Hedge Funds Managerial Skill Revisited: A Quantile Regression Approach

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Abstract

In this paper we revisit the question of measurement of hedge fund managerial skill. Using a plethora of different models, from the simplest ones, employing a linear regression approach, to the more advanced ones, employing a quantile regression approach, we are able to identify and exploit managerial skill. The quantile regression approach enables us to produce robust and accurate estimates of the managerial skill utilizing two different sources of information: (a) the distribution information, regarding how the relationship between the return of the fund and a given variable varies across the conditional quantiles of returns and (b) factor information, regarding the different models that can be used for pricing inference. We show that estimates of the managerial skill based on quantile regressions and robust combination are superior compared to the relevant estimates from the linear pricing equations.

JEL classification: G11; G12

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1 Introduction

Hedge funds have received a vast amount of attention over the last decades. Based on Hedge Fund Research (HFR) estimates the total assets under management (AUM) of the hedge fund industry increased from \$39 billion in 1990 to more than \$2.97 trillion as of the second quarter of 2015. Furthermore, during the same period, the number of active hedge funds rose from 610 to over 10,000. In brief, hedge funds are defined as alternative investment vehicles which follow dynamic trading strategies and have great flexibility by using leverage, short-selling and derivatives. Hedge funds allow for investment strategies that differ significantly from traditional investments, such as mutual funds, which usually employ a non-leveraged, static buy-and-hold strategy. For a detailed recent survey of the academic literature on hedge funds see Agarwal et al (2015).

Linear regression models have been widely used in the hedge fund literature to describe the relationship of hedge fund returns with a set of risk factors. The literature investigating the ability of a variety of factors to explain hedge fund returns and to identify potential useful predictive factors is quite extensive; see, for example, Glosten and Jaganathan (1994), Ackermann, McEnally and Ravenscraft (1999), Liang (1999), Agarwal and Naik (2004), Mitchell and Pulvino (2001), Vrontos, Vrontos, and Giamouridis (2008), Meligkotsidou, Vrontos and Vrontos (2009). Linear regression models focus on modelling the conditional mean and as such describe an average relationship of hedge fund returns with the set of risk factors. Given that hedge fund returns exhibit non-normality patterns, such as fat tails and skewness (Kosowski, Naik and Teo, 2007, Meligkotsidou, Vrontos and Vrontos, 2009), a linear setup might not be adequate. A promising alternative route is to employ quantile regression, which is able to capture the effect of risk factors to the entire distribution of hedge fund returns.

The aim of this study is to provide an alternative approach for measuring managerial skill based on regression quantiles. In this way, we explore managerial skill on the basis of the entire conditional distribution of hedge fund returns. One of the benefits of our approach is that it allows us to identify potential differences in managerial skill across quantiles of returns. Looking at just the conditional mean of the hedge fund return series can 'hide' interesting risk-return characteristics. Especially in cases where the error distribution deviates from normality, i.e. when the distribution is characterised by skewness, has outliers or fat tails, or in general if there is some uncertainty about the shape of the distribution generating the sample, then the standard conditional linear regression approach may not be adequate, and the quantile regression approach provides more robust and more efficient estimates/results. Since the seminal paper of Koenker and Bassett (1978), who first proposed a class of linear regression models for conditional quantiles, a large amount of theoretical and practical work has been done in the area of quantile regression. Several papers suggest new estimation techniques and consider applications of and extensions to the original models (for details, see the review papers of Buchinsky, 1998, and Yu, Lu and Stander, 2003). Applications in the field of finance include work on Value at Risk (Taylor, 1999, Chernozhukov and Umantsev, 2001, Engle and Manganelli, 2004), option pricing (Morillo, 2000), forecasting stock returns (Meligkotsidou, Panopoulou, Vrontos and Vrontos, 2014) and the characterization of mutual fund investment styles (Bassett and Chen, 2001).

Summarising the aim of our paper is to produce robust and accurate estimates of the managerial skill based on quantile regressions. We utilize two different sources of information: distribution information, regarding how the relationship between the return of the fund or the style and a given risk factor varies across the conditional quantiles of returns and factor information, regarding the different models that can be used for pricing inference. We employ a variety of combination of managerial skill and information methodologies and evaluate their ability in an out-of-sample framework for the period 2004-2013. This period contains the recent financial crisis period that plagued the hedge fund industry. To anticipate our key results, our performance evaluation findings suggest that estimates of managerial skill based on quantile regression (especially at left tail quantiles) and simple combination of managerial skill techniques work better than the typically employed linear regression models. Using conditional quantile regression improves our ability to construct style portfolios. Specifically, we show that quantile regression models and the robust combination methods we introduce account for model uncertainty and parameter instability and provide a more powerful framework for constructing style portfolios. This is reflected in the higher values of the Sharpe ratio, and other risk-adjusted performance measures, of the portfolios constructed using the quantile regression approach relative to the linear regression based portfolios. The results of our analysis provide useful insights to finance researchers and practitioners.

The remainder of the paper is organised as follows. Section 2 discusses the proposed methodologies for measuring hedge fund managerial skill. Section 3 describes the linear regression models and introduces their quantile regression counterparts along with the proposed Robust Combination approach for measuring managerial skill. Section 4 describes the data and presents the empirical application, while Section 5 concludes.

2 Hedge Fund Managerial Skill

The evaluation of the performance of different hedge fund strategies is usually based on some measure of the managers' skill. The most commonly used measure is Jensen's alpha, introduced by Jensen (1968), that is the intercept in the mean regression of the fund's excess return on the excess return of some market index. The intuition behind using alpha as a measure of performance is that, taking out the part of the expected return that is explained by the market return the remaining part is explained by the managerial skill. Obvious extensions arise if we consider the alpha of multiple regression models, i.e. regressions of the fund's excess returns on several economic risk factors, built within the Arbitrage Pricing Theory context. Our main objective is to construct funds of funds or portfolios of different strategies based on the top performing funds or strategies.

