Evaluating novel hedge fund performance measures under different economic conditions

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To my beloved parents, to whom I owe the world

Dries and Lillette van Dyk

ABSTRACT

Performance measurement is an integral part of investment analysis and risk management. Investment performance comprises two primary elements, namely; *risk* and *return*. The measurement of return is more straightforward compared with the measurement of risk: the latter is stochastic and thus requires more complex computation. Risk and return should, however, not be considered in isolation by investors as these elements are interlinked according to modern portfolio theory (MPT). The assembly of risk and return into a risk-adjusted number is an essential responsibility of performance measurement as it is meaningless to compare funds with dissimilar expected returns and risks by focusing solely on total return values.

Since the advent of MPT performance evaluation has been conducted within the risk-return or mean-variance framework. Traditional, liner performance measures, such as the Sharpe ratio, do, however, have their drawbacks despite their widespread use and copious interpretations.

The first problem explores the characterisation of hedge fund returns which lead to standard methods of assessing the risks and rewards of these funds being misleading and inappropriate. Volatility measures such as the Sharpe ratio, which are based on mean-variance theory, are generally unsuitable for dealing with asymmetric return distributions. The distribution of hedge fund returns deviates significantly from normality consequentially rendering volatility measures ill-suited for hedge fund returns due to not incorporating higher order moments of the returns distribution. Investors, nevertheless, rely on traditional performance measures to evaluate the risk-adjusted performance of (these) investments. Also, these traditional risk-adjusted performance measures were developed specifically for traditional investments (i.e. non-dynamic and or linear investments). Hedge funds also embrace a variety of strategies, styles and securities, all of which emphasises the necessity for risk management measures and techniques designed specifically for these dynamic funds.

The second problem recognises that traditional risk-adjusted performance measures are not complete as they do not implicitly include or measure all components of risk. These traditional performance measures can therefore be considered one dimensional as each measure includes only a particular component or type of risk and leaves other risk components or dimensions untouched. Dynamic, sophisticated investments – such as those pursued by hedge funds – are often characterised by multi-risk dimensionality. The different risk types to which hedge funds are exposed substantiates the fact that volatility does not capture all inherent hedge fund risk factors. Also, no single existing measure captures the entire spectrum of risks. Therefore, traditional risk measurement methods must be modified, or performance measures that consider the components (factors) of risk left untouched (unconsidered) by the traditional performance measures should be considered alongside traditional performance appraisal measures.

Moreover, the 2007-9 global financial crisis also set off an essential debate of whether risks are being measured appropriately and, in-turn, the re-evaluation of risk analysis methods and techniques.

The need to continuously augment existing and devise new techniques to measure financial risk are paramount given the continuous development and ever-increasing sophistication of financial markets and the hedge fund industry. This thesis explores the named problems facing modern financial risk management in a hedge fund portfolio context through three objectives.

The aim of this thesis is to critically evaluate whether the novel performance measures included provide investors with additional information, to traditional performance measures, when making hedge fund investment decisions. The Sharpe ratio is taken as the primary representative of traditional performance measures given its widespread use and also for being the hedge fund industry's performance metric of choice. The objectives have been accomplished through the modification, altered use or alternative application of existing risk assessment techniques and through the development of new techniques, when traditional or older techniques proved to be inadequate.

Keywords: *Hedge fund; Risk management; Performance measurement; Risk-adjusted performance; Scaled performance measure; Sharpe ratio; Bias ratio; Omega ratio; Treynor ratio.*

OPSOMMING

Die meet van prestasie is ‘n integrale deel van beleggingsanalise en risikobestuur. Beleggingsprestasie bestaan uit twee primêre elemente naamlik; *risiko* en *opbrengs*. Die meeting van opbrengs is meer eenvoudig in vergelyking met die meeting van risiko omrede laasgenoemde stogasties is en dus ‘n meer ingewikkelde berekening vereis. Beleggers moet egter nie die elemente van risiko en obrengs in isolasie oorweeg nie omrede hierdie elemente volgens die moderne portefeulje teorie (MPT) direk verwant is met mekaar. Die konsolidasie van risiko en opbrengs tot ‘n risiko-aangepaste syfer is ‘n noodsaaklike vereiste vir pretasie evaluasie, omrede dit sinloos is om fondse met verskillende verwagte opbrengste en risiko’s te vergelyk deur uitsluitlik op totale opbrengs waardes te fokus.

Pretasie evaluasie geskied sedert die koms van MPT binne die risiko-opbrengs of gemiddelde-variansie raamwerk. Tradisionele, liniêre prestasiemaatstawwe, soos byvoorbeeld die Sharpe verhouding, het egter nadele ten spyte van die wydverspreide gebruik en talle interpretasies daarvan.

Die eerste probleem verken die karakterisering van verskansingsfonds opbrengste wat bepaal dat standaard risiko en opbrengs beoordelings metodes van hierdie fondse misleidend en onvanpas is. Volatiliteitsmaatstawee soos die Sharpe verhouding, wat gebasseer is op die gemiddeld-variansie toerie, is oor die algemeen ongeskik om assimmetriese opbrengs distribusies te hanteer. Die distribusie van verskansingsfonds opbrengste wyk aansienlik af van ‘n normaal verdeling met die gevolg dat volatiliteits gebasseerde maatstawwe ongeskik is vir verskansingsfonds opbrengste, omrede hoër orde momente nie ingekorporeer word nie. Beleggers maak nogtans staat op tradisionele prestasiemaatstawwe om die risiko-aangepaste prestasie van beleggings te evalueer. Hierdie tradisionele risiko-aangepaste prestasiemaatstawwe was egter spesifiek ontwerp vir tradisionele beleggings (dit wil sê nie-dinamiese en of linieêre beleggings). Verskansingsfondse bevat ‘n verskeidenheid strategieë, style en sekuriteite, welke die noodsaaklikheid beklemtoon vir risikobestuur maatstawwe en tegnieke spesifiek vir hierdie dinamiese fondse.

Die tweede probleem erken dat tradisionele risiko-aangepaste pretasiemaatstawwe nie kompleet is nie, aangesien dié maatstawwe nie onvoorwaardelik al die komponente van risiko insluit of meet nie. Hierdie tradisionele prestasiemaatstawwe kan dus as een dimensioneel beskou word aangesien elke maatstaf slegs ‘n spesifieke komponent of tipe risiko oorweeg en ander risiko komponente of dimensies onaangeraak laat. Dinamiese, gesofistikeerde beleggings – soos dié uitgevoer deur verskansingsfondse – word dikwels gekaraktiseer deur multi-risiko dimensionaliteit. Die verskillende risiko tipes waaraan verskansingsfondse blootgestel word staaf die feit dat volatiliteit nie al die inherente veskansingsfonds risikofaktore vasvang nie. Tweedens bestaan daar geen enkele maatstaf wat die hele spektrum van risiko’s vasvang nie. Gevolglik moet tradisionele risikomaatstaf metodes gemodifiseer word, alternatiewelik moet prestasiemaatstawwe, wat risiko komponente oorweeg wat deur tradisionele prestasiemaatstawwe ondeurdag gelaat word, saam met tradisionele prestasie waarderings maatstawwe oorweeg word.

Die 2007-9 globale finansiële krisis het ook ‘n noodsaaklike debat laat onstaan rakende die vraag of risiko’s toepaslik gemeet word, met die gevolg dat risiko-analise metodes en tegnieke geherevalueer word.

Die noodsaaklikheid om deurlopend bestaande finansiële risiko meetings metodes aan te vul en nuwe metodes te bedink is van kardinale belang gegewe die deurlopende ontwikkeling en toenemende gesofistikeerdheid van finansiële markte en die verskansingsfonds industrie. Hierdie proefskrif verken die genoemde probleme wat moderne risikobestuur in ‘n verskansingsfonds portefeulje konteks in die gesig staar, deur middel van drie doelwitte.

Die doel van hierdie proefskrif is om krities te evalueer of die ingeslote oorspronklike prestasiemaatstawwe beleggers met addisionele informasie voorsien, tot dié van tradisionele prestasiemaatstawwe, gedurende die besluitnemingsproses van verskansingfonds beleggings. Die Sharpe verhouding word gebruik as die primêre verteenwoordiger van tradisionele prestasiemaatstawwe gegewe die verhouding se wydverspreide gebruik asook die aanvaarding daarvan as die verskansingfonds industrie se prestasiemaatstaf van keuse. Die doelwitte is bereik deur die modifikasie, veranderde gebruik of alternatiewe toepassing van bestaande risiko assessering

tegnieke asook deur die ontwikkeling van nuwe tegenieke in die geval waar tradisionele of verouderde tegnieke bleik onvoldoende te wees.

Sleutelwoorde: *Verskaningsfonds; Risikobestuur; Prestasie evaluasie; Risiko-aangepaste prestasie; Aangepaste prestasiemaatstaf; Sharpe verhouding; Vooroordeel verhouding; Omega verhouding; Treynor verhouding.*

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PREFACE

The theoretical and practical work described in this thesis was carried out whilst in the employ of the Department of Finance, Risk Management and Banking: University of South Africa, Muckleneuk campus, Pretoria and in collaboration with the School of Economics: North-West University, Potchefstroom under the supervision of Dr. Gary van Vuuren and Dr. André Heymans.

These studies represent the original work of the author and have not been submitted in any form to another University. Where use was made of the work of others, this has been duly acknowledged in the text.

Hedge fund data were obtained from Eurekahedge, the world's largest alternative investment funds research house specialising in hedge fund databases with the financial assistance of the Workwell Research Unit at the North-West University, Potchefstroom campus. Due to the nature of the data, they remain confidential and proprietary and thus the identities of the hedge funds have been omitted from the research. Other data have been sourced from well-known public sources as specifically mentioned in the articles.

The study on hedge fund fraud and how potential fraud measures should augment the use of traditional performance measures (Chapter 2) has been published in Volume 13, Number 4 of the *International Business and Economics Research Journal* (van Dyk, van Vuuren, Heymans, 2014) under the heading "The Bias ratio as a hedge fund fraud indicator: An empirical performance study under different economic conditions".

The work entitled "Hedge fund performance evaluation using the Sharpe and Omega ratios" (Chapter 3) was presented at the Biennial Conference of the Economic Society of South Africa on 25 September 2013 at the University of the Free State, Bloemfontein, South Africa. It has also been published in Volume 13, Number 3 of *the International Business and Economics Research Journal* (van Dyk, van Vuuren, Heymans, 2014) under the same heading.

The comparative study examining scaled and traditional performance measures within a hedge fund context (Chapter 4) has been accepted for publication in the *International Business and Economics Research Journal* (van Dyk, van Vuuren, Heymans, 2014) and is forthcoming in Volume 13, Number 6 under the heading "Hedge fund performance using scaled Sharpe and Treynor measures".

The editor of the *International Business and Economics Research Journal* has provided consent for the articles accepted for publication in the journal to be reproduced in this thesis (letters from the editor are included as Annexures at the end of the thesis).

F. VAN DYK

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION AND BACKGROUND

Even though private investment vehicles were available to wealthy investors during the 1920s, institutional and wealthy private investors have been intrigued by hedge funds since 1949 in what is generally agreed to be the advent of the first hedge fund structure by Alfred Winslow Jones (Jaeger, 2003; Do *et al*., 2005). The public's intrigue surrounding these funds have also escalated over time owing to the profitability of these funds but also colourful and entertaining newspaper stories on some extravagant hedge fund phenomena. After the number of hedge funds dropped from an estimated 140 in 1968 to 68 in 1984 (Lhabitant, 2004), the mid-1980s saw the revival of hedge fund numbers, commonly attributed to the publicity surrounding Julian Robetson's Tiger Fund (Agarwal & Naik, 2002) and to a lesser extent its offshore sibling, the Jaguar Fund (Connor & Woo, 2003). Due to their profitability, hedge funds became venerated during this time whilst the interest in and attention given to hedge funds activities have increased ever since the explosive growth of the hedge fund market during the early 1990s.

The collapse of the Long-Term Capital Management (LTCM)[1] hedge fund in 1998 almost caused the collapse of the global financial system (Haubrich, 2007). LTCM suffered considerable losses triggered by Russian debt default, ultimately resulting in LTCM being bailed out by a consortium of 14 financial institutions under the supervision of the Federal Reserve Bank. Other such incidents include the US$2bn loss in 1998 by George Soro's Quantum Fund, also during the Russian debt crisis, Amaranth Advisors in 2006 and the Madoff Ponzi scheme[2] in late 2008.

Hedge funds occasionally make for entertaining reading but they are an essential part of the larger financial environment and global financial system and afford several benefits to investors, investment managers and the financial market. Hedge funds represent the cutting edge of active management and serve as the catalyst for new and innovative investment strategies and instruments, benefitting financial markets and their participants. Hedge funds contribute to the efficient functioning of financial markets by providing liquidity, improving price discovery and contributing to the broader economy through job creation and tax revenues. Hedge funds also employ substantial leverage (Malkiel & Saha, 2005), mitigate price downturns, seek out inefficiencies and assume risks others generally avoid (Botha, 2007). These funds also provide sophisticated investors with an investment alternative that seeks *absolute* returns as opposed to the *relative* returns sought by passive investment managers. Hedge funds also deliver, on average, economically and statistically significant abnormal performance on both an equal- and value-weighted basis across strategies, domiciles, size categories and time periods (Joenväärä *et al*., 2012). Investor's asset portfolios also receive a diversification benefit through hedge fund investment (Liang, 1999; KPMG, 2012) as some hedge fund strategies are uncorrelated with the broader market while hedge funds in general are characterised by low correlation with traditional asset classes (Fung & Hsieh, 1997; KPMG, 2012). Investment managers also benefit as they are allowed to take advantage of a degree of investment freedom unavailable to traditional or conventional investment managers while also having the prospect of earning handsomely, in monetary terms, given above satisfactory fund performance.

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[1] Long-Term Capital Management L.P. was organised as a Delaware limited partnership, although the fund it operated, Long-Term Capital Portfolio L.P. was organised as a Caymans Island limited partnership (Haubrich, 2007).

[2] Bernard Madoff's fund, Madoff Investment Securities LLC, is often referred to as a hedge fund (e.g. Forbes, 2008) and has also been referred to as "effectively the world's largest hedge fund" (SEC, 2009:2). Financial analyst, Harry Markopolos presented the Securities and Exchange Commission (SEC) with a detailed investigation entitled "The world's largest hedge fund is a fraud" in 2005 (SEC, 2009; Britannica, 2013). It is also been mentioned that the Madoff fund is not organised as a hedge fund yet it acts and trades exactly like one (SEC, 2009; Markopolos, 2010). The "split-strike conversion" or "collar" investment strategy employed by Madoff is a complex yet sound investment strategy that is more likely to be used by a hedge fund than a long-only fund.

Performance is of considerable importance within the hedge fund industry as not only are investor returns based on fund performance, but hedge fund manager compensation is also tied to fund performance. As a result, performance *measurement* is an integral part of investment analysis and risk management with the literature on the topic being both abundant and controversial. Hedge funds, however, remain highly risky investments as stellar returns cannot be obtained without significant risks (Botha, 2007). Moreover hedge funds embrace a variety of strategies, styles and securities all of which emphasise the necessity for risk management measures and techniques designed specifically for these funds.

Investment performance comprises two primary elements, namely; *risk* and *return*. The measurement of return element is more straightforward than the risk element: the former is, to a degree, deterministic, while the latter is stochastic and thus more complex procedures are required for its measurement. Risk, however, means different things to different audiences at different times, but it is well defined as "the combination of exposure and uncertainty" or in a more broad sense as "exposure to uncertainty" (Bacon, 2013:1). Risk and return should, however, not be considered in isolation by investors (Lhabitant, 2004; Bacon, 2013), as these elements are interlinked: modern portfolio theory (MPT) attempts to maximise portfolio expected return for a given amount of market risk, or equivalently minimise the market risk for a given level of expected return (for a risk-averse investor) (Markowitz, 1952; Swisher & Kasten, 2005). MPT thus emphasises that increased risk is an inherent part of higher reward. For the most part, comparisons of hedge fund returns focus solely on total return values. Comparing funds that have dissimilar expected returns and risks in this manner, however, is meaningless. The assembly of risk and return into a risk-adjusted number is one of the primary responsibilities of performance measurement (Lhabitant, 2004) while the task of performance measurement or evaluation has been conducted within the risk-return[3] framework since the advent of MPT. This framework embraces the most important and most frequently used measure[4] — the Sharpe ratio — a risk-adjusted ratio that measures the reward per unit of risk (variability) (Sharpe, 1966). This ratio is conceptually simple and also rich in meaning thereby providing investors with an objective quantitative measure of performance, but despite its widespread use and copious interpretations the Sharpe ratio does have its drawbacks. Some of these drawbacks threaten the Sharpe ratio's suitability within a hedge fund context as a number of empirical studies have challenged the characterisation of hedge fund returns and argued that standard methods of assessing the risks and rewards of these funds are misleading and inappropriate (Getmansky *et al*., 2004). In particular, volatility measures such as the Sharpe ratio, which are based on mean-variance theory[5] are generally unsuitable for dealing with asymmetric return distributions (Lhabitant, 2004). The fact that the distribution of hedge fund returns deviate significantly from normality is acknowledged (Brooks & Kat, 2002; Malkiel & Saha, 2005) consequentially making the Sharpe ratio ill-suited for hedge fund returns as it does not incorporate higher order moments of the return distribution. The literature on performance evaluation that attempts to incorporate higher moments of the return distribution is vast and many researchers replace the denominator (in the Sharpe ratio) with an alternative risk measure – this will be detailed further within the thesis.

A debate regarding the consideration of new or alternative measures, in addition to the Sharpe ratio, to augment hedge fund risk (and risk-adjusted return) measurement has been lively for some time (Taylor, 2005; Perello, 2007; Wiesinger, 2010). The debate stems from risks faced by hedge funds face are not measured sufficiently accurately and that currently employed measures are inadequate or, at times, misrepresented. The Omega ratio and scaled or generalised performance measures have been formed part of this debate.

Another problem concerning traditional and widely used performance measures is that they do not capture all components of risk: hedge funds have exposure to (unconventional) risk components such as operational risk, downside risk, concentration risk, country risk, short-squeeze risk etc, none of

[3] Mean-variance framework/theory.
[4] The Sharpe ratio is also the risk-adjusted metric of choice amongst hedge funds (Lhabitant, 2004; Opdyke, 2007; Schmid & Schmidt, 2007).
[5] The Treynor ratio is also based on mean-variance theory.

which are explicitly taken into account by conventional performance measures. Unsystematic risk, unlike systematic risk, can be diversified away and investors are not rewarded for exposure to this type of risk (Wagner & Lau, 1971). In the Capital Asset Pricing Model (CAPM) world which is an extended derivation of the Capital Market Line (CML), market risk (as measured by beta) is the only risk considered. This is concluded from the fact that the slope of the Security Market Line (SML) is equal to beta (representing market risk). Other risks that could impact investors, for instance, operational type risks and downside (loss) risk, are not implicitly considered by beta. Performance measures that take these additional or unconventional risk components into consideration will therefore provide hedge fund investors with additional information to consider, alongside traditional measures (when making hedge fund investment decisions). No single measure captures the entire spectrum of risks[6], and so performance measures that consider the components of risk left untouched or unconsidered by the traditional performance measures should be considered alongside the traditional measures.

The 2007-9 global financial crisis has been described and diagnosed by many authors (e.g. Acharya & Richardson, 2009; Acharya *et al*., 2010) and also forms an integral part of this thesis as it represents the event around which different economic conditions prevailed thereby affording interesting performance measure analysis. The crisis, which commenced in June 2007, has been described as the most severe financial crisis since the Great Depression of the 1930s (Soros, 2008). Among the principal causes of the crisis was a significant increase in credit defaults (Subramanian & Williamson, 2009) arguably brought about by several years of lax lending standards. The crisis resulted in substantial international distress with the majority of international banks experiencing capital shortages and some defaulting outright while the crisis was further aggravated by banks not being able to acquire and sustain the required liquidity to survive the distressed conditions brought about by the financial crisis (Esterhuysen, 2010). Financial (or credit) crises are generally characterised by considerable credit losses which precipitate sudden liquidity shortages as a second round effect due to the incurred losses' funding requirements. Further liquidity shortages are precipitated by market uncertainty that also characterise these crises. The crisis caused several major financial institutions to fail with some of these being subsequently acquired under duress. The financial crisis did not only impact credit risk, but also other risks - such as fraud risk. The Madoff Ponzi scheme is a relevant example as Bernard Madoff of Madoff Securities LLC2 was arrested in December 2008 for what is considered the largest financial scandal in modern times with losses estimated at US$85bn.

The crisis was borne of several underlying causes, albeit that two inextricably-linked key failures, explain the majority of these. First, the failure of risk management to accurately assess relevant risks and second, the failure of economic agents to respond appropriately to these risks. The ability to quantify the relative importance of risk mis-measurement from the incentives to ignore risk by the economic agents is, however, unlikely (Engle, 2009). The financial crisis therefore started an important debate of whether risks are being measured appropriately, and, in-turn, the re-evaluation of risk analysis methods and techniques.

The rationale for the inclusion of the financial crisis in this thesis is crucial as it provides the opportunity to explore how the included performance measures and the financial markets' characteristics evolve and react over changing economic conditions from a period *prior to*, *during* and *after* severe distress brought about by the 2007-9 global financial crisis.

1.2 PROBLEM STATEMENT

Performance *measurement* is an integral part of investment analysis and risk management, but traditional risk-adjusted performance measures are not complete as they do not implicitly include or measure all components of risk. These widely used traditional performance measures can therefore be considered one dimensional as each measure includes only a particular component or type of risk and thus leaves other risk components or dimensions untouched. Dynamic and sophisticated investments

[6] "...each performance measure answers a specific question; there is no all-round champion" (Lhabitant, 2004:62).

such as those pursued by hedge funds are a prime example of investments with multi-risk dimensions, due to their underlying characteristics.

Also, the fact that the use of traditional performance measures are deemed inappropriate when asset returns are not symmetrically distributed result in the standard performance appraisal methods (i.e. standard methods that assess the risks and rewards) being misleading and inappropriate when applied to these funds. Investors, however, rely on the traditional performance measures to evaluate the risk-adjusted performance of (these) investments. Also, the traditional risk-adjusted performance measures were developed specifically for traditional investments (i.e. non-dynamic and or linear investments).

Given the different types of risks that hedge funds are exposed to makes it obvious that volatility does not capture all the risk factors inherent in hedge funds. Also, no single measure, currently, captures the entire spectrum of risks. Therefore, traditional risk measurement methods must be modified, or performance measures that consider the components (factors) of risk left untouched (unconsidered) by the traditional performance measures should be considered alongside the traditional performance appraisal measures.

1.3 RESEARCH OBJECTIVES

The primary objective of this thesis is to evaluate whether additional novel tools, can be identified for use by hedge fund investors to characterise additional risk components not considered by traditional performance measures. This objective will be accomplished through the modification of existing risk assessment techniques, the altered use of existing techniques and through the development of new techniques. More specifically, the primary objective of this thesis will be achieved by evaluating whether the performance measures included provide hedge fund investors with additional[7] valuable information when making hedge fund investment decisions. For the purpose of this thesis traditional (risk-adjusted) performance measures are primarily represented by the Sharpe ratio as it is the most widely used risk-adjusted performance measure for traditional investments and also the measure of choice within the hedge fund context. The primary objective of this thesis can therefore be rephrased as: to evaluate whether the (additional) performance measures provide hedge fund investors with additional information to that provided by the traditional Sharpe ratio, when making hedge fund investment decisions.

These identified performance measures will also be evaluated under different economic conditions as further valuable insight may be gained into how investments' performance characteristics and the behaviour of hedge fund managers were influenced on account of different economic conditions. Given the impact and consequences of the financial crisis, this provides an ideal situation to use as part of this economic condition evaluation period. This thesis therefore sets the use of the crisis as the focal point within the changing economic conditions evaluation period and thereby creating economic condition periods that include *prior to*, *during* and *after* the crisis.

The following sub-objectives support the primary objective of this thesis:

- evaluate whether the information provided by the Bias ratio provides hedge fund investors with additional information when it is considered in combination with that provided by traditional performance measures[8] (for making hedge fund investment decisions).
  The Bias ratio will also be evaluated over different economic conditions, and its relevance assessed compared with traditional performance measures,
- evaluate whether the Omega measure provides hedge fund investors with additional information in addition to that of traditional performance measures8 (when making hedge fund investment decisions).

[7] Additional is taken to mean in addition to the information provided by commonly used traditional performance measures, such as the Sharpe ratio.
[8] Represented by the Sharpe ratio.

The Omega measure will also be assessed relative to traditional performance measures over different economic conditions,

- evaluate whether the information provided by the scaled performance measures provide hedge fund investors with additional information when this information is considered in combination with the information provided by traditional performance measures[9] (when making hedge fund investment decisions).
  The scaled performance measures include a scaled Sharpe ratio and a scaled Treynor ratio, both of which will be compared with traditional performance measures (i.e. non-scaled versions of these ratios) over different economic conditions, and
- construct a (risk) "dashboard" tool that incorporates the additional performance measures evaluated and the information they convey in a single setting, thereby providing a holistic and enhanced risk-adjusted viewpoint of a particular hedge fund investment to hedge fund investors. As this dashboard tool contains additional risk and performance information in conjunction with the traditional risk-adjusted and other information that is generally available to investors, the dashboard's use by hedge fund investors when making hedge fund investment decisions would be its primary aim.

1.4 MOTIVATION AND RATIONALE

The motivation behind this thesis is two-fold and is presented in the following table along with accompanying rationale and modest background.

Table 1.1: Motivation and rationale of thesis.

Motivation #1	The consideration of "non-priced" risk components.
Rationale	These additional (risk-adjusted) performance measures consider risk components not considered by existing, traditional performance measures.
Background	• Academic criticism of classical or traditional performance measures, such as the Sharpe and Treynor ratios, that are grounded on the mean-variance framework which employs the Capital Asset Pricing Model (CAPM) is not new. In particular, several authors (see Malkiel & Saha, 2005; Koekebakker & Zakamouline, 2007) have highlighted the shortcomings of using the Sharpe ratio for performance evaluation and the mean-variance framework when the underlying investments have (highly) asymmetric return distributions. Hedge fund return distributions and their markedly non-normal characteristics have been extensively discussed in the literature (see Fung & Hsieh, 2001; Lo, 2001; Brooks & Kat, 2002; Malkiel & Saha, 2005). If investors venture into alternative investments outside of the realm of diversified baskets of equities they might have to take on additional forms of risk, such as short option risk. In such cases, performance measures that function well beyond the trade-off between mean and variance will need to come to the fore. The latter points to measures that incorporate higher moments of the return distribution and measures that capture other risk components. • Hedge fund generally employ dynamic investment strategies, which are accompanied by dynamic risk exposures[10] that have significant implications for investors who seek to manage the risk/reward trade-offs of their investments (Chan *et al*., 2005). These dynamic trading strategies pursued by hedge funds can often not be captured by linear performance measures. Using a singular performance measurement framework that does not consider the characteristics

[9] Represented by (traditional) Sharpe and Treynor ratios.
[10] For example, various equity-orientated hedge fund strategies bear significant (left-tail) risk that is ignored by the mean-variance framework (Lhabitant, 2004).

	of the specific strategies is also of limited use to hedge fund investors. • Beta is the appropriate measure of risk under the CAPM methodology and an adequate risk measure for static investments. Beta is, however, inappropriate an inadequate for capturing the risks of a dynamic investment strategy. • Asymmetric distributions also influence the validity of volatility as a risk measure, which in turn impacts the exactness of risk-adjusted performance measures that rely on volatility such as the Sharpe ratio (Lhabitant, 2004). This is especially true for hedge funds employing dynamic trading strategies as the return distributions of such strategies are highly asymmetric.

Motivation #2	Improved hedge fund investment decision making (for hedge fund investors).
Rationale	The use of additional risk-adjusted performance measures, that provide additional information to traditional performance measures, in conjunction with existing, traditional performance measures will enhance hedge fund investment decision making by hedge fund investors.
Background	Hedge fund investors will be better able to scrutinise hedge funds and hedge fund managers with the use of the additional (risk-adjusted) performance measures. This is the case as these additional performance measures will “shine light upon” risk components not ordinarily captured or considered by traditional risk-adjusted performance measures. These additional performance measures will thus provide hedge fund investors with an additional “layer” of measures and information to use to their benefit. For instance, through the information presented by the additional performance measures, hedge fund investors will be able to invest in specific funds that provide more of a certain type of risk, concentration or downside risk for example. To the contrary, hedge fund investors may also use these additional performance measures to make decisions on specific funds they do not wish to invest in: maybe due to the fact that the funds are exposed to too much downside risk, which investors do not desire or cannot absorb in their risk appetite. Additional performance measures alike the Bias ratio will provide hedge fund investors with “due diligence” information, as investors would undoubtedly not want to invest large investment sums with a hedge fund manager that commits fraud (by smoothing returns for example). The value of such additional performance measures (to hedge fund investors) are leveraged by the fact that: • hedge funds require large capital investments, • hedge funds commonly have lock-in periods in which investors cannot gain access to their capital, and • as hedge funds are risky investment vehicles, compared to traditional investment funds, a great number of hedge funds close each year. The above facts make the additional information received by hedge fund investors even more valuable as the additional measures may alter the investors’ investment decision and thereby, possibly: • save investors from losing liquidity for a certain time period, or • save investors the opportunity cost of investing in a fund while another fund would have been more suitable or economically inferior, or • even losing large sums of capital indefinitely.

	With the use of additional performance measures hedge fund investors will gain valuable additional information that will contribute positively and in a complementary manner to traditional risk-adjusted performance measures.

1.5 OVERVIEW

The field of financial risk management is both deep and broad. This thesis focuses on risk management and specifically risk assessment within the investment context which is hedge funds. The subsequent sections offer concise overviews of the novel risk measures evaluated in this thesis as well as the problem each addresses.

Although various alternative risk or risk-adjusted performance measures exist this study focuses on three specific measures that should (potentially) be used to augment the use of the Sharpe ratio. The three specific measures chosen are different per definition, their objectives and also in their suitability for application. The chosen measures are also not purely substitutes for each other or other widely used (traditional) performance measures – these measures should be considered more as complimentary to each other and also to other alternative and more traditional performance measures. Moreover, the measures included in this study are merely a specific selection and not exhaustive of all types of risk or risk dimensions as no single measure captures all risks. Therefore various and numerous additional or alternative measures are potentially necessary to capture specific and additional risks not considered and or captured by traditional risk-adjusted performance measures, such as the Sharpe ratio. The measures presented in Chapters 2 to 4 thus provide individual alternative risk measures that should potentially be considered by hedge fund investors, in addition to traditional risk-adjusted performance measures such as the Sharpe ratio – the specific choice of alternative or additional measure will depend on the objectives and requirements of the investor.

1.5.1 THE BIAS RATIO AS A HEDGE FUND FRAUD INDICATOR

Hedge funds are exposed to the three main types of risks, namely: (i) market risk, (ii) credit risk, and (iii) liquidity risk. These funds are, however, also exposed to other risk classes and these depend, to some degree, to the relevant strategy being employed. For example, merger arbitrage funds are exposed to the risk that the merger may fail, emerging market funds are exposed to country risk, and long/short equity funds are exposed to short-squeeze risk by their brokers. It is, however, the case that volatility does not capture all the risk factors and therefore traditional performance measures should be modified or measures that consider the components of risk left unconsidered by traditional performance measures should augment the use of traditional performance measures.

The Bias ratio, introduced by Abdulali (2006), is a metric devised to highlight possible fund manipulation and provides a practical method for filtering suspicious funds. It is a mathematical technique that exposes possible fund return manipulation by identifying abnormalities in the distribution of returns. The Bias ratio thus serves as a potential red flag for fraud,[11] which is a risk not considered by volatility. This thesis evaluates weather the Bias ratio should be used by hedge fund investors to augment the use of traditional performance measures when making investment decisions.

The Bias ratio is the measure of choice in terms of (possible) fraud detection as it has received some attention, predominantly from industry. The Bias ratio has also demonstrated that it can be effective in detecting suspicious funds as Douady *et al*., (2009) demonstrated with the Madoff case. Also, given that the Bias ratio is still not very well known or widely used, provides an opportunity to further explore, test and present this measure. The most noteworthy alternative measure for detecting suspicious funds, the manipulation-proof performance measure (MPPM) (Goetzmann *et al*., 2007; In, 2009) is, however, lesser known than the Bias ratio, has no confirmed or apparent support from industry and still continues to develop and evolve. The Doubt ratio (DR) (Brown *et al*., 2010) is a relatively new measure with no known scientific or industry following to date. As the Doubt ratio is

[11] Internal and external fraud is considered an operational risk event-type category (BCBS, 2006:305).

based on the MPMM it was not considered. The method employed by Bollen and Pool (2012) of using a collection of quantitative algorithms or performance flags to identify a heighted risk of fraudulent activity is solely an *ex-ante* method while also being complex and intense, both in logic and computation, and is thus deemed inappropriate and not ideal for use by non-professional or unskilled investors.

1.5.2 THE OMEGA MEASURE

The Sharpe ratio is one of the most widely used (traditional) financial metrics in the financial milieu and also the metric of choice for risk-adjusted performance among hedge funds (Lhabitant, 2004; Opdyke, 2007; Schmid & Schmidt, 2007). Volatility-based performance measures, such as the Sharpe ratio, do however have their shortcomings – primarily that they are unsuitable for dealing with asymmetric return distributions. Measures based on the mean-variance framework are therefore ill-suited for use within the hedge fund context as hedge funds are characterised by asymmetric returns distributions. Hedge fund also employ complex and opaque investment strategies which are accompanied by dynamic risk exposures, but simple, linear risk and return performance measures cannot cope with these dynamic strategies.

The Omega ratio, which embraces the empirical return distributions rather than relying on distributional assumptions, is a more effective and a more discriminatory performance measure (Botha, 2007), and therefore more suitable for use within a hedge fund context.

This thesis evaluates the Omega measure by making use of both the Omega ratio and the Omega function, and whether the Omega measure should augment the use of the Sharpe ratio when evaluating hedge fund risk and in the investment decision-making process.

1.5.3 SCALED PERFORMANCE MEASURES

A variety of adjusted, generalised and scaled measures have been proposed by many with this being particularly true for the Sharpe and Treynor ratios. The Sharpe ratio is the metric of choice for risk-adjusted performance among hedge funds (Lhabitant, 2004; Opdyke, 2007; Schmid & Schmidt, 2007) and has various interpretations. The assumption of normally distributed returns is, however, widely considered the most significant drawback of both measures, as both are based on the mean-variance framework which employs the Capital Asset Pricing Model (CAPM) methodology.

The "transformed" versions of these widely used classical or traditional performance measures originate as hedge fund returns distributions have non-normal characteristics thereby leaving volatility measures unsuitable as these measures are not equipped for dealing with asymmetric return distributions. The aim of these "transformed" measures is therefore to account for the asymmetry (tail risk exposures) created by the dynamic strategies hedge funds pursue. These measures attempt to account for the asymmetry by incorporating not only the first and second order moments of the returns distribution, but also the higher-order moments.

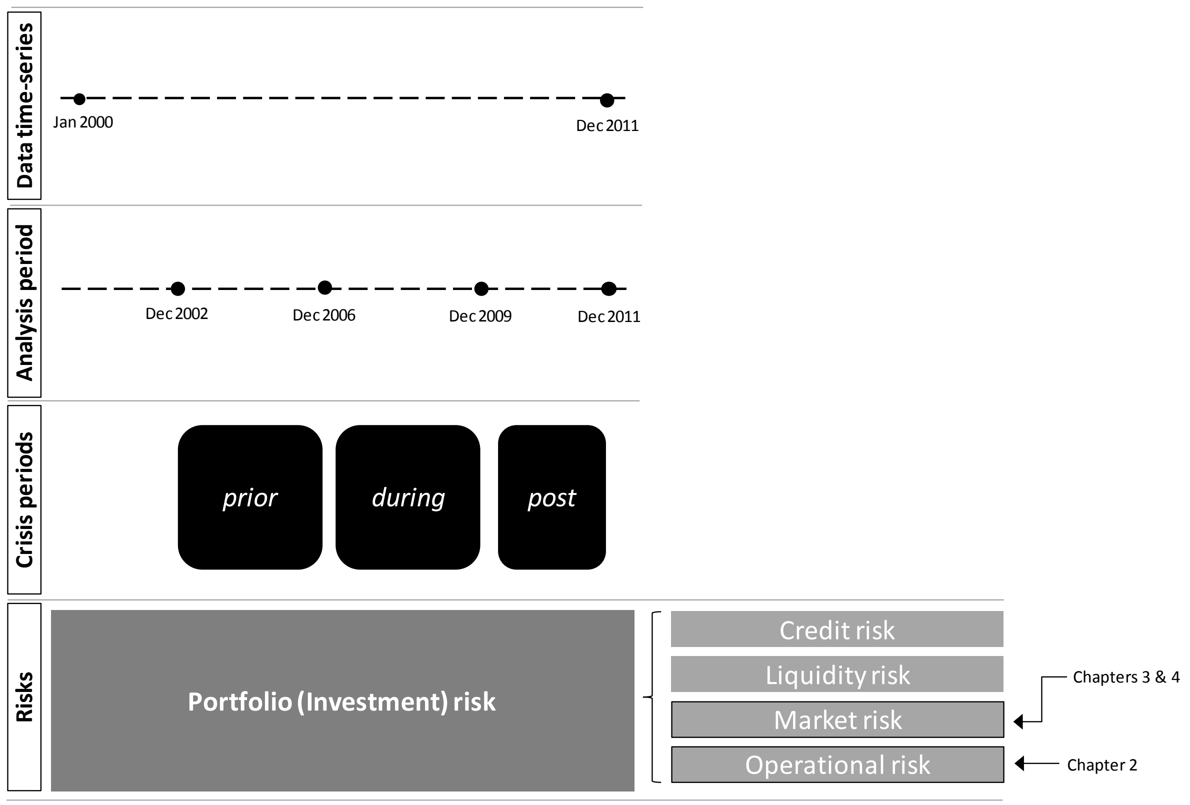
This thesis evaluates scaled versions of the Sharpe and Treynor ratios, based on the scaling methodology of Gatfaoui (2012). The Gatfaoui (2012) scaling methodology is specifically employed as it suits the objectives and the logic behind the desired state remarkably well. Importantly the chosen scaling methodology also lends itself to adaptation. Furthermore, although the Sharpe ratio is the primary focus, the incorporation of the Treynor ratio adds an additional dimension and added depth to the study – providing for a more rounded and elaborate study.

1.6 THESIS OUTLINE

The field of financial risk measurement and management is broad and deep. This also holds true for the field of investment management in which the primary objective is arguably the investment reward received. This thesis focuses on performance measurement when portfolio or investment risk measurement is combined with the measurement of the investment yield – *risk-adjusted performance measurement*. The thesis further asserts and tests whether hedge fund risk is being correctly assessed.

A schematic representation of this thesis is presented in Figure 1.1 and details the structure of the included risks and also the data timelines and crisis phases.

Figure 1.1: Schematic representation of thesis.



Portfolio risk management is arguably linked to certain of the main risk types as classified by the BCBS's Basel accords; market, credit, liquidity and operational risk. The linkage of portfolio risk to these risk types is due to exposure of the investment(s) to these risk types, either individually or as part of a portfolio. The particular risks that the investment or portfolio are exposed to depend on the specific investments' particulars.[12] This thesis will firstly explore the risk of fraud, which according to the BCBS is considered an operational risk event-type (BCBS, 2006:305), within the portfolio risk context and occurs predominantly at the fund manager level. Thereafter the focus will shift to the fund portfolio level and the distributional assumptions which arguably fall under the risk type of market risk.

As the dynamics within each of the identified problem areas are vast, complex and somewhat different, each analytical chapter (Chapters 2-4) presents its own literature review dealing with the specific problem at hand in a focuses and detailed manner.

Chapter 2 addresses fraud (risk), a type of operational risk, within a hedge fund context as hedge fund managers are able to manipulate hedge fund returns which in turn result in untruthful performance metrics often used by hedge fund investors, either private or professional.[13] The chapter argues that traditional performance measures do not account for certain risks, like fraud risk, as these risks are not considered by metrics that rely on volatility as the measure of risk. The chapter explores a fraud indicator, namely the Bias ratio, which is evaluated alongside the Sharpe ratio over different economic conditions while the Bias ratio is demonstrated and applied using the Madoff Ponzi scheme. The aim of the chapter is to ascertain whether hedge fund investors should use the Bias ratio to supplement traditional performance measures, such as the Sharpe ratio, when making hedge fund

[12] For instance, financial instrument(s) invested in; country or countries invested in; market conditions when invested; counterparty particulars; investment practices by investment house or managers; etc.
[13] Professional hedge fund investors are for example, fund of hedge funds.

investment decisions as the Bias ratio provides additional information to that provided by the Sharpe ratio. This chapter also employs a technique that accounts for serial return correlation as standard techniques for annualising Sharpe ratios do not.

Chapters 3 and 4 address the common problem of faulty assumptions of return distributions in a portfolio and market risk framework, and how this influences hedge fund performance appraisal. Large, abrupt movements in portfolio returns are a concern to all market participants and the assumption that returns are normally distributed is severely flawed and potentially damaging. Certain investment strategies employed by hedge funds result in returns having large outliers and asymmetric returns distributions. The result of asymmetric returns distributions is that traditional, linear performance metrics, such as the Sharpe ratio, are rendered ill-suited. Chapter 3 explores the Omega measure. The measure is evaluated relative to the Sharpe ratio, the most widely used traditional risk-adjusted performance measure, over different economic conditions. The chapter details the reasoning and benefits behind the use of the Omega measure within a hedge fund context and the Omega ratio is also applied to construct comparative hedge fund portfolio rankings to that of the Sharpe ratio, over different economic phases. The aim of the chapter is to evaluate whether the Omega measure should augment the Sharpe ratio when making hedge fund investment decisions. As with Chapter 2, a technique that accounts for serial return correlation when annualising Sharpe ratios is employed.

Chapter 4 continues with the problem of faulty return distribution assumptions as per Chapter 3, except this chapter explores scaled performance measures, and whether such measures should augment traditional performance measures when investing in hedge funds. As traditional performance measures based on the mean-variance framework do not account for higher-order return distribution moments these metrics are ill-suited to evaluate investments that use dynamic strategies and have asymmetric return distributions. The chapter evaluates scaled versions of the Sharpe and Treynor ratios, which account for higher-order return distribution moments, in a comparative fashion to the traditional measures. Comparative hedge fund portfolio rankings are also constructed, over different economic phases, using the scaled and traditional Sharpe and Treynor ratios respectively.

Chapter 5 provides concluding thoughts on the main research results from the studies detailed in this thesis. Some suggestions for further research, that is required in this constantly evolving field of portfolio risk management, will be made.

1.7 RESEARCH DESIGN AND PROCEDURE

The research design of this thesis followed the outline below:

Pose research questions: Broad questions were first posed about the inadequateness of risk performance measures within a hedge fund context and also how inaccurate risks were being assessed within the financial environment. The 2007-9 financial crisis highlighted the inaccurate assessment of risks, while even before the financial crisis gaps in risk management theory and practices were becoming apparent and also more difficult to disregard. With the goal of portfolio risk management uppermost, and the fields of investment, market and operational risk in need of further investigation, three topics were decided upon. Chapters 2 to 4 will deal with these issues.

Critical literature review: Critical literature reviews ensued in which existing work by practitioners and researchers in the field was consulted, and was reported on. Often adjustments were only required to existing risk management practices, i.e. no new techniques were needed to solve particular problems. In such cases the existing literature is copious while the literature was less obliging where an entirely new approach to risk practices was required. Nonetheless, popular, well-established mathematical techniques are almost always available for such endeavours and profuse literature exists to address these models.

Theory building/adapting/testing: Augmenting existing risk management ideas for practical implementation into investment or market portfolio usually enjoys rich precedent. In these cases, pursuing existing, well-established methodologies allows slight, yet significant, improvements to be made to risk management practices. Developing new ideas requires much back-testing, validation and endorsement from other practitioners. Ultimately, the bulk of the results reported in this thesis were from empirical analyses of real return (or other) data.

Action research/data collection: Data used were from reputable sources (e.g. Bloomberg™, Barclayhedge, Eurekahedge, Federal Reserve Bank of St. Louis FRED® database, Hedge Fund Research.® Due to the proprietary and confidential nature of hedge fund data, these data are easiest to obtain from a third party vendor. These third party hedge fund data vendors take numerous actions and practices to maximise data correctness and also to minimise data errors and biases. Data biases were minimised and reported and data were relevant,[14] in all cases.

Conceptual development: This research is intended to provide accurate, but highly practical, solutions for use by risk and investment analysts and managers. As a direct result, the primary source of analytical work was Microsoft Excel™ as this is the tool of choice for almost all financial institutions.[15] Although clearly not designed to perform the most advanced statistical or algebraic analysis, Microsoft Excel™ nevertheless performs adequately. These Microsoft Excel™ spreadsheet-based models use visual basic (for applications) (VBA) ® programming language[16] to develop macros for undertaking onerous and repetitive computing tasks. The use of macros involves further testing with dummy data, back-testing and model validation. Results from these practices were found acceptable and strongly agreed with the results from the macro models.

Reflection/theory extension: Results obtained from these models are then critically assessed, analysed and the findings meaningfully presented. It is expected that the analysis will at times involve further, more detailed investigation, possibly using different – or 'cleaned' –data. If the results indicated inconsistencies or contradictions with theory, further research was conducted to augment the existing theoretical explanation for the particular phenomena.

State/disseminate findings: Having analysed the data, obtained meaningful results and displayed these appropriately, the findings were reported in article-style reports for peer review and publication.

Further work: To complement major findings of and ensure the continuation of work not addressed (or that which could not be undertaken due to lack of data or theory) in this thesis, future research was then proposed for risk and investment theorists and practitioners.

1.8 CONCLUSION

The field of risk management is undergoing an upheaval and, possibly, a revolution (Engle, 2009). Risk management is also an important activity for the success of a hedge fund (Stefanini, 2006) and proficient risk management practices and rigorous risk management systems are required in order for hedge funds to survive in highly volatile markets. The risks associated with the complex strategies often adopted by hedge funds are also more complex than those involved in traditional investments.

Although the arrangement of risk and return into a risk-adjusted number is one of the primary responsibilities of performance measurement (Lhabitant, 2004), performance measurement or analysis must always be associated with risk analysis – as performance is connected to the assumption of some risk(s).

More sophisticated performance measures are necessitated as the need to accurately distinguish between good and poor quality investments or funds has not diminished, and in actual fact is ever

[14]Publicly available data were obtained from third party data sources such as Bloomberg™. Some hedge fund data are proprietary and not permitted for public consumption. Permission to present analytical results based on these data was obtained from third party data vendors where required. Due to the confidential and proprietary nature of certain hedge fund data, names of hedge funds have been omitted and in such cases only reference to a fund number is made, which is in no manner connected to the fund.

[15]Standard statistical software, such as SAS,® was used in cases where Excel proved inadequate.

[16]A flexible, functional and highly valuable computer desktop tool available to all quantitative analysts and risk managers alike.

increasing. This thesis aims to contribute to the debate of improved and more suitable hedge fund performance measures by evaluating a select few novel risk measures that should augment traditional performance measures, specifically the most widely used Sharpe ratio.

More accurate performance measures are imperative given that financial instruments and markets become more advanced as time passes, but also as traditional performance measures do not consider the higher moments of the return distribution and do not account for all components of risk. Such improved performance measures are especially applicable and necessitated for hedge funds given hedge fund return characteristics, the dynamic strategies they often employ and the complex environment in which they operate. The benefit of these more sophisticated performance measures is that they will provide hedge fund investors with additional information to consider when making investment decisions. These additional performance measures should be considered alongside traditional performance measures as they provide information in additional to that provide by the traditional measures.

CHAPTER 2

THE BIAS RATIO AS A HEDGE FUND FRAUD INDICATOR: AN EMPIRICAL PERFORMANCE STUDY UNDER DIFFERENT ECONOMIC CONDITIONS

The Bias Ratio as a hedge fund fraud indicator: An empirical performance study under different economic conditions

Francois van Dyk, Gary van Vuuren & André Heymans

Abstract

The Sharpe ratio is widely used as a performance evaluation measure for traditional (i.e. long only) investment funds as well as less-conventional funds such as hedge funds. Based on mean-variance theory, the Sharpe ratio only considers the first two moments of return distributions, so hedge funds - characterised by complex, asymmetric, highly-skewed returns with non-negligible higher moments – may be misdiagnosed in terms of performance. The Sharpe ratio is also susceptible to manipulation and estimation error. These drawbacks have demonstrated the need for augmented measures, or, in some cases, replacement fund performance metrics. Over the period January 2000 to December 2011 the monthly returns of 184 international long/short (equity) hedge funds with investment mandates that span the geographical areas of North America, Europe and Asia were examined. This study compares results obtained using the Sharpe ratio (in which returns are assumed to be serially uncorrelated) with those obtained using a technique which does account for serial return correlation. Standard techniques for annualising Sharpe ratios, based on monthly estimators, do not account for serial return correlation – this study compares Sharpe ratio results obtained using a technique which account for serial return correlation. In addition, this study assess whether the Bias ratio supplements the Sharpe ratio in the evaluation of hedge fund risk and thus in the investment decision-making process. The Bias and Sharpe ratios were estimated on a rolling basis to ascertain whether the Bias ratio does indeed provide useful additional information to investors to that provided solely by the Sharpe ratio.

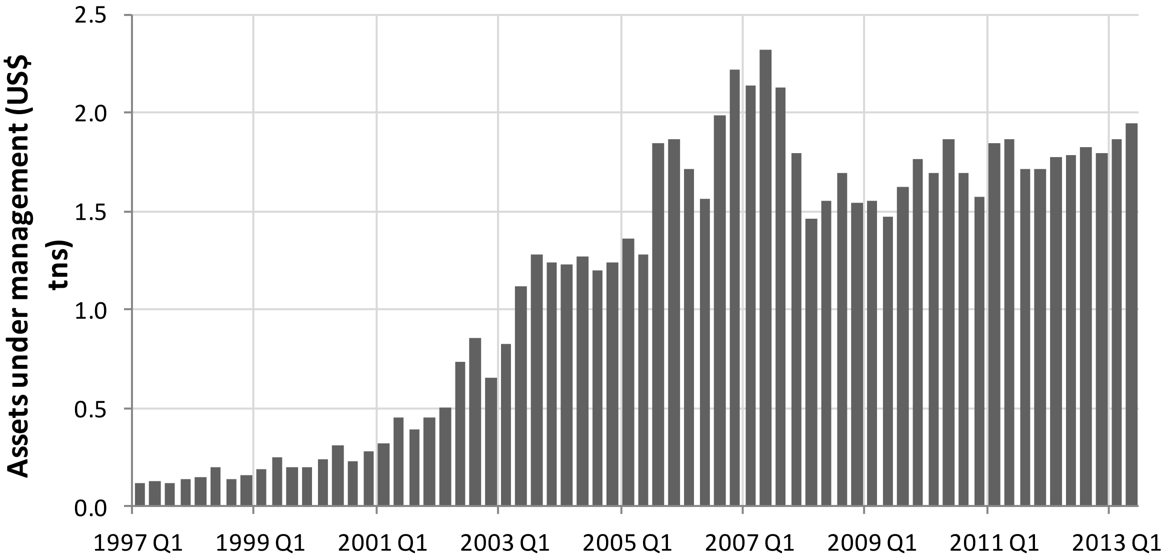
Keywords: *hedge funds, Bias ratio, fraud, risk management, Sharpe ratio*

JEL Classification: *C1, C6, G11, G15, G23, C65, C44, C49, C58*.

1. INTRODUCTION

Institutional investors and wealthy individuals have for a long time been interested in hedge funds as alternative investments to traditional asset portfolios, while the public's interest in the hedge fund industry has also increased through spectacular hedge fund activities, such as the collapse of Long Term Capital Management (LTCM) in the late 1990s. Since the early 1990s, hedge funds have become an increasingly popular asset class as global investment rose from US$50bn in 1990 to US$2.2tn in early 2007 (Barclayhedge, 2013). In March 2012, long/short equity funds accounted for the largest portion – 23% – of the industry by assets (Citi, 2012). The hedge fund industry posted its sturdiest gains, in terms of asset flows and performance, between 2003 to 2007 where after the financial crisis significantly curtailed growth. However, industry growth reversed, declining to US$1.4tn by April 2009 due to substantial investor redemptions and performance-based declines (Eurekahedge, 2012). In April 2013, total assets under management (AUM) for the hedge fund industry had risen to only US$1.9tn (Eurekahedge, 2013) with growth relatively flat, as shown in Figure 1.

