Hedge Fund Strategy, Systematic Risk Exposure, and Performance over Changing Market Condition

Carl R. Chen*
University of Dayton, Dayton, OH 45469, USA

Ying Sophie Huang
Zhejiang University, Hangzhou, Zhejiang 310058, China

Isamu Kato
Nomura Funds Research and Technologies America, Inc,
New York, NY 10281, USA

Abstract

We study hedge fund performance and exposure to systematic risk factors over different market cycles with a sample of 1,821 hedge funds from January 1994 to June 2008. Our findings suggest that hedge funds are exposed to systematic risk factors to a great extent. Minimizing systematic risk exposure by means of, for example, hedging does not always produce good results. Our quantile regression analyses reveal that high-achievers (positive alphas) and low-achievers (negative alphas) are exposed to systematic risk factors differently during various economic regimes. For example, good (bad) fund performance may respond to commodity trend-following returns positively (negatively) in a certain market condition, but vice versa in an opposite market condition. The extent of fund exposure to risk factors thus depends on market regimes, confirming the argument that hedge funds shift strategies. Furthermore, choosing the exposure to the right risk factors according to economic regimes separates good performers from poor ones.

JEL classification: G20; G23
Keywords: Hedge funds, Hedge fund strategies, Market cycles, Quantile regression

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* Corresponding author: Carl R. Chen, Department of Economics and Finance, University of Dayton, 300 College Park, Dayton, OH 45469-2251. Tel: (937)229-2418; Fax: (937)229-2477; E-mail: chen@udayton.edu.

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Abstract

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1. Introduction

In the past decade, hedge funds have experienced tremendous growth – nearly 20% per year. By the end of 2006, there were approximately 9,000 funds managing more than $1 ½ trillion of assets. Although total hedge fund assets under management is still far below that of mutual funds (about $10 trillion), one should not underestimate the importance of hedge fund industry due to its ability to use significant amount of leverage. Hedge funds basically operate in an unregulated, opaque territory and only need to comply with two sections of the 1940 Investment Company Act, 3(c)(1) and 3(c)(7). They also cannot advertise. Hedge funds obtain capital from wealthy individuals, and their portfolios are not limited to traditional equity or bond investments. In fact, commodity, foreign currency, options, futures, swaps, domestic assets and foreign assets are all permitted in their investment portfolios. Furthermore, hedge funds face no short sale constraint. Therefore, hedge fund strategies could range from long/short equity, convertible arbitrage to event-driven and/or emerging markets. With their diverse and complex investment strategies, the name "hedge fund" per se does not tell the whole story, and could be a misnomer.

Given the importance of hedge funds in the financial markets, both regulators and the academia have shown increasingly strong interest in the performance and risk of this seemingly secretive industry. In a congressional testimony, FRB Governor Kevin Warsh argued that the growth of hedge funds has contributed to a broader dispersion of risks in the financial system, which in effect has made the financial system less volatile. For example, in the summer of 2003 when interest rates spiked, liquidity of the interest rate options market was strained by hedgers of mortgage payment risks, which sent the option prices through the roof. Some hedge funds shorted interest rate options and it helped the restoration of market liquidity.[1]

However, the subprime mortgage woes and financial crisis have sparked new concerns regarding the health of hedge funds and their potential negative impact on the already dire economic conditions. This concern is not unfounded. The near bankruptcy of Long-Term Capital Management (LTCM) in 1998 is still in investment community's fresh memory. In 2008, some of the world's most powerful hedge fund managers, including George Soros, have been summoned to testify at the hearings of the House Committee on Oversight and Government Reform and told US lawmakers that hedge funds were an integral part of the financial market bubbles. Although these fund managers generally supported the idea of greater transparency and better reporting requirements in the hedge fund industry, Falcone, manager of the Harbinger Capital Partner did not agree that the hedge fund sector was the main contributor to the financial crisis. This opinion was echoed by the former SEC chairman David Ruder.

This paper adds to the extant literature on hedge funds' exposure to systematic risk factors and shows explicitly how hedge funds performance is related to their strategies over various market conditions. Given that hedge funds are heterogeneous, it should be recognized that the performance and strategies of these funds at the tail distribution reveal crucial information to both investors and financial market regulators. In this paper, we confront this issue employing a quantile regression model and provide important insights.

