The returns of Hedge Funds

A comparative study of performance

Master's Thesis

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Abstract

In this thesis we test the performance of hedge funds against several fund specific variables, mainly fund size. As a measure of the hedge funds performance we employ both excess and risk-adjusted returns. The first part the thesis employs unbalanced panel regressions where hedge funds excess returns are run on several fund specific variables. In the second part several financial performance measures (PM:s) are constructed for each fund and measured against fund size. The results largely confirm the theory from the Berk and Green model predicting decreasing returns to scale for funds. This however seems to be a truth with many modifications as the results differ widely at fund, strategy and geographic focus level. We also get vastly different results when switching between the two ways of measuring performance.

1. Introduction

"Hedge funds are the wildest animal out there with virtually no restriction on what they can do, with regards to acid investments with regards to leverage with regards to whom they employ...the degree of freedom of what these guys can do is extraordinary", Storr (2016)[39] .

Hedge funds are investment vehicles that differ from standard investment forms in a variety of ways. They are less regulated than mutual funds and are therefore prone to take more risky investments. This feature often makes their return distributions non normal compared to the distributions of mutual funds. (In other words their return distributions are not well modeled by a normally distributed stochastic process). A lot of research over the years has been devoted to studying how fund specific factors such as the funds size affect their performance. Most of this research builds on theory of capacity constraints and decreasing returns to scale at fund level from a model developed by Berk and Green (2004)[5].

A common way to check for these capacity constraints has been to regress fund excess returns (the funds return minus the risk-free rate) on some kind of size variable for the fund. Another way to check the same effect has been to instead construct risk adjusted returns for the funds in the form of financial performance measures (PM:s). These have later been regressed on fund size and fund specific variables. Although many studies exist where either one of these procedures has been carried out, very few have combined the two approaches and compared the results. This thesis strives to fill this gap in the literature. In addition to checking how the size of hedge funds affects their performance in form of excess returns the size factors relationship is also checked with risk adjusted returns in form of several financial performance measures (PM:s).

Unbalanced panel models are first run on the excess returns of a sample with 1624 different hedge funds. To create more homogeneous groups, the original sample is divided into smaller groups dependent on geographic focus or strategy employed by the fund.

In the second part of the study 5 financial PM:s are constructed for every fund. The different measures are then run in linear regressions on a mean size factor for each fund. To study the relationship between the PM:s and size factors more throughly the relationship between the two is also plotted in two figures.

The panel data regressions run indicate that hedge funds suffer from *decreasing* returns to scale at the level of both strategy and geographic focus. On the contrary the linear models estimated on the PM:s indicate *increasing* returns to scale at fund level. But, judging from concavity in the figures of the PM:s plotted against their mean size factor, these results seem to indicate at first an increasing but later constant return to scale. Thus seemingly the size of a fund is a positive factor only up to a certain point. Possible explanations of these results are discussed in the results section.

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2. Theory

First, general theory of the firm specific attributes are presented followed by a brief presentation of earlier research. This is followed by sections explaining hedge fund strategies and geographic focus. Finally, a short presentation is given of the employed PM:s.

2.1. ***Fund specific attributes***

2.1.1. Size

Decreasing returns to scale for hedge funds in both size and skill have been predicted in a model by Berk and Green (2004)[5]. Successful funds in their model receive larger inflows of capital. However the model also states decreasing returns to scale for these inflows in both performance and managerial skill. One reason for the negative fund size/performance relationship is their assumption that the fund trading cost is convex in fund size. Fourteen years after this paper was published it is still not clear whether this is true, neither for mutual or hedge funds.

2.1.2. Minimum initial investment

The hedge fund world has for a long time had an air of secrecy and been notorious for only being available to a small exclusive group of investors (Investopedia, 2018[22]; Forbes, 2000[12]). It is not uncommon for the funds to require a minimum initial investment of a hundred thousand or even a million dollars and the successful ones can require a lot more than that (Forbes, 2000)[12]. One would thus think that this explanatory variable should have a positive effect on returns, which also has been shown (Bali et al., 2014)[3].

2.1.3. Total expense ratio (ter)

This is a measure of the total cost for investors to be active in the fund. It is of course a natural question if investors who pay a higher fee are actually compensated for this in form of higher returns.

2.1.4. Age

In some studies age has been shown to have a negative effect on hedge fund returns (Gao et al., 2018[14]; Frumkin and Vandegrift, 2009[13]). One explanation has been that younger funds take on riskier behavior which boosts their returns (Getmansky, 2012)[15]. Another explanation is that younger funds have new and innovative ideas that increase their returns (Aggarwal and Jorion, 2010)[1].

2.2. Earlier research

A large body of literature has over the years tried to estimate models to check the assumptions of decreasing returns to scale or capacity constraints. Golez and Shive (2015)[16] find a large negative decreasing returns to scale relationship at the mutual fund level and, findings by Zhang (2018)[42] include that about 70% of the funds inflow-performance sensitivity seems explainable by the theory developed by Berk and Green (2004)[5]. However some studies have claimed the decreasing returns to scale not to be a universal truth. Ferreira et al. (2013)[11] showed that the relationship differed from one fund country to another.

Employing the same method for risk adjusted return regressions as this thesis[1] Ammann and Moerth (2005)[2] find a positive relationship between size of fund and hedge fund performance measured as risk-adjusted returns. The relationship is claimed to be due to the higher total expense ratio of smaller funds compared to larger ones. Another possible explanation of the results they provide is that larger funds may have smaller risk measured as standard deviation. This increases the value of for example the Sharpe ratio (see 2.5.1). The positive relationship between fund size and performance is however nonlinear (concave downward) and only holds up until a certain fund size is reached (Ammann and Moerth, 2005)[2].

Frumkin and Vandegrift (2009)[13] studied the relationship between returns and size and age on a sample of 50 randomly selected hedge funds. This is done through a panel regression with fixed effects to capture the time independent effect of each hedge fund. The independent variables were: size, age, fund beta value and a time dummy for regulation.[2]. Findings included that both size and age had a negative effect on hedge fund performance measured as excess returns. As an explanation for the negative fund size excess return relationship they state that managers at smaller funds are more free to pursue their individual investment ideas. This is however not true as the fund grows larger as in this case managers have to look into secondary ideas and even further as arbitrage opportunities disappear when the market adjusts.

They also state that age has a negative effect on fund performance as

[1]Although this study did not feature non parametric PM:s (Omega, ASR and Gini measure ratios)

[2]Rule 203(b)(3)-2 (2005) required hedge fund managers to register under the US securities and exchange commission

aging funds experience a so called ”style drift”. This term states that with increasing age hedge fund managers drift away from their area of expertise.

A negative relationship between size and returns has also been shown by Pertrac Corporation (2012)[30]. The authors in this case pooled hedge fund data from many different sources and divided the funds into different subgroups based on the size values. They then compared risk adjusted returns. Doing this it was shown that larger sized funds in general had lower risk adjusted returns. Employing the same methodology for age it was also shown that younger funds outperformed older ones.

Similar factor models to those employed in this thesis have earlier been used on hedge fund data by Bali et al. (2014)[3] and Ferreira et al. (2013)[11].

Bali et al. (2014)[3] run cross-sectional regressions on excess returns using different factor models controlling for fund specific attributes. Risk factors are created through principal component analysis and based on several measures of macroeconomic risk. Findings indicate that systematic risk is a persistent significant factor in explaining hedge fund excess returns.

Ferreira et al. (2013)[11] run cross-sectional regressions with alphas estimated from the Carhart four factor model as dependent variable. They find a negative relationship between fund size and alphas in the case of US funds but not in the case of non US funds.

An overwhelming part of earlier studies on the subject have used cross sectional data for estimation. Despite of this a panel data approach has been recommended to deal with problems of unreliable estimates resulting from the cross-sectional estimations (Slavutskaya, 2014)[36]. A need to include the external macro economic environment as well as the internal structure of the hedge fund industry in studies has also been suggested for further research (Stafylas et al., 2016)[37].

In a very recent article (Cao and Velthuis, 2017)[6] , the authors claim there are no certain evidence of capacity constraints in the hedge fund industry as earlier such claims have been based on results derived from a downward biased LSDV-estimator. Using a 2SLS estimation method from Pastor et al. (2015)[29] they find no evidence of such decreasing returns to scale at the fund level for hedge funds but rather for the industry as a whole. This critique could apply to the first part of our study (and countless similar studies so far that have estimated a decreasing returns to scale relationship using fixed effects). Since I found this reference at a very late point in my investigation it has not influenced my analysis. Moreover in the absence of further work in this area it is not clear to me if their objection is generally accepted.