Figure 1: Hedge funds' assets under management (US$tns), 1997 to quarter 2 of 2013.



Source: Barclayhedge (2013).

Although most comparisons of hedge fund returns concentrate exclusively on total return values, comparing funds with different expected returns and risks in this manner is meaningless. The combination of return and risk into a risk-adjusted number is one of the key tasks of performance measurement (Lhabitant, 2004). The hedge fund industry has adopted a number of risk-adjusted performance measures[1] (some of which are also commonly used in traditional funds) such as the Sharpe and Treynor ratios, Jensen alpha, M^2 and downside (risk) measures such as the Sortino ratio and Value-at-risk (VaR).

The Sharpe ratio is the metric of choice amongst hedge funds and also the most commonly used measure of risk-adjusted performance (Lhabitant 2004; Opdyke, 2007; Schmid & Schmidt, 2007). Proposed by Sharpe as the "reward-to-variability" ratio as a mutual fund comparison tool (see, Sharpe, 1966, 1975, and 1994) the ratio is both conceptually simple and rich in meaning, providing investors with an objective, quantitative measure of performance. It enjoys widespread use and numerous interpretations, but it also has its drawbacks, which will be discussed in Section 2.1. Among others, volatility measures are generally unsuitable for dealing with asymmetric return distributions (Lhabitant, 2004).

Return performance is, however, also key objective for hedge funds, and the hedge fund universe showed an annual return of 8.82% from 1995 until 2003 compared to an annual return of 12.38% for the S&P500 (Malkiel & Saha, 2005). More recently, in 2011 the hedge fund industry reported a 4.6% performance loss, although most of the losses occurred in the third quarter when global equity markets fell by approximately 17% (TheCityUK, 2012). Between 2002 and 2012 average annual returns for hedge funds were 6.3% (TheCityUK, 2012) compared with 5.7% for U.S. bonds,[2] 7.8% for global bonds[3] and 6.0% for the S&P500. The hedge fund industry posted its worst annual performance in 2008 (-20%), its worst since 1990 while total fund liquidations rose to around 775 in 2011, an increase of 4% from 743 in the previous year. Although the total number of funds rose to 9 523 in 2011 this number still fails to eclipse the pre-crisis peak at the end of 2007 of 10 096 funds (Clarke, 2012). According to figures from Hedge Fund Research (HFR), hedge fund launches and total fund numbers have at March 2012 still not returned to their pre-financial crisis levels (Clarke, 2012). In terms of the industry's asset size, AUM declined 27% in 2008 to US$1.4tn (Roxburgh *et al.*,

[1] Usually performance indicators that combine the returns with the risk of the fund (Botha, 2007).
[2] U.S. bonds as measured by the Barclays U.S. Aggregate Bond Index.
[3] Global bonds as measured by the JP Morgan Global Government Bond Index (unhedged).

2009) and even further in March 2009 to US$1.29tn (Eurekahedge, 2010), echoing both asset withdrawals and investment losses.

Investor withdrawals following the financial crisis (when it became clear that hedge funds had not "hedged" well at all) contributed to poor performance. This has led to a high attrition rate[4] (Brown *et al*., 1999, 2001a, 2001b; Liang, 1999) which has also increased significantly over time. Only 90.9% of funds that were alive in 1996 were still alive in 1999, while this declined to 59.5% in 2001 (Kat & Amin, 2001). Furthermore, Kaiser and Haberfelner (2012) found that the attrition rate for hedge funds has nearly doubled since the financial crisis. In the highly competitive world of fund performance, the reporting of monthly returns can exacerbate investor outflows, halt them, reverse them or increase them – depending on the reported figures. The incentive to exaggerate or misrepresent fund performance is strong (see, *e.g.* Feng, 2011; Agarwal & Naik, 2011; Goetzmann *et al*., 2007; Bollen & Pool, 2009). Also as investors pay high fees, typically in the vicinity of a 2% management fee and a 20% performance fee, performance evaluation and an accurate performance evaluation methodology are of vital importance to investors (Lopez de Prado, 2013).

It is possible that the risks that hedge funds face are not measured sufficiently accurately, measures currently employed are inadequate or they are sometimes misrepresented. Consideration of new measures, in addition to the Sharpe ratio, to augment hedge fund risk (and risk-adjusted return) measurement have long been debated (*e.g.* Perello, 2007; Wiesinger, 2010). One such measure is the Bias Ratio, a practical measure for detecting potentially suspicious fund returns (Abdulali, 2006).

This study evaluates whether the Bias ratio should augment the use of the Sharpe ratio when evaluating hedge fund risk and in the investment decision-making process. Not only does the Bias ratio provide information over and above that given by the Sharpe ratio, but the latter is ill-suited to hedge funds (which exhibit complex, asymmetric and highly-skewed return distributions).

The remainder of this paper is structured as follows: Section 2 presents an overview of the existing literature governing fund performance, as well as an overview of both alternative (risk-adjusted) performance measures and the influence on the Sharpe ratio of illiquidity and smoothing. Section 3 introduces the technical details of the Bias ratio, discusses other fraud measures as well as the data employed and concludes with a real-world application of the Bias ratio to a known fraud[5] to validate its applicability and robustness. Section 4 presents the analysis and results along with some comparative summary statistics and Section 5 concludes.

2. LITERATURE STUDY

2.1. Inadequacy of Sharpe Ratio

The Sharpe ratio is one of the most commonly cited statistics in financial analysis and the metric of choice amongst hedge funds, particularly as a measure of risk-adjusted performance (Koekebakker & Zakamouline, 2008; Lhabitant 2004; Lo, 2002; Opdyke, 2007; Schmid & Schmidt, 2007). Also known as the risk-adjusted rate of return (Sharpe, 1966, 1975, 1992, 1994; van Vuuren *et al.*, 2003), it is calculated using:

$$SR = \frac{r_p - r_f}{\sigma\sqrt{T}} \tag{1}$$

where r_P is the cumulative portfolio return measured over T months, r_f is the cumulative risk-free rate of return measured over the same period, and σ is the monthly portfolio volatility (risk). Despite its widespread use, the measure does, however, have some weaknesses, especially within the hedge fund context.

Expected returns and volatilities are non-observable quantities so they must be estimated. The Sharpe ratio is thus determined with inevitable estimation errors. Lo (2002) argued that little attention has

[4] Attrition rate is the liquidation rate of funds.
[5] The Madoff fraud case is used in the application of the Bias ratio.

been given to the statistical properties of the Sharpe ratio given that the accuracy of its estimators rely on the statistical properties of returns, and that these may be very different among portfolios, strategies and over time. By this Lo (2002) concludes that the performance of more volatile investment strategies is more difficult to determine than less volatile strategies. Since hedge funds are generally more volatile than more traditional investments (Ackermann *et al*., 1999; Liang 1999), Sharpe ratio estimates for hedge funds are likely to be less accurate. Numerous statistical tests that provide for Sharpe ratio comparisons between two portfolios have been proposed by, Gibbons, Ross and Shanken (1989) Jobson and Korkie (1981), Lo (2002) and Memmel (2003). However, the unavailability of multiple Sharpe ratio comparisons has led to alternative approaches (*e.g.* Ackermann *et al*., 1999; Maller & Turkington, 2002). It is clear that a more refined approach of interpreting Sharpe ratios is necessary and that such an approach should possibly consider information concerning the investment style or strategy and also the market environment in which the returns are generated. In addition, it has also been demonstrated that the Sharpe ratio is prone to manipulation (see, *e.g.* Goetzmann *et al*., 2002, 2007; Spurgin, 2001).

Brooks and Kat (2002) found that hedge fund indices exhibit low skewness and high kurtosis, while Scott and Horvath (1980) found that investors prefer high first and third moments (mean and skewness) and low second and fourth moments (standard deviation and kurtosis). Asymmetric distributions influence the validity of volatility as a risk measure, which in turn also impacts the accuracy of the Sharpe ratio. Volatility measures only the dispersion of returns around their historical average and given that positive and negative deviations from the average are penalised in an equal manner in the calculation, the concept only makes sense for symmetrical distributions (Lhabitant, 2004). In practice most return distributions are neither normal nor symmetrically distributed, thus even when two investments have the same mean and volatility, they may have significantly different higher moments. This is particularly true for strategies involving dynamic trading, buying and selling options and active leverage management (Lhabitant, 2004) – all strategies employed by hedge funds. The return distributions of such strategies are highly asymmetric and possess “fat tails”, which in turn render volatility less meaningful as a measure of risk. From an investor’s perspective the relevance of the dispersion of returns around an average has been questioned, as most investors perceive risk as a failure to achieve a specific goal such as a benchmark rate (Lhabitant, 2004; Vanguard, 2012). In this situation, risk is only considered as the downside of the return distribution and not the upside: volatility does not capture this difference (Lhabitant, 2004). Investors are also more adverse to negative deviations than to positive deviations of the same magnitude (Lhabitant, 2004).

The Sharpe ratio is based on the mean-variance framework, which employs the CAPM methodology under which the appropriate measure of risk is represented by β:

$$\begin{aligned}\beta_P &= \frac{Cov(r_p, r_{mkt})}{Cov(r_{mkt}, r_{mkt})} \\ &= \frac{Cov(r_p, r_{mkt})}{Var(r_{mkt})}\end{aligned} \tag{2}$$

where r_p and r_{mkt} are the portfolio and market returns, respectively.

Strong assumptions underlie the CAPM, *e.g.* (i) returns are normally distributed, and (ii) investors care only about the mean and variance of returns, so upside and downside risks are viewed with equal dislike (Leland, 1999). These assumptions seldom hold in practice: even if the underlying assets’ returns are normally distributed, the returns of portfolios that contain options on these assets, or use dynamic strategies will not be (Leland, 1999).

Hedge funds generally employ dynamic investment strategies, with accompanying dynamic risk exposures, and these have important implications for investors who seek to manage the risk/reward trade-offs of their investments (Chan *et al*., 2005). For this reason, hedge fund performance is often summarised with multiple statistics.[6] While β is an adequate risk measure for static investments, there is no single measure capturing the risks of a dynamic investment strategy (Chan *et al*., 2005). Linear performance measures can often not capture the dynamic trading strategies that several hedge funds pursue (Agarwal & Naik, 2004) whilst hedge funds employ a range of trading strategies. Analysing all hedge funds using a singular performance measurement framework that does not consider the characteristics of the specific strategies is of limited value. Hedge fund style specific performance measurement models or measures are required in order to capture the differences in management style (Agarwal & Naik, 2004; Fung & Hsieh, 2001, 2004).

A large number of equity-orientated hedge fund strategies bear significant (left-tail) risk that is ignored by the mean-variance framework[7] (Lhabitant, 2004).

2.2. Alternative risk performance measures

The drawbacks of volatility as a measure of risk clarify why alternative risk measures have been sought (Lhabitant, 2004). Many alternative measures replace the Sharpe ratio's denominator (volatility) by an alternative measure of risk. For example, Sortino and Price (1994), as well as Ziemba (2005), substitute standard deviation by downside-deviation. Gregoriou and Gueyie (2003) propose a modified Sharpe ratio as an alternative measure specifically for hedge fund returns by using a modified Value-at-Risk (VaR) instead of standard deviation as the denominator.[8] Dowd (2000) replaces standard deviation by a VaR measure, while conditional VaR may also be used. The Stutzer index is based on the behavioural hypothesis that investors aim to minimise the probability that the excess returns over a given threshold will be negative (Stutzer, 2000). The Omega ratio expresses the ratio of the gains with respects to a chosen threshold to the loss with respect to the same threshold (Shadwick & Keating, 2002). Kaplan and Knowles (2004) introduced the Kappa measures which generalises the Sortino and Omega ratios, while Koekebakker and Zakamouline (2008) derive a formula for a natural extension of the Sharpe ratio that considers the skewness of the distribution.[9]

These alternative performance measures, however, lack solid theoretical underpinnings (considering the Sharpe ratio is based on the expected utility theory) (Koekebakker & Zakamouline, 2008) and do not allow accurate ranking of portfolio performance since ranking based on these measures depends significantly on the choice of threshold. In addition, most of these measures take into account only downside risk, while the upside potential is not considered.

2.3. Influence of illiquidity and return smoothing on Sharpe ratio

Illiquidity and (return) smoothing also have an impact on the Sharpe ratio. Alternative investment returns are often highly serially correlated, due mainly to illiquidity exposure and smoothed returns, although several potential explanations exist (Chan *et al*., 2005; Getmansky *et al*., 2004). Serial correlation is thus used as a proxy for liquidity. In most cases, serial correlation in hedge fund returns is the result of illiquid component securities (Getmansky *et al*., 2004), which can include securities not actively traded and for which market prices are not always readily available. In such instances, the hedge fund manager has considerable discretion in marking the portfolio's value (to arrive at the fund's net asset value (NAV)), while this leads to the reported returns of funds containing illiquid securities appearing to be smoother than true economic returns,[10] and as a consequence this will convey a downward bias on the estimated return variance and yield positive serial return correlation. In the hedge fund context serial correlation is thus mostly likely the outcome of illiquidity exposure,

[6] *E.g.* mean, standard deviation, Sharpe ratio, market beta, Sortino ratio, maximum drawdown etc. (Chan *et al*., 2005).

[7] These left-tail risks originate from hedge fund strategies that exhibit payoffs resembling a short position in a put option on the market index (Lhabitant, 2004).

[8] The standard VaR only considers mean and standard deviation while modified VaR takes both the mean and standard deviation as well as skewness and excess kurtosis into consideration.

[9] This ratio is denoted as the adjusted for skewness Sharpe ratio (ASR).

[10] Returns that fully reflect all available market information (in relation to those securities).

and while non-synchronous trading[11] could be one symptom or by-product of illiquidity, it is not the only aspect of illiquidity that affects hedge fund returns. Bisias *et al.*, (2012), however, found that funds that invest in highly liquid securities (*e.g.* equity funds) have autocorrelations near zero. Funds with high serial autocorrelations indicate returns smoothing although market inefficiencies, time-varying expected returns and leverage and incentive fees with high-water marks could also be the cause (Getmansky *et al*., 2004). Cao *et al*., (2013) estimated that 24% of hedge fund reported return autocorrelation is due to managerial discretion in reporting returns, while the underlying assets are responsible for the remaining 76% of autocorrelation. The amount of autocorrelation due to managerial discretion was found to be higher for funds with greater barriers to liquidity[12] as measured by the length of both the redemption notice period and the lockup period (Cao *et al*., 2013).

In terms of valuation behaviour, Cici *et al.*, (2013) found that a negative coefficient on past holding return exists. This suggests that following lower past returns, a tendency to overvalue the portfolio exists and alternatively, following high past returns, a tendency to undervalue the portfolio exists. Such behaviour hints that part of the valuation behaviour is directly motivated by incentives related to performance considerations. The nature of hedge fund compensation structures which is commonly linked to performance statistics (Do *et al.*, 2005) could encourage returns manipulation through "smoothing", i.e. marking portfolios to less than their actual value in months with large positive returns so as to create a "cushion" for other months with lower returns. Just under half of hedge fund managers were found to modify their data (Patton *et al*., 2012). The data modifications included not only performance improvements, but also downward performance adjustments depending on either relevant performance fee levels or high-water marks. Practices such as return-smoothing practices yield a more consistent set of returns over time, with lower volatility, and ultimately a higher Sharpe ratio, but also high serial correlation. The more illiquid the portfolio, the more leeway the manager has in marking its value and smoothing returns, while also creating serial correlation in the process. Cici *et al*. (2013) showed that valuation deviations are related to stock characteristics and specifically that positions corresponding to highly illiquid stocks display more valuation deviations. Cici *et al*. (2013) also found that a significant fraction of deviations exist among highly liquid positions, suggesting that illiquidity alone cannot explain observed valuation discrepancies.[13] It is therefore imperative that investors know the NAV calculation methodology used as there is a tendency for managers to "manage" optimally their monthly NAV in order to smooth their returns, which in turn also enables a fund to hide risk (Lhabitant, 2004). This problem is particularly severe in two categories of hedge funds namely; (i) hedge funds holding illiquid securities or securities that are difficult to price,[14] and (ii) US onshore limited partnerships.[15] Valuation practices have been found which show no consistent market practice across hedge funds when numerous quotes were available (Lhabitant, 2004). Approximately 50% of fund respondents used an average quote, 36% used subjective judgement, 7% used the median quote, and 7% eliminated the high and low prices and then averaged the remaining quotes. The significance of smoothed returns and serial correlation is considered in greater detail in Getmansky *et al*. (2004) and Lo (2002).

Additional bias in reported Sharpe ratios occurs when monthly Sharp ratios are annualised by multiplying by $\sqrt{12}$. This is the correct procedure if the returns are independently and identically distributed (IID), but for non-IID returns, an alternative procedure that accounts for serial correlation must be used (Lo, 2002). It is, however, important to take illiquidity and smoothed returns into account when evaluating the performance of hedge funds (Getmansky *et al*., 2004).

[11] This trading phenomenon demotes to security prices recorded at different times, but being incorrectly treated as if they were recorded simultaneously.

[12] In this context liquidity refers to the ease or difficulty with which an investor can make or redeem an investment in the fund (Cao *et al*., 2013).

[13] Cici *et al*. (2013) found that roughly 7% of all equity positions are valued at different prices from closing prices as reported to the Centre of Research in Security Prices (CRSP).

[14] Marking to market of these assets is quite often difficult due to either small trading volumes and/or the unavailability of daily true economic traded prices.

[15] As the majority of these funds value their own portfolios.

Conditional serial correlation can, therefore, be considered as an indicator of (possible) fraud, as when true returns are independently distributed and a manager fully reports gains but delays reporting losses the reported returns will feature conditional serial correlation (Bollen & Pool, 2008).

An additional measure that should be considered by investors might include a measure that detects fraudulent activity or has the ability to identify a heightened risk of fraud by hedge funds. One such measure is the Bias ratio, which is introduced in the next section.

3. METHODOLOGY AND DATA

3.1. The Bias ratio

The Bias ratio, introduced by Abdulali (2006), is a metric devised to highlight possible fund manipulation and thus a practical method for filtering suspicious funds. The measure is similar to Benford's law,[16] a comparable leading digits mathematical theory that provides a distinctive method of data analysis (Nigrini, 1999). This method, used by forensic accountants, may be employed to establish the normal level of number duplications in data sets, which thus makes it possible to identify both abnormal digit and number occurrences. Benford's law can be used to identify irregularities which might indicate possible error, fraud, manipulative bias or other inefficiency (Nigrini & Mittermaier, 1997; Raimi, 1976).

The Bias ratio exposes possible fund return manipulation and can thus be used as an indicator (but not ultimate proof) of fraudulent activity. The Bias ratio is similar to a test for randomness, as it is a mathematical technique that identifies abnormalities in the distribution of returns. Bollen and Pool (2012) establish a significant relationship between a variety of suspicious return patterns and the incidence of fraudulent activity and other regulatory violations. The metric calculates the ratio of the frequency of positive returns to the frequency of negative returns to within one standard deviation of the observed return distribution, i.e. it investigates the return distribution's degree of symmetry, by analysing the fund returns to measure how far the returns are from an unbiased distribution. The Bias ratio for a highly liquid fund or portfolio such as an equity index should thus be close to one, while the Bias ratio of a fund that holds highly illiquid securities will be $\gg 1$. The latter occurs when bias is introduced where fund managers have discretion in the valuation process. It is difficult to smooth returns for funds dealing with high liquidity due to valuation set by readily available market prices. Conversely, a high (or increasing) Bias ratio (when dealing in more illiquid securities) is not in itself proving return manipulation, as by nature illiquid securities have a propensity to deliver smoother returns (Le Marois, 2008). This is the case even with an objective valuation process, although a high (or increasing) Bias ratio may still prove that funds dealing in very illiquid securities actively manipulate their returns[17] (Le Marois, 2008). It is, however, important to be aware that return smoothing does not necessarily imply unfair NAV manipulation; it could simply mean that the value is based on an (in-house) subjective rather than an objective process of valuation.

Illiquid securities are often associated with serial correlation of returns, so serial correlation or a very high Sharpe ratio can be taken as a warning indicator, but not necessarily as a conclusive and final verdict. Results statistically support the Bias ratio as an indicator of return smoothing, as well as a statistical relationship between the liquidity of different asset strategies and their Bias ratios (Le Marois, 2008). The Bias ratio can thus assist in detecting NAV manipulation (i.e., subjective pricing) while also being able to recognise the presence of illiquid securities where they should not exist, but the ratio must be interpreted in line with the liquidity of the strategy being observed.[18] The Bias ratio makes a good case as a due-diligence tool for the (diligent) investor as it serves as a warning flag which can then lead to further investigation.

[16] Benford's law is named for physicist Frank Benford (1938).
[17] This practice introduces a severe violation in terms of risk transparency.
[18] A Bias ratio far from the median value, observed for a particular strategy, should be considered as abnormal.

3.2. Other fraud measures

Bollen and Pool (2012) identified (ex-ante) a heightened risk of hedge fund fraud using a collection of quantitative algorithms or performance flags, which require only a time-series of returns. The performance flags used were based on suspicious patterns in reported fund returns consistent with fraudulent activity. Bollen and Pool (2008, 2009) present conditional serial correlation and discontinuity analysis [19] using time series analysis and Gaussian kernel density estimations, respectively.

In (2009) extends a manipulation-proof performance measure (MPPM) (Goetzmann *et al*., 2007) to a measure for detecting suspicious funds. The measure is derived from the MPPM,[20] which is derived from a utility function that bores a fund's implied risk aversion. The method is still to be thoroughly scrutinised.

The Doubt Ratio (DR) is a relatively new measure based on MPMM which detects funds with manipulated performance scores or misreported returns (Brown *et al.*, 2010).

3.3. Data

This study uses the 26 496 monthly returns, net of management and performance fees, from 184 'live' individual[21] hedge funds from a Eurekahedge database data extract between January 2000 and December 2011. Funds without a complete monthly return history for the chosen period were not considered. Monthly returns were chosen as hedge funds universally report performance figures on this basis and it is compatible with investors' month-end, holding-period return. The data do not suffer from survivorship, backfilling or sampling biases, while selection bias cannot be addressed as it would require access to returns from hedge funds that decide not to report.

Table 1 presents the summary statistics, in monthly percentages, for the hedge fund returns as well as some other relevant information. The t-statistics indicate that the mean returns are significantly different from 0 at the 5% significance level for all funds. Also 29 of the 184 funds (15.8%) exhibit normal distributions at the 5% significance level, using the Jarque-Bera (JB) test, while the remaining 155 funds (84.2%) have non-normal distributions.

Table 1: Summary statistics for long/short Equity hedge funds.

	All Funds	**North America**	**Europe**	**Asia**	**Global**
No. of funds	184	85	38	15	46
Sample size	26 496	12 240	5 472	2 160	6 624
Mean Age (years)	15.8	16.5	14.3	14.4	16.1
Mean Size (US$m)	188	143	145	87	346
Return statistics					
μ	0.66	0.76	0.55	0.34	0.66
$t\ (\mu = 0)$	22.48	16.14	11.49	3.92	10.64
σ	4.8	5.2	3.5	4.0	5.1
Median	0.6	5.2	0.6	4.0	0.6
Min	-56.7	-56.7	-20.0	-22.4	-54.7
Max	76.2	76.2	29.6	19.2	39.8
Skewness	0.75	1.14	0.49	-0.15	0.05
Kurtosis	18.4	22.3	10.0	4.9	9.6
ρ_1	0.29	0.21	0.74	0.43	0.21
ρ_2	0.03	0.15	0.59	0.31	0.23

[19] Bollen and Pool's (2009) discontinuity approach revolves around the discontinuity of the observed return distribution around zero by comparing it to the expected distribution which is based on Gaussian kernel estimation.

[20] The MPPM is a decreasing function of the relative risk aversion, given the risk-free rate and the observed returns.

[21] Meaning not fund of funds, which are funds holding a portfolio of other investment funds, or commodity trading advisors (CTA), but funds that invest directly in securities.

	All Funds	North America	Europe	Asia	Global
ρ_3	0.02	0.01	0.55	0.29	0.21
p-value of LB-Q	0.00	0.01	0.00	0.00	0.01

The Ljung-Box Q-statistic measures the overall significance of the first k autocorrelation coefficients, and is asymptotically χ_k^2 under the null hypothesis of no autocorrelation.

All the funds are categorised as long/short equity (strategy) funds. This was preferred as it is the largest among hedge funds, comprising 35% of the industry (Brown *et al.*, 2009). All funds are mandated only in highly liquid markets: mandates in developing markets were omitted from the sample. This ensured that funds are equity funds holding liquid instruments. It can be assumed that all securities held have readily available prices and that no subjective valuations are necessary. On average, first-order return autocorrelations (ρ_1) of all but two geographical areas are ≤ 0.30 – an indication of liquidity (Getmansky *et al.*, 2004). Also, the near zero levels of autocorrelation are consistent with those found by Bisias *et al*. (2012) for liquid securities such as equity funds.

Table 2 presents a breakdown of the representative geographical mandates of the funds as well as the relevant risk-free rate proxies accordingly used. Data on the risk-free rates were sourced from the Federal Reserve Bank of St. Louis (FRED) and Bloomberg.

Table 2: Breakdown of geographical mandates of funds & risk-free rate proxies

Geographical mandate	# funds	Risk-free rate proxy
North America*	85 (46%)	10-year Treasury bond rate (US)
Europe	38 (21%)	10-year Treasury bond rate (Germany)
Asia	15 (8%)	10-year Treasury bond rate (Japan)
Global	46 (25%)	JPMorgan Global Government Bond Index

*Includes one Canadian fund (RFR = 10-year Treasury bond rate (Canada)).

The German 10-year Treasury bond rate as the risk-free rate proxy for the European geographical area is generally accepted[22] (Damodaran, 2008), although a number of other options exist.

Although hedge funds (specifically equity long/short funds), are absolute investments, they are also commonly compared with passive benchmark[23] indices.[24] The data on the passive market benchmark indices were collected from Bloomberg, while the data on the hedge fund benchmark indices were sourced from Eurekahedge, Hedge Fund Research (HFR) and Barclayhedge. Table 3 presents the market and hedge fund benchmark indices used.

Table 3: Market and hedge fund benchmark indices.

Benchmark Market Indices	Region specific	
S&P500, S&P TSX*	North America	
DAX	Europe	
Nikkei 225	Asia	
MSCI World Index	Global	
Benchmark Hedge Fund Indices	**Region specific**	**Style specific**
Eurekahedge North America Long/short Equities Index	North America	Long/short Equity

*The S&P TSX was used for the single Canadian fund that forms part of the North American regional mandate.

[22] One of the reasons for this practice being commonly accepted is that Germany is the largest issuer of bonds in the European geographical area.

[23] Lhabitant (2004) defines the term benchmark as "an independent rate of return (or hurdle rate) forming an objective test of the effective implementation of an investment strategy".

[24] Originally hedge fund effectiveness or performance was not compared relative to a benchmark. According to Lhabitant (2004), hedge fund managers are hired for their skills and they should be allowed to venture wherever their value-creating instincts lead them, without considering benchmarks. Thus hedge fund portfolios should aim to produce positive absolute returns rather than to outperform a particular benchmark.

Tables 4 presents the summary return statistics for the market and hedge fund benchmark indices, for the period January 2000 until December 2011. These statistics are drawn from the monthly returns with the monthly means and standard deviations in percentages.

Table 4: Summary statistics for market and hedge fund benchmark indices.

	S&P500	**DAX**	**S&P TSX**	**Nikkei 225**	**Global Index** +	**L/S HF Index***
Sample size	144	144	144	144	144	144
μ	0.004	0.12	0.35	0.39	0.28	0.76
$t\ (\mu = 0)$	0.01	0.21	0.92	0.81	0.06	3.78
σ	4.71	6.72	4.55	5.80	4.90	2.4
Median	0.60	0.73	1.01	0.13	1.17	0.99
Min	-16.9	-25.4	-16.9	-23.8	-25.48	-6.5
Max	10.8	21.4	11.2	12.9	14.06	10.6
Skewness	-0.43	-0.52	-0.86	-0.53	-1.42	0.01
Kurtosis	3.66	4.88	4.58	3.89	5.16	4.86
ρ_1	0.13	0.07	0.22	0.12	0.31	0.20
ρ_2	-0.07	-0.06	0.07	0.06	0.03	0.04
ρ_3	0.12	0.10	0.06	0.11	0.19	0.04
p**-value of LB-Q**	0.10	0.39	0.01	0.15	0.00	0.01

+ Global index = MSCI World Index.

* L/S HF Index = Eurekahedge North America long/short Equities Index.

Both hedge fund and market indices exhibit non-normal distributions using the Jarque-Bera test at the 5% significance level.

3.4. Methodology

This study used a 36-month rolling (window) period to estimate the relevant statistics and ratios, beginning in January 2000. Monthly returns and risk-free rates were transformed to a geometric annualised basis using the 36-month rolling period.

Annualised Sharpe ratios were calculated from monthly non-IID returns, so the estimation method accounted for serial correlation of returns. This alternative method was used as a (computational) bias occurs when computing annual Sharpe ratios based on monthly means and standard deviations by multiplying these monthly estimates by $\sqrt{12}$. In the case of IID returns the method of computing annualised Sharpe ratios by multiplying by $\sqrt{12}$ is more suitable, but for non-IID returns an alternative procedure that accounts for serial correlation must be used. Lo (2002) showed that ignoring serial correlation in hedge fund returns can yield annualised Sharpe ratios that are overstated by more than 65%.

Table 5 presents some comparative summary statistics between the different methods of computing the annualised Sharpe ratio using the 184 long/short equity hedge funds. Note that the summary statistics in Table 5 are based on annualised geometric returns over a 36-month rolling period with the aim of presenting a statistical comparison between the Sharpe ratio computation methods.

Table 5: Comparative Sharpe ratio summary statistics (all figures annualised).

	Sharpe Ratio	**SC-adjusted Sharpe Ratio**
Sample size	20 056*	20 056
μ	0.38	0.41
σ	0.85	0.95
Median	0.26	0.25
Min	-2.1	-3.8
Max	3.5	5.1

	Sharpe Ratio	SC-adjusted Sharpe Ratio
Skewness	0.49	0.73
Kurtosis	2.86	3.92

*184 funds × 109 (144-35) monthly returns.

The Bias ratio uses return data with mean μ and standard deviation σ. A closed interval $[0.0, +1.0\sigma]$ and a half-open interval $[-1.0\sigma, 0.0)$ need to be defined. The fund return in month i is r_i where $1 \leq i \leq n$ and n is the total number of returns in the data series. The Bias ratio (BR) is then defined as:

$$BR = \frac{\sum_{i=1}^{n} r_i \in [0.0, +1.0\sigma]}{k + \sum_{i=1}^{n} r_i \in [-1.0\sigma, 0.0)} \tag{3}$$

The summation of the numerator is over the closed interval $[0.0, +1.0\sigma]$, while the summation of the denominator is over the half-open interval $[-1.0\sigma, 0.0)$. The small positive constant, k, is included in the formulation to prevent division by zero in instances where there are no returns reported in the interval $[-1.0\sigma, 0.0)$. In continuous terms, Equation (3) may be stated as follows:

$$BR = \frac{\int_{0}^{+\sigma} r dr}{k + \int_{-\sigma}^{0} r dr} \tag{4}$$

The Bias ratio also has the following properties:

1. $0 \leq BR \leq n$;
2. If $r_i \leq 0, \forall i$ then $BR = 0$; and
3. if $r_i > 0, r_i > +1\sigma, \forall i$ then $BR = 0$.

3.5. Application of the Bias ratio to the Madoff case

A fraud measure should potentially have identified suspicious activity quite early on in the well-known Madoff Ponzi scheme,[25] in what is the largest financial scandal in modern times with losses estimated at US$85bn. Madoff Securities LLC, provided investors with modest yet steady returns and claimed to be generating these returns by trading in S&P500 Index options.[26] The Bias ratio of Fairfield Sentry Ltd., (FFS), one of the largest Madoff feeder funds, was investigated and found to have a Bias ratio of between 6 and 7, since August 2005 until its closure in 2007. For comparison, the majority of similar funds[27] scored between 1 and 3 (Douady *et al*., 2009).

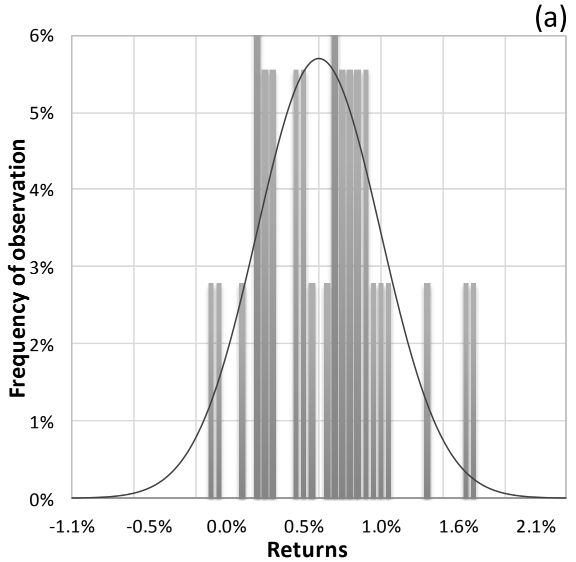
Figure 2a presents the multimodal return distribution of FFS's returns from February 1990 to December 2007. Figure 2b presents the return distribution for each month rolling using a 36-month rolling (window) period. The monthly return data exhibit a monthly mean return of 0.89% while the distribution is highly positively skewed (0.81) and also leptokurtic (3.48). The skewness of the distribution is significant as it is larger than twice the standard error of skewness (SES) (2 × 0.333) (an indication of a considerable non-symmetrical distribution). The distribution also fails the Jarque-Bera test for normality with a JB-statistic of 25.7 by which the null hypothesis (normal distribution) is rejected at both the 5% and 1% significance levels.

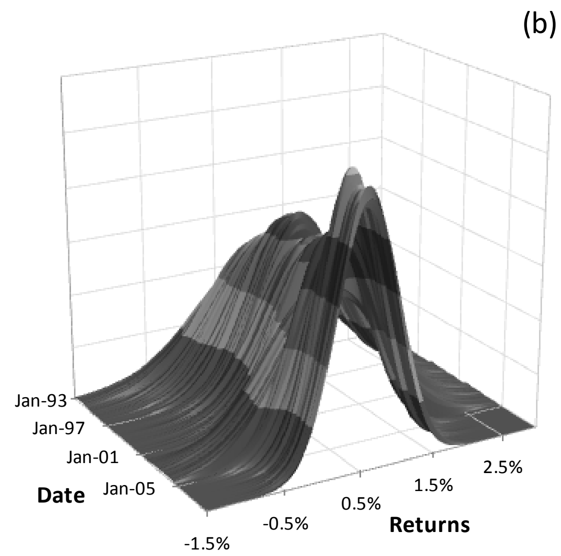
[25] Fraudulent investment operation that pay returns to investors from their own invested funds or paid by subsequent investors rather than from profit.

[26] Also called a "Bull-Spread". This strategy is made up of three positions: a long position on the risk asset S_t, a short position on the call option $C(K_c)$ and a long position on the put option $P(K_p)$ with $K_p > K_c$.

[27] Fairfield Sentry Ltd., is classified as an "equity hedge" type fund according to Hedge Fund Research (HFR) and according to Lhabitant (2004) employed an index arbitrage strategy.

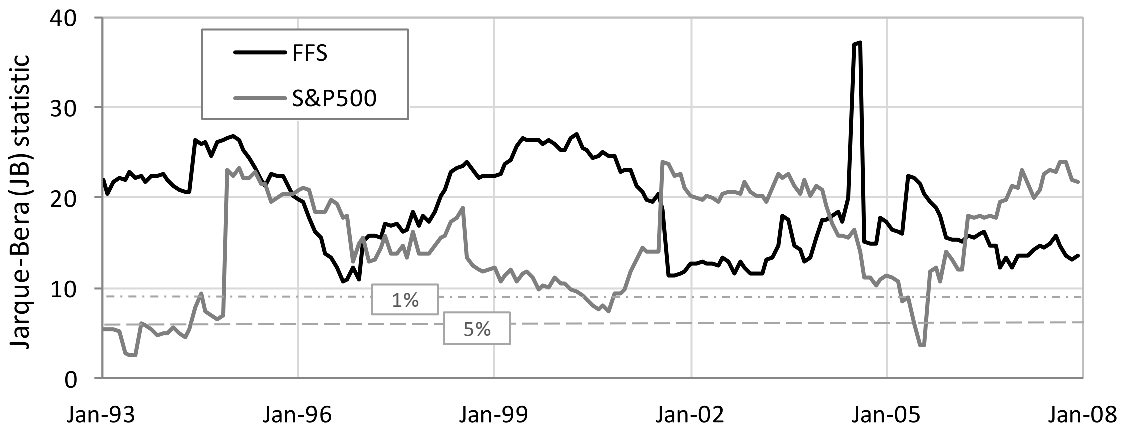
Figure 2: (a) FFS return distribution (February 1990 – December 2007) and (b) FFS return distribution for rolling months using a 36-month rolling period.





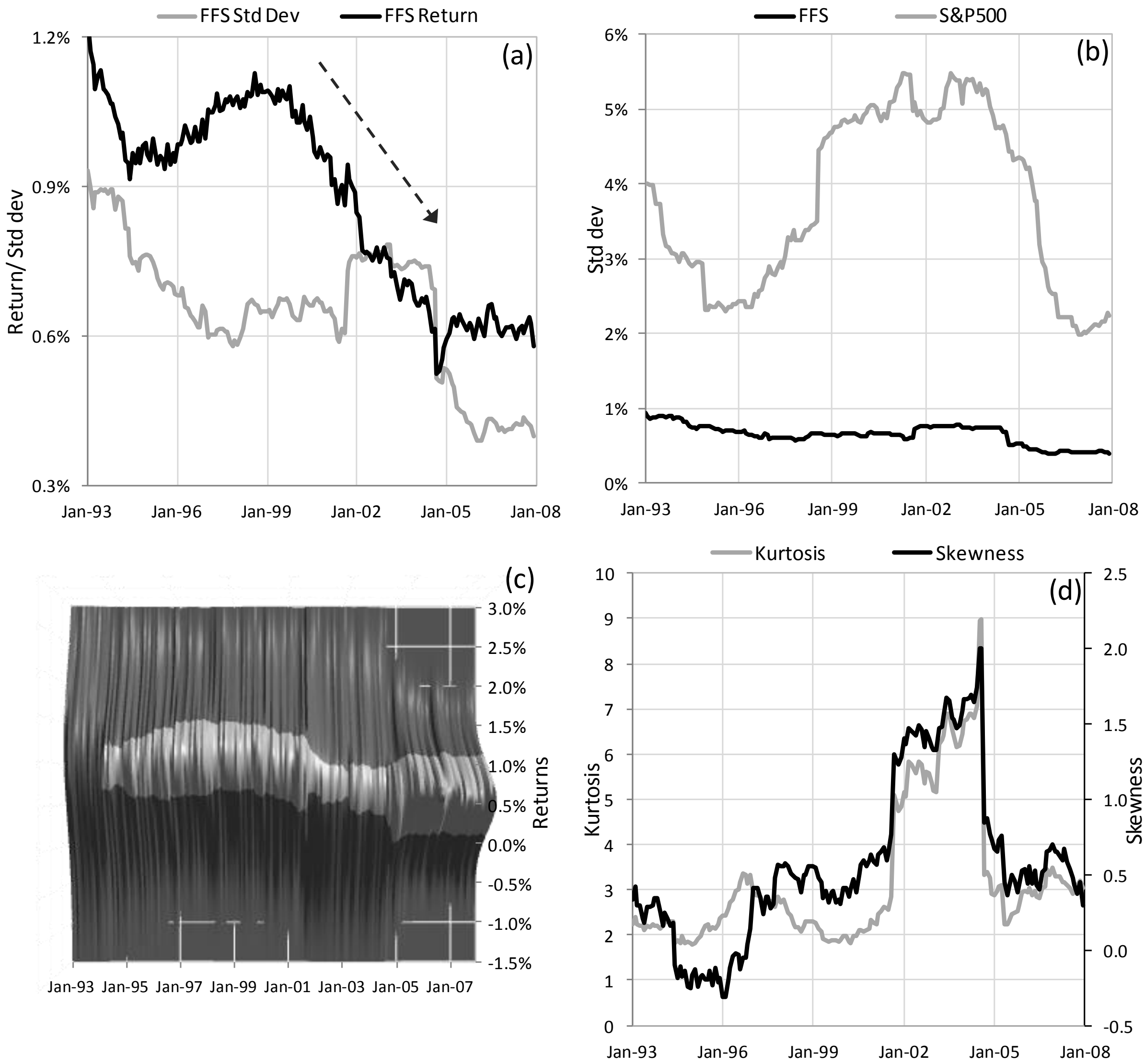
Although FFS's return distribution is non-normal for the entire period under observation it is interesting to note that the normality of FFS's return distribution behaves in a countercyclical manner to that of the S&P500 (Figure 3). Figure 3 is constructed using 36-months of (rolling) monthly data and the JB-statistic values below the topmost horizontal dotted-line, at 9.2, indicates a normal distribution assuming a 99% confidence level. The bottommost horizontal dotted-line, at 6.0 represents a 95% confidence level and again JB-statistic values below this line are indicative of a normal distribution (at this particular confidence level). As Figure 3 is based on rolling monthly returns it also shows how the goodness of fit to a normal distribution the returns distributions of both FFS and the S&P500 changed over the time period under observation.

Figure 3: Rolling JB-test statistic as test for return distribution normality: FFS vs. S&P500.



A 36-month rolling (window) period was used to estimate the central moments of FFS's return distribution for February 1990 to December 2007, resulting in a final analysis period of February 1993 until December 2007. Figure 4a presents FFS's annualised monthly return and standard deviation, while Figure 4d presents the skewness and kurtosis of FFS.

Figure 4: (a) FFS annualised monthly return and standard deviation, (b) Volatility comparison: FFS vs. S&P500, (c) Plan view of FFS (annualised) return distribution through time and (d) FFS skewness and kurtosis.

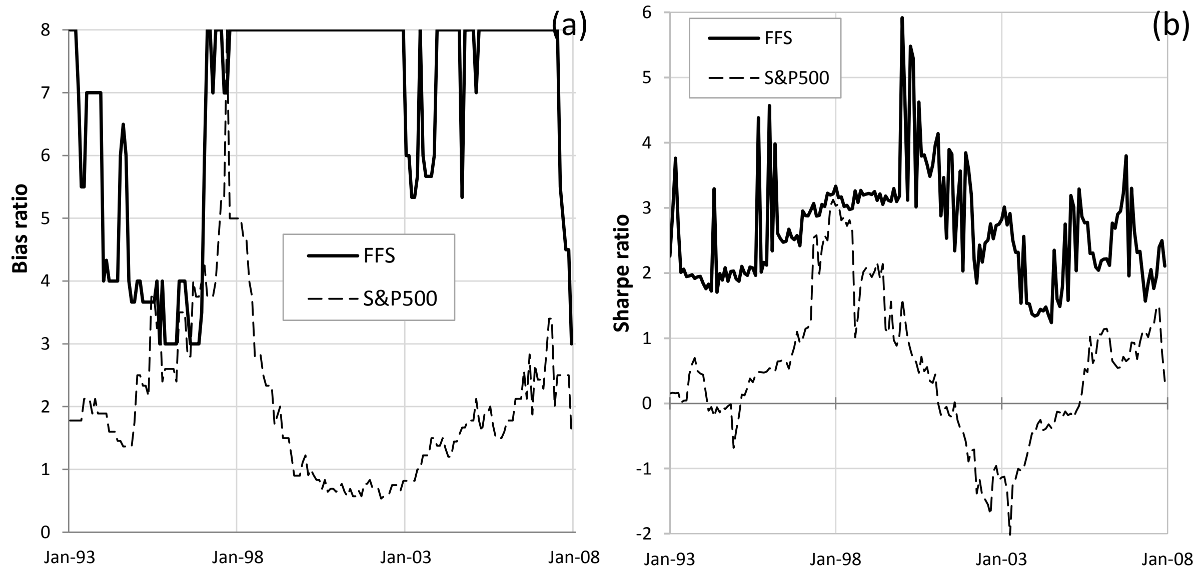


Monthly returns are relatively high and consistently so (Figures 4a and 4c), while volatility is relatively low for such high monthly returns (Figure 4a), and the same compared to the S&P500's volatility (Figure 4b). Note that in Figure 4c the lightest shading area represents FFS's average monthly returns. The combination of consistently high returns and low volatility leads to strangely high Sharpe ratios (Figure 5b), which are also dramatically higher than those of the S&P500. Only 10 out of the 215 months of data available for the FFS feeder fund exhibit negative performance. The monthly returns of FFS are also not correlated with those of the S&P500: the correlation coefficient = 0.014.

Figure 4d draws attention to the high skewness and kurtosis that the return distribution exhibits in comparison to previous values. The negative kurtosis (fat tails) during the earlier part of the time series along with the extremely high kurtosis towards the latter end of the series signal potentially suspicious behaviour. The dramatic increase and decrease of both skewness and kurtosis in September 2001 and September 2004, respectively, are also of interest.

Figure 5a shows the Bias ratios and Figure 5b the (serial correlation-adjusted) Sharpe ratios for FFS and the S&P500 (as comparison) using a 36-month rolling period.

Figure 5: (a) Bias ratio: FFS vs. S&P500 and (b) Sharpe ratio: FFS vs. S&P500.



The Bias ratio of FFS ranges from 3 to 8, while the bulk of other equity hedge funds in the HFR database scored a Bias ratio mostly in the range of 1 to 3. As reference, Beacon Hill's Safe Harbour (a MBS fund) had a Bias ratio of 7 until fraud was discovered in 2002. As the Bias ratio analyses fund returns to measure how far they are from an unbiased distribution, the Bias ratio of an equity index or fund where valuation is based on market prices (i.e. trading liquid securities) would have a Bias ratio typically close to 1. In contract, a fund that smoothes returns will have a much higher Bias ratio. Alternative opinions include that a fund's Bias ratio should be compared to other funds of a similar strategy. Although the Bias ratio goes to infinity, it is capped at 8 in Figure 5a, but this does not have any material impact as a Bias ratio significantly larger than 1 is suspicious and even more so if the Bias ratio is higher than that of comparative funds. Figure 5b also shows how significantly FFS outperforms the market on a risk-adjusted basis (as measured by the Sharpe ratio). It should be remembered that extremely high Sharpe ratios are also cause for suspicion, while suspicion should escalate considering extremely high Sharpe ratios compared to similar funds. Figure 5a and Figure 5b clearly show that FFS's Bias ratio and Sharpe ratio, respectively, are (consistently) abnormally high (over a long time period). The level of both these measures indicate clear warnings.

Also of significance is that FFS's serial correlation coefficients are low ($\rho_1 = -0.19, \rho_2 = 0.20, \rho_3 = 0.10$) while the LB-Q statistic's $p = 0.01$. Although a lower p-value is stronger evidence against the null hypothesis of no serial correlation, the fact that the first-order autocorrelation coefficient is ≤ 0.30 also indicates liquidity. This along with the near zero levels of the autocorrelation coefficients indicate that FFS traded liquid instruments and thus it can be assumed that any relevant irregularities are not due to illiquidity exposures: smoothing practices remain as the only explanation.

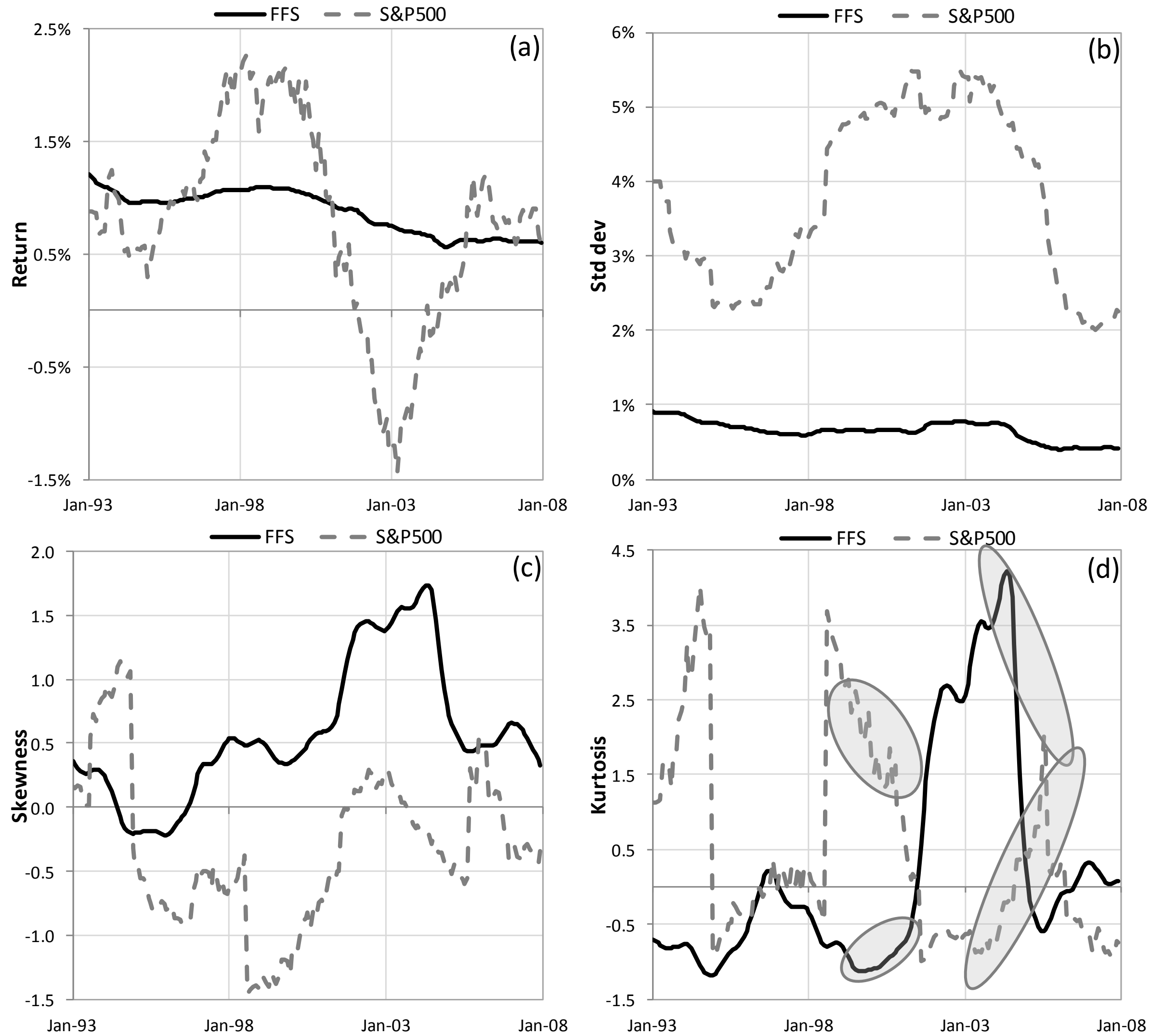
By studying the moments of FFS's returns distribution to those of the relevant market (S&P500), the following out of the ordinary characteristics were identified. These returns distribution characteristics can consequently be thought of as potential warning signals of fraud, as they were discovered through meticulously studying the Madoff case, a scenario that has been formally classified as fraudulent and that included the practice of returns smoothing. These potential fraud warning signals are presented consecutively for ease of interpretation.

The first two warning signals, (Figure 6a and b), are:

1. a highly infrequent negative mean return accompanied by minimal variation of the mean return; and
2. a non-volatile rolling standard deviations of returns being significantly lower than those of the relevant market (Figure 6b). The returns distribution's third and fourth moments deliver the

third and fourth potential warning signals (Figure 6c and 6 respectively). The skewness of FFS's returns distribution is much less volatile than that of the relevant market (S&P500) and almost never negative (Figure 6c). The fourth fraud warning signal shows the returns distribution's kurtosis moving in the opposite direction to the market (Figure 6d). This anti-correlation, (Figure 6d), is evidenced by FFS's kurtosis increasing when the S&P500's kurtosis is decreasing and vice versa. These identified return characteristics emphasise that return characteristics that are dissimilar to those of the relevant market should be treated as warning signals of potential fraudulent activity.

