94	232	28	1	0	2	8	83	47	131	18	75	47	128	18				
Sig @ 0.05									80	44	127	17	74	44	116	15				

Note: This table provides the parametric (AXR) test results for a collective sample of 5619 AIFs from January 1995 to October 2016 [monthly intervals]. The first two 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 n) implies the auto-correlation or persistence amongst positive (winning) cases, the last column provides the adjusted r-squared figures.

Table 3.8: Non-Parametric Performance Persistence

Panel A

Domicile		**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
USA	**Mean**	171.43	170.07	149.92	149.23	4.22	6.16	4.41	4.03
	Total	44572	44218	38979	38801	586	875	975	878
CAYI	**Mean**	155.62	152.53	126.65	126.19	4.01	6.14	4.23	4.74
	Total	40462	39657	32928	32810	557	970	934	1009
LUX	**Mean**	57.09	56.77	50.66	50.62	2.75	2.86	3.01	3.72
	Total	14216	13852	12411	12452	151	206	352	499
IRL	**Mean**	25.85	24.89	23.07	23.18	1.55	1.68	1.63	2.18
	Total	6694	6396	5930	5956	68	126	165	261

Panel B

Investment Strategy		**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
LSE	**Mean**	147.12	143.96	123.45	123.16	3.72	5.71	4.29	4.84
	Total	38250	37429	32097	32021	514	890	919	1026
CTA	**Mean**	94.34	92.85	88.99	88.70	3.07	3.85	3.07	3.08
	Total	24528	24142	23138	23062	362	500	577	569
FIX	**Mean**	72.02	70.84	49.67	49.89	2.35	2.60	2.42	3.38
	Total	18652	18206	12764	12822	167	268	336	571
MLTI	**Mean**	45.20	44.10	36.07	36.01	2.18	2.31	1.82	2.09
	Total	11753	11465	9379	9362	172	238	264	287

Note: This table presents the mean and total number of winning [WW] and losing [LL] periods over the 262 months between Jan 1995 and Oct 2016. Furthermore, it also provides the number of winners-gone [WG] and losers-gone [LG] as well as the new-entrant-winner [NEW] and new-entrant-loser [NEL].

Table 3.9: Non-parametric Performance Persistence Statistics

Panel A

Domicile	Mean/Total CPR	CPR	Mean/Total Z-s	Z@5% [1%]	Mean/Total X2	X2@5% [@1%]	PRW [PRW%]
USA	1.79/1.30	196	1.64/26.96	126 [112]	24.99/727.68	181 [159]	165 [0.63]
CAYI	1.95/1.49	190	2.16/37.58	123 [102]	22.96/1417.15	160 [135]	195 [0.74]
LUX	2.68/1.27	213	0.90/13.91	79 [66]	12.05/193.78	127 [99]	159 [0.61]
IRL	3.27/1.21	213	0.57/7.59	63 [39]	6.76/57.72	109 [64]	161 [0.61]

Panel B

Investment Strategy	Mean/Total CPR	CPR	Mean/Total Z-s	Z@5% [1%]	Mean/Total X2	X2@5% [@1%]	PRW [PRW%]
LSE	2.00/1.39	194	1.78/30.87	115 [102]	23.39/955.35	167 [143]	173 [0.66]
CTA	1.68/1.11	190	0.48/8.01	97 [77]	14.97/64.23	159 [130]	138 [0.53]
FIX	3.19/2.07	224	2.5/44.85	136 [115]	20.22/2033.83	160 [134]	198 [0.76]
MLTI	2.54/1.53	200	1.31/21.81	100 [78]	8.54/477.32	126 [96]	179 [0.68]

Note: This table provides the non-parametric test results for a collective sample of 5619 AIFs from January 1995 to October 2016 [monthly intervals]. The first column shows the average and total CPR; the second column shows the number of months different from CPR's null hypothesis; the third column shows the average and total Z-stat; the fourth column counts the number of months where Z-stat is sig. at 5 and 1%, the following column shows the average and total X^2 figures, and the sixth column counts the number of significant cases. Lastly, PRW shows the number and percentage of AIFs considered repeating winners.

Table 3.10. Non-parametric Performance Persistence: Domicile Combined with the Investment Strategy

Panel A

United States		**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
USA_LSE	**Mean**	103.40	101.70	89.18	88.67	2.77	4.18	3.13	2.60
	Total	26883	26442	23187	23054	338	552	589	507
USA_CTA	**Mean**	64.34	63.63	60.35	60.10	2.31	2.92	2.38	2.22
	Total	16728	16543	15690	15625	236	333	391	344
USA_FIX	**Mean**	16.31	15.69	11.08	11.04	1.45	1.55	1.24	1.40
	Total	4224	4016	2815	2804	45	87	82	101
USA_MLTI	**Mean**	16.70	16.08	13.09	13.07	1.54	1.21	1.23	1.17
	Total	4342	4180	3404	3397	60	70	74	82

Panel B

Cayman Islands		**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
CAYI_LSE	**Mean**	100.30	98.23	82.60	82.30	2.88	4.14	3.15	3.44
	Total	26078	25539	21477	21398	374	637	623	637
CAYI_CTA	**Mean**	20.02	19.19	18.95	18.91	1.44	1.53	1.43	1.41
	Total	5204	4969	4928	4916	82	112	130	121
CAYI_FIX	**Mean**	20.33	19.55	13.60	13.55	1.22	1.77	1.23	1.54
	Total	4941	4654	3182	3184	44	113	87	143
CAYI_MLTI	**Mean**	21.97	21.18	17.80	17.63	1.53	1.64	1.38	1.50
	Total	5668	5444	4467	4442	81	131	138	126

Panel C

Luxembourg		**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
LUX_LSE	**Mean**	19.99	21.85	20.72	20.55	1.57	1.91	1.98	1.88
	Total	4098	3911	3585	3576	47	86	131	145
LUX_CTA	**Mean**	7.15	7.64	7.50	7.49	1.36	1.30	1.41	1.36
	Total	1794	1613	1709	1707	30	35	48	57
LUX_FIX	**Mean**	28.67	31.18	25.18	24.91	1.81	1.91	2.32	2.38
	Total	7282	6922	5641	5680	47	61	137	233
LUX_MLTI	**Mean**	7.01	10.55	10.53	10.64	1.93	1.38	1.63	1.55
	Total	1479	1319	1306	1309	29	22	49	51

Panel D

Ireland		**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
IRL_LSE	**Mean**	14.27	14.16	12.54	12.52	1.31	1.40	1.38	1.64
	Total	3583	3369	3136	3143	38	67	90	126
IRL_CTA	**Mean**	3.58	3.17	3.52	3.49	1.00	1.33	1.09	1.15
	Total	917	767	883	877	18	16	25	30
IRL_FIX	**Mean**	11.16	10.85	10.66	11.00	1.25	1.21	1.37	1.66
	Total	1942	1790	1673	1694	15	23	41	83
IRL_MLTI	**Mean**	1.82	2.02	2.08	2.06	1.25	1.09	1.25	1.31
	Total	4098	3911	3585	3576	47	86	131	145

Note: This table presents the mean and total number of winning [WW] and losing [LL] periods over the 262 months between Jan 1995 and Oct 2016. Furthermore, it also provides the number of winners-gone [WG] and losers-gone [LG] as well as the new-entrant-winner [NEW] and new-entrant-loser [NEL].

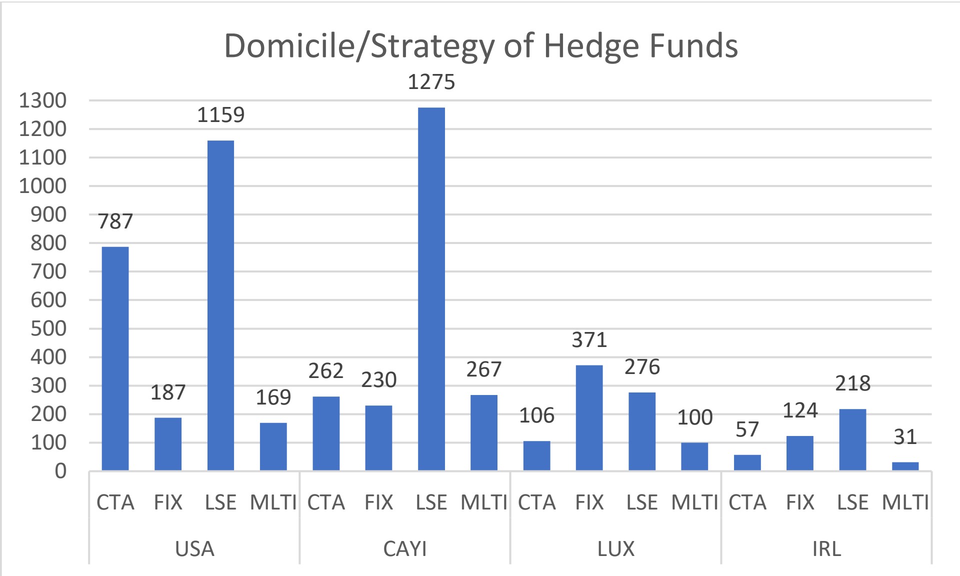
Table 3.11: Non-parametric Performance Persistence: Domicile Combined with the Investment Strategy

Panel A								
USA	**Mean/Total CPR**	**CPR**	**Mean/Total Z-s**	**Z@5% [1%]**	**Mean/Total X2**	**X2@5% [@1%]**	**PRW [PRW%]**	**PRW %**
USA_LSE	2.02/1.33	200	1.36/22.43	116 [105]	18.7/503.79	171 [147]	171	0.65
USA_CTA	1.61/1.13	191	0.45/7.69	82 [65]	9.26/59.21	134 [99]	146	0.56
USA_FIX	3.93/2.15	224	1.30/22.11	79 [45]	4.57/494.73	101 [55]	204	0.78
USA_MLTI	2.77/1.57	212	0.83/13.86	70 [41]	3.77/192.95	89 [54]	173	0.66
Panel B								
Cayman Island	**Mean/Total CPR**	**CPR**	**Mean/Total Z-s**	**Z@5% [1%]**	**Mean/Total X2**	**X2@5% [@1%]**	**PRW [PRW%]**	**PRW %**
CAYI_LSE	2.29/1.45	194	1.61/28.39	114 [94]	16.23/808.27	151 [122]	174	0.66
CAYI _CTA	1.70/1.07	212	0.15/2.31	44 [26]	4.15/5.32	86 [52]	138	0.53
CAYI _FIX	3.73/2.27	221	1.58/25.35	93 [58]	5.81/651.58	105 [67]	200	0.76
CAYI_MLTI	2.53/1.56	202	.91/15.52	72 [45]	4.5/241.92	93 [55]	171	0.65
Panel C								
Luxemburg	**Mean/Total CPR**	**CPR**	**Mean/Total Z-s**	**Z@5% [1%]**	**Mean/Total X2**	**X2@5% [@1%]**	**PRW [PRW%]**	**PRW %**
LUX_LSE	2.57/1.25	216	0.49/6.864	30 [20]	4.15/47.16	45 [31]	129	0.49
LUX_CTA	3.36/0.99	233	0.05/-.167	26 [18]	3.75/0.03	72 [39]	128	0.49
LUX_FIX	3.35/1.57	229	1.14/17.98	72 [59]	11.02/324.63	113 [91]	177	0.68
LUX_MLTI	3.03/1.14	238	0.1/2.42	23 [13]	4.91/5.88	54 [31]	149	0.57
Panel D								
Ireland	**Mean/Total CPR**	**CPR**	**Mean/Total Z-s**	**Z@5% [1%]**	**Mean/Total X2**	**X2@5% [@1%]**	**PRW [PRW%]**	**PRW %**
IRL_LSE	3.25/1.22	213	0.43/5.82	46 [27]	4.19/33.9	80 [55]	139	0.53
IRL_CTA	2.57/0.91	217	-0.06/-1.41	6 [1]	1.85/1.98	40 [10]	104	0.40
IRL_FIX	3.97/1.23	232	0.36/4.294	25 [14]	4.82/18.46	58 [37]	110	0.42
IRL_MLTI	2.42/1.30	241	0.09/2.21	1 [0]	1.82/4.9	16 [1]	143	0.55

Note: This table provides the non-parametric test results for a collective sample of 5619 AIFs from January 1995 to October 2016 [monthly intervals]. The first column shows the average and total CPR; the second column shows the number of months different from CPR's null hypothesis; the third column shows the average and total Z-stat; the fourth column counts the number of months where Z-stat is sig. at 5 and 1%, the following column shows the average and total X^2 figures, and the sixth column counts the number of significant cases. Lastly, PRW shows the number and percentage of AIFs considered repeating winners.

Figures

Figure 1. The Number of Domicile/Strategy Hedge Funds (1995-2016)



Note: This figure shows the number of hedge funds in each domicile, which is further divided based on the investment strategy. The data has been extracted from the Eureka Hedge database. Abbreviations: USA - United States, CAYI - Cayman Islands, LUX - Luxembourg, IRL - Ireland, CTA - Commodity Trading Advisors, FIX - Fixed Income, LSE – Long-Short Equity, and MLTI – Multi-Strategy.

Chapter 4. Gender differences in hedge fund performance.

4.1 Introduction

In recent decades the debate concerning gender differences in the financial investment industry has been the subject of significant attention. However, the analysis of the performance within the hedge fund industry from the gender perspective has been largely unexplored. According to Prequin (2020), hedge funds aggregate US$ 3.61tn assets under management, which is almost the equivalent of Germany's 2019 GDP of US$ 3.84tn (World Bank, 2020). Given the value of the assets under management in the global hedge fund industry, the significance of risk these investment vehicles pose for the global economy is evident. 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, Mazzoli and Palmucci, 2017). Similarly, female mutual fund investors are more risk-averse than their male counterparts (Dwyer, Gilkeson and List, 2002; Powell and Ansic, 1997). By contrast, research on mutual funds finds that few differences exist in the performance and investment behaviour between male and female managers (Atkinson, Baird and Frye, 2003; Bollen and Posavac, 2018). Given the relatively explored mutual fund environment and completely non-existent (similar) research in hedge funds, we explore the following research questions. Are there any differences between the performance of male and female hedge fund managers? Taking into consideration multi-period performance persistence, what is the performance of the male and female hedge fund managers?

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, Vanduffel and Ye, 2019; Fung and Hsieh, 1999). Thus, the analysis of HFs requires a sophisticated approach (Getmansky, Lo and Makarov 2004; Malkiel and Saha 2005; Eling 2006), which extends beyond standardised appraisal methods of the first two moments and metrics such as the SR. Although Eling and Schuhmacher (2007) show that the choice of risk-adjusted measure does not affect the ranking of HF performance, they contend that SR is inadequate in the cases of asymmetrical distribution.

Our study extends the investigation of HF performance beyond the first two moments of the returns' (mean and standard deviation) and incorporates the third (skewness) and fourth (kurtosis). Furthermore, our analysis includes not only a series of risk-adjusted metrics but also the analysis of performance persistence (both parametric and non-parametric).

Although extant literature exists examining male and female fund managers' performance, this is restricted to mutual and retirement funds (e.g., Atkinson et al. 2003; Aggarwal and Boyson, 2016; Bollen and Posavac, 2018). Very little research focuses on performance between genders in the male-dominated hedge funds industry and when it does as is the case with the research conducted by Aggarwal and Boyson (2016), the potential deviations of the higher-order statistics are not examined. The uniqueness of hedge funds lies in their elusive behaviour and the investment opportunities they explore (usually unavailable to other investment entities). These, in turn, cause the asymmetrical distribution, i.e., the deviations of higher-order moments (skewness and kurtosis) and fat tails, leading to a higher number of extreme events than one would normally anticipate (Fung and Hsieh, 1999). Thus, one of the major contributions of this chapter is to incorporate these crucial properties into the examination of male/female hedge fund manager performance to provide a more accurate assessment. Furthermore, the performance persistence aspects were also never considered in the examination of gender differences in any fund environment, let alone hedge funds.

Our analysis uncovers several interesting findings. We show that when using the SR as a measure of investment performance, male and female HF managers produce similar results, in line with previous literature (Aggarwal and Boyson, 2016). However, when considering higher-order statistics, our tests reveal that female HF managers tend to produce lower returns and higher risk 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. This finding not only confirms the previous studies with regards to the higher-order statistic properties crystallising in HFs but also shows their importance in identifying gender differences in HF performance. Further, correlation matrices of risk-adjusted ratios reveal the high average correlation of all metrics against Sharpe ratio for the female Equity managers and their male counterparts (although noticeably lower than females). Concerning the Universe of HFs, both genders exhibit similar correlations. Nevertheless, in either case, our correlations with the Sharpe ratio are significantly below what has been reported by Eling and Schuhmacher (2007). This result further suggests that other risk-adjusted ratios *do* matter in assessing HF performance, at least in the case of male managers where correlations with regards to Sharpe ratio are lower than in female managed HFs.

Lastly, we analyse the performance persistence based on multiple periods: short-term (monthly and bi-monthly), medium-term (quarterly) and long-term (six-monthly and annual). In the non-parametric approach, we observe performance persistence crystallising across all analysed time horizons and genders. The results indicate the most pronounced average performance persistence occurs in female managed HFs (in both clusters). Nevertheless, despite that, the number of months under which the null hypothesis of no persistence is violated is marginally higher for male managers. The non-risk-adjusted parametric method results indicate a solid positive and statistically significant persistence across both portfolios and genders under the monthly time horizon. However, as soon as we move towards the bi-monthly period, both genders in the Equity cluster experience performance reversal (into negative). Contrary, in the Universe portfolio, both genders continue to exhibit positive and statistically significant persistence. The results of the quarterly analysis, on the other hand, are broadly similar to our initial investigation of the monthly persistence - once again, in all cases, we observe positive persistence. Further, the six-monthly analysis indicates the dominance of negative cases for both portfolios and genders except the male managed Universe cluster, which exhibits strong positive persistence. Lastly, under the annual horizon, the female managers continue to exhibit negative persistence in both portfolios, while the opposite is true for the male managers. Under the risk-adjusted parametric analysis, male HF managers exhibit positive performance persistence throughout all time horizons (except Equity annual) in both clusters. In an interesting turn for the female HF managers, the incorporation of risk into the parametric analysis has elevated their funds into mostly positive territory (with some at parity between the number of positive and negative cases). The only time where we have seen weak although negative performance persistence with the female managers was at the monthly horizon in both Equity and the Universe. The general finding of the performance persistence crystalising across all analysed periods (gender aspect aside) is consistent with the earlier work of, for example, Do, Faff and Veeraraghavan (2010) or Ammann, Huber and Schmid (2013). We, like many others, believe that gender differences are an important issue for future research. Even more so, given the almost non-existent coverage of the topic in one of the world's most secretive investment industries, the hedge funds. Furthermore, our study brings further attention to a highly underrepresented group (females) in the financial industry and especially hedge funds (where sole female management stands at approx. 4.5% - see 4.2).

The remaining chapter is organised as follows: Section 4.2 describes the data; Section 4.3 outlines the methods; while Section 3.3 describes the results, and Section 4.5 concludes findings. Lastly, the literature review has been explored in Chapter 2 (sub-section 2.2).

4.2 Data

Our initial sample comprises all 4,327 funds recorded in Morningstar's (MSD) Global Hedge Fund Universe for the period October 1978 - December 2018. From these, we exclude duplicates[14] and funds with a missing manager or the investment strategy details. We also exclude funds that have less than 12 months of returns. Our final sample consists of 1,321 funds, which are then subjected to the winsorization process with the bounds set to 0.05 due to the presence of a very small number of outliers (affecting the male sample and exponentially elevating (positive direction) their performance). We allocate funds into six strategy groups based on the Morningstar Category Classifications (Morningstar, 2016) and the HFRI formulaic methodology (HFRI, 2019), namely: Equity; Arbitrage; Event; Debt; Global; and Multi (Table 4.1). The strategy pools were organised based on the Morningstar Category Classifications (Morningstar, 2016) and the HFRI formulaic methodology (HFRI, 2019). Table 4.1 tabulates the number of hedge funds based on each of the size strategy groups along with those managed by male and female managers. In the analysis, we focus on the Equity strategy (as well as the entire HF Universe for comparison purposes), which is the most saturated investment strategy by both male and female managers and accounts for 25.3% ($914bn) of the HF market (Preqin, 2018). The hedge funds are heavily male-dominated, with 1,261 being managed by male managers and the remaining 60[15] by female managers. Nevertheless, despite the low number of female hedge fund managers, the 60 hedge funds cover the entire examined timeframe between October 1978 and December 2018. The Morningstar database identifies only a fraction of hedge fund manager genders. Thus, due to a relatively small sample of 1321 hedge funds, we check the gender of each manager manually (through a search on Bloomberg and the individual hedge fund websites). Our research focuses only on the most recent, lead hedge fund manager (as extracted from the database).

[14] Duplicates exist because of multiple listings in various currencies and/or share classes e.g. Aggarwal and Jorion (2010), and Bali, Brown and Caglayan (2011).

[15] The only limitation of this study is the number of female hedge fund managers. The hedge fund industry is heavily male dominate, hence the small number of female managers. The suggestion for future research that could potentially alleviate this issue would be to acquire all known hedge fund databases, remove duplicate funds and then analyse the performance/performance persistence.