It is also important to point out that this study employs a vastly different dataset than theirs regarding the strategies the funds employ and regarding the mix of live and defunct funds.

2.3. ***Fund Strategies***

There are 7 different strategy classes included in this thesis. Below follows a presentation of each one.
Motivation for studying how the hedge fund size-performance effect differs between different hedge fund strategies can be found in Naik et al. (2007)[28]. They studied how hedge fund alpha values were related to size by classifying the funds into 8 broad investment categories. For four of them they found the negative effect stated in Berk and Green (2004)[5] but for the rest of the strategies the effect was absent. Naik et al. (2007)[28] give two main motivations for studying how capacity constraints or decreasing returns to scale affected hedge funds at fund level. One is that if some strategies were more prone to experience these types of capacity constraints than others this might affect the distribution of capital to the funds from investors. Another motivation was that funds had factors common to each of the strategies that would affect the ones within each strategy group in similar ways (Naik et al., 2007)[28].
Below follows a short presentation of each of the strategies employed by fund in this thesis. Information about each strategy is, unless other sources are not stated explicitly taken from Barclay Hedge[4] or the Lipper Hedge Fund database.

Long Short Equity (LSE)

This strategy contains the largest number of funds in the study. The strategy is easy to understand as it simply consists of buying stocks that are expected to appreciate and shorting ones that are expected to lose value. Ideally hedge fund managers in this class should be able to timely change their exposures in different market states (Lamm, 2004)[27]. They often display an asymmetric risk/return profile by being able to generate a higher correlation to equity markets in falling markets and a lower correlation to them in falling markets.

Managed futures/CTA (CTA)

CTA or commodity trading advisor provides individual advice regarding the buying and selling of futures contracts. It is a highly diversified class that does not only engage in trading in traditional asset classes but also in instruments like managed future contracts. The funds are often classified as lower risk (due to asset class diversification) and highly liquid type of funds (Investopedia, 2018)[23].

Emerging markets (EME)
As the name implies these are funds that invest in emerging markets (typically on the middle to small scale of the world income range). These are areas where mutual funds are typically not allowed to invest due to high risk. Hedge funds in this area can invest in less conventional types of assets (like real estate, currencies or derivatives) and apply leverage to their investments.

Multi strategies (MULTI)
The funds in this class are classified as being very flexible. They can switch between any of the stated hedge fund strategies to the one that currently gives best opportunities.

Event Driven (EVENT)
These are funds that seek to prosper from corporate mergers (merger arbitrage) or by investing in distressed securities.

Credit focus (CRED)
These are funds that invest primarily in debt. They are often more active during market downturns and often invest in distressed securities.

Global Macro (GLOB)
These are funds that seek to profit from different Geo-political events (Investopedia, 2018)[21]. They are not bound to traditional asset classes like for example long short equity funds and can therefore employ the same variety as CTA/managed futures.

Classification according to the stated strategies are the ones supplied to the database by the funds themselves.

2.4. ***Geographic focus***

Ferreira et al. (2013)[11] claim that capacity constraints in the mutual fund industry apply to US funds but not necessarily to funds with other geographic focus. Another influential theory (Teo, 2009)[38] states that there exists a trade off between increased returns or better access to capital for funds when choosing their geographic focus. I.e funds that choose to invest further from large financial hubs can gain higher returns but have less access to capital. .

2.5. ***Performance Measures***

2.5.1. *Sharpe Ratio*

The Sharpe ratio (Sharpe, 1966)[35] is perhaps the most classic of all performance measures. It is defined as the expected return R_p for a portfolio over a period minus the risk free rate (R_f) divided by the standard deviation for the studied period. This risk measure is based on the mean variance theory of risk and has thus been claimed to be inefficient when data is not normally distributed.

$$S_p = \frac{E(R_p) - R_f}{\sigma_{R_p}} \tag{1}$$

2.5.2. *Omega ratio.*

The Omega ratio was proposed by Keating and Shadwick (2002)[26]. It measures the probability weight of gains vs losses for some threshold τ preferred by an investor. It is computed as the ratio between two cumulative distribution functions. In this thesis it is computed as:

$$\Omega_i(\tau) = \frac{r_i^d - \tau}{LPM_1(\tau)} + 1 \tag{2}$$

Here τ is defined as the investors minimum acceptable return (threshold return) (Kaplan and Knowles, 2004)[25]. LPM here is the lower partial moments also defined as downside risk. It measures risk below a certain minimum acceptable level of return.

2.5.3. *The Yithzaki Gini ratio*

The Yithzaki Gini ratio builds on a measure of risk proposed by Yithzaki (1982)[41] aimed at better capturing the anomalies of data with non normal distributions. It is in this thesis used as an alternative measure for standard deviation aimed at better capturing the variability of the hedge fund's often non normal return distributions.
Let:

$$G_p = \Gamma = \sum_{j=1}^{J} \sum_{k>j}^{J} |Y_j - Y_k| = \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} |Y_j - Y_k| \tag{3}$$

Then the Yithzaki Gini ratio is computed as:

$$Yi_p = \frac{E(R_p) - R_f}{G_p} = \frac{E(R_p) - R_f}{\frac{1}{2}E(|R_p - R_f|)} \tag{4}$$

Here Y_i is the return (R_p) minus the risk free rate (R_f) for observation i in the studied period. G_p can be seen as the alternative measure of standard deviation. As Yi_p indicates this measure is then constructed in the same way as the Sharpe ratio.

2.5.4. Jensen's alpha

Jensen's alpha is defined as:

$$\alpha_J = (R_P - R_F) - \beta_P(R_M - R_F) \tag{5}$$

were R_P is the portfolio return, R_F is the return of the risk free rate and R_M is the market return. This is the classical financial measure of excess returns, i.e returns in excess of what can be explained by the Capital asset pricing model (CAPM) (Sharpe, 1964)[34], see section 4.1.1. This alpha, adjusted for systematic risk was developed by Jensen (1968)[24].

2.5.5. The Adjusted Sharpe ratio

$$ASR = SR * (1 + S/6 * SR - \frac{(K-3)}{24}) * (SR)^2) \tag{6}$$

proposed by Pezier and White (2008)[33], is yet another form of Sharpe ratio aimed at capturing the higher moments (skewness & kurtosis) of hedge funds return distributions. Here SR is the annualized Sharpe ratio, S stand for skewness and K is the kurtosis.

3. Empirical Analysis

The empirical analysis begins with a data section explaining the structure of the data set and several problems encountered while obtaining it. This is followed by a section on the data used for the fund specific attributes.

3.1. ***Data***

Data for the stated variables of the funds have been downloaded from the Lipper Hedge Fund database (TASS). This has been done through the Thompson Reuters Excel add-in.

Although the TASS database report data on about 6000 hedge funds both liquidated and active only a fraction of these funds fulfilled the data requirement needed for this thesis. That is funds that have consecutive return series, data on size of fund, data on age of fund and minimum initial investment.

The data has after being downloaded been combined and cleaned in several steps. Funds with unreasonable values for the explanatory variables (such as negative values for size and minimum initial investments (ii)) have been removed from the sample. To be in accordance with numerous studies in the field the lower date limit of fund data is set to: 1994-01-01 (Bali et al., 2014[3]; Ammann and Moerth, 2005[2]). The upper limit is set to 2018-04-01. Funds to be included in the sample are required to have data for at least 10 consecutive months. 400 Hedge funds in the sample contained gaps placed randomly in the return and fund size series. The longest consecutive series of these funds was extracted while the rest were discarded from the sample. After filtering the dataset we end up with monthly data for a sample of 1624 hedge funds. Information on the funds geographic investment focus and their strategy was provided by TASS.

3.2. ***Fund specific attributes***

3.2.1. Monthly fund returns

This thesis uses monthly return data. They are in the TASS database referred to as monthly rolling performance.

3.2.2. Size of fund (TNA)

The Hedge funds in this thesis employ the measure TNA (total net assets). The measure can widely be regarded as the total dollar value invested in all share classes of the fund. The measure is provided by Lipper Hedge Fund database and is commonly employed in similar studies (Frumkin and Vandegrift, 2009[13]; Bali et al., 2014[3]). This variable is logged before entered into the model.

3.2.3. Minimum initial investment (ii)

The Hedge funds in this thesis employ a Lipper Hedge Fund database measure titled "minimum initial investment". It consists of minimum initial investment (measured in dollars) required for investing in the fund.

3.2.4. Total expense ratio (ter)

This variable measures the total cost of the fund for the investor. It is calculated as the funds total annual costs divided by its total average annual assets.

