“The first half of life consists of the capacity to enjoy without the chance; the last half consists of the chance without the capacity.”
Mark Twain

The Performance of Funds of Hedge Funds:
Do Experience and Size Matter?

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Abstract

This paper is the first to use quantile regression to analyze the impact of experience and size of funds of hedge funds (FHF) on performance. In comparison to OLS regression, quantile regression provides a more detailed picture of the influence of size and experience on FHF return behaviour. Hence, it allows us to study the relevance of these factors for various return and risk levels instead of average return and risk, as is the case with OLS regression. Because FHF size and age (as a proxy for experience) are available in a panel setting, we can perform estimations in an unbalanced stacked panel framework. This study analyzes time series and descriptive variables of 649 FHF drawn from the Lipper TASS Hedge Fund database for the time period January 1996 to August 2007. Our empirical results suggest that experience and size have a negative effect on performance, with a positive curvature at the higher quantiles. At the lower quantiles, however, size has a positive effect with a negative curvature. Both factors show no significant effect at the median.

Keywords: Quantile regression, funds of hedge funds, performance, asset under management, fund age, fund manager’s experience

JEL Classification: G11, G12, G23
1 Introduction

Institutional investors have become increasingly interested in hedge funds over the last two decades. These products have progressed from being exclusively for high-net worth individuals to being an investment alternative for institutional investors like endowments and pension funds. In addition, capital is now flowing into the hedge fund industry at an unprecedented rate. The number of funds is also growing, as well as the amount of research on their risk and return characteristics.

Funds of hedge funds (FHFs), or funds investing in other hedge funds, play a special role within the hedge fund industry. The first FHF was created in Switzerland in 1969, and Europe is still the preferred location for larger FHFs (see Ineichen (2004)). FHFs charge management and performance fees (for diversification, oversight and access) additional to the fees charged by the underlying single hedge fund manager. According to Fothergill and Coke (2001), FHF management fees are generally equivalent to 1%-2% of the assets under management. The performance fee, also called an incentive fee, typically ranges from 15%-25%.

We would expect that the information advantage of experienced FHF managers would more than compensate investors for these fees. However, Brown et al. (2004) find that single hedge funds dominate funds of funds on an after-fee return basis or Sharpe ratio basis. They argue that the disappointing after-fee performance of some FHFs might be explained by the nature of this fee arrangement.

Ineichen (2002) posits that the value-added of a FHF manager is attributable more to manager selection and monitoring than to portfolio construction or management. Also in this context, Liew and French (2005) show that manager selection may be more important than strategy allocation for hedge fund investing. Beckers et al. (2007) show empirically that, over the past fifteen years, FHFs were able to deliver alphas with a high information ratio.
However, FHF$\text{s}$ may be the solution to the problem of negative skewness and positive excess kurtosis of non-normally distributed returns that is associated with single hedge funds.$^1$ For example, Kat (2002) shows that the diversification potential of FHF$\text{s}$ provides skewness protection.

FHF$\text{s}$ are the preferred way for most investors to gain exposure to the hedge fund asset class for the first time. They are ideal for investors who are unfamiliar with hedge funds, or are reluctant to build the infrastructure needed to run a professional selection and portfolio management team.

According to Hedge Fund Research (HFR)$^2$, as of the end of 2007, $798.6$ billion of the $1.87$ trillion total invested in single hedge funds (SHF$\text{s}$) were invested through FHF$\text{s}$. During 2007, FHF$\text{s}$ saw net new inflows of $59.2$ billion, compared to $49.7$ billion in 2006 and $9.5$ billion in 2005. However, the bulk of research on hedge funds thus far has focused mainly on SHF$\text{s}$.

In this paper, we focus on the FHF characteristics age and experience, since investors are most likely to pay close attention to them. As Lhabitant and Learned (2003) show, most FHF$\text{s}$ hold a similar number of underlying single manager hedge funds in their portfolios, usually between fifteen and forty. Thus, one could also argue that smaller FHF$\text{s}$ should outperform larger FHF$\text{s}$ on a return basis, as there is empirical evidence that smaller, younger, single hedge funds outperform older, larger ones (see, for example, Harri and Brorsen (2002) and Getmansky (2004)).