In this paper, we employ an alternative measure of performance, similar in nature to Jensen's alpha, which is based on quantile regression. The quantile regression approach models the entire distribution of hedge fund returns without assuming normality and is more robust to the presence of outliers that could lead to a misleading calculation of alpha and thus of the managerial skill. Besides the important theoretical properties of the quantile regression model, estimating the managerial skill based on a synthesis of the alphas from a series of quantile regressions enables one to identify the presence of managerial skill not on average but also under extreme market conditions. For example, using the quantile regressions in the lower quantiles, such as $\tau = 0.10$, 0.25 a high positive alpha in comparison with a negative alpha (or a high positive alpha in comparison with a lower positive alpha) will identify a fund manager that is more skillful in extreme scenarios like these. On the other hand, using the quantile regressions in the upper quantiles, such as $\tau = 0.75$, 0.90 a high positive alpha in comparison with a lower positive alpha will show that the fund manager depicts more skill in good scenarios also. Thus, instead of finding the managerial ability on average, as is done with the linear regression models, using the quantile regression models we are able to estimate the managerial ability from the synthesis of the respective abilities at different quantiles or different scenarios. Another advantage of employing the managerial skill from the set of quantile regressions is that this procedure allows us to assign relatively higher weight to quantiles of interest, such as those in the tails of the distribution. This is in line with some measures of performance that have appeared in the literature such as L-performance (Darolles, Gourieroux and Jasiak, 2009), Sortino ratio (Sortino and Prince, 1994), Omega (Shadwick and Keating, 2002), among others. Employing quantile regressions we can choose the quantile of interest and then the skill on which we evaluate the managers.

To take advantage of these features, we consider using the alpha and/or the t-statistic of alpha of a quantile regression (single factor or multi-factor) as a measure of performance. Using a number of well-known pricing models for the estimate of the managerial skill we adapt the respective pricing models to a quantile regression framework. We show that estimates of the managerial skill based on quantile regressions are superior in comparison with the relevant estimates from the linear pricing equations. Furthermore, the choice of the set of pricing factors is also a way to characterize the skills of interest (see Darolles and Gourieroux, 2010). Given the long set of candidate explanatory variables, suggested by the extant literature, we address the issue based on two different procedures by carefully integrating the information content in them. We proceed in two directions; estimation of the ultimate managerial skill based on combination of managerial skills and estimation of managerial skill based on combination of information. Combination of managerial skills combines the managerial skills that are generated from simple models each incorporating a part of the whole information set, while estimation of managerial skill based on combination of information brings the entire information set into one super model to generate the ultimate managerial skill. The roots of these approaches can be found in the forecasting literature, see Huang and Lee (2010) and Panopoulou and Vrontos (2015) for an application in hedge funds returns forecasting.

3 Methodology

3.1 Linear Regression Models

Following the extant literature, we employ the following linear factor models; the Capital Asset Pricing Model (CAPM) described in Sharpe (1964) and Lintner (1965), the Fama and French (1993) three factor model, the Carhart (1997) four factor model and the full factor model. These models typically relate the excess hedge fund returns with a variety of risk factors. Below we provide a brief description of these models.

CAPM:

$$r_t = \alpha + \beta_1 RM_t + \varepsilon_t, \tag{1}$$

where r_t is the fund return in excess of the monthly return on three month Treasury

Bill and RM is the excess market return over the three month Treasury Bill.

Fama and French three factor model:

$$r_t = \alpha + \beta_1 RM_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t, \quad (2)$$

where SMB and HML are the "size" and "value" factors of Fama and French (1993), respectively.

Carhart four factor model:

$$r_t = \alpha + \beta_1 RM_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_t, \quad (3)$$

where MOM is the "winner minus loser" factor for capturing the momentum effect of Carhart (1997).

Full factor model:

$$r_t = \alpha + \sum_{i=1}^{N} \beta_i f_{it} + \varepsilon_t, \quad (4)$$

where f_{it}, $i = 1, ..., N$, is in general the return of factor i at time t.

We model the hedge fund returns by using different information variables - pricing factors, f_{it}. Specifically we use the Fung and Hsieh factors, (Fung and Hsieh, 2001): Return of PTFS Bond lookback straddle (BTF), Return of PTFS Currency Lookback Straddle (CTF), Return of PTFS Commodity Lookback Straddle (CMTF), Return of PTFS Short Term Interest Rate Lookback Straddle (STITF), Return of PTFS Stock Index Lookback Straddle (SITF), the Fama and French's 'size' (SMB) and 'book-to-market' (HML) as well as Carhart's 'momentum' factor (MOM), and also Fama and French's Long Term Reversal (LTR) and Short Term Reversal (STR), and Market Excess Return (RM). Furthermore we use the returns on the Morgan Stanley Capital International (MSCI) world excluding the USA index (MXUS), the MSCI emerging markets index (MEM), and the Default yield spread (DFY).

In all the above specifications, the errors ε_t are assumed to be independent and identically normally distributed with mean equal to 0 and variance σ^2.

3.2 Quantile Regression Models

As aforementioned, these linear regression models can model the conditional expectation and not the entire conditional distribution of the funds excess returns. To address this issue, we employ quantile regression models, which allow for a higher degree of flexibility. Specifically, risk factors are allowed to respond asymmetrically at the various parts of hedge fund returns distribution. In this respect, we use quantile regression models (Koenker and Bassett (1978), Buchinsky (1998), Yu, Lu and Stander (2003)) to model the entire distribution of hedge fund returns via modeling a set of conditional quantiles. Information from different quantile regression models can be utilized with the aim to construct a robust and more accurate estimate of managerial skill. More in detail, we consider quantile regression models with a single or more pricing factors of the form

$$r_t = \alpha^{(\tau)} + \sum_{i=1}^{N} \beta_i^{(\tau)} f_{it} + \varepsilon_t \tag{5}$$

where $\tau \in (0,1)$ denotes the τth quantile of r_t, and the errors ε_t are assumed independent from an error distribution $g_\tau(\varepsilon)$ with the τth quantile equal to 0, i.e. $\int_{-\infty}^{0} g_\tau(\varepsilon) d\varepsilon = \tau$. Model (5) suggests that the τth conditional quantile of r_t given $f_{it}, i = 1, ..., N$, is $Q_\tau(r_t|f_{it}) = \alpha^{(\tau)} + \sum_{i=1}^{N} \beta_i^{(\tau)} f_{it}$, where the intercept and the regression coefficients depend on τ. The coefficient $\beta_i^{(\tau)}$ shows how the ith factor affects the fund returns at the level of the τth quantile. The $\alpha^{(\tau)}$'s are likely to be different for different τ's, revealing a larger amount of information about the managerial skill in comparison with the α of conditional mean regression. The following models/ specifications are employed:

Quantile CAPM:

$$r_t = \alpha^{(\tau)} + \beta^{(\tau)} RM_t + \varepsilon_t, \tag{6}$$

Quantile Fama and French three factor model:

$$r_t = \alpha^{(\tau)} + \beta_1^{(\tau)} RM_t + \beta_2^{(\tau)} SMB_t + \beta_3^{(\tau)} HML_t + \varepsilon_t, \tag{7}$$