As this measure has only been available for 240 funds in the sample its effect on excess returns is tested in a separate panel regression independent of strategy and geographic focus.

3.2.5. Age

This variable measures the number of days the fund has been active. It is based on the launch date variable provided by Lipper Hedge Fund database.

As downloading information on which funds were liquidated was proven not possible this variable has been constructed in 2 different ways:

The first way was to construct the variable as the difference between the date that the fund stopped reporting returns to the database and the launch date.

As many of the funds of in the sample have turned out to still be active, but just stopped reporting data for one of the variables TNA (total net assets) or R_p (returns), I construct this variable as the difference between the final month included in the study (2018-04-01) and the launch date.

The differences in panel estimations between these 2 approaches were negligible and I have therefore chosen to stay with the the first approach.

4. Method

The method section begins with a short presentation of the different financial factor models employed. After this a presentation of the different models used for the regressions on excess and risk-adjusted returns is given together with econometric specifications.

4.1. ***Factor models***

Several different factor models[3] that commonly have been used in the literature are employed throughout this thesis. Common for these types of factor models is that they take into account the stock returns on different markets. Below follows a brief introduction of each one used in this thesis.

4.1.1. The CAPM

The capital asset pricing model is a classic workhorse when measuring excess returns and estimating systematic risk:

$$(R_P - R_F) = \beta_P(R_M - R_F) \tag{7}$$

R_P is here being the monthly rolling returns, R_F is the risk free rate and R_M is the market return. The estimated β_p measures systematic risk.

[3]Data for the factor models and risk-free rate are taken from the website of Kenneth R. French.

4.1.2. The Fama-French three factor model

The classical Fama-French factor model builds on the CAPM adding two more factors:

$$(R_{P_{i,t}} - R_{F_t}) = \alpha_i + \beta_1(R_{M_t} - R_{F_t}) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{i,t} \quad (8)$$

These factors build on the work by Fama and French (1993)[9] They use three factors to describe stock returns. To do this they construct portfolios with stocks of different characteristics. They then measure certain ratios between these portfolios with hope of outperforming CAPM in describing stock returns. In the Fama-French 3 factor model they add 2 additional factors to the CAPM model, SMB and HLM. SMB (small minus big) measures the performance of stocks from small vs big companies and HML (high minus low) measures the performance of stocks with high book to market value vs stocks with small book to market value.

4.1.3. The Carhart four factor model

$$(R_{P_{i,t}} - R_{F_t}) = \alpha_i + \beta_1(R_{M_t} - R_{F_t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + \epsilon_{i,t} \quad (9)$$

Carhart (1997)[7] adds a fourth factor to Fama-French:s model, introducing the MOM-momentum factor (here labeled WML). This factor should account for tendencies of stocks to continue rising if going up or continue decreasing if going down.

4.1.4. The Fama-French five factor model

$$(R_{P_{i,t}} - R_{F_t}) = \alpha_i + \beta_1(R_{M_t} - R_{F_t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 CMA_t + \beta_5 RMW_t + \epsilon_{i,t} \quad (10)$$

In Fama and French (2015)[10] the authors add two more factors. The first one (RMW) measures the ratio between firms that are most profitable vs the ones that are the least profitable. The second one (CMA) measures the returns from firms that invest aggressively vs firms that invest conservatively.

4.2. ***Unbalanced Panel Regression (UPR)***

The panel data set used is unbalanced, meaning that all funds do not have data for equal time periods. As the hedge funds in the sample are of different ages and some have been liquidated, this has been necessary to adequately reflect the world hedge fund environment.

When possible we employ individual fixed effects to capture the individual differences between hedge funds in the sample. In the cases when due to time independent fund specific factors this has not been possible the study has used pooled regressions. As a robustness check separate regressions with fund specific variables and time fixed effects (time dummies) are also estimated (see Tables B.10 and B.11). As a further robustness check, UPR:s are also estimated when the data is split up into two distinct time periods, one before and one after the financial crisis of 2008, (see Appendix B.2). Two panel unit root tests, the Fisher-type (Choi, 2001)[8] and the Im, Pesaran and Shin (2003)[20] unit root tests are used to check for stationarity of the variables in the UPR:s. As these tests assume cross sectional independence the regressions also employ a PCD-test (Pesaran, 2004)[31].

All UPR:s are estimated with robust standard errors (Huber, 1967[19]; White, 1980[40]) to account for heteroskedasticity and serial correlation. Individual fixed effect UPR:s are at first run with the size factor (TNA), each of the different factor models and a variable for time trend. The time trend variable is constructed to control for a linear time trend, that is it equals (1,2...t_n) were n equals the final date observation in the sample. The general formula for the unbalanced panel regressions with fixed effects is:

$$(R_{P_{i,t}} - R_{F_t}) = \alpha_i + \beta_1 TNA_{i,t} + \beta_2 trend_t + FM_{t,j} + \epsilon_{i,t} \tag{11}$$

Here FM_t is one of the 4 different factor models used, i is an index for each individual fund and $trend_t$ is a variable for a linear time trend. The index j stands for the funds geographic focus and α_i are the individual fixed effects for each fund.

Firstly, this model is estimated on the funds grouped by strategy. Secondly, the same thing is done on the funds grouped by geographic focus.

As the difference in explanatory power between the different factor models in (11) was negligible the Fama-French three factor model is chosen for further analysis. That is we use the following formula in our regressions:

$$(R_{P_{i,t}} - R_{F_t}) = \alpha_i + \beta_1 tna_{i,t} + \beta_2 (R_{M_{t,j}} - R_{F_t}) + \beta_3 SMB_{t,j} + \beta_4 HML_{t,j} + \beta_5 trend_t + \epsilon_{i,t} \quad (12)$$

The Fama-French three factor model will hereafter be labeled as $FF3$. The results for this model (12) for funds divided by strategy and geographic focus can be found in Tables 1 and 3. In the next step this model is once again estimated with pooled OLS adding the fund specific variables for age and minimum initial investment:

$$(R_{P_{i,t}} - R_{F_t}) = \alpha + \beta_1 tna_{i,t} + \beta_2 ii_i + \beta_3 age_{i,t} + FF3_{t,j} + \beta_7 trend_t + \epsilon_{i,t} \quad (13)$$

Here ii_i is the minimum initial investment variable and $age_{i,t}$ is the variable for age. Results from equation (13) can be found in Tables 2 and 4.

A final UPR (Table 5) is estimated lowering the fund sample to 240 hedge funds (funds that have data on total expense ratio) then estimating the same model again adding the variable for total expense ratio:

$$(R_{P_{i,t}} - R_{F_t}) = \alpha + \beta_1 tna_{i,t} + \beta_2 ii_i + \beta_3 age_{i,t} + \beta_4 ter_i + FF3_{t,j} + \beta_8 trend_t + \epsilon_{i,t} \quad (14)$$

Here ter_i equals the total expense ratio.

4.2.1. A note on Cross sectional dependence (CSD)

As my aim with dividing funds according to strategies and geographic focus is to divide the large sample into smaller more homogeneous groups some form off correlation in the cross section is inevitable. Several of the estimated panels reject the null hypothesis of cross sectional independence from a the PCD-test (Pesaran, 2004)[31]. As both of the unit root tests earlier performed assumed cross sectional independence I also perform the Pesaran, (2007)[32] unit root test. As this test also indicates stationarity I chose to proceed with the estimations and handle the problems with CDS with robust standard errors and robustness tests with time fixed effects. This is also in line with how Ferreira et al. (2013)[11] deal with these problems. As a final robustness test in the Appendix I also report regressions that include cross sectional dependence robust standard errors (Hoechle, 2007)[18] (see Tables B.16 and B.17).

4.3. ***Regressions on risk-adjusted returns***

The total fund sample TNA is sorted into percentiles[4]. The excess returns are then sorted after these percentiles. The five different PM:s[5] in the theory part are constructed for the fund returns in each percentile. Finally five linear OLS models are run with the mean TNA of each percentile as explanatory and each of the PM:s as dependent variable. As a robustness check the PM:s of the individual funds are also run on their individual mean size data.

$$SR_i = \beta_0 + \beta_1 mtna_i + \epsilon_i \tag{15}$$

$$ASR_i = \beta_0 + \beta_1 mtna_i + \epsilon_i \tag{16}$$

$$Omega_i = \beta_0 + \beta_1 mtna_i + \epsilon_i \tag{17}$$

$$Y_i = \beta_0 + \beta_1 mtna_i + \epsilon_i \tag{18}$$

$$\alpha_i = \beta_0 + \beta_1 mtna_i + \epsilon_i \tag{19}$$

Here SR_i is the Sharpe ratio, ASR_i is the Adjusted Sharpe ratio, $Omega_i$ is the Omega ratio, Y_i is the Sharpe ratio with Gini mean difference (G-Sharpe) and α_i is Jensen's alpha.