Figure 6: (a) Mean return: FFS vs. S&P500, (b) Standard deviation: FFS vs. S&P500 returns, (c) Skewness: FFS vs. S&P500 and (d) Kurtosis: FFS vs. S&P500.



*Figures are based on (rolling) monthly returns using 36-months.

The Bias ratio should also be consulted and scrutinised. The Bias ratio of FFS behaves in the opposite fashion to that of the market (S&P500 – Figure 5a). This is highlighted by the observation that FFS's Bias ratio is highest when the Bias ratio of the S&P500 is at its lowest and also that FFS's Bias ratio is decreasing when that of the S&P500 is increasing. As mentioned prior, out of the ordinary high Sharpe ratios can also be cause for suspicion and that suspicion should rise in the event of abnormally high Sharpe ratios compared to similar funds. Figure 5b shows that FFS's Sharpe ratio is always higher than that of the S&P500s and FFS's Sharpe ratio is never negative. Also worth noting is that FFS's Sharpe ratio is low when the S&P500's Sharpe ratio is high, compared to the general spread between the two Sharpe ratio series over the time period.

The reverse behaviour of FFS's Jarque-Bera (JB) statistic, as a test for normality of the return distribution, compared to that of the S&P500 might arguably also be considered as a potential signal of suspicious or fraudulent activity (Figure 3).

4. ANALYSIS AND RESULTS

4.1. Ill-suitedness of the Sharpe ratio

Table 6 presents higher moment estimates for the hedge fund data to point out how ill-suited the Sharpe ratio is for (these) hedge fund return data, or how inaccurate (these) hedge fund data are for use with the Sharpe ratio. In terms of skewness, Table 6 indicates that funds from all the geographical mandated areas, except global mandated funds, exhibit excess skewness (> 0.50), mostly positive. Asia mandated funds exhibit negative skewness. Table 6 also indicates that the funds from all geographical areas are severely leptokurtic and significantly so according to the standard error of kurtosis (SEK).

Table 6: Hedge fund higher moment estimates.

	All Funds	North America	Europe	Asia	Global
Skewness	0.75	1.14	0.49	-0.15	0.05
S.E. Skewness (SES)	0.18	0.27	0.40	0.63	0.36
Kurtosis	18.40	22.29	10.01	4.87	9.58
S.E. Kurtosis (SEK)	0.36	0.53	0.79	1.26	1.44

The Jarque-Bera (JB) test indicates that only 29 of out the 184 funds (15.8%) exhibit normal distributions at the 5% significance level, while the remaining 155 funds (84.3%) have non-normal return distributions. Figure7 depicts the state of normality of the return distributions for both the funds (Figure 7b) and the relevant market indices (Figure 7a) through time. Figure 7a and 7b are constructed using 36-months of rolling monthly data while the two horizontal dotted-lines represent the thresholds for distribution normality at the 1% and 5% significance levels respectively. Jarque-Bera (JB) test statistical values below these thresholds are indicative of normal distributions at the relevant level of significance.

Figure 7: (a) Rolling JB-test statistic of relevant market indices and (b) average rolling JB-test statistic for all funds and also for hedge funds per geographical mandate, over time.

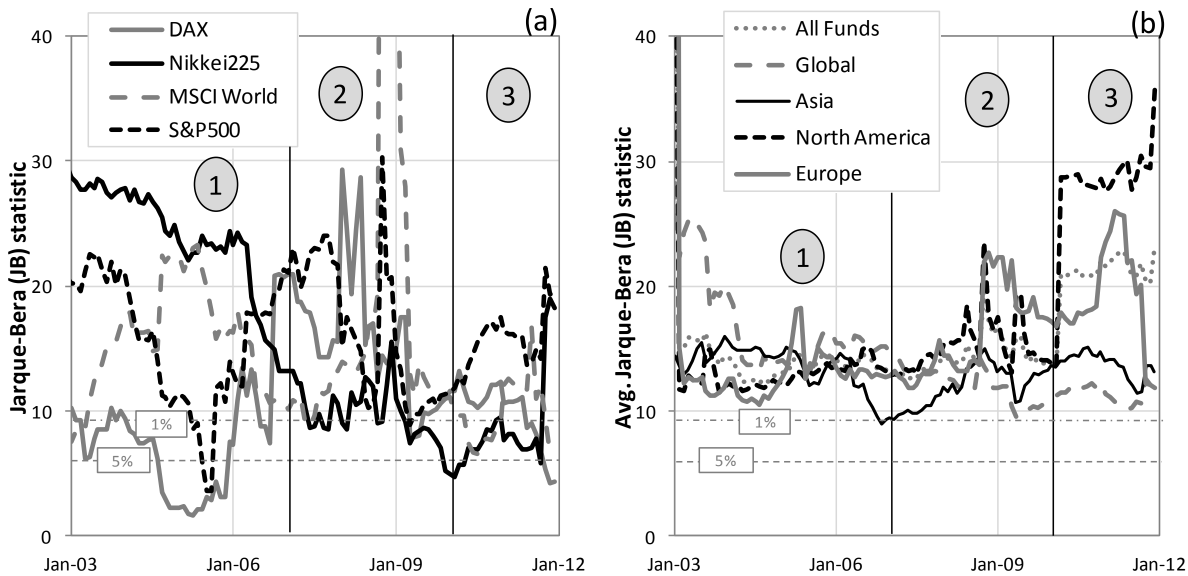


Figure 7 is also divided into three phases or periods by the vertical lines. Each of these three periods represents a specific period relating to the 2007 financial crisis; (1) *pre*-crisis, (2) *during* the crisis, and (3) *post*-crisis (i.e. after the height of the crisis). Figure 7a indicates that some of the market indices pass the (rolling) goodness of fit test for normal return distributions at either or both the 1% and 5% significance levels (horizontal dotted-lines) using the JB-test statistic. The instances where a few market indices do pass as normal distributions, however, only occur in limited cases and for short and limited time spans. The (rolling) average JB-test statistic, as per Figure 7b, depicts that funds from all regional mandates are non-normal for the entire time period under investigation with the exception of the Asian mandated funds that show return distribution normality but only for November 2006 – this is fairly insignificant considering the Asian mandated funds are, on average, only considered normal for 1 out of 109 rolling months. Also noticeable is the rapid and elaborate increase (further) away from normality during 2008, and also high non-normality for North American and European mandated funds. By further comparing the average normality of funds for a specific regional mandate to its relevant market index it is apparent that trends and trend changes and also the magnitude of change do, for the most part, not coincide while at certain times rather odd comparative behaviour is witnessed.

Figure 8a presents the skewness and Figure 8b the kurtosis of the funds grouped per mandated geographic region by means of a candlestick like chart indicating the mean, maximum and minimum of these distribution moments.

Figure 8: (a) Skewness of individual funds per region and (b) Kurtosis of individual funds per region.

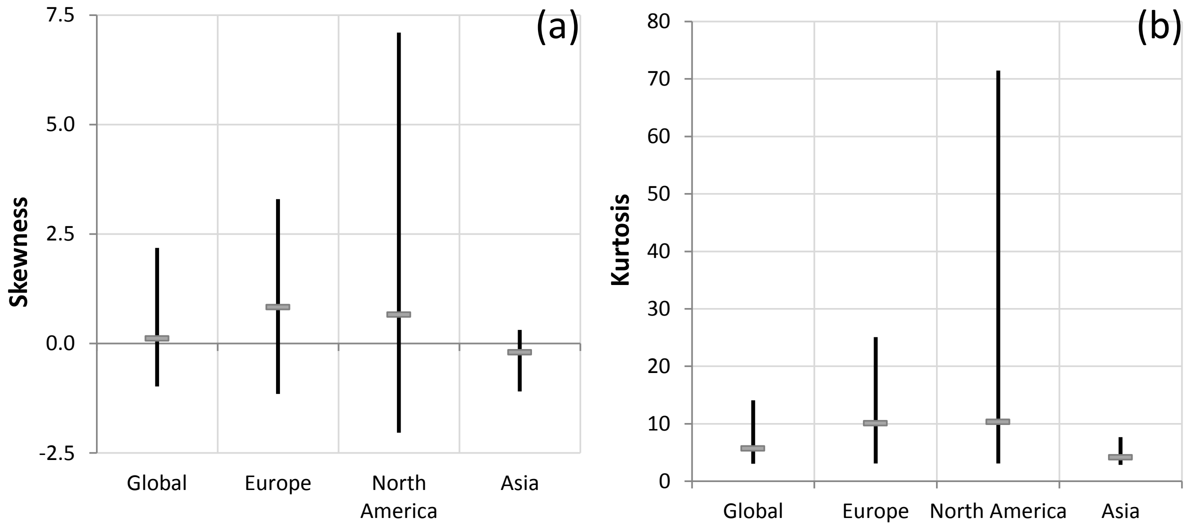
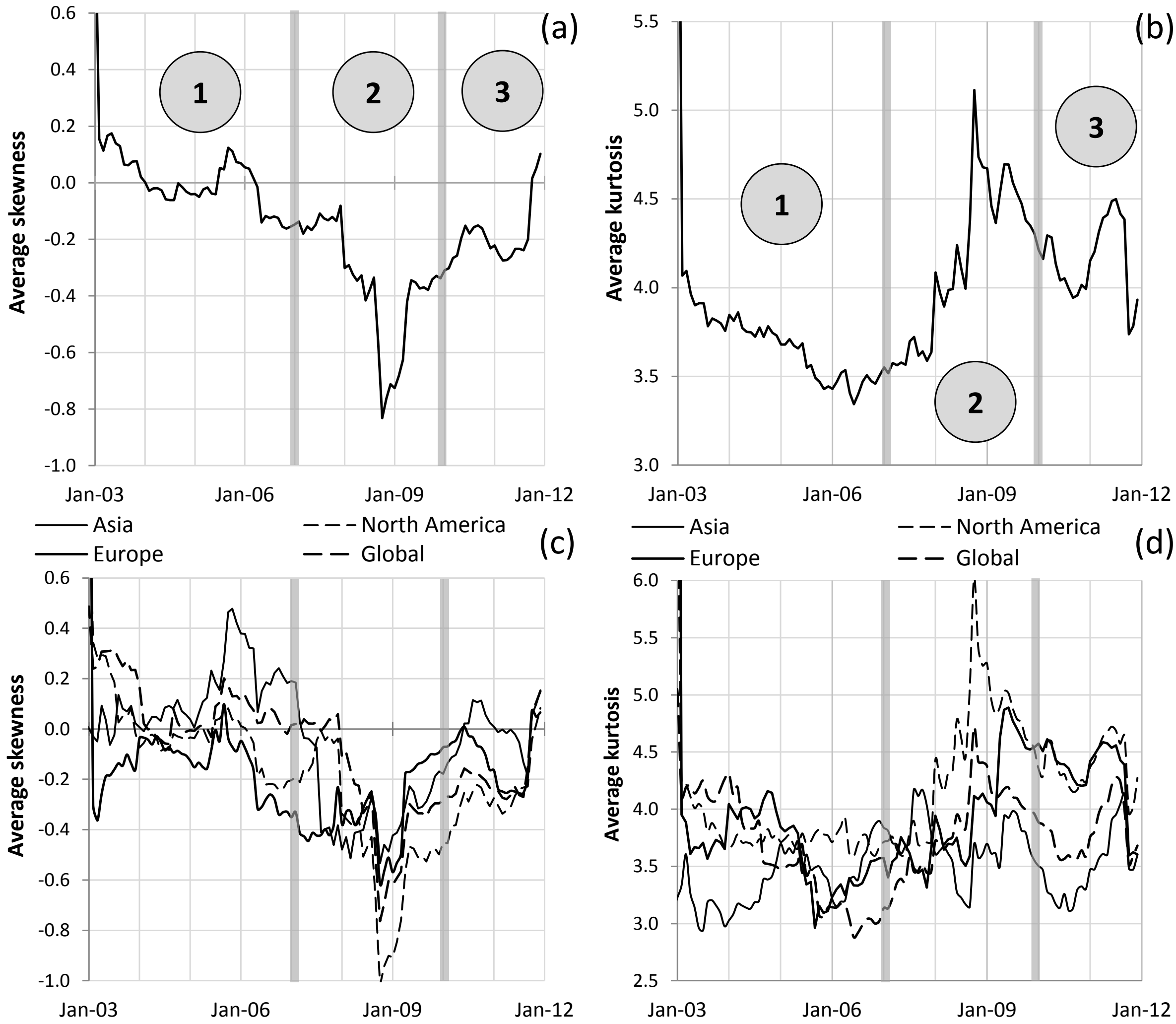


Table 6 in conjunction with Figures 7 and 8 confirm that most of the return distributions of these hedge funds are not ideally suited for Sharpe ratio application. The 15.8% of funds that show evidence of normal distributions through the JB-test might be possible exceptions. This will, however, leave investors requiring to tests each fund for normality before applying the Sharpe ratio, which is not ideal.

To further demonstrate how ill-suited these funds' distributions are to the Sharpe ratio, not only at a point-in-time but also through time, the rolling skewness and kurtosis are presented in Figure 9. Figure 9 presents the average skewness (Figure 9a) and kurtosis (Figure 9b) by using the 36-month rolling period. Figure 9 is again divided into three phases or periods by means of vertical lines with each period representing a specific period relating to the 2007 financial crisis consistent with those declared earlier (see Figure 7).

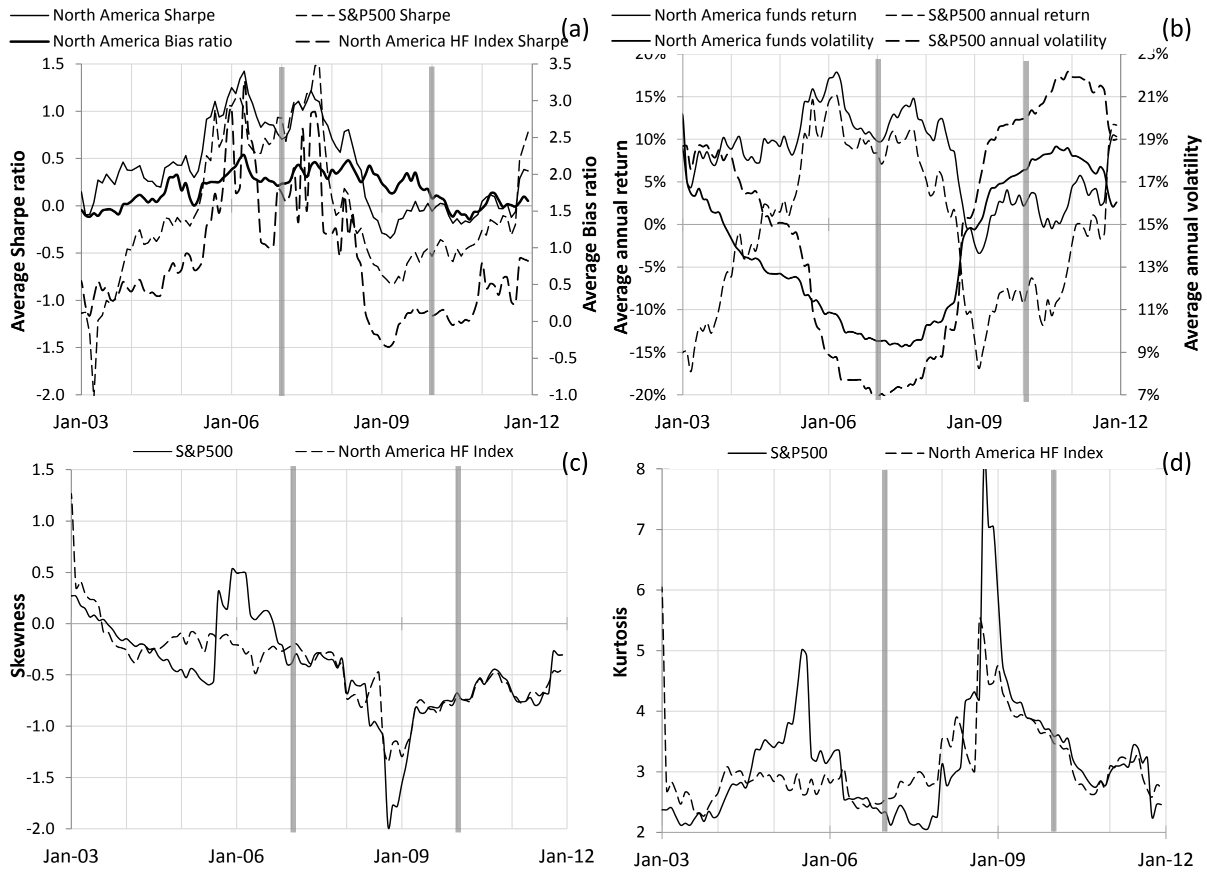
Figure 9: Average values, through time, for (a) skewness – all funds, (b) kurtosis – all funds, (c) skewness – per region and (d) kurtosis – per region.



The average skewness turned considerably negative during the financial crisis, while average kurtosis, which was at high levels prior, reached extreme levels. The data presented in Table 6 along with Figures 7, 8 and 9, strengthen the case that the Sharpe ratio is not adequately compatible with the distributions of these hedge funds.

The Bias and Sharpe ratios were also analysed using the rolling period analysis method. For this, the results focusing on funds mandated for the North America region are presented in Figure 10.

Figure 10: (a) North America funds average Sharpe ratio vs. average Bias ratio, (b) North America funds average annual return vs. average annual volatility, (c) North America funds' benchmarks* skewness and (d) North America funds' benchmarks kurtosis.



* Hedge fund index in Figure 10: Eurekahedge North America Long/Short Equities Hedge Fund Index.

The higher moments of the hedge fund benchmarks, as depicted in panels (c) and (d) of Figure 10, also indicate the inappropriateness (of these return distributions) for the use of the Sharpe ratio. Panels (c) and (d) also indicate the altered behaviour for these higher moments of the return distribution around the time period of the recent financial crisis. The financial crisis also impacted the returns of these funds along with their volatility (Figure 10b). Figure 10b shows the decline in returns and the increase in volatility for both these mandated funds and the S&P500 during the crisis time period. Figure 10a presents the average Bias and average Sharpe ratios specifically for the funds with North America mandates (along with the Sharpe ratios for relevant benchmarks). From Figure 10a it is evident that the average Bias ratio for the funds with North America mandates are relatively higher around the financial crisis. The average Sharpe ratios for these mandated funds are also consistently higher than those of the benchmarks, except for a period of extreme volatility (late 2005 until the end of 2007) in the relevant hedge fund index (see Figure 10a).

4.2. Identifying suspicious funds using Madoff identified warning signals

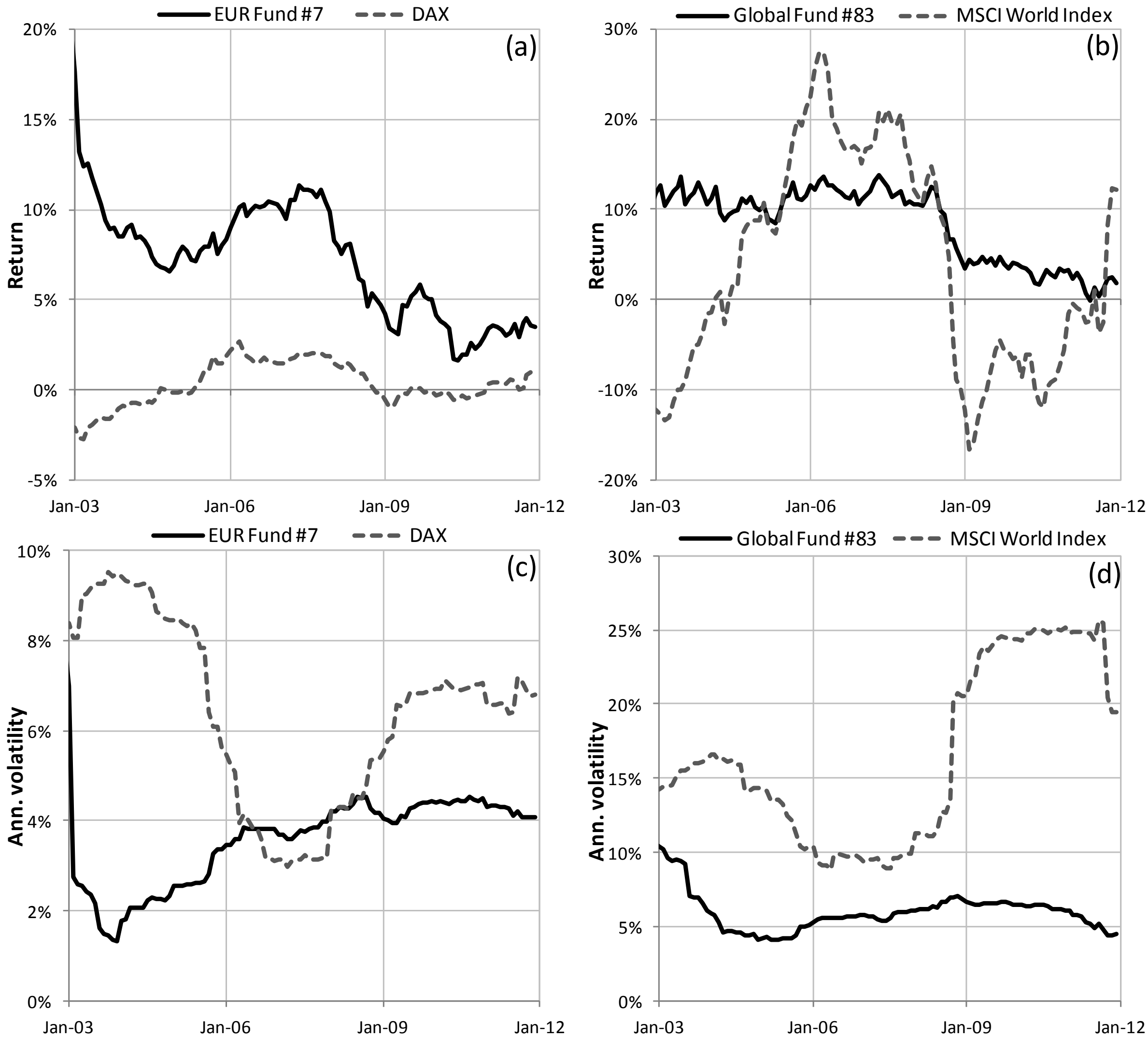
Using the identified warning signals from the Madoff case (Section 3.5) this section presents two funds[28] from the funds sample that exhibit extraordinary characteristics and which can be considered as potential warning signals of fraudulent or suspicious behaviour. The first of the identified funds (fund #7) has a European regional mandate while the second has a global mandate (fund #83). The methodology and 36-month rolling analysis as discussed in Section 3.4 and as used in the Madoff

[28] A number of funds (15 in total) were identified using the warning signals from the Madoff case. Two characteristic funds are presented in this section to show how these warning signals could be used to identify potentially fraudulent funds.

application case (Section 3.5) are again used. The identified warning signals are presented graphically with the relevant market indices as indicated in Section 3.3.

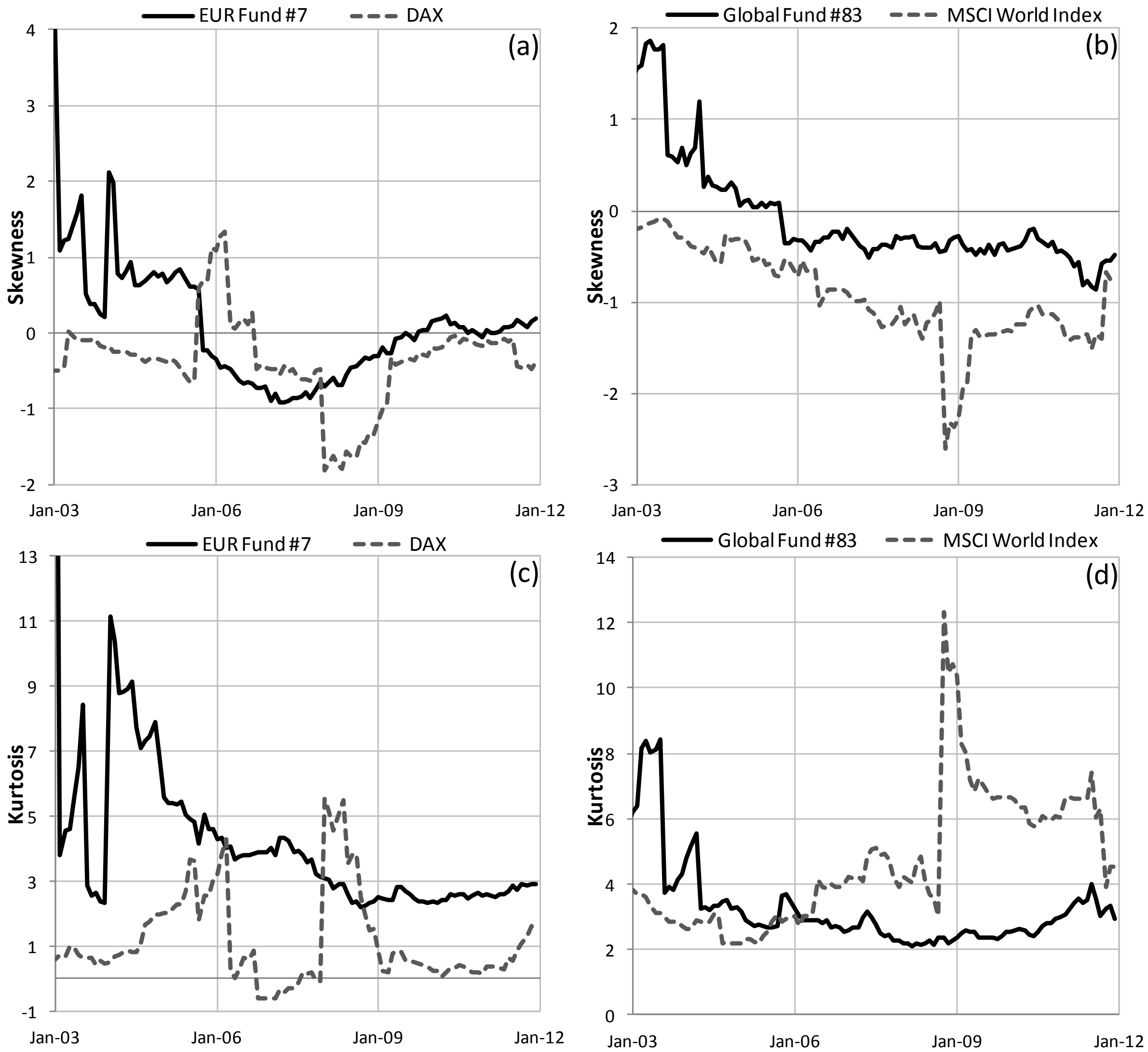
Figures 11a and 11b show that neither of the funds have negative annualised mean returns while both funds also, for the most part, exhibit return levels that are never negative and are also above that of their relevant market indices. Figure 11b, in particular, highlights the low levels of mean variation for the global fund. According to Figures 11c and 11d, fund #7 and fund #83 display annual volatilities that are both significantly lower and less variable than that of their respective market indices.

Figure 11: (a) Annualised return: EUR fund #7 vs. DAX, (b) Annualised return: Global fund #83 vs. MSCI World, (c) Annualised volatility: EUR fund #7 vs. DAX and (d) Annualised volatility: Global fund #83 vs. MSCI World.



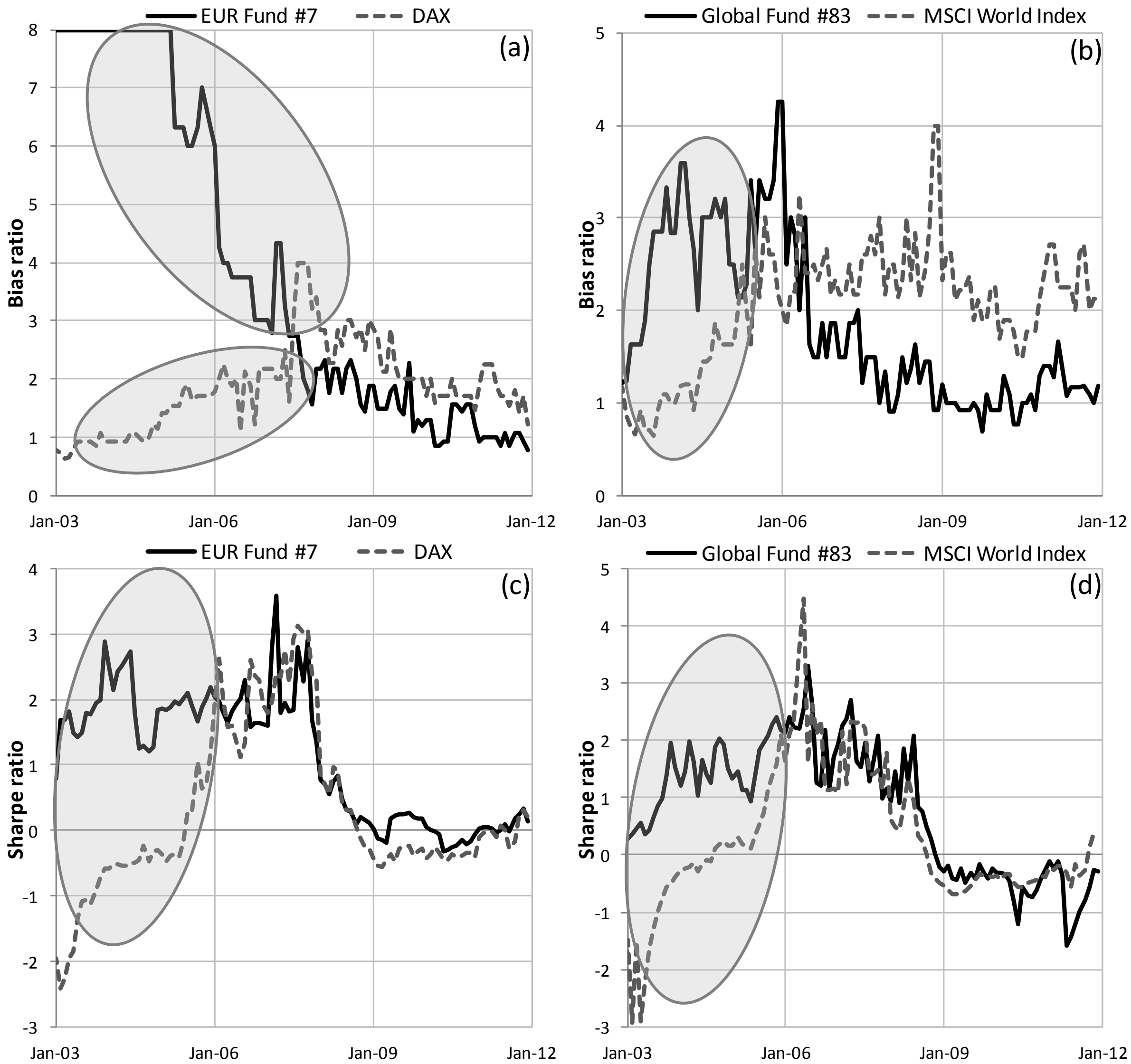
Figures 12a and 12b show that the skewness of both funds is much less volatile than their respective market indices, while also being positive for longer periods of time than the market indices. Figures 12c and d illustrate the mostly anti-correlated nature of both funds' kurtosis in relation to their respective market benchmarks.

Figure 12: (a) Skewness: EUR fund #7 vs. DAX, (b) Skewness: Global fund #83 vs. MSCI World, (c) Kurtosis: EUR fund #7 vs. DAX and (d) Kurtosis: Global fund #83 vs. MSCI World.



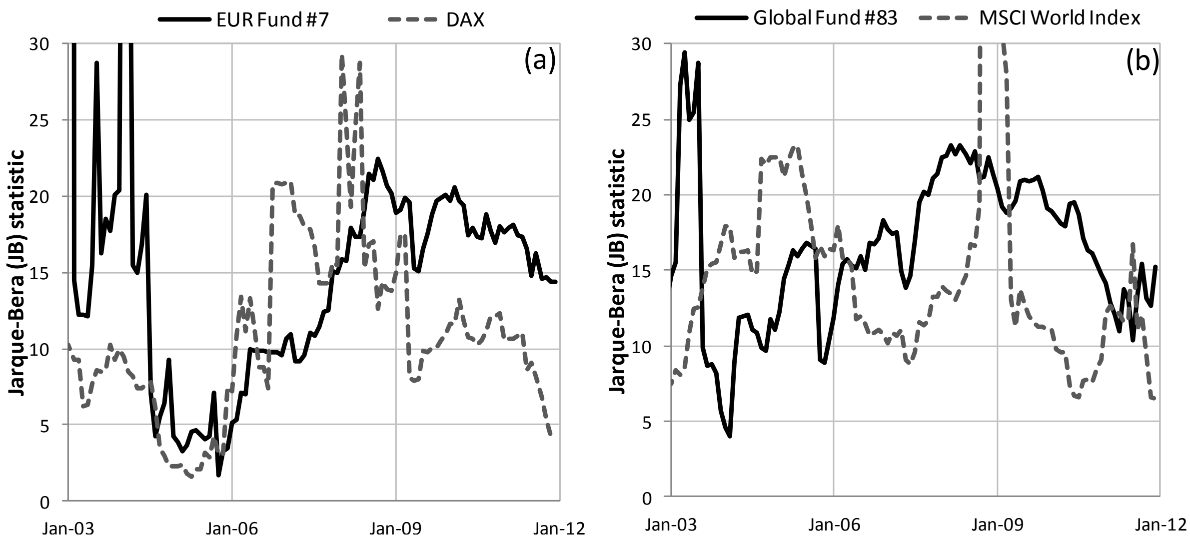
The Bias ratios of both identified funds show similar characteristics to FFS's Bias ratio (see Section 3.5) in that the ratios exhibit an opposite, and to some extent, anti-correlated relationship to that of the relevant market (Figure 13). The abnormally high Bias ratios of both funds are visible in Figures 13a and 13b and these ratios are especially abnormal for the period at the initial stages of the observation period – during this period the funds' Bias ratios are significantly larger than those of the respective markets. Figures 13c and 13d convey that both funds mostly deliver positive Sharpe ratios, and also positive Sharpe ratios of a considerable level on a regular frequency. The funds also predominantly produce larger Sharpe ratios than those of their respective market indices. Moreover, the funds' and market's Sharpe ratios do appear to follow each other's trend, although there are instances where this trend following phenomenon breaks down – leading to occurrences where a low market Sharpe ratio is simultaneous to a high fund Sharpe ratio. The instances with abnormally high fund Bias ratios also coincide with high fund Sharpe ratios relative to those of the respective markets. This is relevant as abnormally high Sharpe ratios are also cause for potential concern and or suspicion.

Figure 13: (a) Bias ratio: EUR fund #7 vs. DAX, (b) Bias ratio: Global fund #83 vs. MSCI World, (c) Sharpe ratio: EUR fund #7 vs. DAX and (d) Sharpe ratio: Global fund #83 vs. MSCI World.



The Madoff case also exhibited a potential signal of suspicious or fraudulent behaviour through the predominantly reverse behaviour of its Jarque-Bera (JB) statistic, as a return distribution normality test, relative to that of the market. Figure 14a and 14b present the rolling Jarque-Bera (JB) statistic for fund #7 and fund #83 respectively and also relative to the JB-statistics of their relevant market benchmarks.

Figure 14: (a) JB-stat: EUR fund #7 vs. DAX and (b) JB-stat: Global fund #83 vs. MSCI World.



Alike the Madoff case a largely reverse or opposite behaviour in terms of return distribution normality, through the JB-statistic, relative to that of the relevant market benchmark can be observed for both funds (Figure 14a and Figure 14b).

4.3. Selective statistics over different economic conditions

Selective summary performance statistics focusing on returns, Sharpe and Bias ratios for both the hedge funds and the relevant market benchmarks to these funds are presented in this section. As the statistics are partitioned into three phases it highlights the altering characteristics of the funds and their market benchmarks throughout different economic periods. The three phases represent the periods *prior*, *during*, and *post* the 2007 financial crisis. December 2002 until December 2006 constitutes phase 1, January 2007 until December 2009 phase 2, and January 2010 until December 2011 phase 3. The rolling annual calculation methodology based on 36-months, as discussed in Section 3.4, is employed in this section. Also, although the Bias ratio goes to infinity it is capped at 8 in this section, but this does not have any material impact as a Bias ratio significantly larger than 1 is suspicious and even more so if the Bias ratio is higher than that of comparative funds.

The changing characteristics during the three economic phases are presented in Figure 15 through the average Sharpe ratio and also the average annual return and standard deviation for all funds in this study. The summary statistics for all funds per phase is conveyed in Table 7.

Figure 15: Average annual return and standard deviation and also Sharpe ratio for all hedge funds.

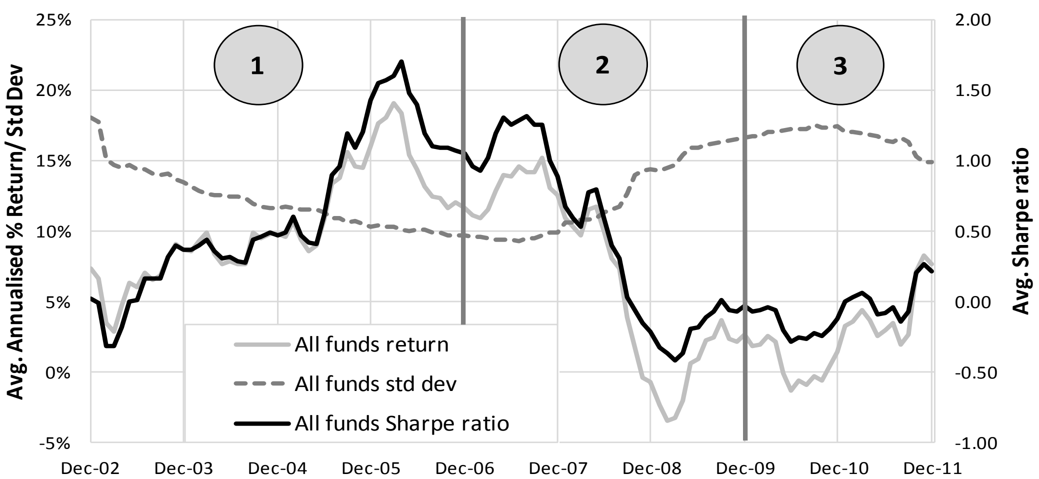


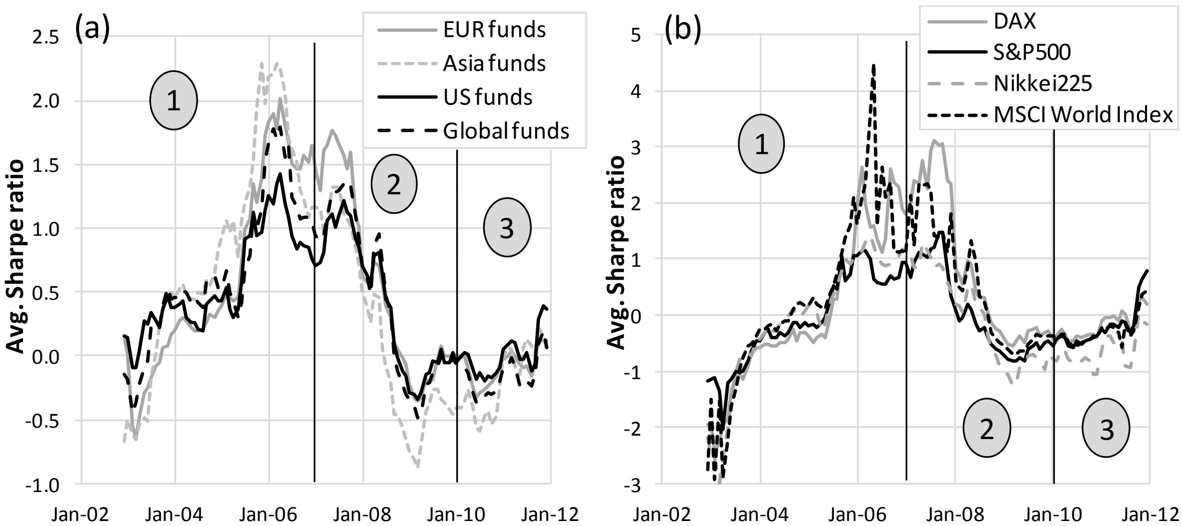
Figure 15 shows the impact of the 2007 financial crisis as a decrease in the average Sharpe ratio of all funds in phase 2 suggests. This figure further draws attention to the decrease in the average returns across all funds in conjunction with a nearly simultaneous increase in volatility during the crisis period. Of further significance is that mostly during phase 2, the period during the 2007 financial crisis, the average Sharpe ratio of all funds reduces to below zero which implies that a risk-less asset would have performed better on average during this time compared the analysed funds sample. The visual results in Figure 15 are reverberated in the summary statistics as per Table 7, which indicates similar declining average returns and Sharpe ratios for all funds from phase 1 through to phase 3. Both the average and median Bias ratio increase from phase 1 to phase 2 where after decreasing in phase 3 to its lowest level throughout all phases – indicating that suspicious fund behaviour peaked in the period during the crisis. Interestingly the standard deviation of returns and the Sharpe ratio reduce over time indicating that the performance spectrum between funds diminishes, on average. Similarly the Bias ratio's standard deviation also decreases moving through phase 1 to phase 3.

Table 7: Summary statistics for all hedge funds per phase.

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Return statistics			Bias ratio statistics			Sharpe ratio statistics		
n	9016	6624	4416	9016	6624	4416	9016	6624	4416
μ	10.41%	6.86%	2.39%	1.78	1.94	1.45	0.63	0.43	-0.07
σ	10.93%	10.20%	8.38%	1.11	1.05	0.62	1.03	0.92	0.54
Median	9.59%	7.33%	2.21%	1.50	1.67	1.36	0.54	0.31	-0.11
Min	-44.96%	-48.39%	-36.57%	0.29	0.26	0.25	-3.79	-1.95	-2.30
Max	59.50%	42.39%	74.39%	8.00	8.00	7.00	5.07	4.39	4.12

Figure 16 shows the average Sharpe ratios of both funds and their respective regional market indices. From this figure, it is apparent that funds and market indices from all the included regions behaved similarly across the three phases. None of the regional funds or benchmarks indicates significantly better performance than any other during or post financial crisis. Asian funds, however, performed better, on average, shortly prior to the crisis but also performed the worst, on average, during the crisis period (Figure 16a).

Figure 16: (a) Average fund Sharpe ratios per region and (b) average market index Sharpe ratios, through time.



The summary statistics in terms of returns, Bias and Sharpe ratios for the funds grouped by regional mandates are presented in Table 8 to facilitate comparisons. Table 9 presents the corresponding summary statistics for the relevant regional market benchmarks.

Table 8: Summary statistics for regionally grouped hedge funds per phase.

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Return statistics			**Bias ratio statistics**			**Sharpe ratio statistics**		
North American Hedge Funds									
n	4165	3060	2040	4165	3060	2040	4165	3060	2040
μ	10.52%	6.90%	3.45%	1.76	1.98	1.58	0.57	0.41	-0.001
σ	11.16%	10.15%	9.11%	0.98	1.15	0.71	0.94	0.85	0.55
Median	9.61%	7.61%	2.42%	1.50	1.70	1.45	0.49	0.32	-0.07
Min	-44.96%	-48.39%	-36.57%	0.29	0.26	0.25	-2.35	-1.61	-1.92
Max	59.50%	36.52%	68.29%	8.00	8.00	7.00	4.71	4.39	4.12
European Hedge Funds									
n	1862	1368	912	1862	1368	912	1862	1368	912
μ	8.30%	7.23%	1.52%	2.23	2.01	1.28	0.65	0.58	-0.08
σ	9.49%	9.20%	6.68%	1.66	1.08	0.43	1.19	1.04	0.56
Median	7.42%	7.17%	1.98%	1.67	1.75	1.22	0.51	0.41	-0.11
Min	-23.33%	-16.56%	-18.82%	0.39	0.70	0.37	-2.90	-1.59	-2.19
Max	42.97%	37.65%	32.60%	8.00	8.00	3.14	5.07	4.15	2.40
Asian Hedge Funds									
n	735	540	360	735	540	360	735	540	360
μ	11.32%	3.73%	-1.11%	1.47	1.78	1.32	0.83	0.19	-0.19
σ	11.07%	11.58%	7.15%	0.61	1.03	0.46	1.04	1.01	0.61
Median	10.31%	3.46%	-0.53%	1.37	0.45	0.25	0.77	0.13	-0.11
Min	-16.67%	-22.70%	-18.10%	0.44	0.73	0.56	-2.11	-1.95	-2.30
Max	43.61%	42.39%	14.73%	3.60	7.67	3.00	4.28	2.88	1.13
Global Hedge Funds									
n	2254	1656	1104	2254	1656	1104	2254	1656	1104
μ	11.66%	7.51%	2.29%	1.54	1.85	1.40	0.66	0.44	-0.16
σ	11.31%	10.42%	8.22%	0.68	0.79	0.56	1.05	0.89	0.46
Median	11.47%	7.67%	2.83%	1.44	1.71	1.38	0.59	0.30	-0.18
Min	-29.69%	-33.59%	-24.35%	0.31	0.53	0.32	-3.79	-1.79	-2.07
Max	52.70%	38.64%	74.64%	6.67	7.33	4.75	4.73	3.26	1.82

The mean of both returns and the Sharpe ratios decline moving through phase 1 to phase 3 (see Table 8). The mean Bias ratios for all regions except Europe increase from phase 1 to phase 2, but then fascinatingly decrease to their lowest levels through all phases in phase 3 – this is not the case for the mean Sharpe ratios. The same pattern is portrayed by the standard deviation of the Bias ratios. Also worth nothing is that mean Asian hedge fund returns did not increase into positive territory from phase 2 to phase 3 as the funds from the other regional mandates did (see μ and median for returns in Table 8). This phenomenon is again echoed for the Asian market as represented by the Nikkei 225 in Table 9. Weighing up the mean returns for the hedge funds per region against their relevant market benchmark indicate that although these funds did not perform very well in absolute terms, they did outperform their respective markets in phase 3 - this was not the case during the crisis (phase 2). During phase 1, all the funds outperformed their respective market benchmarks in terms of return performance. The mean Sharpe ratios of particularly phase 3 of Tables 8 and 9 highlight that at times it could have served investors better to hold riskless assets rather than investments in these funds or even a basket of the market index.

Table 9: Summary statistics for market indices per phase.

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Return statistics			**Bias ratio statistics**			**Sharpe ratio statistics**		
n	49	36	24	49	36	24	49	36	24
US Market Index – S&P500									
μ	-1.54%	9.14%	-1.80%	1.62	2.27	1.90	0.0002	0.84	-0.18
σ	19.17%	13.29%	5.63%	0.48	0.47	0.62	1.34	1.30	0.233
Median	-6.02%	10.91%	-3.62%	1.60	2.25	1.59	-0.39	0.36	-0.26
Min	-31.68%	-12.80%	-9.35%	0.82	1.50	1.30	-2.41	-0.56	-0.46
Max	35.05%	26.51%	9.25%	2.83	3.40	3.40	2.64	3.12	0.32
European Market Index – DAX									
μ	0.86%	9.14%	-1.80%	1.33	2.60	1.76	-0.08	0.05	-0.23
σ	9.75%	13.29%	5.63%	0.48	0.61	0.25	0.79	0.77	0.36
Median	1.82%	10.91%	-3.62%	1.15	2.54	1.70	-0.16	-0.20	-0.33
Min	-17.28%	-12.80%	-9.35%	0.62	1.62	1.23	-2.04	-0.82	-0.59
Max	15.14%	26.51%	9.25%	2.25	4.00	2.25	1.15	1.49	0.78
Asian Market Index – Nikkei 225									
μ	1.77%	-1.07%	-11.29%	0.93	1.51	0.93	-0.09	0.06	-0.64
σ	15.69%	14.41%	5.90%	0.26	0.45	0.27	1.13	0.77	0.29
Median	1.29%	3.18%	-12.40%	0.89	1.48	0.89	0.002	-0.17	-0.72
Min	-26.81%	-22.41%	-19.73%	0.57	0.86	0.56	-2.98	-0.82	-1.07
Max	29.24%	17.25%	1.57%	1.50	2.71	1.50	1.43	1.49	0.03
Global Market Index – MSCI World									
μ	6.42%	4.95%	-3.46%	1.69	2.48	2.10	0.29	0.52	-0.28
σ	12.43%	12.88%	6.37%	0.70	0.55	0.36	1.56	1.04	0.26
Median	8.08%	10.02%	-4.66%	1.62	2.33	2.12	0.17	0.38	-0.35
Min	-13.36%	-16.59%	-11.89%	0.64	1.89	1.50	-2.93	-0.69	-0.56
Max	27.41%	20.99%	12.29%	3.25	4.00	2.71	4.48	2.33	0.42

5. SUMMARY AND CONCLUSION

The Sharpe ratio was supplemented with the Bias ratio as a performance measure in the fund hedge context as the Sharpe ratio is, for instance, influenced by both illiquidity and returns smoothing. 'Live', individual, long/short, equity hedge funds, sourced from the Eurekahedge database covering the period January 2000 to December 2011 and spanning geographical mandates that included North America, Europe, Asia and global were used. In order to correct for non-IID errors a Sharpe ratio annualisation method that considers the serial correlation of returns was used – the study presents comparative summary statistics between the different methods of computing annualised Sharpe ratio. In terms of methodology this study used a 36-month rolling (window) period to estimate the relevant statistics and ratios.

Even though the Bias ratio has gained some acceptance since its introduction in 2006, a known fraud case was required to confirm that the Bias ratio is indeed a convincing measure of fraud detection, or rather a red flag indicator of possible fraudulent behaviour. The Madoff Ponzi scheme was the chosen case – this case has been used in other Bias ratio related studies, and the Bias ratio was confirmative in these studies (e.g. Douady *et al*., 2009). The Bias ratio largely confirmed possible suspicious or fraudulent behaviour as estimated from monthly returns of one of the largest Madoff feeder funds, Fairfield Sentry Ltd (FFS). Also, by studying the moments of FFS's returns distribution to those of the relevant market (S&P500) some out of the ordinary characteristic or patterns were identified that can be thought of as potential warning signals of fraudulent or suspicious behaviour.

Using the identified warning signals from the Madoff case two funds from the funds sample were identified that exhibited similar out of the ordinary characteristics. These warning signals, for both the Madoff case as well as the two identified funds, were presented graphically and in brief comprise: (i) seldom negative mean returns with minimal variation of the mean return; (ii) standard deviation of returns that are significantly lower than that of the relevant market and also shows minimal variation; (iii) returns distribution skewness that is much less volatile compared to that of the relevant market, and also seldom negative skewness; (iv) returns distribution kurtosis that behaves in an anti-correlated manner to that of the market; (v) a Bias ratio that behaves in an opposite fashion to that the market; and (vi) a Sharpe ratio that is almost always higher than that of the market and also almost never negative. In addition, abnormally high Sharpe ratios compared to similar funds are also a cause for suspicion. Essentially, the identified characteristics emphasise that return characteristics that are dissimilar to those of the relevant market should be thought of as warning signals of possible fraudulent activity.

The first of the three results sections (see Section 4.1) illustrated how ill-suited the Sharpe ratio is for (these) hedge fund return data, or how inaccurate (these) hedge fund data are for use with the Sharpe ratio. This section confirmed the Sharpe ratio's ill-suitedness by focusing on the normality of the return distributions (JB-test) and the return distributions' higher moments from both a static and 36-month rolling perspective. Results indicate that return distributions moved further from normal(ity) during the crisis period (December 2006 – December 2009) while kurtosis increased and skewness turned negative, both dramatically, during this period.

The final results section aimed to highlight the changing characteristics of hedge funds and their respective market benchmarks over the varying economic conditions around the 2007 financial crisis, and thus a selective statistical analysis of returns was conducted. Results indicate a decrease in the average return as well as a simultaneous increase in volatility across all funds during the crisis period with average Sharpe ratios often falling below zero. Average mean Bias ratios increase from *pre-* to *during* the crisis where after it decreases in the period *post* the crisis to its lowest levels throughout the three phases. Geographically, it was found that funds and market indices from all included regions behave similarly across the three phases and none of the regional funds or benchmarks indicates significantly better performance than another *during* or *post* the financial crisis. In the period prior to the crisis Asian funds performed better, on average. For market indices, an immediate increase in risk after the onset of the financial crisis was observed: North American and European markets (indices) were less risky *during* the crisis period compared to those in Asia and globally. Hedge funds from all regions outperformed their relevant market indices *prior* to the crisis.