Quantile Carhart four factor model:

$$r_t = \alpha^{(\tau)} + \beta_1^{(\tau)} RM_t + \beta_2^{(\tau)} SMB_t + \beta_3^{(\tau)} HML_t + \beta_4^{(\tau)} MOM_t + \varepsilon_t, \tag{8}$$

Quantile full factor model:

$$r_t = \alpha^{(\tau)} + \sum_{i=1}^{N} \beta_i^{(\tau)} f_{it} + \varepsilon_t, \tag{9}$$

Managerial skill can be estimated using either $\alpha^{(\tau)}$ or the t-statistic of $\alpha^{(\tau)}$ in the quantile regressions presented above using various quantiles of interest especially the left tail ones (extreme negative returns). The $\beta^{(\tau)}$ parameters from the quantile regressions show the impact of a number of factors on the entire conditional distribution of hedge fund returns. Focusing on betas helps in uncovering potential differences in factor effects across quantiles of returns; see for example Meligkotsidou, Vrontos and Vrontos (2009).

3.3 Managerial Skill based on Synthesis of Regression Quantiles

Given that we have a plethora of risk factors and their sensitivities for a variety of quantiles, we propose the following way to efficiently aggregate this information in our estimate of the managerial skill within the quantile regression setup. This approach, which we name Robust Combination (RC), constructs robust estimates of the managerial skill from a set of quantile regressions (Section 3.3.1). We also go one step further and combine the robust estimates of managerial skill obtained from different pricing variables using simple combination methods in order to produce a final estimate of the managerial skill (Section 3.3.2). In what follows, we denote the managerial skill by $Skill$, and as aforementioned this can be either α or the t-statistic of α in the linear regressions or $\alpha^{(\tau)}$ or the t-statistic of $\alpha^{(\tau)}$ in the quantile regressions.

3.3.1 Managerial Skill based on Regression Quantiles

Managerial skill ($Skill$) based on the estimated quantile models (6)-(9) employing a set of factors i is estimated by combining specific quantile managerial skills, such as $Skill_i^{(0.25)}$, $Skill_i^{(0.50)}$ and $Skill_i^{(0.75)}$. Following the lines of Meligkotsidou, Panopoulou, Vrontos and Vrontos (2014), we employ the Tukey's (1977) trimean and Gastwirth (1966) three-quantile estimators for the mean. These are denoted by RC1 and RC2 and are given by the following equations:

$$
\begin{aligned}
RC1 &: \quad Skill_i = 0.25 \cdot Skill_i^{(0.25)} + 0.50 \cdot Skill_i^{(0.50)} + 0.25 \cdot Skill_i^{(0.75)}. \\
RC2 &: \quad Skill_i = 0.3 \cdot Skill_i^{(\frac{1}{3})} + 0.4 \cdot Skill_i^{(\frac{1}{2})} + 0.3 \cdot Skill_i^{(\frac{2}{3})}.
\end{aligned}
$$

Furthermore, we use the analogue (for the managerial skill) of the alternative five-quantile estimator, suggested by Judge, Hill, Griffiths, Lutkepohl and Lee (1988), which attaches more weight on extreme positive and negative events as follows:

$$
\begin{aligned}
RC3 : Skill_i &= 0.05 \cdot Skill_i^{(0.10)} + 0.25 \cdot Skill_i^{(0.25)} + 0.40 \cdot Skill_i^{(0.50)} \\
&+ 0.25 \cdot Skill_i^{(0.75)} + 0.05 \cdot Skill_i^{(0.90)}
\end{aligned}
$$

In addition to the above three estimators, we consider a fourth one (RC4) which combines information from a larger set of conditional quantiles, based on the following formula:

$$RC4 : Skill_i = 0.05 \cdot Skill_i^{(0.50)} + 0.05 \sum_{\tau \in S} Skill_i^{(\tau)},$$

where $S = \{0.05, 0.10, ..., 0.95\}$.

Finally, we employ a fifth estimator (RC5) which places more emphasis on the lower quantiles (adverse market conditions):

$$
\begin{aligned}
RC5 : \ Skill_i &= 0.2 \cdot Skill_i^{(0.10)} + 0.2 \cdot Skill_i^{(0.20)} + 0.2 \cdot Skill_i^{(0.30)} \\
&+ 0.2 \cdot Skill_i^{(0.40)} + 0.2 \cdot Skill_i^{(0.5)}
\end{aligned}
$$

Let us give two examples in order to depict how the RC schemes could be used. In the case of the quantile CAPM, the set of risk factors i consists of only the excess market return over the three month Treasury Bill (RM), thus based on RC1 the $Skill_i$ is given by the weighted average of the t-statistics of alphas of the three quantile regressions at $\tau = 0.25, 0.50, 0.75$. When we use the quantile Fama and French 3-factor model the set of factors employed is $\{RM, SMB, HML\}$. In this case based on RC1 the $Skill_i$ is given by the weighted average of the t-statistics of alphas of the three quantile regressions at $\tau = 0.25, 0.50, 0.75$ based on eq. (7) where the set of factors $\{RM, SMB, HML\}$ is employed for each quantile regression.

The approach described above is used for the quantile CAPM, Fama and French

3-factor model, Carhart's 4-factor model and the full factor model.

3.3.2 Combining Schemes of Linear and Quantile Models

When a large number of factors is employed simultaneously, as for example in the case of the full factor model, the model may suffer from overparameterisation and imprecision in standard errors estimates associated with the t-statistics employed to assess managerial skill. This model is referred to in the literature as the 'kitchen sink' model (Goyal and Welch, 2008) and in the context of predictability produces inferior results. To this end, we propose an alternative way stemming from the forecast combination literature (Stock and Watson, 2004).[1] Specifically, we estimate N univariate models each one corresponding to a candidate factor and in this way retrieve $Skill_i$ $i = 1, ..., N$ and then employ a synthesis of the skills from the univariate models in order to get the ultimate skill ($Skill^{(C)}$). This approach can be employed in the same way for both linear and quantille models.

Figure 1 below presents a graphical illustration of the steps involved in the linear approach and Figure 2 in the quantile approach.