[4]Employing the framework of Ammann and Moerth (2005)[2]

[5]Sharpe ratio, Omega, ASR, G-sharpe and Jensen's alpha

5. Results from regressions on excess returns

5.1. ***Regressions on fund strategies***

Having estimated all of the factor models very little difference is noticed between them. Little gain in explanatory value can seem to be gained from including more factors in the model than the ones in FF3 (or even CAPM). I have therefore chosen to stay with the FF3 model. This is to avoid over-specification of the model by including unnecessary parameters. The choice of factor model is not the main focus of the thesis which lies on the fund specific attributes.

Table 1: Fama-French 3 factors, fixed effects (individual), regressions on strategy

	Dependent variable:						
				y			
	LSE	CTA	EME	MULTI	EVENT	CRED	GLOB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	-0.109^{***}	-0.287	0.070	0.260^{***}	-0.176^{***}	-0.383^{***}	0.015
	(0.033)	(0.179)	(0.092)	(0.100)	(0.051)	(0.069)	(0.085)
Mkt.RF	0.527^{***}	0.079^{***}	0.768^{***}	0.559^{***}	0.394^{***}	0.294^{***}	0.404^{***}
	(0.022)	(0.025)	(0.048)	(0.034)	(0.043)	(0.042)	(0.053)
SMB	0.317^{***}	-0.021	0.417^{***}	0.367^{***}	0.323^{***}	0.097^{***}	0.095^{**}
	(0.025)	(0.046)	(0.046)	(0.037)	(0.044)	(0.031)	(0.047)
HML	0.005	-0.032	-0.045	-0.042	0.082^{***}	0.060^{***}	-0.147^{***}
	(0.026)	(0.030)	(0.049)	(0.034)	(0.032)	(0.019)	(0.041)
trend	-0.005^{***}	-0.005^{***}	-0.006^{***}	-0.012^{***}	-0.002^{*}	0.001	-0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Observations	37,801	23,606	14,980	19,170	8,418	6,398	8,020
R^2	0.264	0.005	0.157	0.188	0.244	0.156	0.100
Adjusted R^2	0.256	-0.005	0.148	0.175	0.236	0.146	0.085
Note:							*p<0.1; **p<0.05; ***p<0.01

The results from the unbalanced panel regressions (UPR:s) on fund strategy can be seen in Table 1. All stated panel unit root test reject the H_0 of non stationarity at a 1% level for both the return series, fund specific variables and the variables from the factor models.

The FF3 model does a reasonably good job at explaining excess returns from the different strategies with R^2 values of around 20%. The funds beta values (coefficients for Mkt.RF) are according to theory. The lowest value belongs to the CTA/managed futures class which is labeled as having the lowest risk amongst the fund strategies. The highest Beta value belong to the Emerging markets class which usually is labeled as a high risk class.

The hedge fund strategies Long short equity, Event driven and Credit focus display a negative relation with TNA (total net assets) and excess returns. These results indicate that there exists a decreasing returns to scale relationship between fund size and excess returns for these classes. The results are in line with Frumkin and Vandegrift (2009)[13]. However they make no difference between funds belonging to different strategies, and therefore do not seem concerned with heterogeneity between different strategy groups in the fund sample. For one class (Multi strategies) the relationship between fund size and excess returns is positive. This means that this strategy actually has increasing returns to scale. When splitting up the time period in robustness tests (see Appendix B.2) the results seem more or less stable for the strategies exhibiting decreasing returns to scale but not for the Multi strategy class.

Although we show that certain strategies exhibit capacity constraints as in Naik et al. (2007)[28] the strategies that suffer from this in our study are not the same as in theirs.

This shows the value in performing an updated review of their work. There are several possible explanations to this. Either the effect of capacity constraints on strategy level is time and situation dependent (even though our robustness tests (Tables B.12 and B.14) speak against this). Another explanation could be their way of measuring performance as alpha values instead of excess returns.

Even though the effect does not seem constant over time it is still interesting to point out that the Multi strategy class is the only fund class that has a significant positive coefficient on the variable TNA. This could highlight the need for funds to switch between strategies that are currently the most profitable. Sticking too long with one strategy would according to the results mean lower returns and decreasing returns to scale.

Unbalanced Panel regressions when we add variables for fund minimum initial investment (ii) and age are found in Table 2. As seen age seems as in numerous studies (Frumkin and Vandegrift, 2009[13]; Pertrac, 2012[30]; Gao et al., 2018[14]) to have a negative effect on fund performance. One explanation for this is the style drift factor. Another one is that younger funds more easily can avoid bureaucracy and conduct changes under the radar.

The fact that the TNA values are not consistent between the pooled regressions and the ones with fixed effects could be explained by the correlation between the fund size and age variable. In Table A.8 in Appendix A.1 we switch the age variable with the one for TNA to find the TNA once again more consistent with Table 1. A notable difference is that in Table A.8 the class Emerging Markets now shows signs of increasing returns to scale.

The difference in results between Tables 1 and A.8 highlight the peculiarities of hedge funds as a type of investment vehicle. Very much regarding the hedge funds performance is dependent on the individual skill of the manager. Even though the strategy groups are more homogeneous groups than in the whole sample heterogeneity is still large between the individual funds. Trying to proxy for this by adding fund specific time independent variables is not easy.

That the minimum initial investment variable is positive is in line with what has been shown in Bali et al. (2014)[3]. It indicates that funds that can afford to set this minimum initial investment bar high are actually more successful funds that deliver higher returns.

Table 2: Fama-French 3 factors, pooled panel, regressions on strategy

	Dependent variable:						
				y			
	LSE	CTA	EME	MULTI	EVENT	CRED	GLOB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	-0.018	-0.055	0.081^{***}	0.132^{***}	-0.079^{***}	-0.109^{***}	-0.006
	(0.016)	(0.043)	(0.028)	(0.039)	(0.027)	(0.027)	(0.035)
Age	-0.121^{**}	-0.002	-0.003	-0.271^{**}	-0.226^{***}	0.064	-0.015
	(0.049)	(0.055)	(0.125)	(0.109)	(0.083)	(0.091)	(0.122)
ii	0.042^{***}	0.051^{***}	0.050	0.027^{***}	0.137^{***}	0.023	0.030^{**}
	(0.016)	(0.020)	(0.041)	(0.007)	(0.033)	(0.019)	(0.013)
Mkt.RF	0.526^{***}	0.078^{***}	0.767^{***}	0.558^{***}	0.394^{***}	0.296^{***}	0.402^{***}
	(0.021)	(0.025)	(0.048)	(0.034)	(0.043)	(0.042)	(0.053)
SMB	0.316^{***}	-0.022	0.414^{***}	0.374^{***}	0.326^{***}	0.100^{***}	0.099^{**}
	(0.024)	(0.045)	(0.045)	(0.036)	(0.044)	(0.031)	(0.046)
HML	0.004	-0.032	-0.044	-0.039	0.081^{***}	0.052^{***}	-0.148^{***}
	(0.026)	(0.030)	(0.049)	(0.033)	(0.031)	(0.018)	(0.041)
trend	-0.006^{***}	-0.005^{***}	-0.007^{***}	-0.008^{***}	-0.002^{*}	-0.003^{***}	-0.007^{***}
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.320^{***}	1.887^{**}	-0.319	1.253	2.204^{**}	2.439^{***}	1.703^{**}
	(0.494)	(0.760)	(1.220)	(0.844)	(0.910)	(0.698)	(0.857)
Observations	37,801	23,606	14,980	19,170	8,418	6,398	8,020
R^2	0.261	0.004	0.157	0.184	0.241	0.149	0.099
Adjusted R^2	0.261	0.004	0.156	0.183	0.240	0.148	0.099
Note:							*p<0.1; **p<0.05; ***p<0.01

5.2. ***Regressions on geographic focus***

Table 3: Fama-French 3 factors, fixed effects (individual), regressions on geo-focus