While quantile regression is regularly used in many applied fields of economics, this paper is the first to use quantile regression to empirically investigate the relationship between FHF size and experience and their performance. The advantage of quantile regression is that the influence of fund characteristics on return and risk can be modeled simultaneously,

$^1$ See, e.g., Fung and Hsieh (1999), Kat (2004), Cremers et al. (2005), and Füss et al. (2007).

whereas the spread between quantiles for a prespecified size or age reflects the FHF return risk. Moreover, our study is based on an extensive database of 649 FHFs that come from the Lipper TASS Hedge Fund database for the January 1996 through August 2007 period. The size and age data of FHFs are available not only on a cross-sectional basis, but also along a time continuum, so we use an unbalanced stacked panel for the estimation.

The paper is structured as follows. The next section discusses the source of FHF success, and provides hypotheses about the possible influences of FHF characteristics on their risk/return performance. Section 3 briefly explains the methodology of quantile regression, while section 4 presents the data and the descriptive statistics. The empirical results and their implications are also discussed, and some caveats are highlighted. Section 5 provides our conclusions.

2 Fund Characteristics and Performance

Based on the argument that what is true for SHFs may also be true for FHFs, we first provide an overview of the SHF literature. Thereby, we focus on the variables fund size and experience (proxied by age) as performance-determining factors. These are the only time series variables available from commercial hedge fund databases, and are considered the primary selection criteria by institutional investors (Allen (2007)).

Note that other possible performance-influencing variables, such as performance fees, minimum investment and status (open/closed), are normally provided with only the most recent information. Because those variables are replaced by current figures, i.e. when new

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3 The standard OLS assumption of normally distributed error terms often does not hold. Hence, optimal properties of standard regression estimators are not robust to moderate departures from normality. Quantile regression results, however, are robust against outliers in tailed distributions. Another advantage of quantile regression over conventional regression that focuses on the mean is the ability to capture the entire conditional distribution of the dependent variable. Finally, a quantile regression approach avoids the restrictive assumption that the error terms are identically distributed at all points on the conditional distribution.
information is submitted to the database, we do not use them here since only one data point is available.

2.1 Experience

In the early years of their careers, hedge fund managers are more likely to use innovative trading strategies that attempt to seek out and profit from obscure market price anomalies. However, when new competitors enter the market (e.g., because the trading strategy becomes well-known or through spin-offs), we assume the profits from price anomalies diminishes in accordance with arbitrage theory.

We also assume that newer FHF managers will be more open to innovative trading strategies because they lack the experience that most “new” SHFs fail in the first two to three years of operation. However, Howell (2001) shows that, even after adjusting for this fact, the youngest decile of SHFs beats the oldest decile by 970 basis points per annum. Therefore, our first hypothesis is as follows:

**Hypothesis 1a:** In general, younger FHFs outperform older FHFs.

In earlier years, company cultures are often characterized by a strong team spirit and hard work. According to the hedge fund life cycle model of Kaiser (2008), however, these tendencies may be lost as assets under management and a certain level of wealth increase, while the number of working hours decreases. This saturation could be one explanation for decreasing SHF returns over time.

Only SHFs with the ability to continually find good investment opportunities will survive and become experts at finding new trading strategies. This means that there exists some kind of “natural” style drift over the course of a hedge fund’s life. Thus, if we
approximate for experience with age, we can expect that SHFs will achieve higher returns again after a phase of reorientation. Also, assuming a low FHF turnover due to the length of in-depth operational and quantitative due diligence, as well as taking the low liquidity of SHFs into account, we can state that:

Hypothesis 1b: After an “adolescent” phase, the performance of FHF will again increase.

2.2 Size

Gregoriou and Rouah (2002) note that the bureaucracy resulting from increased assets under management and the demands of a more institutional investor base, e.g. in terms of transparency, can cause companies to lose their entrepreneurial edge. They also note that as fund size increases, larger positions must be traded, which can result in higher costs and decreasing profits in less liquid markets.