Insert Table 4.1

4.2.1 Descriptive Statistics

In the first instance, we analyse the risk and return employing standard metrics such as the mean return (4.1) and the annualised standard deviation (4.2).

$$r_i^p = \frac{r_{i1} + \cdots r_{in}}{n} \tag{4.1}$$

$$\sigma_{mA} = \sqrt{\frac{\sum(x-\bar{x})^2}{n}} / \sqrt{12} \tag{4.2}$$

However, given the previous literature (Getmansky et al. 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 the return distribution. Thus, we test for the autocorrelation (4.3) 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, for example, sub-prime (distressed) RMBS's (Residential Mortgage-Backed Securities) (Kat, 2002).

$$\mathrm{AC}_{k=1}\ AC_1 = \frac{\sum_{t=k+1}^{AC}(Y_t-\bar{Y})(Y_{t-k}-\bar{Y})}{\sum_{t=1}^{AC}(Y_t-\bar{Y})^2} \tag{4.3}$$

The significance of the autocorrelation is tested with Ljung-Box (4.4) (Ljung and Box, 1978) statistic:

$$LB = T(T+2)\sum_{j=1}^{k}\frac{T_j^2}{T-J} \tag{4.4}$$

Subsequently, we assess the higher moments of the return distribution, such as skewness (4.5) and kurtosis (4.6). The asymmetrical distribution of hedge funds is their widely known property, resulting from the difficulties in the valuation of illiquid securities (within their holdings) and investments in derivatives (Favre and Signer, 2002; Kat, 2002; Eling, 2006). Furthermore, it is often said that the assumption of normality is inappropriate for hedge funds (unlike with stocks and bonds) (Geman and Kharoubi, 2003).

$$S = \frac{1}{N}\sum_{i=1}^{N}(\frac{y_i - \bar{y}}{\hat{\sigma}})^3 \qquad (4.5)$$

$$K = \frac{1}{N}\sum_{i=1}^{N}(\frac{y_i - \bar{y}}{\hat{\sigma}})^4 \qquad (4.6)$$

To test the significance of the *S* and *K*, we employ the Jarque-Bera (4.7) distribution test for both 0.05 and 0.01 confidence.

$$JB = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \qquad (4.7)$$

Insert Table 4.2

Table 4.2 presents the descriptive statistics of the returns of Equity HFs (Panel A) and the Universe of HFs (Panel B). The average return in the Equity cluster indicates female managers superiority (at 0.83 versus 0.71 for the males). Similarly, the female managed HFs also dominate (although minimally by 0.05 of a per cent) in the Universe cluster. This observation is consistent with the previous literature concerning gender-related investor behaviour (Barber and Odean, 2001; Choi et al., 2002). Concerning the higher-order statistics, despite minimally lower average returns, male managed funds exhibit more attractive levels of skewness. Concerning the higher-order statistics, despite minimally lower average returns, male managed funds exhibit more attractive (positive) levels of skewness. The positive skewness and positive excess kurtosis are highly attractive for the risk-averse investors (Kat, 2003; Eling, 2006) as they magnify the probability of substantial gains. The investors prefer to decrease the extreme negative events and prefer positive (as opposed to negative) skewness (what indicates that the left tail is fatter than the right one), as the underlying motivation for HFs is their ability to generate positive returns in stagnated or bearish markets. Moreover, in most cases, HFs advertise extreme risk which naturally results in negative skewness and positive kurtosis (similar to a short put option) (Agarwal and Naik, 2000). Importantly, HF returns have fat tails, which lead to a higher number of extreme events than one would normally anticipate (Fung and Hsieh, 1999). The omission of the existence of negative skewness combined with positive kurtosis has crystalised at the collapse of the Long-Term-Capital-Management (LTCM) in 1998 and as Bali, Gokcan and Liang (2007) and Bali and Gokcan (2004) states initiated the industry to start accounting for the higher-order moments beyond the mere mean-variance assessment of performance. Thus, the fusion of the positive skewness and kurtosis, although not completely unique is a desirable departure from the standard expectation of negative skew and positive kurtosis crystallising specifically in hedge funds.

The Ljung-Box test for the autocorrelation of returns rejects the null hypothesis of no autocorrelation, while 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. It is important to note that the data has been subjected to winsorization.

4.3 Methods

To examine the gender differences in hedge fund performance, we consider several techniques. Firstly, we measure risk-adjusted performance employing classical risk-adjusted metrics such as the Sharpe ratio and Jensen Alpha. Second, we adopt metrics based on the lower partial moments such as Omega, Sortino, Kappa 3 and the Upside Potential. We further use Calmar, Sterling, and Burke - drawdown-based metrics. Lastly, we employ Excess return on Value at Risk, Conditional Sharpe and Modified Sharpe. In addition, we follow Eling and Schuhmacher (2007) and examine the correlation of all the risk-adjusted metrics and construct a Spearman rank correlation matrix.

Finally, we complement the analysis by conducting performance persistence testing by examining multiple time horizons. Specifically, we perform both non-parametric testing presenting a contingency table of the winners and losers and parametric testing using regressions. In both cases, we focus on multiple periods: short (monthly and bi-monthly), medium (quarterly) and long (six-monthly and annual).

4.3.1 Risk-Adjusted Ratios

Risk-adjusted ratios such as the Sharpe ratio and Jensen Alpha are direct derivatives of Markowitz's portfolio theory (Markowitz, 1952). Their general utility makes them the most widely used metric in prior literature (Sharpe, 1966; Dhrymes, 2017).

4.3.1.1 Classic Ratios

Sharpe Ratio

The Sharpe ratio (4.8) 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.

$$SR = \frac{r_i^p - r_f}{\sigma^p} \qquad (4.8)$$

Jensen Alpha

The Jensen Alpha (4.9) 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.

$$Jensen = \left(r_i^d - r_f\right) - (r_{rp}^d - r_f)\beta \qquad (4.9)$$

4.3.1.2 Lower Partial Moment Ratios (LPM)

The lower partial moments (LPM) measure the risk through negative deviations of the HFs returns with regards to a minimum acceptable return (MAR) (Fishburn, 1977). Since the LPM considers only the negative deviations of the analysed time series, it seems to be a more appropriate measure of risk than standard deviation – as σ considers both negative and positive deviations. Thus, in this section, we examine the following ratios: Omega, Kappa 3 and Upside Potential.

Omega

The Omega ratio (4.10) refers to the excess return over the minimum acceptable 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 to by Kazemi, Schneeweis, and Gupta (2004) as the Omega-Sharpe.

$$Omega = \frac{r_i^d - \tau}{LPM_{1(\tau)}} + 1 \qquad (4.10)$$

Sortino

The Sortino ratio (4.11) refers to the excess return over the minimum target return and the LPM. Its physiology is similar to Shape's ratio, in 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).

$$Sortino_i(\tau) = \frac{r_i^d - \tau}{\sqrt[2]{LPM_2(\tau)}} \qquad (4.11)$$

Kappa 3

The Kappa 3 ratio (4.12) refers to the excess return over the minimum acceptable 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.

$$Kappa_i(\tau) = \frac{r_i^d - \tau}{\sqrt[3]{LPM_3(\tau)}} \qquad (4.12)$$

Upside Potential

The Upside Potential ratio (4.13) 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.

$$UP_i = \frac{HPM_{li}(\tau)}{\sqrt[2]{LPM_2(\tau)}} \qquad (4.13)$$

4.3.1.3 Drawdown Ratios

The drawdown-based metrics represent a special class in the realm of alternative risk versus reward ratios. Their uniqueness relies on the ease of their interpretation and simultaneous difficulty in analysing their operational properties (Schuhmacher and Eling, 2011). This section examines the following ratios: Calmar, Sterling, Burke.

Calmar

The Calmar ratio (4.14) measures the fund’s performance through the return versus drawdown risk (Young, 1991). The Calmar ratio is, in essence, smoothed version of the Sterling ratio as it employs smoothed values for both numerator and denominator.

$$Calmar_i = \frac{r_i^d - \tau}{-MD_1} \qquad (4.14)$$

Sterling

The Sterling ratio (4.15) (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 (as a risk metric), it is more sensitive to the outliers than the Calmar ratio.

$$Sterling_i = \frac{r_i^d - r_f}{\frac{1}{N}\sum_{j=1}^{N} -MD_j} \qquad (4.15)$$

Burke

The Burke ratio (4.16) 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).

$$Burke_i = \frac{r_i^d - r_f}{\sqrt{\sum_{j=1}^{N} MD_j^2}} \qquad (4.16)$$

4.3.1.4 Ratios Based on the Value at Risk (VaR)

This part discusses the methods based on the VaR, which measures the worst expected loss over the analysed period at a predefined confidence interval (Jorion, 2001). The metrics based on the VaR are simply based on the quantile Z_a of the distribution of the time-series returns. The VaR approach concentrates on the return properties of analysed HFs. As previously identified (Getmansky et al. 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 lower-order moments. Thus, this part focuses on the Sharpe ratio (*SR*) and Value at Risk (*VaR*) and their modifications incorporating the higher orders of return distribution (skewness (*S*) and kurtosis (*K*)): The *Modified SR* and *VaR* (*MSR* / *MVaR*).

Excess Return on Value at Risk

The Excess Return on value at Risk (4.17) measures the excess risk over the Value at Risk (VaR) (Dowd, 2002).

$$ErVaR_i = \frac{r_i^d - r_f}{VaR_i} \tag{4.17}$$

Conditional Sharpe Ratio

Conditional SR (4.18) measures the expected loss only considering the values, which exceed VaR (Albrecht and Koryciorz, 2003).

$$CSR_i = \frac{r_i^d - r_f}{CVaR_i} \tag{4.18}$$

Modified Sharpe Ratio

To get a better insight into the risk approach of both male and female hedge fund managers, we have to first calculate standard VaR (4.19), 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."

$$VaR = -\left(Z_a \sigma_{Am} + r_i^p\right) w \tag{4.19}$$

To integrate the deviations of higher moments of return distributions (*S* and *K*), we apply Favre and Galeano's (2002) Modified VaR (MVaR) (4.20), in which the alpha value of the standard VaR has been replaced with Cornish-Fisher expansion (4.21).

$$MVaR = -\left(Z_{CF} \sigma_{Am} + r_i^d\right) w \tag{4.20}$$

$$Z_{CF} = Z_a + \frac{1}{6}(Z_a^2 - 1)S_i + \frac{1}{24}(Z_a^3 - 3Z_a)K_i - \frac{1}{36}(2Z_a^3 - 5Z_a)S_i^2 \tag{4.21}$$

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) (4.22), incorporates the effects of the *S* and *K*. The Modified SR measures the excess return over the portfolio's MVaR. The metric incorporates the effects of the higher moments of the return distribution.

$$MSR = \frac{r_i^p - r_f}{MVaR_i} \quad (4.22)$$

4.3.2 Performance Persistence

The following section describes the two most common performance persistence measures. The first measure pertains to widely applied non-parametric contingency tables, while the second one, parametric, focuses entirely on the regressions.

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/gender of the manager. 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 (4.23), suggesting no persistence at all.

$$CPR = \frac{(WWxLL)}{(WLxLW)} \quad (4.23)$$

The statistical significance of the CPR results is measured with Z-statistic (4.24). Thus, if the Z-stat value of 1.96 (5%) or 2.58 (1%) is exceeded, we can observe significant performance persistence.

$$Z = \frac{\ln(CPR)}{a_{ln_{(CPR)}}} = \frac{\ln{(CPR)}}{\sqrt{\frac{1}{WW}+\frac{1}{WL}+\frac{1}{LW}+\frac{1}{LL}}} \quad (4.24)$$

The chi-square (4.25) 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.

$$X^2 = \frac{\left(WW-(\frac{(WW+WL)(WW+LW)}{n})\right)^2}{\frac{(WW+WL)(WW+LW)}{n}} + \frac{\left(WL-(\frac{(WW+WL)(WL+LL)}{n})\right)^2}{\frac{(WW+WL)(WL+LL)}{n}} + \frac{\left(LW-(\frac{(LW+LL)(WW+LW)}{n})\right)^2}{\frac{(LW+LL)(WW+LW)}{n})} + \frac{\left(LL-(\frac{(LW+LL)(WL+LL)}{n})\right)^2}{\frac{(LW+LL)(WL+LL)}{n}} \qquad (4.25)$$

We also provide an additional metric of the percentage of repeating winners (PRW) (4.26).

$$PRW = \frac{WW}{WW+WL} \qquad (4.26)$$

In terms of the parametric approach, we use two types of regressions, the XR (4.27) and AXR (4.28). Both regressions are similar to Do et al. (2010)with one notable difference, our benchmark variables are medians and not average returns of the aggregated HF groups. Furthermore, we consider a vast number of time horizons in our work as well as previously unexplored gender aspects. 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.

$$XR_{it} = a_n D_n + a_p D_p + \beta_{i,n} D_n XR_{i,t-1} + \beta_{i,p} D_p XR_{i,t-1} + \varepsilon_{it} \qquad (4.27)$$

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

$$AXR_{it} = a_n D_n + a_p D_p + \beta_{i,n} D_n AXR_{i,t-1} + \beta_{i,p} D_p AXR_{i,t-1} + \varepsilon_{it} \qquad (4.28)$$

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

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 levels 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.

4.4 Empirical Results

The following two sections present the results of two approaches undertaken in this chapter. First, we discuss the results of the twelve risk-adjusted ratios (divided into classic, lower partial moment, drawdown, and based on VaR). Second, we report the results of the performance persistence approaches: the non-parametric (contingency tables) and parametric (regressions) models.

4.4.1 Risk-Adjusted Ratios

Table 4.3 presents the results of the gender-based risk-adjusted-ratio analysis for both the Equity-only and the entire HF Universe. The average Sharpe ratio stands at 0.14 for both male and female HF managers. Equally, both male and female HF managers outperform the market, on average, by one basis point.

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 4.3, Panel B presents the results for the Omega, Sortino, Kappa 3 and Upside Potential Ratios. All 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 4.2), the above results are not surprising: Female (male) HF returns tend to exhibit more significant negative (positive) skewness, and LPM ratios penalize negatively skewed returns relative to positively skewed returns. The departure from normality in hedge funds in addition to the fat tails issue also includes the asymmetry and the short option behaviour, where the intermittent significant losses appear scattered among frequent low returns (Dennis and Mayhew, 2002; Perez, 2004). Thus, in many instances rendering the low yet positive returns insignificant. It is important to notice that these properties are mostly prevalent in hedge funds. As much as long investors stray away from the negative skewness (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000), there are some hedge funds capable of generating returns through the sale of negative skewness. Similarly, the hedge funds exhibiting negative kurtosis can also generate returns (due to the kurtosis premium being negative)

(Agarwal, Bakshi and Huij, 2009). Furthermore, the negative skewness of hedge funds can be also offset by placing them in a portfolio of stocks and bonds due to their low correlation with each other (Eling, 2006).

Table 4.3, 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 some time as a measure of risk. Two of the three Drawdown-based measures show almost no differences between male and female HF managers. The Calmar ratio shows that male HF managers tend to over-perform female HF managers when accounting for drawdown risk.

Table 4.3, Panel D, reports risk-adjusted performance metrics based on VaR. We estimate the Excess return on value at risk (ErVaR), Conditional SR and Modified SR measures. VaR performance-based measures utilise the maximum possible 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 LPM-based measures' findings and reflects the highly negative skewness of HFs managed by females (see Table 4.3: Panel B).

Insert Table 4.3

Similar to Eling and Schuhmacher (2007), we also provide a complimentary overview of the rank correlation of the risk-adjusted metrics. Table 4.4 presents the results of this analysis focusing solely on Equity focused HFs (Table 4.4) and Table 4.5 on the universe of HFs. In both cases, the data has been separated based on the gender of the HF manager. Our matrices do not exhibit a high correlation of magnitude of 0.92-0.99 in all cases. Instead, for the male managed Equity HFs (Panel A), the correlation coefficient for the Sharpe ratio at its lowest is 0.50 (Calmar ratio) and the highest at 0.88 (MSR). In Panel B (female managed HFs), the lowest correlation with the Sharpe ratio is 0.38 (Calmar ratio), with the highest 0.99 (MSR). The average of the ratios based on the VaR (0.87) and the LPM (0.76) has the highest correlation with the Sharpe ratio in Panel A, while the same is true for the ratios based on VaR (0.99) and LPM (0.92) in Panel B. Overall, the number of coefficients exceeding 0.60 correlation (excluding diagonal 1.00 values) for males is 46 out of 66, while for females 53/66. This result is comparable with the findings of Pedersen and Rudholm-Alfvin (2003) concerning the HF universe.

Insert Table 4.4

The aggregated HF universe (Table 4.5) paints a slightly different picture. Panel A shows that the lowest correlation coefficient value with regards to the Sharpe ratio is 0.54 (Calmar ratio), with the highest being 0.83 (Kappa 3). Similar values can be found in Panel B, where the minimum correlation coefficient is 0.54 (Calmar ratio), and the maximum is 0.91 (MSR). The average of the ratios based on the LPM (0.76) has the highest correlation with Sharpe ratio in Panel A, while the same is true for the ratios based on VaR (0.76) in Panel B. Overall, the number of coefficients exceeding 0.60 correlation (excluding diagonal 1.00 values) for males is 39 out of 66, while for females 54/66. As was the case with Table 4.4 (Panel B), the risk-adjusted metrics in female managed HFs (Table 4.5) also exhibit a much higher correlation with the Sharpe ratio than those of their male counterparts. This finding aligns with the results in Eling and Schuhmacher (2007), implying that in our case, the Sharp ratio is a sufficient metric for the female managed HFs, regardless of whether we are focusing on Equity-only or the aggregated universe portfolios.

Insert Table 4.5

4.4.2 Performance Persistence

4.4.2.1 Non-Parametric

The following section examines non-parametric performance persistence based on the gender of the HF manager. As mentioned earlier, the analysis focuses on the Equity HFs. Nonetheless, we also provide the figures for the aggregated HF Universe for comparison. Furthermore, to increase the granularity of our analysis, we have calculated performance persistence for short-term (monthly and bi-monthly), medium-term (quarterly and six-monthly) and long-term (annually).

Tables 4.6 (4.7) and 4.8 (4.10) present the results of the non-parametric analysis for female and male equity HFs managers, respectively - aggregating 815 HFs (see Table 4.1). Notably, the percentage difference between the number of WW's and LL's is more significant amongst female managers. In almost all periods, the female managed HFs are dominated with negative performance persistence, while the male managed funds achieve parity between the wins and losses in 6-monthly and annual periods. For the female managers, the dynamics change towards monthly and bi-monthly periods where the gap between the WW and LL cases narrows. The lowest average CPR for male managers stands at 1.72 (annual), with the highest at 2.51 (six-monthly). Simultaneously, the lowest average CPR for female managers stands at 2.32 (quarterly) and the highest at 3.08[16] (6-monthly). The null hypothesis of no persistence (i.e., CPR= 1) is violated in all periods for both genders. The Z-statistic further shows that of the 220/375 (208/375) months (CPR≠ 1) in male (female) managed HFs, the 25 (11) are significant @1% and 91 (4) @5%. Lastly, despite the average PRW being higher for female managers across all periods, the number of months where the PRW is greater than 50% is much higher amongst male managed funds.

Insert Table 4.6

Insert Table 4.7

Turning our attention to the aggregated HF Universe, we examine the results in Tables 4.8 and 4.9. The aggregated HF Universe represents six major HF strategies with a collective number of 1321 HFs (see Table 4.1). In this scenario, we observe a significant increase in the number of LL cases in the female managed HFs as compared to the previous assessment of the Equity Universe (the Equity HFs constitute 62% of the entire HF Universe). On the contrary, the percentage differences between the winners and losers in male managed HFs substantially decrease to the point of parity and even a performance persistence reversal under the annual horizon. In this particular case, male HF managers achieve positive performance persistence with 2.2% (WW= 114.03 versus LL= 111.57). Moreover, the changes in CPR are also noticeable, with the lowest (highest) for the male managers at 1.89 (2.28) and the female at 2.27 (3.91). Nevertheless, the CPR levels across the male managed portfolios are broadly similar (Tables 4.6 and 4.9). The exception to this is the monthly horizon in female managed HFs, where the CPR increases by 30.4% (from the equity-only to the universe portfolio). Regardless of the portfolios' CPR value differences, the changes in the number of time intervals exhibiting performance persistence (CPR≠ 1) are minuscule. The average PRW figures are still dominating amongst female HF managers, while the number of cases where the PRW is greater than 50% in most cases belongs to male managers.

Insert Table 4.8

Insert Table 4.9

The results of the analysis (for both genders) undoubtedly confirm the existence of performance persistence across all analysed periods. According to CPR, the most pronounced performance persistence occurs in a short-term (monthly) period for the female Equity managers (CPR= 3.91). However, it is worth mentioning that under the assumption of the CPR's statistical sig., female Equity managers exhibit performance persistence in 199/375 months. Whereas the highest number of statistically significant months in a short-term (monthly) persistence analysis occurs under the male managed HF Universe (225/375 with a CPR= 2.28).

4.4.2.2 Parametric

In this part, we turn our attention to the parametric analysis, although at this point, non-risk adjusted, which is less commonly used in prior literature.

Table 4.10 and Table 4.11 presents the results of the gender-based (MAL/FEM) non-risk adjusted analysis for both the Equity-only (EQU) and the entire HF Universe (ALL). As we observe in Table 4.10 (Panel A), the percentage of statistically significant cases versus the number of Beta coefficients is higher for male managed Equity HFs and stands at 18.9% versus 17.4% for the female managed funds. Interestingly, the percentage differences reverse when comparing against the aggregated portfolio (Table 4.11: Panel A).

Slightly decreasing granularity, we are moving onto the bi-monthly intervals as shown in Panel B (Table 4.10/4.11). Consequently, we are observing a minimal downward shift in the number of statistically significant cases in all portfolios. The male managed HFs continue to exhibit marginal positive dominance in the aggregated portfolio. Interestingly, the same cannot be said about the Equity HFs, which are minimally dominated (66 to 63) by the negative and statistically significant cases. Thus, indicating the negative persistence. On the contrary, the female managed HFs maintain the parity between the number of negative and positive cases in the Equity cluster while exhibiting positive persistence in the aggregated universe.

The quarterly (medium-term) results in Panel C (Table 4.10/4.11) show that the female managed funds in both portfolios continue to exhibit similar properties. On the other hand, the male managed HFs return to profitability, as the number of cases indicating positive performance increases drastically relative to the previously analysed time horizon. Despite using different HF databases, the other authors have also confirmed the existence of quarterly persistence in both HFs (Agarwal and Naik, 2000) and funds of HFs (Steri et al., 2009).

Moving towards the long-term analysis, we discover that the number of negative cases dominates the Equity portfolio for both genders under a six-monthly time interval. What's even more interesting is that the HFs across all portfolios manifest the ability to switch from losers to winners and vice versa (depending on the time horizon). Nonetheless, the HFs under the six-monthly time horizon, regardless of gender, exhibit losing (or near) performance persistence. The only exception we can call out is the male managed Universe, where the number of statistically significant and positive cases stands at 143 versus 141 negatives.

A similar situation occurs at the annual level for the female managers, where the HFs in both clusters are dominated with negative cases. The situation for the male managed equity HFs overturns and begins to exhibit minor domination in the positive territory. While the aggregated universe shows continuous and highly significant (at the annual horizon) positive performance persistence. Interestingly, we note that our risk-adjusted R^2 is significantly higher in comparison to Do et al. (2010) for both genders across all time horizons.

Insert Table 4.10

Insert Table 4.11

The complementary risk-adjusted-performance persistence analysis has been aggregated in Table 4.12 and Table 4.13. Panel A concerning male HF managers in both clusters shows similar magnitude results to our earlier non-risk adjusted analysis. Thus, winning and statistically significant performance persistence dominates. On the contrary, and despite the increase in the number of female managed HFs, both clusters reverse into the statistically significant negative Betas. In general, we find a weak short-term (monthly) negative performance persistence crystallising under female management.