Figure 1: Robust Combination Approach - Linear Models

$$
\begin{array}{lccccc}
\text{Variables} & f_1 & f_2 & ... & f_N & \\
 & \downarrow & \downarrow & ... & \downarrow & \\
\text{Linear Model} & Skill_{f_1} & Skill_{f_2} & ... & Skill_{f_N} & \\
 & \rightarrow & \rightarrow & \rightarrow & \rightarrow & Skill
\end{array}
$$

Figure 2: Robust Combination Approach - Quantile Models

$$
\begin{array}{cccccc}
\text{Quantiles/ Variables} & f_1 & f_2 & ... & f_N & \\
... & \downarrow & \downarrow & ... & \downarrow & \\
Q_{25} & \downarrow & \downarrow & ... & \downarrow & \\
Q_{50} & \downarrow & \downarrow & ... & \downarrow & \\
Q_{75} & \downarrow & \downarrow & ... & \downarrow & \\
... & \downarrow & \downarrow & ... & \downarrow & \\
 & Skill_{f_1} & Skill_{f_2} & ... & Skill_{f_N} & \\
 & \rightarrow & \rightarrow & \rightarrow & \rightarrow & Skill
\end{array}
$$

[1] For a recent contribution on equity premium predictability, see Rapach, Strauss and Zhou (2010).

Once we have estimated $Skill_i$ for all the candidate specifications, we produce combination estimates of managerial skill, $Skill^{(C)}$, which are weighted averages of the N single estimates of $Skill_i$

$$Skill^{(C)} = \sum_{i=1}^{N} w_i^{(C)} Skill_i \tag{10}$$

where $w_{i,t}^{(C)}, i = 1, ..., N$ are the a priori combining weights at time t. In this study, we consider the simplest combining scheme, i.e. the mean combining scheme, which is the one that attaches equal weights to all individual models, i.e. $w_{i,t}^{(C)} = 1/N$, for $i = 1, ..., N$.[2] For example, in the case of linear models we estimate the managerial skills using the t-statistics of alphas from the N univariate regression models and then using equation (10) we estimate the ultimate managerial skill. In a similar way, we estimate managerial skill from quantile regression models at each quantile of interest. For example, when the $RC1$ scheme is employed we estimate first the managerial skill based on the first risk factor, $Skill_1$, employing the quantile regression at $\tau = 0.25, 0.50, 0.75$, which is given by the weighted average of the t-statistics of alphas of the three quantile regressions. We repeat this procedure for the rest $N - 1$ factors, in order to obtain $Skill_i$, $i = 1, ..., N$ and finally applying equation (10) we estimate the ultimate managerial skill.

4 Numerical Illustration

4.1 Data

We illustrate the proposed quantile regression approach using hedge fund index data from Hedge Fund Research (HFR). The HFR indices are equally weighted average returns of hedge funds and are computed on a monthly basis. In our analysis, we use directional strategies that bet on the direction of the markets, as well as non-directional strategies whose bets are related to diversified arbitrage opportunities rather than to the movement of the markets. In particular, we consider eleven HFR substrategy indices which include event driven (ED) substrategies such as Distressed/Restructuring (DR) and Merger Arbitrage (MA), Equity Hedge (EH) substrategies such as Equity

[2] Alternatively, we could employ the trimmed mean and median combination schemes. The trimmed mean combination scheme sets $w_{i,t}^{(C)} = 1/(N-2)$ and $w_{i,t}^{(C)} = 0$ for the smallest and largest skills, while the median combination scheme is given by the median of the skill estimates based on single variable models. For more on combining schemes one can see Stock and Watson (2004).

Market Neutral (EMN), Quantitative Directional (QD), Sector - Technology/Healthcare (TH), Short Bias (SB) and Relative Value (RV) substrategies such as Fixed Income-Asset Backed (FIAB), Fixed Income-Convertible Arbitrage (FICA), Fixed Income-Corporate Index (FICI), Multi-Strategy (MS) and Yield Alternatives (YA). Our study of these hedge funds uses net-of-fee monthly excess returns for a period of twenty years (in excess of the three month US Treasury Bill) from January 1994 to December 2013. Our out-of-sample evaluation period is equal to ten years. Our choice of these substrategies is based on data availability. We include only substrategies that have 20 years of data. We exclude strategies such as Fund of Funds and Emerging Markets and strategies with only one substrategy for the full period. Given that we evaluate quantile models at extreme quantiles like for example 5% or 10% we need to have at least 120 observations in order to estimate the parameters of the model.

4.2 Portfolio Construction and Performance Evaluation

In this section, we consider the benefits of the proposed methodology in constructing fund of funds. Our main objective is to construct an equally weighted portfolio of hedge funds strategies based on our approach and its ability to identify the top performing hedge fund strategies. The evaluation of the relative performance of the constructed portfolios is based on a variety of performance measures in a recursive out-of-sample fashion.

The strategies are selected based on their ranking which is made according to the t-statistic of alpha. We use the t-statistic of alpha because of the superior properties that it has in comparison with the alpha. For each model, we formulate portfolios in a recursive out-of sample fashion. Our implementation is concerned with the performance of the strategies for the last ten years from January 2004 to December 2013, i.e. for the last 120 months. We use the estimation period sample to estimate models (1-9) and we obtain estimates of the parameters for each model and for each class of models. Next, we obtain the estimated t-statistic of alphas for the substrategies considered, and we rank the strategies according to the manager's skill based on the t-statistic of alphas. The substrategies employed belong to ED, EH or RV strategy. For all classes of models we formulate equally weighted portfolios (each weight is equal to 1/3) based on the top performing substrategy in each strategy. Note, that the estimation period is redefined iteratively every six months in a recursive out-of-sample fashion, the estimation sample is augmented by six monthly observations at each step in order to utilize all the available information.

We examine whether the various specifications lead to differences in the ranking of substrategies and, hence, in the performance of the constructed portfolios. In this way, they could have potential economic impact for a fund manager that wishes to invest in the top performing substrategies. We expect that our proposed approach, which captures the stylized facts of hedge fund returns will produce the best performing portfolios.