Ammann and Moerth (2006) argue that “to find the first ten investment ideas for a hedge fund manager is easier than finding the first hundred ideas.” Several studies have shown that SHF profits decrease as assets under management increase. Following the findings of Lhabitant and Learned (2003), we assume that smaller FHF should allocate to smaller SHFs, and that bigger FHF should allocate to bigger SHFs. Because of their past successes (often the result of their size), bigger SHFs can impose high minimum investments and low liquidity that cannot be borne by smaller FHFs. Thus, on a return basis, smaller FHF should outperform bigger FHF, similarly to how younger SHFs outperform older ones.

Fung et al. (2006) find that alpha-producing FHF$s$ attract far greater and steadier capital inflows than their lower-producing counterparts. However, these capital inflows in turn adversely affect their ability to produce alpha in the future. Berk and Green (2004) posit a rational model of active portfolio management in which diminishing returns to scale, combined with the inflow of new capital into better-performing funds, leads to the erosion of superior performance over time. Therefore, we hypothesize that:

**Hypothesis 2a:** Smaller FHF$s$ with low amounts of assets under management will have higher performance than larger FHF$s$.

The most successful FHF$s$ will continue to increase their assets. However, as per hypothesis 2a, if large or fast-growing FHF$s$ underperform smaller ones, they are likely to lose their accumulated capital and ultimately liquidate. Thus, only FHF$s$ with sustainable capital growth over time will survive.

After a FHF has reached a certain size, it is considered experienced enough to select high-performing SHF$s$. Additionally, large FHF$s$ have lower operational costs than smaller ones. We therefore hypothesize that:

**Hypothesis 2b:** Due to sustainable growth and increased experience, large FHF$s$ are likely to continue to improve performance.

However, as is clear from the last argument, size and age are positively correlated. Older hedge funds tend to be larger. Thus, in order to estimate performance in terms of size and age, we need to take interaction terms into account.
3 The Methodology of Quantile Regression

One advantage of the quantile regression method is that it estimates the expectation and the distribution of a variable. Conditional expectations can be generated at various points of the distribution of the dependent variable. Hence, a one-to-one translation of the distribution into a risk measure is possible. Quantile regression estimates the weighted absolute deviations instead of only conditional mean function, and therefore is more robust against large outliers (Fitzenberger et al. (2001)).

The sample mean can be derived by minimizing the squared sum of residuals, where the median is derived by minimizing the sum of absolute residuals. Positive and negative deviations thus truncate each other, and for odd observations the median remains a matter of symmetry. For even observations, however, the median is not clearly defined. By solving the optimization problem above, a point close to the median with alternative solutions is obtained. It cannot be specified whether the median is in the upper or lower observation, or whether it is somewhere in between. According to the derivation of the median, a weighted least absolute deviations (LAD) estimator can also be used to estimate a regression function for other quantiles. The following univariate model is assumed:

\[ y_{it} = x'_{it} \beta_{it} + u_{it} \quad \text{Quant}_{t}(y_{it} | x_{it}) = x'_{it} \beta_{t} \]  

(1)

with \( i=1…N \) and \( t=1…T \) observations, and where \( Q_{t}(y_{it} | x_{it}) \) denotes the \( t \) th conditional quantile of \( y_{it} \) given \( x_{it} \).

Koenker and Hallock (2001) argue that other quantiles can be achieved by asymmetrically weighting the sum of the absolute residuals according to:

\[ \min \sum_{i=1}^{N} \rho_{\tau}(y_{it} - x'_{it} \beta_{t}) \]

(2)
where $\rho_\tau$ are the weights, and $\sum p_\tau |y_{it} - x_{it}' \beta_\tau|$ is the sum of the absolute weighted residuals.