The bi-monthly risk-adjusted results for the Equity cluster are significantly different from what we have seen in the non-risk-adjusted analysis (Table 4.10/4.11: Panel B). The male managed funds are no longer dominated by losing performance persistence and instead flourish with a significant positive lead. While the Universe cluster continues to exhibit positive persistence. In terms of the female managed HFs, they exhibit positive persistence across the board, unlike in the non-risk-adjusted and losing Equity cluster.

In the quarterly data (Panel C), we observe a similar number of significant cases as in the non-risk-adjusted analysis. However, this time, female managed portfolios exhibit parity between the number of statistically significant positive and negative cases, while male HFs notably exhibit positive performance persistence.

As we have seen earlier (Table 4.10: Panel D), under long-term six-monthly analysis, both male and female managed Equity HFs exhibited negative performance persistence. This time, however, the accountability for risk (Table 4.12: Panel D) has caused a performance reversal (into positive) under male management and parity under female management. In the Universe cluster, male managers continued to maintain positive persistence, although with a smaller lead than before the risk adjustment. Also, the female Universe moves away from the solid negative persistence into a parity between the number of negative and positive Betas. Lastly, the annual (Table 4.12: Panel E) results indicate performance reversal for male (into negative) and female Equity managers (into parity). The Universe cluster, on the contrary, allows male managers to maintain a positive, although very weak, persistence (as opposed to the strong persistence seen in Table 4.11: Panel E). Furthermore, female managed funds are promoted into the positive territory after performance reversal. Thus, exhibiting a positive long-term persistence. Similarly, as it was in the case of the non-risk adjusted analysis, the R^2 values are significantly higher than those reported by Do et al. (2010) - across all time horizons.

Insert Table 4.12

Insert Table 4.13

4.5 Conclusion

Despite the surge in academic studies that investigate the role of gender in risk-taking and investment performance, the literature, in general, is silent about the risk-adjusted performance of female fund managers and their male counterparts. Furthermore, the avenue of performance persistence concerning gender also remains unexplored. Thus, the main contribution of this study is to account for the higher-order moments and their implications in the assessment of the performance of the male and female hedge fund managers previously unseen in the literature. Another significant contribution, also for the first time in the known literature, considers multi-period performance persistence (both non-parametric and parametric) of the male and female managers. In this chapter, we use 12 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 accounting for higher-order statistics, female HF managers tend to produce lower returns and take higher risks than their male counterparts. Importantly, as we have seen earlier in the chapter, the implications of the higher-order moments in hedge funds are of the utmost importance. While the basic reliance on the lower-order moments (mean and variance) provides distorted results, in most cases underestimating variance and overestimating SR. 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. Moreover, the correlation between the Sharp ratio and the other risk-adjusted metrics in Equity HFs managed by females (male) is the highest of all clusters and, on average, stands at 0.83 (0.76). This is followed by the Universe HFs managed by female (male) managers with 0.71 (0.70). Given the findings in the literature (e.g., Eling and Schuhmacher, 2007), these results imply that other metrics do matter as they are providing disparate, uncorrelated results when juxtaposed against the Sharpe ratio.

The non-parametric approach undoubtedly confirms the existence of performance persistence across all analysed periods and genders. The results indicate that the most pronounced average performance persistence occurs in female managed HFs (in both clusters). Nevertheless, despite that, the number of months under which the null hypothesis of no persistence is violated is marginally higher for male managers.

The examination of the non-risk adjusted parametric method results reveals an interesting pattern, as we observe a positive and significant performance persistence in both portfolios for the monthly (short) time horizon. The moment we start decreasing granularity and move towards bi-monthly (short) periods in the Equity cluster, both male and female managed HFs experience weak performance persistence reversal (into negative). On the contrary, under the Universe portfolio, both genders continue to exhibit positive and statistically significant performance persistence. The quarterly (medium-term) analysis, on the other hand, is broadly similar to our initial investigation of the short-term monthly persistence. In all cases and regardless of gender, the portfolios exhibit positive performance persistence. Moving on towards the long-term view (six-monthly), we observe the dominance of negative cases except for the male managed Universe HFs, where the values strongly establish positive persistence. Lastly, the annual horizon of the performance persistence is also overrun by the statistically significant coefficients crystallising in the negative (positive) territory for females (males) in both portfolios.

When it comes to the risk-adjusted performance persistence analysis, we observe continuous positive performance persistence amongst male managers throughout all time horizons (except Equity annual) in both clusters. Interestingly, the accountability for additional risk amongst female managed funds has, in most cases, elevated them into either positive persistence territory or parity. The only occasions where female managed HFs exhibit weak negative persistence occur under the monthly horizon in both clusters[17].

[17] This study employs methods exceeding the basic mean-variance approach in the performance assessment of male/female hedge fund managers. Thus, we are unable to compare these results in/directly with the likes of Aggarwal and Boyson (2016) or even Niessen-Ruenzi and Ruenzi (2015) concerning the mutual funds. Furthermore, since the literature concerning male/female performance persistence does not exist, we are unable to draw in/direct contrasts.

Tables

Table 4.1: Number of Hedge Funds				
Investment strategy	**Universe**	**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 4.2: Moments of Order Statistics								
Panel A								
Equity	**Male**				**Female**			
	$\mathbf{r_p}$	$\boldsymbol{\sigma_m}$	**S**	$\mathbf{K_{(ex)}}$	$\mathbf{r_p}$	$\boldsymbol{\sigma_m}$	**S**	$\mathbf{K_{(ex)}}$
Average	0.71	4.20	0.01	0.21	0.83	4.28	-0.17	0.10
Min	-5.44	0.09	-2.54	-1.41	-0.34	0.74	-1.33	-0.81
Max	7.21	20.76	4.73	22.88	1.75	11.64	0.93	3.25
Median	0.69	3.89	-0.04	-0.19	0.826	4.03	-0.14	-0.22
Jarque-Bera (J-B)	7.26***				6.59***			
Ljung-Box (L-B)	3.22***				3.56***			
# of obs.	779				36			
Panel B								
Universe	**Male**				**Female**			
	$\mathbf{r_p}$	$\boldsymbol{\sigma_m}$	**S**	$\mathbf{K_{(ex)}}$	$\mathbf{r_p}$	$\boldsymbol{\sigma_m}$	**S**	$\mathbf{K_{(ex)}}$
Average	0.69	3.54	0.03	0.31	0.74	3.37	-0.12	0.34
Min	-5.44	0.02	-2.54	-1.41	-0.35	0.10	-2.15	-0.81
Max	7.21	21.60	4.73	40.38	1.75	11.64	1.62	5.54
Median	0.66	3.10	-0.04	-0.16	0.68	3.14	-0.14	-0.18
Jarque-Bera (J-B)	8.81***				8.51***			
Ljung-Box (L-B)	5.91***				6.69***			
# of obs.	1261				60			

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 **. The monthly the risk-free rate of 0.209 has been computed from 10-year US Treasury Bonds, which as of April 2019 stands at 2.51% annual return.

Table 4.3 Results: Risk-Adjusted Metrics				
	Male EQ	Female EQ	Male UV	Female UV
Panel A: Classic Ratios				
Sharpe Ratio	0.14	0.14	0.25	0.25
Jensen Alpha	0.007	0.008	0.007	0.007
Panel B: Lower Partial Moment Ratios				
Omega Ratio	0.66	0.55	1.31	0.99
Sortino Ratio	0.30	0.26	0.49	0.43
Kappa 3 Ratio	0.22	0.19	0.34	0.31
Upside Potential Ratio	0.94	0.87	1.24	1.07
Panel C: Drawdown Ratios				
Calmar Ratio	0.016	0.007	0.064	0.068
Sterling Ratio	0.39	0.41	0.49	0.48
Burke Ratio	0.34	0.35	0.54	0.40
Panel D: Ratios Based on the Value at Risk				
ErVaR	0.10	0.08	0.20	0.12
CSR	0.11	0.09	0.83	0.13
MSR	0.09	0.09	0.13	0.13
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 4.4 Rank Correlation of the Risk-Adjusted Metrics for Equity HFs

Panel A

Male Equity HFs	*Sharpe Ratio*	*Jensen*	*Omega Ratio*	*Sortino Ratio*	*Kappa 3 Ratio*	*UPR*	*Calmar Ratio*	*Sterling Ratio*	*Burke Ratio*	*Excess Var*	*CSR*	*MSR*
Sharpe Ratio	**1.00**											
Jensen	**0.76**	**1.00**										
Omega Ratio	**0.76**	0.46	**1.00**									
Sortino Ratio	**0.83**	0.55	**0.98**	**1.00**								
Kappa 3 Ratio	**0.85**	0.57	**0.97**	**1.00**	**1.00**							
Upside Potential Ratio	**0.60**	0.43	**0.65**	**0.71**	**0.71**	**1.00**						
Calmar Ratio	0.50	0.35	0.56	0.55	0.55	0.11	**1.00**					
Sterling Ratio	**0.75**	**0.83**	**0.67**	**0.72**	**0.73**	0.55	0.41	**1.00**				
Burke Ratio	**0.75**	**0.83**	**0.67**	**0.72**	**0.72**	0.55	0.41	**1.00**	**1.00**			
Excess Var	**0.87**	0.59	**0.96**	**0.99**	**1.00**	**0.69**	0.57	**0.73**	**0.72**	**1.00**		
Conditional Sharpe Ratio	**0.86**	0.57	**0.97**	**0.99**	**1.00**	**0.72**	0.54	**0.73**	**0.72**	**1.00**	**1.00**	
MSR	**0.88**	0.57	**0.88**	**0.90**	**0.91**	0.41	**0.67**	**0.66**	**0.66**	**0.92**	**0.91**	**1.00**
Average	0.78	0.61	0.83	0.84	0.83	0.57	0.60	0.82	0.78	0.97	0.95	1.00
Median	0.80	0.57	0.92	0.90	0.82	0.55	0.56	0.73	0.72	1.00	0.95	1.00

Panel B

Female Equity HFs	*Sharpe Ratio*	*Jensen*	*Omega Ratio*	*Sortino Ratio*	*Kappa 3 Ratio*	*UPR*	*Calmar Ratio*	*Sterling Ratio*	*Burke Ratio*	*Excess Var*	*CSR*	*MSR*
Sharpe Ratio	**1.00**											
Jensen	**0.67**	**1.00**										
Omega Ratio	**0.93**	**0.65**	**1.00**									
Sortino Ratio	**0.97**	**0.67**	**0.99**	**1.00**								
Kappa 3 Ratio	**0.98**	**0.67**	**0.98**	**1.00**	**1.00**							
Upside Potential Ratio	**0.79**	0.46	**0.92**	**0.91**	**0.89**	**1.00**						
Calmar Ratio	0.38	0.45	0.24	0.28	0.29	0.10	**1.00**					
Sterling Ratio	**0.72**	**0.88**	**0.73**	**0.75**	**0.74**	**0.60**	0.43	**1.00**				
Burke Ratio	**0.72**	**0.88**	**0.73**	**0.74**	**0.74**	0.59	0.43	**1.00**	**1.00**			
Excess Var	**0.98**	**0.65**	**0.95**	**0.99**	**1.00**	**0.87**	0.32	**0.73**	**0.72**	**1.00**		
Conditional Sharpe Ratio	**0.98**	**0.67**	**0.96**	**0.99**	**1.00**	**0.87**	0.31	**0.74**	**0.73**	**1.00**	**1.00**	
MSR	**0.99**	**0.67**	**0.97**	**0.99**	**1.00**	**0.86**	0.33	**0.74**	**0.73**	**1.00**	**1.00**	**1.00**
Average	0.84	0.70	0.85	0.85	0.83	0.70	0.47	0.84	0.80	1.00	1.00	1.00
Median	0.95	0.67	0.96	0.99	0.94	0.86	0.38	0.74	0.73	1.00	1.00	1.00

Note: This table provides the correlation matrix of the risk-adjusted metrics for the Equity HF portfolios - divided by gender.

Table 4.5 Rank Correlation of the Risk-Adjusted Metrics for All HFs

Panel A

Male All HFs	Sharpe Ratio	Jensen	Omega Ratio	Sortino Ratio	Kappa 3 Ratio	UPR	Calmar Ratio	Sterling Ratio	Burke Ratio	Excess Var	CSR	MSR
Sharpe Ratio	**1.00**											
Jensen	**0.61**	**1.00**										
Omega Ratio	**0.72**	0.27	**1.00**									
Sortino Ratio	**0.81**	0.36	**0.98**	**1.00**								
Kappa 3 Ratio	**0.83**	0.38	**0.96**	**1.00**	**1.00**							
Upside Potential Ratio	**0.67**	0.26	**0.90**	**0.91**	**0.91**	**1.00**						
Calmar Ratio	0.54	0.15	**0.78**	**0.78**	**0.77**	**0.71**	**1.00**					
Sterling Ratio	**0.61**	0.59	0.48	0.55	0.56	0.45	0.33	**1.00**				
Burke Ratio	**0.65**	**0.64**	0.51	0.58	0.59	0.48	0.35	**0.99**	**1.00**			
Excess Var	**0.65**	0.30	**0.71**	**0.74**	**0.75**	**0.67**	0.57	0.42	0.46	**1.00**		
Conditional Sharpe Ratio	**0.80**	0.36	**0.95**	**0.97**	**0.97**	**0.89**	**0.75**	0.53	0.57	**0.87**	**1.00**	
MSR	**0.75**	0.33	**0.82**	**0.82**	**0.81**	**0.70**	**0.61**	0.44	0.47	**0.62**	**0.79**	**1.00**
Average	0.72	0.42	0.81	0.82	0.79	0.70	0.60	0.68	0.62	0.83	0.90	1.00
Median	0.70	0.36	0.86	0.82	0.79	0.70	0.59	0.53	0.52	0.87	0.90	1.00

Panel B

Female All HFs	Sharpe Ratio	Jensen	Omega Ratio	Sortino Ratio	Kappa 3 Ratio	UPR	Calmar Ratio	Sterling Ratio	Burke Ratio	Excess Var	CSR	MSR
Sharpe Ratio	**1.00**											
Jensen	0.60	**1.00**										
Omega Ratio	**0.70**	0.25	**1.00**									
Sortino Ratio	**0.71**	0.28	**1.00**	**1.00**								
Kappa 3 Ratio	**0.70**	0.28	**0.99**	**1.00**	**1.00**							
Upside Potential Ratio	**0.64**	0.19	**0.99**	**0.99**	**0.99**	**1.00**						
Calmar Ratio	0.54	0.12	**0.89**	**0.88**	**0.87**	**0.89**	**1.00**					
Sterling Ratio	**0.81**	**0.78**	**0.67**	**0.69**	**0.68**	**0.62**	0.52	**1.00**				
Burke Ratio	**0.82**	**0.78**	**0.69**	**0.71**	**0.70**	**0.64**	0.53	**0.99**	**1.00**			
Excess Var	**0.67**	0.26	**0.99**	**1.00**	**1.00**	**0.99**	**0.87**	**0.67**	**0.69**	**1.00**		
Conditional Sharpe Ratio	**0.69**	0.27	**0.99**	**1.00**	**1.00**	**0.99**	**0.87**	**0.67**	**0.70**	**1.00**	**1.00**	
MSR	**0.91**	0.45	**0.92**	**0.92**	**0.92**	**0.89**	**0.78**	**0.80**	**0.81**	**0.89**	**0.91**	**1.00**
Average	0.73	0.42	0.91	0.91	0.90	0.86	0.76	0.83	0.80	0.96	0.95	1.00
Median	0.70	0.28	0.99	0.99	0.95	0.89	0.83	0.80	0.75	1.00	0.95	1.00

Note: This table provides the correlation matrix of the risk-adjusted metrics for the aggregated HF portfolios - divided by gender.

Table 4.6 Non-Parametric Performance Persistence for the Equity HFs									
Panel A	**Monthly**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	66.40	69.79	61.31	62.00	2.23	2.07	11.88	8.74
	STD	67.43	67.83	61.97	61.98	1.61	1.59	56.08	46.87
Female	AVG	4.78	4.89	4.43	4.43	1.05	1.18	4.75	5.67
	STD	2.92	2.79	2.73	2.73	0.21	0.39	6.50	6.60
Panel B	**Bi-Monthly**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	67.36	69.64	60.36	61.41	3.28	3.26	15.52	14.04
	STD	68.62	68.79	61.84	61.75	2.53	3.09	63.00	59.51
Female	AVG	4.77	4.81	4.55	4.49	1.06	1.13	4.75	5.67
	STD	2.91	2.81	2.78	2.78	0.23	0.34	6.50	6.60
Panel C	**Quarterly**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	68.66	70.88	58.38	58.47	4.39	4.44	20.05	19.05
	STD	68.50	67.85	60.83	60.62	3.50	4.07	74.25	70.69
Female	AVG	4.68	4.87	4.50	4.47	1.24	1.15	4.75	8.50
	STD	2.91	2.76	2.71	2.73	0.55	0.36	6.50	7.50
Panel D	**6-Monthly**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	70.05	71.28	56.26	56.33	7.60	7.79	35.18	32.75
	STD	69.87	69.03	58.24	57.40	7.44	7.42	94.88	91.24
Female	AVG	4.96	5.19	4.16	4.17	1.35	1.18	4.00	16.00
	STD	2.87	2.84	2.58	2.53	0.68	0.39	6.00	0.00
Panel E	**Annually**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	69.39	69.78	56.07	54.60	12.89	14.86	55.29	49.13
	STD	66.32	63.12	57.68	58.10	10.77	16.28	114.35	108.24
Female	AVG	4.95	5.25	4.20	4.33	1.21	1.58	4.00	16.00
	STD	2.93	2.96	2.20	2.30	0.41	0.86	6.00	0.00

Note: This table presents the mean [AVG] and standard deviation [STD] number of winning [WW] and losing [LL] periods for the Equity HFs. Furthermore, it also provides the number of winners-gone [WG] and losers-gone [LG] as well as the new-entrant-winner [NEW] and new-entrant-loser [NEL].

Table 4.7 Non-Parametric Performance Persistence for the Equity HFs							
Panel A							
Monthly	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	2.39/3.21	218	1.12/3.1	25 [91]	10.71/19.98	131 [36]	241 [.58]
Female	2.72/3.7	183	.28/1.21	11 [4]	1.74/2.02	10 [17]	171 [.6]
Panel B							
Bi-Monthly	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	1.92/1.6	109	1.01/3.37	10 [43]	12.21/24.03	64 [18]	114 [.56]
Female	3.06/7.07	91	.25/1.25	1 [4]	2.02/2.73	7 [13]	86 [.6]
Panel C							
Quarterly	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	2.12/1.8	79	1.16/3.31	7 [32]	12.04/21.3	44 [16]	80 [.56]
Female	2.32/2.5	56	.24/1.17	4 [1]	1.67/2.	4 [9]	54 [.59]
Panel D							
6-Monthly	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	2.51/2.57	41	1.7/2.98	7 [18]	13./22.28	28 [7]	42 [.59]
Female	3.08/3.48	29	.53/1.08	4 [0]	1.79/1.89	2 [5]	29 [.61]
Panel E							
Annually	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	1.72/.93	19	1.32/2.37	2 [8]	12.12/10.41	17 [5]	21 [.57]
Female	2.99/5.4	14	.3/1.14	2 [0]	2.07/1.87	1 [2]	13 [.6]

Note: This table presents the results for the Cross-Product Ratio (CPR), Z-statistic (Z-s), Chi-square (X2) calculation and the percentage of repeating winners (PRW) for the Equity HFs. Furthermore, each panel representing a time horizon consists of data for both male and female HF managers. Additional abbreviations: AVG - mean, STD - standard deviation. Please note the CPR column refers to the number of periods violating the null hypothesis of the CPR metric, while the PRW shows the number and percentage of HFs considered as repeating winners.

Table 4.8 Non-Parametric Performance Persistence for the Universe HFs									
Panel A	**Monthly**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	110.24	111.35	95.81	96.12	2.91	2.55	16.89	14.55
	STD	109.42	110.46	97.78	97.84	2.05	1.97	89.22	81.84
Female	AVG	6.52	7.79	6.51	6.53	7.75	9.67	1.03	1.04
	STD	5.46	5.20	4.64	4.61	11.69	12.26	0.18	0.19
Panel B	**Bi-Monthly**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	110.92	112.87	93.37	94.62	4.39	4.37	23.19	21.27
	STD	113.04	114.07	96.40	96.61	3.42	3.75	103.78	98.44
Female	AVG	6.50	7.68	6.48	6.51	7.75	9.67	1.12	1.11
	STD	5.54	5.33	4.63	4.61	11.69	12.26	0.32	0.31
Panel C	**Quarterly**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	109.91	110.49	93.03	92.61	6.32	6.05	30.95	30.71
	STD	111.71	111.81	94.18	94.52	4.75	5.23	124.14	120.85
Female	AVG	6.26	7.51	6.62	6.54	1.29	1.12	6.40	28.00
	STD	5.62	5.29	4.62	4.66	0.54	0.32	10.80	0.00
Panel D	**6-Monthly**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	111.79	112.62	92.53	91.36	11.60	10.63	52.08	53.08
	STD	113.70	113.63	90.57	89.72	9.58	9.73	156.80	156.26
Female	AVG	6.66	8.13	6.23	6.00	6.40	28.00	1.60	1.23
	STD	5.62	5.35	4.18	4.19	10.80	0.00	0.86	0.52
Panel E	**Annually**	**WW**	**LL**	**WL**	**LW**	**WG**	**LG**	**NEW**	**NEL**
Male	AVG	114.03	111.57	88.72	87.40	21.72	21.59	89.86	79.13
	STD	108.60	108.50	88.00	89.46	16.10	20.48	196.93	186.04
Female	AVG	6.31	7.54	6.14	6.27	6.40	28.00	1.82	1.75
	STD	5.47	5.34	4.05	4.04	10.80	0.00	0.86	0.97

Note: This table presents the mean [AVG] and standard deviation [STD] number of winning [WW] and losing [LL] periods for the Universe HFs. Furthermore, it also provides the number of winners-gone [WG] and losers-gone [LG] as well as the new-entrant-winner [NEW] and new-entrant-loser [NEL].