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[1] See the testimony before the Committee on Financial Services, U.S. House of Representatives, by FRB Governor Kevin Warsh on July 11, 2007. http://www.federalreserve.gov/newsevents/testimony/warsh20070711a.htm.

Most of the literature on hedge funds has been focusing on the following topics: performance, performance persistence, fund failure, and corporate governance. Ackermann, McEnally and Ravenscraft (1999) report that hedge funds consistently outperform mutual funds, but not standard market indices. Agarwal and Naik (2000) find the existence of persistence in fund performance. However, Capocci and Hübner (2004) find limited evidence of persistence in fund performance. Baquero et al. (2005) report positive persistence in hedge fund quarterly returns after controlling for investment style, and to a lesser extent, in annual returns. Fung et al. (2008) examine the performance persistence of funds-of-funds and find that a subset of funds-of-funds consistently deliver alphas. This group of alpha delivering funds attracts steadier capital flows, which attenuates their ability to continue to deliver alphas. Kosowski et al. (2007) detect persistent performance at the annual horizon for hedge funds using a robust bootstrap procedure. Relative to the OLS alphas, the bootstrap method yields a 5.5% annual increase in alpha of the spread between the top and the bottom hedge fund deciles. Others such as Chen and Liang (2007) obtain evidence of hedge funds' timing ability. Massoud et al. (2011) investigate and find evidence of the conflict of interest when hedge funds make syndicated loans and take short positions in the equity of the borrowing firms. Titman and Tiu (2011) find that lower R-squared funds perform better. Finally, Li et al. (2011) find managerial characteristics affect hedge fund performance.

Another strand of literature examines the failure of hedge funds. Liang (2000) examines the survivorship bias in hedge fund studies and argues that poor performance is the main reason for a fund's disappearance. Brown et al. (2001) find that a fund's survival depends on its absolute performance, relative performance, excess volatility, and fund age. Liang and Park (2010) present evidence that hedge funds with larger downside risks have a higher hazard rate. Aragon (2007) contends that hedge funds with lockup restrictions earn higher returns than those without lockup restrictions. Additionally, Brown et al. (2008) argue that large funds-of-funds perform better than smaller funds-of-funds because they are able to absorb the high cost of due diligence.

Prior studies in mutual funds and equity managers highlight the pitfalls of assuming a constant risk exposure when measuring performance (Ferson et al., 1996; Christopherson et al., 1998). These concerns are especially relevant for hedge funds since hedge funds invest dynamically in a wide range of asset markets, not just equity market, leading to time-varying risk exposure. Fund managers are free to change strategies and leverages in response to economic conditions (Bollen and Whaley, 2009). However, little is understood regarding the dynamics of hedge funds' strategies as hedge funds seldom reveal their changing strategies.

This paper contributes to the hedge fund literature by investigating a few important and intriguing issues that have not been studied: Are hedge funds exposed to systematic risk factors? Or, are they "hedged" as suggested by the name? Is hedge fund performance affected by the choice of risk exposure? Do hedge funds change strategies by altering their exposure to different risk factors? Are hedge funds' choices of strategies and risk exposures economic condition dependent? In this paper, we address these questions employing a quantile regression model.

Since hedge funds employ a wide spectrum of financial instruments and portfolio strategies, they are inherently heterogeneous and the return distribution is non-Gaussian. Alphas and risk factor loadings derived from standard regression analyses give only the values of conditional means, which might not be the optimal way to interpret their relationships with fund returns. In the presence of such concerns, it would be judicious to work within a more flexible framework, and in our case, a quantile regression approach to analyze hedge fund performance. The major advantage of this approach is that it allows us to examine the differences in fund exposure to systematic risks across a wide spectrum of return distributions. Through quantile regression analysis, we are able to uncover hedge fund strategies that distinguish stellar from poor performance and show how these strategies vary over market cycles. Our findings offer rich information regarding funds' good/poor performance as a result of their exposure to systematic risk factors in various market conditions. The evidence presented in this study thus casts new lights on the understanding of the hedge fund industry and contributes to the fast-growing empirical literature exploring hedge fund trading behaviors in this largely opaque territory.