The so-called check function (see Koenker and Bassett (1978) and Koenker (2005)), with $z = y_{it} - \hat{y}_{it}$ defined as follows, is:

$$
\rho_\tau |z| = \begin{cases} 
\tau(z) & \text{for } z \geq 0 \\
(1-\tau)|z| & \text{for } z < 0 
\end{cases}
$$  \tag{3}

Rewriting this equation leads to

$$
\min_{\beta} \sum_{i=1}^{N} p_\tau (y_{it} - x_{it}' \beta_\tau) = \sum_{i=1}^{N} \left[ \tau I(y_{it} > x_{it}' \beta_\tau) + (1-\tau)I(y_{it} < x_{it}' \beta_\tau) \right] |y_{it} - x_{it}' \beta_\tau| 
$$  \tag{4}

where $I(\cdot)$ is an indicator function that takes the value of 1 if the event is true, and 0 otherwise (Fitzenberger et al. (2001)). This regression describes the $\tau$ th quantile of the return $y_{it}$ of an individual FHF, depending on the $x_{it}$ characteristic for experience or size. By considering $\tau = 0.5$ for the median, this procedure can be visualized in Figure 1:

Note that values smaller than the median have a negative linear slope, and values larger than the median have a positive one. Because there are odd numbers of observations and none are alike, we can obtain a clearly defined turning point. However, it is not differentiable. In order to obtain the minimum, we must apply an iterative process.

4 Empirical Results of Quantile Regression

4.1 Data and Descriptive Statistics

There are always some drawbacks to using commercially available hedge fund databases. There may be biases, such as survivorship bias and the backfilling bias, which have been discussed extensively in the literature (see Ackermann et al. (1999), Fung and Hsieh (2000), Amin and Kat (2003), Schneeweis et al. (1996), Brown et al. (1999), and Füss and Kaiser (2007)). However, as Fung and Hsieh (2002) note, researchers can mitigate these
biases by using FHF data, because most SHF index problems are not applicable to FHF time series.

For example, survivorship bias stems from the fact that indices are calculated from a pool of still existing funds (most defunct funds cease to report performance long before liquidation). This is not applicable to FHF time series, however, because they treat defunct funds as immediately defunct. Additionally, the survivorship bias in FHF indices has been estimated by Liang (2004) to be at about 0.70% p.a., while most studies on SHFs show a range from 1.51% (Capocci et al. (2005)) to about 3.74% (Malkiel and Saha (2005)).

We use the Lipper TASS Hedge Fund database here, which contains descriptive variables and time series for 1,341 FHF. The database is first cleaned rigorously by removing FHFs from the sample and converting base currencies into USD. We eliminate different FHF share classes, and keep the share class with the longest track record in the database. If this track record was not in USD, we converted it using the relevant exchange rates as of August 31, 2007.

After the cleaning process, we are left with a sample of 794 FHFs. After further excluding FHFs with less than a twelve-month track record, our final sample consists of 649 FHFs, with an observation period from January 1996 to August 2007. The unbalanced panel data set includes a maximum of 139 observations per FHF; 37 appear over the whole sample period. The other FHFs appear at a frequency equally distributed over the whole sample. Almost 85% of all FHFs are listed in USD.

For more information about the database, see http://www.lipperweb.com/products/tass.asp.

The remaining funds are listed in Euros (11.1%), CHF (1.8%), GBP (0.8%), CAD (0.6%), AUD (0.5%) and JPY (0.5%). When a fund is not listed in USD, we convert the assets under management to USD for the time period January 1996 through August 2007. Note also that the funds are domiciled in twenty-two countries, but more than half are in the Cayman Islands, the United States and Bermuda.
Table 1 gives the descriptive statistics. The monthly average return performance is around 0.76%, with a standard deviation of 2.21%. However, extreme values exist at a minimum of about -50%, and a maximum of about 69% p.m. Age has a mean of five years and a maximum of twenty-seven years. Average size is $139 million, and the median is $47.5 million. This results in a highly right-skewed distribution. Minimum size starts at $20,000, and goes up to a maximum of $8.7 billion.

Figure 2 plots the average logarithmic fund size against the average age. As one can see, there is interrelationship between these two characteristics. Small funds are always young and old funds are always large. However, this relationship does not hold the other way round, because old funds with small asset size do not exist. Furthermore, one cannot conclude from the observation of a young fund that it is large and, the other way round the observation of a large fund does not automatically mean that it is old. Most funds are young and have a substantial amount of assets under management.