Table 4.9 Non-Parametric Performance Persistence for the Universe HFs							
Panel A							
Monthly	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	2.28/3.22	225	1.52/3.61	25 [121]	15.54/27.85	163 [38]	246 [.55]
Female	3.91/13.95	199	.53/1.39	22 [15]	2.54/3.08	24 [41]	247 [.67]
Panel B							
Bi-Monthly	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	2./1.8	112	1.6/4.09	14 [60]	19.92/35.39	76 [23]	127 [.55]
Female	3.01/4.14	98	.52/1.45	12 [5]	2.78/3.55	13 [19]	123 [.67]
Panel C							
Quarterly	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	1.93/1.54	78	1.61/3.72	9 [42]	17.61/27.14	57 [12]	86 [.55]
Female	2.27/2.87	58	.38/1.47	5 [4]	2.58/3.75	8 [9]	78 [.66]
Panel D							
6-Monthly	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	2.03/1.54	36	2.03/3.64	2 [20]	20.16/32.2	29 [11]	45 [.57]
Female	3.13/3.27	33	.85/1.28	3 [2]	2.64/2.71	3 [9]	42 [.7]
Panel E							
Annually	**AVG/STD CPR**	**CPR**	**AVG/STD Z-s**	**Z@5% [1%]**	**AVG/STD X2**	**X2@5% [@1%]**	**PRW [PRW%]**
Male	1.89/1.07	18	2.25/2.69	0 [13]	20.24/18.53	22 [4]	21 [.57]
Female	3./4.12	15	.71/1.13	0 [1]	2.78/2.59	2 [4]	24 [.69]

Note: This table presents the results for the Cross-Product Ratio (CPR), Z-statistic (Z-s), Chi-square (X2) calculation and the percentage of repeating winners (PRW) for the Universe HFs. Furthermore, each panel representing a time horizon consists of data for both male and female HF managers. Additional abbreviations: AVG - mean, STD - standard deviation. Please note the CPR column refers to the number of periods violating the null hypothesis of the CPR metric, while the PRW shows the number and percentage of HFs considered as repeating winners.

Table 4.10 The Non-Risk-Adjusted Parametric Performance Persistence for the Equity HFs										
Panel A										
XR m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	-2.456	-2.480	3.440	3.617	0.169	0.136	0.082	0.157	0.550	0.575
Sigma	1.726	1.790	1.870	1.999	0.250	0.321	0.287	0.294	0.120	0.113
Max	0.106	0.374	9.478	16.739	0.838	3.541	0.584	2.165	0.713	1.000
Min	-9.152	-15.673	-0.236	-0.803	-0.225	-0.993	-1.108	-0.752	0.170	0.116
Pos	1	23	34	772	25	519	23	544		
Sig 0.05	0	5	33	748	3	76	4	103		
Neg	34	751	1	3	10	256	11	232		
Sig 0.05	31	666	0	0	0	8	0	4		
Panel B										
XR bi-m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	-1.766	-1.722	2.763	2.871	0.079	0.180	0.159	0.159	0.513	0.532
Sigma	1.337	3.355	1.644	1.709	0.353	0.463	0.363	0.467	0.163	0.152
Max	0.233	78.459	8.801	13.613	1.441	6.867	1.248	4.247	0.809	0.987
Min	-6.907	-17.368	-0.393	-3.744	-0.665	-2.778	-0.460	-3.532	0.002	-0.152
Pos	3	33	34	738	21	512	23	513		
Sig 0.05	0	10	31	681	2	66	2	63		
Neg	32	712	1	9	14	236	12	236		
Sig 0.05	27	523	0	0	2	4	0	9		
Panel C										
XR q	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	-0.584	-1.237	2.470	2.471	0.148	0.082	0.088	0.126	0.489	0.541
Sigma	2.097	1.544	1.422	1.524	0.555	0.790	0.281	0.502	0.313	0.171
Max	10.031	19.634	7.276	11.295	2.767	6.150	1.229	2.609	0.846	1.000
Min	-3.173	-11.240	0.103	-4.909	-0.579	-16.886	-0.435	-3.534	-0.828	-0.500
Pos	3	58	34	704	20	460	24	456		
Sig 0.05	1	21	30	617	1	48	1	70		
Neg	32	653	0	12	15	259	11	263		
Sig 0.05	16	375	0	0	0	12	0	13		
Panel D										
XR 6m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	-0.916	-1.012	1.751	1.564	0.191	0.350	0.230	0.239	0.472	0.475

Sigma	0.773	2.391	0.787	1.937	0.362	2.567	0.290	0.683	0.233	0.361
Max	0.350	19.537	3.179	8.554	0.932	59.799	0.971	7.550	0.850	1.000
Min	-3.319	-43.964	0.415	-31.405	-0.405	-2.821	-0.301	-2.775	-0.191	-3.204
Pos	4	120	27	575	23	443	23	435		
Sig 0.05	1	29	21	387	2	87	0	69		
Neg	24	482	0	31	5	169	5	170		
Sig 0.05	8	189	0	2	0	10	0	11		
Panel E										
XR a	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	-1.278	-1.028	1.197	1.251	0.927	0.616	0.409	0.198	0.532	0.483
Sigma	0.770	1.909	0.539	1.424	0.954	1.636	0.338	2.335	0.230	0.276
Max	0.415	1.766	1.974	15.225	2.397	9.751	1.293	17.759	0.919	0.973
Min	-2.548	-25.939	0.409	-14.648	-2.057	-19.131	-0.403	-36.527	0.089	-0.283
Pos	1	87	18	329	17	296	18	256		
Sig 0.05	0	4	9	124	8	55	1	58		
Neg	18	252	0	9	2	40	1	78		
Sig 0.05	9	72	0	2	0	3	0	0		

Note: This table presents the non-risk-adjusted parametric performance persistence test results for the Equity (EQU) HFs. The data has been divided into five different time intervals, monthly (m), bi-monthly (bi-m), quarterly (q), six-monthly (six-m) and annually (a). 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) relates to 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. Abbreviations: FEM denotes female managed HFs, while MAL, male equity HFs.

Table 4.11 The Non-Risk-Adjusted Parametric Performance Persistence for the Universe HFs

Panel A										
XR m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	-1.752	-1.948	2.616	2.973	0.245	0.188	0.227	0.225	0.520	0.547
Sigma	1.799	1.918	2.009	2.174	0.346	0.401	0.409	0.402	0.174	0.150
Max	0.569	2.832	9.478	19.444	1.344	3.541	1.730	2.816	0.984	1.000
Min	-9.152	-23.164	-0.571	-1.802	-0.225	-2.516	-1.108	-1.615	0.100	0.073
Pos	9	137	55	1221	45	859	41	895		
Sig 0.05	3	39	51	1111	8	152	11	209		
Neg	49	1108	4	30	13	386	17	357		
Sig 0.05	39	912	1	9	0	10	0	10		
Panel B										
XR bi-m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	-1.266	-1.342	2.174	2.306	0.190	0.246	0.278	0.235	0.484	0.508
Sigma	1.440	2.794	1.715	2.200	0.500	0.589	0.538	0.581	0.196	0.186
Max	1.316	78.459	8.801	33.285	2.172	9.826	2.184	5.508	0.990	0.998
Min	-6.907	-17.368	-0.682	-18.744	-0.961	-2.778	-0.640	-3.532	0.002	-0.283
Pos	13	170	53	1157	37	869	40	847		
Sig 0.05	3	35	45	982	4	131	5	141		
Neg	44	1043	5	63	20	347	18	374		
Sig 0.05	33	690	0	11	2	7	1	14		
Panel C										
XR q	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	-0.206	-0.890	1.934	2.040	-0.040	0.092	0.145	0.161	0.467	0.519
Sigma	2.407	1.582	1.445	1.589	1.305	0.986	0.384	0.626	0.280	0.213
Max	12.245	19.634	7.276	18.466	2.767	6.150	1.430	3.324	0.988	1.000
Min	-3.173	-11.240	-0.567	-4.909	-9.042	-22.354	-0.462	-9.956	-0.828	-1.843
Pos	13	217	53	1121	31	727	38	755		
Sig 0.05	5	76	43	920	1	97	4	113		
Neg	43	933	2	40	25	436	18	414		
Sig 0.05	20	479	1	5	0	19	0	22		
Panel D										
XR 6m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	-0.664	-0.695	1.486	1.345	0.457	0.313	0.317	0.257	0.477	0.477

Sigma	1.091	2.661	0.908	1.782	1.356	2.055	0.932	1.128	0.245	0.377
Max	1.734	53.320	3.179	13.662	9.351	59.799	4.977	7.550	0.999	1.000
Min	-5.102	-43.964	-0.162	-31.405	-0.405	-3.276	-3.357	-16.675	-0.191	-3.204
Pos	13	288	45	899	40	722	39	730		
Sig 0.05	3	76	29	555	7	141	2	143		
Neg	36	680	2	89	8	266	10	258		
Sig 0.05	10	242	0	8	0	15	m	18		
Panel E										
XR a	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	-0.750	-0.780	0.808	0.974	0.736	0.396	0.540	0.350	0.574	0.501
Sigma	0.917	2.214	0.670	2.347	0.918	2.061	0.411	2.944	0.236	0.288
Max	0.415	6.675	1.974	15.225	3.188	9.751	1.630	55.323	0.919	0.989
Min	-2.548	-28.186	-0.798	-46.625	-2.057	-21.119	-0.403	-36.527	0.089	-0.398
Pos	11	218	28	539	31	493	32	450		
Sig 0.05	3	25	11	212	13	101	9	146		
Neg	22	362	4	37	2	79	1	115		
Sig 0.05	9	100	1	8	0	7	0	1		

Note: This table presents the non-risk-adjusted parametric performance persistence test results for the Universe (ALL) HFs. The data has been divided into five different time intervals, monthly (m), bi-monthly (bi-m), quarterly (q), six-monthly (six-m) and annually (a). 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) relates to 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. Abbreviations: FEM denotes female managed HFs, while MAL, male equity HFs.

Table 4.12 The Risk-Adjusted Parametric Performance Persistence for the Equity HFs										
Panel A										
AXR m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	-0.0004	-0.001	0.511	0.655	-0.002	0.004	-0.006	-0.019	0.112	0.094
Sigma	0.400	0.632	0.537	0.559	0.033	0.200	0.098	0.781	0.168	0.146
Max	1.332	13.537	1.330	5.161	0.076	5.036	0.237	1.755	0.988	0.994
Min	-0.588	-3.511	-1.669	-0.782	-0.092	-0.915	-0.371	-21.387	-0.017	-0.464
Pos	13	281	33	739	18	388	17	427		
Sig 0.05	3	36	25	506	2	19	1	39		
Neg	22	493	1	37	17	387	18	348		
Sig 0.05	2	42	0	2	3	16	2	30		
Panel B										
AXR bi-m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	-0.081	0.089	0.673	0.642	0.006	-0.036	-0.022	-0.005	0.070	0.101
Sigma	0.449	1.798	0.629	0.672	0.060	1.252	0.139	0.265	0.137	0.203
Max	1.095	42.288	2.217	5.351	0.204	9.757	0.108	5.384	0.333	0.976
Min	-1.328	-5.820	-0.091	-3.511	-0.216	-29.525	-0.775	-1.658	-0.466	-1.197
Pos	11	316	34	680	16	395	19	381		
Sig 0.05	1	42	18	376	0	16	2	25		
Neg	24	431	1	69	19	353	16	368		
Sig 0.05	5	29	0	4	0	14	0	19		
Panel C										
AXR q	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	-0.060	-0.019	0.537	0.489	0.003	0.038	0.000	-0.035	0.097	0.122
Sigma	0.435	0.647	0.494	1.926	0.100	0.723	0.166	0.656	0.284	0.247
Max	0.894	2.845	1.793	3.767	0.358	17.629	0.422	4.890	0.826	0.997
Min	-1.405	-7.440	-0.323	-43.853	-0.218	-3.866	-0.712	-11.703	-1.059	-1.075
Pos	14	323	30	651	16	357	20	366		
Sig 0.05	1	42	19	283	1	20	1	32		
Neg	21	389	4	65	19	361	15	353		
Sig 0.05	0	11	0	3	1	7	1	20		
Panel D										
AXR 6m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	0.196	0.203	0.364	0.531	0.034	0.019	-0.124	-0.038	0.069	0.155

Sigma	0.404	1.022	0.727	1.255	0.148	0.868	0.534	1.171	0.292	0.426
Max	1.452	14.699	1.536	18.217	0.664	12.325	0.629	14.840	0.918	0.999
Min	-0.279	-8.250	-2.749	-4.104	-0.272	-7.294	-2.082	-16.092	-0.640	-3.204
Pos	18	402	25	496	19	325	13	302		
Sig 0.05	1	72	9	187	1	25	1	30		
Neg	10	200	3	108	9	287	14	305		
Sig 0.05	0	10	0	10	0	11	1	26		
Panel E										
AXR a	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-EQU	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**	**FEM-EQU**	**MAL-EQU**
Mean	0.385	0.843	0.783	0.775	0.809	-0.020	-0.060	0.091	0.172	0.151
Sigma	1.916	2.109	0.621	1.910	3.894	0.850	0.194	2.679	0.289	0.336
Max	3.322	17.325	2.722	13.446	17.265	4.157	0.463	37.870	0.805	0.862
Min	-6.429	-9.862	-0.128	-15.413	-0.714	-10.263	-0.512	-9.071	-0.321	-0.734
Pos	13	270	17	298	9	169	9	169		
Sig 0.05	1	41	2	56	1	15	1	6		
Neg	6	64	1	37	10	170	9	168		
Sig 0.05	1	1	0	1	2	11	0	12		

Note: This table presents the results for the risk-adjusted parametric performance persistence test for the Equity (EQU) HFs. The data has been divided into five different time intervals, monthly (m), bi-monthly (bi-m), quarterly (q), six-monthly (six-m) and annually (a). 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) relates to 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. Abbreviations: FEM denotes female managed HFs, while MAL, male equity HFs.

Table 4.13 The Risk-Adjusted Parametric Performance Persistence for the Universe HFs										
Panel A										
AXR m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	0.107	0.077	0.646	0.702	0.016	0.001	-0.011	-0.009	0.146	0.136
Sigma	0.426	0.596	0.526	0.586	0.144	0.179	0.084	0.625	0.218	0.193
Max	1.332	13.537	1.398	5.161	1.074	5.036	0.237	1.755	0.988	0.999
Min	-0.588	-3.511	-1.669	-2.326	-0.092	-0.915	-0.371	-21.387	-0.254	-0.464
Pos	29	544	56	1185	32	611	31	692		
Sig 0.05	10	170	42	838	3	38	1	59		
Neg	29	700	2	67	26	635	28	559		
Sig 0.05	3	56	0	4	4	26	3	40		
Panel B										
AXR bi-m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	0.081	0.129	0.753	0.696	0.003	-0.024	-0.0002	-0.003	0.124	0.147
Sigma	0.480	1.556	0.592	0.669	0.133	1.011	0.121	0.244	0.218	0.239
Max	1.151	42.288	2.217	5.351	0.773	9.757	0.232	5.384	0.988	0.997
Min	-1.328	-18.751	-0.091	-3.511	-0.343	-29.525	-0.775	-2.384	-0.544	-1.197
Pos	27	618	56	1115	24	637	35	651		
Sig 0.05	9	157	33	680	1	28	5	46		
Neg	30	596	2	107	33	580	23	570		
Sig 0.05	5	38	0	5	1	19	0	29		
Panel C										
AXR q	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	0.088	0.061	0.633	0.561	0.091	0.023	0.016	-0.030	0.152	0.159
Sigma	0.531	0.649	0.553	1.564	0.687	0.584	0.164	0.648	0.281	0.270
Max	2.085	4.916	2.741	4.236	5.142	17.629	0.682	4.890	0.894	0.997
Min	-1.405	-7.440	-0.323	-43.853	-0.218	-3.866	-0.712	-11.703	-1.059	-1.075
Pos	30	592	50	1062	23	581	34	605		
Sig 0.05	8	136	33	514	2	35	2	51		
Neg	26	560	5	102	33	582	22	563		
Sig 0.05	1	22	0	8	1	11	0	41		
Panel D										
AXR 6m	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	0.278	0.259	0.599	0.806	0.461	0.045	-0.156	0.182	0.136	0.195

Sigma	0.481	1.442	1.097	4.980	3.168	1.071	0.684	5.954	0.365	0.441
Max	1.659	34.701	6.294	120.744	22.375	25.767	0.656	181.036	0.996	1.000
Min	-0.504	-8.250	-2.749	-7.047	-0.720	-7.294	-3.832	-16.092	-0.978	-3.204
Pos	33	671	42	820	31	532	24	497		
Sig 0.05	7	177	18	338	1	46	1	54		
Neg	15	293	6	169	18	460	24	490		
Sig 0.05	1	14	0	18	1	17	0	43		
Panel E										
AXR a	**Alpha n**		**Alpha p**		**Beta n**		**Beta p**		**Adj R2**	
	FEM-ALL	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**	**FEM-ALL**	**MAL-ALL**
Mean	0.433	0.688	0.795	0.729	0.559	-0.035	0.155	0.080	0.335	0.198
Sigma	1.571	1.813	0.698	1.558	2.991	0.703	0.779	2.097	0.374	0.351
Max	3.322	17.325	2.936	13.446	17.265	4.157	3.662	37.870	0.856	0.938
Min	-6.429	-9.862	-0.424	-15.413	-0.714	-10.263	-0.512	-9.071	-0.422	-0.734
Pos	26	476	29	501	16	283	17	295		
Sig 0.05	6	77	10	145	1	19	5	21		
Neg	7	94	3	66	17	296	15	279		
Sig 0.05	1	2	0	2	2	20	0	30		

Note: This table presents the risk-adjusted parametric performance persistence test results for the Universe (ALL) HFs. The data has been divided into five different time intervals, monthly (m), bi-monthly (bi-m), quarterly (q), six-monthly (six-m) and annually (a). 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) relates to 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. Abbreviations: FEM denotes female managed HFs, while MAL, male equity HFs.

Chapter 5. Hedge Fund Flows: Managers' Ethnicity.

5.1 Introduction

Ethnic/racial identification is often considered an early dimension of self-identification, although not as early as gender. The learning process during which the individuals ascertain frameworks for classifying their (and others) ethnic/racial association usually occurs during childhood. Such classification, if associated with emotion and affect, may become significantly embedded in selfhood and lead to various outcomes (Epstein, 1978). Moreover, as Jenkins (2008) points out, the debate considering whether ethnicity is primordial or situational is still ongoing. The most recent events of the last decade show us the struggles in combatting significant inequalities within our societies. As Politico (2019) reports, between 2014 and 2019, the European Parliament (EP) has employed only 17 out of 751 (or 2.3%) MEPs representing minority non-white backgrounds. Furthermore, this number is expected to decrease in post-Brexit Europe as all MEPs (in the EP) of South Asian origin come from the United Kingdom. The other common inequality arena is religion, where the most recent data shows us the exponential increase in the discriminatory, antisemitic incidents between 2009 and 2019 across Europe (EU Agency for Fundamental Rights, 2020) (especially evident in Germany, the United Kingdom and France). Lastly, we cannot forget about gender inequality. The European Commission (EC) estimates the gender pay gap has remained almost unchanged in the last decade and revolves around 14% (European Commission, 2018).

We could provide countless examples of lesser/greater injustices at every level, regardless of granularity (global, continental, national, regional). Although what we find particularly interesting is the fact that these inequalities extend as far as the fund/asset management environment. Kumar, Niessen-Ruenzi and Spalt (2015) observe that "the foreignness", derived from or associated with the name of the fund manager, generates a bias in decision-making amongst the investors, which subsequently affects the capital allocation. As much as the gender pay gap is debatable and highly dependent on many factors, Niessen-Ruenzi and Ruenzi (2015) find that female mutual fund managers attract substantially lower capital inflows despite the adaptation of more reliable strategies and generation of the same returns as their male counterparts. These kinds of biases do not support rational statistical discrimination and instead ‘irrational prejudice’ towards a specific group (Becker, 1971; Phelps, 1972). As we show in the literature review (Chapter 2, sub-section 2.3), investor behaviour is highly dependent on a multitude of factors. In many cases, these behaviours are formed and influenced during childhood or in association with a particular group. As far as the in-group environment is concerned, the fear of rejection and even expulsion/punishment plays an important role. This in effect generates a singularly directed behaviour, which would not occur on an individual basis with the same intensity (Zdaniuk and Levine, 2001; Fehr and Gachter, 2002). The inequalities are very much a part of our daily lives; in many cases, they prevail undetected for decades and can crystallise in almost any dimension, most commonly from politics, through religion, to finance. We further discuss the above-mentioned aspects in the literature review in Chapter 2, sub-section 2.3.

Thus, in this chapter, we envisage answering the following research questions. Can the ethnicity (derived from the first name) of a hedge fund manager affect the level of capital inflows in a hedge fund? This is the first research of its kind to examine hedge funds and potential inflow bias associated with managers' ethnicity. Our study's initial focus is to examine the capital inflows considering the ethnic profile of each manager in our dataset. Subsequently, after determining the capital inflows, this chapter poses another research question. Do the hedge fund returns justify the capital inflows? This time, this research question identifies whether the investors’ decision-making, results from rational statistical discrimination or a potential ‘irrational prejudice’ towards the specific group of hedge fund managers. We believe that the revival of this type of research (especially in the areas such as hedge funds, which were not previously explored in the literature under this perspective) can provide a direct benefit and support to the spread of diversity in the corporate investment world. Regarding our methodology, in the first instance, we determine the most appropriate regression based on the type of data we have. In effect, we employ the Random-Effects Generalised Least Squares regression (we also provide the Ordinary Least Squares regression merely for comparison purposes). The determination as to which models we should employ was based on the application of the Hausman and Breusch-Pagan Lagrangian Multiplier tests.

To further explore the performance dimension, we examine both clusters' performance focusing on the metrics incorporating higher-order statistics (3rd order being skewness and 4th kurtosis). The HFs are commonly known to exhibit negative skewness and positive kurtosis, which from the perspective of the risk-averse investor is undesirable as it increases the probability of significant losses in cases where the returns' distribution is normal (Favre and Signer, 2002; Kat, 2003; Eling, 2006). The analysis we have adopted has been divided into the classic metrics (direct derivatives of the Markowitz's (1952) portfolio selection theory) including Sharpe ratio and Jensen Alpha; Lower Partial Moments Ratios (LPM) including Omega, Sortino, Kappa 3 and Upside Potential; Drawdown Ratios including Calmar, Sterling and Burke; Value at Risk (VaR) based ratios including Excess Value at Risk, Conditional Sharpe Ratio and Modified Sharpe Ratio[18].

Our research reveals a peculiar picture as soon as we look into the descriptive statistics. We quickly learn that most HF managers (91% to be specific) represent a solely White[19] background. At the same time, the rest is a result of a combination of Asian and Latino managers. Our attention increases as we look into the average monthly flows into *Pctother* funds, which represent 2.9% of all average monthly inflows into the *Pctwhite* funds. Surprisingly, the average monthly returns for *Pctother* are higher than for *Pctwhite* HFs across the entire time-series of 252 months (1999-2019). Interestingly, both clusters' average monthly returns converge during and after the severe market distress period, such as the most recent global recession of 2007-2009. A final yet equally important observation we can derive from the initial descriptive statistics is the fact that in almost all cases (except the high watermark), the fees (management, performance, redemption) and thresholds (hurdle rate, lock-ups, advanced notice) are higher for the *Pctother* HFs. Thus, making them more expensive to maintain and therefore less appealing to the average investor.