	Dependent variable:						
				y			
	Global	US	North Am	CAN	Europe	Asia Pac	Asia (ex-jap)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	-0.148^{**}	-0.148^{***}	-0.130	-0.055	-0.025	-0.105	-0.135
	(0.067)	(0.049)	(0.096)	(0.109)	(0.060)	(0.077)	(0.127)
Mkt.RF	0.328^{***}	0.397^{***}	0.457^{***}	0.892^{***}	0.461^{***}	0.600^{***}	0.696^{***}
	(0.018)	(0.032)	(0.066)	(0.050)	(0.030)	(0.097)	(0.081)
SMB	0.154^{***}	0.213^{***}	0.242^{***}	0.139^{**}	0.356^{***}	0.553^{***}	0.412^{***}
	(0.022)	(0.029)	(0.049)	(0.057)	(0.049)	(0.108)	(0.062)
HML	-0.038^{**}	0.030	-0.005	0.375^{***}	-0.077^{**}	-0.116^{*}	0.240^{***}
	(0.019)	(0.032)	(0.046)	(0.084)	(0.031)	(0.066)	(0.050)
trend	-0.005^{***}	-0.003^{***}	-0.005^{***}	-0.015^{**}	-0.008^{***}	-0.005^{**}	-0.004^{***}
	(0.0005)	(0.001)	(0.002)	(0.007)	(0.001)	(0.002)	(0.001)
Observations	74,998	17,489	4,183	2,673	6,428	4,912	2,287
R^2	0.051	0.156	0.258	0.329	0.322	0.179	0.436
Adjusted R^2	0.040	0.148	0.249	0.309	0.313	0.168	0.428
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 3 displays the panel regressions on the funds divided by geographic focus. Capacity constraints seem to exist also when dividing funds by geographic focus. Similarly to Ferreira et al. (2013)[11] effects of decreasing returns to scale are found for funds with US geographic focus. What is somewhat surprising is that the same effect is significant for funds with a global investment focus.

That US funds that are especially close to capital suffer from the decreasing returns to scale are in line with theory from Teo (2009)[38]. This would indicate that funds trade higher returns for closeness to capital. The negative TNA coefficient for the Global class could mean that the funds that label their geographic focus as global still invest mostly near the large financial hubs.

The coefficients of age and minimum initial investment (ii) are found in Table 4. We see that the coefficient on age (negative) and the coefficient on ii (positive) are of the same signs as the UPR:s where the funds are divided by strategy (Table 2).

Table 4: Fama-French 3 factors, pooled panel, regressions on geo-focus

	Dependent variable:						
				y			
	Global	US	North Am	CAN	Europe	Asia Pac	Asia (ex-jap)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	−0.027	−0.010	−0.066*	−0.146***	−0.001	0.035	0.142**
	(0.017)	(0.028)	(0.038)	(0.042)	(0.021)	(0.064)	(0.060)
Age	−0.092**	−0.217***	0.003	−0.158	−0.278***	−0.298	−0.070
	(0.037)	(0.082)	(0.143)	(0.113)	(0.077)	(0.184)	(0.170)
ii	0.060***	0.015	0.129***	0.001	0.044**	0.012	0.100
	(0.010)	(0.030)	(0.042)	(0.038)	(0.019)	(0.071)	(0.088)
Mkt.RF	0.327***	0.398***	0.456***	0.890***	0.461***	0.597***	0.696***
	(0.018)	(0.032)	(0.066)	(0.050)	(0.030)	(0.097)	(0.081)
SMB	0.156***	0.212***	0.243***	0.153***	0.353***	0.547***	0.413***
	(0.022)	(0.029)	(0.050)	(0.057)	(0.049)	(0.106)	(0.062)
HML	−0.039**	0.030	−0.005	0.369***	−0.080***	−0.131**	0.238***
	(0.019)	(0.032)	(0.046)	(0.083)	(0.031)	(0.066)	(0.050)
trend	−0.005***	−0.003***	−0.003**	−0.008**	−0.008***	−0.008***	−0.006***
	(0.0005)	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)
Constant	1.973***	2.970***	0.376	5.367***	3.589***	3.651*	−1.346
	(0.369)	(0.891)	(1.354)	(1.327)	(0.809)	(2.091)	(1.775)
Observations	74,998	17,489	4,183	2,673	6,428	4,912	2,287
R^2	0.051	0.153	0.255	0.329	0.322	0.175	0.435
Adjusted R^2	0.051	0.152	0.254	0.327	0.321	0.174	0.434
Note:							*p<0.1; **p<0.05; ***p<0.01

5.3. ***Regressions with total expense ratio***

The Total expense ratio variable (*ter*) is not significant when using it's normal values in the regression. However when constructing dummy variables for funds with the highest values of the variable (top 2 deciles) the effect is significant and negative for funds whose *ter* is in the top decile (d10). These results would indicate that the funds total expense ratios to some degree is not increasing with it's returns. In other words the Hedge funds that are the most costly to investors take out fees that are unjustifiable.

Table 5: FF3 Regressions with Total expense ratio

	Dependent variable:	
	y	
	(1)	(2)
tna	0.033*	0.031*
	(0.017)	(0.017)
ii	0.022***	0.019***
	(0.005)	(0.005)
age	−0.00003**	−0.00003**
	(0.00002)	(0.00001)
xMkt.RF	0.579***	0.579***
	(0.033)	(0.033)
xSMB	0.325***	0.325***
	(0.028)	(0.029)
xHML	−0.028	−0.028
	(0.029)	(0.029)
trend	−0.006***	−0.006***
	(0.001)	(0.001)
ter	−0.035	
	(0.027)	
d9		−0.189
		(0.133)
d10		−0.226**
		(0.114)
Constant	0.726**	0.752**
	(0.330)	(0.322)
Observations	22,561	22,561
R^2	0.260	0.261
Adjusted R^2	0.260	0.260
Note:	*p<0.1; **p<0.05; ***p<0.01	

6. Results from regressions on risk-adjusted returns

6.1. ***Linear models***

In Table 6 we show the results from the regressions on the risk-adjusted returns when the data is divided into 100 discrete bins (see 4.3). The linear model shows the same positive relationship between size and fund returns as in Ammann and Moerth (2005)[2].

Table 6: Regressions on Risk-Adjusted returns 1

	Dependent variable:				
	SHARPE	ASR	OMEGA	G-Sharpe	Alpha
	(1)	(2)	(3)	(4)	(5)
MTNA	0.014^{***}	0.054^{***}	0.046^{***}	0.012^{***}	0.012^{***}
	(0.002)	(0.006)	(0.007)	(0.002)	(0.001)
Constant	-0.126^{***}	-0.638^{***}	0.662^{***}	-0.083^{***}	-0.181^{***}
	(0.027)	(0.097)	(0.126)	(0.029)	(0.021)
Observations	100	100	100	100	100
R^2	0.454	0.492	0.295	0.343	0.496
Adjusted R^2	0.448	0.487	0.288	0.337	0.491
Residual Std. Error (df = 98)	0.032	0.116	0.150	0.034	0.025
Note:					*p<0.1; **p<0.05; ***p<0.01

This could be due to the fact that larger funds have lower idiosyncratic risk. As many of the PM:s are negatively related to idiosyncratic risk this would increase the ones for higher funds. A flaw in this theory is that the alpha also seems to be increasing with size. This PM is more dependent on systematic risk and the earlier reasoning would thus not apply in this case. When looking at Table 7 (where each fund in the samples PM is regressed against the actual mean size data for the same fund) this relationship however is not as clear anymore which is reflected in the much lower explanatory power (R^2) for these regressions.

Table 7: Regressions on Risk-Adjusted returns 2

	Dependent variable:				
	SHARPE	ASR	OMEGA	G-Sharpe	Alpha
	(1)	(2)	(3)	(4)	(5)
MTNA	0.026***	0.046	0.318**	0.025***	0.018***
	(0.003)	(0.031)	(0.141)	(0.003)	(0.001)
Constant	−0.279***	−0.575	−2.567	−0.265***	−0.293***
	(0.050)	(0.528)	(2.419)	(0.047)	(0.024)
Observations	1,618	1,618	1,618	1,618	1,618
R^2	0.047	0.001	0.003	0.047	0.085
Adjusted R^2	0.046	0.001	0.002	0.046	0.085
Residual Std. Error (df = 1616)	0.240	2.521	11.547	0.227	0.116
Note:					*p<0.1; **p<0.05; ***p<0.01

This means that the methodology used in Ammann and Moerth (2005)[2] could lead to misleading conclusions if not double checked with regressions against risk-adjusted returns on the actual data.