The need to accurately distinguish between poor and good quality fund returns has not diminished, and in actual fact is ever increasing. Higher moments of the return distributions must be accounted for if accurate fund comparisons (in terms of risk-adjusted returns) are desired.

The Bias ratio, though not a perfect measure, presents firm and encouraging arguments that a measure that detect or red flags potential fraudulent or suspicious behaviour should augment the use of the Sharpe ratio. Not only does the Bias ratio consider a risk dimension that is not considered by the Sharpe ratio, but the Sharpe ratio is also influenced by fraudulent behaviour such as returns smoothing that may be flagged by a measure such as the Bias ratio. In essence, measures that account for moments of the returns distribution structure not considered by the Sharpe ratio will prove valuable to investors and such measures should arguably be considered to supplement the use of the Sharpe ratio. The latter will also enhance the justified call for greater transparency concerning hedge fund performance and reporting.

Exploring and comparing alternative fraud measures and using a suitable ranking methodology to compare fund rankings of the Sharpe and Bias ratios will undeniably contribute to the research areas of hedge fund fraud, behaviour and performance.

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CHAPTER 3

HEDGE FUND PERFORMANCE EVALUATION USING THE SHARPE AND OMEGA RATIOS

Hedge fund performance evaluation using the Sharpe and Omega ratios

Francois van Dyk, Gary van Vuuren & André Heymans

Abstract

The Sharpe ratio is widely used as a performance evaluation measure for traditional (i.e. long only) investment funds as well as less-conventional funds such as hedge funds. Based on mean-variance theory, the Sharpe ratio only considers the first two moments of return distributions, so hedge funds – characterised by asymmetric, highly-skewed returns with non-negligible higher moments – may be misdiagnosed in terms of performance. The Sharpe ratio is also susceptible to manipulation and estimation error. These drawbacks have demonstrated the need for augmented measures, or, in some cases, replacement fund performance metrics. Over the period January 2000 to December 2011 the monthly returns of 184 international long/short (equity) hedge funds with geographical investment mandates spanning North America, Europe and Asia were examined. This study compares results obtained using the Sharpe ratio (in which returns are assumed to be serially uncorrelated) with those obtained using a technique which does account for serial return correlation. Standard techniques for annualising Sharpe ratios, based on monthly estimators, do not account for this effect. In addition, this study assesses whether the Omega ratio supplements the Sharpe Ratio in the evaluation of hedge fund risk and thus in the investment decision-making process. The Omega and Sharpe ratios were estimated on a rolling basis to ascertain whether the Omega ratio does indeed provide useful *additional* information to investors to that provided by the Sharpe ratio alone.

Keywords: *hedge funds, Omega ratio, Sharpe ratio, risk management*

JEL Classification: *C02, C16, C22, C44, G01, G11, G23, G32*.

1. INTRODUCTION

Even before the advent of the first hedge fund structure by Alfred Winslow Jones in 1949 institutional investors as well as wealthy individuals have been interested in hedge funds as early as the 1920s when several private investment vehicles were available to wealthy investors. The public's interest in these funds has also increased through some extravagant hedge fund phenomena, such as the collapse of Long Term Capital Management (LTCM)[1] in the late 1990s, Amaranth Advisors[2] in 2006 and the Madoff Ponzi scheme[3] in late 2008. Since the early 1990s, hedge funds have become an increasingly popular asset class as global investment increased from US$50bn in 1990 to US$2.2tn in early 2007 (Barclayhedge, 2013). Between 2003 and 2007 the hedge fund industry posted its sturdiest gains, in terms of asset flows and performance whereafter the financial crisis significantly curtailed growth. Due to substantial investor redemptions and performance-based declines industry growth reversed,

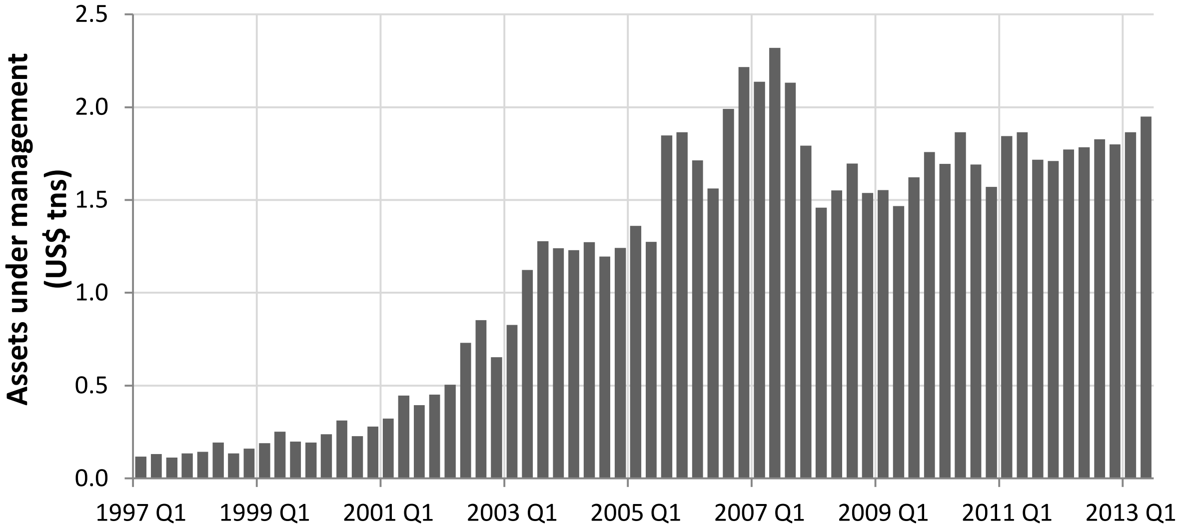
[1] A large US based hedge fund that nearly caused the collapse of the global financial system in 1998 due to high-risk arbitrage bond trading strategies. The fund was highly leveraged when Russia defaulted on its debt causing a flight to quality. The fund suffered massive losses, and was ultimately bailed out with the assistance of the Federal Reserve Bank and a consortium of banks.

[2] To date, Amaranth Advisors marked the most significant loss of value for a hedge fund. The hedge fund attracted assets under management of US$9bn whereafter faulty risk models and non-rebounding gas prices resulted in failure for the funds' energy trading strategy as it lost US$6bn on natural gas futures in 2006. Amaranth was also charged with the attempted manipulation of natural gas futures prices. Refer to Till (2007) for further details.

[3] Considered the largest financial scandal in modern times with losses estimated at US$85bn, Madoff Securities LLC provided investors with modest yet steady returns and claimed to be generating these returns by trading in S&P 500 index options employing an index arbitrage strategy. Madoff Securities did, however, commit fraud through a Ponzi scheme structure.

declining to US$1.4tn by April 2009 (Eurekahedge, 2012). Total assets under management (AUM) for the hedge fund industry has risen to only US$1.89tn by the end of June 2013 (Eurekahedge, 2013a) after posting its first decline (US$2.94bn) of 2013 in June. The industry also suffered US$3.8tn of new outflows during 2012 (Eurekahedge, 2013b). Figure 1 presents the AUM for the hedge fund industry since 1997 until quarter 2 of 2013.

Figure 1: Hedge funds' assets under management (US$tns) since 1997.



Source: Barclayhedge (2013).

The combination of a benevolent interest rate environment[4] combined with indifferent regulatory scrutiny along with a shortage in viable investment alternatives has promoted the growth of the hedge fund industry (Botha, 2007).

On top of their (net) assets size, hedge funds occupy a vital function in the global securities markets while the hedge fund industry provides value to investors, markets and the broader economy. In terms of performance, hedge funds deliver, on average, economically and statistically significant abnormal performance on both an equal- and value-weighted basis and also across strategies, domiciles, size categories and time-periods (Joenväärä *et al*., 2012).[5] Although there is evidence that hedge funds are affected by financial market stresses, there is no thorough academic evidence that indicates that hedge funds cause economic instability. Furthermore, Getmansky *et al*. (2012) found that hedge funds have exposure to systemic risk, but not that they contribute to it and that they suffer from, rather than cause, forced liquidations. It could be argued that due to their essentially counter-cyclical nature hedge funds in reality reduce instability and lessen systemic risk.

Hedge funds also contribute to the efficient functioning of financial markets as they are important providers of liquidity in various financial markets while evidence also exists that hedge funds provide liquidity through short sales. These funds are also responsible for improving price discovery and through both job creation[6] and tax revenues[7] contribute to the broader economy. Also hedge funds employ substantial leverage (Malkiel & Saha, 2005), assume risks that other will not, mitigate price downturns and seek out inefficiencies (Botha, 2007). Apart from the prospect of double- and triple-digit returns, investors are tempted to invest in hedge funds for the persuasive motive that hedge fund

[4] Many hedge fund strategies rely on borrowed funds to leverage investment positions and so a kind interest rate environment is highly positive (Botha, 2007).

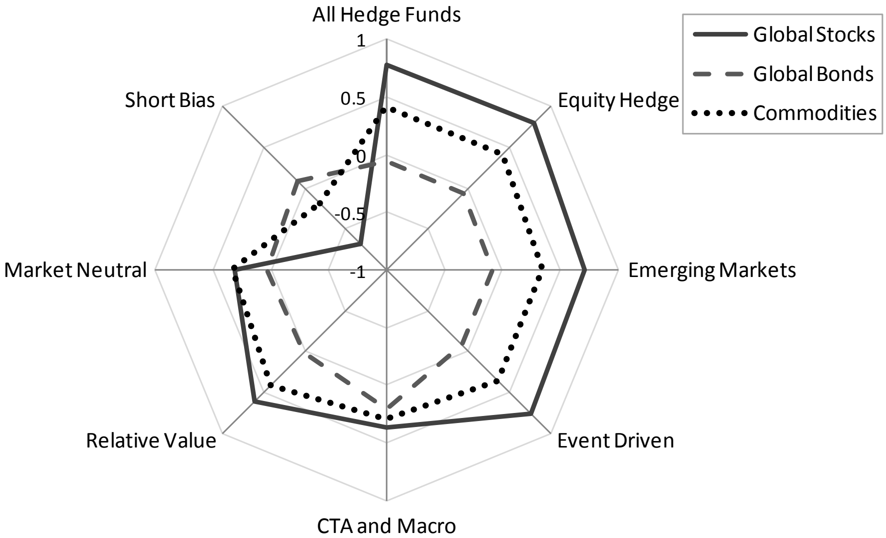
[5] Apart from average performance over a given time period it has recently been shown that hedge fund performance persists at annual horizons, while it was shown prior to only persist over quarterly horizons.

[6] AIMA 2010 global survey indicated that world’s hedge fund industry employs an estimated 300 000 people (KPMG, 2012).

[7] 2009 survey by Open Europe found that the hedge fund and private equity industries contribute €9bn to the European Union in tax revenues. The survey estimated that in the UK alone the industry contributes £3.2bn to tax revenues (KPMG, 2012).

returns seem uncorrelated with market indices, i.e. the broader market. This is the rationale for the "hedge" in hedge funds: they enjoy relatively low correlations with traditional asset classes (Fung & Hsieh, 1997) and so offer investors attractive diversification benefits for asset portfolios (Liang, 1999) (see Figure 2). Survey results from SEI Knowledge Partnership showed that institutional investors are less interested on achieving absolute returns than they are on capturing differentiated, non-correlated returns[8] (SEI, 2013). These alternative investments embrace a variety of different strategies, styles and securities and hence the necessity for risk management measures and techniques designed specifically for these funds is undeniable. In spite of the promised diversification benefit on hand, these funds remain highly risky investments as stellar returns cannot be obtained without significant risks (Botha, 2007).

Figure 2: Correlations between hedge funds and main asset classes (Jan 1994 – Dec 2011).



Source: KPMG (2012). Global stocks = MSCI World Total Return Index, Global Bonds = JP Morgan Global Aggregate Bond Total Return Index, Commodities = S&P GSCI Commodity Total Return Index. Hedge fund performance using HFR equal-weighted index and strategy indices.

While for the most part comparisons of hedge fund returns focus solely on total return values, comparing funds in this manner that have dissimilar expected returns and risks is meaningless. The arrangement of risk and return into a risk-adjusted number is one of the primary responsibilities of performance measurement (Lhabitant, 2004). A number of risk-adjusted[9] performance measures (of which some are commonly used in traditional funds) have been adopted by the hedge fund industry, such as the Sharpe and Treynor ratios, Jensen alpha, M^2 and downside (risk) measures in the Sortino ratio and Value-at-Risk (VaR).

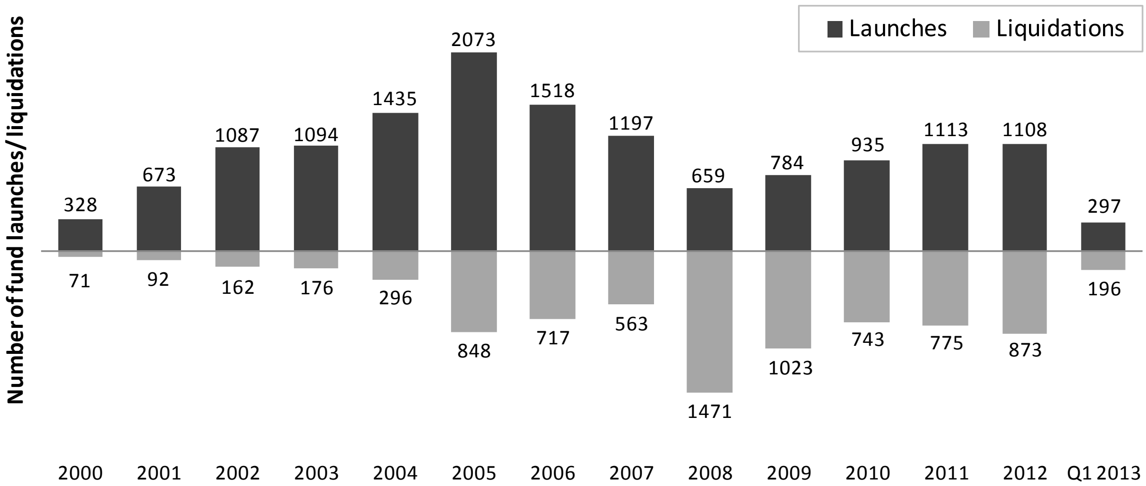
Amongst hedge funds, the Sharpe ratio is the metric of choice and also the most commonly used measure of risk-adjusted performance (Lhabitant, 2004; Opdyke, 2007; Schmid & Schmidt, 2007). Proposed by Sharpe as the "reward-to-variability" ratio as a comparison tool for mutual funds (Sharpe, 1966, 1975 and 1994) the ratio is conceptually uncomplicated and also rich in meaning, providing investors with an objective, quantitative measure of performance. The ratio benefits from widespread use and copious interpretations, but also has its shortcomings. Being unsuitable for dealing with asymmetric return distributions are, among others a drawback of volatility measures (Lhabitant, 2004).

The hedge fund universe witnessed an annual return of 8.82% between 1995 and 2003 compared to the 12.38% annual return for the S&P500 (Malkiel & Saha, 2005). More recently, in 2011 the hedge

[8] Around 47% of senior investment professionals at 107 institutions surveyed rated diversification as their primary objective when investing in hedge funds. 2nd placed objective = absolute returns (20%), 3rd = decreased volatility (13%).
[9] Usually performance indicators that combine the returns with the risk of the fund (Botha, 2007).

fund industry reported a 4.6% loss with most losses occurring during the third quarter when global equity markets declines by approximately 17% (TheCityUK, 2012). In 2012 the industry grew its total assets by US$64.5bn to reach US$1.77tn while returns were also the lowest for a positive year, 6.12%, compared to the 13.75% return of the MSCI World Index (Boyd, 2013). In the same year, launch activity slowed while the fund closure rate was the highest since the financial crisis. Annual hedge fund launch and liquidation numbers from 2000 until Q1 2013 are presented in Figure 3.

Figure 3: Number of hedge funds launched and liquidated per year since 2000 until Q1 2103.



Source: SEI (2013) as based on data from Hedge Fund Research (HFR).

Between 2002 and 2012 average annual returns for hedge funds were 6.3% (TheCityUK, 2012) compared to 5.7% for U.S. bonds,[10] 7.8% for global bonds[11] and 6.0% for the S&P500. In 2008 the hedge fund industry posted its worst annual performance (-20%), with this also being its worst since 1990. In 2011 fund liquidations also rose to 775, an increase of 4% from 743 in 2010. Albeit that the total number of funds rose to 9 523 in 2011 and further to 10 100 at the end of 2012 (TheCityUK, 2013) this number still fails to eclipse the pre-crisis peak of 10 096 at the end of 2007 (Clarke, 2012). In terms of the industry's asset size, AUM declined 27% in 2008 to US$1.4tn (Roxburgh *et al*., 2009) and then even further in March 2009 to US$1.29tbn (Eurekahedge, 2010), echoing both asset withdrawals and investment losses.

Investor withdrawals subsequent to the financial crisis added to poor performance, as it became apparent that hedge funds had not "hedged" at all. This has led to a high attrition rate[12] (Liang, 1999) which over time has also increased significantly. Of the funds that were alive in 1996 only 90.9% were still alive in 1999, with this figure declining further to 59.5% in 2001 (Kat & Amin, 2001). Additionally, Kaiser and Haberfelner (2012) found that since the financial crisis the attrition rate for hedge funds has nearly doubled. It is so that in the ruthless world of fund performance, the reporting of monthly returns can, depending on the reported figures, intensify investor outflows, halt them, reverse them or increase them. A strong motivation to exaggerate or misrepresent fund performance therefore exists, as not only can perceived stronger performance bolster capital inflows, but also reinforce a fund's existence and increase manager incentive fees (see Feng, 2011; Agarwal & Naik, 2011; Goetzmann *et al*., 2007; Bollen & Pool, 2009). As investors also pay high fees, typically around a 2% management fee and a 20% performance fee, performance evaluation and an accurate performance evaluation methodology are of critical importance to investors (Lopez de Prado, 2013).

A number of empirical studies have challenged the characterisation of hedge fund returns and argued that standard methods of assessing the risks and rewards of these funds are misleading (Getmansky *et*

[10] U.S. bonds as measured by the Barclays U.S. Aggregate Bond Index.
[11] Global bonds as measured by the JP Morgan Global Government Bond Index (unhedged).
[12] Attrition rate is the liquidation rate of funds.

al., 2004). The possibility exists that the risks that hedge funds face are not measured sufficiently accurately and that currently employed measures are inadequate or at times misrepresented. A debate regarding the consideration of new or alternative measures, in addition to the Sharpe ratio, to augment hedge fund risk (and risk-adjusted return) measurement has been lively for some time (Perello, 2007; Taylor, 2005; Wiesinger, 2010). Omega a (relatively recent) measure is topical in the debate.

This study evaluates whether the Omega measure should augment the use of the Sharpe ratio when evaluating hedge fund risk and in the investment decision-making process. The Omega measure not only provides information over and above that given by the Sharpe ratio, but the latter is ill-suited to hedge funds (which exhibit complex, asymmetric and highly-skewed return distributions).

The remainder of this paper is structured as follows: Section 2 presents an overview of the existing literature governing fund performance and the unsuitability of the Sharpe ratio within the hedge fund context. The section also presents an overview of alternative (risk-adjusted) performance measures and, due to its relevancy, performance measures based on lower partial moments. Section 3 introduces the Omega measure, some modifications to the measure as well as the data and methodology employed. Section 4 presents the analysis and results and Section 5 concludes.

2. LITERATURE STUDY

2.1. Inadequacy of Sharpe Ratio

The Sharpe ratio is one of the most commonly cited statistics in financial analysis and the risk-adjusted performance metric of choice amongst hedge funds (Koekebakker & Zakamouline, 2008; Lhabitant 2004; Lo, 2002; Opdyke, 2007; Schmid & Schmidt, 2007). Known also as the risk-adjusted rate of return (Sharpe, 1966, 1975, 1992, 1994; van Vuuren *et al*., 2003), it is calculated using:

$$SR = \frac{r_p - r_f}{\sigma_p \sqrt{T}} \tag{1}$$

where r_P is the cumulative portfolio return measured over T months, r_f is the cumulative risk-free rate of return measured over the same period, and σ_p is the portfolio volatility (risk) measured over T months using the conventional standard deviation formula, namely:

$$\sigma_p = \frac{1}{T-1}\sum_{t=1}^{T}(r_t - \mu)^2 \tag{2}$$

where r_t is the portfolio return, measured at *t*-intervals over the full period under investigation, T and μ is the average portfolio return over the full period. In spite of its widespread use, the Sharpe ratio does, however, have some failings, especially within the hedge fund context.

Because expected returns and volatilities are non-observable quantities, they must be estimated, so the Sharpe ratio is frequented by inevitable estimation errors. Little attention has been given to the Sharpe ratio's statistical properties given that the accuracy of its estimators rely on the statistical properties of returns, and that these may be very dissimilar among portfolios, strategies and over time (Lo, 2002). The performance of more volatile investment strategies is more difficult to determine than that of less volatile strategies (Lo, 2002). Given that hedge funds are in general more volatile than more traditional investments (Ackermann *et al*., 1999; Liang 1999), estimates for the Sharpe ratios of hedge funds are likely to be less accurate. Various statistical tests comparing the Sharpe ratios between two portfolios have been proposed by Gibbons *et al*. (1989), Jobson and Korkie (1981), Lo (2002) and Memmel (2003), yet, the unavailability of multiple Sharpe ratio comparisons has piloted alternative approaches (see, e.g. Ackermann *et al*., 1999; Maller & Turkington, 2002). A more refined technique for construing Sharpe ratios is needed and that such a technique should possibly consider information relating to the style of investment and the market environment in which the returns are generated. It has also been established that the Sharpe ratio is susceptible to manipulation (e.g. Goetzmann *et al*., 2002, 2007; Spurgin, 2001).

While the distribution of hedge fund returns and their distinctly non-normal characteristics have been widely portrayed in the literature (see, e.g. Brooks & Kat, 2002; Fung & Hsieh, 2001; Lo, 2001; Malkiel & Saha, 2005), Brooks and Kat (2002) established that hedge fund indices show evidence of low skewness and high kurtosis. Scott and Horvath (1980) also determined that investors have a preference for high first and third moments (mean and skewness) and low second and fourth moments (standard deviation and kurtosis). Asymmetric distributions influence the validity of volatility as a risk measure, which ultimately impacts the accuracy of the Sharpe ratio. Volatility merely measures the dispersion of returns around their historical average and given that positive and negative deviations (from the average) are penalised in an equal manner in the computation, the concept only bears weight for symmetrical distributions (Lhabitant, 2004). Most return distributions are neither normal nor symmetrically distributed in practice, and so even when two investments have an identical mean and volatility, these investments may exhibit substantially different higher moments. This is mainly the case for strategies that entail dynamic trading, buying and selling of options and active leverage management (Lhabitant, 2004): all strategies used by hedge funds. Such strategies have return distributions that are highly asymmetric and have "fat tails", which leads to volatility being a less-meaningful measure of risk. The relevance of the dispersion of returns around an average has also been queried from an investor's viewpoint, as most investors perceive risk as a failure to achieve a specific goal such as a benchmark rate (Lhabitant, 2004; Vanguard, 2012). In such circumstances, risk is solely considered as the downside of the return distribution and not the upside: the difference is not capture by volatility (Lhabitant, 2004). Investors are also more adverse to negative deviations than to positive deviations of the same extent (Lhabitant, 2004).

The Sharpe ratio is founded on the mean-variance framework, which makes use of the Capital Asset Pricing Model (CAPM) methodology under which the appropriate measure of risk is represented by β:

$$\begin{aligned}\beta_P &= \frac{Cov\left(r_p, r_m\right)}{Cov(r_m, r_m)} \\ &= \frac{Cov\left(r_p, r_m\right)}{Var(r_m)}\end{aligned} \tag{3}$$

where r_p and r_m are the portfolio and market returns, respectively and β_P is the portfolio β.

Strong assumptions underlie the CAPM and include that (i) returns are normally distributed, and (ii) investors care only about the mean and variance of returns, so upside and downside risks are viewed with equal dislike (Leland, 1999). These assumptions rarely hold in practice: even if the underlying assets' returns are normally distributed, the returns of portfolios that contain options on these assets, or use dynamic strategies will not be (Leland, 1999). Dynamic investment strategies are generally employed by hedge funds, which are accompanied by dynamic risk exposures. For investors who seek to manage the risk/reward trade-offs of their investments, this has significant implications (Chan *et al*., 2005). It is for this reason that hedge fund performance is often summarised with multiple statistics.[13] Although β is an adequate measure of risk for static investments, there is no single measure capturing the risks of dynamic investment strategies (Chan *et al*., 2005). Agarwal and Naik (2004) assert that linear performance measures often cannot capture the dynamic trading strategies pursued by several hedge funds. Analysing all hedge funds using a singular performance measurement framework that does not regard the characteristics of the specific strategies is of limited value. As a manner to capture the differences in management style, hedge fund style specific performance measurement models or measures are required (Agarwal, & Naik, 2004; Fung & Hsieh, 2001).

[13] e.g. mean, standard deviation, Sharpe ratio, market β, Sortino ratio, maximum drawdown etc. (Chan *et al*., 2005).

A great number of equity-orientated hedge fund strategies also bear significant (left-tail) risk that is disregarded by the mean-variance framework[14] (Lhabitant, 2004).

2.2. Alternative risk performance measures

The shortcomings of volatility as a measure of risk explain why alternative risk measures have been sought after (Lhabitant, 2004). An alternative measure of risk replaces the Sharpe ratio's denominator (volatility) in many alternative measures. For instance, under the mean-downside deviation framework Sortino and Price (1994) as well as Ziemba (2005) substitute standard deviation by downside-deviation. Other downside risk measures use drawdown[15] in the denominator to measure risk. For instance, the Calmar ratio (CR) is the quotient of the excess return over risk-free rate and the maximum loss (i.e. maximum drawdown) incurred in the relevant period (Young, 1991). As a substitute to maximum drawdown, the Sterling ratio employs the average of a number of the smallest drawdowns, within a certain time period, to measure risk (Lhabitant, 2004). This substitution makes the Sterling ratio less sensitive to outliers than the Calmar ratio.

The Burke ratio is also less sensitive to outliers than the Calmar ratio, as risk is expressed as the square root of the sum of the squares of a certain number of the smallest drawdowns (see Burke, 1994). Under the mean-VaR framework Gregoriou and Gueyie (2003) suggest a modified Sharpe ratio as an alternative measure specifically for hedge fund returns by using a Modified VaR[16] (MVaR) instead of standard deviation as the denominator. Dowd (2000) substitutes standard deviation by a VaR measure, while conditional VaR[17] may also be made use of. Additionally the Stutzer index has its foundation on the behavioural hypothesis that investors seek to minimise the probability that the excess returns over a given threshold will be negative (Stutzer, 2000).

The Risk Coverage Ratio (RCR), a measure aimed more at operational and enterprise risk management, is fundamentally similar to the Sharpe ratio (Kaye, 2005). The numerator of the RCR equals excess return over the risk-free rate while the denominator is the expected downside result multiplied by the probability of a downside result. In essence the ratio's intuitive meaning comes to how many times the risk is "covered" by the expected return. Thus the RCR's denominator is the chance of losing multiplied by the expected loss while the Omega ratios' numerator can be thought of as the chance of winning multiplied by the expected amount in case of the win (Kaye, 2005).

Compatibility of alternative measures with a utility function has also led to well-known Sharpe ratio generalisations. The generalised Sharpe ratio (GSR) (Hodges, 1998) extends the Sharpe ratio and is equivalent to the traditional Sharpe ratio for ranking portfolios with normally distributed returns and when the utility function is exponential, but its range of applicability extends to any type of return distribution. The GSR's drawbacks are its restriction to exponential utility functions and that it requires an expected utility maximisation.

Another utility theory compatibility approach, the Adjusted Sharpe ratio (ASR), uses a Taylor series expansion of an exponential utility function to account for higher moments of the return distribution. ASR explicitly adjusts for higher (central) moments by incorporating a penalty factor for negative third and fourth moments (Koekebakker & Zakamouline, 2008) .

Some of these alternative performance measures, however, short solid theoretical underpinnings (considering the Sharpe ratio is based on the expected utility theory) and do not allow accurate ranking of portfolio performance since ranking based on these measures depends significantly on threshold selection (Koekebakker & Zakamouline, 2008). Moreover some of these measures only

[14] These left-tail risks are brought about by hedge fund strategies that exhibit payoffs resembling a short position in a put option on the market index (Lhabitant, 2004).

[15] Drawdown is defined as "the decline in net asset value from the highest historical point" (Lhabitant, 2004:55), and thus describes the loss incurred over a certain period of time (Wiesinger, 2010).

[16] The standard VaR only considers mean and standard deviation while modified VaR considers both the means and the standard deviation as well skewness and (excess) kurtosis.

[17] Artzner *et al*. (1997) introduced Conditional VaR (CVaR) to remedy against the shortcoming that VaR does not make a statement about the loss if VaR is exceeded.

account for downside risk while upside potential is not considered. Measures based on VaR also have a number of questionable shortcomings (Wiesinger, 2010). For instance, not only is VaR sensitive to the underlying parameters and the employed methods of calculation but VaR also relies on risk factors being normally distributed, which in a hedge fund context makes the VaR measure far from ideal.

2.3. Performance measures based on lower partial moments

Computational complexities in determining the efficient portfolios in a return versus semi-variance[18] framework and ensuring that the risk metric is based on a solid theoretical foundation[19] are discouraging issues for "downside" risk measures (Markowitz, 1959). Generally, downside risk metrics based on extremes or quantiles are not compatible with utility theory, while metrics based on lower partial moments (LPM) may be compatible with some. This section discusses the foremost risk performance measures based on LPM, as not only can the Omega ratio be classified under this category, but measures based on LPM do not assume normal return distributions (Shadwick & Keating, 2002). LPM evaluates risk by only considering deviations that fall below an ex-ante defined threshold.[20] From a sample of n returns, an LPM of the order m can be empirically estimated by employing the following equation for discrete observations (Kaplan & Knowles, 2004):

$$LPM_m = \frac{1}{n}\sum_{i=1}^{n} \max(\tau - r_i; 0)^m \tag{4}$$

where τ is the minimum return threshold and r_i is a single realised return. Higher returns are associated with higher risk (volatility), but the requirement for low volatility[21] is less relevant for hedge funds than low *downside* volatility[22] (Botha, 2007). This has given rise to two kinds of downside volatility measures: the Sortino ratio and maximum drawdown (MDD) (also see Section 2.2). The Sortino ratio, closely related[23] to the Sharpe ratio and first introduced by Sortino and van der Meer (1991), does not assume risk factors are normally distributed. It is defined as the quotient of the difference between the average return and a return threshold or minimum acceptable return (MAR) (often the risk-free rate) and the downside volatility, i.e. returns below the threshold or MAR. The Sortino ratio (SOR) is defined as (Botha, 2007):

$$SOR(\tau) = \frac{\mu - \tau}{\sqrt{\int_{\infty}^{T} (\tau - R_t)^2 dF(R)}} \tag{5}$$

where μ is the average return, τ is the chosen return threshold, R_t is the random one-period fund return, $F(.)$ is the cumulative density function for total returns on an investment, and T is the sample size, measured in intervals of t. Downside volatility can, however, be interpreted as the square root of the LPM of order 2, which leads to the following version of the Sortino ratio where LPM is used as a risk measure (Kaplan & Knowles, 2004):

$$SOR(\tau) = \frac{\mu - \tau}{\sqrt[2]{LPM_2(\tau)}} \tag{6}$$

[18] Semi-variance is the same notion as "downside deviation" or "downside volatility".
[19] By establishing some compatibility with an acceptable utility function.
[20] This defined threshold can either be the distribution mean or a different sort of minimum return, for instance the minimum acceptable return (MAR).
[21] Lower volatility is also much more important for traditional funds.
[22] "Downside volatility" is the same as "downside deviation". It is defined as the volatility of returns below a specific threshold return. Volatility is given by $\sigma = \frac{1}{N-1}\sum_{i=1}^{N}(r_i - \mu)^2$, while downside volatility is given by $\sigma_d = \frac{1}{N-1}\sum_{i=1}^{N}(r_{di} - r_t)^2$ where N is the number of data points, r_i are the time indexed returns, μ is the mean return, r_{di} are the returns for which $r_{di} < r_t$ and r_t is a chosen threshold return (Botha, 2007).
[23] It may also regarded as a modification of the Sharpe ratio as it only substitutes the volatility by downside volatility, which only considers the negative deviations from the minimum acceptable return (threshold).

To uncover a more generalised risk-adjusted performance measure Kaplan and Knowles (2004) fashioned the Kappa-measure. They showed that both the Omega and the Sortino ratio are merely special cases of Kappa, as the n parameter determines if the Omega, Sortino or a different risk-adjusted measure is produced.[24] The n^{th} lower partial moment function is defined as (Harlow, 1991):

$$LPM_{\mathrm{n}}(\tau) = \int_{-\infty}^{t} (\tau - R)^{\mathrm{n}} dF(R) \tag{7}$$

and substituting Equation (7) into Equation (5) provides an alternative and wholly equivalent definition of the Sortino ratio (Equation 6). Kappa, is a generalisation of this quantity (Kaplan & Knowles, 2004), thus:

$$K_n(\tau) = \frac{\mu - \tau}{\sqrt[n]{LPM_n(\tau)}} \tag{8}$$

Additionally, the Gain-Loss ratio (GLR) (Bernardo & Ledoit, 2000)[25] and the Upside-Potential ratio (UPR) (Sortino *et al.*, 1999) are performance measures that consider both LPM and higher partial moments (HPM). The GLR compares the expected value of positive to negative returns, where positive returns are returns which exceed the return threshold and negative returns do not. The expected positive returns are considered as the HPM of order 1 while the negative expected returns are measured by LPM. The UPR considers an investor preference of wanting upside potential accompanied by downside protection, and thus the ratio more strongly weighs downside deviations from the minimum return threshold. The numerator of the UPR captures the upside potential as measured by expected positive returns over a minimum threshold while the denominator represents the downside deviation.[26] A more generalised form of the GLR and the UPR is the Farinelli-Tibiletti ratio (FTR) (Farinelli & Tibiletti, 2008) while the GLR and UPR can be considered special cases of the FTR (Farinelli & Tibiletti, 2008). The FTR can be explained as the ratio of a HPM of order p and a LPM of order q, with these parameters being real numbers specifically selected to represent an investor's (risk) preferences. In contrast the GLR assumes a risk-neutral investor and the UPR a risk-averse investor below the threshold and a risk-neutral investor above.

3. METHODOLOGY AND DATA

3.1. The Omega measure

Frameworks and performance measures that assume return normality are evidently inadequate for hedge fund analysis as hedge fund return distributions are markedly non-normal. More advanced models that incorporate skewness and kurtosis fall short in adequately embodying investors' preferences for all moments of the distribution when returns depart greatly from normality (Favre-Bulle & Pache, 2003). Hedge fund returns are typically far from normal and "*to properly evaluate the performance of portfolios with a non-normal return distribution, the entire distribution has to be considered. Ideally, this should be done without having to make any prior assumptions regarding the type of distribution*." (Amin & Kat, 2001:7). The Omega measure as introduced by Shadwick and Keating (2002) and Cascon *et al*. (2003) delivers a framework that fulfils these requirements as the Omega measure considers the return distribution in its entirety and also requires no parametric assumption of the distribution.[27] With an objective of a "universal" performance measure, the measure is designed to overcome the inadequacies of performance measures based on the mean-variance

[24] Setting the parameter as $n = 1$ yields Omega (K_1), while $n = 2$ yields the Sortino ratio (K_2). Although any number is possible for the n parameter, Kappa 3 (K_3) appears to be the most frequently used version of the Kappa (Eling & Schumacher, 2006b; Kaplan & Knowles, 2004).

[25] The original version of the GLR (Bernardo & Ledoit, 2000) does not explicitly define a return threshold (thus $\tau = 0$). For this original version, Omega does not yield the same results as the GLR although it can be shown that GLR is equal to Omega (see Kazemi *et al*., 2003).

[26] HPM of order 1 can be used to calculate the average positive returns and LPM of order 2 for the downside deviation.

[27] The Omega requires no parametric assumption of the distribution as the measure is a function of the return level (Favre-Bulle & Pache, 2003).

framework. Although a recent development, Kazemi *et al*. (2003) argue that the measure is not a new concept in finance[28] but they agree that it is based on novel interpretations of existing performance measurement techniques.

The Omega ratio considers returns above and below a given return threshold and determines the probability-weighted ratio of gains to losses relative to the return threshold. Mathematically this is defined as (Botha, 2007):

$$\Omega(\tau) = \frac{\int_{\tau}^{\infty}(1 - F(R_t))dR}{\int_{\infty}^{\tau} F(R_t)dR} \tag{9}$$

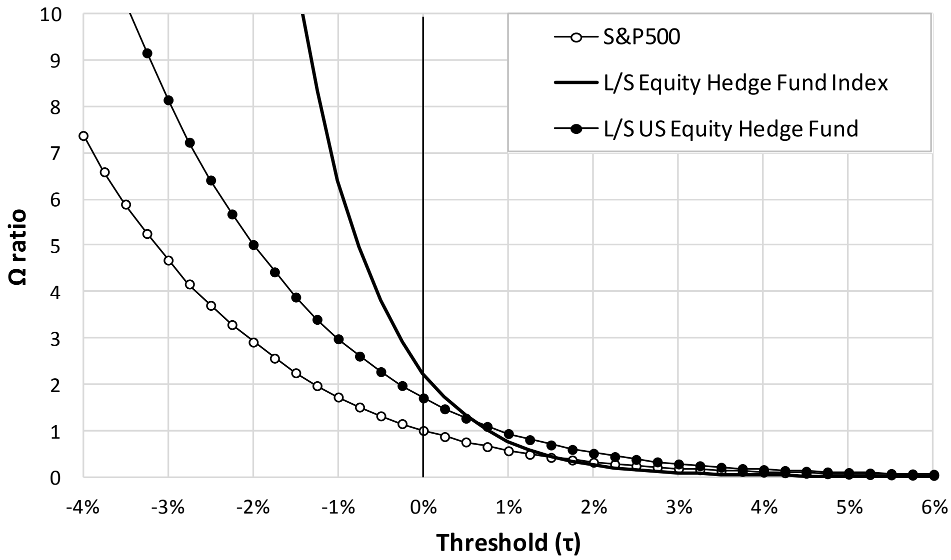
where $\Omega(\tau)$ is the Omega ratio estimated at a given threshold, τ, R_t is the random one-period return on either an investment or funds, and $F(.)$ is the cumulative density function (cdf) of an investments' total returns. Hence at a given level of τ, the number $\Omega(\tau)$ is the probability-weighted ratio of gains to losses relative to the chosen threshold, τ (Cascon *et al*., 2003), as any investor returns above the loss threshold are considered as gains and returns below as losses. At any given return threshold, selected by the practitioner, the portfolio with the highest value should always be preferred. Furthermore, no threshold level is "better" than another as the choice of threshold reflects a particular risk preference.

The Omega ratio is expressed as a *gains to losses* ratio which is in contrast to most performance ratios which take the form of [expected return]/risk. As a direct consequence of its form, the Omega ratio is sensitive to the *potential* of excess returns. Its sensitivity to sample size is also a limitation as at least 40 to 50 observations are required to obtain results of a stable nature (Botha, 2007; Sharma, 2005). This necessity of a sizeable sample is no more tedious than numerous other performance measures that have endured despite their dependence on ample data (Botha, 2007). Additional detail on sample size sensitivity is provided by Favre-Bulle and Pache (2003).

The Omega function is merely the Omega ratio evaluated at all threshold levels, from the highest observed return to the lowest. Hence, the Omega function is the Omega *ratio* in continuous form. Considering the extremes of the function, at first, is helpful in order to comprehend the shape of the Omega function and the information it provides (see Figure 4, for example). To the left of the origin on the x-axis, as the value of the threshold is chosen to be increasingly more negative, fewer and fewer returns will count as losses in the data set. At some point the chosen threshold will be lower than the lowest return in the data, and it is at this point that the denominator in Equation (9) becomes 0 and the ratio tends to infinity. For a small number of negative returns, or at least not very large negative returns, the more rapidly the ratio sets out to infinity and this means less downside risk for the given portfolio. To the right of the x-axis origin, increasingly fewer returns greater than the chosen threshold are found, until eventually none. At the point where no returns are greater than the threshold the numerator in Equation (9) (and also the ratio) becomes 0. The interpretation is that the longer it takes the Omega ratio to tend to 0, the greater the potential for positive returns (or gains). Generally, the steeper the slope of the Omega function, the lower the risk.

[28] As it can be described by the ratio of option prices (see Section 3.2).

Figure 4: Typical Omega functions for (a) the S&P500, (b) Eurekahedge North American long/short equities hedge fund index and (c) US long/short equity hedge fund, over Jan 2000 to Dec 2011 for comparison.



The Omega function coincides with the investor's perception of upside and downside and requires no specification or assumption of the investor's utility function and suits any risk-averse investor – this conforms to the requirement that performance evaluation should be performed without assumptions concerning a risk-averse investor's utility function. All that is to be considered is that more money is preferred to less. The function can, however, accommodate any utility function characterising an investor.

The Omega function exhibits the following basic properties: (i) it is equivalent to the distribution itself and embodies all its moments,[29] (ii) it is a decreasing function of τ, (iii) at the mean it takes the value of 1, and (iv) Omega's shape makes risk profiles clear (Cascon *et al*., 2003).

The application of Omega as a measure of performance is particularly appropriate for non-normal return distributions[30] (Favre-Bulle & Pache, 2003) while Keating and Shadwick (2002) point out that the Omega may be functional across a wide range of financial analysis and a range of hedge fund styles or strategies. Furthermore, unlike the Sharpe and Sortino ratios, the Omega ratio discounts multimodal distributions. Estimation error risk can also be reduced, as Omega is computed directly from the return distribution and measures the combined impact of all moments instead of each one individually (Favre-Bulle & Pache, 2003). Favre-Bulle and Pache (2003) also argue that within portfolio construction, the Omega offers a superior definition of risk and reward and as a consequence may outperform optimisation performed with less precise measures.

Numerous studies have grouped funds by style and ranked them using different measures, and irrespective of the measure used the ranking tend to be very similar (e.g. Nguyen-Thi-Thanh, 2010; Laing, 1999). It has been shown that Omega has a low correlation with the Sharpe ratio and a reasonable assumption is therefore that Omega rankings are not highly correlated with those of other traditional ratios. This is attributed to the additional higher moment information that Omega captures and traditional mean-variance analysis does not (MoneyMate, 2009). However, when returns are normally distributed or when higher moments are insignificant, Omega tends to agree with traditional measures (Keating & Shadwick, 2002).

[29] The Omega function carries the same information as the distribution. When comparing a single output between funds, incorrect conclusions are possible.

[30] Because the Omega function incorporates *all* moments of a distribution. However, even for normally distributed returns, Omega provides additional information as it considers the investor's preferences (for gains and losses) (Favre-Bulle & Pache, 2003).

Omega based rankings are also always possible, irrespective of the threshold – unlike the Sharpe ratio where ranking of negative-earning funds is inaccurate (de Wet, 2006). De Wet (2006) found that Omega also tends to produce different results from other higher-moment measures, accenting that moments of order five and higher should and do have an impact on performance measurement. It is not possible to determine precisely which moments have the most influence as Omega measures the total influence of all the moments (Favre-Bulle & Pache, 2003).

Omega Metrics, although not the focus of this study, is another interesting development on the Omega front. Omega Metrics is a natural generalisation of the Sharpe ratio and rewards a distribution for the size of its mean and for the degree of concentration around the mean. In contrast to mean-variance measures, Omega Metrics considers asymmetry and accounts explicitly for fat tails thus making it well-suited to hedge funds. Despite these advantages, Omega Metrics has not, however, enjoyed substantial acceptance since its development (Shadwick, 2004; Keating, 2004).

3.2. Omega modifications and combinations

With growing acceptance of the Omega ratio by both practitioners and academics, modified versions of the Omega ratio have proliferated.

Kazemi *et al*. (2003) introduced the Sharpe-Omega: a variation of Omega that maintains all of its desirable features, provides the same information as Omega and always ranks investments the same as Omega. The contribution of this measure is that it provides a measure of risk that is more intuitive than Omega and that is also more similar to the Sharpe ratio. Kazemi *et al*. (2003) showed that Omega can be written as:

$$\Omega(\mathrm{L}) = \frac{C(L)}{P(L)} = \frac{E\ [\max(x-\tau;0)]}{E\ [\max(\tau-x;0)]} \tag{10}$$

were $C(L)$ is the price of a European call option written on the investment and $P(L)$ is essentially the price of a written European put option.[31] The Sharpe-Omega of an investment is given by (Kazemi *et al*., 2003):

$$\text{Sharpe} - \text{Omega} = \frac{\text{Expected return} - \text{Threshold}}{\text{Put Option Price}} \tag{11}$$

The Excess Omega Return, developed by Sortino *et al*. (1997), is the excess return actually earned on a risk-adjusted basis. It portrays the variation between the Omega return of the investment portfolio and the Omega return of the style benchmark. The geometric realised return(s), the style beta, the style downside variance and an indicator of risk-aversion are included in the calculation.

Varadi (2012) proposed G-Omega, a simple Omega modification that attends to three failings of the Omega, namely: (i) it is skewed by outliers,[32] (ii) the sum measurement fails to account for the proper ratio of upside versus downside return potential in the absence of a difference in frequency between the two, and (iii) it fails to account for the impact of compounding returns.[33] Quintessentially, the G-Omega is solely focused on the compounding upside versus compounding downside potential, as it uses the geometric average returns above and below the threshold.

MoneyMate Fund Ratings' rating methodology combines the Omega ratio with another measure, downside deviation, to produce innovative risk-adjusted performance fund ratings. Downside deviation is chosen as the "combination" measure so as to *additionally* penalise downside risk[34] as

[31] Kazemi *et al*. (2003) asserted that the Omega's numerator represents the "cost" of acquiring the return above a threshold and the denominator the "cost" of protecting a return below the threshold.

[32] As it simply captures the ratio of the sums above and below the threshold and through this frequency could be a source of estimation error. G-Omega does not take frequency into account (Varadi, 2012).

[33] It merely takes the sum of returns versus the threshold.

[34] below the Omega threshold (MAR), that is in this case the rate of return earned on a risk-free investment.

well as to differentiate among no-gain funds.[35] Downside deviation also aids in offsetting unintuitive results that may come about by Omega being sensitive to the potential for excess returns. The methodology estimates standard deviation over the preceding 36 months using weekly total returns, whereafter the weekly standard deviation is annualised to correspond to volatility over a single year (MoneyMate, 2009).

3.3. Data

The 26 496 monthly returns, net of management and performance fees, from 184 'live' individual[36] hedge funds sourced from a Eurekahedge database data extract between January 2000 and December 2011 were used for this study. Funds with an incomplete monthly return history for the selected period were disregarded. Seeing that hedge funds universally report performance figures on a monthly basis and also as it is compatible with investors' month-end, holding-period return, monthly returns were chosen. Also, the data do not suffer from biases in the form of survivorship, backfilling or sampling while selection bias cannot be addressed as this would necessitate access to returns from hedge funds that decide not to report.

Table 1 presents the summary statistics, in monthly percentages, for the hedge fund returns as well as some other pertinent information. The t-statistics indicate that the mean returns are significantly different from 0 at the 5% significance level for all funds. Furthermore, 29 of the 184 funds (15.8%) show signs of normal distributions at the 5% significance level, using the Jarque-Bera (JB) test, while the remaining 155 funds (84.2%) exhibit non-normal distributions.

Table 1: Summary statistics for long/short Equity hedge funds.

	All Funds	**North America**	**Europe**	**Asia**	**Global**
No. of funds	184	85	38	15	46
Sample size	26 496	12 240	5 472	2 160	6 624
Mean Age (years)	15.8	16.5	14.3	14.4	16.1
Mean Size (US$m)	188	143	145	87	346
Return statistics					
μ	0.66	0.76	0.55	0.34	0.66
$t\ (\mu = 0)$	22.48	16.14	11.49	3.92	10.64
σ	4.8	5.2	3.5	4.0	5.1
Median	0.6	5.2	0.6	4.0	0.6
Min	-56.7	-56.7	-20.0	-22.4	-54.7
Max	76.2	76.2	29.6	19.2	39.8
Skewness	0.75	1.14	0.49	-0.15	0.05
Kurtosis	18.4	22.3	10.0	4.9	9.6
ρ_1	0.29	0.21	0.74	0.43	0.21
ρ_2	0.03	0.15	0.59	0.31	0.23
ρ_3	0.02	0.01	0.55	0.29	0.21
p-value of LB-Q	0.00	0.01	0.00	0.00	0.01

The Ljung-Box Q-statistic measures the overall significance of the first k autocorrelation coefficients, and is asymptotically χ_k^2 distributed under the null hypothesis of no autocorrelation.

It should be noted that all funds included are categorised as long/short equity (strategy) funds. This strategy of fund was chosen as it is the largest strategy among hedge funds constituting 35% of the industry (Brown *et al.*, 2009). In quarter 2 of 2013 this strategy also continued to be the most commonly sought strategy by institutional hedge fund investors, with 47% of investor searches in this quarter included a long/short equity component (Preqin, 2013). All funds have mandates only in

[35] Investments with no recorded gains over the risk-free rate.

[36] Implying funds that invest directly in securities and not fund of funds, which are funds holding a portfolio of other investment funds, or commodity trading advisors (CTA).

highly liquid markets as funds mandated in developing markets were omitted from the sample. This practice ensured that all funds are equity funds holding solely liquid securities. It can therefore be assumed that all securities held have readily available prices and that no subjective valuations are necessary. As an indication of liquidity the first-order return autocorrelations (ρ_1) of all but two geographical areas are ≤ 0.30 (Getmansky *et al*., 2004). The near zero levels of autocorrelation, for liquid securities such as equity funds, are consistent with those found by Bisias *et al*. (2012).

Table 2 exhibits an informational breakdown of the representative geographical mandates of the funds along with the relevant risk-free rate proxies accordingly used. Data on the risk-free rates were sourced from Bloomberg and the Federal Reserve Bank of St. Louis (FRED).

Table 2: Breakdown of geographical fund mandates & risk-free rate proxies

Geographical mandate	# Funds	Risk-free rate proxy
North America*	85 (46%)	10-year Treasury bond rate (US)
Europe	38 (21%)	10-year Treasury bond rate (Germany)
Asia	15 (8%)	10-year Treasury bond rate (Japan)
Global	46 (25%)	JPMorgan Global Government Bond Index

*Includes one Canadian fund (RFR = 10-year Treasury bond rate (Canada)).

The use of the German 10-year Treasury bond rate as proxy for the risk-free rate of the European geographical area is generally accepted[37] (Damodaran, 2008), albeit that a number of alternative options exist.

Hedge funds are commonly weighed against passive benchmark[38] indices,[39] although hedge funds (particularly equity long/short funds) are absolute investments.[40] Passive market benchmark indices data were sourced from Bloomberg whereas hedge fund benchmark indices data were sourced from Eurekahedge, Hedge Fund Research (HFR) and Barclayhedge. Table 3 presents the market and hedge fund benchmark indices used.

Table 3: Market and hedge fund benchmark indices.

Benchmark Market Indices	Region specific	
S&P500, S&P TSX*	North America	
DAX	Europe	
Nikkei 225	Asia	
MSCI World Index	Global	
Benchmark Hedge Fund Indices	**Region specific**	**Style specific**
Eurekahedge North America Long/short Equities Index	North America	Long/short Equity

*The S&P TSX was included as one North American fund was a Canadian fund.

Summary return statistics for market and hedge fund benchmark indices, January 2000 until December 2011, are presented in Table 4. Statistics in the named tables are drawn from the monthly returns with the monthly means and standard deviations in percentages.