We evaluate the different models using unconditional (out-of-sample) measures. In particular, we consider the realized returns, the portfolio risk and the risk adjusted realized returns. We calculate the mean return ($E(r_p)$) within the out-of-sample period and the cumulative return (CR) at the end of the period. As measures of risk we compute the standard deviation of returns (σ), as well as the downside risk. The latter measures only the negative deviations from some reference value, since positive deviations from this value are considered to be desirable. The downside risk (deviation), DD, is given by

$$DD = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\min(0, r_{p_t} - RV)^2},$$

where RV is the reference value, which is taken to be zero in our study. The reference value can be thought of as a minimum acceptable return. As a measure of risk adjusted performance we consider the Sharpe ratio (Sharpe, 1966, 1994) which is commonly used in the performance literature[3]. The Sharpe ratio is calculated as the ratio of the average portfolio return, $E(r_p)$, and the portfolio's standard deviation of returns, σ, i.e.

$$SR = \frac{E(r_p)}{\sigma}.$$

Furthermore, we consider an alternative measure of risk adjusted performance, namely the Sortino ratio (Sortino and van der Meer, 1991, Sortino and Price, 1994), which has several advantages over the Sharpe ratio. First, unlike Sharpe ratio, it does not depend on the normality assumption which may not be valid in the case of pension fund returns. Second, the Sortino ratio, instead of using the standard deviation as a measure of risk, measures risk by the downside deviation. That is, the Sortino ratio is

[3] See also Darolles and Gourieroux (2010) for a battery of Sharpe performance measures, which by the information taken into account in the computation and the potential use of the fund by the investor.

calculated as the ratio of the average return and the downside risk, i.e.

$$SOR = \frac{E(r_p) - RV}{DD}.$$

In addition we use a performance measure that takes into account the quantiles of the portfolio returns, the Adjusted Sharpe Index defined as

$$ASI = \frac{Q^{0.50}(r_p)}{Q^{0.75}(r_p) - Q^{0.25}(r_p)}$$

dividing the median with the interquantile range, (Gregoriou, 2006). Further we report downside deviation (DD), Value at Risk (VaR) and Conditional Value at Risk (CVaR).

4.3 Empirical Findings

In Tables 1-5 we report the unconditional (out-of-sample) performance evaluation measures for the different models employed. Specifically, we calculate and present the average portfolios' returns, the portfolios' standard deviations and downside risks, the cumulative returns and the risk adjusted performance measures, namely the Sharpe ratio and the Sortino ratio, for our approaches. Below we discuss the results obtained in the case of portfolios constructed using the top performing strategies.

Table 1 reports our findings when comparing the linear CAPM with the quantile CAPM for quantiles of interest corresponding to the left part of the conditional distribution of hedge fund returns, i.e. $\tau = 0.10$, 0.25, 0.33, 0.50. The last five columns correspond to the five robust combination approaches (RC1-RC5) which utilise an array of quantiles. Our findings suggest that the best performing model is the RC5 closely followed by the combination schemes RC1-RC4 and the quantile CAPM at $\tau = 0.25$ and 0.33. The portfolios constructed based on these models give a Sharpe Ratio of 0.71 and 0.69, respectively. In terms of cumulative returns, RC5 and the quantile CAPM at $\tau = 0.10$ rank first attaining values of 83% and 81%,respectively. In terms of riskiness, quantile CAPM models (with the exception of $\tau = 0.10$ and $\tau = 0.50$), and RC methods display the lowest risk and outperform the traditional linear CAPM model. Similarly, all portfolios based on these quantile regression models and robust combination models outperform the simple CAPM in terms of Sharpe Ratio, Sortino Ratio, Adjusted Sharpe Index, Cumulative Return, Mean Return and Median Return. The majority of these portfolios have also lower VaR, Standard Deviation and Downside Deviation in comparison with the standard CAPM.

Table 1. Performance of CAPM and Quantile CAPM

	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.41	0.50	0.47	0.47	0.43	0.47	0.47	0.47	0.47	0.51
$Q_{50}(r_P)$	0.57	0.75	0.65	0.65	0.64	0.65	0.65	0.65	0.65	0.69
$SD(r_P)$	0.78	1.03	0.68	0.68	0.89	0.68	0.68	0.68	0.68	0.71
$DD(r_P)$	0.46	0.67	0.38	0.38	0.62	0.38	0.38	0.38	0.38	0.38
$VaR_{0.05}$	-1.33	-0.88	-0.73	-0.73	-1.33	-0.73	-0.73	-0.73	-0.73	-0.79
$VaR_{0.10}$	-0.58	-0.73	-0.45	-0.45	-0.52	-0.45	-0.45	-0.45	-0.45	-0.46
$CVaR_{005}$	-1.68	-2.75	-1.44	-1.44	-2.40	-1.44	-1.44	-1.44	-1.44	-1.44
$CVaR_{0.10}$	-1.29	-1.76	-1.00	-1.00	-1.66	-1.00	-1.00	-1.00	-1.00	-1.03
CR	0.63	0.81	0.74	0.74	0.67	0.74	0.74	0.74	0.74	0.83
SR	0.53	0.48	0.69	0.69	0.48	0.69	0.69	0.69	0.69	0.71
SOR	0.90	0.75	1.24	1.24	0.70	1.24	1.24	1.24	1.24	1.33
ASI	0.69	0.81	0.90	0.90	0.89	0.90	0.90	0.90	0.90	0.86

Next, we compare the Fama and French 3-factor model with its quantile analogue ($\tau = 0.10, 0.25, 0.33, 0.50$) and the five robust combination approaches (Table 2). Our findings suggest that the best performing model is the quantile regression model at $\tau = 0.25$, with second best the quantile regression model at $\tau = 0.33$. The portfolios constructed based on these models give Sharpe Ratios of 0.55 and 0.53, respectively, and cumulative returns of 134% and 94% for the ten year out-of sample period. We have to note that the RC2 method ranks second in terms of returns, while the simple linear CAPM outperforms the RC1, RC3, and RC4 combination methods based on the SR. All portfolios based on quantile regression models and robust combination models outperform the simple 3-factor model in terms of Adjusted Sharpe Index and have lower VaR.

Table 2. Performance of Fama French 3-Factor Model - Linear and Quantile

	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.56	0.56	0.56	0.72	0.53	0.52	0.63	0.51	0.51	0.56
$Q_{50}(r_P)$	0.74	0.76	0.69	0.96	0.76	0.80	0.87	0.75	0.73	0.75
$SD(r_P)$	1.32	1.12	1.01	1.35	1.14	1.28	1.42	1.33	1.30	1.25
$DD(r_P)$	0.78	0.68	0.60	0.75	0.71	0.85	0.88	0.87	0.86	0.84
$VaR_{0.05}$	-2.11	-1.37	-1.33	-2.05	-1.68	-1.33	-1.58	-1.33	-1.33	-1.19
$VaR_{0.10}$	-1.36	-0.77	-0.50	-1.16	-0.96	-1.05	-1.09	-1.16	-0.92	-0.74
$CVaR_{005}$	-2.73	-2.75	-2.24	-2.72	-2.75	-3.09	-3.26	-3.21	-3.21	-3.33
$CVaR_{0.10}$	-2.20	-1.86	-1.64	-2.10	-2.00	-2.17	-2.29	-2.24	-2.09	-2.13
CR	0.93	0.95	0.94	1.34	0.87	0.84	1.09	0.82	0.81	0.95
SR	0.42	0.50	0.55	0.53	0.46	0.41	0.44	0.38	0.39	0.45
SOR	0.71	0.82	0.93	0.96	0.74	0.61	0.71	0.58	0.59	0.67
ASI	0.46	0.78	0.78	0.51	0.65	0.58	0.48	0.50	0.49	0.87