6.2. ***Plots of risk-adjusted returns***

Figure 1: Risk-adjusted returns, 100 discrete bins

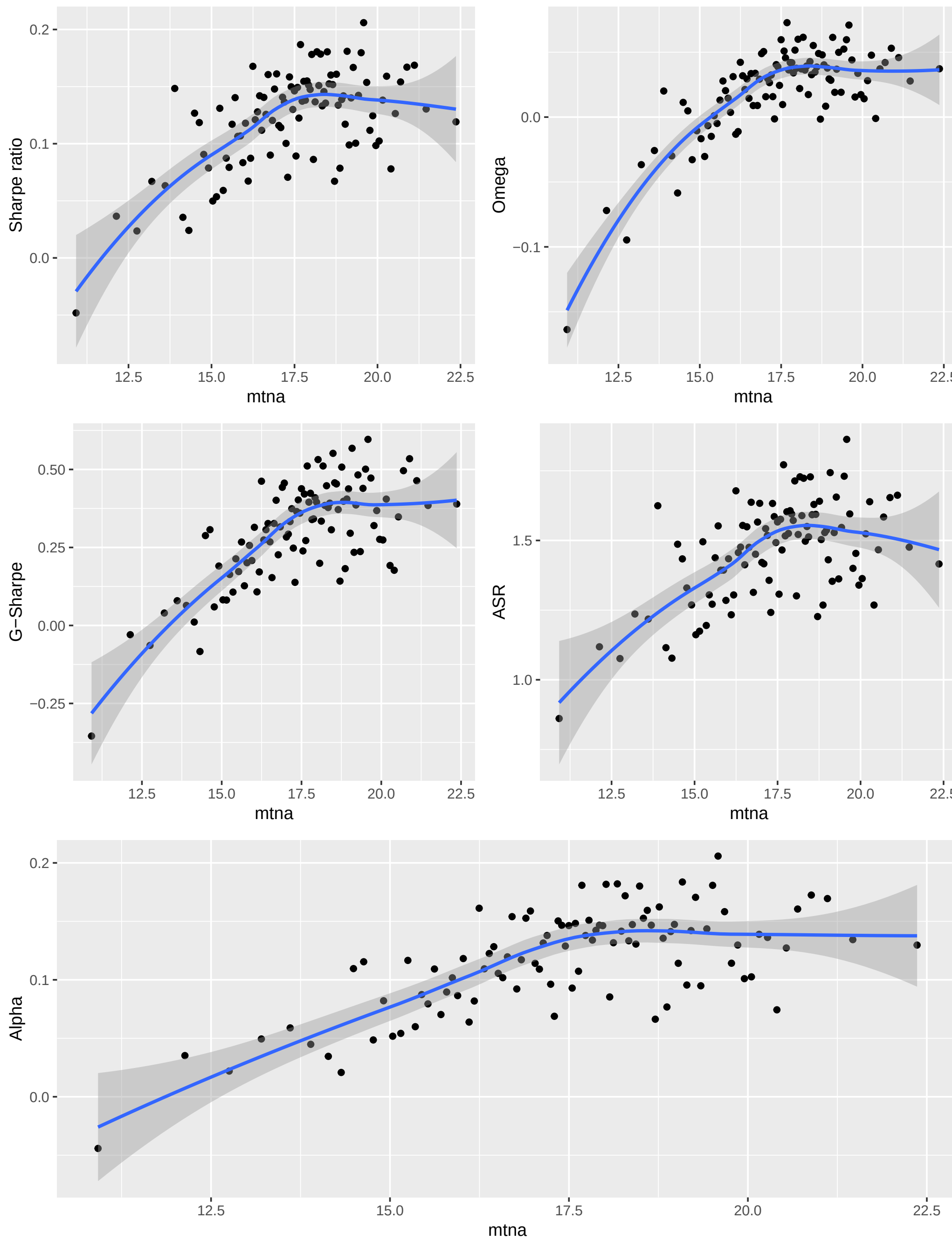

Figure 2: Risk-adjusted returns, actual data

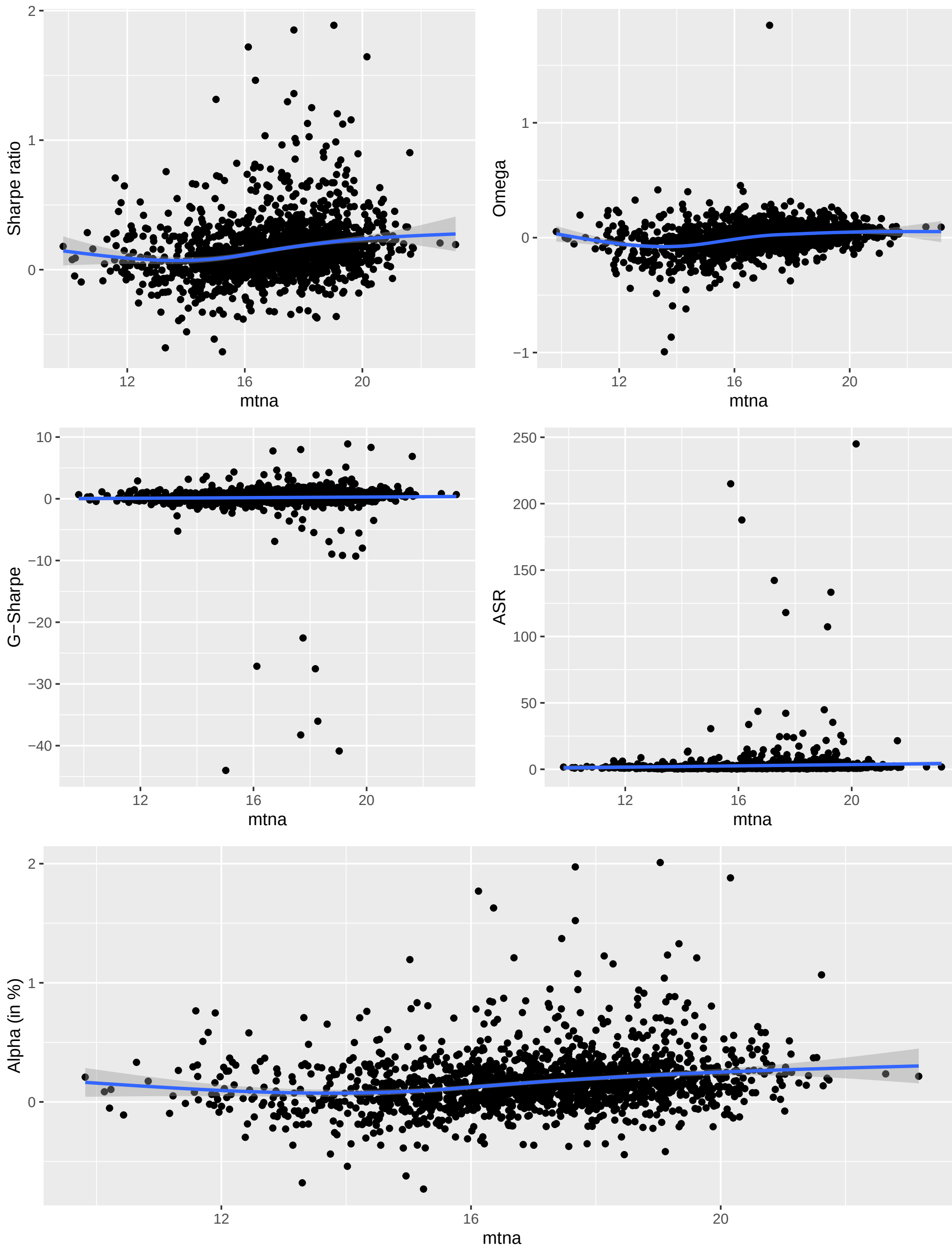

Figure 1 displays the relationship between the PM for each of the 100 discrete bins and it's corresponding mean size factor.

The variables in Figure 1 exhibit a firstly linear relationship that later turns constant. The variables in Figure 2 display a much lower linear relationship but mostly a constant one. Without consulting the plots one would easily think that the effects of decreasing returns to scale were totally absent when regressing risk-adjusted returns on size. However judging from Figure 1 the effect of size on risk-adjusted performance seems to at first be be positive but later turn constant.

This indicates that hedge funds, at fund level exhibit positive returns to scale up to a certain point where it instead becomes constant. When looking at Figure 2 the positive effect size has on a hedge funds performance is much weaker than the same relationship in Figure 1. These results also point toward the individual heterogeneity between hedge funds. The difference between the plots in Figure 1 and 2 may at first seem surprising. However grouping the funds in Figure 2 into large homogeneous groups with respect to fund size (which is what has been done in Figure 1) would serve to increase the weak linear relationship from Figure 2, since it means that we cancel most effects by other factors than size. Therefore the relationship in Figure 1 (although it could seem misguiding) should mainly be seen as a way of emphasizing general tendencies between the size of fund and performance variables in Figure 2.