[37] One of the reasons for this is that Germany is the largest bond issuer in the European geographical area.
[38] The term benchmark is defined by Lhabitant (2004) as "an independent rate of return (or hurdle rate) forming an objective test of the effective implementation of an investment strategy".
[39] This statement refers to the weighing up of the performance of hedge funds against a benchmark.
[40] Albeit recent change, originally the effectiveness or performance of hedge funds were not compared relative to a benchmark. Hedge fund managers are hired for their skills and they should be allowed to venture wherever their value-creating instincts take them, without considering benchmarks (Lhabitant, 2004). Thus hedge fund portfolios should aim to produce positive absolute returns rather than to outperform a particular benchmark.

Table 4: Summary statistics for market and hedge fund benchmark indices.

	S&P500	DAX	S&P TSX	Nikkei 225	Global Index [+]	L/S HF Index[*]
Sample size	144	144	144	144	144	144
μ	0.004	0.12	0.35	0.39	0.28	0.76
$t\ (\mu = 0)$	0.01	0.21	0.92	0.81	0.06	3.78
σ	4.71	6.72	4.55	5.80	4.90	2.4
Median	0.60	0.73	1.01	0.13	1.17	0.99
Min	-16.9	-25.4	-16.9	-23.8	-25.48	-6.5
Max	10.8	21.4	11.2	12.9	14.06	10.6
Skewness	-0.43	-0.52	-0.86	-0.53	-1.42	0.01
Kurtosis	3.66	4.88	4.58	3.89	5.16	4.86
ρ_1	0.13	0.07	0.22	0.12	0.31	0.20
ρ_2	-0.07	-0.06	0.07	0.06	0.03	0.04
ρ_3	0.12	0.10	0.06	0.11	0.19	0.04
p**-value of LB-Q**	0.10	0.39	0.01	0.15	0.00	0.01

[+] Global index = MSCI World Index.

[*] L/S HF Index = Eurekahedge North America long/short Equities Index.

Both the hedge fund and market indices exhibit non-normal distributions using the Jarque-Bera test at the 5% significance level.

3.4. Methodology

A rolling (window) period of 36-months, beginning January 2000, was used to estimate the relevant statistics and ratios. The 36-month rolling period was used to transform the monthly returns and risk-free rates to a geometric annualised basis.

The annualised Sharpe ratios were calculated from monthly returns that are not independently and identically distributed (IID), so the estimation method considered the serial correlation of returns. This alternative method was employed as a (computational) bias arises when annual Sharpe ratios are computed from monthly means and standard deviations by multiplying by $\sqrt{12}$. The method of computing annualised Sharpe ratios by multiplying by $\sqrt{12}$ is more suitable when returns are IID, but in the case of non-IID returns an alternative procedure that considers serial correlation (of returns) must be used. Disregarding serial correlation in hedge fund returns understate Sharpe ratios and can yield annualised estimates that are overstated by more than 65% as well as inconsistent hedge fund rankings (Lo, 2002). To adjust for non-IID returns, Lo (2002) proposed a measure known as the $\eta(q)$SR or annualised autocorrelation adjusted Sharpe ratio:

$$\eta(q)\text{SR with } \eta(q) = \frac{q}{\sqrt{q + 2\sum_{k=1}^{q-1}(q-k)\rho_k}} \tag{12}$$

where SR is the traditional Sharpe ratio on a monthly basis, ρ_k is the k^{th} autocorrelation for returns, and q=12. Table 5 conveys a selection of comparative summary statistics concerning the different annualised Sharpe ratio computation methods based on the 184 long/short equity hedge funds. The summary statistics in Table 5 are based on annualised geometric returns over a 36-month rolling period to facilitate presenting a statistical comparison between the Sharpe ratio computation methods.

Table 5: Comparative Sharpe ratio summary statistics (annualised figures).

	Sharpe Ratio	SC-adjusted Sharpe Ratio
Sample size	20 056*	20 056
μ	0.38	0.41
σ	0.85	0.95

	Sharpe Ratio	SC-adjusted Sharpe Ratio
Median	0.26	0.25
Min	-2.1	-3.8
Max	3.5	5.1
Skewness	0.49	0.73
Kurtosis	2.86	3.92

*184 funds × 109 (144-35) monthly returns.

A time-rolling Omega function was produced for each fund by estimating the Omega ratio over the selected threshold returns range (from -9% to +4% in discrete 0.25% increments) using the 36-month rolling method. The following equation was to estimate the Omega ratio (Botha, 2007):

$$\Omega(\tau) = \frac{\int_{\tau}^{\infty}(1 - F(R_t))dR}{\int_{\infty}^{\tau} F(R_t)dR} \tag{9}$$

where $\Omega(\tau)$ is the Omega ratio estimated at a given threshold, τR_t, is the random one-period return on either an investment or funds, and $F(.)$ is the cumulative density function (cdf) of an investments' total returns. For instance, the Omega ratio is estimated at each of the threshold returns (-9% through to +4%) by using 36-months of monthly returns data from January 2000 to December 2002 to create an Omega function for December 2002. By "rolling" the analysis period forward by one month and repeating the same process, an Omega function is created for the next month, and so forth. This is done for each fund in order to obtain an Omega function for each fund rolling over time. Figure 5 presents a representative Omega function comparison for a point-in-time and also over time. Note that the Omega value (y-axis) on all rolling Omega figures is truncated at 15 as values larger than this do not reveal much more about the nature of the fund returns.

Figure 5: Omega function of European mandated long/short equity hedge fund for (a) point-in-time (Dec 2002), and (b) rolling through time (Jan 2000 – Dec 2011).

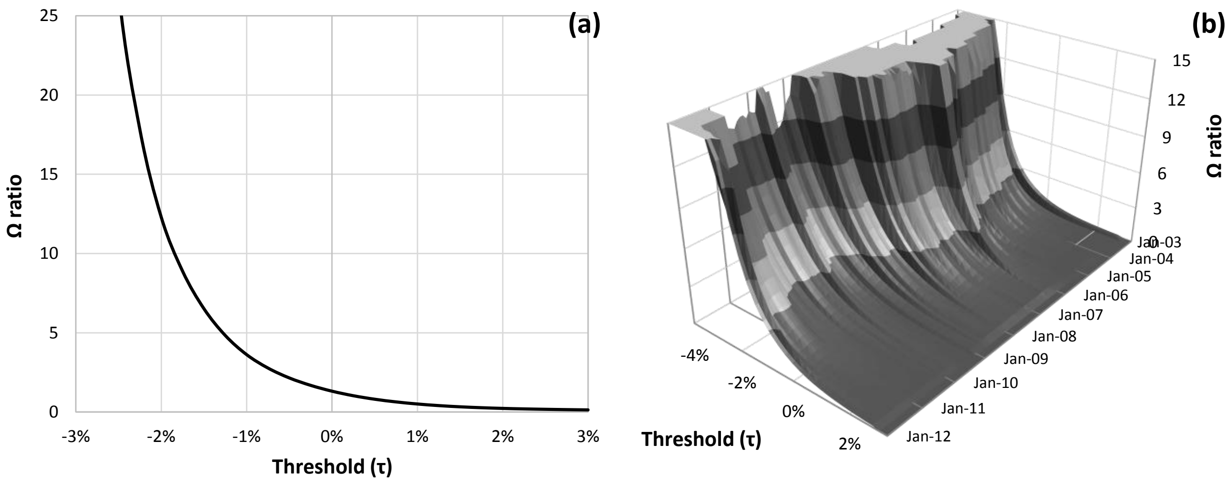


Figure 5a illustrates the Omega function at a specific point-in-time (Dec 2002) based on 36-months of data. Figure 5b, the rolling Omega function, shows the change of the Omega function's slope for this specific European fund over time. From this specific viewing angle the change in the function's slope in the downside, representing risk, can be clearly seen as time passes. Figure 5b thus conveys additional information and perspective to an investor compared to Figure 5a.

The subsequent section presents analysis and results by discussing how the rolling Omega function adds a supplementary perspective for investors compared to the point-in-time Omega function. The section will also delve into comparative fund rankings between the Sharpe and Omega ratios over time.

4. ANALYSIS AND RESULTS

4.1 The visual value of a rolling Omega function

The rolling Omega function has the added advantage of providing a supplementary perspective compared to the point-in-time Omega function. This is so as a hedge fund investor can visually see and compare the characteristics of a given fund with another fund or benchmark. Generally investors will use the relevant information to construct a fund's Sharpe and Omega ratios, which when graphed looks similar to Figure 6. Figure 6 presents the rolling Sharpe and point-in-time Omega function's of a randomly selected US long/short equity hedge fund (fund #167) as well as an appropriate benchmark for this specific fund, the S&P500.

Figure 6: (a) Rolling Sharpe ratio for a US long/short equity hedge fund along with that of the S&P500 for Dec 2002 until Dec 2011, and (b) point-in-time (Dec 2002 and Dec 2011) Omega functions for US long/short equity hedge fund and S&P500.

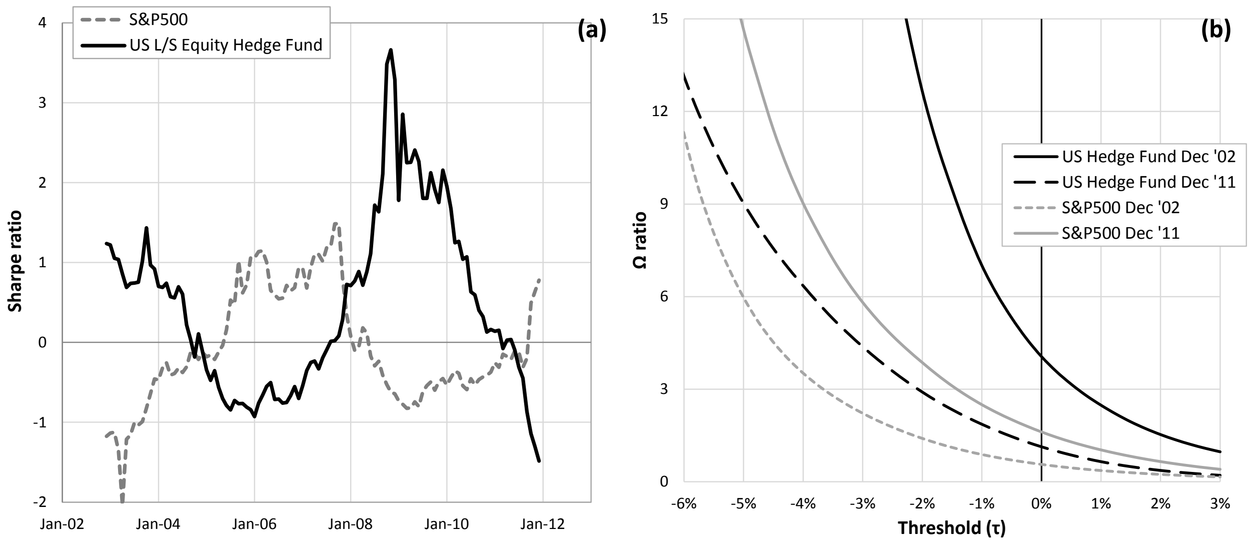
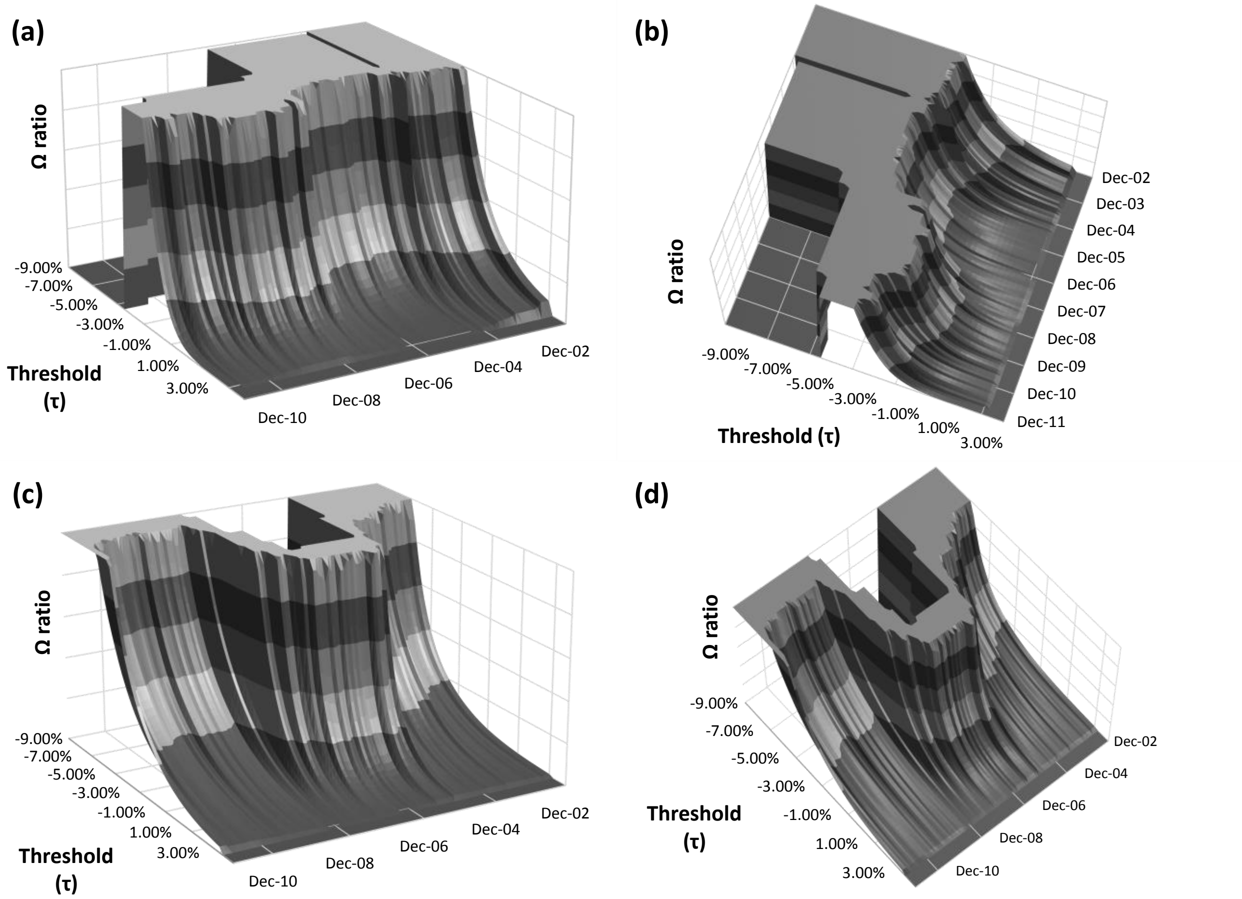


Figure 7 shows the rolling Omega function again for the same randomly selected US long/short equity hedge fund (fund #167) as well as that of the S&P500 from two viewing perspectives. Figure 7 presents these rolling Omega functions from two viewing angles to draw attention to the fact that the viewing perspective can be customised to highlight specific characteristics.

Figure 7: (a & b) Rolling Omega function for US long/short equity hedge fund, and (c & d) rolling Omega function for the S&P500 from different viewing perspectives.



Thus a bonus value of the rolling Omega function lies in the additional perspective through the visualisation that it delivers while the point-in-time Omega function becomes cluttered quickly when graphing a number of Omega functions. By observing the rolling Omega characteristics of the US hedge fund (Figure 7a and b) and comparing it to that of the S&P500 (Figures 7c and d) it indicates this specific funds' rather countercyclical characteristics (compared to the US market). This countercyclical observation from the rolling Omega function is comparable with the information offered by the Sharpe ratio (Figure 6a). Thus given similar input scenarios the rolling Omega ratio tends to show at least as much information as the rolling Sharpe ratio, or stated differently, it shows similar results.

4.2 Comparative Sharpe vs. Omega fund rankings

This section compares the rankings of the sample of hedge funds using both the Sharpe and Omega ratios at different points of economic activity as investors frequently use rankings to differentiate between potential fund investments from unpromising fund investments. The (36-month) rolling Sharpe and Omega ratios are again used, as described in Section 3.4, and three points-in-time were selected in accordance with the phases of this study. Phase 1 (*pre-crisis*) is represented by December 2006, phase 2 (*during*) by December 2009 and phase 3 (*post*) by December 2011. Points-in-time are used as these are required if Omega ratios are to be used, and as Omega functions are not suitable for this exercise.[41] At each point-in-time examined the corresponding risk-free rate for the applicable regional fund mandate is used as the threshold (τ) relevant for the Omega ratio estimations. Owing to space constraints the top and bottom 20 funds in the sample are identified at December 2009

[41] As per Botha (2007), when ranking funds using the Omega measure, the Omega ratio should be used and not the Omega function.

according to the Sharpe ratio, and then ranked backwards and forwards in time within the full fund data sample of 184 funds. Hereafter the Omega ratios are calculated at the relevant points-in-time, the funds ranked and then the fund rankings of the Sharpe and Omega compared.

Figure 8: Sharpe ratio vs. Omega ratio values for the top and bottom 20 funds in the sample for (a) phase 1, (b) phase 2 and (c) phase 3. Sharpe ratio vs. Omega ratio rank for the top and bottom 20 funds in the sample for (d) phase 1, (e) phase 2, and (f) phase 3.

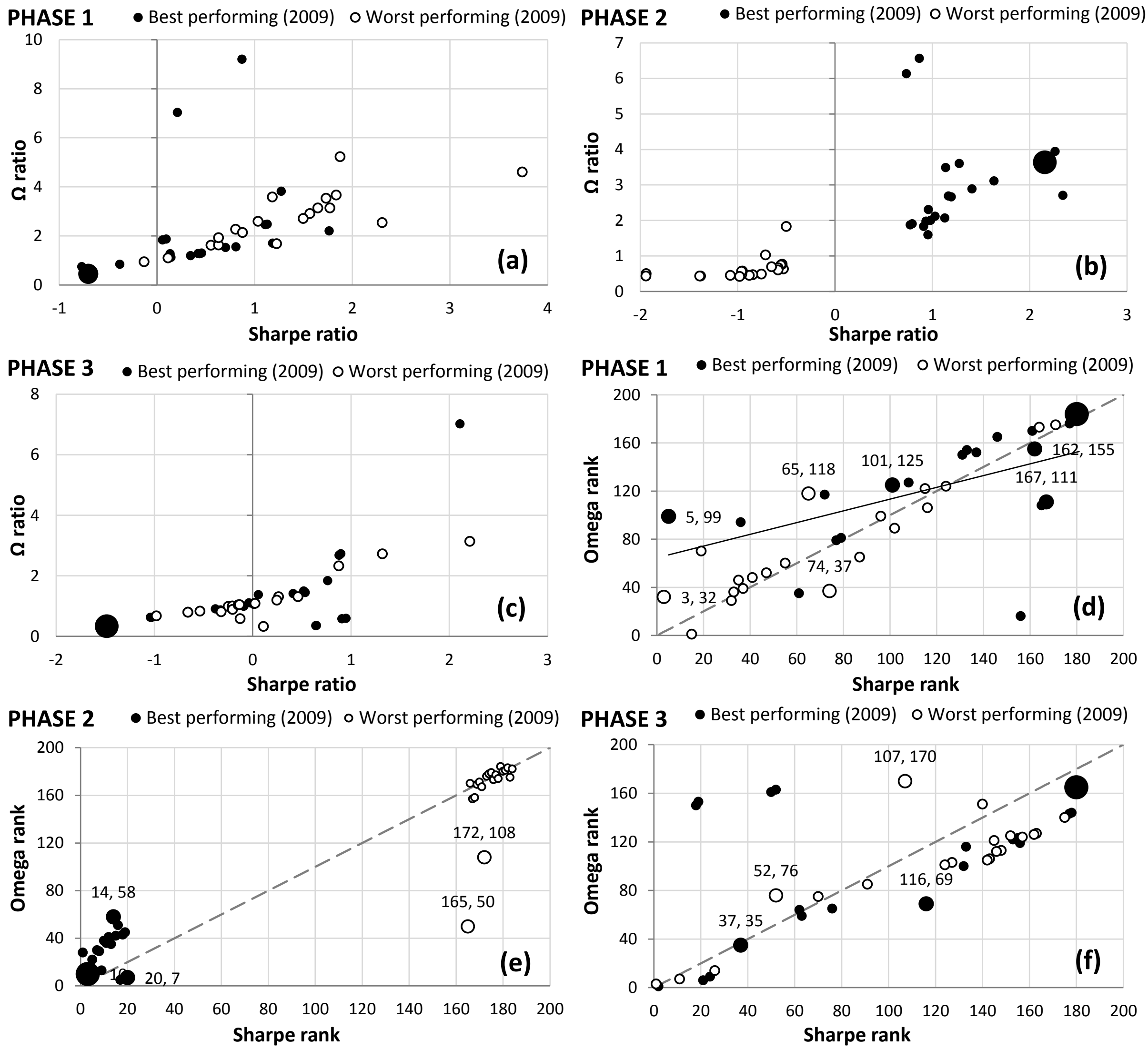


Figure 8 presents comparative Sharpe and Omega values as well as rankings for the top and bottom 20 funds for the three economic phases. Figure 8 clearly indicates the noticeable shift in fund performance during the crisis as opposed to prior, as a visible distinction is evident between strong and weak performing funds. Also evident from Figure 8b (representing the phase during the crisis) is that a large contingent of the top performing funds cluster around a Sharpe ratio equal to 1 - just rewarding investors with a parallel amount of return for the amount of risk taken on-board. Thus even the top performing funds did not deliver exceptional performance compared to performance expectations during normal economic conditions. However, during this particular period this level of performance would be classified as exceptional – and thus why these funds are the top funds during phase 2.

During the crisis period (Figure 8b and 8e) both good and bad performing funds were clearly identified and valued accordingly by both the Sharpe and Omega ratios. The visual results from Figure 8 is also similar to those found by Botha (2007) in that for low Sharpe and Omega ratios the ranking of the funds is alike. However, for higher Sharpe ratios the ranking accuracy deteriorates to a degree – this is, however, interestingly less the case during phase 2 which represents the period during the crisis.

It is moreover apparent that some of the top funds during the crisis performed badly prior to the crisis. This suggests that investors would possibly not have selected these funds prior to the crisis due to mediocre or weak risk-adjusted performance, and yet these funds performed the best during the crisis. As an example of this, see and compare the positioning of the indicated fund (Fund #167 as the larger datum point) in Figures 8a, 8b and 8c.

The comparative fund rankings based on the Sharpe and Omega ratios for phases 1 to 3 are presented in Figures 8d, 8e and 8f respectively. The numbers next to the filled points are the (Sharpe ratio, Omega ratio) rank coordinates.

In the period prior to the financial crisis a wider discrepancy between the Sharpe and Omega ratio rankings existed than compared to the period during the crisis, (this phenomenon is to some extent reinitiated in the post-crisis phase). It is once again visibly clear, although now according to fund rankings, that there was a clear distinction between the best and worst performing funds during the financial crisis period (phase 2). During the crisis period the Sharpe and Omega ratios also generally ranked the funds similarly, although there were a small number of exceptions (see funds in southeast region of Figure 8e). The comparative rankings reiterates the point made earlier that selecting a highly ranked fund prior to the crisis resulted in a weak rank for the same fund during the crisis period – as some of the worst ranked funds during the crisis are ranked rather highly in the period prior to the crisis. As an example of this phenomenon see and compare the ranking position of the indicated fund (fund #167 indicated by larger datum) in Figures 8d, 8e and 8f.

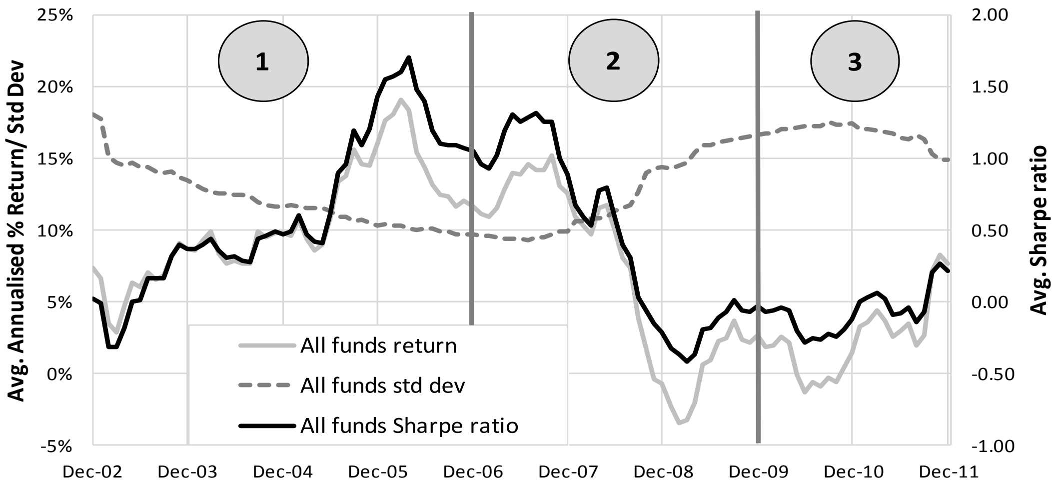
Both Sharpe ratio and Omega ratio rankings agree well for lower rankings, although there is less agreement between the rankings based on these measures for higher ranked funds – these higher ranked will be more closely scrutinised by investors as they will generate the most investor interest. It is, however, interesting that during the height of the 2007 economic crisis these two performance measures were in considerable (fund ranking) agreement for both low and high ranked funds, compared to the economic periods both prior and after the crisis.

4.3 Selective statistics over different economic conditions

This section presents some selective summary performance statistics in the form of returns, Sharpe and Omega ratios for both the hedge funds in this study and relevant benchmarks to these funds in market indices. This highlights the changing characteristics of the funds and their market benchmarks throughout different economic periods, as the statistics are partitioned into three phases. The three phases represent the periods *prior*, *during*, and *post* the 2007 financial crisis. January 2002 until December 2006 constitutes phase 1, January 2007 until December 2009 phase 2, and January 2010 until December 2011 phase 3. This section employs a rolling annual calculation methodology based on 36-months, as discussed in Section 3.4

The changing characteristics of all funds during the three phases are presented in Figure 9 through the average Sharpe ratio as well as the average annual return and standard deviation for all funds employed in this study. Table 6 presents the summary statistics for all funds per phase.

Figure 9: Average annual return and standard deviation and also Sharpe ratio for all hedge funds.



From Figure 9 the impact of the 2007 financial crisis can be seen through a decrease in the average Sharpe ratio of all funds during phase 2. Figure 9 also draws attention to the decrease in average returns across all funds along with the almost simultaneous increase in volatility. Also, mostly during phase 2 which presents the period *during* the 2007 financial crisis, the average Sharpe ratio of all funds falls to below zero which implies that a risk-less asset would have performed better on average during this time compared to the analysed funds sample. The visual results in Figure 9 are echoed in the summary statistics as in Table 6, which shows similar declining average returns and Sharpe ratios for all funds from phase 1 through to phase 3. The average Omega ratios also decreases through time, while interestingly the standard deviation of the returns, Sharpe and Omega ratios reduce over time indicating that the performance spectrum between funds on average diminishes.

Table 6: Summary statistics for all hedge funds per phase.

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Return statistics			Sharpe ratio statistics			Omega ratio statistics		
n	9016	6624	4416	9016	6624	4416	184	184	184
μ	10.41%	6.86%	2.39%	0.63	0.43	-0.07	3.34	1.76	1.27
σ	10.93%	10.20%	8.38%	1.03	0.92	0.54	4.39	2.22	0.88
Median	9.59%	7.33%	2.21%	0.54	0.31	-0.11	2.20	1.11	1.15
Min	-44.96%	-48.39%	-36.57%	-3.79	-1.95	-2.30	0.46	0.42	0.02
Max	59.50%	42.39%	74.37%	5.07	4.39	4.12	32.79	12.98	7.01

The average Sharpe ratios of both funds and their relevant market indices, per region, are presented in Figure 10. From this figure, is it clear that funds and market indices from all the included regions behaved similarly across the three phases. None of the regional funds or benchmarks indicate significantly better performance than any other during or post the financial crisis. However, Asian funds performed better, on average, shortly prior to the crisis but also performed the worst during the crisis period (Figure 10a).

Figure 10: (a) Average fund Sharpe ratios per region and (b) average market index Sharpe ratios, through time.

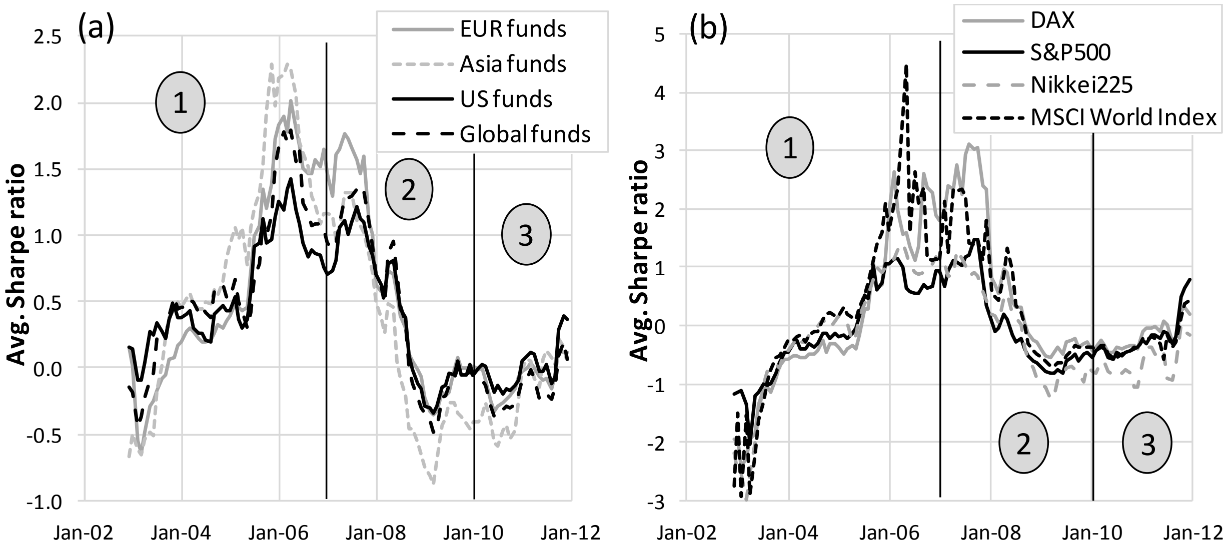
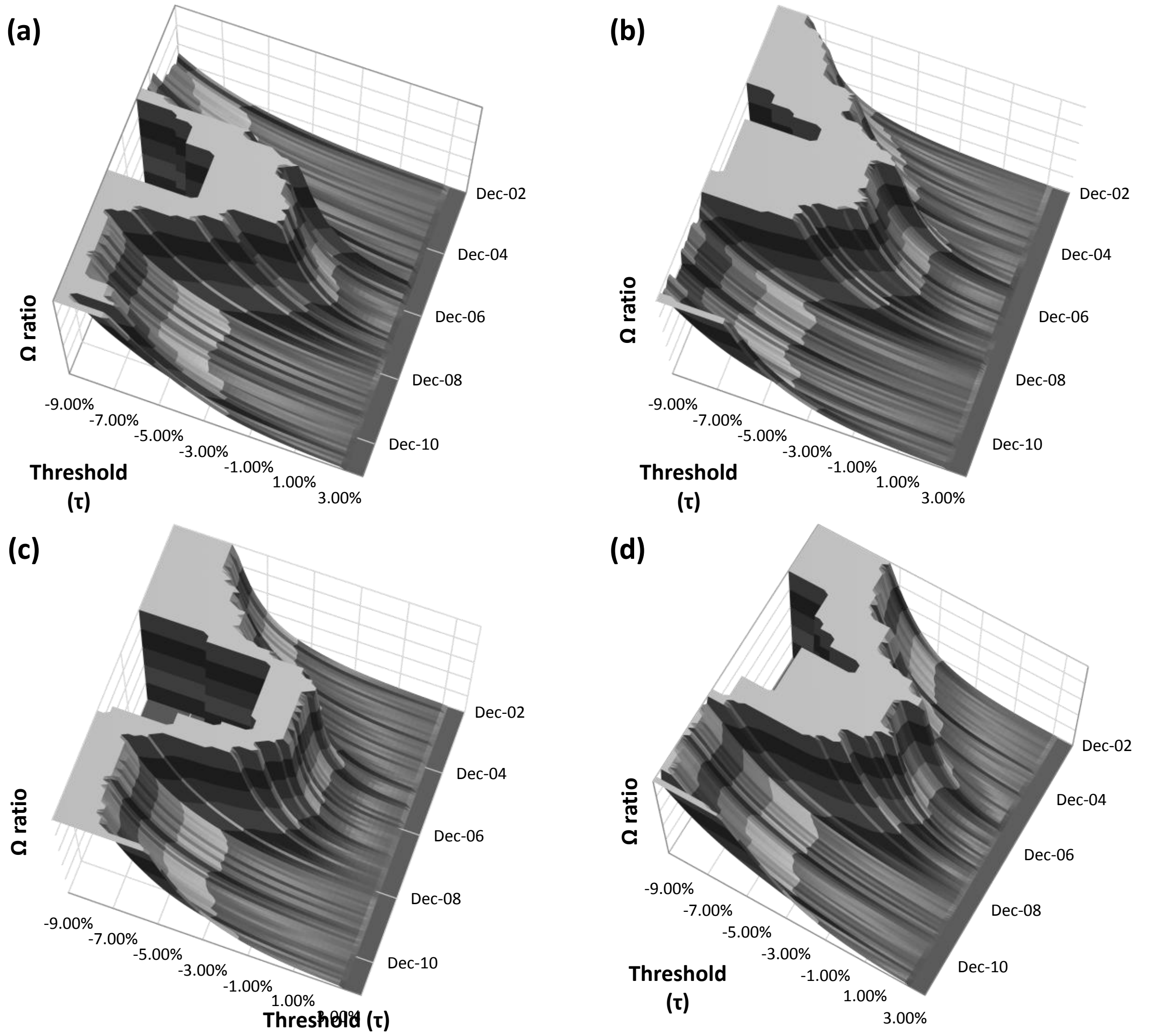


Figure 11: Rolling Omega function for (a) European market index (DAX), (b) Asian market index (Nikkei 225), (c) US market index (S&P500) and (d) World market index (MSCI world index).



The rolling Omega functions for the relevant market indices are shown in Figure 11a through d. The steepness of the slope of the Omega function for all markets dramatically decrease immediately after the onset of the financial crisis. This feature is indicative of an increase in risk as steeper slopes are characteristic of lower risk (less variation in upside and downside variability) compared with flatter slopes. A comparison of slopes shows that the US and European markets (indices) were less risky during the crisis compared with those in Asia and globally.

Table 7 presents the summary statistics in terms of returns, Sharpe and Omega ratios for the funds grouped by regional mandates. Table 8 presents the corresponding summary statistics for the relevant regional market benchmarks.

Table 7: Summary statistics for regionally grouped hedge funds per phase.

	Phase 1	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**
	Return statistics			**Sharpe ratio statistics**			**Omega ratio statistics**		
North American Hedge Funds									
n	4165	3060	2040	4165	3060	2040	85	85	85
μ	10.52%	6.90%	3.45%	0.57	0.41	-0.001	1.83	1.18	1.67
σ	11.16%	10.15%	9.11%	0.94	0.85	0.55	1.06	0.60	0.97
Median	9.61%	7.61%	2.42%	0.49	0.32	-0.07	1.50	1.01	1.51
Min	-44.96%	-48.39%	-36.57%	-2.35	-1.61	-1.92	0.46	0.44	0.33
Max	59.50%	36.52%	68.29%	4.71	4.39	4.12	7.58	3.94	7.01
European Hedge Funds									
n	1862	1368	912	1862	1368	912	38	38	38
μ	8.30%	7.23%	1.52%	0.65	0.58	-0.08	2.59	1.15	1.34
σ	9.49%	9.20%	6.68%	1.19	1.04	0.56	1.29	0.65	0.58
Median	7.42%	7.17%	1.98%	0.51	0.41	-0.11	2.50	0.94	1.28
Min	-23.33%	-16.56%	-18.82%	-2.90	-1.59	-2.19	0.84	0.42	0.42
Max	42.97%	37.65%	32.60%	5.07	4.15	2.40	6.14	3.11	3.14
Asian Hedge Funds									
n	735	540	360	735	540	360	15	15	15
μ	11.32%	3.73%	-1.11%	0.83	0.19	-0.19	2.53	0.93	1.16
σ	11.07%	11.58%	7.15%	1.04	1.01	0.61	0.92	0.49	0.35
Median	10.31%	3.46%	-0.53%	0.77	0.13	-0.11	2.37	0.74	1.87
Min	-16.67%	-22.70%	-18.10%	-2.11	-1.95	-2.30	1.52	0.44	0.67
Max	43.61%	42.39%	14.73%	4.28	2.88	1.13	5.23	1.84	1.86
Global Hedge Funds									
n	2254	1656	1104	2254	1656	1104	46	46	46
μ	11.66%	7.51%	2.29%	0.66	0.44	-0.16	7.02	3.60	0.49
σ	11.31%	10.42%	8.22%	1.05	0.89	0.46	7.49	3.80	0.33
Median	11.47%	7.67%	2.83%	0.59	0.30	-0.18	5.19	2.70	0.39
Min	-29.69%	-33.59%	-24.35%	-3.79	-1.79	-2.07	1.11	1.03	0.02
Max	52.70%	38.64%	74.37%	4.73	3.26	1.82	32.79	19.89	1.77

From Table 7 (above), the mean of both returns and the Sharpe ratios decline moving through phase 1 to phase 3. The mean Omega ratios decline from phase 1 to phase 2, but then interestingly increase in phase 3 – this is not the case for the mean Sharpe ratios. Also of interest is that the returns of Asian hedge funds did not increase into positive territory from phase 2 to phase 3 as the funds from the other regional mandates did (see μ and median for returns in Table 7). This phenomena is again echoed for the Asian market as represented by the Nikkei 225 in Table 8. Comparing the mean returns for the hedge funds per region with their relevant market benchmark it comes to light that although these funds did not perform very well in absolute terms, they did outperform their respective markets in phase 3. In terms of phase 1 return performance, all the funds over performed their respective market benchmarks. The mean Sharpe ratios in phases 2 and 3 of Tables 7 and 8 again highlights that at times it could have served investors better to hold riskless assets rather than investments in these funds or even a basket of the market index.

Table 8: Summary statistics for market indices per phase.

	Phase 1	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**
	Return statistics			**Sharpe ratio statistics**			**Omega ratio statistics**		
n	49	36	24	49	36	24	49	36	24
US Market Index – S&P500									
μ	-1.54%	9.14%	-1.80%	0.0002	0.84	-0.18	1.11	1.09	1.69
σ	19.17%	13.29%	5.63%	1.34	1.30	0.233	0.58	0.56	1.03
Median	-6.02%	10.91%	-3.62%	-0.39	0.36	-0.26	0.93	0.95	1.27
Min	-31.68%	-12.80%	-9.35%	-2.41	-0.56	-0.46	0.41	0.35	0.53
Max	35.05%	26.51%	9.25%	2.64	3.12	0.32	2.41	2.08	4.02
European Market Index – DAX									
μ	0.86%	9.14%	-1.80%	-0.08	0.05	-0.23	1.32	1.90	0.98
σ	9.75%	13.29%	5.63%	0.79	0.77	0.36	0.90	1.17	0.18
Median	1.82%	10.91%	-3.62%	-0.16	-0.20	-0.33	0.86	1.52	0.93
Min	-17.28%	-12.80%	-9.35%	-2.04	-0.82	-0.59	0.37	0.56	0.75
Max	15.14%	26.51%	9.25%	1.15	1.49	0.78	3.80	3.93	1.38
Asian Market Index – Nikkei 225									
μ	1.77%	-1.07%	-11.29%	-0.09	0.06	-0.64	1.36	1.22	0.74
σ	15.69%	14.41%	5.90%	1.13	0.77	0.29	0.84	0.71	0.15
Median	1.29%	3.18%	-12.40%	0.002	-0.17	-0.72	1.05	1.14	0.73
Min	-26.81%	-22.41%	-19.73%	-2.98	-0.82	-1.07	0.37	0.37	0.56
Max	29.24%	17.25%	1.57%	1.43	1.49	0.03	3.43	2.33	1.10
Global Market Index – MSCI World									
μ	6.42%	4.95%	-3.46%	0.29	0.52	-0.28	3.72	4.21	0.35
σ	12.43%	12.88%	6.37%	1.56	1.04	0.26	3.18	3.18	0.06
Median	8.08%	10.02%	-4.66%	0.17	0.38	-0.35	2.46	3.64	0.35
Min	-13.36%	-16.59%	-11.89%	-2.93	-0.69	-0.56	0.84	0.91	0.27
Max	27.41%	20.99%	12.29%	4.48	2.33	0.42	12.18	10.67	0.45

5. SUMMARY AND CONCLUSION

The Omega function was used to augment the Sharpe ratio as a performance measure in the hedge fund context. 'Live', individual, long/short, equity hedge funds, sourced from the Eurekahedge database and spanning geographical mandates that included North America, Europe, Asia and global were used, covering the period January 2000 to December 2011. A Sharpe ratio annualisation method that considers the serial correlation of returns was also used to correct for non-IID errors.

Results were presented in three sections. Firstly, using a 36-month rolling (window) analysis, Omega functions were constructed by estimating the Omega ratio over a range of return thresholds over time. These may assist investors, to (i) observe the change in the Omega function over time for either a fund or its applicable benchmark and (ii) compare the change in the Omega function over time between funds. This additional perspective thus provides investors with information as to how a fund performed during specific periods, for instance the 2007 financial crisis.

Secondly, comparative Sharpe versus Omega fund values and rankings were assembled using the 36-month rolling method at different points of economic activity (*pre*-, *during*, and *post* crisis) to gauge how these measures value and rank funds over changing economic conditions. The top and bottom 20 ranked funds in the data sample were identified at a point during the crisis period according to the Sharpe ratio, and then ranked both backwards and forwards in time within the full data sample. Noticeable shifts in fund performance during the 2007 crisis were observed. A large contingent of top performing funds was also found to cluster around a Sharpe ratio of 1 during this period. A clear distinction is evident between the best and worst performing funds during the crisis period. In comparison the periods prior and post the financial crisis sees a wider discrepancy between the Sharpe and Omega ratio rankings. The fund rankings are alike for funds with low Sharpe and Omega ratios a result similar to that found by Botha (2007) while for higher Sharpe ratios the ranking accuracy deteriorates somewhat – less so in the case during the crisis period. Moreover it is found that some of the top funds during the crisis performed poorly prior to the crisis suggesting that investors would possibly not have selected these funds prior to the crisis due their mediocre or weak risk-adjusted performance. Most interesting is the fact that during the crisis period these two performance measures were in considerable agreement in terms of fund ranking for both low and high ranked funds, compared to the economic period both prior and after the crisis.

Thirdly, to highlight the changing characteristics of hedge funds and their respective market benchmarks over the varying economic conditions around the 2007 financial crisis, a selective statistical analysis of returns was conducted. Results indicate a decrease in the average return as well as a simultaneous increase in volatility across all funds during the crisis period with average Sharpe ratios often falling below zero. Mean Omega ratios increase after the crisis while mean Sharpe ratios do not. Geographically, it was found that funds and market indices from all included regions behave similarly across the three phases and none of the regional funds or benchmarks indicate significantly better performance than another *during* or *post* the financial crisis. In the period prior to the crisis Asian funds performed better, on average. For market indices, an immediate increase in risk after the onset of the financial crisis was observed: North American and European markets (indices) were less risky during the crisis period compared to those in Asia and globally. Hedge funds from all regions outperformed their relevant market indices prior to the crisis.

The need to accurately distinguish between poor and good quality fund returns has not diminished, and in actual fact is ever increasing. Higher moments of the return distributions must be accounted for if accurate fund comparisons (in terms of risk-adjusted returns or fund rankings) are desired.

The Omega function, though not a perfect measure, presents an arguably substantial enhancement compared with traditional performance measures as it describes a large extent of the underlying distribution structure, which is highly relevant and significant to hedge funds. The rolling Omega function also demonstrates its added value as investors can gauge the risk and return characteristics of specific investments, through time, by customising viewing perspectives.

Considerations for future research should, however, be aimed at a method that uses the Omega function when ranking funds as the Omega function considers the full distribution and not just a single return threshold as is the case with the Omega ratio that is currently being used to rank funds.

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CHAPTER 4

HEDGE FUND PERFORMANCE USING SCALED SHARPE AND TREYNOR MEASURES

Hedge fund performance using scaled Sharpe and Treynor measures

Francois van Dyk, Gary van Vuuren & André Heymans

Abstract

The Sharpe ratio is widely used as a performance measure for traditional (i.e. long only) investment funds, but because it is based on mean-variance theory, it only considers the first two moments of a return distribution. It is, therefore, not suited for evaluating funds characterised by complex, asymmetric, highly-skewed return distributions such as hedge funds. It is also susceptible to manipulation and estimation error. These drawbacks have demonstrated the need for new and additional fund performance metrics. The monthly returns of 184 international long/short (equity) hedge funds from four geographical investment mandates were examined over an 11 year period. This study contributes to recent research on alternative performance measures to the Sharpe ratio and specifically assesses whether a scaled-version of the classic Sharpe ratio should augment the use of the Sharpe ratio when evaluating hedge fund risk and in the investment decision-making process. A scaled Treynor ratio is also compared to the traditional Treynor ratio. The classic and scaled-versions of the Sharpe and Treynor ratios were estimated on a 36-month rolling basis to ascertain whether the scaled ratios do indeed provide useful *additional* information to investors to that provided solely by the classic, non-scaled ratios.

Keywords: *hedge funds, risk management, Sharpe ratio, Treynor ratio, Scaled performance measure*

JEL Classification: *C1, C02, C6, G10, G11, G14, G15, G23*

1. INTRODUCTION

In 1949 Alfred Jones started an investment partnership that is regarded as the first hedge fund, although wealthy individuals and institutional investors have been interested in hedge funds or 'private investment vehicles' since around the 1920s (Jaeger, 2003). By 1968 there was an estimated 140 live hedge funds while by 1984 the number had dropped to 68 (Lhabitant, 2002). The mid-1980s saw a revival of hedge funds that is commonly ascribed to the publicity surrounding Julian Robertson's Tiger Fund (Agarwal & Naik, 2002) and to a lesser extent its offshore sibling, the Jaguar Fund (Connor & Woo, 2003). During this time hedge funds became admired for their profitability[1] and since the explosive growth in the hedge fund market during the early 1990s interest in hedge funds and their activities by regulators, investors and money managers has been ever increasing. The interest in hedge funds was further helped along owing to some headline-making news and extravagant hedge fund phenomena, such as the collapse of Long Term Capital Management (LTCM)[2] in the late 1990s, the loss of US$2bn in 1998 by George Soros' Quantum Fund during the Russian debt crisis, Amaranth Advisors[3] in 2006 and the Madoff Ponzi scheme[4] in late 2008. More

[1] An 1986 article in Institutional Investor magazine noted that since its inception in 1980, Tiger Fund had a 43% average annual return (Agarwal & Naik, 2002; Connor & Woo, 2003).

[2] A large US based hedge fund that nearly caused the collapse of the global financial system in 1998 due to high-risk arbitrage bond trading strategies. The fund was highly leveraged when Russia defaulted on its debt causing a flight to quality. The fund suffered massive losses, and was ultimately bailed out with the assistance of the Federal Reserve Bank and a consortium of banks.

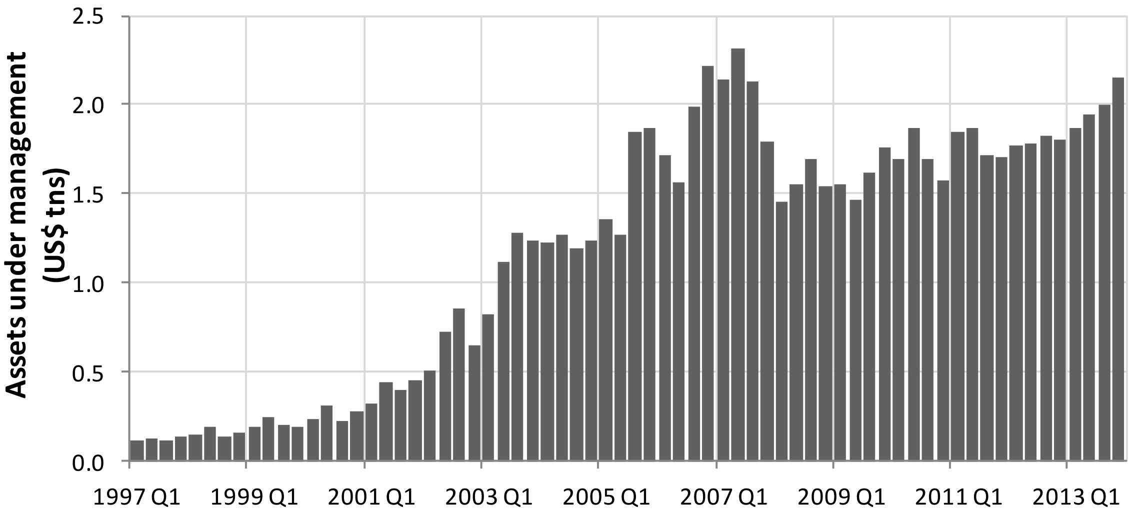
[3] To date, Amaranth Advisors marked the most significant loss of value for a hedge fund. The hedge fund attracted assets under management of US$9bn where after faulty risk models and non-rebounding gas prices resulted in failure for the funds' energy trading strategy as it lost US$6bn on natural gas futures in 2006. Amaranth was also charged with the attempted manipulation of natural gas futures prices. Refer to Till (2007) for further details.

[4] Considered the largest financial scandal in modern times with losses estimated at US$85bn, Madoff Securities LLC provided investors with modest yet steady returns and claimed to be generating these returns by trading in S&P 500 index

recent reasoning behind the heightened interest in hedge funds can be explained by the poor performance exhibited by traditional asset investments (Almeida & Garcia, 2012).

During the 1990s, global investment in hedge funds increased from US$50bn in 1990 to US$2.2tn in early 2007 (Barclayhedge, 2014a). Over the period 2003 to 2007, the hedge fund industry posted its most significant gains, in terms of performance and asset flows, where after the financial crisis growth reduced significantly. Industry growth reversed, declining to US$1.4tn by April 2009 due to substantial investor redemptions and performance-based declines (Eurekahedge, 2012). In 2012 the hedge fund industry suffered US$3.8tn of new outflows (Eurekahedge, 2013c) although during 2013 recovery for the industry was significant as hedge funds attracted net asset flows of US$124.7bn during the first 11 months and also realised their best year of performance-based gains since 2010[5] (Eurekahedge, 2014b). Short bias strategy funds ended 2013 27.15% in the red, thereby surpassing the previous year's record loss of 24.12% (Barclayhedge, 2014b). According to Deutsche Bank's 12th annual Alternative Investor Survey, hedge fund assets under management (AUM) are expected to reach US$3tn by the end of 2014 (Deutsche Bank, 2014). Approximately 80% of respondents to the survey also stated that hedge funds performed as expected or better in 2013,[6] while almost half of institutional investors increased their hedge fund allocation in 2013 and that 57% planned an allocation increase in 2014 (Deutsche Bank, 2014). Figure 1 presents the AUM for the hedge fund industry for 1997 to 2013.

Figure 1: Hedge funds' assets under management (US$tn), quarterly since 1997.



Source: Barclayhedge (2014a).

The recent (2007-9) financial crisis' impact on hedge funds, and their performance compared to more traditional asset classes and benchmarks also make for noteworthy reading. The average annual hedge fund return between 2002 and 2012 was 6.3% (TheCityUK, 2012) compared to 5.7% for U.S. bonds,[7] 7.8% for global bonds[8] and 6.0% for the S&P500. The 2013 comparison notes that the Barclay Hedge Fund Index gained 11.21% (Barclayhedge, 2014b) compared to returns of 29.6% for the S&P500 (CNBC, 2013) and -2.1% for U.S. bonds (Financial Times, 2014). In 2008 the hedge fund industry posted its worst annual performance since 1990 (-20%). In 2011 fund liquidations also rose to 775, an increase of 4% from 743 in 2010. Even though the total number of funds rose to 9 523 in 2011 and further to 10 100 at the end of 2012 (TheCityUK, 2013) this number still (2014) fails to eclipse the

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options employing an index arbitrage strategy. Madoff Securities did, however, commit fraud through a Ponzi scheme structure.