Our results reveal that hedge funds in general are exposed to systematic risk factors, and high-performing and low-performing funds respond to risk factors differently depending on market regimes, suggesting that hedge funds change strategies based upon their expectations of economic conditions. For example, good performers tend to have less exposure to the commodity trend-following risk factor during the pre-internet bubble period, but have significantly more exposure to the same risk factor during the post-internet bubble period. Conversely, good performers are found to have larger exposure to the bond trend-following risk factor during the pre-internet bubble period, but such exposure to the same risk factor declines during the post-internet bubble period. Hedge funds, therefore, are exposed to systematic risk factors and the success (failure) of a fund partially depends on its ability to efficiently time these risk factors. Minimizing risk exposure via means such as hedging does not always ensure fund performance. We thus provide robust evidence that funds switch between different strategies and risk exposures based upon their expectations and their abilities to do so would determine their performance. This finding echoes the argument of Bollen and Whaley (2009) that hedge funds shift strategies.

The rest of the paper is organized as follows. Data and descriptive statistics are presented in Section 2. Section 3 discusses the methodology. Detailed quantile regression results are reported in Section 4. Section 5 conducts robustness analyses. Section 6 concludes.

2. Data Source and Descriptive Statistics

2.1. Data

We obtain hedge fund data from the Lipper/TASS database (hereafter TASS). TASS provides monthly data on variables such as fund net-of-fee returns and assets under management. Fund characteristics, such as starting date, management fee, minimum account balance, incentive fee, redemption notice, lockup period and fund strategies are also reported. However, since TASS contains data collected from voluntary reporting, missing data are not unusual. Selection bias and survivorship bias have been discussed in many previous hedge fund studies. The survivorship bias is mitigated as our database contains both live and graveyard funds. We include data from January 1994 to June 2008.[2] TASS currently provides performance data on 9060 hedge funds, among which 4,941 are "Live Funds" and 4,119 are "Graveyard Funds". We select funds using

[2] Our data starts from 1994 because the graveyard fund data were created by TASS in 1994.

the following criteria: fund base currency is USD; there is a continuous performance track record of 36 months or more and a minimum fund asset under management (AUM) of $25 million. This procedure produces 1,686 live funds and 135 graveyard funds, i.e. a total of 1,821 hedge funds for our study. Funds-of-funds and commodity trading advisors (CTA) are excluded from our sample. TASS reports on ten hedge fund portfolio strategies although the actual number of strategies could be more. These ten strategies are: event driven, long/short equity, equity market neutral, convertible arbitrage, fixed income arbitrage, dedicated short bias, emerging markets, managed futures, global macro, and “other” which mainly includes various kinds of multi-strategies. Long/short strategy has the largest sample size of 703 funds, while dedicated short bias strategy is employed by only 10 funds.

In addition to the hedge fund data, we also obtain Fama-French three-factor variables from January 1994 to June 2008 from French’s research website. Furthermore, Fung and Hsieh (2001) claim that because hedge fund strategies generate option-like returns, linear-factor models using benchmark asset indices are less effective in explaining fund returns. Therefore, they use lookback straddles to model trend-following strategies and show that these strategies can better explain hedge fund returns. We obtain these trend-following returns from the research web site of Hsieh.[3] Specifically, Fung and Hsieh (2001) propose five trend-following strategies: Return of Primitive Trend-Following Strategy (PTFS) for bond lookback straddle (PTFSBD); currency lookback straddle (PTFSFX); commodity lookback straddle (PTFSCOM); short-term interest rate

[3] http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-Fac.xls.

lookback straddle (PTFSIR); and stock index lookback straddle (PTFSSTK). These data also range from January 1994 to June 2008.

2.2 Descriptive Statistics

We report some descriptive statistics in Tables 1, 2, and 3. In Table 1, values of sample mean, standard deviation, 3rd and 4th moments, and maximum and minimum values for a set of fund variables are reported. These values are calculated for each individual fund first; then average values are taken for all funds. Monthly returns either greater than 70% or less than -50% are treated as outliers and are deleted for further analysis. A total of 1,821 funds have consecutive returns of 36 months or more, and the mean monthly return for all funds is 1.03%, with a maximum of 5.58% and a minimum of -1.45%. The maximum and minimum returns reported in Table 1 represent a fund's "average" return over the life of the fund, hence are less dramatic than the statistics reported in Table 2. The age of a fund is calculated as the difference between the last observation year and the year the fund started. The average age of all funds under study is 8.11 years, with a standard deviation of 4.24 years. The average management fee is 1.64%; the average incentive fee is 18.17% with a maximum as high as 50%; the average lockup period is 4.12 months with a maximum of 90 months; and the average redemption notice is 37.2 days with a maximum of 180 days. The standard deviation of fund returns is 3.53%.