7. Conclusion

The aim of this thesis has been to investigate the relationship between a hedge fund's performance and several of its characteristics. The most scrutinized of these fund characteristics has been the fund's size measured as TNA (total net assets). While earlier studies when investigating the same relationship usually measure performance as either being of the form excess returns or as risk-adjusted returns this study combines the two approaches on a single dataset.

When using unbalanced panel data regressions to investigate the relationship between fund size and performance the results generally point towards a negative relationship between increased fund size and excess returns. Three of the strategies exhibit decreasing returns to scale and two (Emerging markets and Multi strategies) show signs of increasing returns to scale. For the strategies that exhibit decreasing returns to scale the effect seems constant over time. As to which types of strategies that exhibit these capacity constraints, our results are not comparable with the study of Naik et al. (2007)[28]. This could depend on our different data samples.

Geographically the results from our study support the notion from Ferreira et al. (2013)[11] in that a negative returns to scale relationship exists for American funds but not necessarily in general. The evidence of capacity constraints is strongest for American funds and funds that invest in emerging markets instead seem to have increasing returns to scale. This might be related to results from Teo (2009)[38] that funds sacrifice higher returns for closeness to capital.

How variables such as age and minimum initial investment (ii) effect fund performance is consistent with results from earlier studies. Generally age seems to correlate negatively with performance while minimum initial investment instead has a positive correlation. In this case it is probably the success of the fund that permits it to have a high minimum initial investment fee and there is no casual relation in the opposite direction.

We can also state that the funds in our sample that have the highest total expense ratios have lower excess returns. This indicates that the most costly funds to invest in do not compensate their investors enough in form of higher returns.

Regressing the funds risk-adjusted performance measures on their mean value of assets gives contrasting or even contradictory results. Judging from these regressions there is a positive relationship between fund size and performance. However when plotting the results from the second form of regressions they seem to indicate that hedge funds exhibit an initially positive but later constant returns to scale.

The results thus partly support theory from the Berk and Green model but the overall picture is considerably more complicated. This is especially true if one divides the funds according to strategy or geographic focus. There also seems to be considerable differences if one considers performance as excess or risk-adjusted returns. All this may help to explain why the Berk and Green model still is a subject of active discussion.

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Appendix A.

Appendix A.1.

Strategy and Geographic focus regressions without age

Table A.8: Fama-French 3 factors, strategy, fixed effects (individual, without AGE)

	Dependent variable:						
	y						
	LSE	CTA	EME	MULTI	EVENT	CRED	GLOB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	-0.027^{*}	-0.055	0.081^{***}	0.105^{***}	-0.106^{***}	-0.103^{***}	-0.008
	(0.016)	(0.041)	(0.029)	(0.034)	(0.027)	(0.026)	(0.027)
ii	0.038^{**}	0.051^{***}	0.050	0.029^{***}	0.148^{***}	0.028	0.030^{**}
	(0.016)	(0.020)	(0.041)	(0.006)	(0.030)	(0.017)	(0.013)
Mkt.RF	0.526^{***}	0.078^{***}	0.767^{***}	0.559^{***}	0.393^{***}	0.296^{***}	0.402^{***}
	(0.021)	(0.025)	(0.048)	(0.034)	(0.043)	(0.042)	(0.053)
SMB	0.316^{***}	-0.022	0.414^{***}	0.374^{***}	0.326^{***}	0.100^{***}	0.099^{**}
	(0.024)	(0.045)	(0.045)	(0.036)	(0.044)	(0.031)	(0.046)
HML	0.004	-0.032	-0.044	-0.039	0.081^{***}	0.052^{***}	-0.148^{***}
	(0.026)	(0.030)	(0.049)	(0.033)	(0.032)	(0.018)	(0.041)
trend	-0.005^{***}	-0.005^{***}	-0.007^{***}	-0.006^{***}	-0.001	-0.003^{***}	-0.007^{***}
	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.426^{***}	1.872^{**}	-0.343	-0.830	0.484	2.851^{***}	1.593^{***}
	(0.328)	(0.752)	(0.473)	(0.608)	(0.652)	(0.475)	(0.491)
Observations	37,801	23,606	14,980	19,170	8,418	6,398	8,020
R^2	0.261	0.004	0.157	0.183	0.240	0.149	0.099
Adjusted R^2	0.261	0.004	0.156	0.183	0.239	0.148	0.099
Note:							*p<0.1; **p<0.05; ***p<0.01

Table A.9: Fama-French 3 factors, geo, fixed effects (individual, without AGE)

	Dependent variable:						
	y						
	Global	US	North Am	CAN	Europe	Asia Pac	Asia (ex-jap)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	-0.034^{**}	-0.027	-0.066^{*}	-0.165^{***}	-0.030	0.013	0.137^{**}
	(0.016)	(0.029)	(0.036)	(0.037)	(0.024)	(0.065)	(0.060)
ii	0.058^{***}	0.023	0.129^{***}	-0.013	0.043^{*}	0.014	0.104
	(0.010)	(0.031)	(0.042)	(0.039)	(0.024)	(0.076)	(0.088)
Mkt.RF	0.327^{***}	0.398^{***}	0.456^{***}	0.891^{***}	0.460^{***}	0.597^{***}	0.696^{***}
	(0.018)	(0.032)	(0.066)	(0.051)	(0.030)	(0.097)	(0.081)
SMB	0.156^{***}	0.212^{***}	0.243^{***}	0.153^{***}	0.354^{***}	0.547^{***}	0.413^{***}
	(0.022)	(0.029)	(0.050)	(0.057)	(0.049)	(0.106)	(0.062)
HML	-0.039^{**}	0.030	-0.005	0.369^{***}	-0.078^{**}	-0.132^{**}	0.238^{***}
	(0.019)	(0.032)	(0.046)	(0.083)	(0.031)	(0.066)	(0.050)
trend	-0.005^{***}	-0.003^{***}	-0.003^{***}	-0.008^{**}	-0.007^{***}	-0.006^{***}	-0.006^{***}
	(0.0005)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)
Constant	1.273^{***}	1.154^{**}	0.401	4.575^{***}	1.708^{***}	1.357	-1.925^{**}
	(0.301)	(0.539)	(0.635)	(1.230)	(0.586)	(1.316)	(0.880)
Observations	74,998	17,489	4,183	2,673	6,428	4,912	2,287
R^2	0.051	0.152	0.255	0.328	0.320	0.174	0.435
Adjusted R^2	0.051	0.152	0.254	0.327	0.320	0.173	0.434

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix B.

Appendix B.1.

Regressions on strategies and geographic focus with time fixed effects

Table B.10: Regressions on strategy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	rp	rp	rp	rp	rp	rp	rp
tna	-0.101**	-0.308	0.122	0.209	-0.168***	-0.234**	0.0297
	(-3.18)	(-1.79)	(1.30)	(1.96)	(-3.46)	(-3.08)	(0.34)
_cons	2.895	-2.243	27.30***	-1.558	5.707***	6.794***	-3.073*
	(1.65)	(-0.68)	(20.92)	(-1.64)	(3.67)	(6.75)	(-2.52)
N	37801	23606	14980	19170	8418	6398	8020

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.11: Regressions on geographic focus

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	rp	rp	rp	rp	rp	rp	rp
tna	-0.149*	-0.150***	-0.139	0.0165	-0.0692	0.00421	-0.156
	(-2.31)	(-3.38)	(-1.43)	(0.17)	(-1.15)	(0.04)	(-0.89)
_cons	-1.462	2.770	2.539	5.409***	-0.755	0.326	1.613
	(-0.56)	(1.16)	(1.82)	(4.35)	(-0.85)	(0.33)	(0.79)
N	74998	17489	4183	2673	6428	4912	2287

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix B.2.