[5] Long/short equities strategies accounted for almost half of the gains in 2013 (Eurekahedge, 2014b).

[6] According to the Deutsche Bank Alternative Investor Survey, allocations to hedge funds returned a weighted average of 9.3% in 2013 according to the. Equity long/short and event driven funds also proved the most sought after strategies (Deutsche Bank, 2014).

[7] U.S. bonds as measured by the Barclays U.S. Aggregate Bond Index.

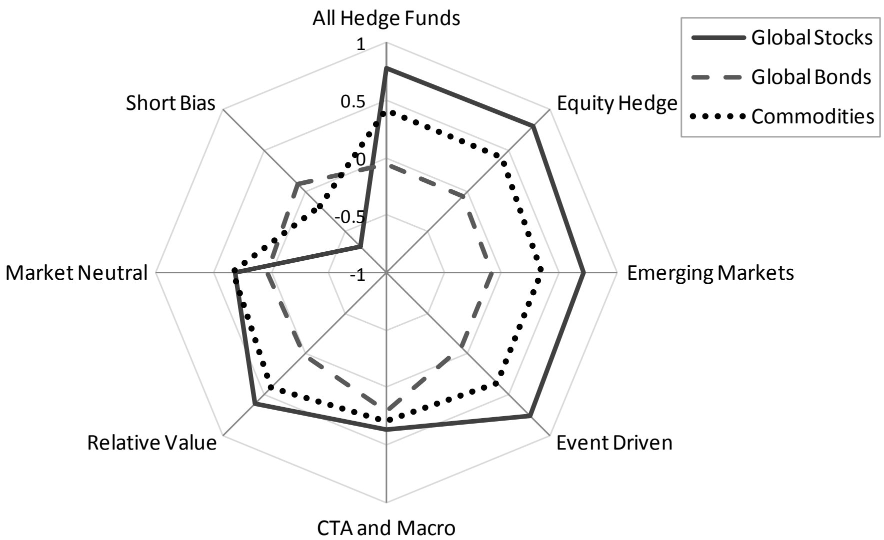
[8] Global bonds as measured by the JP Morgan Global Government Bond Index (unhedged).

pre-crisis peak of 10 096 at the end of 2007 (Clarke, 2012). In terms of the industry's asset size, 2008 saw AUM decline 27% to US$1.4tn (Roxburgh *et al*., 2009) and then even further in March 2009 to US$1.29tbn (Eurekahedge, 2010), reflecting both asset withdrawals and investment losses.

Investor withdrawals subsequent the financial crisis added to poor performance, as it became evident that hedge funds had not "hedged" at all. This has resulted in a high attrition rate[9] (Liang, 1999) which over time has also increased significantly. Only 91% of funds that were alive in 1996 were still alive in 1999, while this declined to 59.5% in 2001 (Kat & Amin, 2001). Kaiser and Haberfelner (2012), in addition, found that since the financial crisis the attrition rate for hedge funds has nearly doubled. In the ruthless world of fund performance, the reporting of monthly returns can exacerbate investor outflows, halt them, reverse them or increase them – depending on the reported figures. A strong incentive to exaggerate or misrepresent fund performance therefore exists, as not only does stronger performance bolster capital inflows, but it also reinforces a fund's existence and increases manager incentive fees (see Goetzmann *et al*., 2007; Bollen & Pool, 2009; Agarwal *et al*., 2011; Feng, 2011). As investors also pay high fees, typically in the vicinity of a 2% management fee and a 20% performance fee, performance evaluation and an accurate performance evaluation methodology are of critical importance to investors (Lopez de Prado, 2013).

Hedge funds are often seen as a way of improving portfolio performance. For both hedge funds and investors, performance measurement is an integral part of investment analysis and risk assessment. It is, however, also the case that investors are enticed to invest in hedge funds for the influential motive that the returns of these funds appear uncorrelated with the broader market. Hedge funds are generally characterised by low correlations with traditional asset classes and hence put forward potentially attractive diversification benefits for asset portfolios (Fung & Hsieh, 1997; Liang, 1999; Kat & Lu, 2002; KPMG, 2012). Figure 2 presents the correlation between various hedge fund strategies and main asset classes for the period 1994 to 2011.

Figure 2: Correlations between hedge funds and main asset classes (Jan. 1994 – Dec. 2011).

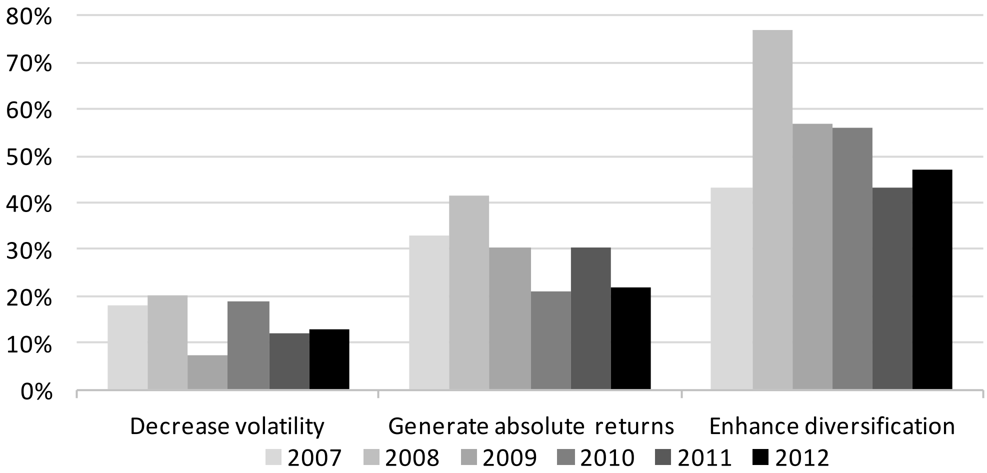


Source: KPMG (2012). Global stocks = MSCI World Total Return Index, Global Bonds = JP Morgan Global Aggregate Bond Total Return Index, Commodities = S&P GSCI Commodity Total Return Index. Hedge fund performance using HFR equal-weighted index and strategy indices.

Survey results from SEI Knowledge Partnership (SEI, 2007; 2009 – 2013) also show that institutional investors are less concerned with achieving absolute returns than they are with obtaining differentiated, non-correlated returns (see Figure 3). Figure 3 also points to the heightened investor demand for the diversification benefit hedge funds offered during the recent financial crisis period.

[9] Liquidation rate of funds.

Figure 3: Primary objective of institutional investors when investing in hedge funds.



Source: SEI (2007; 2009 through 2013). Diversification category includes both diversification and non-correlation with other asset classes.

As these alternative investments, which are hedge funds, embrace a variety of diverse strategies, styles and securities, specifically designed risk assessment techniques and measures are necessitated. Regardless of the potential diversification benefit being offered, these funds remain highly risky investments as stellar returns cannot be obtained without significant risk (Botha, 2007). Malkiel and Saha (2005) also state that although being outstanding diversifiers, hedge funds are risky due to the cross-sectional variation and the range of individual hedge fund returns being far greater than those of traditional asset classes. Hedge fund investors thus take on considerable risk in selecting a poorly performing or failing fund.

Although most comparisons of hedge fund returns concentrate exclusively on total return values, comparing funds with different expected returns and risks in this manner is meaningless. The arrangement of risk and return into a risk-adjusted number is one of the primary responsibilities of performance measurement (Lhabitant, 2004). According to Eling and Schuhmacher (2006) financial analysts and, often, individual investors rely on risk-adjusted return, i.e. performance measures in order to select among available investment funds, and since the seminal work of Jensen (1968), Treynor (1965) and Sharpe (1966), performance measures have been the focus of much attention from both practitioners and researchers. These measures are mostly used by researchers to evaluate market efficiency while practitioners use them in at least two instances: (i) to evaluate past performance (in the hope that the measure is a reliable indicator of future performance), and (ii) to measure performance and compare the results of one fund to its competitors or those of a representative market of benchmark (Nguyen-Thi-Thanh, 2010). Nguyen-Thi-Thanh (2010) argues that in the literature on portfolio performance evaluation, two kinds of portfolio performance measures come to light. The first kind evaluates the fund managers' skills,[10] i.e. their timing and selectivity ability and include measures such as Treynor, Jensen and other multi-factor models. The second kind includes measures such as the Sharpe ratio which relates to measures that lead to complete fund ranking. The latter type are primarily used in the first, or screening, phase to create a shortlist of the best performing funds on which further detailed quantitative and or qualitative analysis will be applied, before the investment decision is made. To warrant that performance measures are not easily gamed by unskilled managers and also that investors do not pay manager for strategies that they themselves can easily replicate,

[10] A rich literature has developed on methodologies that test for fund manager skills. These techniques can be classified into two main approaches; (i) returns-based performance evaluation, and (ii) portfolio holdings-based performance evaluation (Wermers, 2011).

Chen and Knez (1996) propose that a performance measure should; (i) be fit for purpose, i.e. be reasonably useable, (ii) be scalable, (iii) be continuous and (iv) exhibit monotonicity.[11]

Evidence indicates that fund managers are not fully using the performance measurement techniques proposed by the literature. The results of a 2008 survey by Amenc *et al*., (2008) indicate that the majority of survey respondents do not use sophisticated approaches and that a large gap exists between practices and academic models. The survey results highlight that the Sharpe ratio (80%) and the Information ratio (80%) are the most widely used performance evaluation measures among asset managers. Amongst hedge funds, the Sharpe ratio is the metric of choice and also the most commonly used measure of risk-adjusted performance (Lhabitant, 2004; Opdyke, 2007; Schmid & Schmidt, 2007). Proposed by Sharpe as the "reward-to-variability" ratio as a mutual fund comparison tool (see, Sharpe, 1966, 1975, and 1994) the ratio is both conceptually simple and rich in meaning, providing investors with an objective, quantitative measure of performance. It enjoys widespread use and various interpretations, but it also has its drawbacks. Being unsuitable for dealing with asymmetric return distribution are, among others a drawback of volatility measures (Lhabitant, 2004; Almeida & Garcia, 2012). Academic criticism of the classic capital asset pricing model (CAPM) performance measure is not new and a number of authors have pointed out the shortcomings of using both the Sharpe ratio for performance evaluation and the mean-variance framework for portfolio construction when the underlying returns distributions are highly non-symmetric. According to Almeida and Garcia (2012) the key is to risk-adjust hedge fund payoffs in a manner that account for the asymmetry (tail risk exposures) created by the dynamic strategies hedge funds pursue. A suitable risk-adjusted performance measure for hedge funds will therefore not only be based on returns' means and volatilities, which are not adequate given the deviations from normality exhibited by hedge fund returns, but also on higher-order moments of the hedge fund returns distribution. Similar reasoning brought Leland (1999:30) to the conclusion that is additionally described as a daunting task - "any risk measure in this world must capture an infinite number of moments of the return distribution".

This brings forward the aim of this study of evaluating whether scaled (risk-adjusted) performance measures, in the form of scaled Sharpe and Treynor[12] ratios, should augment the use of the classical or traditional Sharpe and Treynor ratios when evaluating hedge fund risk and consequently in the investment decision-making process. The rationale behind this is that the scaled performance measures provide a more suitable evaluation of hedge fund risk-adjusted performance since the traditional Sharpe and Treynor ratios are ill-suited to hedge funds.

The analysis is built upon data sourced from the Eurekahedge database. It contains data from 184 'live' hedge funds which have a developed market focus from four geographical investment mandates. The analysis covers the years 2000 through 2011, which is advantageous for three reasons. First, the results do not suffer from survivorship and backfilling biases to the same extent that plague a greater amount of the older hedge fund research.[13] Second, unlike many other studies that are limited to analysis that only include bull markets,[14] the chosen time period contains bull and bear markets, allowing fund analysis in different market conditions. Third, the chosen time period contains a critical event, the 2007-9 global financial crisis, which is considered in additional detail during analysis and in sub-periods.

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[11] The assignment of higher measures for more skilled managers and lower measures for less-skilled ones (Chen & Knez, 1996).

[12] Reasons for the inclusion of the Treynor ratio (in this study) are: (i) the Treynor ratio it is a commonly used performance measures, (ii) the Treynor ratio suffers from a similar drawback to the Sharpe ratio due to not accounting for higher-order moments of the return distribution, (iii) the addition of the Treynor ratio differentiates this study as numerous studies pertaining to the incorporation of higher-order moments into the Sharpe ratio have been conducted, and (iv) the addition of the Treynor ratio adds another element of analysis to the study.

[13] Prior to 1994 most hedge fund data vendors (databases) did not cover dissolved hedge funds. Hedge fund data prior to 1994 are thus not very reliable. The unreliability of data prior to 1994 is discussed by Fung and Hsieh (2000), Liang (2000) and Li and Kazemi (2007).

[14] Capocci *et al*. (2005) found that the market phase may influence the results. Ding and Shawky (2007) stress the importance of considering different market cycles when analysing hedge fund performance. Also see Brown *et al*. (1999).

The methodology used in this study is based on the ratio scaling methodology by Gatfaoui (2012), while this study also builds upon and differentiates itself from the prior research in the following manners:

- A (36-month) rolling (geometric) analysis period is used compared to the static (month-by-month) methodology of Gatfaoui (2012).
- The data time-series include periods from *pre*, *during* and *post* the recent financial crisis, compared to the research data by Gatfaoui (2012) that only include the periods *pre* and *during* the crisis.
- The ratio analysis and comparisons are performed on 'live' individual hedge funds as well as market and hedge fund indices from four geographical investment mandates. The comparative ratio analysis by Gatfaoui (2012) focuses solely on various hedge fund strategy applicable market indices.

The remainder of this paper is structured as follows: Section 2 presents an existing literature overview of hedge fund performance measurement, alternative performance measures and the ill-suitedness of the Sharpe ratio as a hedge fund performance measure. Section 3 introduces the scaled Sharpe and Treynor measures as well as the data and methodology employed. Section 4 presents the analysis and results and Section 5 concludes.

2. LITERATURE STUDY

2.1. Hedge fund performance measurement

In the hedge fund industry performance is of considerable import as not only is investor returns based on fund performance, but hedge fund manager compensation is also tied to fund performance. As a result, performance *measurement* is an integral part of investment analysis and risk management. The literature on the topic is abundant and controversial.

Fund performance evaluation can be classified into two major approaches: (i) returns-based and (ii) portfolio holdings-based. Both approaches have been applied by researchers in simplistic as well as more sophisticated and innovative manners, and each approach has its advantages and disadvantages (Wermers, 2011). Returns-based approaches, for instance, rely on less information from fund managers and is therefore particularly useful where little information is disclosed, such as in hedge fund markets. Returns data are available on a more frequent basis even where portfolio holdings are on hand. The returns-based performance approach is, however, the focus of this study.

The abundance of literature on performance measurement in the hedge fund industry stems from the fact that performance measurement is a key facet of the quantitative analysis required in the rigorous process of fund selection. Géhin (2006) describes (quantitative) fund selection as more than a challenging task on account of: (i) the increasing number of funds, (ii) short fund track records, (iii) fund managers not having equal talent, and (iv) the hedge fund universe's opacity. The quantitative analysis of hedge funds consequently requires genuine expertise and must moreover be sophisticated. The controversial nature of the literature can arguably also be attributed to the numerous qualities of hedge funds, as these funds invest in a heterogeneous range of asset classes[15] and that a broad range of strategies are covered that are in turn characterised by different risk and return profiles.[16] The same reasons responsible for the abundance and controversial nature of the literature can arguably also be attributed as the reasons behind specific focus areas being especially prominent within the literature, for instance - the choice of performance measure in hedge fund performance evaluation, the role of the measure choice on performance evaluation[17] and the consistency of these measures. Prior research

[15] Examples of the financial assets that hedge funds invest in include, equities, bonds, swaps, currencies, sophisticated derivative securities, convertible debt and mortgage-backed securities.

[16] Hedge funds can for example employ directional and non-directional strategies. Directional strategies aim to benefit from market trends and include fund strategies such as macro, short-selling and emerging markets. Non-directional strategies have weak correlation with the related market and include strategies such as distressed securities, market neutral, convertible arbitrage and event driven.

[17] See for example Eling & Schuhmacher (2006), Nguyen-Thi-Thanh (2007, 2010) and Prokop, (2012).

on hedge fund performance rankings produced by common risk-adjusted performance measures also shows remarkable homogeneity[18], and thus results in the same investment decision. Even though prior and current hedge fund performance studies have been criticised for the performance methods employed and conflicting conclusions, these studies contribute to a growing improvement in the understanding of alternative investments. Identifying a performance measure that can serve as a robust proxy for a number of other measures could thus significantly aid performance measurement by private and professional investors (Prokop, 2012).

Lastly, unlike traditional investments that invest only in traditional asset classes, hedge funds include options and derivative products. These sophisticated financial instruments create various further complications seeing that the commonly used performance measures, which were developed based on modern portfolio theory, were specifically designed for traditional asset classes or investments and in particular for equity investments.[19] The key task of performance measurement, however, remains to condense risk and return into one useful risk-adjusted number (Lhabitant, 2004) that can thereafter be used to make sound investment decisions.

2.2. Inadequacy of traditional performance measures

Risk-adjusted performance measures can be classified into one of two categories, namely 'absolute' or 'relative' performance measures. The former is considered such as no benchmarks are used in the calculation with the Sharpe and Treynor ratios being the most common measures within this category. Jensen's alpha (Jensen, 1968) is an example of a relative risk-adjusted performance measure and in contrast to absolute performance measures these employ a benchmark (Géhin, 2006).

The Sharpe ratio is one of the most commonly cited statistics in financial analysis and the metric of choice amongst hedge funds, particularly as a measure of risk-adjusted performance (Lo, 2002; Lhabitant 2004; Opdyke, 2007; Schmid & Schmidt, 2007; Koekebakker & Zakamouline, 2008). Also known as the risk-adjusted rate of return, it measures the relationship between the risk premium[20] and the standard deviation of the fund returns (Sharpe, 1966, 1975, 1992, 1994). Another popular indicator of fund performance is the reward to variability or Treynor ratio (Treynor, 1965), and is defined through the relation of the risk premium and systematic risk[21] of the portfolio (beta).[22] The Sharpe and Treynor ratios are similar in that they both divide the fund's excess return by a numerical risk measure. The Sharpe ratio, however, employs total risk, which is appropriate when evaluating the risk return relationship of a poorly diversified portfolio while the Treynor ratio uses systematic (market) risk, which is the relevant measure of risk when evaluating a fully diversified portfolio (Jagric *et al*., 2007). For fully diversified portfolios, total and systematic (market) risk are equal, and fund rankings based on total risk and systematic risk should be identical for a well-diversified portfolio.[23] Despite the widespread use of these measures they do have some failings.

Parameters and statistics for both the Sharpe and Treynor ratios in expected returns, volatilities and beta[24] are non-observable quantities and, as they must be estimated, these are fraught with estimation errors.

The Sharpe ratio's statistical properties have been afforded only modest consideration, which is surprising given that the accuracy of the Sharpe ratio's estimators rely on the statistical properties of returns and that these may be very different among portfolios, strategies and over time (Lo. 2002).

[18] See for example Kooli *et al*. (2005), Nguyen-Thi-Thanh (2007) and Prokop, (2012).
[19] Some factors have been included to suit other asset classes (Sharpe, 1992; Elton *et al*., 1993)
[20] Risk premium is defined as the additional expected return from holding a risky asset rather than a riskless asset – i.e. the difference between the expected return (on an investment) and the estimated risk-free return.
[21] Systematic risk is also known as "market risk", "undiversifiable risk" or "volatility".
[22] The Treynor ratio, unlike the Sharpe ratio, should not be used on a stand-alone basis as beta is a measure of systematic (market) risk only. This is so as Choosing a stand-alone investment portfolio on the basis of the Treynor ratio may be inclined to maximise excess return per unit of systematic (market) risk, but not excess return per unit of total risk except if each investment is well diversified (Anson *et al*., 2012).
[23] This is the case as the total risk is reduced (through diversification) to leave only systematic risk.
[24] Beta consists of variance and co-variance.

The performance of more volatile investment strategies is more difficult to determine compared to less volatile strategies (Lo, 2002). Since hedge funds are generally more volatile than more traditional investments (Ackermann *et al*., 1999; Liang 1999), hedge fund Sharpe ratio estimates are likely to be less accurate. Several statistical tests that look into comparing Sharpe ratios between two portfolios have been proposed by Jobson and Korkie (1981), Gibbons *et al*. (1989), Lo (2002) and Memmel (2003). Conversely, the unavailability of multiple Sharpe ratio comparisons has led to the search and development of alternative approaches (e.g. Ackermann *et al*., 1999; Maller & Turkington, 2002). It is nonetheless apparent that a more refined Sharpe ratio interpretation approach is necessary whilst information pertaining to the investment style or strategy and also the market environment which produced the returns should possibly be considered by such an approach. Additionally, it has been established that the Sharpe ratio is susceptible to manipulation (e.g. Spurgin, 2001; Goetzmann *et al*., 2002, 2007).

The Treynor ratio also has its drawbacks. Firstly the measure validity depends significantly on the hypothesis that the fund's beta is stationary.[25] The selection of the correct benchmark is also critical when employing the Treynor ratio (Eling, 2006; Ambrosio, 2007).

The assumption of normally distributed returns is widely considered the most significant drawback of both measures, as both are based on the mean-variance framework which employs the Capital Asset Pricing Model (CAPM) methodology. Strong assumptions underlie the CAPM, *e.g.* (i) returns are normally distributed, and (ii) investors care only about the mean and variance of returns, so upside and downside risks are viewed with equal dislike (Leland, 1999). Hedge fund returns distributions and their markedly non-normal characteristics have been extensively portrayed in the literature (see, e.g. Fung & Hsiesh, 2001; Lo, 2001; Brooks & Kat, 2002; Malkiel & Saha, 2005). Brooks and Kat (2002) established that hedge fund indices show evidence of low skewness and high kurtosis while Eling (2006), Eling and Schumacher (2006) and Taleb (2007) found hedge fund return distributions to be negatively skew and to possess positive excess kurtosis.[26] [27]

Also, under the CAPM methodology the appropriate measure of risk is represented by beta while the named CAPM assumptions rarely hold in practice. Even if the underlying assets' returns are normally distributed, the returns of portfolios that contain options on these assets, or use dynamic strategies will not be (Leland, 1999).Hedge funds generally employ dynamic investment strategies, with accompanying dynamic risk exposures and these have important implications for investors who seek to manage the risk/reward trade-offs of their investments (Chan *et al*., 2005). For this reason, hedge fund performance is often summarised with multiple statistics.[28] While beta is an adequate risk measure for static investments, there is no single measure capturing the risks of a dynamic investment strategy (Chan *et al*., 2005). Linear performance measures can often not capture the dynamic trading strategies that several hedge funds pursue (Agarwal & Naik, 2004) whilst hedge funds make use of a range of trading strategies. Analysing all hedge funds using a singular performance measurement framework that does not consider the characteristics of the specific strategies is of limited value. Therefore it is necessary for hedge fund style specific performance measurement models or measures to capture the differences in management style (Fung & Hsieh, 2001, 2004; Agarwal & Naik, 2004). A large number of equity-orientated hedge fund strategies also bear significant (left-tail) risk that is ignored by the mean-variance framework[29] (Lhabitant, 2004).

Asymmetric distributions further influence the validity of volatility as a risk measure, which in turn impacts the exactness of the Sharpe ratio. Volatility solely measures the dispersion of returns around

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[25] i.e. that the fund manager does not adapt the portfolio's weights according to future market variation expectations (Eling, 2006).

[26] Hedge fund index returns and market benchmarks exhibit generally the same stylised facts, i.e. negative skewness and positive excess kurtosis (Gatfaoui, 2012).

[27] Investors show a preference for high first (mean) and third (skewness) moments and low second (standard deviation) and fourth (kurtosis) moments (Scott & Horvath, 1980).

[28] E.g. mean, standard deviation, Sharpe ratio, market beta, Sortino ratio, maximum drawdown etc. (Chan *et al*., 2005).

[29] These left-tail risks originate from hedge fund strategies that exhibit payoffs resembling a short position in a put option on the market index (Lhabitant, 2004).

their historical average and since positive and negative deviations (from the average) are penalised in an equivalent manner in the computation, the concept is only logical and legitimate for symmetrical distributions (Lhabitant, 2004). In reality, return distributions are neither normal nor symmetrically distributed, and so even when two investments have an identical mean and volatility, they may exhibit substantially different higher moments. This is especially true for strategies that entail dynamic trading, buying and selling of options and active leverage management (Lhabitant, 2004) – all strategies regularly employed by hedge funds. The return distributions of such strategies are highly asymmetric and possess "fat tails", which leads to volatility being a less-meaningful measure of risk. The relevance of the dispersion of returns around an average has also been queried from an investor's viewpoint, as most investors perceive risk as a failure to achieve a specific goal such as a benchmark rate (Lhabitant, 2004). In such circumstances, risk is only considered as the downside of the return distribution and not the upside: the difference is not captured by volatility (Lhabitant, 2004). Also, investors are more adverse to negative deviations than to positive deviations of the same magnitude (Lhabitant, 2004).

2.3. Alternative risk performance measures

Lhabitant (2004) gives the drawbacks of volatility as a measure of risk as the reason behind the search for alternative risk measures. The Sharpe ratio's denominator (volatility) is replaced by an alternative measure of risk in many alternative risk performance measures. For example, under the mean-downside deviation framework Sortino and Price (1994) as well as Ziemba (2005) substitute standard deviation by downside-deviation. Other downside risk measures, such as the Calmar ratio[30] (CR), Sterling ratio[31] and Burke ratio[32] use drawdown[33] in the denominator to quantify risk.

Gregoriou and Gueyie (2003) propose a modified Sharpe ratio, under the mean-VaR framework, as an alternative measure specifically for hedge fund returns by employing a Modified VaR[34] (MVaR) in place of standard deviation as the denominator. Also, Dowd (2000) uses a VaR measure as a standard deviation replacement, whilst conditional VaR (CVaR)[35] can be used as well. In addition, the Stutzer index is another performance measure that is slightly different yet still relevant. The Stutzer index is founded on the behavioural hypothesis that investors aim to minimise the probability that the excess returns over a given threshold will be negative (Stutzer, 2000).

Performance measures based on lower partial moments (LPMs) include the Omega ratio and the Kappa measure. The Omega ratio expresses the ratio of the gains to losses with respect to a chosen (return) threshold (Shadwick & Keating, 2002) and it implicitly adjusts for both skewness and kurtosis in the return distribution. An Omega ratio conversion, the Omega-Sharpe ratio, generates ranking statistics that are in similar form to the Sharpe ratio and identical to Omega rankings. The Kappa measures, as introduced by Kaplan and Knowles (2004), generalises the Sortino and Omega ratios. Also of importance is the Sortino ratio which is a natural extension of the Sharpe and Omega-Sharpe ratios that uses downside risk in the denominator (see Sortino & van der Meer, 1991).

Alternative performance measures' compatibility with utility functions has also led to familiar generalisations of the Sharpe ratio. The generalised Sharpe ratio (GSR) (Hodges, 1998) is an extension of the Sharpe ratio and delivers equivalent fund rankings to the traditional Sharpe ratio when returns are normally distributed and the utility function is exponential. The advantage of the

[30] The Calmar ratio (CR) is the quotient of the excess return over risk-free rate and the maximum loss (i.e. maximum drawdown) incurred in the relevant period (Young, 1991).

[31] The Sterling ratio uses the average of a number of the smallest drawdowns, within a certain time period, to measure risk (Lhabitant, 2004).

[32] The Burke ratio expresses risk as the square root of the sum of the squares of a certain number of the smallest drawdowns (see Burke, 1994).

[33] Drawdown is defined as "the decline in net asset value from the highest historical point" (Lhabitant, 2004:55), and thus describes the loss incurred over a certain period of time (Wiesinger, 2010).

[34] The standard VaR only considers mean and standard deviation while modified VaR considers both the means and the standard deviation as well skewness and (excess) kurtosis.

[35] Artzner *et al*. (1997) introduced Conditional VaR (CVaR) to remedy against the shortcoming that VaR does not make a statement about the loss if VaR is exceeded.

GSR is that its range of applicability extends to any type of return distribution while its main drawbacks being its restriction to exponential utility functions and that it requires an expected utility maximisation. The Adjusted Sharpe ratio (ASR), a natural extension compatible with utility theory, uses a Taylor series expansion of an exponential utility function to account for return distributions' higher moments (see Koekebakker & Zakamouline, 2008). Pezier and White (2006) further suggest making use of the ASR which explicitly corrects for higher moments by including a penalty factor for negative skewness and excess kurtosis.

Several of these alternative performance measures, however, fall short of having firm theoretical foundations (considering the Sharpe ratio is based on the expected utility theory) and do not permit accurate ranking of portfolio performance given that ranking based on these measures depends significantly on the choice of threshold. Most of these measures also only consider downside risk while the upside potential is not accounted for. Performance measures with a VaR foundation also have a number of problematic failings (Wiesinger, 2010). For instance, VaR is criticised for not being a coherent risk measure, as far as non-normal distributions are concerned, as it does not conform to the requirements[36], specifically to that of the sub-additivity property, and thus does not support diversification. Although VaR remains a popular measure of risk, it is sensitive to the underlying parameters and the employed calculation method whilst also relying on the risk factors being normally distributed, making this measure flawed in a hedge fund context. The Conditional Value-at-Risk (CVaR)[37] based Sharpe ratio, called the Conditional Sharpe ratio (CSR), overcomes essential standard deviation defects by replacing the Sharpe ratio's denominator (i.e. standard deviation) with CVaR. Not only is CVaR a coherent risk measure (Pflug, 2000), but it is also considered a more consistent measure of risk than VaR and can be used in risk-return analysis similar to the Markowitz mean-variance approach (Rockafellar & Uryasev, 2000).

3. METHODOLOGY AND DATA

3.1. Scaled Sharpe and Treynor ratios

Traditional risk-adjusted performance measures such as the Sharpe and Treynor ratios (Treynor, 1965; Sharpe, 1966) are founded on a Gaussian return assumption and a mean-variance efficient state. Asset returns, and specifically hedge fund returns, however, often violate the Gaussian assumption (Fung & Hsieh, 1997; Lo, 2001; Eling, 2006; Taleb, 2007) and hedge fund strategies' returns are known to exhibit (persistent) patterns of skewness and kurtosis (Eling & Schuhmacher, 2006).[38] Employing classic performance measures for performance assessment is therefore a biased approach as these classic measures do not account for return distribution's higher moments. For instance, standard deviation as used in the denominator of the classic Sharpe ratio as a proxy for risk does not appreciate positive skewness, which is commonly considered an attractive feature for a rational investors (see for example, Kraus & Litzenberger, 1976 and Kane 1982), but on the contrary penalises for it. Concerns pertaining to comparability in risk assessment and asset performance valuation thus produce a need for robust and reliable performance measures, which account for higher returns distribution moments – skewness at least, and kurtosis when possible. The scaled Sharpe and Treynor ratios, as used in this study, are adjusted modifications of these well-known performance measures to account to some extent for skewness and kurtosis that describe the deviations from normality. Thus the classic Sharpe and Treynor ratios are adjusted for asymmetries in both the upside and downside deviations from the mean asset returns by weighting the upside and downside deviation risks. This accounting for skewness and kurtosis generally alters hedge fund performance ranking.

[36] See requirements (of a coherent risk measure) proposed by Artzner *et al*. (1997).

[37] CVaR is also called mean excess loss, mean shortfall or tail VaR.

[38] It is well known that hedge fund return distributions' deviations from normality are statistically significant Zakamouline (2011) and that hedge fund return distributions are negatively skew with positive excess kurtosis (Eling, 2006; Eling & Schumacher, 2006; Taleb, 2007). According to Black (2006) skewness and kurtosis also reflect the event and liquidity risks taken on by hedge funds while Brooks and Kat (2002) highlight the high Sharpe ratios in the presence of negative skewness and positive excess kurtosis.

Adjustments to classical performance measures to account for return asymmetries, remains relevant and further contributes to the literature on performance evaluation that takes non-normality of return distributions into account.

3.2. Data

A total of 26 496 monthly returns, net of management and performance fees,[39] from 184 'live' individual[40] hedge funds between January 2000 and December 2011 were used. These monthly returns were sourced from a Eurekahedge database data extract and funds with an incomplete monthly return history for the chosen period were not considered. As hedge funds universally report performance figures on a monthly frequency, this basis was used as it is also compatible with investors' month-end, holding-period return. Hedge fund databases can potentially suffer from several biases that may have a significant impact on performance measurement. The data do not suffer from the most common biases of the variety; survivorship, backfilling, or sampling while selection bias cannot be dealt with as it would call for access to returns from hedge funds that decide not to report.

Summary statistics, in monthly percentages, for the hedge fund returns as well as some other apposite information is presented in Table 1. The t-statistics indicate that the mean returns are significantly different from 0 at the 5% significance level of all funds. Moreover, 29 out of the 184 funds (15.8%) show evidence of normal distributions at the 5% significance level, using the Jarque-Bera (JB) test, while the left over 155 funds (84.2%) exhibit non-normal distributions.

Table 1: Summary statistics for long/short Equity hedge funds.

	All Funds	**North America**	**Europe**	**Asia**	**Global**
No. of funds	184	85	38	15	46
Sample size	26 496	12 240	5 472	2 160	6 624
Mean Age (years)	15.8	16.5	14.3	14.4	16.1
Mean Size (US$m)	188	143	145	87	346
Return statistics					
μ	0.66	0.76	0.55	0.34	0.66
$t\ (\mu = 0)$	22.48	16.14	11.49	3.92	10.64
σ	4.8	5.2	3.5	4.0	5.1
Median	0.6	5.2	0.6	4.0	0.6
Min	-56.7	-56.7	-20.0	-22.4	-54.7
Max	76.2	76.2	29.6	19.2	39.8
Skewness	0.75	1.14	0.49	-0.15	0.05
Kurtosis	18.4	22.3	10.0	4.9	9.6
ρ_1	0.29	0.21	0.74	0.43	0.21
ρ_2	0.03	0.15	0.59	0.31	0.23
ρ_3	0.02	0.01	0.55	0.29	0.21
p-value of LB-Q	0.00	0.01	0.00	0.00	0.01

The overall significance of the first k autocorrelation coefficients is measured by the Ljung-Box Q-statistic and is asymptotically χ_k^2 under the null hypothesis of no autocorrelation.

All of the funds included are categorised as long/short equity (strategy) funds. This strategy of fund was favoured as this particular strategy is the largest among hedge funds, comprising 35% of the industry (Brown, *et al*., 2009). More recent figures, as at the end of November 2013, confirm that the long/short strategy is the most sought after as this strategy attracted US$78bn of the US$1.99tr that make up the total assets in the hedge fund industry (Eurekahedge, 2013c). All funds are mandated

[39] Raw returns usually produce upward biased performance measures since fees tend to positively skew related performance measures. According to Wermers (2010) this drawback advocates the use of net-of-fees returns in that net returns represent a real performance proxy for hedge funds.

[40] Meaning not fund of funds, which are funds holding a portfolio of other investment funds, or commodity trading advisors (CTA), but funds that invest directly in securities.

only in highly liquid markets as funds mandated in developing markets were omitted from the sample - this ensured that funds are equity funds holding liquid instruments. Consequently it can be assumed that all securities held have readily available prices and that no subjective valuations are required. This practice also minimises the stale price bias within the data sample (Géhin, 2006). As an analytic indication of liquidity the first-order return autocorrelation (ρ_1) of all but two geographical areas are ≤ 0.30 (Getmansky *et al*., 2004). The near zero levels of autocorrelation, for liquid securities such as equity funds, are also consistent with those found by Bisias *et al*. (2012).

An informational breakdown of the representative geographical mandates of the funds as well as the relevant risk-free rate proxies accordingly used are presented in Table 2. Data on the risk-free rates were sourced from the Federal Reserve Bank of St. Louis (FRED) and Bloomberg.

Table 2: Breakdown of geographical mandates of funds & risk-free rate proxies.

Geographical mandate	# funds	Risk-free rate proxy
North America*	85 (46%)	10-year Treasury bond rate (US)
Europe	38 (21%)	10-year Treasury bond rate (Germany)
Asia	15 (8%)	10-year Treasury bond rate (Japan)
Global	46 (25%)	JPMorgan Global Government Bond Index

*Includes one Canadian fund (RFR = 10-year Treasury bond rate (Canada)).

As a proxy for the European geographical areas risk-free rate, the use of the German 10-year Treasury bond rate is generally accepted[41] (Damodaran, 2008), although a number of alternative options exist.

Hedge funds are commonly weighed against passive benchmark[42] indices,[43] even though hedge funds (particularly long/short strategy funds) are absolute investments. The data on the passive market benchmark indices were sourced from Bloomberg whereas hedge fund benchmark indices were sourced from Eurekahedge, Hedge Fund Research (HFR) and Barclahedge. Table 3 exhibits the market and hedge fund benchmark indices used.

Table 3: Market and hedge fund benchmark indices.

Benchmark Market Indices	Region specific	
S&P500, S&P TSX*	North America	
DAX	Europe	
Nikkei 225	Asia	
MSCI World Index	Global	
Benchmark Hedge Fund Indices	**Region specific**	**Style specific**
Eurekahedge North America Long/short Equities Index	North America	Long/short Equity
Barclayhedge European Equities Index	Europe	Equities
Eurekahedge Asian Hedge Fund Index	Asia	-
Hedge Fund Research (HFR)(X) Global HF Index	Global	-

*The S&P TSX was used for the sole Canadian fund that forms part of the North American regional mandate.

The summary return statistics for the market and hedge fund benchmark indices for the period January 2000 until December 2011 are presented in Table 4. Table statistics are drawn from the monthly returns with the monthly means and standard deviations in percentages.

[41] Part of the logic for this practice being commonly accepted is that Germany is the largest issuer of bonds in the European geographical area.

[42] Lhabitant (2004:116) defines the term benchmark as "an independent rate of return (or hurdle rate) forming an objective test of the effective implementation of an investment strategy".

[43] Incipient hedge fund performance was not compared relative to a benchmark. According to Lhabitant (2004) hedge fund managers are hired for their skills and they should be allowed to venture wherever their value-creating instincts lead them, without considering benchmarks. Thus hedge fund portfolios should aim to produce positive absolute returns rather than to outperform a particular benchmark.

Table 4: Summary statistics for market and hedge fund benchmark indices.

	S&P500	DAX	S&P TSX	Nikkei 225	Global Index+	L/S HF Index*
Sample size	144	144	144	144	144	144
μ	0.004	0.12	0.35	0.39	0.28	0.76
$t\ (\mu = 0)$	0.01	0.21	0.92	0.81	0.06	3.78
σ	4.71	6.72	4.55	5.80	4.90	2.4
Median	0.60	0.73	1.01	0.13	1.17	0.99
Min	-16.9	-25.4	-16.9	-23.8	-25.48	-6.5
Max	10.8	21.4	11.2	12.9	14.06	10.6
Skewness	-0.43	-0.52	-0.86	-0.53	-1.42	0.01
Kurtosis	3.66	4.88	4.58	3.89	5.16	4.86
ρ_1	0.13	0.07	0.22	0.12	0.31	0.20
ρ_2	-0.07	-0.06	0.07	0.06	0.03	0.04
ρ_3	0.12	0.10	0.06	0.11	0.19	0.04
p**-value of LB-Q**	0.10	0.39	0.01	0.15	0.00	0.01

+ Global index = MSCI World Index.

* L/S HF Index = Eurekahedge North America long/short Equities Index.

Both hedge fund and market indices exhibit non-normal distributions using the Jarque-Bera test at the 5% significance level.

3.3. Methodology

A 36-month rolling (window) period, beginning in January 2000, was used to estimate the relevant statistics and ratios. Monthly returns and risk-free rates were transformed to a geometric annualised basis using the 36-month rolling period.

The annualised Sharpe and Treynor ratios were calculated from monthly returns that are not independently and identically distributed (IID). According to Lo (2002) a computation bias arises when annual Sharpe ratios are computed from monthly means and standard deviation by multiplying by the square root time, in this case $\sqrt{12}$, as monthly returns data are annualised. Lo (2002) continues that the method of computing annualised Sharpe ratios by multiplying by the square root of time is more suitable when returns are IID, but when returns are non-IID an alternative procedure that considers serial correlation (of returns) must be used. It is also well established that hedge fund returns exhibit significant first-order auto-correlation (see Books and Kat, 2002) and this first-order auto-correlation introduces a serial dependence that, by itself, explains why returns are both non-identically distributed and non-normal. Thus the IID normal assumption is not supported by hedge fund returns data and although the assumption is often used it can be described as “a convenient leap of faith that simplifies the math involved” (Bailey & Lopez de Prado, 2013). Also, the IID normal assumption is often said to be justified on a sufficiently large sample under Central Limit Theorems (CLTs) – this is false, as CLTs require either independence or at least weak dependence, and normality is also not evident over time in the presence of dependence. Although the measure proposed by Lo (2002), known as the $\eta(q)$SR or annualised autocorrelation adjusted Sharpe ratio, is founded and its use advocated, this study does not employ it as the focus is fully on the scaling methodology concerning the named risk-adjusted performance measures that account for higher (returns distribution) moments. Purely for the purpose of illustrating the impact of the Lo (2002) annualised autocorrelation adjusted Sharpe ratio methodology a selection of comparative summary statistics, using the 184 long/short equity hedge funds, are conveyed in Table 5. Note that the summary statistics in Table 5 are based on annualised geometric returns over a 36-month rolling period with the sole aim of presenting a statistical comparison between the annualised Sharpe ratio computation methods. For further details pertaining to the adjustment for non-IID returns refer to Lo (2002).

Table 5: Comparative Sharpe ratio summary statistics (all figures annualised).

	Sharpe Ratio	SC-adjusted Sharpe Ratio
Sample size	20 056*	20 056
μ	0.38	0.41
σ	0.85	0.95
Median	0.26	0.25
Min	-2.1	-3.8
Max	3.5	5.1
Skewness	0.49	0.73
Kurtosis	2.86	3.92

*184 funds × 109 (144-35) monthly returns.

Using the 36-month rolling method, monthly time-rolling annualised Sharpe and Treynor ratios were estimated in both traditional or classic and scaled forms for each fund and relevant market and hedge fund indices. Equation (1) was used to estimate the traditional or classic Sharpe ratio (Sharpe, 1966, 1975, 1992, 1994; van Vuuren *et al.*, 2003):

$$SR = \frac{r_p - r_f}{\sigma_p \sqrt{t}} \tag{1}$$

where r_P is the cumulative portfolio return measured over t months, r_f is the cumulative risk-free rate of return measured over the same period. σ_p is the portfolio volatility (risk) measured over t months using the conventional standard deviation formula, namely:

$$\sigma_p = \frac{1}{T-1}\sum_{t=1}^{T}(r_t - \mu)^2 \tag{2}$$

where r_t is the portfolio return, measured at t-intervals over the full period under investigation, T, and μ is the average portfolio return over the full period. The scaled Sharpe ratio (SSR) was calculated using (Gatfaoui, 2012):

$$SSR = W_-\left(\frac{r_{p-} - r_f}{\sigma_{p-}}\right) + W_+\left(\frac{r_{p+} - r_f}{\sigma_{p+}}\right) \tag{3}$$

where SSR is a skew-specific adjusted risk premium (SSRP) with S_- and S_+ being left-skew specific (LSSARP) and right-skew specific (RSSARP) adjusted risk measures respectively – thus effectively downside and upside Sharpe ratios. r_{p-} and r_{p+} are monthly returns below and above the monthly arithmetic average return for the rolling 36-month period respectively.[44] Similarly, σ_{p-} and σ_{p+} represent the standard deviation of the returns as identified as either below or above the monthly arithmetic average return for the rolling 36-month period. $W_- = n_-/n$ and $W_+ = n_+/n$ are weights, based on the monthly returns and the monthly arithmetic average return within the corresponding 36-month rolling period, and r_f is the risk-free rate. Upon the completion of classifying returns into either the upside or downside based on the 36-month rolling arithmetic average return, both upside and downside returns and standard deviations were estimated in a geometric annualised fashion using a 36-month rolling period.

The traditional Treynor ratio was estimated by using (Treynor, 1965):

$$TR = \frac{r_{p,t} - r_{f,t}}{\beta_p} \tag{4}$$

[44] Returns equal to the (36-month rolling) monthly arithmetic average return are classified as r_{p-}.

where r_P is the annualised portfolio return measured over t months, r_f is the annualised risk-free rate of return measured over the same period. β_p is the beta (systematic risk) of the portfolio using the conventional beta formula, namely:

$$\beta = \frac{cov(r_p, r_m)}{\sigma_m^2} = \frac{cov(r_p - r_{f,} r_m - r_f)}{\sigma_m^2} \tag{5}$$

The scaled Treynor ratio (STR) was calculated using (Gatfaoui, 2012):

$$STR = \frac{r_p - r_f}{\beta^*} \tag{6}$$

$$\text{with } \beta^* = \frac{W_{m-}\,\sigma_{pm-} + W_{m+}\,\sigma_{pm+}}{W_{m-}\,\sigma_{m-}^2 + W_{m+}\,\sigma_{m+}^2}$$

where

$\sigma_{m-}^2 = \sum_{t=1, m_t \leq \mu_m}^{n} (m_{t-}\mu_m)^2 / n_{m-}$,

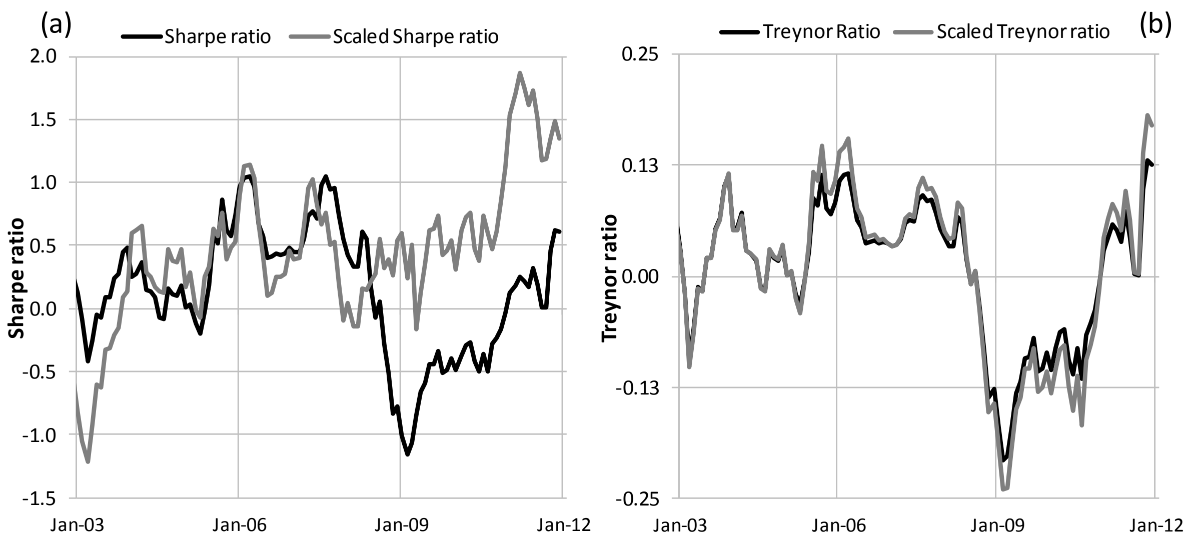
$\sigma_{m+}^2 = \sum_{t=1, m_t > \mu_m}^{n} (m_{t+}\mu_m)^2 / n_{m+}$,

$\sigma_{pm-} = \sum_{t=1, m_t \leq \mu_m}^{n} \left(p_t - r_f\right)(m_t - \mu_m)/n_{m-}$ and

$\sigma_{pm+} = \sum_{t=1, m_t > \mu_m}^{n} \left(p_t - r_f\right)(m_t - \mu_m)/n_{m+}$.

$W_{m-} = n_{m-}/n$ and $W_{m+} = n_{m+}/n$ are weights, based on the monthly returns and the monthly arithmetic average return within the corresponding 36-month rolling period. Similar to the scaled Sharpe ratio, the monthly scaled Treynor ratio estimations are geometrically annualised, although portions of the estimation procedure are carried out using monthly returns and monthly arithmetic averages. Figure 4 presents a comparative illustration of the traditional and the scaled versions of both the Sharpe and Treynor ratios.

Figure 4: Comparative illustration of traditional vs. scaled versions of (a) Sharpe ratio, and (b) Treynor ratio for fund #109, a North American fund.



The subsequent section presents analysis and results by first highlighting how ill-suited the Sharpe ratio is for use within a hedge fund context due to the non-normality of hedge fund returns. The section will also explore comparative fund rankings between classic or traditional risk-adjusted measures and scaled versions of these measures that account for higher moments of the hedge fund returns distribution. To conclude, the section will present some comparative selective statistics over different economic phases.

4. ANALYSIS AND RESULTS

4.1. Inappropriateness of the Sharpe ratio (non-normal returns)

Higher moment estimates of the returns data are presented in Table 6 which indicates that funds from all the geographical mandated areas exhibit, mostly positive, excess skewness (> 0.50), with the exception of globally mandated funds. Asian funds exhibit negative skewness. Table 6 also shows that the fund returns from all geographical areas are severely leptokurtic.

Table 6: Hedge fund higher moment estimates.

	All Funds	North America	Europe	Asia	Global
Skewness	0.75	1.14	0.49	-0.15	0.05
S.E. Skewness (SES)	0.18	0.27	0.40	0.63	0.36
Kurtosis	18.40	22.29	10.01	4.87	9.58
S.E. Kurtosis (SEK)	0.36	0.53	0.79	1.26	1.44

According to the Jarque-Bera (JB) test only 29 out of the 184 funds (15.8%) exhibit normal distributions at the 5% significance level, whereas the remaining 155 funds (84.3%) show evidence of having non-normal returns distributions. Figure 5 depicts the returns distribution's state of normality for both the relevant market indices (Figure 5a) and the funds (Figure 5b) through time. Figure 5a and Figure 5b are both constructed using 36-months of rolling monthly data whereas the thresholds for distribution normality at the 1% and 5% significance levels are represented by the two horizontal dotted-lines. Jarque-Bera (JB) test statistical values below these thresholds are indicative of normal distributions at the relevant level of significance.

Vertical lines are also used to partition Figures 5a and 5b into three periods or phases. Each of these three periods corresponds to a specific stage relating to the 2007 financial crisis; (1) *pre*-crisis, (2) *during* the crisis, and (3) *post*-crisis (i.e. after the height of the crisis). According to Figure 5a some of the market indices pass the (rolling) goodness of fit test for normal return distributions, by means of the JB-test statistic, at either or both the 1% and 5% significance levels (represented by the horizontal dotted-lines). The instances where some market indices do pass as normal distributions, however, only occur in limited cases and for short and limited time spans. Figure 5b shows that funds from all regional mandates are non-normal for the full time period under investigation with the exception of Asian funds that exhibit return distribution normality but only for November 2006 – this is, however, fairly insignificant considering the Asian funds are, on average, only deemed normal for 1 out of 109 rolling months. Also evident, from Figure 5b, is the rapid and elaborate increase (further) away from normality during 2008, along with the high non-normality for North American and European funds. By also comparing the average normality of funds for a specific regional mandate to its relevant market index, it is apparent that trends, trend changes and the magnitude of change do, for the most part, not coincide, while at certain times rather odd comparative behaviour is observed.

Figure 5: (a) Rolling JB-test statistic of relevant market indices and (b) average rolling JB-test statistic for all funds and also for hedge funds per geographical mandate, over time.