4.2 Estimation Results

In order to estimate FHF performance, we use the following semilogarithmic model:

\[
\log(r_{it}) = \hat{\tau}_{0,\tau} + \hat{\beta}_1 \log(Age_{it}) + \hat{\beta}_2 \log(Age_{it}^2) + \hat{\gamma}_1 \left[\log(AuM_{it}) \times \log(Age_{it})\right] + \hat{\alpha}_1 \log(AuM_{it}) + \hat{\alpha}_2 \log(AuM_{it})^2
\]

(5)

where \( \tau \) is the respective quantile, \( i = 1, \ldots, N \) and \( t = 1, \ldots, T \). We transform assets under management (AuM) into log values, and use age as a proxy for experience.

Return \( r_{it} \) can also be interpreted as the log difference of net asset values, \( r_{it} = \log(nav_{it}) - \log(nav_{it-1}) \). We include squared variables and an interaction term for both age and size. This is necessary because of the assumption that older funds have accumulated
more capital over time (which is verified by the positive correlation between age and assets under management). For the sake of comparison, we estimate a quantile regression as well as an OLS.

We derive the standard errors by using Efron and Gong’s (1983) bootstrap approach. We thus take 1,000 bootstrapping resamples $B$ into consideration. Assuming the actual distribution equals the empirical distribution, we can calculate the bootstrapping standard errors $\hat{\sigma}_B$ as follows:

$$\hat{\sigma}_B = \left( \frac{1}{B-1} \sum_{j=1}^{B} \left[ s(X^*_j) - s(\cdot) \right]^2 \right)^{1/2}$$

where $s(X^*_j) = \{X^*_j, X^*_j, \ldots, X^*_j \}$ for $j = 1, \ldots, B$, and $s(\cdot) = \frac{1}{B} \sum_{j=1}^{B} s(X^*_j)$. For large $B$, Efron and Gong (1983) show that the bootstrap standard deviation is close to the true standard deviation of the population.

Figure 3 presents our estimation results graphically. The quantile regression is estimated for different quantiles between 10 and 90 percent, with the grey area as standard error. For comparison the OLS is also estimated with the dashed lines as standard error. The constant involves a hypothetical FHF with age zero and no assets under management.\(^7\) Thus, to analyze the effect of the respective variable, we must add the constant\(^8\), which is upward-sloping because lower quantiles have lower returns than higher quantiles. If the coefficient of a variable is also upward-sloping, this will increase the gap between the lower and higher quantiles, which will also increase risk.

\(^7\) To conserve space, the table of estimated coefficients is not shown here, but is available from the authors upon request.

\(^8\) The constant is not equal over each quantile. Therefore, the respective quantiles can have different absolute returns, even though the coefficients of one variable are equal over all quantiles.
Accordingly, if the coefficient of a variable is downward-sloping, this will decrease the gap, and reduce risk. If an upward-sloping coefficient crosses the abscissa, the respective variable will have a negative effect at the lower quantiles, and a positive effect at the higher quantiles. In the crossing point, the variable will eventually have no effect on performance at the respective quantile. In fact, the variable will have a permanent effect in the same direction over all quantiles only if the coefficient is positive or negative for all quantiles.

Note that when the slope of a coefficient is close to zero, the effects of the variable are the same for all quantiles. In this case, no quantile regression is required, because neither the distribution nor the risk will change over the quantiles. There is also no heteroskedasticity in the data, and OLS estimation would provide the same information. In Table 2, we use an $F$-test to test for equality of the respective coefficients in the quantiles.

We can see from the estimation output of Figure 3 that age has a negative effect on FHF returns. Hence, as per hypothesis 1a, we can assume that older hedge funds underperform younger ones. However, we can conclude from Table 2 that the coefficients of age do not differ significantly from each other. We thus assume the effect of age is the same in all quantiles.

Furthermore, hypothesis 1b stated that FHF performance is likely to increase again after a certain age. Unfortunately, coefficient $\hat{\beta}_2$ is not significant for all quantiles, but the median and upper quantiles show positive signs. On the other hand, the OLS estimation and the lower quantile exhibit negative signs, which suggest that our second hypothesis holds only for higher quantiles.
The respective coefficients of each quantile again do not differ significantly from each other. The interaction term has a significantly positive sign over all quantiles, but we detect no significant differences in the coefficients of the respective quantiles.