Regressions when splitting up the time period

Table B.12: Fama-French 3 factors, fixed effects (individual), strategy, 1994-2007

	Dependent variable:						
	y						
	LSE	CTA	EME	MULTI	EVENT	CRED	GLOB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	−0.146*	−0.902	−0.031	−0.235**	−0.209***	−0.501***	−0.329***
	(0.082)	(0.664)	(0.302)	(0.110)	(0.081)	(0.086)	(0.121)
Mkt.RF	0.494***	−0.002	0.804***	0.483***	0.305***	0.112**	0.370***
	(0.038)	(0.040)	(0.098)	(0.095)	(0.055)	(0.051)	(0.033)
SMB	0.383***	0.153*	0.312**	0.332***	0.243***	0.047	0.314***
	(0.037)	(0.085)	(0.126)	(0.064)	(0.046)	(0.029)	(0.062)
HML	0.097*	0.227***	0.071	0.025	0.090*	−0.019	0.057
	(0.053)	(0.042)	(0.102)	(0.088)	(0.052)	(0.023)	(0.077)
trend	−0.012***	0.004	0.002	−0.002	0.001	0.001	0.004
	(0.002)	(0.009)	(0.012)	(0.005)	(0.003)	(0.004)	(0.005)
Observations	8,072	5,774	2,303	1,696	2,196	806	922
R^2	0.199	0.007	0.140	0.198	0.176	0.128	0.191
Adjusted R^2	0.186	−0.006	0.120	0.177	0.161	0.107	0.172

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.13: Fama-French 3 factors, fixed effects (individual), geo, 1994-2007

	Dependent variable:						
	y						
	Global	US	North Am	CAN	Europe	Asia Pac	Asia (ex-jap)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	-0.460^{*}	-0.277^{***}	-0.263^{**}	0.595^{***}	0.302	0.357	-0.687^{***}
	(0.261)	(0.105)	(0.130)	(0.167)	(0.274)	(0.698)	(0.199)
Mkt.RF	0.222^{***}	0.422^{***}	0.467^{***}	0.927^{***}	0.454^{***}	0.573^{***}	1.016^{***}
	(0.032)	(0.054)	(0.148)	(0.036)	(0.037)	(0.176)	(0.068)
SMB	0.228^{***}	0.304^{***}	0.289^{***}	1.353^{***}	0.612^{***}	0.497^{***}	0.185^{***}
	(0.045)	(0.039)	(0.055)	(0.287)	(0.177)	(0.157)	(0.028)
HML	0.151^{***}	0.113^{**}	0.174	1.101^{***}	-0.258^{***}	0.207^{*}	0.016
	(0.033)	(0.049)	(0.140)	(0.132)	(0.099)	(0.106)	(0.107)
trend	−0.001	−0.003	−0.003	-0.051^{***}	-0.032^{***}	−0.003	0.003
	(0.004)	(0.002)	(0.003)	(0.010)	(0.007)	(0.018)	(0.014)
Observations	14,460	5,070	653	80	958	654	171
R^2	0.012	0.165	0.235	0.620	0.188	0.122	0.613
Adjusted R^2	−0.004	0.153	0.214	0.583	0.168	0.094	0.589
Note:							*p<0.1; **p<0.05; ***p<0.01

Table B.14: Fama-French 3 factors, fixed effects (individual), strategy, 2010-2018

	Dependent variable:						
	y						
	LSE	CTA	EME	MULTI	EVENT	CRED	GLOB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	-0.186^{***}	−0.583	0.078	−0.046	-0.288^{***}	-1.074^{***}	-0.189^{*}
	(0.056)	(0.440)	(0.228)	(0.116)	(0.095)	(0.213)	(0.103)
Mkt.RF	0.504^{***}	−0.014	0.900^{***}	0.518^{***}	0.384^{***}	0.305^{***}	0.298^{***}
	(0.025)	(0.029)	(0.061)	(0.056)	(0.047)	(0.056)	(0.043)
SMB	0.325^{***}	0.105^{*}	0.396^{***}	0.356^{***}	0.296^{***}	0.120^{***}	0.229^{***}
	(0.028)	(0.059)	(0.074)	(0.052)	(0.051)	(0.039)	(0.057)
HML	0.007	0.110^{***}	-0.214^{***}	-0.191^{***}	0.075^{**}	0.013	-0.121^{**}
	(0.041)	(0.039)	(0.074)	(0.056)	(0.035)	(0.038)	(0.058)
trend	-0.005^{***}	0.001	−0.007	−0.003	0.003	0.033^{***}	0.003
	(0.001)	(0.004)	(0.008)	(0.005)	(0.003)	(0.009)	(0.003)
Observations	14,233	9,114	4,923	4,100	3,601	1,667	2,005
R^2	0.279	0.004	0.316	0.247	0.257	0.159	0.155
Adjusted R^2	0.269	−0.008	0.304	0.231	0.246	0.141	0.139
Note:							*p<0.1; **p<0.05; ***p<0.01

Table B.15: Fama-French 3 factors, fixed effects (individual), geo, 2010-2018

	Dependent variable:						
	y						
	Global	US	North Am	CAN	Europe	Asia Pac	Asia (ex-jap)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TNA	−0.334**	−0.191**	−0.253**	−0.154	0.116	−0.231*	−0.515*
	(0.170)	(0.082)	(0.109)	(0.388)	(0.162)	(0.135)	(0.287)
Mkt.RF	0.286***	0.395***	0.480***	1.030***	0.412***	0.674***	0.892***
	(0.023)	(0.035)	(0.083)	(0.090)	(0.034)	(0.129)	(0.075)
SMB	0.234***	0.235***	0.249***	0.543**	0.341***	0.675***	0.215***
	(0.032)	(0.031)	(0.075)	(0.212)	(0.095)	(0.142)	(0.061)
HML	0.043	0.031	−0.071	−0.571***	−0.218***	−0.222	0.213***
	(0.029)	(0.041)	(0.091)	(0.114)	(0.057)	(0.160)	(0.078)
trend	−0.002	−0.001	−0.004	−0.025	−0.015***	0.010*	0.004
	(0.002)	(0.002)	(0.003)	(0.021)	(0.004)	(0.006)	(0.012)
Observations	25,914	7,717	1,295	255	1,845	1,603	469
R^2	0.042	0.175	0.294	0.590	0.262	0.200	0.750
Adjusted R^2	0.028	0.165	0.281	0.572	0.249	0.183	0.743
Note:							*p<0.1; **p<0.05; ***p<0.01

Appendix B.3.

Regressions with CSD robust standard errors

Table B.16: Regressions using CSD robust standard errors, strategy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	rp	rp	rp	rp	rp	rp	rp
tna	-0.109**	-0.287	0.0696	0.260	-0.176***	-0.383***	0.0153
	(-2.64)	(-1.57)	(0.52)	(1.94)	(-4.05)	(-4.81)	(0.16)
Mkt_RF	0.527***	0.0786	0.768***	0.559***	0.394***	0.294***	0.404***
	(33.83)	(1.28)	(14.35)	(16.83)	(21.53)	(8.81)	(9.02)
SMB	0.317***	-0.0206	0.417***	0.367***	0.323***	0.0973**	0.0950
	(12.91)	(-0.18)	(5.19)	(7.19)	(11.31)	(2.64)	(1.72)
HML	0.00478	-0.0319	-0.0454	-0.0421	0.0816*	0.0600	-0.147*
	(0.13)	(-0.34)	(-0.57)	(-0.53)	(2.57)	(1.57)	(-2.29)
trend	-0.00546***	-0.00470*	-0.00610	-0.0121***	-0.00209*	0.000681	-0.00751**
	(-5.48)	(-2.34)	(-1.69)	(-4.33)	(-2.26)	(0.31)	(-3.31)
_cons	3.354***	6.430	0.309	-1.758	4.005***	7.463***	1.644
	(5.00)	(1.96)	(0.15)	(-0.94)	(5.08)	(5.70)	(1.19)
N	37801	23606	14980	19170	8418	6398	8020

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.17: Regressions using CSD robust standard errors, geographic focus

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	rp	rp	rp	rp	rp	rp	rp
tna	-0.148*	-0.148***	-0.130*	-0.0552	-0.0246	-0.105	-0.135
	(-1.99)	(-3.67)	(-2.08)	(-0.39)	(-0.37)	(-0.97)	(-0.78)
Mkt_RF	0.328***	0.397***	0.457***	0.892***	0.461***	0.600***	0.696***
	(12.94)	(28.04)	(19.03)	(14.05)	(16.14)	(14.64)	(19.03)
SMB	0.154**	0.213***	0.242***	0.139	0.356***	0.553***	0.412***
	(2.70)	(8.76)	(7.43)	(1.47)	(4.93)	(4.95)	(7.98)
HML	-0.0384	0.0297	-0.00500	0.375*	-0.0773	-0.116	0.240***
	(-0.69)	(1.15)	(-0.10)	(2.11)	(-1.01)	(-1.29)	(3.46)
trend	-0.00517***	-0.00343***	-0.00487**	-0.0155	-0.00779**	-0.00521	-0.00422
	(-4.49)	(-4.16)	(-3.10)	(-1.40)	(-2.80)	(-1.64)	(-0.94)
_cons	4.026**	3.769***	3.678***	4.549*	2.311	3.328*	3.498
	(3.08)	(5.06)	(3.77)	(2.05)	(1.93)	(2.05)	(1.41)
N	74998	17489	4183	2673	6428	4912	2287

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$