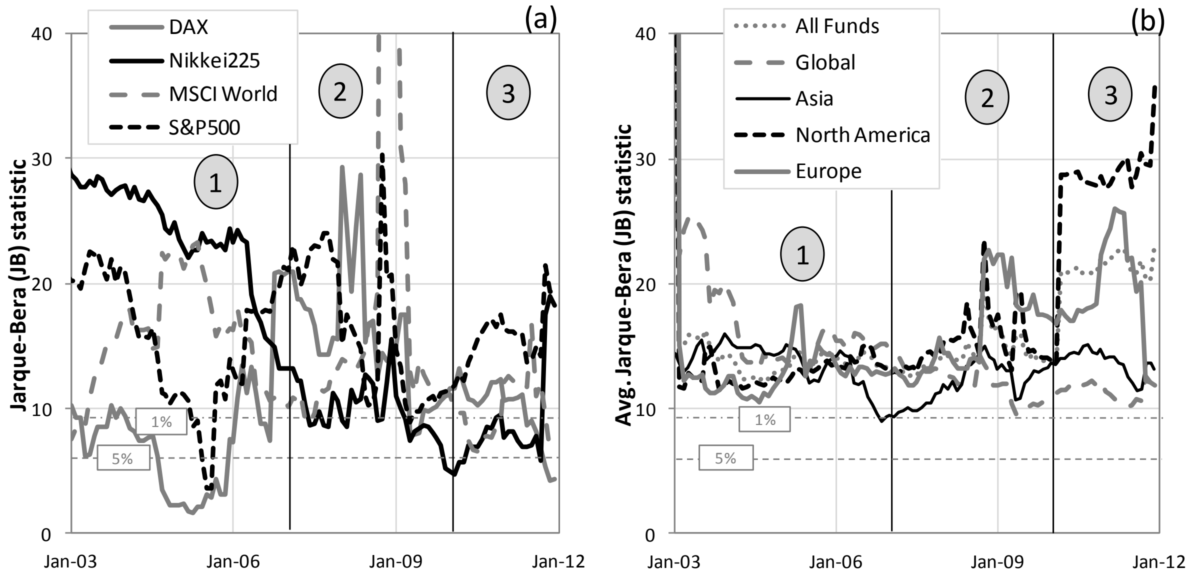
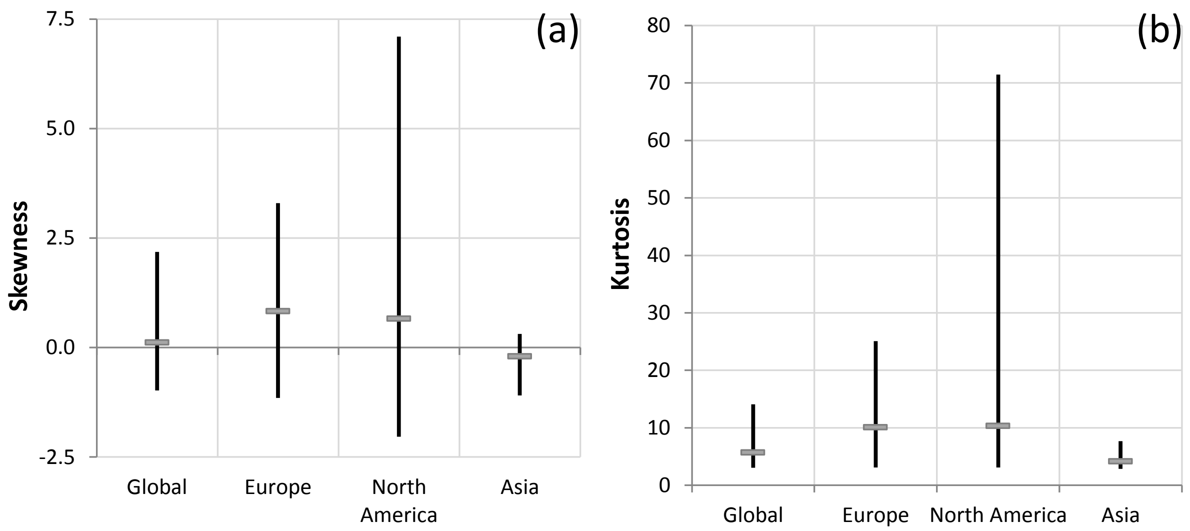


Figure 6a shows the skewness and Figure 6b the kurtosis of the funds grouped per geographic region.

Figure 6: (a) Skewness of individual funds per region and (b) kurtosis of individual funds per region.



Figures 5 and 6 collectively with Table 6 confirm that most of the return distributions of these hedge funds are not ideally suited for Sharpe ratio application. The 15.8% (29 of 184) of funds that show evidence of normal distributions as per the JB-test might be possible exceptions – however, this will require investors to test each fund for normality before applying the Sharpe ratio, which is far from ideal. To further reveals how ill-suited these funds' return distributions are to Sharpe ratio application, not only at a point-in-time but also through time, the rolling skewness and kurtosis are presented in Figure 7. Using the 36-month rolling period, Figure 9 shows the average skewness (Figure 7a) and kurtosis (Figure 7b). Figure 7 is also partitioned into three periods by way of vertical lines – each period again representing a specific period relating to the 2007 financial crisis, consistent with those declared earlier (see Figure 5).

Figure 7: Average values, through time, for (a) skewness – all funds, (b) kurtosis – all funds, (c) skewness – funds per region and (d) kurtosis – funds per region.

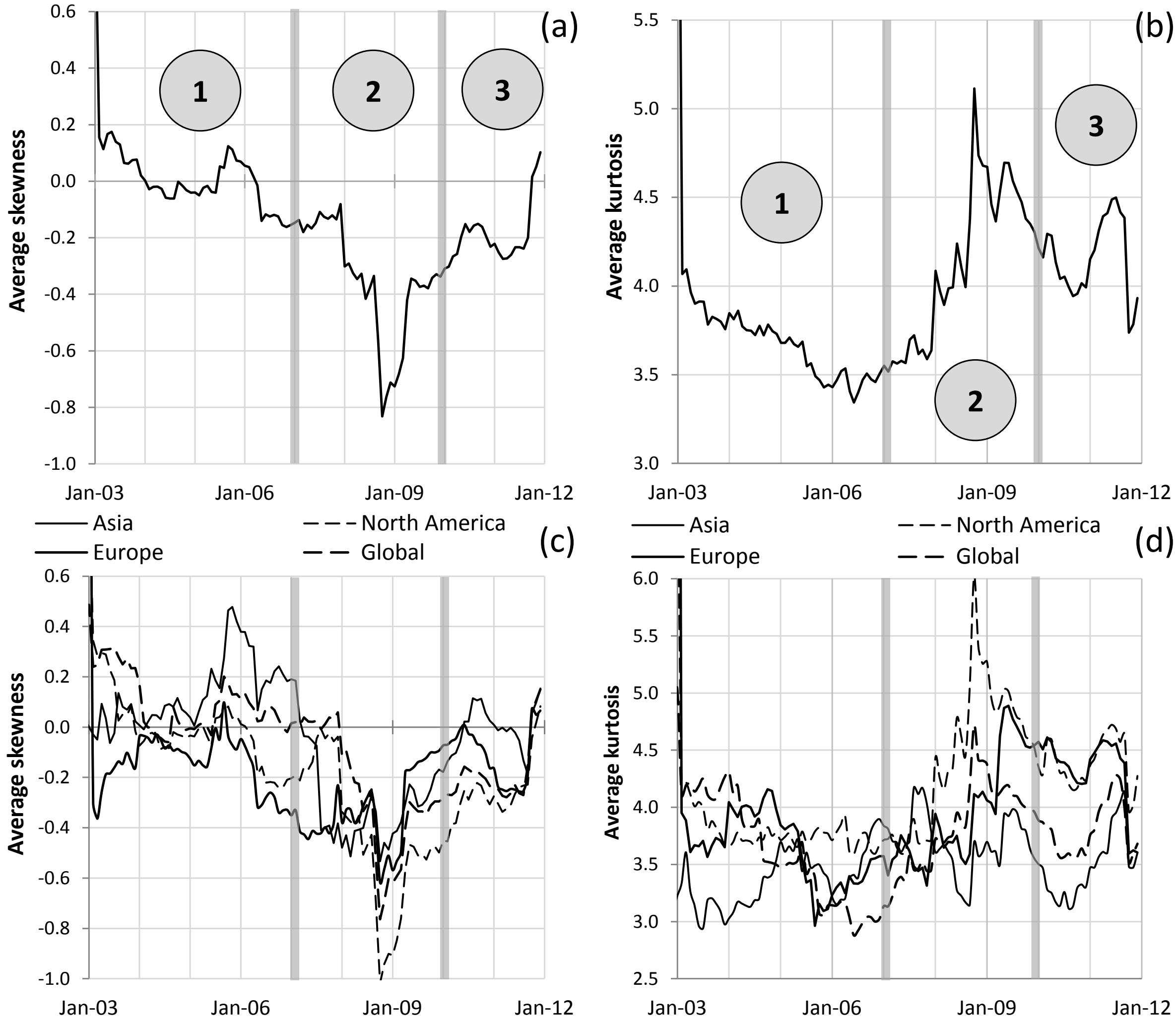
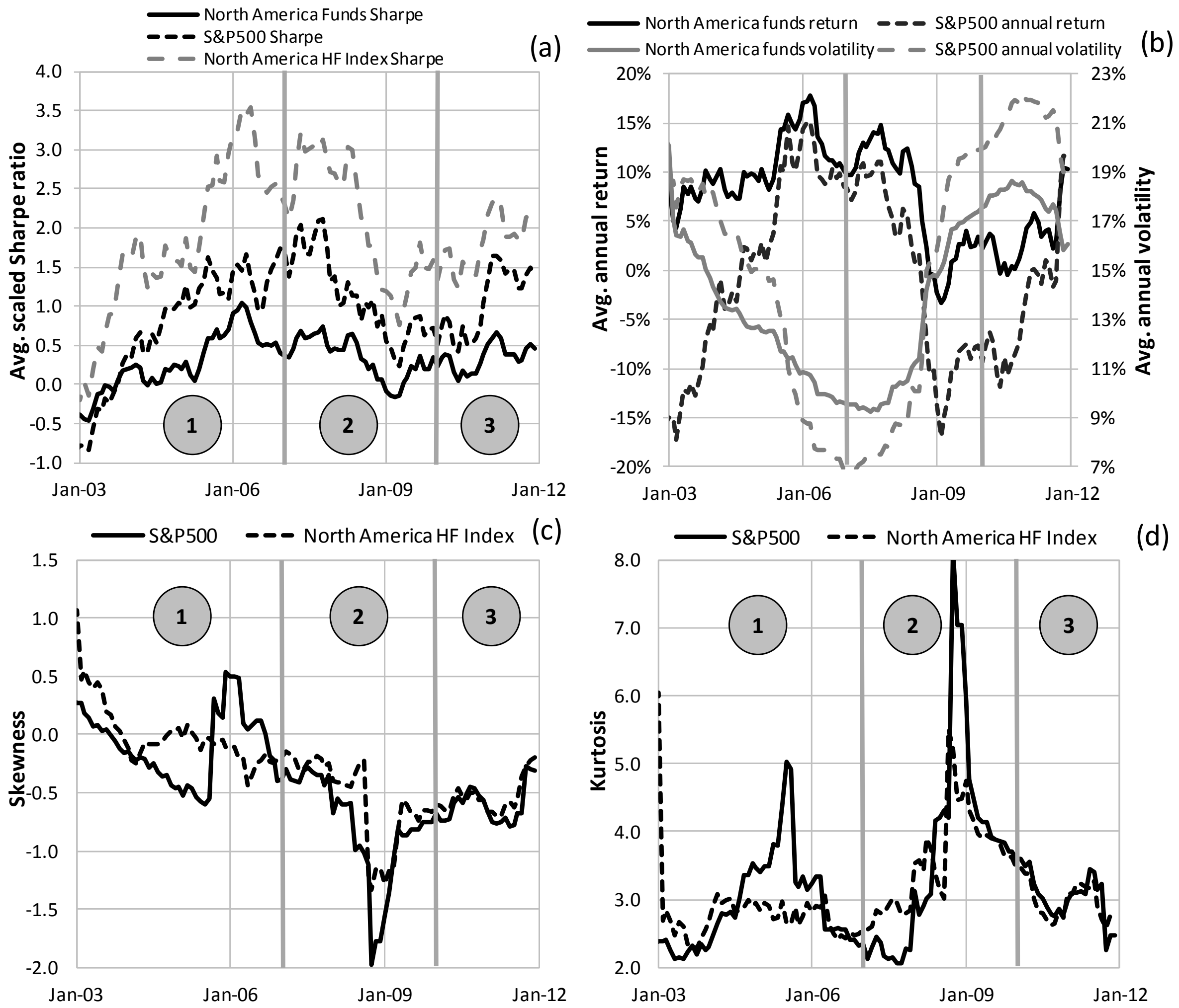


Figure 7 shows that during the 2007 crisis period the average skewness turned considerably negative, whereas average kurtosis, which was at high level prior, reached extreme levels. Figure 7 can thus be added to Figures 5 and 6 and Table 6, thereby strengthening the case that the (traditional) Sharpe ratio is not adequately compatible with the return distributions of these hedge funds as these distributions exhibit non-normal characteristics.

When considering a specific geographic region, for example North America as presented in Figure 8, the relevant statistics also indicate to the non-normality of returns for North American funds as well as the North American market index (S&P500) and the North American hedge fund index. Figure 8 was constructed using the rolling period analysis method and statistics are presented on an annual basis.

Figure 8: (a) Average scaled Sharpe ratio: North America funds vs. S&P500 vs. North America HF Index, (b) average annual return and volatility: North America funds vs. S&P500, (c) skewness: S&P500 vs. North America HF Index, and (d) kurtosis: S&P500 vs. North America HF Index.



* Hedge fund index in Figure 10 = Eurekahedge North America Long/Short Equities Hedge Fund Index.

The higher moments of the hedge fund benchmarks, as depicted in panels (c) and (d) of Figure 8, also indicate the inappropriateness (of these return distributions) for the use of the Sharpe ratio. Panels (c) and (d) also indicate the altered behaviour for these higher moments of the return distribution around the time period of the recent financial crisis. The financial crisis also impacted the returns of these funds along with their volatility (Figure 8b). Figure 8b shows the decline in average returns and the increase in average volatility for both these mandated funds and the S&P500 during the crisis time period. Figure 8a presents the average scaled Sharpe ratios specifically for the funds with North America mandates along with the scaled Sharpe ratios for relevant benchmarks. The average scaled Sharpe ratio for the funds with North America mandates are relatively lower compared to those of both the market and hedge fund indices. Figure 8a also shows that the funds and benchmarks follow a similar trend over time, and that during the crisis period a decline in the trend is obvious.

4.2. Comparative performance measurement: Traditional vs. scaled

This section presents comparative rankings of the sample of hedge funds using both the traditional and scaled Sharpe and Treynor ratios at different points of economic activity, seeing that investors frequently use rankings to differentiate between potential fund investments from less promising fund investments. The emphasis is on comparing the rankings of the traditional measure to those of the scaled measure, within each type of measure (Sharpe and Treynor).

The (36-month) rolling Sharpe and Treynor ratios are again used, as described in Section 3.3, and three points-in-time were selected in accordance with the identified phases. Phase 1 (*pre-crisis*) is represented by December 2006, phase 2 (*during*) by December 2009 and phase 3 (*post*) by December 2011. Points-in-time are used since a static point produces an easier and more stable method to work with rankings and also as static point-in-time methods are most commonly used in practice when considering the ranking of funds. Owing to space constraints the top and bottom 25 funds in the sample are identified at December 2009 (i.e. *during* the crisis period) according to either the traditional Sharpe or Treynor ratio, and then ranked backwards and forwards in time within the full fund data sample of 184 funds.

4.2.1 Traditional vs. scaled Sharpe ratio rankings

The comparative traditional and scaled Sharpe values as well as rankings for the top and bottom 25 funds for the three economic phases are presented in Figure 9. Figure 9 indicates the shift in fund performance during the crisis period as opposed to prior, as a division is apparent between strong (best) and weak (worst) performing funds. Although the funds are scattered fairly randomly during period prior the crisis, both the traditional and scaled Sharpe ratios respectively value (Figure 9a) and rank (Figure 9d) the best performing funds a bit higher than the worst performing funds. Phase 3 shows that the scaled Sharpe ratio both value (Figure 9c) and rank (Figure 9e) a large number of the worst performing funds higher (better) than the traditional Sharpe ratio - this is more obvious for the ranking than the valuation. During the pre- and post-crisis periods the best performing funds are distinguishable from the worst performing funds, again more in rank than in value. Discrepancies (in terms of risk-adjusted values) between funds are smaller for the periods prior and after the crisis compared to the period during the crisis – these discrepancies are not only observable between all funds, but even more stressed between the best and worst performing funds.

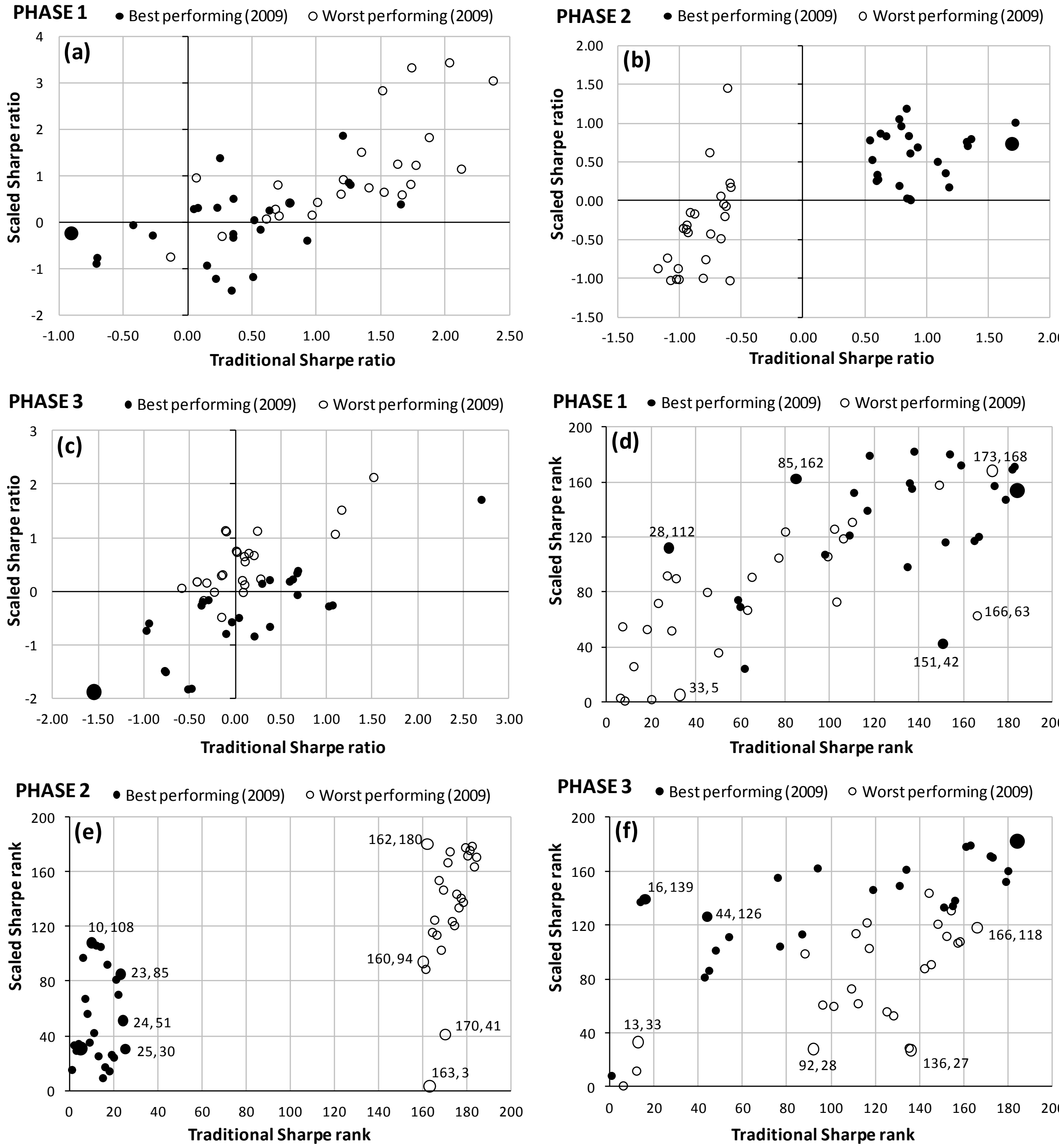
In the phase 2 period a clear distinction is apparent between the best and worst performing funds while also from Figure 9b (representing the phase during the crisis) a large contingent of the best performing funds cluster around values between 0.5 and 1, for both the traditional and scaled Sharpe ratios – just rewarding investors with an equal return for the amount of risk taken on-board. Hence, even the top performing funds did not deliver exceptional risk-adjusted performance compared to performance expectations during normal economic conditions. Still, during this period this level of performance would be classified as exceptional – and thus the rationale that these funds are the top funds during phase 2.

During the crisis period (Figure 9b and 9e) both good and bad performing funds were identified valued. For this period there is also no clear indication of any relationship between the valuing and or ranking rationale of the traditional and scaled Sharpe ratios. Period 2 does show that the traditional Sharpe ratio tends to value funds somewhat higher compared the scaled Sharpe ratio. This lower risk-adjusted valuation by the scaled Sharpe ratio, in comparison to the traditional Sharpe ratio, makes perfect sense as the scaled ratio accounts for the increased risk due to the higher levels of skewness and kurtosis that characterised the period (see Figures 5b and 7) and also Figure 10 as a further example. Some discrepancies do, however, exist between how the traditional and scaled Sharpe ratios rank and value funds.

It is moreover apparent that some of the top funds during the crisis performed badly prior to the crisis and *vice versa*. This suggests that investors would possibly not have selected these funds prior to the crisis due to mediocre or weak risk-adjusted performance, and yet these funds performed the best during the crisis. Compare, for example, the positioning of the indicated fund (fund #167 as the larger datum point) in Figures 9a, 9b and 9c. The performance of this particular fund (fund #167) deteriorated in phase 3 to an even lower (risk-adjusted) level than it recorded in phase 1.

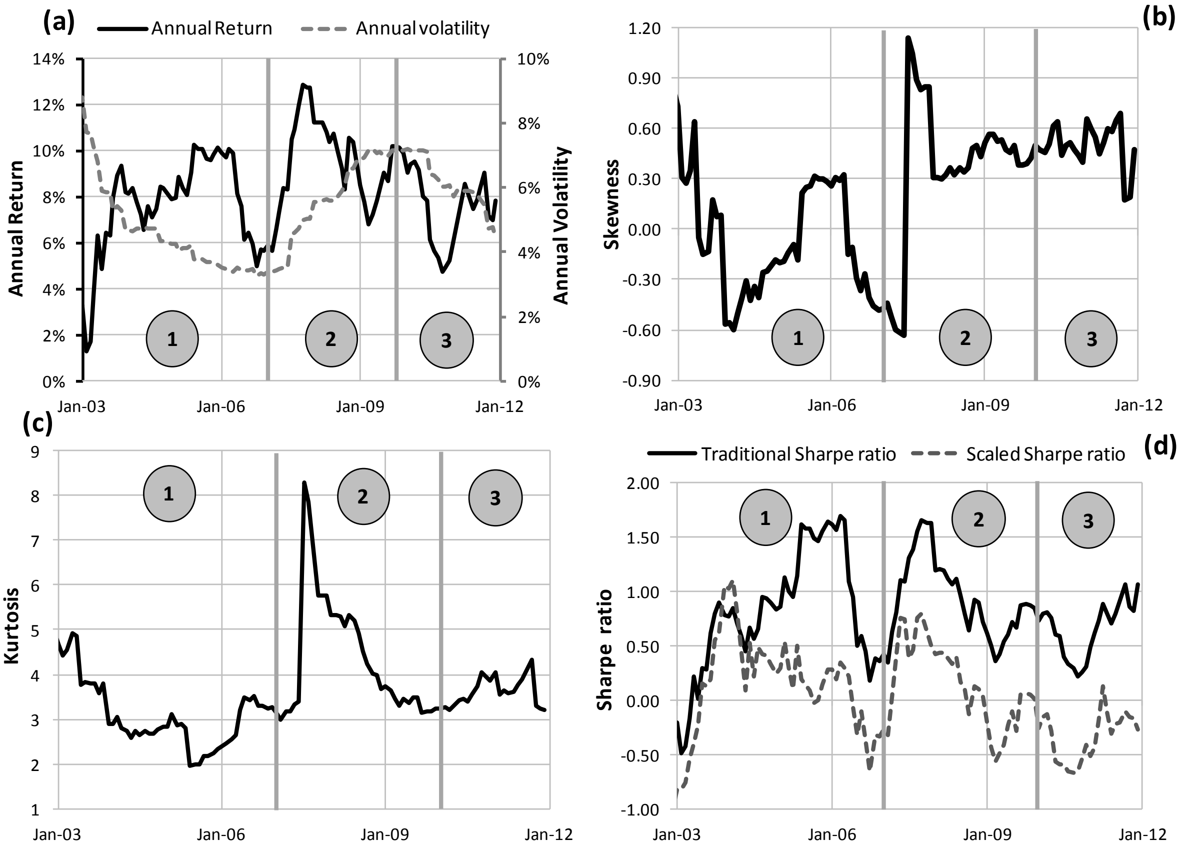
The comparative fund rankings based on the traditional and scaled Sharpe ratios for phases 1 to 3 are presented in Figures 9d, 9e and 9f respectively. The numbers next to the data points are the (traditional Sharpe, scaled Sharpe) rank coordinates.

Figure 9: Traditional vs. scaled Sharpe ratio values for the top and bottom 25 funds in the sample for (a) phase 1, (b) phase 2 and (c) phase 3. Traditional vs. scaled Sharpe rank for the top and bottom 25 funds in the sample for (d) phase 1, (e) phase 2, and (f) phase 3.



In the period prior the financial crisis a wider discrepancy between the traditional and scaled Sharpe ratios existed than compared to the period during the crisis, (this phenomenon is to some extent reinitiated in the post-crisis phase). From Figure 9e it is clear, although now according to fund rankings, that there was a clear distinction between the best and worst performing funds during the crisis period (phase 2). During the crisis period (phase 2) the traditional and scaled Sharpe ratios also generally ranked the funds similarly – meaning that both measures ranked the best performing funds higher than the worst performing funds. This is evidenced by the majority of the best performing funds being located in the southwest region and the bulk of the worst performing funds in the northeast region of Figure 9e. A small number of exceptions (see funds in southeast region of Figure 9e) are observed – fund #34 is ranked as low as 163rd by the traditional Sharpe ratio while the scaled Sharpe ratio ranks this same fund as high as 3rd. There are also instances in which the two ratios do not rank coherently, as fund #144 is, for example, ranked 10th by the traditional Sharpe ratio but a distant 108th by the scaled Sharpe ratio. Figure 10 shows the characteristics, particularly the skewness (Figure 10b) and kurtosis (Figure 10c), of fund #144 that contribute to this particular fund being both valued, on a risk-adjusted basis, and ranked much lower (worse) by the scaled Sharpe ratio compared to the traditional Sharpe ratio in phase 2, as shown in Figure 10d.

Figure 10: Fund #144 (a) annual return vs. annual volatility, (b) skewness, (c) kurtosis, and (d) traditional vs. scaled Sharpe ratio.



This analysis of fund #144 along with Figures 9e and 10 present a clear and logical case that the scaled Sharpe ratio incorporates the risk contained in the return distribution's higher moments (skewness and kurtosis), which are crucial to hedge fund performance analysis.

The comparative rankings reiterates the point made earlier that selecting a highly ranked fund prior to the crisis resulted in a weak (low) rank for the same fund during the crisis period – as some of the worst ranked funds during the crisis are ranked rather highly in the period prior to the crisis. As an example of this phenomenon see and compare the ranking position of the indicated fund (fund #167 indicated by larger datum point) in Figures 9d, 9e and 9f.

In conclusion, the scaled Sharpe ratio is arguably an improvement on the traditional Sharpe ratio as far as non-normal return distributions are concerned while it can be considered as a measure that should augment the use of the traditional Sharpe ratio.

4.2.2 Traditional vs. scaled Treynor ratio rankings

Figure 11 presents the comparative traditional and scaled Treynor values and rankings for the top and bottom 25 funds across the three economic phases. Although the Treynor and Sharpe ratios are not directly comparable[45] a number of similar observations are apparent. For instance, similar to the Sharpe ratio analysis (see Figure 9), Figure 11 also signifies a shift in fund performance during the

[45] Or stated differently, accounting for different types of risk – total vs. systematic (market).

crisis period as opposed to prior while from Figure 11e a marked division between strong (best) and weak (worst) performing funds is apparent.

Another observation similar to the Sharpe ratio case is that during the pre-crisis period, both the traditional and scaled Treynor ratios respectively value and rank the best performing funds higher than the worst performing funds. Interestingly, the scaled Treynor ratio both value (Figure 11c) and rank (Figure 11e) a number of the worst performing funds lower (worse) than the traditional Treynor ratio – this phenomenon is more noticeable for the ranking. When considering traditional Treynor ratio's valuation the pre- and post-crisis periods show a degree of clustering among the best performing funds, while the valuation by the scaled Treynor ratio tends to be more dispersed and also during phase 1 lower than that of the traditional measure. Phase 2 (the period during the crisis) shows a wider dispersion of funds, in terms of valuation for both measures (Figure 11b), while it is also observed that both measures value a large number of funds below 0 – the latter is more evident from the perspective of the traditional Treynor ratio. Thus, during phase 2, the scaled Treynor ratio values the best performing funds slightly higher than the traditional measure. Figures 11a, 11b and 11c show the discrepancies, in terms of risk-adjusted values, to be smaller between funds, prior and after the crisis compared to during the crisis period – these value differences are more apparent when comparing the best and worst performing funds.

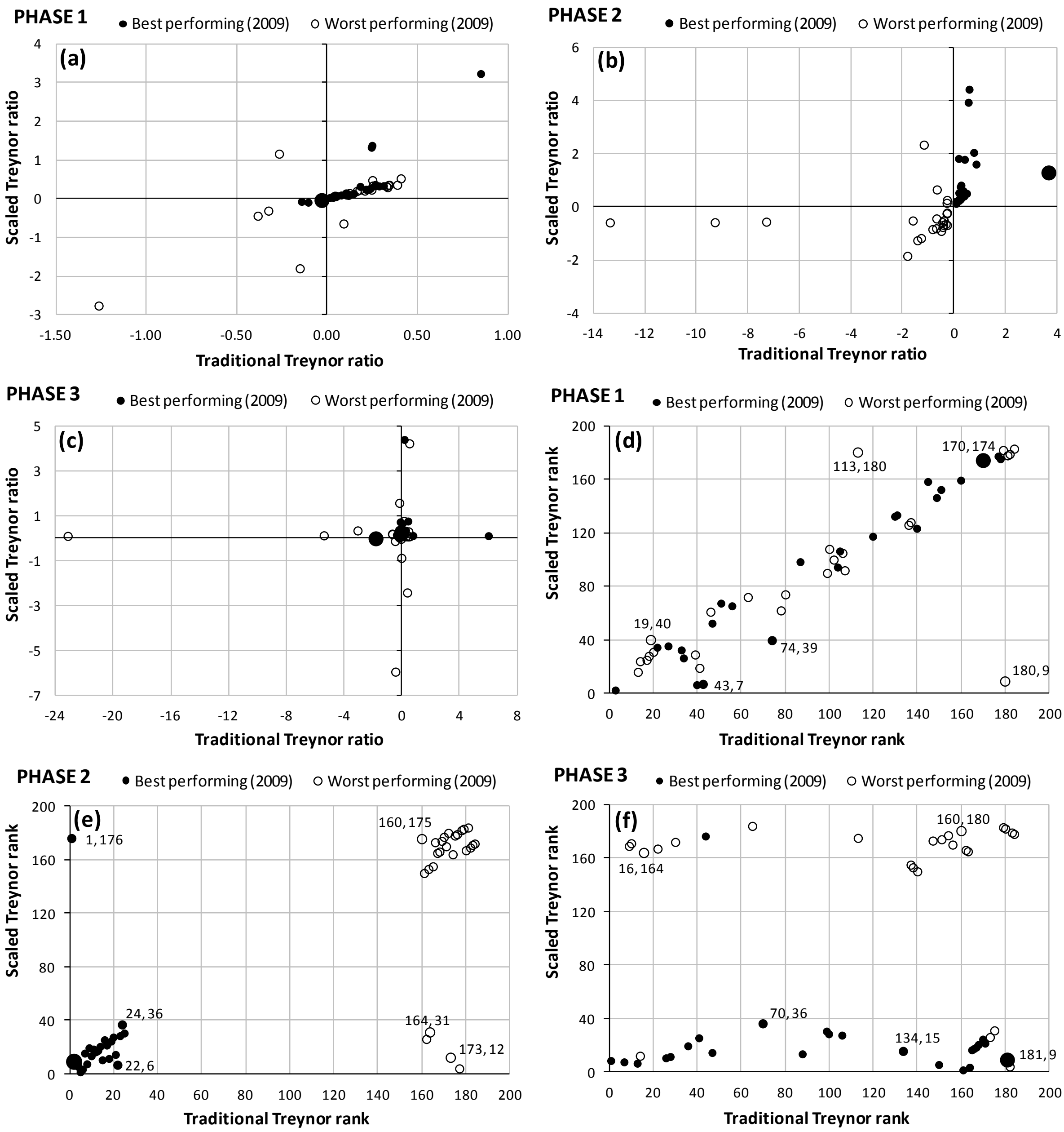
Phase 2 delivers a clearer distinction between the best and worst performing funds. A large group of the best performing funds are valued just above 0 while a large group of funds are valued between 0 and -2, by both the traditional and scaled Treynor ratios. The former is indicative that during the crisis period most of the best performing funds rewarded investors with an amount just exceeding the parallel amount of reward for the amount of accepted risk. So, according to Treynor ratios even the top performing funds did not deliver exception performance compared to performance expectations during normal economic conditions – during this exacting period, however, this level of performance would be classified as exceptional and therefore why these funds are the top funds during phase 2. In addition, it is interesting to note that during phase 3 the majority of funds, especially the best performing funds, delivered even lower Treynor ratios than during phase 2, according to both Treynor measures.

No pattern is evident between the Treynor valuation of the traditional or scaled measures, and some valuation and ranking discrepancies between the two Treynor measures do exist.

Some of the top performing funds during the crisis performed poorly prior the crisis and *vice versa*. This suggests that these funds would not have been the choice of investors prior the crisis due to mediocre or weak risk-adjusted performance, however, these performed the best during the crisis. The larger datum point of fund #167 is once again an example of this and provides an opportunity to compare the positioning of the fund through the three phases (see Figures 11a, 11b and 11c).

Figures 11d, 11e and 11f respectively present the comparative fund rankings derived from the traditional and scaled Treynor ratios for phases 1 through 3. The numbers next to the data points are the (traditional Treynor, scaled Treynor) rank coordinates.

Figure 11: Traditional Treynor ratio vs. scaled Treynor ratio values for the top and bottom 25 funds in the sample for (a) phase 1, (b) phase 2 and (c) phase 3. Traditional Treynor ratio vs. scaled Treynor ratio rank for the top and bottom 25 funds in the sample for (d) phase 1, (e) phase 2, and (f) phase 3.



In terms of ranking, the period prior the crisis exhibits a random though somewhat analogous ranking between the traditional and scaled Treynor measures, as the fund rankings are located in straight line along the diagonal. Moving from phase 1 to phase 2 a noticeable shift in performance is clear and a very clear distinction between the best and worst ranked funds exist during the crisis period (see Figure 11e). Also evident is that during the crisis period the traditional and scaled Treynor ratios generally ranked the funds similarly – meaning that both measures predominantly ranked the best performing funds higher (better) than the worst performing funds. This is, as with the Sharpe ratio analysis, evidenced by the bulk of the best performing funds being located in the southwest region of Figure 11e whilst the majority of the worst performing funds are located in the northeast region. A number of exceptions are, however, observed – see funds in the northwest and southeast regions of Figure 11e. Fund #148 is an example of this exception phenomenon and is ranked 164th by the traditional Treynor ratio while being ranked as high as 31st by the scaled Treynor ratio. Very interesting is that in the period after the crisis (phase 3), the best and worst performing funds remain significantly distinct from each other - the worst performing funds are located in a horizontally spread manner in the northern region of Figure 11e while best performing funds are to be found in a similar horizontal spread but in the southern region. The difference between this fund distinction during phase 3, from that of phase 2, is that the traditional and scaled Treynor ratios do not rank the funds similarly as either high (best) or low (worst). During this phase, the period after the crisis, there seems to exist an exceptionally random ranking of both the best and worst performing funds by both measures with no particular ranking pattern or relationship. The only observation that is obvious is that the scaled Treynor ratio almost wholly ranks the best performing funds high (best) and the worst performing funds as low (worst).

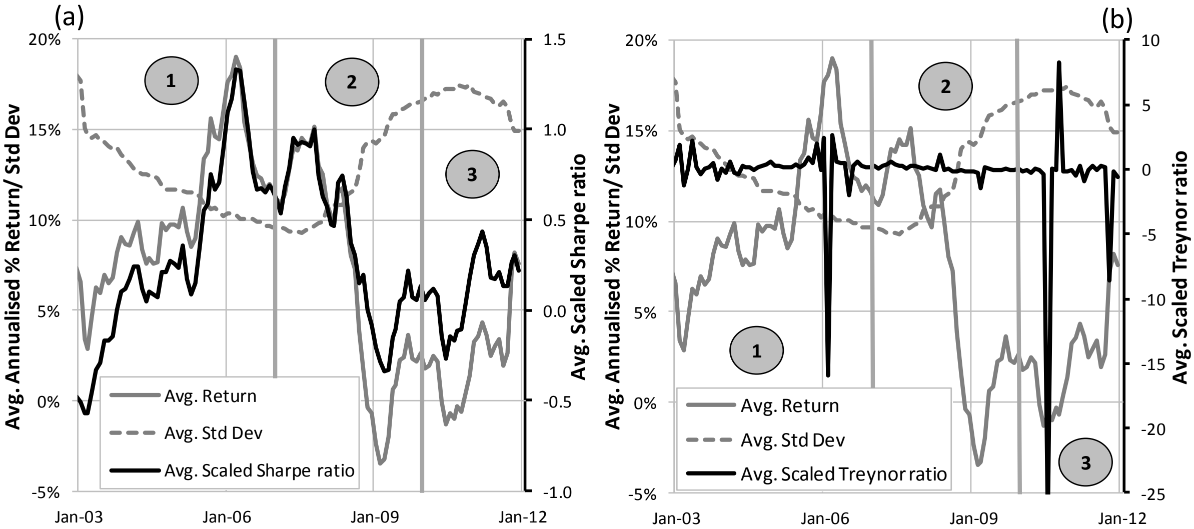
As with the Sharpe ratio analysis, the comparative Treynor rankings repeats the point that selecting a highly ranked fund prior to the crisis resulted in a weak (low) rank for the same fund during the financial crisis period – as some of the worst ranked funds during the crisis are ranked rather highly in the period prior to the crisis. See and compare the ranking position of the indicated fund (fund #167 indicated by the larger datum point) in Figures 11d, 11e and 11f as an example of this phenomenon. Refer to Appendix 4, Figures 34A and 4B which detail the comparative traditional and scaled betas, over time, for the Treynor ratio.

4.3 Selective statistics over different economic conditions

This section presents some selective summary performance statistics focusing on returns and scaled Sharpe and Treynor ratios for both the hedge funds and the relevant market benchmarks. Refer to the Appendix for selective summary statistics concerning both the traditional (i.e. unscaled) and scaled versions of the Sharpe and Treynor ratios with the following breakdown; Appendix 1A shows the summary statistics for the traditional Sharpe and Treynor ratios for all hedge funds and Appendix 1B the traditional Sharpe and Treynor ratios for hedge fund grouped geographically. Appendix 2A details the statistics for traditional Sharpe and Treynor ratios for the relevant market indices. Appendix 3A contains the summary statistics for returns as well as scaled Sharpe and Treynor ratios for the regional hedge fund indices while Appendix 3B presents the traditional Sharpe and Treynor ratios for these hedge fund indices. The statistics are partitioned into three phases to highlight the altering characteristics of the funds and the relevant benchmarks throughout different economic periods. The three phases represent the periods *prior*, *during*, and *post* the 2007 financial crisis. January 2002 until December 2006 constitutes phase 1, January 2007 until December 2009 phase 2, and January 2010 until December 2011 phase 3. The rolling annual calculation methodology based on 36-months, as discussed in Section 3.4, is employed in this section.

Figure 12 exhibits the changing characteristics during the three economic phases through the average annual returns and standard deviation for all funds. Panel (a) of Figure 12 shows the average scaled Sharpe ratio and panel (b) the average scaled Treynor ratio, for all funds in this study. The summary statistics for all funds per phase is conveyed in Table 7.

Figure 12: Average annual return and standard deviation and (a) scaled Sharpe ratio, and (b) scaled Treynor ratio, for all hedge funds.



The impact of the 2007 financial crisis is seen in Figure 12 through a decrease in the average scaled Sharpe ratio of all funds during phase 2. Figure 12 also shows the decrease in the average return across all funds in tandem with a near simultaneous increase in volatility during the crisis period. Of further significance is that mostly during phase 2, the period *during* the 2007 financial crisis, the average scaled Sharpe ratio of all funds reduces to below zero which implies that a risk-less asset would have performed better on average during this time compared the analysed funds sample.

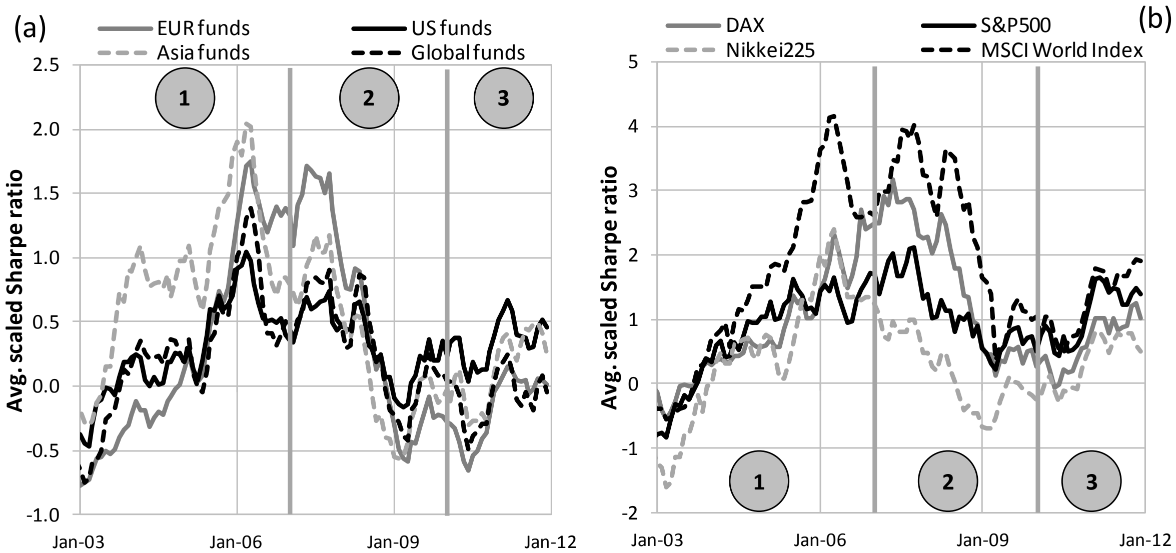
The scaled Treynor ratio as presented in Figure 12b does not provide any information of extraordinary surprise as the scaled Treynor ratio is relatively constant at the same level throughout, apart from the few observed extreme values. The results in Figure 12 are reflected in the summary statistics in Table 7, which indicates a similar trend between the average scaled Sharpe and Treynor ratios of a slight increase from phase 1 to phase 2 and thereafter a (relative larger) decrease moving from phase 2 to phase 3. Table 7 shows that the average return of all funds decreases over time while the standard deviation of returns and the scaled Sharpe ratio also reduce over time indicating a diminishing performance spectrum between funds, on average.

Table 7: Summary statistics for all hedge funds per phase.

	Phase 1	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**
	Return statistics			**Scaled Sharpe ratio**			**Scaled Treynor ratio**		
n	9016	6624	4416	9016	6624	4416	9016	6624	4416
μ	10.41%	6.86%	2.39%	0.31	0.56	0.11	0.01	0.06	-1.25
σ	10.93%	10.20%	8.38%	1.06	1.00	0.82	33.16	4.22	81.70
Media	9.59%	7.33%	2.21%	0.27	0.50	0.15	0.14	0.04	-0.05
Min	-44.96%	-48.39%	-36.57%	-2.80	-2.31	-2.55	-2954.2	-260.49	-4925.3
Max	59.50%	42.39%	74.39%	5.33	4.53	2.60	474.84	115.97	1545.35

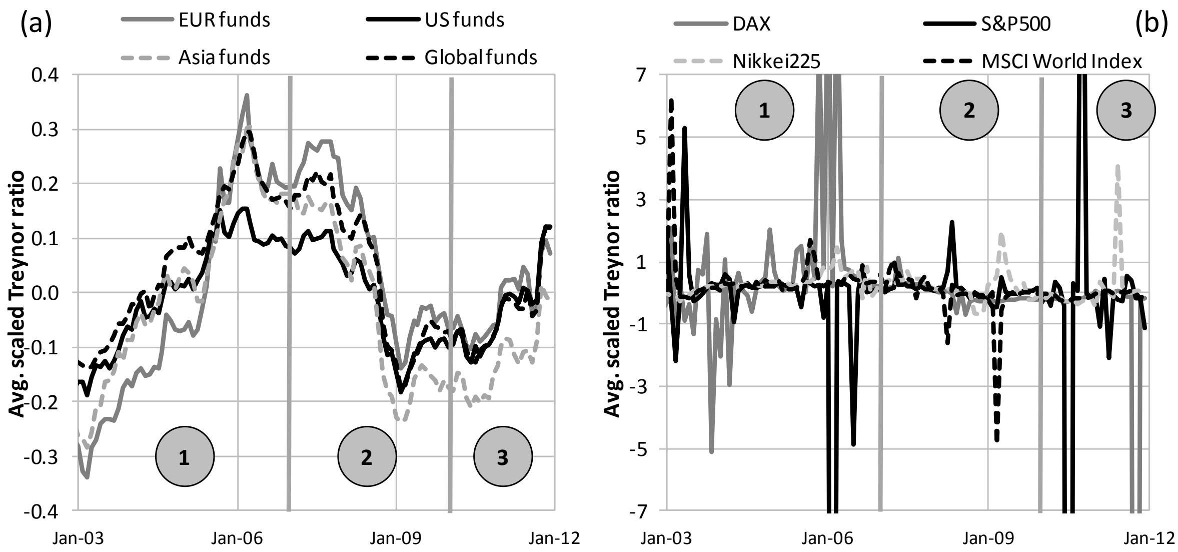
Figure 13 presents the average scaled Sharpe ratios of both funds and their relevant market benchmarks, per region. From this figure, it is apparent that funds and also market benchmarks from the included regions behaved similarly across the three phases. From Figure 13a it is interesting that funds from most regional mandates exhibit significant scaled Sharpe ratio increases and decreases at similar times. None of the regional funds indicate significant better performance than any other during or post the financial crisis. Asian funds, however, performed better, on average, shortly prior to the crisis while European funds also enjoyed a short period of superior risk-adjusted performance during the crisis period (phase 2) (Figure 13a). Figure 13b shows that the market benchmark for global mandated funds (MSCI World Index) performed better that other included market benchmarks for a period prior to the crisis and also during the crisis, while the market benchmark for Asian funds (Nikkei225) generally underperformed other market benchmarks, especially for the period during the crisis period.

Figure 13: (a) Average fund scaled Sharpe ratios per region and (b) average market index scaled Sharpe ratios, through time.



The average scaled Treynor ratios of both funds and their relevant market benchmarks, per region, are presented in Figure 14. From Figure 14a it is once again apparent that funds from all the regions behaved in a similar manner across the three phases. Similar to Figure 13a, Figure 14a indicates that funds from most regional mandated areas exhibit risk-adjusted increases and decreases at similar times. These points of significant scaled Treynor ratio increases and decreases are thus very similar to those of the scaled Sharpe ratio. Interestingly the general pattern through time, as exhibited by the scaled Sharpe and Treynor ratios, are also very similar. Similar to the average scaled Sharpe ratios, none of the regional funds indicate significant better performance than any other during or post the financial crisis. Asian funds, however, show slightly lower risk-adjusted performance during the post phase (phase 3) (Figure 14a). Figure 14b shows a number of scaled Treynor ratio extreme values at various points through time from different regional market benchmarks with relative stable results at a constant level otherwise. The period prior to the crisis, phase 1, indicates more scaled Treynor ratio volatility, mostly from the European funds' market benchmark (DAX).

Figure 14: (a) Average fund scaled Treynor ratios per region and (b) average market index scaled Treynor ratios, through time.



To facilitate comparisons, the summary statistics in terms of fund returns, scaled Sharpe and Treynor ratios, grouped by regional mandates, are presented in Table 8. Table 9 presents the corresponding summary statistics for the relevant regional market benchmarks.

Table 8: Summary statistics for regionally grouped hedge funds per phase.

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Return statistics			**Scaled Sharpe ratio**			**Scaled Treynor ratio**		
North American Hedge Funds									
n	4165	3060	2040	4165	3060	2040	4165	3060	2040
μ	10.52%	6.90%	3.45%	0.27	0.34	0.34	-0.58	0.14	-1.87
σ	11.16%	10.15%	9.11%	0.96	0.80	0.85	46.96	3.27	115.18
Median	9.61%	7.61%	2.42%	0.25	0.34	0.38	0.12	0.03	-0.03
Min	-44.96%	-48.39%	-36.57%	-2.80	-2.31	-2.44	-2954.2	-49.87	-4952.3
Max	59.50%	36.52%	68.29%	3.76	3.75	2.60	443.46	115.97	1545.35
European Hedge Funds									
n	1862	1368	912	1862	1368	912	1862	1368	912
μ	8.30%	7.23%	1.52%	0.27	0.54	-0.17	0.74	-0.03	-1.83
σ	9.49%	9.20%	6.68%	1.28	1.22	0.63	17.26	1.33	51.49
Median	7.42%	7.17%	1.98%	0.05	0.33	-0.13	0.15	0.02	-0.08
Min	-23.33%	-16.56%	-18.82%	-2.52	-1.80	-1.83	-240.90	-24.25	-1555.1
Max	42.97%	37.65%	32.60%	5.33	4.53	2.13	474.84	30.70	4.21
Asian Hedge Funds									
n	735	540	360	735	540	360	735	540	360
μ	11.32%	3.73%	-1.11%	0.85	0.28	0.13	0.31	0.22	0.09
σ	11.07%	11.58%	7.15%	0.87	0.99	0.54	0.94	2.15	3.28
Median	10.31%	3.46%	-0.53%	0.90	0.08	0.14	0.23	0.05	-0.08
Min	-16.67%	-22.70%	-18.10%	-1.36	-1.28	-1.05	-6.18	-7.52	-5.49
Max	43.61%	42.39%	14.73%	3.79	3.49	1.43	13.88	41.35	60.70
Global Hedge Funds									
n	2254	1656	1104	2254	1656	1104	2254	1656	1104
μ	11.66%	7.51%	2.29%	0.25	0.32	-0.09	0.40	-0.06	-0.07

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Return statistics			**Scaled Sharpe ratio**			**Scaled Treynor ratio**		
σ	11.31%	10.42%	8.22%	1.05	0.94	0.86	8.77	6.95	0.58
Median	11.47%	7.67%	2.83%	0.25	0.29	0.08	0.16	0.07	-0.05
Min	-29.69%	-33.59%	-24.35%	-2.66	-2.05	-2.55	-80.26	-260.49	-11.60
Max	52.70%	38.64%	74.64%	3.39	3.34	2.15	400.97	28.48	5.55

From Table 8 (above), the mean returns decline moving through phase 1 to phase 3. The mean of the scaled Sharpe and Treynor ratios for all regions show no distinct or constant pattern when moving between phases. Highest and lowest scaled Sharpe ratio levels occur during phase 1, while the scaled Treynor ratio statistics show no evident pattern.

The standard deviation of both returns and scaled Sharpe ratios are also at their highest levels, for most regions, during phase 1. Mean Asian hedge fund returns did not increase into positive territory from phase 2 to phase 3 as the funds from other regional mandates did (see μ and median for returns in Table 8). This phenomenon is again echoed for the Asian market as represented by the Nikkei 225 in Table 9. Comparing the mean returns for the hedge funds per region with their relevant market benchmark indicate that although these funds did not perform very well in absolute terms, they did outperform their respective markets in phase 3 - this was not the case during the crisis (phase 2). During phase 1, all the funds outperformed their respective market benchmarks in terms of return performance. The mean scaled Sharpe ratios of particularly phase 3 of Tables 8 and 9 highlight that at times it could have served investors better to hold riskless assets rather than investments in these funds or even a basket of the market index.