<<Insert Table 1 here>>

In Table 2, we report descriptive statistics for individual return observations. A total of 169,484 returns are available for analysis. The mean of these returns is 1.06% with a maximum of 64.75% and a minimum of -49.86%. We also break the whole sample into three subperiods and a unique sub-subperiod: namely, 01/1994 ~ 03/2000 (pre-internet bubble period); 04/2000 ~ 09/2003 (internet bubble period); 10/2003 ~ 06/2008 (post internet bubble period); and 01/2007 ~ 06/2008 (subprime mortgage crisis period). The first subperiod has the smallest number of observations, reflecting the infancy stage of the hedge fund industry. This subperiod, however, generates the highest mean raw return of 1.59%. Although stock markets took a hard hit during the period of internet bubbles, hedge funds managed to deliver a positive 0.99% monthly mean return (almost 12% annualized), which is slightly higher than the average return during the post-internet bubble period. The sample period from January 2007 to June 2008 is singled out for further scrutiny, as this is a unique time period haunted by the subprime mortgage woes.[4] Although the mean return is lower than those in other subperiods, hedge funds on average can still render a positive 0.68% monthly return.[5]

<< Insert Table 2 here>>

Table 3 presents the descriptive statistics of fund performance based upon various portfolio strategies. Funds that are self-described as long/short style account for the majority of the sample (704 funds), while only ten funds adopt the dedicated short bias style. As for the mean returns, emerging market style funds yield the highest average monthly return at 1.65%, while dedicated short bias funds provide the lowest average return at 0.31%. Since volatilities differ across fund styles, the last column reports the mean return per unit of volatility. The fund style that generates the highest volatility-

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[4] While one cannot pinpoint exactly when the onset of the subprime mortgage crisis is, some major events started out in December 2006 and early 2007. For example, during this period, Ownit Mortgage filed for bankruptcy protection; HSBC took a $10.6 billion charge; and ResMae Mortgage filed for bankruptcy protection.

[5] Our sample period ends in June 2008. The financial crisis and economic recession, however, continue well into 2009.

adjusted return is convertible arbitrage (2.0419), while the lowest is yielded by dedicated short bias funds (0.7986).

<<Insert Table 3 here>>

3. Methodology

Because hedge funds employ a great variety of strategies, they are inherently heterogeneous. Traditional modeling of hedge fund performance produces only the conditional mean values and essentially ignores the behavior of funds at the tails of the distribution. It is known that hedge funds tend to shift strategies depending on economic conditions, but little evidence regarding the resultant performance due to strategy changes has been documented. Examining risk exposures for funds at the tails of the performance distribution during various market cycles would reveal those risk factors that contribute to the good/poor performance in each cycle and uncover hedge funds' strategies in response to economic changes. Furthermore, given the potential significant impact of hedge fund health on the broad financial markets, the comprehension of fund performance at the tails of the performance distribution certainly contains more practical implications for policy makers and regulatory bodies. To achieve this research objective, we employ a quantile regression model to study hedge fund performance.

A two-step procedure is used in our analysis. In the first step, we run the following regression using OLS:

$$\tilde{R}_{it} = \sum_{i=1}^{n-1} \gamma_i D_i + \pi \tilde{R}_{i,t-1} + \mu_{it} \qquad (1)$$

where $\tilde{R}_{it}$ is the net-of-fee monthly return for fund *i* at time *t* minus the 3-month T-bill rate; D_i is the fund dummy, while $\tilde{R}_{i,t-1}$ is the lagged excess monthly return. Therefore, Equation (1) is equivalent to a firm-fixed-effect model with the lagged excess return as an exogenous variable. μ_{it} extracted from Equation (1) thus measures the fund's excess monthly return net of firm-fixed-effect and momentum/reversal effect, because by construction μ_{it} is orthogonal to any unobservable fund effect and to the lagged fund excess return. Incorporating lagged fund returns into the regression also mitigates the problem of potential return serial correlations. In the second step, we then construct a regression model for quantile analysis as follows:[6]