Stepping up to the regression, we can confidently report that our results are in line with similar literature, where the minority (e.g., managers with the name that is perceived as foreign or the gender of the manager being female) asset managers experience significantly lower flows into their funds despite

[18] Please refer to section 5.3 for details.
[19] Denoted as *Pctwhite*, while the combination of Asian and Latino managers as *Pctother*.

providing better returns/performance. However, in our case, the magnitude of the results is much higher. We observe 57 percentage points fewer capital inflows into the HFs managed by the representatives of the racial/ethnic minority (as opposed to White/Caucasian HF managers). Furthermore, the results do not support rational statistical discrimination as the minority HF managers generate higher raw returns.

The results of the risk-adjusted analysis also uncover interesting findings. Under Markowitz's (1952) classical approach, we observe a notable difference between the average Sharpe ratios, with the *Pctother* being higher by approximately 44%. Although, as soon as we look into the LPM based metrics, we learn that the *Pctwhite* HFs are minimally better managing the negative deviations of the returns' distribution. Thus, they are slightly better at minimising the probability of the extreme loss occurrence and operating their portfolios at a higher efficiency as compared with the *Pctother*. Furthermore, the risk involved in the generation of the returns in the *Pctwhite* HFs is lower according to the Upside Potential Ratio (the prelude of this could have been observed in the basic assessment of our descriptive statistics). When it comes to metrics employing the average annual compounded rate of return, both clusters operate at the same level. However, under the assumptions of the compounded annualised return, *Pctother* funds carry a slight advantage. Lastly, the Excess VaR stands at the same level for both *Pctwhite* and *Pctother* managers. Although, the accountability for higher-order statistics through the Modified and Conditional Sharpe Ratio aligns with the earlier findings, providing the *Pctother* with a further, yet statistically insignificant, advantage.

Like many other researchers, we strongly believe that the future exploration of topics concerning ethnic/racial imbalances in fund management is very important. We are delighted to provide the first research of this kind, which addresses ethnic/racial imbalances within the HFs industry, where the collective assets under management of US$ 3.61tn (Prequin, 2020) exhibit a significant influence on global economic stability.

The remaining sections of this chapter are organised in the following way: Section 5.2 describes the data and data cleaning process; Section 5.3 focuses on methods and is divided into three sub-categories (Variables, Regression and Risk-Adjusted Metrics); while section 5.4 provides the description of the results and Section 5.5 concludes findings. Lastly, the literature review has been explored in Chapter 2 (sub-section 2.3).

5.2 Data

5.2.1 General Data Overview

This research employs the data from the Morningstar Direct database, which in the current form as of December 2020 consists of 6649 HFs. According to Massa, Reuter and Zitzewitz (2010), Morningstar Direct is one of the most precise databases when it comes to managers' identity information. The timeframe of our research spans between January 1999 and December 2019[20]. The data cleaning process begins with the removal of all HFs with less than 12 months of historical net returns and missing manager details (which downsizes the population to 2229 HFs) - the same process is applied to the separate extract of the net flows (where the number of HFs downsizes to 1127). We also remove HFs, which do not report their net flows; the same applies to the corresponding HFs in the net return's dataset. After aligning two datasets (net returns and net flows), we end up with 1076 HFs. In the last step, we remove the duplicate funds, where the correlation between the funds is higher than or equal to 0.85 (our approach is slightly more aggressive than the one employed by Aggarwal and Jorion (2010), which was set at 0.99 correlation, as we eliminate not only highly correlated share class duplicates but also the fund listings in various currencies), simultaneously downsizing our dataset to 770 unique HFs. Both flows and the returns are then subjected to the winsorisation process, where the bounds are set to 0.05.

Our cleaned dataset is then categorised based on the race and ethnicity of the HF managers. In our classification, we employ the demographic dataset created by Tzioumis (2018)[21]. In brief, his approach was to create a unique list of first names based on the three proprietary mortgage datasets. The combined, voluminous dataset was then used to classify the applicants' ethnicity into six categories, which were previously present in two Censuses (2000 and 2010).

Since our analysis relies on the ability to extract names of HF managers', we additionally exploit the 2004 Securities and Exchange Commission (SEC) 33-8458 rule (SEC, 2004), which required all mutual funds and closed-ended funds (some hedge funds) (Hastings, 2004) to disclose managers (management team) names. As we learn from Kumar et al. (2015), before October 2004, approx. 34% of funds did

[20] Due to the number of non-*Pctwhite* HF managers making appearance only around 1999.
[21] Please see Tziomis (2018) for details.

not disclose the manager/management team member names (instead of labelling them as “anonymous” or “team managed” - a practice that still happens in some of the funds).

Using Tzioumis’s (2018) list of the 4250 unique first names and their probabilities of occurring under a specific race/ethnicity, we manage to easily classify 686 of 770 HF managers (Table 5.1). The remaining 84 HF manager names were found manually, through an online search (based on the HF or the umbrella-fund name), and then their names were classified using Tzioumis’s (2018) race/ethnicity name association list. In addition, given the relatively small sample of hedge funds in our analysis, we manually verify the accuracy of Tzioumis’s (2018) method (through a search on Bloomberg and the individual hedge fund websites).

We have also adopted the same naming conventions where the non-Hispanic White is labelled *Pctwhite*, non-Hispanic Asian is *Pctapi* and Hispanic, or Latino is *Pcthispanic*. Although, due to the low number of HF managers representing the Asian and Hispanic ethnicities, we have decided to combine them to form one category, denoted as *Pctother*. Sadly, the application of Tzioumis’s (2018) framework does not indicate the existence of Black HF managers in our dataset, which does not mean they are not present in the overall Morningstar Direct dataset.

*** Insert Table 5.1 ***

In a further attempt to visualise the annual fluctuations of the racial/ethnic disparities between the number of HF managers, we have plotted our cleaned data on a graph (Figure 1). Figure 1 indicates that the number of *Pctother* HF managers begins to appear in 1999, initially with a 3% share, which then increases to 10% a decade later and stabilises at 11% from 2014 onwards. In addition, we have also provided the list of the top 20 most common HF manager names (Figure 2).

*** Insert Figure 1 ***

*** Insert Figure 2 ***

As an additional insight, Table 5.2 provides the HF managers' descriptive statistics with the most common first names. For example, HF managers named Robert, Adam and Jeffrey attract the most capital (flows) overall. Whereas, when it comes to the average returns, it is Adam, Michael, and Eric - despite some of the highest average capital flows, Robert and Jeffrey rank 5th and 12th, respectively. Also, in the rec period, Christophers generate the highest average returns, while the flows belong to Kevins. Overall, considering all rankings, John and Paul were most likely to provide the optimal balance between the capital inflows and generation of returns.

*** Insert Table 5.2 ***

5.2.2 Descriptive Statistics

Table 5.3 reports the descriptive statistics of our final sample of 770 HFs (Jan 99-Dec 19) classified based on the ethnic association of the HF manager. In the first instance, we observe that the average HF size for the *Pctwhite* cluster dwarfs the combination of the other two (*Pctother*). Furthermore, not surprisingly, the net average (as well as the median) flows of the *Pctwhite* are also significantly above the *Pctother*. An interesting observation can be also attributed to the results of the t-test, which regarding the difference between the inflows of the two clusters remains statistically insignificant. Thus, indicating there is no difference between the level of flows in *Pctwhite* and *Pctother*. The logical implication is that the significant and positive average inflows into the *Pctwhite* HFs would, in effect, be a result of superior returns (Huang, Wei and Yan, 2007). Thus, given these observations, we have also decided to investigate the net returns to see whether or not they justify the substantial differences in the average/median net flows between the ethnically classified funds. Interestingly, the *Pctother* cluster dominates the returns despite its average monthly inflows representing approx. 69.5% of all average monthly inflows in *Pctwhite* funds. Not surprisingly, the skewness of the returns is also negative amongst *Pctwhite* HFs what correlates with their lower (in contrast to *Pctother*) average returns (the t-test also indicates the significance at 0.05).

As much as it seems a paradox (*Pctwhite* attracting significant net inflows, as compared to the *Pctother* generating the higher average returns), a similar situation has been observed in gender-related studies (see literature review) and documented by Niessen-Ruenzi and Ruenzi (2015). At the time, it was identified as 'irrational prejudice towards' female mutual fund managers as opposed to rational statistical discrimination. To further examine both flows and the returns and thus provide even deeper insight, we have dissected our sample into three different periods around the most recent economic depression of 2007-2009. The whole purpose of it is to learn how our ethnically classified HF managers dealt with the most recent period of significant economic/market distress and how it affected the flows. In all three periods, the *Pctother* HFs minimally dominate *Pctwhite* in terms of the average returns. During the recession (rec) period, we can see a significant drop in the average returns in both clusters, which then emerge in the post-rec. As we can observe, the flows in the pre-recession period in *Pctwhite* HFs attract approx. \$2.31M per month (on average), while the *Pctother* attracts less than a quarter of this figure (\$0.55M) - also, the t-test indicates statistical significance at 0.05.

Furthermore, the rec period shows that the flows for both *Pctwhite* and *Pctother* are negative (in fact converting into outflows). While the flows for both clusters in the post-rec period are positive, it is the *Pctother* that takes the greater share of the average monthly flows. Regarding the fees (management, performance, and redemption), by far, the highest on average can be found amongst the *Pctother* HFs with *Pctwhite* funds charging the least. Furthermore, the *Pctother* HFs' hurdle rate is minimally lower, meaning these funds will apply performance fees charges sooner than those in the other cluster (when the fund generates on average >=1.43% profit). However, from the perspective of the high watermarks, the *Pctother* HFs are the most attractive investment. The new investors' inability to redeem the assets is expressed by a lock-up period, which is on average the shortest for the *Pctwhite* HFs. While the advanced notice required for the redemptions is similar across both clusters, although minimally higher for the *Pctother* funds. Lastly, despite the aforementioned differences, the manager's average tenure across both clusters is approximately 11 years.

*** Insert Table 5.3 ***

5.3 Methods

This section consists of two parts. In the first instance, we outline the regression model we have adopted, while the second part focuses on several risk-adjusted metrics.

5.3.1 Regression

Prior to the regression analysis, we first define all variables in Table 5.4. Furthermore, Table 5.4 also explains the source and a combination of the variables used in calculations.

*** Insert Table 5.4 ***

To decide whether we should employ fixed or random effects, we first use the Hausman specification test (1) (Hausman, 1978; Green, 2008). The null hypothesis of this test indicates the preferred model (either fixed or random effects). Since the results of the chi-square are not statistically significant (@ 0.05) at 0.995 level, we focus on the Random-Effects model (5.1) in the first place (Table 5.6 and 5.8, Panel B).

$$Var\left[b-\hat{\beta}\right] = Var[b] + Var\left[\hat{\beta}\right] - Cov\left[b,\hat{\beta}\right] - Cov[\hat{\beta},b] \qquad (5.1)$$

In a subsequent step, we use the Breusch-Pagan Lagrangian Multiplier $BP(LM)$ test (5.2), where $\hat{\epsilon}^2 = [\epsilon_1^2\ \epsilon_2^2 \ldots \epsilon_T^2], 1 = [1\ 1 \ldots 1]^T$. The statistical test is the chi-square, where the number of d.f. equals to the number of regressors in the Z matrix (Breusch and Pagan, 1979). The test helps to decide between the Random-Effects Generalised Least Squares (GLS) regression and the Ordinary Least Squares (OLS) regression. As seen in Tables 5.6 and 5.8 (Panel B), the result is statistically significant with a chi-square of less than 0.01. Thus, we fail to reject the null hypothesis and conclude that the Random-Effects test is appropriate. Nevertheless, for the sake of contrast, we also include the results of the OLS approach. The regression model we use can be seen in equation (5.3), where the μ_i corresponds to the individual-specific effect and ε_i is an error term. The variables employed in this regression (5.3) are as follows. The dependent variable, in this case, is denoted as Flow and refers to the inflows of capital Flow=(〖TNA〗_(i,t)- 〖TNA〗_(i,t-1))/ 〖TNA〗_(i,t-1) -r_(i,t), where the TNA stands for Total Net Assets (Ammann et al. 2018). Regarding the independent variables, Eth_w refers to Ethnicity and takes the form of the dummy variable, where number 1 corresponds to Pctother and 0 to Pctwhite; Returnp refers to the monthly net returns as a percentage; Inter_eth_r is an interactive variable created out of the Eth_w and Returnp; Mfee stands for management fees; Pfee stands for performance fees; Rfee stands for redemption fees; Hrate stands for hurdle rate; Hwmark stands for high watermark; Lock_u stands for lock up (expressed in months); Adv_n stands for advanced notice (in months); Man_t stands for managers' tenure (in years).

Regarding the variables used in the regression, please see Table 5.2.

$$BP(LM) = \frac{(\hat{\epsilon}^2 - \hat{\sigma}^2 1)^T \, Z(Z^T Z)^{-1} Z^T (\hat{\epsilon}^2 - \hat{\sigma}^2 1)^T}{\sum_{i=1}^{n} \epsilon_i^2 / (n-k)} \qquad (5.2)$$

$$Flow(\hat{y}) = \beta_0 + \beta_1 eth\_w_1 + \beta_2 returnp_2 + (\beta_1 eth\_w_1 * \beta_2 returnp_2) + \beta_3 mfee_3 + \beta_4 pfee_4 + \beta_5 rfee_5 + \beta_6 hrate_6 + \beta_7 hwmark_7 + \beta_7 lock\_u_7 + \beta_7 adv\_n_7 + \beta_7 man\_t_7 + \mu_i + \varepsilon_i \qquad (5.3)$$

5.3.2 Risk-Adjusted Metrics

Further to our earlier analysis, we have also computed the risk-adjusted metrics for both clusters. Table 5.10 presents the results, which are divided into four tiers: classic, lower partial moment, drawdown, and the value at risk-based ratios.

In our analysis, the classic ratios comprise the Sharpe ratio and Jensen Alpha. Both of these ratios are directly related to Markowitz's portfolio theory (Markowitz, 1952). The Sharpe ratio, in particular, is the most widely used metric in the finance-related literature (Sharpe, 1966; Dhrymes, 2017). While the classic ratios consider both positive and negative deviations of the returns, the same cannot be said about the lower partial moments (LPM), which measure the risk considering only negative deviations with respect to the minimum acceptable return (MAR) (Fishburn, 1977). Therefore, the LPM metrics provide an improved measure of risk as compared to the classical approach. The next risk-adjusted metric class, the Upside Potential ratios, combines the lower and higher partial moments to assess the investment appeal (the application of the increased weighting to the returns below the MAR) (Sortino, van der Meer, and Plantinga, 1999). The drawdown-based ratios are particularly relevant to HFs. These metrics combine the returns with the average of all the most unfavourable drawdowns in each year. Furthermore, they are also thought to be easy to interpret, while their operational properties are difficult to analyse (Schuhmacher and Eling, 2011). Lastly, the metrics based on the Value at Risk (VaR) measure the worst expected loss over the given period at a predefined confidence interval (Jorion, 2001). In order to incorporate the effects of the higher orders of return distribution (skewness and kurtosis), we follow Getmansky, Lo and Makarov (2004), Malkiel and Saha (2005) and Eling (2006) and compute VaR and M(Modified)VaR to be able to calculate M(Modified)Sharpe Ratio.

5.3.2.1 Classic Ratios

Sharpe Ratio

The return to variability ratio (5.4) with the assumption of normal distribution (Sharpe, 1966).

$$SR = \frac{r_i^p - r_f}{\sigma^p} \quad (5.4)$$

Jensen Alpha

The Jensen Alpha (5.5) indicates the over/underperformance as compared with the market.

$$Jensen = \left(r_i^d - r_f\right) - (r_{rp}^d - r_f)\beta \qquad (5.5)$$

5.3.2.2 Lower Partial Moment Ratios (LPM)

Omega

The Omega ratio (5.6) measures the excess return over MAR and the first-order LPM_1. Due to the similarity with the Sharpe ratio, it has been referred to as Omega-Sharpe (Kazemi, Schneeweis, and Gupta, 2004).

$$Omega = \frac{r_i^d - \tau}{LPM_{1(\tau)}} + 1 \qquad (5.6)$$

Sortino

The Sortino ratio (5.7) measures the excess return over the minimum target return and the second-order LPM_2 (Kaplan and Knowles, 2004).

$$Sortino_i(\tau) = \frac{r_i^d - \tau}{\sqrt[2]{LPM_2(\tau)}} \qquad (5.7)$$

Kappa 3

The Kappa 3 ratio (5.8) measures the excess return over MAR and the third-order LPM_3. Similarly, to the other LPM based ratios, it does not assume a normal distribution.

$$Kappa_i(\tau) = \frac{r_i^d - \tau}{\sqrt[3]{LPM_3(\tau)}} \qquad (5.8)$$

Upside Potential

The Upside Potential ratio (5.9) measures the return over the MAR.

$$UP_i = \frac{HPM_{1i}(\tau)}{\sqrt[2]{LPM_2(\tau)}} \qquad (5.9)$$

5.3.2.3 Drawdown Ratios

Calmar

The Calmar ratio (5.10) measures the performance through the (smoothed) returns versus drawdown risk (Young, 1991).

$$Calmar_i = \frac{r_i^d - \tau}{-MD_1} \tag{5.10}$$

Sterling

The Sterling ratio (5.11) measures risks through the application of the average drawdown (Lhabitant, 2004, p.84).

$$Sterling_i = \frac{r_i^d - r_f}{\frac{1}{N}\sum_{j=1}^{N} -MD_j} \tag{5.11}$$

Burke

The Burke ratio (5.12) measures the adjusted risk. As opposed to the Sharpe ratio, Burke's denominator consists of a square root of the sum of squares of the smallest drawdowns (Burke, 1994).

$$Burke_i = \frac{r_i^d - r_f}{\sqrt{\sum_{j=1}^{N} MD_j^2}} \tag{5.12}$$

5.3.2.4 Ratios Based on the Value at Risk (VaR)

Excess Return on Value at Risk

The Excess Return on VaR (5.13) measures the excess risk over VaR (Dowd, 2002).

$$ErVaR_i = \frac{r_i^d - r_f}{VaR_i} \tag{5.13}$$

Conditional Sharpe Ratio

Conditional SR (5.14) measures the expected loss considering the values, which exceed VaR (Albrecht and Koryciorz, 2003).

$$CSR_i = \frac{r_i^d - r_f}{CVaR_i} \tag{5.14}$$

Modified Sharpe Ratio

The return to variability ratio, which includes the effects of the skewness and kurtosis (5.15). In order to obtain this metric, we have computed VaR (5.16) $Z_a = -2.33$ (0.99 CI) (Jorion, 2001, p. xxii) and then to integrate deviations of higher moments of return distributions MVaR (5.17) with quintile Alpha replaced with Cornish-Fisher expansion (5.18) (Eling, 2006).

$$MSR = \frac{r_i^p - r_f}{MVaR_i} \tag{5.15}$$

$$VaR = -\left(Z_a \sigma_{Am} + r_i^p\right) w \tag{5.16}$$

$$MVaR = -\left(Z_{CF} \sigma_{Am} + r_i^d\right) w \tag{5.17}$$

$$Z_{CF} = Z_a + \frac{1}{6}(Z_a^2 - 1)S_i + \frac{1}{24}(Z_a^3 - 3Z_a)K_i - \frac{1}{36}(2Z_a^3 - 5Z_a)S_i^2 \tag{5.18}$$

5.4 Empirical Results

5.4.1 Regression Results

Table 5.6 shows the Random-Effects (RE) GLS model result, while table 5.7 provides the OLS model for comparison. It is worth noting that the OLS calculations in Table 5.7 include year fixed-effects. We have also undertaken the OLS regression excluding year fixed-effects and noted that the only significant difference occurs in the *Ethnicity* coefficient (column 1), where the value of -0.691 is replaced with -0.634. The results in both tables (5.6 and 5.7), regardless of the model, show that the flows in HFs managed by the *Pctother* are much lower than in *Pctwhite*. Nevertheless, despite a substantial difference in the number of HFs in both clusters (Table 5.1), the results are not statistically significant. While the economic perspective implies that the HFs managed by the *Pctother* grow by around 69 to 76 percentage points less than similar funds managed by the *Pctwhite* (depending on the model). The other control variables exhibiting statistical significance (@ 0.05) are marked with the asterisk (* at 0.01/** at 0.05/*** at 0.10). Interestingly, the *'Returns'* coefficient for the *Pctother* funds is highly positive and also statistically significant under the GLS (some cases) OLS (all cases) assumption. Furthermore, the other variables exhibiting statistical sig. are *'High Watermark', 'Lock-ups'* and *'Managers' Tenure'*. In addition to the regression results, we also provide a correlation table of the variables used in the analysis (Table 5.5). Table 5.5 shows, that the correlations between the variables range between -0.09 (for *Flow*/*Man_t*) and 0.47 (for *Pfee*/*Hwmark*).

*** Insert Table 5.5***

*** Insert Table 5.6 ***

*** Insert Table 5.7 ***

We further focus on the analysed timeframe and isolate the period between 2013 and 2019, where the number of *Pctother* hedge fund managers exceeds 10 per cent saturation (in each year). Once again, we provide regression analysis for both models as shown in tables 5.8 (GLS) and 5.9 (OLS). The statistical significance of the results is less prevalent than in the period between 1999 and 2019 for both GLS and OLS regressions. However, what draws particular attention, is the emergence of the *Ethnicity* variable as statistically significant at 0.10 for all coefficient combinations (columns 1,2 and 4) in table 5.9 (OLS).

*** Insert Table 5.8 ***

*** Insert Table 5.9 ***

The overall results of our regression analysis indicate that the investors' preference lies in the HFs managed by the *Pctwhite* managers. The investor bias we observe, where the HFs generating better performance/returns attract much fewer capital inflows, should not come as a surprise. The earlier studies into the investor bias in mutual funds exposed similar behaviour. Kumar et al. (2015) show that the fund managers with a foreign name[22] attract much less capital (-9.8 percentage points) yet exhibit better performance. The same goes for other 'minority' managers, this time gender-related. As Niessen-Ruenzi and Ruenzi (2015) find, female mutual fund managers, attract around 11.2 percentage points less capital than their male counterparts (they also generate higher returns than male managers). Interestingly, the 11.2 percentage points difference seems economically trivial compared to our findings where the *Ethnicity* factor creates a gap in excess of 58.5 and 57.6 percentage points for GLS and OLS, respectively (within the 1999-2019 timeframe). Interestingly, for the period spanning 2013 to 2019, we report that the *Ethnicity* factor exceeds 94.9 for the GLS regression and 96.1 for the OLS (with OLS observations being statistically significant at 0.10).