Table1B in Appendix 1B details comparative summary statistics to Table 8 with an altered focus of traditional Sharpe and Treynor ratios. Table 2A in Appendix 2A provides comparative summary statistics to Table 9, but detailing the traditional Sharpe and Treynor ratios for the relevant market benchmarks.

Table 9: Summary statistics for market indices per phase.

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Return statistics			**Scaled Sharpe ratio**			**Scaled Treynor ratio**		
n	49	36	24	49	36	24	49	36	24
US Market Index – S&P500									
μ	-1.54%	9.14%	-1.80%	0.72	1.14	1.05	0.01	-0.01	-0.04
σ	19.17%	13.29%	5.63%	0.74	0.53	0.43	0.10	0.10	0.07
Media	-6.02%	10.91%	-3.62%	0.97	1.05	1.13	0.02	0.02	-0.04
Min	-31.68%	-12.80%	-9.35%	-0.85	0.23	0.42	-0.19	-0.18	-0.13
Max	35.05%	26.51%	9.25%	1.73	2.12	1.65	0.16	0.11	0.12
European Market Index – DAX									
μ	0.86%	9.14%	-1.80%	0.81	1.66	0.63	-0.02	0.09	-0.02
σ	9.75%	13.29%	5.63%	0.83	1.01	0.40	0.20	0.14	0.06
Media	1.82%	10.91%	-3.62%	0.58	1.92	0.68	-0.07	0.11	-0.04
Min	-17.28%	-12.80%	-9.35%	-0.54	0.12	-0.07	-0.34	-0.14	-0.10
Max	15.14%	26.51%	9.25%	2.70	3.17	1.26	0.36	0.28	0.10
Asian Market Index – Nikkei 225									
μ	1.77%	-1.07%	-11.29%	0.48	0.21	0.33	0.02	-0.01	-0.13
σ	15.69%	14.41%	5.90%	1.04	0.57	0.40	0.17	0.15	0.06
Media	1.29%	3.18%	-12.40%	0.61	0.16	0.45	0.01	0.03	-0.13
Min	-26.81%	-22.41%	-19.73%	-1.61	-0.70	-0.29	-0.28	-0.24	-0.21

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Return statistics			**Scaled Sharpe ratio**			**Scaled Treynor ratio**		
Max	29.24%	17.25%	1.57%	2.40	1.24	0.80	0.31	0.18	0.02
Global Market Index – MSCI World									
μ	6.42%	4.95%	-3.46%	1.56	2.49	1.27	0.06	0.05	-0.04
σ	12.43%	12.88%	6.37%	1.41	1.12	0.49	0.13	0.13	0.07
Media	8.08%	10.02%	-4.66%	1.52	2.85	1.35	0.08	0.10	-0.05
Min	-13.36%	-16.59%	-11.89%	-0.54	0.36	0.48	-0.14	-0.18	-0.13
Max	27.41%	20.99%	12.29%	4.15	4.03	1.93	0.30	0.22	0.12

5. SUMMARY AND CONCLUSION

Scaled versions of the traditional or classic Sharpe and Treynor ratios were used to augment the traditional measures as performance measure in a hedge fund context. 'Live', individual, long/short equity hedge funds, sourced from the Eurekahedge database and spanning geographical mandates that in included North America, Europe, Asia and global were used, spanning the period January 2000 to December 2011. These scaled risk-adjusted performance measures account for higher-order moments (skewness and kurtosis) of return distributions seeing that the traditional versions of these measures do not. The latter is widely known shortcoming of the traditional measures and result in these measures being unfit for use with asymmetric returns, which is a characteristic of hedge funds. In methodological terms, this study used a 36-month rolling (window) period to estimate the relevant statistics and ratios.

As the use of most traditional performance measures, like the Sharpe ratio, are not appropriate considering non-normal returns, the normality of the funds were statistically investigated. To discover the state of normality of the hedge funds within the funds sample a normality test or analysis was performed using the Jarque-Bera (JB) test, while a number of other relevant statistics were also used to gauge and present the state of normality. The majority (84.3%) of the funds, within the sample, showed evidence of having non-normal return distributions at the 5% significance level. These goodness of fit tests for normal return distributions, using the JB test, were performed and presented for the entire time-series and partitioned into phases corresponding the 2007 financial crisis, namely; pre, during and after. This partitioning practice was employed throughout the study and aids in viewing how a particular characteristic or phenomenon evolved during the different economic phases that surround the 2007 financial crisis. Results indicate that return distributions move further from normal(ity) during the crisis period (December 2006 – December 2009) and that skewness turned rapidly and significantly negative, during the financial crisis, while extreme levels of excessive positive kurtosis were evident for both funds and regional market indices.

Results were thereafter presented in two sections. Firstly, comparative traditional versus scaled Sharpe and Treynor values and rankings were assembled using the 36-month rolling method at different points of economic activity (*pre-*, *during*, and *post* crisis) to gauge how these measures value and rank funds over changing economic conditions. The top and bottom 25 funds in the data sample were identified at a point during the crisis period according to the traditional Sharpe and Treynor ratios, respectively, and thereafter ranked both backwards and forwards in time within the full data sample.

Sharpe ratio findings - Noticeable shifts in fund performance during the 2007 financial crisis were observed. A clear distinction between strong (best) and weak (worst) performing funds is apparent while discrepancies, in terms of risk-adjusted values, between funds are smaller for the period prior and after the crisis compared to during the crisis.

During the crisis period a large contingent of the top performing funds were also found to cluster around values between 0.5 and 1, for both the traditional and scaled Sharpe ratios. Also, the traditional Sharpe ratio had the propensity to value funds somewhat higher compared to the scaled

Share ratio, during the crisis period. This lower risk-adjusted valuation by the scaled measure is shown to be realistic and validated as the scaled measure accounts for the increased risk due to the higher levels of skewness and kurtosis that characterised this particular period. Moreover it is found that some of the top funds during the crisis performed poorly prior to the crisis suggesting that investors would possibly not have selected these funds prior to the crisis due their mediocre or weak (Sharpe) risk-adjusted performance.

Treynor ratio findings - Similar to the Sharpe ratio, the Treynor ratio valuation and ranking analysis also signified a shift in fund performance during the crisis period as opposed to prior, while a marked division is evident between the strong (best) and weak (worst) performing funds. The risk-adjusted value discrepancies between funds, are wider during the crisis period compared to prior or after, for both measures. A number of the worst performing funds are valued and ranked lower (worse) by the scaled measure than the traditional measure during the crisis. Also, during the crisis period a large group of the top performing funds are valued just above 0 while a large group of funds are valued between 0 and -2, by both the traditional and scaled measures.

During the crisis the traditional and scaled Treynor measures did generally rank the funds similarly – meaning that both measures predominantly ranked the best performing funds higher (better) than the worst performing funds. In the after crisis period, the best and worst performing funds remain significantly distinct from each other albeit that during this period the traditional and scaled Treynor measures do not rank the funds similarly as either high (best) or low (worst). An exceptionally random ranking of both the best and worst performing funds by both measures with no particular ranking pattern or relationship seem to exist. The only observation that is obvious is that the scaled Treynor ratio almost wholly ranks the best performing funds high (best) and the worst performing funds as low (worst). Similar to the Sharpe ratio, it is again found that some of the top funds during the crisis performed disappointingly prior to the crisis suggesting that investors would possibly not have selected these funds prior to the financial crisis due to their mediocre or weak (Treynor) risk-adjusted performance.

Secondly, to highlight the changing characteristics of hedge funds and their respective market benchmarks over the varying economic conditions around the 2007 financial crisis, a selective statistical analysis of returns and the scaled Sharpe and Treynor ratios were conducted. Results show a decrease in the average return of all funds over time. The same is true for the standard deviation of returns and the scaled Sharpe ratio, indicating a diminishing performance spectrum between funds, on average. Moving through the periods, the average Sharpe and Treynor ratios increased slightly during the crisis period and then decrease significantly more in the period thereafter.

Negative scaled Sharpe and Treynor ratios are also more prevailing during the period after the crisis. Comparing the mean returns for the hedge funds per region with their relevant market benchmark indicate that although these funds did not perform very well in absolute terms, they did outperform their respective markets after the crisis - this was not the case during the crisis. Prior the crisis, all the funds outperformed their respective market benchmarks in terms of return performance. The mean scaled Sharpe ratios, of particularly after the crisis, emphasise that at times it could have served investors better to hold riskless assets rather than investments in these funds or even a basket of the market index.

The need to accurately distinguish between good and poor quality fund returns has not diminished, and in actual fact is ever increasing. More sophisticated risk-adjusted performance measures are therefore required to augment classical or traditional performance measures. Higher moments of the return distributions must also be accounted for if accurate and trustworthy fund comparisons (in terms of risk-adjusted returns) are desired, and even more so if the popularity of hedge fund investing continues to grow. The scaled Sharpe and Treynor ratios are arguable improvements on the traditional Sharpe and Treynor ratios as far as non-normal return distributions are concerned and can be considered as measures that should augment the use of the traditional Sharpe and Treynor ratios.

Future research considerations may be aimed at exploring and comparing the classical or traditional Sharpe and Treynor ratios to scaled versions, which account for higher-order moments, using similar scaling methodology albeit with the added element of allowing for the serial correlation of returns that are non-IID by using the annualised autocorrelation adjusted Sharpe ratio methodology as proposed by Lo (2002). A similar study that includes both the traditional and scaled performance measures along with a third, objective, measure that accounts for higher moments, such as the Omega ratio is another consideration.

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APPENDIX 1A

Table 1A: Traditional Sharpe and Treynor ratio summary statistics for all hedge funds, per phase.

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Traditional Sharpe ratio			Traditional Treynor ratio		
n	9016	6624	4416	9016	6624	4416
μ	0.60	0.37	-0.07	0.07	0.01	-0.31
σ	0.91	0.83	0.50	31.23	1.82	14.54
Median	0.56	0.33	-0.11	0.14	0.04	-0.04
Min	-2.13	-1.74	-1.54	-2376.49	-130.04	-888.29
Max	3.51	3.31	2.86	923.90	25.00	170.83

APPENDIX 1B

Table 1B: Traditional Sharpe and Treynor ratio summary statistics for hedge funds, grouped geographically, per phase.

	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
	Traditional Sharpe ratio			Traditional Treynor ratio		
n	49	36	24	49	36	24
North American Hedge Funds						
μ	0.56	0.37	0.004	-0.65	0.03	-0.33
σ	0.86	0.82	0.52	40.48	0.88	20.42
Median	0.49	0.33	-0.07	0.11	0.04	-0.02
Min	-1.45	-1.74	-1.54	-2376.49	-10.98	-888.29
Max	3.23	3.31	2.86	49.05	22.89	170.83
European Hedge Funds						
μ	0.55	0.46	-0.12	1.58	-0.11	-0.65
σ	1.03	0.90	0.51	32.45	3.73	9.54
Median	0.53	0.44	-0.12	0.22	0.03	-0.06
Min	-2.13	-1.63	-1.35	-174.97	-130.04	-275.18
Max	3.51	2.69	1.51	923.90	25.01	15.88
Asian Hedge Funds						
μ	0.79	0.25	-0.13	0.22	0.004	-0.03
σ	0.91	0.90	0.46	0.27	0.62	-0.23
Median	0.78	0.23	-0.11	0.23	0.04	-0.05
Min	-1.41	-1.40	-1.26	-0.57	-10.60	-0.56
Max	3.20	2.41	0.90	0.99	1.41	0.86
Global Hedge Funds						
μ	0.62	0.35	-0.16	0.11	0.07	-0.10
σ	0.88	0.77	0.44	1.56	0.46	0.32
Median	0.60	0.30	-0.19	0.15	0.07	-0.07
Min	-1.70	-1.45	-1.30	-60.62	-2.66	-3.10
Max	3.43	2.35	1.99	17.28	10.51	0.85

APPENDIX 2A

Table 2A: Traditional Sharpe and Treynor ratio summary statistics for market indices per phase.

	Phase 1	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**
	Traditional Sharpe ratio			**Traditional Treynor ratio**		
n	49	36	24	49	36	24
US Market Index – S&P500						
μ	0.27	0.23	-0.16	-0.02	-0.01	-0.04
σ	0.82	0.82	0.34	0.20	0.10	0.07
Median	0.10	0.17	-0.18	-0.07	0.02	-0.04
Min	-1.01	-1.03	-0.58	-0.34	-0.18	-0.13
Max	1.69	1.46	0.60	0.36	0.11	0.12
European Market Index – DAX						
μ	0.18	0.83	-0.08	-0.02	0.09	-0.02
σ	0.97	1.08	0.24	0.20	0.14	0.06
Median	-0.22	0.67	-0.16	-0.07	0.11	-0.04
Min	-1.15	-0.65	-0.40	-0.34	-0.14	-0.10
Max	1.97	2.42	0.38	0.36	0.28	0.10
Asian Market Index – Nikkei 225						
μ	0.20	0.10	-0.47	0.02	-0.01	-0.13
σ	0.93	0.81	0.23	0.17	0.15	0.06
Median	0.07	0.18	-0.48	0.01	0.03	-0.13
Min	-1.33	-1.03	-0.76	-0.28	-0.24	-0.21
Max	1.99	1.22	0.07	0.31	0.18	0.02
Global Market Index - MSCI World						
μ	0.65	0.68	-0.14	0.06	0.05	-0.04
σ	1.16	1.05	0.30	0.13	0.13	0.07
Median	0.55	0.81	-0.20	0.08	0.10	-0.05
Min	-0.97	-0.79	-0.50	-0.14	-0.18	-0.13
Max	2.98	2.30	0.62	0.30	0.22	0.12

APPENDIX 3A

Table 3A: Summary statistics for regionally grouped hedge fund indices per phase.

	Phase 1	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**
	Return statistics			**Scaled Sharpe ratio**			**Scaled Treynor ratio**		
n	49	36	24	49	36	24	49	36	24
North American Hedge Fund Index*									
μ	0.10	0.08	0.06	1.80	2.11	1.81	-0.001	-0.02	-0.09
σ	0.02	0.04	0.02	1.00	0.76	0.34	0.34	0.22	0.19
Median	0.10	0.09	0.06	1.67	2.13	1.84	0.06	0.04	-0.10
Min	0.05	-0.002	0.03	-0.19	0.76	1.24	-0.66	-0.44	-0.32
Max	0.16	0.14	0.11	3.55	3.23	2.39	0.63	0.26	0.34
European Hedge Fund Index#									
μ	0.08	0.08	0.04	1.95	2.92	0.66	-1.15	0.28	-0.09
σ	0.03	0.04	0.01	1.29	1.33	0.25	3.39	0.48	0.31
Median	0.07	0.09	0.04	1.48	3.30	0.63	-1.24	0.44	-0.20
Min	0.02	0.01	0.01	-0.36	0.75	0.19	-14.56	-0.56	-0.50
Max	0.15	0.14	0.06	4.76	4.96	1.12	6.79	0.95	0.60
Asian Hedge Fund Index+									
μ	0.12	0.10	0.05	2.01	2.39	0.72	-0.04	-0.03	-0.42
σ	0.04	0.06	0.03	0.61	0.89	0.28	0.70	0.54	0.20
Median	0.13	0.11	0.05	1.99	2.32	0.73	0.07	0.11	-0.43
Min	0.03	0.01	0.01	0.68	0.96	0.27	-1.52	-0.89	-0.67
Max	0.20	0.19	0.10	3.50	4.09	1.22	1.05	0.69	0.06
Global Hedge Fund Index‡									
μ	0.07	0.02	-0.03	1.17	1.51	1.27	0.10	0.23	-0.10
σ	0.02	0.05	0.02	0.40	0.62	0.33	0.85	0.52	0.29
Median	0.06	0.04	-0.03	1.21	1.62	1.34	0.33	0.32	-0.17
Min	0.04	-0.05	-0.06	0.25	0.39	0.69	-1.85	-0.54	-0.42
Max	0.11	0.07	0.03	1.73	2.61	1.75	1.07	1.10	0.66

* North American hedge fund index: Eurekahedge North America long/short equities hedge fund index.
# European hedge fund index: Barclayhedge European equities index.
+ Asian hedge fund index: Eurekahedge Asian hedge fund index.
‡ Global hedge fund index: HFR(X) global hedge fund index.

APPENDIX 3B

Table 3B: Traditional Sharpe and Treynor ratio summary statistics for regionally grouped hedge fund indices per phase.

	Phase 1	**Phase 2**	**Phase 3**	**Phase 1**	**Phase 2**	**Phase 3**
	Traditional Sharpe ratio			**Traditional Treynor ratio**		
n	49	36	24	49	36	24
North America Hedge Fund Index*						
μ	1.59	1.27	0.62	-0.02	-0.04	-0.08
σ	0.54	0.88	0.27	0.25	0.20	0.16
Median	1.51	1.54	0.58	0.04	0.04	-0.10
Min	0.66	-0.07	0.26	-0.51	-0.45	-0.29
Max	2.67	2.63	1.20	0.37	0.21	0.26
European Hedge Fund Index‡						
μ	1.80	1.40	0.46	-0.73	0.24	-0.09
σ	0.59	0.91	0.21	1.84	0.42	0.26
Median	1.69	1.45	0.49	-0.63	0.38	-0.17
Min	0.55	0.07	0.07	-4.84	-0.53	-0.44
Max	3.18	2.81	0.82	2.46	0.76	0.42
Asian Hedge Fund Index+						
μ	2.14	1.49	0.48	-0.02	0.01	-0.37
σ	0.72	1.13	0.29	0.65	0.45	0.17
Median	2.30	1.36	0.45	0.05	0.08	-0.40
Min	0.52	0.04	0.09	-1.34	-0.63	-0.58
Max	3.51	3.41	1.16	0.98	0.62	0.05
Global Hedge Fund Index#						
μ	1.79	0.45	-0.33	0.10	0.10	-0.11
σ	0.52	0.85	0.31	0.64	0.30	0.23
Median	1.72	0.75	-0.41	0.37	0.20	-0.16
Min	1.00	-0.68	-0.69	-1.47	-0.41	-0.37
Max	2.87	1.66	0.50	0.80	0.47	0.47

* North American hedge fund index: Eurekahedge North America long/short equities hedge fund index.
‡ European hedge fund index: Barclayhedge European equities index.
+ Asian hedge fund index: Eurekahedge Asian hedge fund index.
# Global hedge fund index: HFR(X) global hedge fund index.

APPENDIX 4

Figure 4A: Average traditional vs. scaled beta as in Treynor ratios, over time - all hedge funds.

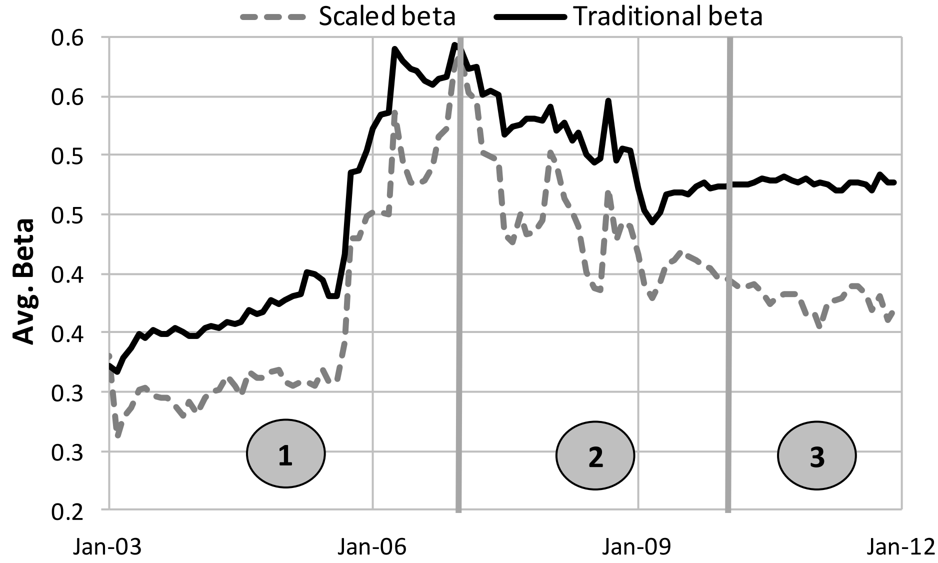
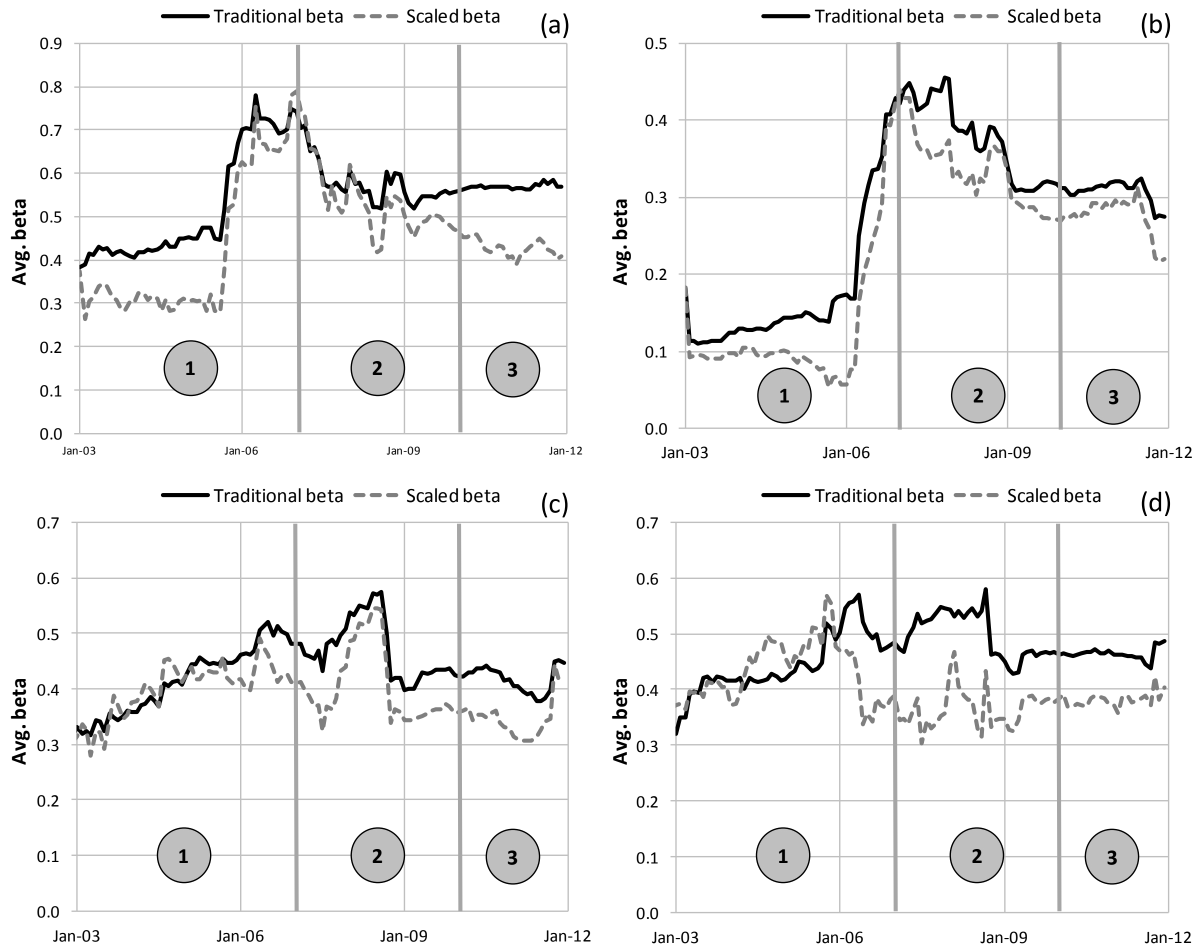


Figure 4B: Average traditional vs. scaled beta used as in Treynor ratios – for hedge funds per geographical mandate, over time: (a) North America, (b) Europe, (c) Asia, and (d) Global.



CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 SUMMARY AND CONCLUSIONS

Financial markets and products are ever-increasing in complexity and sophistication. Innovative financial products arise in the pursuit of profit, but the need to measure the risk involved remains. Risk measurement and management, however, constantly lags behind as more data are required to accurately assess risk. Contemporary financial risk management consequently employs immense resources to measure, manage and report risks present in financial markets and products. The goal of modern financial risk management is thus not only to use existing risk measurement methods to assess risks, but also to adapt these existing models or to devise new models in order to deal with escalating financial market development and financial product innovation. The 2007-9 financial crisis highlighted the problem of inappropriate or inaccurate risk measurement and has in-turn led to the re-evaluation of risk analysis methods and techniques.

Performance measurement is of considerable importance as the need to accurately distinguish between funds – based on performance – has not diminished. In fact, it is increasing. This is also the case within the highly competitive hedge fund industry as investor returns and fund manager compensation are tied to fund performance while performance can also mean either the survival or closure of a fund.

Traditional performance measures are, however, not ideally suited and often deemed inappropriate to the world of hedge funds, as these measures were specifically designed for traditional (i.e. long-only) investments. Also, the often complex investment strategies frequently employed by hedge funds bring about equally complex and often multi-dimensional risk exposures for which traditional performance measures are not equipped. It is therefore often argued, by both researchers and practitioners, that more sophisticated performance measures are required to appraise hedge fund performance. An alternative to this is that more sophisticated performance measures augment classical or traditional performance measures when relevant and required.

In light of the above, the continuous improvement of existing risk measures and the invention of techniques to measure and manage new types of risk are crucially important.

Also, as no single risk or risk-adjusted performance measure currently (2014) captures all risk types or dimensions due to these measures being designed to capture specific, and predominantly singular or limited, risk elements or characteristics, various and several measures are potentially necessitated to augment traditional risk or risk-adjusted performance measures. Alternative or additional risk or risk-adjusted performance measures should therefore be chosen and applied in accordance with investor requirements and objectives - in terms of the specific or additional risk dimensions or characteristics that necessitate capturing - while the appropriateness of the alternative measure will also depend on the traditional performance measures being used and the relevant drawbacks and inadequate nature of these measures.

This thesis explored two distinct problems facing modern risk management in a portfolio context through the primary research question/problem: *evaluate whether additional novel performance tools can be identified for use by hedge fund investors to characterise additional risk components not considered by traditional performance measures*. This thesis explored three fields of hedge fund risk and risk assessment methodologies. The contributions are outlined in the subsequent sections.

5.1.1 THE BIAS RATIO AS A HEDGE FUND FRAUD INDICATOR: AN EMPRICAL PERFORMANCE STUDY UNDER DIFFERENT ECONOMIC CONDITIONS

Accurate fund performance measurement is important as the need to accurately distinguish between superior and dismal performing funds is ever-increasing, due in part to the continuous increase in financial market sophistication and financial product complexity. Performance appraisal is also highly relevant within the hedge fund world as fund performance is the basis of both investor returns and hedge fund manager compensation. The continued existence of a hedge fund can also be coupled to fund performance as stellar performance may lead to new capital inflows and the survival of a fund, while dismal performance may result in capital outflows and even possibly fund closure.

Hedge fund attritions have almost doubled since the financial crisis (Kaiser & Haberfelner, 2012). The reason behind the fund closures can therefore be considered part of a debate set-off by the financial crisis, pertaining to the fundamental question of whether risks are being measured inappropriately. This debate has led to the introduction of new risk analysis methods and techniques as existing measured were arguably ill-equipped at identifying risks adequately. Current (April 2014) risk assessment methods therefore require re-assessment as part of modern risk management’s goal is to adapt existing models or to devise new models when the situation requires.

Incentives exist for hedge fund managers to behave fraudulently and manipulate performance statistics (e.g. return's smoothing) since both manager compensation and potential fund survival are coupled to fund performance.

The study explores the premise that traditional risk-adjusted performance measures are not complete as all components of risk are not implicitly included nor measured. The response to this ties in with the problem statement and objectives of this thesis - whether additional performance measures should be used to augment traditional performance measures as these additional measures provide additional information to that conveyed by traditional measures. A fraud detection measure, namely the Bias ratio, was considered as the additional measure to potentially augment traditional measures.

Even though the Bias ratio has gained some acceptance since its introduction in 2006, analysis largely confirms the ratio to be a convincing measure after applying it to a confirmed fraud case (the Madoff Ponzi scheme). The Bias ratio was also employed to identify characteristics of potential suspicious fund behaviour which were demonstrated to successfully identify potential suspicious funds. Findings therefore confirmed that, although not perfect, the Bias ratio does provide investors with additional information to consider when making hedge fund investment decisions and that the Bias ratio is indeed a measure that should augment the Sharpe ratio. By using the Bias ratio alongside the Sharpe ratio hedge fund investors or fund of hedge fund managers can accordingly obtain an indication of potential suspicious behaviour of performance manipulation.

5.1.2 HEDGE FUND PERFORMANCE EVALUATION USING THE SHARPE AND OMEGA RATIOS

The demise of Long Term Capital Management in 1998 and Amaranth Advisors in 2006 did not only make for interesting newspaper reading, but also contributed to the ever-increasing pressure on hedge funds and the hedge fund industry to submit to regulation. .

Performance measurement remains important as the need to accurately distinguish between good and poor quality funds is greater than ever, partly due to the mounting pressure on hedge funds. In the highly competitive world of hedge funds, superior performance remains the only guarantee for fund survival, albeit accurate and impartial performance measurement is necessitated from the perspective of hedge fund investors. Traditional risk-adjusted performance measures, although well-established and widely used, embrace a mean-variance regime. Measures based on mean-variance theory are, however, widely considered to be obsolete when return distributions are highly non-normal, such as in the case of hedge funds. Higher statistical moments of return distributions must be taken into account if an accurate ranking of funds is desired.

The work in Chapter 3 assembles comparative Sharpe versus Omega fund values and rankings at different points of economic activity (*pre-*, *during*, and *post* crisis) to gauge how these measures value and rank hedge funds over changing economic conditions. The work also highlights the added value of the rolling Omega function – investors can gauge the risk and return characteristics of specific investments through time by customising viewing perspectives.

The Omega function, though not a perfect measure, represents a substantial enhancement compared to traditional performance measures as it describes a large extent of the underlying (P/L) distribution structure, which is highly relevant to hedge funds. It is also found that the Sharpe ratio consistently misallocates the best performing funds. The Omega measure thus makes a strong case to augment the Sharpe ratio when making hedge fund investment decisions.

5.1.3 HEDGE FUND PERFORMANCE USING SCALED SHARPE AND TREYNOR MEASURES

Disclosing a risk-adjusted number is a primary responsibility of performance measurement and financial analysts: investors rely on risk-adjusted returns, i.e. performance measures to select among available funds. The accurate and impartial measurement of fund performance is thus crucial as hedge fund investors would take on considerable risk when selecting funds based on inaccurate or flawed fund rankings. Given that hedge funds embrace a variety of diverse strategies, styles and securities, specifically designed risk assessment techniques and measures are required.

Traditional performance measures, such as the Sharpe and Treynor ratios, are governed by the mean-variance framework. However, such mean-variance based measures are widely considered inappropriate (and almost obsolete) when return distributions are highly non-normal. Hedge fund return distributions also exhibit non-normal characteristics, specifically negative skewness and positive excess kurtosis. Such non-symmetrical return distributions result in standard performance measurements being misleading and inappropriate when applied to these non-normal distributions. The fact that investors, however, rely on traditional performance measures to evaluate the risk-adjusted performance of investments characterised by non-normal return distributions again points to the need for specifically designed risk assessment techniques and performance measures. Higher moments of the return distributions must be accounted for if accurate fund comparisons (in terms of risk-adjusted returns) are desired.

Chapter 4 assembles comparative traditional versus scaled Sharpe and Treynor values and rankings at different points of economic activity (*pre-*, *during*, and *post* crisis) to gauge how these measures value and rank hedge funds over changing economic conditions.

Results show that the scaled Sharpe and Treynor ratios offer improvements over the traditional Sharpe and Treynor ratios as far as non-normal return distributions are concerned. These scaled measures can therefore be considered measures that should augment the use of the traditional Sharpe and Treynor ratios.

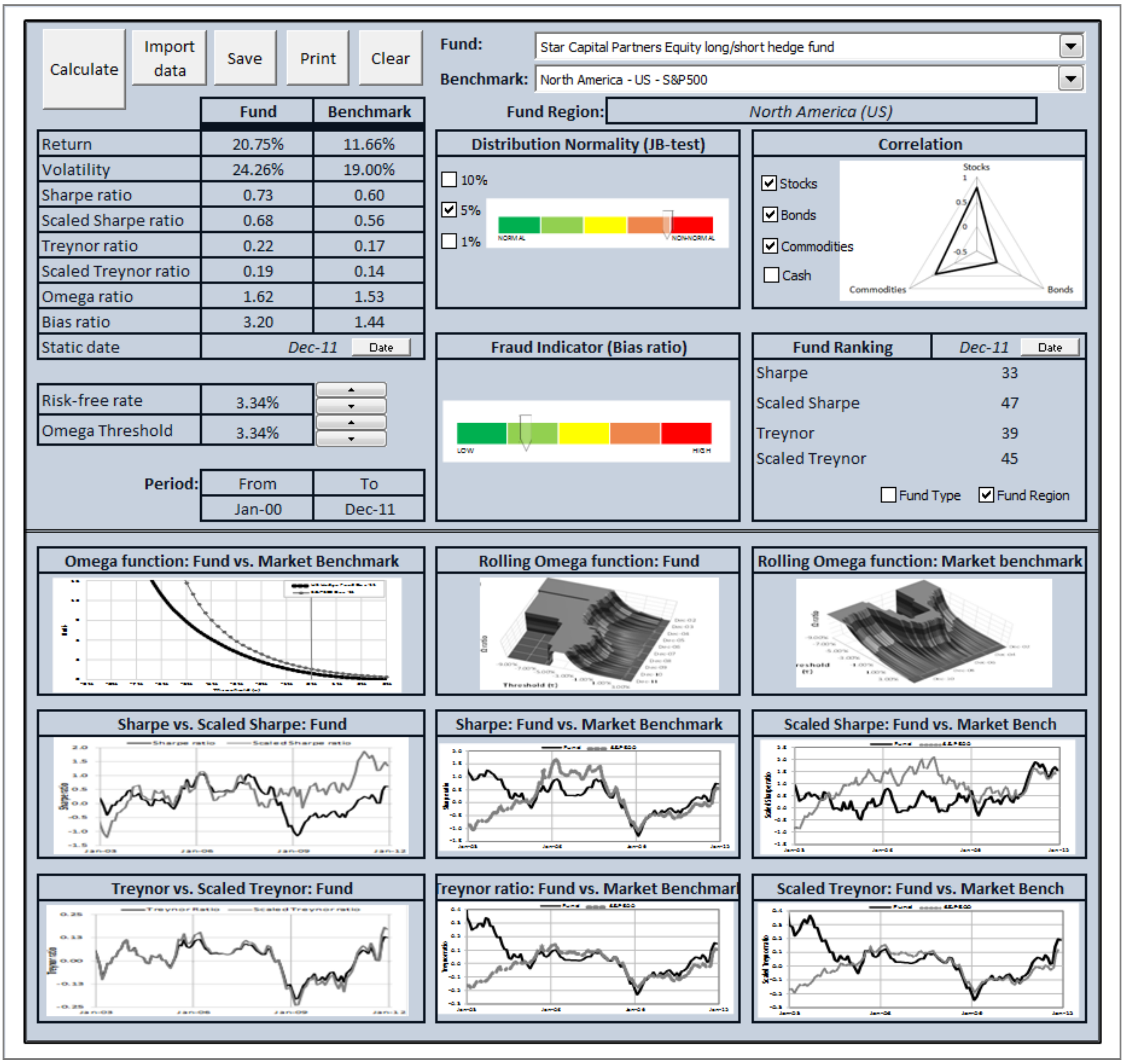
5.1.4 RISK DASHBOARD

The fourth objective of this thesis is to construct a risk dashboard tool that incorporates the additional performance measures evaluated and the information they convey. This dashboard tool would thereby provide a holistic and enhanced viewpoint of risk and risk-adjusted performance of a particular hedge fund investment to investors. The primary use of such a dashboard tool would be to provide investors with supplementary information when making hedge fund investment decisions, as the dashboard would contain additional risk and performance information to that of traditional risk-adjusted and other information that is generally available to investors.

The risk dashboard illustrated in Figure 5.1 contains information conveyed by widely used traditional performance measures such as the Sharpe and Treynor ratios as well as other valuable information such as the investments correlation with main asset classes. The dashboard also supplies additional information through the novel performance measures evaluated in this thesis, amongst others: (i) a gauge concerning the normality of the funds' returns distribution, (ii) a fraud indicator based on the

Bias ratio, (iii) Bias ratio values for the fund and the market benchmark, (iv) the Omega ratio at a specific return threshold, (v) point-in-time (static) Omega functions for the fund and the market benchmark, (vi) rolling Omega functions for the fund as well as the market benchmark, (vii) scaled Sharpe and Treynor ratios for the fund and the market benchmark, and (viii) traditional vs. scaled Sharpe and Treynor ratio graphs over time.

Figure 5.1: Illustration of a risk dashboard.



A risk dashboard similar to the one presented in Figure 5.1 is easily constructed and also customisable to the requirements of the user using freely available software packages such as SAS® or Microsoft Excel.™ Microsoft Excel's Visual Basic for Applications (VBA)® also makes it possible for users to automate the generation of the information, gauges and graphs contained in the dashboard given relevant data sources are available and accessible and that suitable data architecture exists. The automation of a dashboard and the information it contains is also possible for other software packages such as SAS.®

A risk dashboard tool would be to the benefit of hedge fund investors during the investment decision making process as information provided by the(se) additional , novel performance measures augment the information traditional performance measures provide to investors.

5.2 RECOMMENDATIONS

5.2.1 THE BIAS RATIO AS A HEDGE FUND FRAUD INDICATOR

Suspicious hedge fund behaviour remains an area of concern due to opaque information from the hedge fund industry. The incentive for fraudulent behaviour or performance manipulation also remains high as stellar performance is cardinal for fund survival (i.e. capital inflows, but also minimal or no capital outflows) while also being coupled to fund manager compensation.

The work in Chapter 2 showed encouraging arguments that the Bias ratio does indeed flag potential fraudulent or suspicious behaviour, and is therefore in agreement with previous findings pertaining to the efficiency and value of the ratio. Investigating and comparing alternative fraud measures and employing an appropriate ranking methodology to compare fund rankings of fraud and performance measures will undeniably contribute to the research areas of hedge fund fraud, behaviour and performance. Future research into not only fraud detection measures but also manipulation-proof performance measures (see Goetzmann *et al.*, 2007) will also serve the hedge fund industry and investors well. Solutions to the problem of dealing with illiquidity and how it impacts efforts to capture (the practice of) returns smoothing is also an area where further extensive research will be welcomed.

5.2.2 THE OMEGA MEASURE

The Omega function, though not perfect measure, presents a substantial enhancement compared with traditional performance measures as it describes a large extent of the underlying (P/L) distribution structure, which is relevant and significant to hedge funds. Chapter 3 also demonstrated the added value investors can obtain from the rolling Omega function – risk and return characteristic of investment can be gauged, through time and over a range of return thresholds, by customising viewing perspectives.

Although the work in Chapter 3 follows recommendations by Botha (2007) that the Omega ratio should be studied using returns *during* and *after* the 2007-9 financial crisis, future research should be aimed at a method that employs the Omega function when ranking funds. The latter will be immensely valuable as the Omega function considers the full distribution and not just a single return threshold as is the case with the Omega ratio that is at present (April 2014) being used to rank funds. Suggestions for this might include using integral calculus to estimate the area under the Omega function or developing a method that aggregates multiple Omega threshold values from both the upside and downside into a singular Omega ratio value. The further exploration of the rolling Omega function and its application might also prove to be a rich and alternative area of study.

5.2.3 SCALED SHARPE AND TREYNOR MEASURES

Research on generalised, scaled and altered risk-adjusted performance measures such as the Sharpe and Treynor ratios is vast but on-going as it is acknowledged that classical performance measures are not appropriate for investments that exhibit non-normal return distributions. It is moreover acknowledged and proved in Chapter 4 that hedge fund returns have non-normal return distributions and that more sophisticated performance measures are required to capture higher-order moments of the return distribution.

Future research into more sophisticated performance measures that incorporate higher-order moments should continue as no single existing performance measure can be considered champion – each measure arguably assesses a particular risk. Future research considerations may be aimed at:

- a similar performance ranking study to the work in Chapter 4 that includes both the traditional and scaled performance measures, but with the addition of a third objective measure that also accounts for higher moments. The Omega ratio may be a strong possible contender for the role of this third measure,

- exploring and evaluating the classical Sharpe and Treynor ratios to scaled versions, employing the same or comparable scaling methodology albeit with the added facet of allowing for serial correlation of returns that are non-IID, i.e. using an annualised autocorrelation adjusted Sharpe ratio methodology similar to that as proposed by Lo (2002).

5.3 CONTRIBUTION

The ways in which the three studies constitute this thesis and contribute to portfolio risk management theory and practice, are outlined in Table 5.1.

Table 5.1: Summary of thesis contributions.

Attribute: Assess whether the Bias ratio is a relevant measure of hedge fund fraud or indicator of possible fraudulent behaviour. The Sharpe ratio is supplemented by the Bias ratio as the former is influenced by illiquidity and returns smoothing.

Problem statement: Traditional risk-adjusted performance measures are not complete as they do not implicitly account for all risk components. The Bias ratio is evaluated to determine whether it provides additional (risk) information in addition to that supplied by traditional measures, specifically the Sharpe ratio.

Analysis: Accepted for publication in *International Business and Economic Review*, forthcoming.

Contribution: The Madoff Ponzi scheme was analysed in a meticulous manner and the Bias ratio thereafter applied to the Madoff fraud case in a pragmatic manner so as to confirm whether the Bias ratio is a convincing measure of fraud detection or suspicious behaviour.

The application of the Bias ratio to the Madoff fraud case led to the identification of unordinary characteristics. This study is unique by employing the characteristics as potential warnings signals to identify potentially suspicious funds or fund behaviour.

Also, selective statistics pertaining to the measures included in the study over the different economic phases of the 2007-9 financial crisis were put forth. The information these statistics convey provide valuable insight into the changing performance characteristics of hedge funds and market indices *pre*, *during* and *after* the 2007-9 financial crisis.

Attribute: Rank and value hedge fund portfolios according to risk-adjusted performance measures, in the Sharpe and Omega ratios, over different economic phases.

Problem statement: The Sharpe ratio is ill-suited for portfolios with non-normal P/L distributions. Therefore the Omega measure is evaluated to determine whether it provides additional information to consider, in additional to the information provided by the Sharpe ratio.

Analysis: Published in *International Business and Economic Review*, 13 (3), May/June 2014.

Contribution: The Omega ratio is a better ratio as it makes use of the entire empirical P/L distribution, thereby incorporating all moments of the distribution. The study produced comparative Sharpe and Omega ratio valuations and rankings over economic phases, *pre*, *during* and *after* the 2007-9 financial crisis. This study is the first to produce comparative hedge fund valuations and rankings around the 2007-9 financial crisis period.

The study is the first to construct fund and market benchmark comparisons by means of a rolling Omega function which provides performance information over both a period of time and over a range of return thresholds. In comparison the Omega ratio conveys information only for a specific (static) point-in-time and a single return threshold. The visual value of a rolling Omega function also provides an alternative manner whereby funds can be compared to contender funds or benchmarks.

Selective performance statistics over different economic phases were also presented. These performance statistics afford valuable insight into the changing performance characteristics of hedge funds and market indices *pre*, *during* and *after* the 2007-9 financial crisis.

Attribute: Rank and value hedge fund portfolios according to risk-adjusted performance over different economic phases.

Problem statement: Mean-variance performance measures, such as the Sharpe and Treynor ratios, are ill-suited for portfolios with non-normal P/L distributions, as these traditional measures do not account for higher-order return distribution moments. Evaluate whether scaled performance measures provide additional information to consider in addition to traditional performance measures.

Analysis: Accepted for publication in *International Business and Economic Review*, forthcoming.

Contribution: Extends previous work to produce an altered (non-static) application method to a methodology that scales the (traditional) Sharpe and Treynor ratios in order to incorporate higher-order moments. The Sharpe and Treynor scaling methodology was used to produce comparative fund valuations and rankings to that of the traditional measures.

The study is also the first to:

- produce these comparative fund valuations and rankings over economic phases, *pre*, *during* and *after* the 2007-9 financial crisis. Previous studies merely include the periods *pre* and *during* the crisis while this study also includes the period *post* crisis.
- use the particular scaling methodology with the use of individual hedge funds and market and hedge fund indices – previous studies focused solely on hedge fund strategy applicable market indices.

Selective performance statistics over different economic phases were also put forward. These performance statistics offer valuable insight into the changing performance characteristics of hedge funds and hedge fund and market indices *pre*, *during* and *after* the 2007-9 financial crisis.

Chapter 2 addressed the risk of fraud, which is considered a type of operational risk, within a hedge fund context. Hedge fund managers not only have incentive, but are also able to manipulate hedge fund returns which result in untruthful performance metrics. The chapter argued that traditional performance measures do not account for certain risks, like fraud risk, as these risks are not implicitly considered by mean-variance based measures, i.e. metrics that rely on volatility as the measure of risk. The Bias ratio, which is a fraud indicator, was explored and evaluated alongside the Sharpe ratio, which was corrected for correlation of returns that are non-IID. This fraud detecting ratio was applied to the Madoff Ponzi scheme fraud case which confirmed the ratio to be a convincing measure of fraud detection. The Bias ratio was also, amongst other performance metrics and statistics, used to identify unordinary characteristics which were employed as warning signals to successfully identify potentially suspicious funds.

The Sharpe ratio a widely used performance metric and also the risk-adjusted performance metric of choice within the hedge fund industry. Measures such as the Sharpe ratio assume that return distributions of hedge fund investment portfolios are normally distributed since they prescribed to the mean-variance regime. This assumption has been acknowledged as flawed, especially so considering hedge fund return distributions. The Omega ratio offers a superior measure of relative portfolio performance, as demonstrated with the application to a selection of international long/short equity hedge funds returns. Chapter 3 constructed comparative fund rankings using the Omega and Sharpe ratios with the latter allowing for serial correlation of non-IID returns using an annualised autocorrelation adjusted Sharpe ratio methodology. A unique aspect to this chapter was the construction and use of a rolling Omega function which provides (visual) information over a range of return thresholds and over a period of time. The results and analysis were presented in Chapter 3.

Traditional risk-adjusted performance measures, specifically the Sharpe and Treynor ratios, are also not ideally suited for use within a hedge fund context as these measures do not account for higher return distribution moments that often characterise hedge fund returns. Chapter 4 recognises this problem by constructing and applying scaled Sharpe and Treynor ratios that incorporate the higher-order moments not considered by traditional versions of these measures. These scaled performance measures were also used to produce individual hedge fund rankings and valuations comparative to those of the traditional measures, *pre*, *during* and *after* the 2007-9 financial crisis – previous research employed the scaling methodology to construct comparative hedge fund strategy related market indices rankings, and merely for the periods *pre* and *during* crisis.

5.4 FINAL STATEMENT

Risk management was noticeably absent in hedge fund investing for many years and risk was intuitively managed without any specific regulatory guidance. Risk management has, however, become a critical function in the world of hedge funds for both investors and fund managers. Hedge fund managers also either adopt risk management as a value-adding tool from a proprietary perspective or recognise it as a means to facilitate and improve communication with clients and enhance confidence in their actions. A clear trend on the part of hedge fund investors pertaining to risk management concepts and practices from accepting to requesting is also observable. From an investor's perspective modern, financial risk management should comprise: (i) understanding the risk exposures of the hedge fund, (ii) measuring the exposures of the hedge fund to each risk factor and aggregating these exposures at fund level, (iii) aggregating the risk of individual hedge funds to obtain the risk of a portfolio of funds, and (iv) selecting which risks to bear and which risks to avoid.

Measuring risk is, however, a passive activity and unfortunately adds little value. It is only when the measuring of risk progresses into the management of risk that long-term, risk-adjusted returns of a hedge fund portfolio are enhanced. The accurate measurement of risk, however, remains a prerequisite for the effective management of risk.

The 2007-9 global financial crisis has also altered the role of risk management and the role of risk managers. The crisis highlighted that the measurement of financial risks and the measurement methods necessitate re-evaluation while the prominence and authority of risk managers and the practice of risk management has increased. It is imperative that risk management matches the inevitable and ever-increasing state of financial innovation so as to remain relevant. This would entail comprehending what previous risk models inform of the underlying risk environment, the revision and adjustment of these previous risk models when they cease to be relevant and the development of new models when required. As the risk milieu is vast and complex, the areas of concern dealt with in this thesis essentially represent only a small fraction of the work that is continually required. Nevertheless, significant progress toward enhanced portfolio risk management, specifically within a hedge fund context, can be – and has been – made through the implementation of the studies detailed in this research.

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ANNEXURE

CONSENT LETTERS FROM JOURNAL EDITORS

The Clute Institute

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February 5, 2014

Professor Francois van Dyk
University of South Africa
Department of Finance, Risk Management and Banking

Dear Professor van Dyk:

Based on the recommendations of two independent reviewers and the editor regarding current editorial requirements, your manuscript entitled "Hedge Fund Performance Evaluation Using The Sharpe And Omega Ratios" has been accepted for publication in the International Business & Economics Research Journal. This acceptance is valid for one year.

As a condition of publication, the authors give permission to the Clute Institute to publish their manuscript in hardcopy and online with full copyright protection and the right to disseminate the manuscript to the widest possible readership. Authors retain full, but non-exclusive rights to their manuscript. This means that authors may use their manuscript in any way they see fit without obtaining permission from the Clute Institute provided that appropriate credit to the Clute Institute is noted.

A formatted draft of your manuscript will be emailed for approval to the contact author prior to publication, and at the time of publication, each author will receive a complimentary PDF copy of their manuscript. Please be sure that we are provided with email addresses for each author. For journal rating purposes, we are including email addresses in the author biographies.

Congratulations on your successful acceptance, and thank you for allowing the Clute Institute to publish your manuscript.

Please refer to IBER-6450 in future correspondence.

Regards,

Ronald C. Clute, Ph.D., Director

Promoting and publishing quality academic research since 1985

May 1, 2014

Professor Prancois van Dyk
Professor Gary van Vuuren
Professor Andre Heymans

Dear Professors:

Based on the recommendations of two independent reviewers and the editor regarding current editorial requirements, your manuscript entitled "The Bias Ratio As A Hedge Fund Fraud Indicator: An Empirical Performance Study Under Different Economic Conditions" has been accepted for publication in the International Business & Economics Research Journal. This acceptance is valid for one year.

As a condition of publication, the authors give permission to the Clute Institute to publish their manuscript in hardcopy and online with full copyright protection and the right to disseminate the manuscript to the widest possible readership. Authors retain full, but non-exclusive rights to their manuscript. This means that authors may use their manuscript in any way they see fit without obtaining permission from the Clute Institute provided that appropriate credit to the Clute Institute is noted.

A formatted draft of your manuscript will be emailed for approval to the contact author prior to publication, and at the time of publication, each author will receive a complimentary PDF copy of their manuscript. Please be sure that we are provided with email addresses for each author. For journal rating purposes, we are including email addresses in the author biographies.

Congratulations on your successful acceptance, and thank you for allowing the Clute Institute to publish your manuscript.

Please refer to IBER-6449 in future correspondence.

Regards,

Ronald C. Clute

Ronald C. Clute, Ph.D., Director

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July 7, 2014

Professor Francois van Dyk
Professor Gary van Vuuren
Professor Andre Heymans

Dear Professors:

Based on the recommendations of two independent reviewers and the editor regarding current editorial requirements, your manuscript entitled "Hedge Fund Performance Using Scaled Sharpe And Treynor Measures" has been accepted for publication in the International Business & Economics Research Journal. This acceptance is valid for one year.

As a condition of publication, the authors give permission to the Clute Institute to publish their manuscript in hardcopy and online with full copyright protection and the right to disseminate the manuscript to the widest possible readership. Authors retain full, but non-exclusive rights to their manuscript. This means that authors may use their manuscript in any way they see fit without obtaining permission from the Clute Institute provided that appropriate credit to the Clute Institute is noted.

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Please refer to IBER-6754 in future correspondence.

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Ronald C. Clute

Ronald C. Clute, Ph.D., Director

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