Figure 4 shows the marginal effects of performance with respect to age calculated by the following equation:

$$\frac{\delta r_{i,t}(\tau)}{\delta \text{Age}_{i,t}} = \hat{\beta}_{1,t} + 2\hat{\beta}_{2,t}\text{Age}_{i,t} + \hat{\gamma}_{1,t} \log\left(\text{AuM}_{i,t}\right)$$  \hspace{1cm} (7)

The marginal effects of age are presented for the median, the OLS regression, the 90 and 10 percent quantile, respectively. The marginal effects of the median are negative for young and small FHF. These effects get positive for large funds. The impact of increasing fund age on the marginal effects is at most moderate. Accordingly, the expected performance decreases for small FHF and increases large FHF with aging. Therefore, we have to reformulate or hypothesis 1b. The performance of FHF will not automatically increase after adolescence, but only under the condition of a sustainable asset growth. The OLS estimation leads generally to the same results as the median, but with a slightly stronger rise.

Because the coefficients of age, the squared age and the interaction effect are equal over all quantiles, one can assume that slopes of the median, the 90 and 10 percent quantile are about the same and therefore the conditional risk is constant.

Hypotheses 2a and 2b state that returns decrease with lower assets under management, but at a positive curvature. However, this holds only for higher quantiles, as we note from the estimation output in Figure 3. The coefficients of size are downward-sloping, with positive signs at the lower quantiles and negative signs at the higher quantiles.

At medium quantiles, the effect is not significantly different from zero. For the squared assets, we find the opposite slope, with coefficients again close to zero at the medium
quantiles. This is not surprising, however, because otherwise the conditional performance of lower quantiles could eventually exceed the performance of higher quantiles, which is by definition impossible.

We note further that high quantiles have a positive curvature, medium quantiles have no curvature, and low quantiles have a negative curvature. Thus, heteroskedasticity exists, and the performance distribution changes with the dependence of size. Smaller funds have higher risk than larger ones, but risk eventually increases again for very large funds. This may be because smaller FHFs are better equipped to discover SHFs that trade small market niches, but they may need a higher percentage of capital to enter those niches. Thus, they may accept a larger amount of risk, even at the danger of losing all their assets. This is depicted by the huge gap between the 10% and 90% quantiles for small FHFs (see also Figure 6). Liang (2003) provides another explanation. He shows that larger SHFs are audited more frequently than smaller SHFs, which could of course also be true for FHFs. Gregoriou et al. (2008) find evidence that FHFs with high exposure to bond indices but low exposure to equity indices survive longer.

Because of the low number of observations, we must be careful when interpreting a logarithmic size smaller than 15 and larger than 21. We can calculate the marginal effects as follows:

\[
\frac{\delta r_{i}(\tau)}{\delta \log (AuM_{i})} = \hat{\alpha}_{1,\tau} + 2\hat{\alpha}_{2,\tau} \log (AuM_{i}) + \hat{\gamma}_{1,\tau} \text{Age}_{i}
\]

Figure 5 shows again the marginal effects of size for the median, the OLS regression, and the 90 and 10 percent quantile, respectively. There are no significant effects for the median and only a minor effect for the OLS estimation. However, for the 90 percent quantile negative marginal effects were found, which rise with increasing age and size and eventually...
even become positive. On the other hand, there are positive marginal effects for the 10 percent quantile which decreases with increasing age and size and eventually become negative.