[22] The individuals based in the USA were asked to classify the names of the mutual fund managers – regarding their potentially 'foreign' origin.

5.4.2 Risk-Adjusted Metrics

Table 5.10 presents the results of the risk-adjusted metrics analysis for both clusters (*Pctwhite* and *Pctother*). We can observe a notable difference between the average Sharpe ratios in a classic approach, with the *Pctother* being significantly higher (by approx. 44%). The Jensen Alpha for both remains almost the same (approx. 1 BPS above the market), although the T-Test indicates significance at 0.05. Regarding the LPM ratios (Table 5.10, Panel B), we can see that the *Pctwhite* HFs minimally dominate *Pctother* in three out of four metrics. Both HF clusters exhibit a high Omega ratio, which is quite favourable from the investor's perspective, as it minimises the probability of extreme loss occurrence. The Sortino ratio indicates that the *Pctwhite* portfolios operate at a slightly higher efficiency as compared with the *Pctother*. Interestingly, the Kappa ratio, otherwise known as 'the attractiveness rank', is the same for both clusters.

As we also observe, the Upside Potential ratio is higher for the *Pctwhite* HFs, which means the risk involved in the generation of the returns is lower – it also correlates with *Pctwhite*'s lower average (returns) standard deviations (Table 5.5). Regarding drawdown-based ratios, both types of HFs exhibit the same Calmar ratio, implying that their performance is similar on a performance adjusted basis. Under the Sterling ratio's assumptions, which, unlike the Calmar ratio, do not employ the average annual compounded rate of return but instead compounded annualised return, *Pctother* funds carry a slight advantage (significant at 0.05). Furthermore, *Pctother*'s advantage also extends to the Burke ratio (significant at 0.05). Lastly, the VaR metrics are almost in all cases dominated by *Pctother* HFs (except ErVaR, where they are the same). Not surprisingly, both CSR and MSR, amongst *Pctother*, are dominant (as was the case earlier with the classical ratios).

*** Insert Table 5.10 ***

5.5 Conclusion

This chapter has explored a conjecture that the investors are biased against the ethnic minority (Pctother) HF managers. Given the gravity of this topic (where the ethnic/racial associations are discussed), it is essential to understand previous multidisciplinary literature. The exploration of the ethnic/racial literature review (Chapter 2 [2.3]) has shown that investment decisions do not merely stay within the risk/return framework. As many cross-referenced multidisciplinary studies show, human behaviours are driven by self-identification (on ethnic/racial grounds), the in/out-group associations and fear of group expulsion/rejection. These combined (or even isolated factors) force certain behaviours and choices, which to many may appear to be deprived of logic, yet in fact, they are a result of complex psycho-social connections. It is pivotal to acknowledge these human dependencies while evaluating the results presented in this chapter. The findings we have presented provide a unique contribution to the literature concerning hedge funds, social biases, and discrimination. Our major contribution to the literature is the exploration of the previously uncharted territory of race/ethnicity within the context of hedge funds. Secondly, we have discovered that the ethnic/racial minorities receive much lower capital inflows despite generating higher returns, what according to other researchers (Kumar et al., 2015; Niessen-Ruenzi and Ruenzi, 2015) investigating mutual fund's gender performance and the foreignness of a manager's name (relative to the flows of capital into the mutual funds) accounts to irrational prejudice and not rational statistical discrimination (Phelps, 1972). The results of our analysis unequivocally indicate that the Pctother HFs receive significantly fewer capital inflows than their Pctwhite counterparts. In fact, the effect is approximately six (nine) times higher for the period 1999-2019 (2013-2019) than has been discovered in similar literature concerning the 'foreignness' of the manager's name or the manager's gender in mutual funds. Furthermore, the returns (and performance from the perspective of the majority of risk-adjusted metrics) generated by the Pctother HF managers are higher than Pctwhite. These results alone lead us to an inevitable conclusion that has also been reached by our academic counterparts in earlier cases of similar research, namely, to reject the notion of statistical discrimination. Our research shows that the potential investor bias towards the ethnic minority HF managers can exhibit significant implications within the HF environment itself. Furthermore, as we have presented in the literature review, ethnically associated biases can thrive across the ether for decades and when and if they crystallise in HFs (given the collective AuM), they can contribute to bending the rules of global economics. Moreover, this is the first research of its kind not only concerning hedge fund focused environments but the entire fund-related world. Furthermore, the results of this study directly contribute to the revival of the debate concerning ethnic and racial inequalities in corporate finance. This study's results prove that despite years of advancement in socio-cultural relations, there is still a lot of work that needs to be done to balance the scales.

Tables

Table 5.1 The Ethnicity of HF Managers'		
Ethnicity	**All HFs**	**% of Total**
Pctwhite	703	91%
*Pctother**	67	9%
Total	770	100%
Note: This table provides an overview of the managers' ethnicity in 770 HFs. *Combination of Asian and Hispanic HF managers.		

Table 5.2 Descriptive Statistics of the HF Managers with the Most Common First Names* (1999-2019)																	
Name	**Count**	Ranking	**Flows**	Ranking	**Returns**	Ranking	**Returns (pre-rec)**	Ranking	**Returns (rec)**	Ranking	**Returns (post-rec)***	Ranking	**Flows (pre-rec)**	Ranking	**Flows (rec)**	Ranking	**Flows (post-rec)**
David	35	19	-2258168.70	16	0.607	8	0.871	17	-0.021	14	0.308	2	5687963.82	20	-2539010.06	15	-667185.60
John	25	9	739233.12	6	0.880	6	0.935	7	0.458	8	0.414	7	1153981.21	2	835293.45	12	-132908.32
Michael	18	12	209576.87	2	1.098	14	0.525	4	0.645	5	0.458	15	288152.91	5	564626.22	3	194399.25
Mark	11	16	-504626.49	13	0.684	11	0.697	12	0.236	12	0.354	19	-307615.85	13	-449610.98	14	-448117.13
Robert	11	1	21281054.33	5	0.894	12	0.694	5	0.544	2	0.532	6	2342704.59	7	166408.13	17	-811144.48
Jeffrey	10	3	1895629.20	12	0.690	9	0.765	9	0.301	4	0.487	4	3178568.04	17	-1171500.70	6	28155.04
Kevin	9	8	772306.54	8	0.780	2	1.291	20	-0.366	7	0.415	18	84615.90	11	-437178.04	10	-117383.29
Martin	8	11	454014.65	9	0.775	15	0.515	18	-0.180	10	0.376	8	720376.62	10	-363588.37	2	450207.13
Stephen	8	4	1676763.50	14	0.634	19	0.210	15	0.062	20	0.128	16	250000.00	9	36594.43	5	75226.23
Christopher	8	13	176796.63	4	0.899	13	0.625	1	1.331	6	0.438	14	294256.22	4	658754.42	9	-59312.78
Charles	8	15	-159469.39	10	0.742	3	1.038	16	0.037	3	0.505	3	3984374.10	18	-1451071.01	18	-1871411.38
Peter	8	5	1313911.27	15	0.622	1	1.356	19	-0.336	9	0.377	5	2788180.54	12	-445537.58	20	-3536281.88
George	8	14	127538.16	18	0.580	16	0.420	10	0.296	15	0.297	11	526480.67	14	-667510.12	13	-327877.24
Eric	7	7	937586.82	3	0.903	20	0.187	11	0.282	13	0.318	1	7338751.67	3	829748.94	11	-122348.80
Marc	7	20	-3140549.21	20	0.361	7	0.913	13	0.187	19	0.146	12	356488.39	19	-2174187.49	19	-2106062.83
Paul	7	6	987309.62	17	0.588	4	0.962	3	0.720	17	0.261	9	658655.15	1	1042527.90	1	1982689.38
Andrew	7	18	-653494.53	11	0.694	10	0.760	2	0.728	11	0.367	13	301825.99	15	-768192.60	16	-673633.15
Richard	6	17	-581237.38	7	0.842	5	0.946	8	0.388	1	0.611	17	90343.38	8	80697.21	8	-49092.16
Adam	6	2	3019234.68	1	1.258	17	0.378	6	0.476	16	0.275	20	-1537830.99	16	-980776.19	4	157642.50
Matthew	6	10	660457.28	19	0.503	18	0.371	14	0.114	18	0.202	10	631048.35	6	297605.16	7	6325.48

Note: This table shows the top 20 most popular HF manager names*, which are sorted based on the frequency of occurrence (Count). The following columns consist of overall average 'Flows'/'Returns' and returns/flows pre/during/post the great recession of 2007-2009. Every column is accompanied by the 'Ranking' column for ease of reference (high-to-low). *The entire table has been collated using primary HF managers' names (relevant to HFs where there is more than one HF manager).

Table 5.3 Descriptive Statistics				
Variable	**The ethnicity of the HF Manager**		**T-Test (0.05)**	**All HFs**
	Pctwhite	***Pctother***		
Flows ($M)	1.20 (0.029)^{TNA}	0.72 (-0.785)^{TNA}	0.33	1.15
Flows (median) ($M)	0.57	0.24	0.21	0.54
Fund Size ($M)	6331.01	181.76	0.23	5795.95
Returns	0.67	0.83	0.04	0.68
Returns (median)	0.68	0.82	0.11	0.70
Returns σ	3.19	3.91	0.06	3.25
Returns Skew	-0.05	0.06	0.02	-0.04
Flows Skew	0.20	0.24	0.89	0.20
Returns Kurt	-0.32	-0.28	0.54	-0.32
Flows Kurt	4.40	7.72	0.08	4.68
Returns (pre-rec)	0.74	0.89	0.45	0.75
Returns (rec)	0.30	0.31	0.95	0.30
Returns (post-rec) *	0.36	0.41	0.54	0.37
Returns (pre-rec) σ	1.77	1.81	0.91	1.77
Returns (rec) σ	2.65	2.77	0.81	2.66
Returns (post-rec)* σ	3.06	3.74	0.07	3.12
Flows (pre-rec) ($M)	2.31	0.55	0.01	2.16
Flows (rec) ($M)	-0.09	-0.42	0.69	-0.12
Flows (post-rec) ($M) *	0.39	0.43	0.88	0.39
Management Fees	1.32	1.50	0.01	1.34
Performance Fees	15.36	17.97	0.00	15.59
Redemption Fees	0.76	1.13	0.04	0.79
Hurdle Rate	1.47	1.43	0.90	1.46
High Watermark	0.85	0.91	0.12	0.86
Lock-ups (months)	4.0	5.2	0.19	4.11
Advanced Notice (months)	3.0	3.1	0.68	35.74
Managers' Tenure (years)	11.4	11.0	0.58	11.33

Note: This table shows the number of HF characteristics based on the managers' ethnicity (*Pctwhite* = White, *Pctother* = Asian + Hispanic). 'Flows ($M)/(median)' is the average/median of all reported monthly flows**, while the component in brackets represents $Flow = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}$ (Ammann et al. 2018); 'Fund Size' variable is set to Millions of $US ($M); 'Returns /(median)' is the average $r_i^p = \frac{r_{i1} + \cdots r_{in}}{n}$/median of all reported monthly returns**; 'Flows/Returns (Skew) $S = \frac{1}{N}\sum_{i=1}^{N}(\frac{y_i - \bar{y}}{\hat{\sigma}})^3$/(Kurt) $K = \frac{1}{N}\sum_{i=1}^{N}(\frac{y_i - \bar{y}}{\hat{\sigma}})^4$ describe skewness and the excess kurtosis of both flows and returns**; 'Returns/Flows (pre-rec-post)' focus on specific time-intervals of our entire sample; 'Management', 'Performance', 'Redemption' fees and 'Hurdle Rate' are denoted as percentages varying between 0.02-4%, 1-50%, 0.1-10% and 1.5-20% respectively; the 'High Watermark' is a binary variable with 1 = Yes and No = 0; 'Lock-ups', 'Advanced Notice' periods are presented in months (where applicable), while the 'Managers' Tenure' in years. Furthermore, all average/median calculations exclude 0 values. Additionally, we provide a two-sample t-test between the means of *Pctwhite* and *Pctother*.

Abbreviations: great recession period pre/post is denoted as *rec.
*The HFs established after the (rec) period is not taken into consideration in this instance.
**The currency of all variables (where applicable) is $US.

Table 5.4 Variables		
Name	**Description**	**Source**
Flow	$Flow = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}$	(Ammann et al. 2018)
Eth_w	The dummy variable created out of this division is Ethnicity, where number 1 corresponds to *Pctother* and 0 to *Pctwhite*	Coding based on an extract from Morningstar Direct and methodology proposed by Tzioumis (2018) - see section 3 Data.
Returnp	Monthly net percentage	Morningstar Direct
Inter_eth_r	*Eth_w* * *Returnp* to form an interactive variable	
Mfee	Management fees	
Pfee	Performance fees	
Rfee	Redemption fees	
Hrate	Hurdle Rate	
Hwmark	High Watermark	
Lock_u	Lock-ups (months)	
Adv_n	Advanced Notice (months)	
Man_t	Managers' Tenure (years)	
Note: This table describes the composition and the source of variables used in this chapter's calculations.		

Table 5.5 Variable Correlations

	Flow	*Eth_w*	*Returnp*	*Inter_eth_r*	*Mfee*	*Pfee*	*Rfee*	*Hrate*	*Hwmark*	*Lock_u*	*Adv_n*	*Man_t*
Flow	1											
Eth_w	-0.0068	1										
Returnp	0.0054	0.0123	1									
Inter_eth_r	-0.0024	0.1484	0.309	1								
Mfee	0.0048	0.0809	-0.0031	0.0128	1							
Pfee	0.0034	0.0894	0.0173	0.0181	0.1267	1						
Rfee	0.0018	0.104	0.0069	0.0325	0.0706	0.0523	1					
Hrate	-0.0016	-0.0272	-0.0043	-0.0084	0.0581	-0.0036	0.0522	1				
Hwmark	0.0049	0.0457	0.0094	0.0157	0.015	0.4662	0.0584	0.0111	1			
Lock_u	-0.0077	0.0384	0.0252	0.0121	0.0355	0.0548	0.0546	0.1206	0.0763	1		
Adv_n	-0.0061	0.0148	0.0042	0.0007	0.053	-0.0813	-0.0539	0.0709	0.004	0.2724	1	
Man_t	-0.0099	0.0012	-0.0013	0.0003	0.0269	0.1215	-0.0252	-0.0944	0.0661	0.0539	0.0334	1

Note: This table provides the correlation between the variables used in the regression analysis. The variables are defined in the following way: *Flow*: $Flow = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}$ (Ammann et al. 2018); *Eth_w*: this dummy variable refers to the ethnicity/race of a hedge fund manager, where number 1 corresponds to *Pctother* and 0 to *Pctwhite*; *Returnp*: refer to the monthly net percentage returns; *Inter_eth_r*: refer to the multiplication of *Eth_w* * *Returnp* to form an interactive variable; *Mfee*, *Pfee*, *Rfee*: refer to management, performance and redemption fees respectively (stored as percentages); *Hrate*: refer to hurdle rates (stored as percentages); *Hwmark*: refer to high watermark fees (stored as the binary 1/0); *Lock_u*: refer to lock-up period (stored as the number of months); *Adv_n*: refer to advanced notice (stored as the number of months); *Man_t*: refer to the length of managers' tenure (stored in years). All variables are extracted/built on the basis of data extracted from the Morningstar Direct.

Table 5.6 Fund Flow Regression GLS 1999-2019						
	RE GLS (SE) 1	**RE GLS (SE) 2**	**RE GLS (SE) 3**	**RE GLS (SE) 4**	**RE GLS (SE) 5**	**RE GLS (SE) 6**
Panel A						
Ethnicity (Pctother)			-0.585 (0.602)	-0.64 (0.611)		-0.76 (0.617)
Returns	5.218 (2.743)***	4.177 (2.881)	5.246 (2.743)**	5.33 (2.744)**	4.074 (2.88)	4.056 (2.882)
Inter_eth_r		11.978 (9.308)			12.099 (9.304)	13.534 (9.393)
Management Fees		0.305 (0.281)		0.329 (0.282)		0.329 (0.282)
Performance Fees		-0.015 (0.023)		-0.013 (0.023)		-0.013 (0.023)
Redemption Fees		0.033 (0.146)		0.055 (0.147)		0.053 (0.147)
Hurdle Rate		-0.014 (0.069)		-0.018 (0.069)		-0.017 (0.069)
High Watermark		0.724 (0.51)		0.724 (0.51)		0.723 (0.51)
Lock-ups (months)		-0.031 (0.022)		-0.03 (0.022)		-0.03 (0.022)
Advanced Notice (months)		-0.002 (0.004)		-0.002 (0.004)		-0.002 (0.004)
Managers' Tenure (years)		-0.03 (0.019)***		-0.03 (0.019)***		-0.031 (0.019)***
Adj. R2	0.0035	0.0088	0.0002	0.0099	0.0028	0.01
Observations	120,785					
Panel B						
Hausman FE chi2	n/a	0.132	0.9301	0.701	0.99	0.735
Breusch-Pagan LM chi2	0*					

Note: Panel A of this table presents the GLS model results (with Standard Errors in brackets) – including fixed year effects. The table is divided into six columns depending on the number of coefficients employed in each regression. In Panel B, we see the results of Hausman and Breusch-Pagan LM chi2 results. The variables presented in this table are defined in the following way: *Flow*: $Flow = \frac{TNA_{i,t}-TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}$ (Ammann et al. 2018);
Eth_w: this dummy variable refers to the ethnicity/race of a hedge fund manager, where number 1 corresponds to *Pctother* and 0 to *Pctwhite*; *Returnp*: refer to the monthly net percentage returns; *Inter_eth_r*: refer to the multiplication of *Eth_w* * *Returnp* to form an interactive variable; *Mfee*, *Pfee*, *Rfee*: refer to management, performance and redemption fees respectively (stored as percentages); *Hrate*: refer to hurdle rates (stored as percentages); *Hwmark*: refer to high watermark fees (stored as the binary 1/0); *Lock_u*: refer to the lock-up period (stored as the number of months); *Adv_n*: refer to advanced notice (stored as the number of months); *Man_t*: refer to the length of managers' tenure (stored in years). All variables are extracted/built on the basis of data extracted from Morningstar Direct. The * indicates statistical significance at 0.01, ** at 0.05, and *** at 0.10.

Table 5.7 Fund Flow Regression OLS 1999-2019						
	RE OLS (SE) 1	**RE OLS (SE) 2**	**RE OLS (SE) 3**	**RE OLS (SE) 4**	**RE OLS (SE) 5**	**RE OLS (SE) 6**
Ethnicity (Pctother)			-0.576 (0.447)	-0.572 (0.454)		-0.691 (0.462)
Returns	5.839 (2.782)**	4.976 (2.919)***	5.916 (2.783)**	6.018 (2.784)**	4.858 (2.918)***	4.802 (2.921)***
Inter_eth_r		10.322 (9.23)			10.301 (9.222)	12.934 (9.394)
Management Fees		0.232 (0.2)		0.254 (0.2)		0.253 (0.2)
Performance Fees		-0.019 (0.017)		-0.018 (0.017)		-0.018 (0.017)
Redemption Fees		0.011 (0.106)		0.03 (0.107)		0.029 (0.107)
Hurdle Rate		-0.005 (0.048)		-0.009 (0.048)		-0.008 (0.048)
High Watermark		0.808 (0.357)**		0.804 (0.357)**		0.802 (0.357)**
Lock-ups (months)		-0.03 (0.016)***		-0.029 (0.016)***		-0.029 (0.016)***
Advanced Notice (months)		-0.002 (0.003)		-0.002 (0.003)		-0.002 (0.003)
Managers' Tenure (years)		-0.032 (0.013)*		-0.032 (0.013)*		-0.032 (0.013)*
Adj. R2	0.0097	0.0011	0.0098	0.0035	0.0088	0.01
Observations	120,785					

Note: This table presents the OLS model results (with Standard Errors in brackets) – including fixed year effects. The table is divided into six columns depending on the number of coefficients employed in each regression. The variables presented in this table are defined in the following way: *Flow*: $Flow = \frac{TNA_{i,t}-TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}$ (Ammann et al. 2018); *Eth_w*: this dummy variable refers to the ethnicity/race of a hedge fund manager, where number 1 corresponds to *Pctother* and 0 to *Pctwhite*; *Returnp*: refer to the monthly net percentage returns; *Inter_eth_r*: refer to the multiplication of *Eth_w * Returnp* to form an interactive variable; *Mfee*, *Pfee*, *Rfee*: refer to management, performance and redemption fees respectively (stored as percentages); *Hrate*: refer to hurdle rates (stored as percentages); *Hwmark*: refer to high watermark fees (stored as the binary 1/0); *Lock_u*: refer to the lock-up period (stored as the number of months); *Adv_n*: refer to advanced notice (stored as the number of months); *Man_t*: refer to the length of managers' tenure (stored in years). All variables are extracted/built on the basis of data extracted from the Morningstar Direct. The * indicates statistical significance at 0.01, ** at 0.05, and *** at 0.10.

Table 5.8. GLS Fund Flow Regression 2013-2019						
	GLS (SE) 1	**GLS (SE) 2**	**GLS (SE) 3**	**GLS (SE) 4**	**GLS (SE) 5**	**GLS (SE) 6**
Panel A						
Ethnicity (Pctother)			-0.949 (0.706)	-0.963 (0.714)		-0.981 (0.72)
Returns	5.638 (4.185)	7.066 (4.402)*	5.695 (4.185)	5.762 (4.187)	6.951 (4.401)	6.879 (4.405)
Inter_eth_r		-13.969 (14.06)			-13.535 (14.054)	-11.559 (14.168)
Management Fees		0.355 (0.339)		0.385 (0.339)		0.385 (0.34)
Performance Fees		0.005 (0.028)		0.008 (0.773)		0.008 (0.028)
Redemption Fees		0.045 (0.174)		0.065 (0.71)		0.067 (0.175)
Hurdle Rate		-0.036 (0.084)		-0.04 (0.635)		-0.04 (0.084)
High Watermark		0.554 (0.626)		0.554 (0.376)		0.556 (0.626)
Lock-ups (months)		-0.034 (0.027)		-0.033 (0.215)		-0.033 (0.027)
Advanced Notice (months)		-0.004 (0.005)		-0.004 (0.455)		-0.004 (0.005)
Managers' Tenure (years)		-0.05 (0.024)**		-0.05 (0.034)**		-0.05 (0.024)**
Adj. R2	0.0002	0.0118	0.0009	0.0129	0.0002	0.0129
Observations	59,664					
Panel B						
Hausman FE chi2	n/a	0.112	0.866	0.632	0.993	0.699
Breusch-Pagan LM chi2	0*					

Note: Panel A of this table presents the GLS model results (with Standard Errors in brackets) – including fixed year effects. The table is divided into six columns depending on the number of coefficients employed in each regression. In Panel B, we see the results of Hausman and Breusch-Pagan LM chi2 results. The variables presented in this table are defined in the following way: *Flow*: $Flow = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}$ (Ammann et al. 2018); *Eth_w*: this dummy variable refers to the ethnicity/race of a hedge fund manager, where number 1 corresponds to *Pctother* and 0 to *Pctwhite*; *Returnp*: refer to the monthly net percentage returns; *Inter_eth_r*: refer to the multiplication of *Eth_w* * *Returnp* to form an interactive variable; *Mfee*, *Pfee*, *Rfee*: refer to management, performance and redemption fees respectively (stored as percentages); *Hrate*: refer to hurdle rates (stored as percentages); *Hwmark*: refer to high watermark fees (stored as the binary 1/0); *Lock_u*: refer to the lock-up period (stored as the number of months); *Adv_n*: refer to advanced notice (stored as the number of months); *Man_t*: refer to the length of managers' tenure (stored in years). All variables are extracted/built on the basis of data extracted from the Morningstar Direct. The * indicates statistical significance at 0.01, ** at 0.05, and *** at 0.10.