Table 3 reports our results with respect to the Carhart 4-factor model along with the quantile analogue ($\tau = 0.10$, 0.25, 0.33, 0.50) and the five robust combination approaches. The best performing model is the quantile regression model at $\tau = 0.10$, which attains a Sharpe Ratio of 0.52 and an average return of 0.62%. The portfolio constructed based on the robust combination method RC5 ranks first in terms of returns attaining a cumulative return of 112% and an average return of 0.64%. The alternative quantile models and RC methods perform similarly attaining Sharpe Ratios of 0.40 to 0.43. The majority of portfolios based on quantile regression models and robust combination models outperform the 4-factor linear model in terms of Sharpe Ratio, Sortino Ratio and Adjusted Sharpe Index and have lower VaR, CVaR, Standard Deviation and Downside Deviation.

Table 3. Performance of Carhart 4-Factor Model - Linear and Quantile

	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.53	0.62	0.52	0.61	0.57	0.57	0.58	0.58	0.58	0.64
$Q_{50}(r_P)$	0.72	0.89	0.72	0.80	0.86	0.85	0.86	0.83	0.84	0.92
$SD(r_P)$	1.35	1.19	1.31	1.41	1.41	1.36	1.37	1.38	1.38	1.48
$DD(r_P)$	0.85	0.69	0.86	0.90	0.92	0.88	0.88	0.88	0.89	0.93
$VaR_{0.05}$	-2.17	-1.37	-1.47	-2.05	-2.06	-1.47	-1.47	-1.47	-1.47	-2.06
$VaR_{0.10}$	-1.36	-0.81	-0.93	-0.89	-1.09	-1.14	-1.14	-1.06	-1.05	-1.16
$CVaR_{005}$	-3.02	-2.75	-3.25	-3.46	-3.50	-3.25	-3.25	-3.25	-3.32	-3.50
$CVaR_{0.10}$	-2.36	-1.90	-2.24	-2.43	-2.44	-2.27	-2.27	-2.27	-2.32	-2.50
CR	0.87	1.08	0.84	1.05	0.96	0.96	0.99	0.99	0.99	1.12
SR	0.39	0.52	0.40	0.43	0.40	0.42	0.43	0.42	0.42	0.43
SOR	0.62	0.89	0.60	0.68	0.62	0.65	0.67	0.67	0.66	0.69
ASI	0.45	0.80	0.46	0.56	0.48	0.50	0.50	0.48	0.50	0.48

Table 4 has a similar structure with the previous tables and focuses on the performance of the various specifications of the full factor model. This model employs all 14 factors at hand and as such we expect increased estimation error due to overparameterisation. This feature is common in both quantile and linear models. It can however be alleviated via our proposed methodology (RC approaches based on mean combination scheme) which is discussed below. Consistent with our findings so far, linear specifications fall short when compared to quantile and RC models. The best performing method is the RC1 method followed by RC3, RC2, RC5 and the quantile regression model at $\tau = 0.50$. The portfolios constructed based on these models give Sharpe Ratios of 0.61, 0.58 and 0.54 respectively. Cumulative returns safely exceed 90% for all quantile models and robust specifications with the exception of RC4. In a similar vein, these portfolios are the ones that appear less risky. As such, all portfolios based on quantile regression models and robust combination models outperform the full factor linear model in terms of Sharpe Ratio, Sortino Ratio and Adjusted Sharpe Index and have also lower CVaR, Standard Deviation and Downside Deviation.

Table 4. Performance of Full Factor Model - Linear and Quantile

	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.48	0.56	0.54	0.58	0.63	0.63	0.64	0.60	0.49	0.60
$Q_{50}(r_P)$	0.85	0.81	0.69	0.76	0.71	0.69	0.72	0.69	0.71	0.77
$SD(r_P)$	1.73	1.47	1.22	1.24	1.17	1.04	1.18	1.04	1.42	1.11
$DD(r_P)$	1.24	0.87	0.77	0.75	0.55	0.43	0.57	0.46	1.06	0.59
$VaR_{0.05}$	-2.10	-2.49	-2.13	-1.82	-1.52	-1.05	-1.48	-1.30	-1.35	-1.12
$VaR_{0.10}$	-1.58	-1.41	-0.78	-0.75	-0.68	-0.60	-0.73	-0.65	-0.68	-0.65
$CVaR_{005}$	-4.44	-3.02	-3.07	-3.04	-2.06	-1.59	-2.06	-1.64	-3.60	-2.26
$CVaR_{0.10}$	-3.16	-2.48	-2.16	-2.04	-1.50	-1.18	-1.61	-1.29	-2.33	-1.56
CR	0.74	0.92	0.90	0.98	1.12	1.11	1.12	1.04	0.77	1.04
SR	0.28	0.38	0.45	0.47	0.54	0.61	0.54	0.58	0.34	0.54
SOR	0.39	0.64	0.70	0.77	1.15	1.46	1.12	1.32	0.46	1.02
ASI	0.45	0.49	0.69	0.67	0.53	0.58	0.52	0.55	0.64	0.67

Finally, Table 5 reports our findings for the alternative way of employing all the factors and suitably combining them. In this way, all models include only one variable/ factor at a time and their outcome (skill) is combined (mean combining scheme) to produce the final managerial skill. Linear, quantile and RC specifications efficiently aggregate information from the 14 factors at hand. Consistent with our findings so far, linear specifications fall short when compared to quantile and RC models. All RC and quantile specifications perform extremely well and in a similar manner attaining a Sharpe Ratio of 0.74. Cumulative returns safely exceed 74% for all quantile models and robust specifications combined with a low volatility of 0.68. Following this approach, we get robust results.

Comparing Table 4 and 5, we have to note that even in a linear regression framework, the mean combining scheme is able to produce superior SRs (0.28 vs. 0.30). In a quantile regression setting, our mean combining scheme is superior to the full factor quantile one judging from the related Sharpe Ratios along with all RC specifications. The striking difference between the findings of the two approaches (Tables 4 and 5) is the substantial reduction in the portfolios' riskiness. Specifically, mean combination schemes are associated with a significant reduction in SD, DD, VaR and CVaR. In this respect, portfolios generated via the mean combining scheme bear lower risk than the ones generated based on the full factor alternative and attain higher risk adjusted returns. This feature is quite appealing and probably stems from the reduced estimation error attached to models with just one variable at a time.