Hypotheses 2a and 2b have to be rejected. The expected performance is independent of the asset size. However, conditional risk decreases rapidly with the fund size. Again, the combined increase of age and size amplified this result. The strength of quantile regression then becomes explicit. If one would use an OLS estimation to calculate expected performance, one would find no significant size effects. Even if the median also leads to no significant effects, the other quantiles provide information about the distribution of conditional performance. The expected performance, the risk and the relationship between expected performance and risk can be directly drawn from Figure 6.⁹

<< Figure 6 about here >>

Figure 6 shows the fitted performance in dependence of size and age for the median, the OLS regression, and the 90 and 10 percent quantile, respectively. The expected performance can be drawn from the median or the OLS estimation. Even though both methods generally produce the same results, the effects of the OLS estimation are somewhat stronger. The highest expected return can be found for young funds with little assets under management as well as for old funds with huge amounts of capital. The lowest expected return is produced by funds which are either large and young or old and small. The conditional risk can be drawn from the 90 and 10 percent quantile. For small fund size a huge gap between those quantiles can be detected, which indicates high conditional risk. However, with increasing size this gap diminishes. The effect of age on conditional risk is moderate in comparison to size.

⁹ In contrast, when using OLS estimation techniques, we would need to calculate the risk or, e.g., the Sharpe ratio, separately.
In Table 3 the seminal findings are concluded. From the two characteristics size and age, which are easily observable, one can adjust portfolios according to the expected risk and return classification. The worst FHF are mainly those which are old and small. They have a low expected performance and a high conditional risk. However, as we saw from Figure 2 no FHF of that kind exist in our dataset. Hence, one could follow that these kinds of FHF go out of business very quickly due to their bad performance. When investing into a young FHF, one can choose between high expected return and high conditional risk or low expected return and low conditional risk according to the size of the FHF. The larger the FHF become, the lower the conditional risk and expected return. The best investment would be into an old fund with substantial assets under management. These funds have a high expected performance and a low conditional risk. Unfortunately, the number of FHF with these characteristics is limited.

5 Conclusions

This study provides new information about the influence of certain FHF characteristics – size and experience – on return/risk performance by using quantile regression. The advantages of this method in comparison to OLS regression are twofold: 1) quantile regression offers a detailed picture about FHF performance characteristics in various return quantiles, and 2) quantile regression can be used to estimate not only the expectation, but also the distribution of a variable. This enables us to directly translate the distribution into a risk measure, so that the influence of fund characteristics on return and risk can be modeled simultaneously. The spread between quantiles for a prespecified size or age reflect the risk in FHF returns.

Our empirical results show that return performance decreases for small FHF and increases for large FHF when experience rises. This means that surviving a specific period is
not enough to improve performance – a sustainable growth is also required. Our findings are supported by Ammann and Moerth (2008) who can show empirically based on cross-sectional regression analyses that larger FHFs exhibit higher returns, lower standard deviations and higher Sharpe ratios, and by Brown, Fraser and Liang (2008) who argue that effective due diligence is very expensive and that therefore, due to economics of scale larger FHFs have higher returns. However, it is difficult to interpret the effect on FHFs that are older than twenty years because of a lack of data.

It is necessary to differentiate the effect of size on FHF performance even further. Medium-size FHFs have the best performance only for lower return quantiles. For median returns, size has more or less no effect, while in the upper quantiles it is U-shaped. This means that size alone has no effect on expected performance. Conclusions about performance can only be drawn by the simultaneous observation of size and experience. However, smaller FHFs exhibit higher risk than larger ones, although risk eventually increases again for very large FHFs.

We promote a quadrant scheme, where the best performance is achieved by large and experienced FHF, which are unfortunately very limited. Old funds which were not able to require many assets have the worst performance. By adjusting the asset size of a young FHF, an investor can control expected returns and risk. Thereby, larger FHFs go hand in hand with lower risk and lower returns.
References


Figure 1: Check Function of the Median
Figure 2: Plotting FHFs’ Average Age against Average Log Size
Figure 3: Estimation Results of Quantile and OLS Regression
Figure 4: Marginal Effects of Age for the Median, OLS, 10%-Quantile, and 90%-Quantile
Figure 5: Marginal Effects of Log Size for Median, OLS, 10%-Quantile, and 90%-Quantile
Figure 6: Performance depending on Log Size and Age
Table 1: Descriptive Statistics of Monthly Data from Unbalanced Panel

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<th>Performance (in %)</th>
<th>Age (in years)</th>
<th>Size (in mil. USD)</th>
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$H_0$: All coefficients are equal
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