Table 5.9 OLS Fund Flow Regression 2013-2019						
	OLS (SE) 1	**OLS (SE) 2**	**OLS (SE) 3**	**OLS (SE) 4**	**OLS (SE) 5**	**OLS (SE) 6**
Ethnicity (Pctother)			-0.961 (0.585)***	-0.975 (0.592)***		-0.97 (0.599)***
Returns	5.195 (4.221)	6.789 (4.437)	5.284 (4.222)	5.368 (4.223)	6.638 (4.435)	6.522 (4.439)
Inter_eth_r		-15.467 (14.018)			-14.855 (14.009)	-11.957 (14.175)
Management Fees		0.356 (0.279)		0.386 (0.28)		0.386 (0.28)
Performance Fees		0.007 (0.023)		0.01 (0.023)		0.01 (0.023)
Redemption Fees		0.039 (0.144)		0.059 (0.144)		0.061 (0.144)
Hurdle Rate		-0.032 (0.069)		-0.037 (0.069)		-0.037 (0.069)
High Watermark		0.585 (0.518)		0.583 (0.518)		0.586 (0.518)
Lock-ups (months)		-0.034 (0.022)		-0.033 (0.022)		-0.033 (0.022)
Advanced Notice (months)		-0.004 (0.004)		-0.004 (0.004)		-0.004 (0.004)
Managers' Tenure (years)		-0.05 (0.02)***		-0.05 (0.02)***		-0.05 (0.02)***
Adj. R2	0.0002	0.012	0.001	0.013	0.0002	0.013
Observations	59,664					

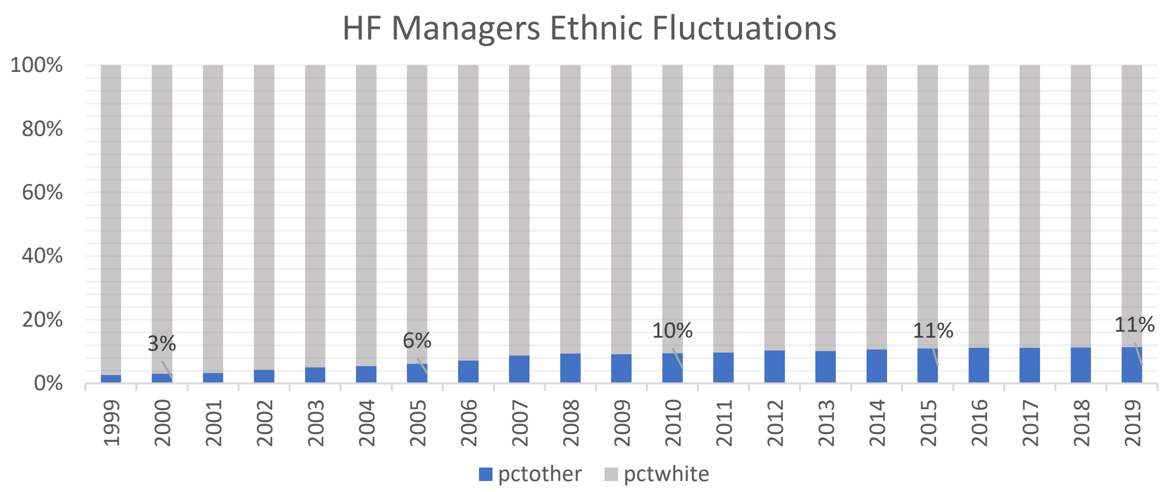
Note: This table presents the OLS model results (with Standard Errors in brackets) – including fixed year effects. The table is divided into six columns depending on the number of coefficients employed in each regression. The variables presented in this table are defined in the following way: *Flow*: $Flow = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}$ (Ammann et al. 2018); *Eth_w*: this dummy variable refers to the ethnicity/race of a hedge fund manager, where number 1 corresponds to *Pctother* and 0 to *Pctwhite*; *Returnp*: refer to the monthly net percentage returns; *Inter_eth_r*: refer to the multiplication of *Eth_w * Returnp* to form an interactive variable; *Mfee*, *Pfee*, *Rfee*: refer to management, performance and redemption fees respectively (stored as percentages); *Hrate*: refer to hurdle rates (stored as percentages); *Hwmark*: refer to high watermark fees (stored as the binary 1/0); *Lock_u*: refer to the lock-up period (stored as the number of months); *Adv_n*: refer to advanced notice (stored as the number of months); *Man_t*: refer to the length of managers' tenure (stored in years). All variables are extracted/built on the basis of data extracted from the Morningstar Direct. The * indicates statistical significance at 0.01, ** at 0.05, and *** at 0.10.

Table 5.10 Risk-Adjusted Metrics			
Metric	**The ethnicity of the HF Manager**		
	Pctwhite	***Pctother***	**T-Test (0.05)**
Panel A: Classic Ratios			
Sharpe Ratio	0.18	0.26	0.11
Jensen Alpha	0.07	0.08	0.03
Panel B: Lower Partial Moment Ratios			
Omega Ratio	0.92	0.89	0.87
Sortino Ratio	0.56	0.39	0.18
Kappa 3	0.27	0.28	0.83
Upside Potential Ratio	1.30	1.05	0.16
Panel C: Drawdown Ratios			
Calmar Ratio	0.03	0.03	0.10
Sterling Ratio	0.55	0.63	0.05
Burke Ratio	0.46	0.52	0.05
Panel D: Ratios Based on the Value at Risk			
ErVaR	0.20	0.20	0.10
CSR	0.44	0.53	0.13
MSR	0.21	0.30	0.32

Note: This table presents the risk-adjusted metrics categorised into four panels: classic, lower partial moment, drawdowns and value at risk. Furthermore, the columns corresponding to *Pctwhite* and *Pctother* denote the racial/ethnic associations of the hedge fund managers. The difference between the two groups is estimated with the T-Test in the last column.

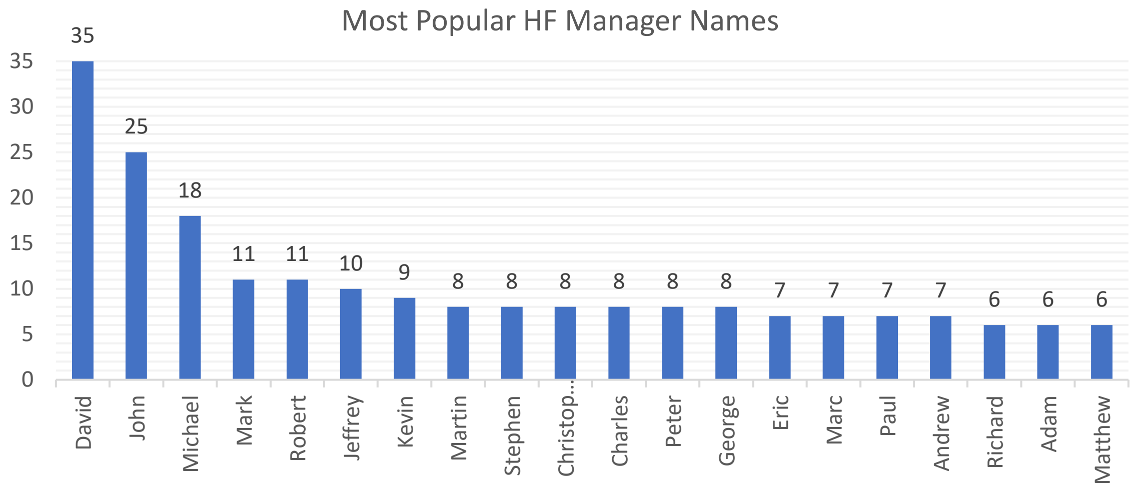
Figures

Figure 1. The Annual Ethnic Fluctuations of the HF Managers (1999-2019)



Note: This figure shows the percentage fluctuation in the number of HFs managed by *Pctwhite* and *Pctother* managers between January 1999 and December 2019. The data has been extracted from the Morningstar Direct database (Global Hedge Funds).

Figure 2. Top 20 Most Popular HF Manager Names (1999-2019)



Note: This figure shows the count of the most common names amongst the primary HF managers in the period 1999-2019.

Chapter 6. Conclusion of the Thesis

The importance of hedge funds has been highlighted in this thesis several times. Most importantly, hedge funds with their US$ 3.61tn (Prequin, 2020) in assets under management exhibit a significant influence over global financial stability. Despite the wealth of research conducted in the area of hedge fund performance, risk and corporate governance, the literature remains silent on the combined effects of geolocation and strategy, gender differences in performance and risk, and the flow-performance relationship amongst ethnic minority hedge fund managers. Therefore, the main aim of this doctoral research is to address the gaps mentioned above. More specifically, Chapter 3 answers the question "Does the geolocation and investment strategy effects impact the estimation of risk in performance persistence measurement dynamics?"; Chapter 4 investigates "Is there a difference in the risk-adjusted performance and performance persistence between male and female hedge fund managers?"; while Chapter 5 answers, "Does the racial association of the hedge fund manager affect the investment choice of the investor?".

Chapter 3 of this thesis documents the difference in performance persistence from the perspective of domicile, strategy and the combination of both. The area of coverage spans the four most hedge fund saturated domiciles and the four most commonly employed investment strategies. We use the dataset of 5619 for the period between 1995 and 2016. The results indicate short-term performance persistence individually across all combinations (the domicile, the investment strategy and the combination of both). Furthermore, the combination of the two aforementioned clusters exhibits diminished persistence as well as its loss and occasional reversal. The parametric (non-risk-adjusted) analysis reveals dominant and statistically significant negative performance persistence in portfolios combined with IRL and the USA domiciled hedge funds. Similar occurrence takes place in the geo-strategic combinations and domiciles employing LSE or MLTI strategies. Whereas the parametric yet risk-adjusted approach shows changes in the outcomes for several domiciles and the investment strategies, where previously founded negative performance is elevated into the positive and statistically significant levels. Overall, the result of the study shows that the dependence on either domicile or strategy for the analysis of the performance persistence can be misleading. The frequent omission or underestimation of the domicile factor has not provided a complete risk-accountability, much needed in the hedge fund environment. This chapter primarily provides a significant contribution to hedge fund investors. The results indicate the potential of capita loss where there is no accountability for the combined effects of domicile and strategy.

Furthermore, Chapter 4 has taken another step into the area of risk-adjusted performance and performance persistence. Although, this time through a prism of a hedge fund managers' gender. Employing the dataset with 1321 hedge funds and a timeframe between 1978 and 2018, I have identified that the comparison of male and female managers under the assumptions of metrics based on the lower-order statistics provides similar/same results. Whereas the application of metrics beyond lower-partial statistics reveals that female managers marginally underperform in relation to generation of returns and risk management as compared with their male counterparts. The returns of female managed hedge funds are, on average, negatively skewed, while the performance measures employed in the analysis identify negative deviations and penalize these funds relative to the ones managed by males (where the skewness of returns is in the positive territory). Regarding the performance persistence analysis, both male and female managed hedge funds were found to exhibit varying levels of persistence. Under the non-parametric assumptions, female managed funds have, on average, dominated their male counterparts in the overall number of cases. Nevertheless, it was the male managed funds that exhibited the majority of dominance in cases that were statistically significant. In the parametric (non-risk-adjusted) approach, I have observed a mix of negative and positive persistence fluctuations between both genders. Although, the last approach, with the accountability for risks crystallising in hedge funds, has proven that the male managers have exhibited stronger (and almost in all cases of analysed horizons) positive performance persistence. The main contribution of this chapter is to reinvigorate the debate around female presence within the financial industry. Furthermore, the previous hedge fund related literature has not provided any answers regarding gender differences in risk, performance and/or performance persistence.

The relative minority that female managers represent in the hedge fund industry has led me to my next research question, which has been analysed in Chapter 5. Chapter 5 continues the focus on the minority representative hedge fund managers, this time, however, from the racial/ethnic perspective.

The cleaned dataset consists of 770 hedge funds and a timeframe between 1999-2019. The results have proven without a shadow of a doubt that racial/ethnic minority hedge fund managers receive significantly lower flows of capital into their hedge funds. The impact is profound as the capital inflows are approximately six times higher than those reported in the similar literature on mutual funds concerning the 'foreignness' of the manager's name or manager's gender. The findings are specifically interesting as the minority hedge fund managers generate higher raw returns than their non-minority counterparts. Thus, inevitably leading to a similar conclusion as expressed in the mutual fund literature and the rejection of the notion of rational statistical discrimination. The findings presented in Chapter 5 contribute to the literature concerning hedge funds, social biases and discrimination. Furthermore, as was also the case in a previous chapter, they raise awareness regarding the numbers of race/ethnic minority hedge fund managers within one of the most secretive investment industries in the world.

Despite the contributions mentioned above, this thesis also has several limitations. First, the databases employed throughout this thesis do not contain the entire, complete hedge fund universe - this limitation could be addressed by a merger of all known, mainstream hedge fund databases (provided there is unrestricted access). Thus, potentially leading to changes in the results, especially in areas identifying merely marginal differences (be it between geolocations/strategies, genders or ethnic associations). Furthermore, a data merger between hedge fund databases could be beneficial and allow for insight into other regions/strategies (depending on hedge fund saturation). Second, the literature concerning in-depth gender differences including the accountability for crucial statistical properties, such as predominantly negative skewness and positive kurtosis, autocorrelation, biases, and fat tails of the return's distribution in hedge funds (e.g., Kat, 2003; Eling, 2006, Fung and Hsieh, 1999) does not exist. Thus, not allowing for direct contrast between the results this thesis has generated - other than the in-direct contrast with the mean-variance focused work of Argawal and Boyson (2016). The same applies to Chapter 5, as the hedge fund managers' ethnicity has never been considered in the analysis of flows. Third, further limitations may concern the mainstream performance and performance persistence methods employed in this thesis. Fourth, in all chapters, although with particular emphasis on Chapters 4 and 5, there may be cultural and regional biases impacting the investors' decisions (whether or not they should invest in a hedge fund managed by a male/female or an ethnic minority). This kind of research would require a more in-depth cross-discipline examination.

This thesis is directly applicable in practice in several areas. First, through the previously unseen contrasts, Chapter 3 of the thesis provides the potential hedge fund investor with a unique view. The investor can easily infer that the domicile or a strategy may not provide them with a level of insight that the combination of both does. Furthermore, the chapter also signifies the importance of the performance persistence methods as their results differ depending on their mechanics (non-parametric and/or parametric non/risk-adjusted). Chapter 4 continues to examine the performance persistence with the addition of risk-adjusted performance metrics. Similar to the previous chapter, we can also observe the significance of metrics employed in the analysis. Furthermore, this time, the chapter divides the data into two gender-based clusters and shows that the time horizon of the research plays a pivotal role and allows investors to plan more strategically. Lastly, Chapter 5 considers the capital flows into hedge funds, which are clustered based on the fund manager's race/ethnicity. This approach yet again looks at the minority hedge fund managers (right after the earlier gender-focused chapter) and how the investors perceive them. Furthermore, both clusters' performance is assessed in an attempt to identify whether the flows are performance or perhaps race/ethnicity related. In this case, the potential future investor can ascertain the current and previous investors' reasoning and realise the impact of racial/ethnic factors.

References

Ackermann C., McEnally R., and Ravenscraft D., (1999) “The Performance of Hedge Funds: Risk, Return, and Performances.” Journal of Finance, 54 (3), pp. 833-874.

Agarwal V., and Naik N. Y., (2000a) “Multi-Period Performance Persistence Analysis of Hedge Funds.” Journal of Financial and Quantitative Analysis, 35 (3), pp. 327-342.

Agarwal V., and Naik N. Y., (2000b) “On Taking the Alternative Route: Risks, Rewards, and Performance Persistence of Hedge Funds.” Journal of Alternative Investments, 2 (4), pp. 6-23.

Agarwal V., and Naik N. Y., (2004) “Risks and Portfolio Decisions Involving Hedge Funds.” The Review of Financial Studies, 17 (1), pp. 63-98.

Agarwal V., Bakshi G., and Huij J. (2009) Do Higher-Moment Equity Risks Explain Hedge Fund Returns? Working Paper

Aggarwal R. K., and Jorion P., (2010) “The Performance of Emerging Hedge Funds and Managers.” Journal of Financial Economics, 96 (2010), pp. 238-256.

Aggarwal R., Boyson N. M. (2016) “The performance of female hedge fund managers.” Review of Financial Economics, Vol. 29, pp. 23-36.

Agnew J., Balduzzi P. and Sundén A. (2003) “Portfolio choice and trading in a large 401(k) plan.” The American Economic Review, Vol. 93, pp. 193–215.

Albrecht P. and Koryciorz S. (2003) “Bestimmung des Conditional Value-at-Risk bei Normal- bzw. Lognormalverteilung” Mannheimer Manuskripte zur Risikotheorie, Portfolio Management und Versicherungswirtschaft Nr. 142.

Amenc N., El Bied S., and Martellini L., (2003) “Predictability in Hedge Fund Returns.” Financial Analysts Journal, 59 (5), pp. 32-46.

Ammann M., Bauer C., Fischer S., and Müller P. (2018) “The impact of the Morningstar Sustainability Rating on mutual fund flows.” European Financial Management, Vol. 25 (3), pp. 520-553.

Ammann M., Huber O., and Schmid M., (2013) “Hedge Fund Characteristics and Performance Persistence.” European Financial Management, Vol. 19 (2), pp. 209-250.

Atkinson S.M., Baird S.B. and Frye M.B. (2003) “Do female mutual fund managers manage differently?” Journal of Financial Research, Vol. 26 (1), pp.1-18.

Babalos V., Caporale G. M. and Philippas N. (2015) “Gender, Style Diversity, and Their Effect on Fund Performance.” Research in International Business and Finance, Vol. 35, September 2015, pp. 57-74.

Bae K. H., and Yi J., (2012) “Performance Persistence and Flow Restrictions in Hedge Funds.” Working Paper, York University.

Bali T. G., Brown S. J., and Caglayan M. O., (2011) “Do Hedge Funds’ Exposures to Risk Factors Predict Their Future Returns?” Journal of Financial Economics, 101 (1), pp. 36-68.

Bali T.G., Gokcan S. (2004) “Alternative Approaches to Estimating VaR for Hedge Fund Portfolios.” Schachter Barry (Ed.), Intelligent Hedge Fund Investing, Risk Books, Incisive Media PLC (2004), pp. 253-277.

Bali T.G., Gokcan S., Liang B. (2007) “Value at Risk and the Cross-Section of Hedge Fund Returns” Journal of Banking and Finance, Vol. 31, pp. 1135-1166.

Baquero G., Ter Horst J., and Verbeek M., (2005) “Survival, Look-Ahead Bias and the Persistence in Hedge Fund Performance.” Journal of Financial and Quantitative Analysis, Vol. 40 (3), pp. 493-517.

Barber B. M., Odean T. (2001) “Boys will be Boys: Gender, Overconfidence and Common Stock Investment.” The Quarterly Journal of Economics, Vol. 116 (1), pp. 261-292.

Bares P. A., Gibson R., and Gyger S., (2003) “Performance in the Hedge Funds Industry: An Analysis of Short and Long-Term Persistence.” The Journal of Alternative Investments, 6 (3), pp. 25-41.

Becker G. S. (1971) “The Economics of Discrimination” (University of Chicago Press: Chicago) 2nd edn.

Berk J., and Green R. (2004) “Mutual fund flows and performance in rational markets.” Journal of Political Economy, Vol. 112, pp. 1269-1295.

Bernard C., Vanduffel S. and Ye J. (2019) “A New Efficiency Test for Ranking Investments: Application to Hedge Fund Performance.” Economics Letters, Vol. 181 (1), pp. 203-207.

Bertrand M. and Mullainathan S. (2004) "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." American Economic Review, Vol. 94 (4), pp. 991-1013.

Bodie Z., Kane A., Marcus A. J., (2005) “Investments.” The sixth ed. McGraw Hill, New York.

Bollen N. P. B. and Posavac S. (2017) “Gender, Risk Tolerance, and False Consensus in Asset Allocation Recommendations.” Journal of Banking and Finance, Vol. 87, pp. 304-317.

Bollen N. P. B., and Whaley R. E., (2009) “Hedge fund risk dynamics: Implications for performance appraisal.” Journal of Finance, 64, pp. 985-1035

Boyson N. M., (2003) “Do Hedge Funds Exhibit Performance Persistence? A New Approach.” Working Paper, Krannert Graduate School of Management.

Brachinger H.W., Schubert R., Brown M., and Gysler, M. (1999) “Financial Decision Making: Are Women Really More Risk-Averse? American Economic Review, Vol. 89, pp. 381-385.

Breusch T. S. and Pagan A. R. (1979) “A Simple Test for Heteroscedasticity and Random Coefficient Variation.” Econometrica, Vol. 47 (5), pp. 1287-1294.

Brown S. J., and Goetzmann W. N., (2003) “Hedge Funds with Style.” Journal of Portfolio Management, 29 (2), pp. 101-112.

Brown S. J., Goetzmann W. N., and Ibbotson R. G., (1999) “Offshore Hedge Funds: Survival and Performance 1989–1995.” Journal of Business, Vol. 72 (1), pp. 91-117.

Brown S., and Goetzmann W., (1995) “Performance Persistence.” Journal of Finance, 50 (2), 679-698.

Bucher-Koenen T., Lusardi A., Alessie R. and Van Rooij M. (2017) “How Financially Literate Are Women? An Overview and New Insights” The Journal of Consumer Affairs, Summer 2017, pp. 255-283.