Table 5. Performance of Mean Combining Scheme - Linear and Quantile

	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.33	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
$Q_{50}(r_P)$	0.58	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65
$SD(r_P)$	1.10	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68
$DD(r_P)$	0.88	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
$VaR_{0.05}$	-1.33	-0.73	-0.73	-0.73	-0.73	-0.73	-0.73	-0.73	-0.73	-0.73
$VaR_{0.10}$	-0.65	-0.45	-0.45	-0.45	-0.45	-0.45	-0.45	-0.45	-0.45	-0.45
$CVaR_{005}$	-3.04	-1.44	-1.44	-1.44	-1.44	-1.44	-1.44	-1.44	-1.44	-1.44
$CVaR_{0.10}$	-2.01	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
CR	0.47	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74
SR	0.30	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
SOR	0.38	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24	1.24
ASI	0.70	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90

Next, we focus on the composition of the portfolios formed on the basis of our alternative methodologies. In this way, we gain insight on the differences in rankings obtained with the different approaches and the persistence in rankings which has a direct impact on portfolio turnover. Tables 6-10 report the related findings for the methodologies employed. Specifically, we report the number of times each sub-strategy is picked to participate in the portfolio. As already mentioned, we rebalance the portfolio every six months over the 10-year out-of-sample period, i.e. we have 20 rebalancing periods. At each rebalancing period, the best substrategy belonging to the ED, EH and RV strategies gets an equal weight.

The composition of the portfolios formed on the linear and quantile CAPM is given in Table 6. With respect to the linear CAPM, we note that the MA substrategy of ED and the EMN sub-strategy of EH always rank first and participate in the portfolio. Regarding RV substrategies, FIAB is ranked first in more than half rebalancing periods (11 periods), followed by FICA that is preferred in 8 of 20 periods. Contrary to the linear model, quantile models and RC methods always rank FIAB first. With respect to EH, EMN is also ranked first. Turning to the ED strategy, quantile models at $\tau = 0.25$ and $\tau = 0.33$ along with RC1-RC4 methods pick the MA as the preferred strategy similarly to the linear model. The best performing method, RC5, is the one that picks DR in 3 out of 20 rebalancing periods.

Table 6. Portfolios of CAPM and Quantile CAPM

	DR	MA	EMN	QD	TH	SB	FIAB	FICA	FICI	MS	YA
Linear	0	20	20	0	0	0	11	8	0	1	0
Q10	11	9	20	0	0	0	20	0	0	0	0
Q25	0	20	20	0	0	0	20	0	0	0	0
Q33	0	20	20	0	0	0	20	0	0	0	0
Q50	10	10	20	0	0	0	20	0	0	0	0
RC1	0	20	20	0	0	0	20	0	0	0	0
RC2	0	20	20	0	0	0	20	0	0	0	0
RC3	0	20	20	0	0	0	20	0	0	0	0
RC4	0	20	20	0	0	0	20	0	0	0	0
RC5	3	17	20	0	0	0	20	0	0	0	0

Turning to the Fama French 3-factor model, Table 7 reports the portfolio composition. The linear model picks the MA substrategy of ED and the Sector TH of EH in all rebalancing periods, in contrast with the quantile and RC specifications where a greater variability is present. For example, the best performing quantile models at $\tau = 0.25$ and $\tau = 0.33$ select DR in 4 and 15 cases, respectively, and MA in 16 and 5 periods. FIAB is ranked first in all rebalancing periods when quantile and RC models are employed, while it is picked in 11 periods in the linear approach. Overall, a greater portfolio turnover is associated with quantile and RC methods compared with the linear model.

Table 7. Portfolios of linear 3-Factor and Quantile 3-Factor model

	DR	MA	EMN	QD	TH	SB	FIAB	FICA	FICI	MS	YA
Linear	0	20	0	0	20	0	11	9	0	0	0
Q10	20	0	18	2	0	0	20	0	0	0	0
Q25	4	16	9	0	11	0	20	0	0	0	0
Q33	15	5	0	0	20	0	20	0	0	0	0
Q50	17	3	14	1	5	0	20	0	0	0	0
RC1	9	11	6	1	13	0	20	0	0	0	0
RC2	13	7	0	0	20	0	20	0	0	0	0
RC3	7	13	4	1	15	0	20	0	0	0	0
RC4	8	12	5	3	12	0	20	0	0	0	0
RC5	17	3	13	0	7	0	20	0	0	0	0

Table 8 reports the 4-factor portfolio composition. Similar to the 3-factor case, the linear model picks the MA substrategy of ED and the Sector TH of EH in the majority of the rebalancing periods (20 and 18, respectively). On the other hand, the quantile and RC specifications exhibit greater variability. For example, the best performing quantile model at $\tau = 0.10$ selects DR in 19 periods and EMN in 16 periods. As far as RV strategy is considered, the linear model ranks FIAB first in 11 periods while the best performing quantile model ranks FIAB first in 19 periods.

Table 8. Portfolios of linear 4-Factor and Quantile 4-Factor model

	DR	MA	EMN	QD	TH	SB	FIAB	FICA	FICI	MS	YA
Linear	0	20	0	2	18	0	11	7	0	2	0
Q10	19	1	16	4	0	0	19	1	0	0	0
Q25	7	13	3	1	13	3	20	0	0	0	0
Q33	16	4	0	1	14	5	20	0	0	0	0
Q50	12	8	0	0	20	0	20	0	0	0	0
RC1	9	11	0	1	19	0	20	0	0	0	0
RC2	10	10	0	1	19	0	20	0	0	0	0
RC3	7	13	0	4	16	0	20	0	0	0	0
RC4	7	13	0	8	12	0	20	0	0	0	0
RC5	17	3	0	0	20	0	20	0	0	0	0

Table 9 reports our findings for the full factor linear and quantile specifications. Contrary to the previous linear specifications, a greater variability is present in the linear full factor model. Specifically, DR and MA are equally selected in 10 periods each, and the same holds for the EH strategy where QD and TH are selected in 9 and 10 times, respectively. Regarding the best performing method, namely RC1, we note that MA is ranked first in 16 out of 20 cases, EMN and TH are equally selected in half of the cases and finally FIAB is the most frequantly selected in 14 of the cases. The RC3 method that is the second best forms portfolios in a similar manner with a few differences. For example, MA is picked in 18 times instead of 16 and FIAB in 13 instead of 14 cases.

Table 9. Portfolios of Linear and Quantile Full Factor Models

	DR	MA	EMN	QD	TH	SB	FIAB	FICA	FICI	MS	YA
Linear	10	10	1	9	10	0	4	4	0	12	0
Q10	20	0	9	11	0	0	1	0	0	19	0
Q25	20	0	14	6	0	0	16	0	0	4	0
Q33	11	9	11	5	4	0	20	0	0	0	0
Q50	9	11	7	0	11	2	14	1	0	5	0
RC1	4	16	10	0	10	0	14	2	0	4	0
RC2	10	10	10	0	10	0	14	3	0	3	0
RC3	2	18	10	0	10	0	13	2	0	5	0
RC4	1	19	9	0	11	0	9	3	0	8	0
RC5	10	10	11	9	0	0	13	0	0	7	0

Portfolio composition in the case of mean combining scheme is very different compared to the models considered so far. Reduced portfolio turnover is apparent in linear, quantile and RC methods. Irrespective of the model employed, MA and EMN substrategies are ranked first in all rebalancing periods. However, FIAB is ranked first in all rebalancing periods when the quantile and RC methods are employed, while FIAB is ranked first in 10 out of 20 periods in the linear case. For the rest of the cases, the linear model selects FICA and MS in 8 and 2 periods, respectively. This difference in the portfolio composition accounts for the superiority of quantile and RC methods. More importantly, these methods are associated with no portfolio turnover and as such the performance measures are even more appealing from a practical perspective.

Table 10. Portfolios of Mean Combining Scheme - Linear and Quantile

	DR	MA	EMN	QD	TH	SB	FIAB	FICA	FICI	MS	YA
Linear	0	20	20	0	0	0	10	8	0	2	0
Q10	0	20	20	0	0	0	20	0	0	0	0
Q25	0	20	20	0	0	0	20	0	0	0	0
Q33	0	20	20	0	0	0	20	0	0	0	0
Q50	0	20	20	0	0	0	20	0	0	0	0
RC1	0	20	20	0	0	0	20	0	0	0	0
RC2	0	20	20	0	0	0	20	0	0	0	0
RC3	0	20	20	0	0	0	20	0	0	0	0
RC4	0	20	20	0	0	0	20	0	0	0	0
RC5	0	20	20	0	0	0	20	0	0	0	0

Next, we turn to the recent financial crisis period (2007-2009) which was quite difficult for hedge funds as many successful hedge fund managers were hit with significant losses. Elevated credit, liquidity and systemic risk constitutes this period very different from the period prior to 2007 or after 2009. We check whether our main findings pertain during turbulent periods, as well. Table 11 reports the average return, standard deviation and Sharpe Ratios for the models/ specifications considered. Overall, for the CAPM, Full Factor and the Mean Combining Scheme, our findings point to superiority of quantile and RC methods. For example, in the case of the Full Factor model (Panel D), the Sharpe ratio of the linear model is 0.08 while the respective figures for RC1-RC3 and RC5 are well above 0.40. In the case of the mean combining scheme, the linear model attains a SR of 0.01, while the quantile and RC specifications achieve a SR of 0.32. In the cases of the 3-factor and 4-factor models, results are mixed, as the 3-factor quantile model at $\tau = 0.25$ and $\tau = 0.33$ generate higher Sharpe Ratios than the linear model, while this holds for the 4-factor quantile model at $\tau = 0.10$. Finally, we should also note that similar to the full period analysis, the mean combining scheme for quantile and RC specifications are associated with the creation of low risk portfolios as indicated by the standard deviation. Findings of Table 11 show that the proposed quantile and RC methods provide good results during volatile periods also and serve also as a robustness check for the empirical results reported in Tables 1-5.

Table 11. Performance during the 2007-2009 crisis

Panel A. CAPM - Linear and Quantile										
	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.26	0.24	0.30	0.30	0.07	0.30	0.30	0.30	0.30	0.30
$SD(r_P)$	1.07	1.50	0.95	0.95	1.34	0.95	0.95	0.95	0.95	0.95
SR	0.25	0.16	0.32	0.32	0.06	0.32	0.32	0.32	0.32	0.32
Panel B. Fama French 3-Factor Model - Linear and Quantile										
3F	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.44	0.21	0.46	0.55	0.21	0.21	0.35	0.25	0.23	0.32
$SD(r_P)$	1.78	1.52	1.46	1.77	1.52	1.89	2.07	1.98	1.95	1.89
SR	0.25	0.13	0.31	0.31	0.13	0.11	0.17	0.13	0.12	0.17
Panel C. Carhart 4-Factor Model - Linear and Quantile										
	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.37	0.36	0.25	0.30	0.25	0.25	0.25	0.25	0.22	0.35
$SD(r_P)$	1.89	1.63	1.98	2.08	1.98	1.98	1.98	1.98	1.97	2.07
SR	0.20	0.22	0.13	0.15	0.13	0.13	0.13	0.13	0.11	0.17
Panel D. Full Factor Model - Linear and Quantile										
	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.21	0.31	0.28	0.34	0.66	0.66	0.63	0.63	0.24	0.53
$SD(r_P)$	2.45	2.04	1.61	1.63	1.47	1.47	1.52	1.52	2.33	1.29
SR	0.08	0.15	0.17	0.21	0.45	0.45	0.41	0.41	0.10	0.41
Panel E. Mean Combining Scheme - Linear and Quantile										
	Linear	Q10	Q25	Q33	Q50	RC1	RC2	RC3	RC4	RC5
$E(r_P)$	0.01	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
$SD(r_P)$	1.77	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
SR	0.01	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32

5 Conclusions

We have developed an alternative modeling approach for the estimation of managerial skill which is based on quantile regression models and produces robust estimates of the managerial skill utilizing two different sources of information: (a) the distribution information, regarding how the relationship between the return of the fund and a given variable varies across the conditional quantiles of returns and (b) factor information, regarding the different models that can be used for pricing inference. We show that estimates of the managerial skill based on quantile regressions and the synthesis of different quantile regression are superior in comparison with the relevant estimates from the linear pricing equations in terms of standard risk-adjusted performance measures such as Sharpe Ratio, Sortino Ratio and Adjusted Sharpe Index. We show that robust combination methodologies (RC1-RC5) are producing superior results irrespective of the weighting scheme employed for the synthesis of the quantiles. Furthermore the portfolios based on lower quantiles, such as for $\tau = 0.10$, 0.25, 0.33 produce superior performance relative to the linear regression analogue.

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