Buraschi A., Kosowki R., and Fabio T., (2014) "When There Is No Place to Hide': Correlation Risk and the Cross-Section of Hedge Fund Returns." The Review of Financial Studies, 27 (2), pp. 581-616.

Burke G. (1994) "A Sharper Sharpe Ratio." Futures, Vol. 23 (3), pp. 56-57.

Capocci D., (2013) "Complete Guide to Hedge Funds and Hedge Fund Strategies (Global Financial Markets)." 2013 ed. Edition, Palgrave Macmillan, pp. 63

Capocci D., and Hubner G., (2004) "Analysis of Hedge Fund Performance." Journal of Empirical Finance, 11 (1), pp. 55-89.

Capocci D., Corhay A., and Hübner G., (2005) "Hedge Fund Performance and Persistence in Bull and Bear Markets." The European Journal of Finance, 11 (5), pp. 361-392.

Carpenter J. N., and Lynch A. W., (1999) "Survivorship Bias and Attrition Effects in Measures of Performance Persistence." Journal of Financial Economics, 54 (3), 337-374.

Chamberlain G. (1983) "A characterization of the distributions that imply mean-variance utility functions." Journal of Economic Theory, Vol. 29 (1), pp. 185-201.

Charness G., Rigotti L. and Rustichini A. (2007) "Individual Behavior and Group Membership." American Economic Review, Vol. 97 (4), pp. 1340-1352.

Chen K., and Passow A., (2003) "Quantitative Selection of Long-Short Hedge Funds." FAME Research Paper, Geneva.

Choi J. J., Laibson D. and Metrick A. (2002) "How Does the Internet Affect Trading? Evidence from Investor Behaviour in 401(k) Plans." Journal of Financial Economics, Vol. 64, pp. 397-421.

Cohen L. (2009) "Loyalty-based portfolio choice." Review of Financial Studies, Vol. 22, pp. 1213-45.

Cooper M. J., Gulen H., and Rau P. R. (2005) "Changing names with style: Mutual fund name changes and their effects on fund flows." Journal of Finance, Vol. 60 (6), pp. 2825-2858.

Dennis, P., and S. Mayhew, 2002, "Risk-Neutral Skewness: Evidence from Stock Options," Journal of Financial and Quantitative Analysis, 37, 471–493.

Dhrymes P., J. (2017) “Portfolio theory: origins, Markowitz and CAPM based selection.” In: Guerard J., B. (ed.) “Portfolio Construction, Measurement, and Efficiency.”, pp. 39-48. Springer

Do V., Faff R., and Veeraraghavan M., (2010) “Performance Persistence in Hedge Funds: Australian Evidence.” Journal of International Financial Markets, Institutions and Money, Vol. 20 (4), pp. 346-362.

Doise P. W., Csepeli B. G., Dann K. H. D., Gouge B. C., Larsen K., and Ostell S. A. (1972) “An experimental investigation into the formation of intergroup representations.” European Journal of Social Psychology, Vol. 2 (2), pp. 202-204.

Dorn D. and Huberman G. (2005) “Talk and Action: What Individual Investors Say and What They Do.” Review of Finance, Vol. 9, pp. 437-481.

Dowd K. (2000) “Adjusting for Risk: An Improved Sharpe Ratio.” International Review of Economics and Finance, Vol. 9 (3), pp. 209-222.

Dwyer P. D., Gilkeson J. H. and List J. A. (2002) “Gender Differences in Revealed Risk-Taking: Evidence from Mutual Fund Investors.” Economics Letters, Vol. 76 (2), pp. 151-158.

Edwards F., and Caglayan M., (2001) “Hedge Fund Performance and Manager Skill.” Journal of Futures Markets, 21 (11), pp. 1003-1028.

Eling M. (2006) “Autocorrelation, Bias, and Fat Tails: Are Hedge Funds Really Attractive Investments?” Derivatives Use, Trading & Regulation, Vol. 12 (1), pp. 28-47.

Eling M. and Schuhmacher F. (2007) “Does the Choice of Performance Measure Influence the Evaluation of Hedge Funds?” Journal of Banking & Finance, Vol. 31 (9), pp. 2632-2647.

Eling M., (2009) “Does Hedge Fund Performance Persist? Overview and New Empirical Evidence.” European Financial Management 15 (2), pp. 362-401.

Eling M., Schuhmacher F. (2006) “Hat die Wahl des Performancemaßes einen Einfluss auf die Beurteilung von Hedgefonds-Indizes?” Kredit und Kapital Vol. 39 (3), pp. 419-454.

Epstein A. L. (1978) “Ethos and Identity: Three Studies in Ethnicity.”, Aldine Transaction.

EU Agency for Fundamental Rights (2020) “Antisemitism: Overview of Antisemitic Incidents Recorded in the European Union 2009-2019.” Available at: https://fra.europa.eu/sites/default/files/fra_uploads/fra-2020-antisemitism-overview-2009-2019_en.pdf (Accessed: 10 January 2021)

European Comission (2018) “The gender pay gap situation in the EU.” Available at: https://ec.europa.eu/info/policies/justice-and-fundamental-rights/gender-equality/equal-pay/gender-pay-gap-situation-eu_en (Accessed: 10 January 2021)

Favre L. and Galeano J. A. (2002) “Mean-Modified Value-at-Risk Optimization with Hedge Funds.” Journal of Alternative Investments, Vol. 5 (2), pp. 21-25.

Favre L. and Signer A. (2002) “The Difficulties of Measuring the Benefits of Hedge Funds.” Journal of Alternative Investments, Vol. 5 (1), pp. 31-42.

Fehr E. and Gachter S. (2002) “Altruistic Punishment in Humans.” Nature, 415, pp. 137-140.

Feng L. and Seasholes M. (2008) “Individual Investors and Gender Similarities in an Emerging Stock Market.” Pacific-Basin Finance Journal, Vol. 16, pp. 44-60.

Ferreira M. A., Keswani A., Miguel A. F., and Ramos S. B. (2012) “The flow-performance relationship around the world.” Journal of Banking and Finance, Vol. 36, pp.1759-1780.

Fishburn P., C. (1977) “Mean-Risk Analysis with Risk Associated with Below-Target Returns”. The American Economic Review, Vol. 67, pp. 116-126.

Fung W. and Hsieh D. A. (1999) “Is Mean-Variance Analysis Applicable to Hedge Funds?” Economics Letters, Vol. 62 (1), pp. 53-58.

Fung W., and Hsieh D., (1997) “Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds.” The Review of Financial Studies, 10 (2), 275-302.

Geman H., Kharoubi C. (2003) “Hedge Funds Revisited: Distributional Characteristics, Dependence Structure and Diversification, Journal of Risk, Vol. 5 (4), pp. 55-73

Getmansky M., Lo A. W. and Makarov I. (2004) "An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns." Journal of Financial Economics, Vol. 74 (3), pp. 529-609.

Gonzalez M. O., Papageorgiou N. A., and Skinner F. S., (2016) "Persistent Doubt: An Examination of Hedge Fund Performance." European Financial Management, 22 (4), pp. 613-639.

Goodman C. J. and Mance S. M. (2011) "Employment loss and the 2007–09 recession: an overview." Monthly Labor Review, Vol. 134 (4), pp. 3-12.

Greene J. T., Hodges C. W., and Rakowski D. A. (2007) "Daily mutual fund flows and redemption policies." Journal of Banking and Finance, Vol. 31, pp. 3822-3842.

Greene W. H. (2008) "Econometric Analysis." 6th ed., Upper Saddle River, N.J. Prentice-Hall.

Gregoriou G. N., Gueyie J., P. (2003) "Risk-Adjusted Performance of Funds of Hedge Funds Using a Modified Sharpe Ratio." Journal of Alternative Investments, Vol. 6 (3), pp. 77-83.

Gregoriou G.N., Sedzro K., Zhu J. (2005) "Hedge fund performance appraisal using data envelopment analysis." European Journal of Operational Research, Vol. 164 (2005), pp. 555-571.

Gruber M. J. (1996) "Another puzzle: The growth in actively managed mutual funds." Journal of Finance, Vol. 51, pp. 783-810.

Harari H. and McDavid J. W. (1973) "Name stereotypes and teachers' expectations." Journal of Educational Psychology, Vol. 65 (2), pp. 222-225.

Harri A., and Brorsen B. W., (2004) "Performance Persistence and the Source of Returns for Hedge Funds." Applied Financial Economics, 14 (2), pp. 131-141.

Harvey, C., and A. Siddique, 2000, "Conditional Skewness in Asset Pricing Tests," Journal of Finance, 55(3), 1263–1295.

Hastings P. (2004) "New Disclosure Requirements for Portfolio Managers of Registered Management Investment Companies" Available at www.paulhastings.com (Accessed: 01 December 2020)

Hatch M. J. and Schultz M. (2004) "Organizational Identity: A Reader." Oxford University Press, pp. 56-65.

Hausman J. A. (1978) “Specification Tests in Econometrics.” Econometrica, Vol. 46 (6), pp. 1251-1271.

Henn J., and Meier I., (2004) “Performance Analysis of Hedge Funds.” in Dichtl, H., J. M. Kleeberg, and C. Schlenger (eds.): “Handbuch Hedge Funds, Uhlenbruch, Bad Soden/Ts.”, pp. 435-466.

Hentati-Kafell R. and Peretti P., (2015) “Generalized Runs to Detect Randomness in Hedge Funds Returns.” Journal of Banking and Finance, 50 (1), pp. 608-615.

Hewstone, M., Rubin M., and Willis H. (2002) “Intergroup bias.” Annual Review of Psychology, Vol. 53, pp. 575-604.

HFRI (2019) “HFRI Hedge Fund Indices Defined Formulaic Methodology.” Available at https://www.hedgefundresearch.com (Accessed 10 April 2019)

Honora D.T. (2002) “The relationship of gender and achievement to future outlook among African American adolescents.” Adolescence, Vol. 37, pp. 301-316.

Huang J., Wei K. D., and Yan H. (2007) “Participation Costs and the Sensitivity of Fund Flows to Past Performance.” Journal of Finance, Vol. 62 (3), pp. 1273-1311.

Ippolito R. A. (1992) “Consumer reaction to measures of poor quality: Evidence from the mutual fund industry.” Journal of Law and Economics, Vol. 35, pp. 45-70.

Jagannathan R., Malakhov A. and Novikov D. (2010) “Do hot hands exist among hedge fund managers? An empirical evaluation.” Journal of Finance, Vol. 65, pp. 217-255

Jain P. C., and Wu J. S. (2000) “Truth in mutual fund advertising: Evidence on future performance and fund flows” Journal of Finance, Vol. 55, pp. 937-958.

Jenkins R. (2008) “Rethinking Ethnicity”, 2nd edition

Jenkins R. (2014) “Social Identity”, 4th edition

Jensen M., (1968) “The performance of mutual funds in the period 1945–1968.” Journal of Finance Vol. 23 (2), pp. 389-416.

Jianakoplos N.A. and Bernasek, A., (1998) “Are Women More Risk-Averse?” Economic Inquiry, Vol. 36, pp. 620-630.

Joenvaara J., Kosowski R., and Tolonen P., (2012) “New 'Stylized Facts' About Hedge Funds and Database Selection Bias.” Working Paper, Imperial College Business School.

Johnson J. E. V. and Powell P. L. (1994) "Decision Making, Risk and Gender: Are Managers Different?" British Journal of Management, Vol. 5 (2), pp. 123-38.

Jorion P. (2000) “Risk Management Lessons from Long-Term Capital Management.” European Financial Management, Working Paper, UC Irvine Graduate School of Management.

Jorion P. (2001) “Value at Risk.” McGraw-Hill, pp. xxii

Jung J. H., Kumar A., Lim S. S. and Yoo C. Y. (2019) “An analyst by any other surname: Surname favorability and market reaction to analyst forecasts.” Journal of Accounting and Economics, Vol. 67 (2), pp. 306-335.

Kao G. (2000) “Group Images and Possible Selves among Adolescents: Linking Stereotypes to Expectations by Race and Ethnicity.” Sociological Forum, Vol. 15 (3), pp. 407-430.

Kaplan P. and Knowles J. (2004) “Kappa: A Generalized Downside Risk-Adjusted Performance Measure.” Journal of Performance Measurement, Vol. 8 (3), pp. 42-54.

Kat H. M. (2002) “Some Facts about Hedge Funds.” World Economics, Vol. 3 (2), pp. 93-123.

Kat H. M. (2003) “10 Things That Investors Should Know about Hedge Funds.” Journal of Wealth Management, Vol. 5 (4), pp. 72-81.

Kazemi H., Schneeweis T. and Gupta B. (2004) “Omega as a Performance Measure” Journal of Performance Measurement, Vol. 8 (3), pp. 16-25.

King E. B., Mendoza S. A., Madera J. M., Hebl M. R. and Knight J. L. (2006) “What's in a Name? A Multiracial Investigation of the Role of Occupational Stereotypes in Selection Decisions.” Journal of Applied Social Psychology, Vol. 36 (5), pp. 1145-1159.

King M. R., and Maier P. (2009) "Hedge Funds and Financial Stability: Regulating Prime Brokers Will Mitigate Systemic Risks." Journal of Financial Stability, Vol. 5 (3), pp. 283-297.

Koh F., Koh W. T. H., and Teo M., (2003) “Asian Hedge Funds: Return Persistence, Style, and Fund Characteristics.” Working Paper, Singapore Management University.

Kosowski R., Naik N., and Teo M., (2007) “Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis.” Journal of Financial Economics, 84 (1), pp. 229-264.

Kostovetsky L. (2015) “Whom Do You Trust? Investor-Advisor Relationships and Mutual Fund Flows.” The Review of Financial Studies, Vol. 29 (4), pp. 898-936.

Kouwenberg R., (2003) “Do Hedge Funds Add Value to a Passive Portfolio?” Journal of Asset Management, 3 (4), pp. 361-382.

Kraus, A., and R. Litzenberger, 1976, “Skewness Preference and the Valuation of Risk Assets,” Journal of Finance, 31(4), 1085–1100.

Kumar A., Niessen-Ruenzi A. and Spalt O. G. (2015) “What’s in a Name? Mutual Fund Flows When Managers Have Foreign-Sounding Names.” The Review of Financial Studies, Vol. 28 (8), pp. 2281-2321.

Kunda Z. (1999) “Social Cognition: Making Sense of People.” Cambridge: MIT Press.

Leon A. and Moreno M. (2015) “Lower Partial Moments under Gram Charlier Distribution: Performance Measures and Efficient Frontiers” Working Paper. Available at: www.ucm.es

Lhabitant F. S. (2007) “Handbook of Hedge Funds.” pp. 482-484.

Liang B., (1999) “On the Performance of Hedge Funds.” Financial Analysts Journal, 55 (1999), pp. 72-85.

Liang B., (2000) “Hedge Funds: The Living and the Dead.” Journal of Financial and Quantitative Analysis, 35 (3), pp. 309-326.

Ljung G.M. and Box G. E. P. (1978) “On a Measure of Lack of Fit in Time Series Models.” Biometrika, Vol. 65, pp. 297-303.

Malkiel B. and Saha A. (2005) “Hedge Funds: Risk and Return.” Financial Analysts Journal Vol. 61, pp. 80-88.

Marinelli N., Mazzoli C. and Palmucci F. (2017) “How Does Gender Really Affect Investment Behavior?” Economics Letters, Vol. 151, pp. 58-61.

Markowitz H. M. (1952) “Portfolio Selection” Journal of Finance, Vol. 7 (1), pp. 77-91.

Massa M, Reuter J, Zitzewitz E (2010) “When should firms share credit with employees? Evidence from anonymously managed mutual funds.” J. Financial Econom. 95(3):400–424.

Morningstar (2016) “The Morningstar Category Classifications” Available at www.morningstardirect.morningstar.com (Accessed 01 October 2019)

Nanda V., Wang Z., and Zheng L. (2004) “Family values and the star phenomenon.” Review of Financial Studies, Vol. 17, pp. 667-698

Niessen-Ruenzi A. and Ruenzi S. (2015) “Sex Matters: Gender Bias in the Mutual Fund Industry.” Management Science, Vol. 65 (7), pp. 3001-3025.

Odean T. (1998) "Volume, Volatility, Price, and Profit When All Traders Are Above Average.” Journal of Finance, Vol 53 (6), pp. 1887-1934.

Park J. M., and Staum J. C., (1998) “Performance Persistence in the Alternative Investment Industry.” Working Paper, Paradigm Capital Management.

Patel S. and Sarkissian S. (2017) “To Group or Not to Group? Evidence from Mutual Fund Databases.” Journal of Financial and Quantitative Analysis, Vol. 52 (5), pp. 1989-2021.

Pavlenko-Lutton L. and Davis E. (2015) “Morningstar Research Report: Fund Managers by Gender” Available at http://www.morningstar.com (Accessed 18 December 2018)

Pedersen C. S., Rudholm-Alfvin T. (2003) “Selecting a Risk-Adjusted Shareholder Performance Measure.” Journal of Asset Management, Vol. 4 (3), pp. 152-172.

Perez P., G. (2004) An approach to the non-normal behavior of hedge fund indices using Johnson distributions. Finance Department, ESSEC, May 2003.

Pfingsten A., Wagner P., Wolferink C. (2004) "An empirical investigation of the rank correlation between different risk measures." Journal of Risk, Vol. 6 (4), pp. 55-74.

Phelps E. (1972) "The Statistical Theory of Racism and Sexism." American Economic Review, Vol. 62, pp. 659-661.

Politico (2019) "Racism persists in the heart of the EU: The fight to end unequal treatment of people of color moves at a glacial pace in the EU." Available at: https://www.politico.eu/article/europe-struggles-combatting-racial-discrimination-brussels-bubble/ (Accessed: 10 January 2021)

Powell M. and Ansic D. (1997) "Gender Differences in Risk Behaviour in Financial Decision-Making: An Experimental Analysis." Journal of Economic Psychology, Vol. 18 (6), pp. 605-628.

Preqin (2020) "2020 Prequin Global Hedge Fund Report." Available at: www.preqin.com (Accessed 20 Sept 2020)

Prequin (2018) "Prequin Global Hedge Fund Report 2018." Available at: www.preqin.com (Accessed on 20 Jan 2019).

Rittereiser C. M., and Kochard L. E., (2010) "Top Hedge Fund Investors: Stories, Strategies, and Advice.", John Wiley & Sons

Röder F. and Walter A. (2019) "What Drives Investment Flows into Social Trading Portfolios" The Journal of Financial Research, Vol. 42 (2), pp. 383-411.

Schmidt U. and Traub S. (2002) "An Experimental Test of Loss Aversion." Journal of Risk and Uncertainty, Vol. 25, pp. 233-249.

Schuhmacher F., Eling M., (2011) "Sufficient Conditions for the Expected Utility to Imply Drawdown-Based Performance Rankings." Journal of Banking & Finance 35 pp. 2311–2318

SEC (2004) “Disclosure Regarding Portfolio Managers of Registered Management Investment Companies; Final Rule” Available at: www.sec.gov (Accessed: 01 December 2020)

Sharpe W. F. (1966) “Mutual Fund Performance” The Journal of Business, Vol. 39 (1), pp. 119-138.

Shih J. (2002) “…Yeah, I could hire this one, but I know it’s gonna be a problem: How ethnicity, nativity, and gender affect employers’ perceptions of job seekers.” Ethnic and Racial Studies, Vol. 25, pp. 99-119.

Sirri E. R., and Tufano P. (1998) “Costly search and mutual fund flows.” Journal of Finance, Vol. 53, pp. 1589-1622.

Solomon D. H., Soltes E., and Sosyura D. (2014) “Winners in the spotlight: Media coverage of fund holdings as a driver of flows.” Journal of Financial Economics, Vol. 113, pp 53-72.

Sortino F., van der Meer R. and Plantinga A. (1999) “The Dutch Triangle.” Journal of Portfolio Management, Vol. 26 (1), pp. 50-58.

Stafylas D., Anderson K., and Uddin M. (2016) “Recent advances in hedge funds’ performance attribution: Performance persistence and fundamental factors.” International Review of Financial Analysis, Vol. 43, pp. 48-61.

Steri R., Giorgino M., and Viviani D., (2009) "The Italian Hedge Funds Industry: An Empirical Analysis of Performance and Persistence." Journal of Multinational Financial Management, Vol. 19 (1), pp. 75-91.

Sun Z., Wang A., and Zheng L., (2012) “The Road Less Travelled: Strategy Distinctiveness and Hedge Fund Performance.” Review of Financial Studies, 25 (1), pp. 96-143.

Swanson D.P., Cunningham M. and Spencer M.B. (2003) “Black males’ structural conditions, achievement patterns, normative needs, and “opportunities.” Urban Education, Vol. 38, pp. 608-633.

Tajfel H. and Turner J. C. (1979) “An integrative theory of intergroup conflict.” In Hatch M. J. and Schultz M. (2004) “Organizational Identity: A Reader.”, pp. 56-65. Oxford University Press

The Hedge Fund Journal (2010) “IFSL Hedge Funds 2010” Available at https://thehedgefundjournal.com/ifsl-hedge-funds-2010/ (Accessed 20 Sept 2020)

Tzioumis K. (2018) “Demographic aspects of first names” Scientific Data, Vol. 5, Article 180025. Available at: https://doi.org/10.1038/sdata.2018.25

Van Vugt M. and Hart C. M. (2004) “Social identity as social glue: The origins of group loyalty.” Journal of Personality and Social Psychology, Vil. 86, pp. 585-598.

Van Vugt M. and Park J. H. (2009) “Guns, Germs, and Sex: How Evolution Shaped Our Intergroup Psychology.” Social and Personality Psychology Compass, Vol. 3 (6), pp. 927-938.

World Bank (2020) “GDP (current US$).” Available at www.data.worldbank.org (Accessed 20 Sept 2020)

Xing X., Anderson R. I. and Hu Y. (2016) “What's a name worth? The impact of a likeable stock ticker symbol on firm value.”, Journal of Financial Markets, Vol. 31, pp. 63-80.

Young T. (1991) “Calmar Ratio: A Smoother Tool.” Futures, Vol. 20 (11), pp. 40-41.

Zdaniuk B. and Levine J. M. (2001) “Group loyalty: Impact of members’ identification and contributions.” Journal of Experimental Social Psychology, Vol. 37, pp. 502-509.

Zizzo D. J. (2011) “You are not in my boat: common fate and discrimination against outgroup members.” International Review of Economics, Vol. 58, pp. 91-103.

Zopounidis C., Benkraiem R., and Kalaitzoglou I. (2021) “Financial Risk Management and Modeling.”, Springer Nature Switzerland AG