$$\begin{aligned}\mu_{it} &= \alpha_0 + \beta_1\tilde{R}_{mt} + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 PTFSBD_t + \beta_5 PTFSFX_t + \beta_6 PTFSCOM_t \\ &+ \beta_7 PTFSIR_t + \beta_8 PTFSSTK_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where μ_{it} is the filtered return (orthogonized excess monthly return) for fund *i* at time *t*; $\tilde{R}_{mt}$ is the CRSP value-weighted market return minus the 3-month T-bill rate; SMB_t and HML_t are small-minus-big and high-minus-low risk factors in the Fama-French three-factor model; PTFSBD, PTFSFX, PTFSCOM, PTFSIR, and PTFSSTK are trend-following risk factors proposed by Fung and Hsieh (2001) to measure hedge fund trend-following strategies in bonds, foreign currencies, commodities, short-term interest rates, and stock index, respectively; ε_{it} is the regression error term. α_0 (Alpha) in Equation (2),

[6] We employ a two-step procedure because combining a firm-fixed-effect model with quantile regressions is technically and practically difficult if not impossible, especially when the number of funds in our analysis exceeds 1,800. We also run quantile regressions in a single step model without considering firm-fixed-effect. Conclusions are not materially different. The magnitudes of alphas, however, are larger in a single step model. These results are available upon request.

therefore, measures hedge fund performance after systematic risk factors are controlled for.

It should be noted that the alphas and betas estimated using traditional OLS method are the conditional means of hedge fund alphas and loadings of risk factors. Notably, these conditional means have limited informational value for two reasons. First, it is naive and even erroneous to assume that all funds employ homogeneous trading strategies and are exposed to the same set of risk factors. Interpretation of the factor loadings will thus be non-optimal if the traditional regression analysis is used. Second, while it may be interesting to know the conditional mean performance of hedge funds in general, it is far more informative to assess and understand the behavior of funds at the tails of the distribution. This is particularly true when funds effectively change strategies over economic cycles. Indeed, Bollen and Whaley (2009) argue that estimated abnormal returns may be incorrect if exposures to the risk factors actually vary through time but are instead assumed to be constant. A fund's strategy, e.g., commodity trend following, which works well in an environment of skyrocketing energy prices, may very likely be suboptimal in a period of flat oil prices. A fund's exposure to the systematic risk factors at the right (wrong) time will enhance (reduce) its returns. Examining fund performance at the distribution tails thus allows us to uncover the difference in strategies between good and bad performers. Finally, performance of funds at the tails also entails more regulatory implications, and most importantly the negative impact of fund failure on the whole financial market can only come from funds at the left tail of the performance distribution. Agarwal and Naik (2004) show that a large number of equity-oriented hedge fund strategies exhibit payoffs resembling that of a short position in a put option on the market index and thus bear significant left-tail risk. However, such risk is often ignored by the traditional mean-variance framework.

In the context of hedge funds with heterogeneous strategies, some concerns arise as the OLS regressions only model the relationship between covariates X and the conditional mean of Y variable. On the other hand, quantile regressions model the relationship between covariates X and the conditional quantiles of Y variable; hence is very applicable when extreme scenarios are of particular interest. For example, in medical research where the mother characteristics of severely underweighted infants are the key research interest, traditional regressions estimating the conditional mean relationship do not provide much useful information. Environmental studies also are more interested in the upper quantiles of pollution levels as the conditional quantile estimates convey more information for public health policies. Similarly, quantile regression allows us to better examine systematic risk factors that distinguish good from poor hedge fund performance.

The conditional quantile regression analysis developed by Koenker and Bassett (1978) and Koenker and Hallock (2001) accounts for the skewed distribution of fund performance and can be used to draw more appropriate inferences with respect to the factor loadings across the performance distribution. There are several advantages of using quantile regressions over simple OLS regressions. First, when the data are heterogeneous, quantile regressions permit inferences about the influence of regressors conditional on the distribution of the endogenous variable. Second, because quantile regressions estimate conditional quantile functions, as such, quantile regressions are appropriate when the data show a significant degree of variations. Therefore, quantile regressions can capture information about the slope of the regression line at different quantiles of the endogenous variable (fund performance) given the set of exogenous variables (risk factors). Third, since there is no distributional assumption about the error term in the model, quantile regression estimates provide model robustness. General concepts of the quantile regression can be illustrated as follows.

Given that the ϕ^{th} conditional quantile of μ_i is linear in x_i ($\phi \in (0,1)$) and assume that (μ_i, x_i), i = 1,….,n, whereby μ_i represents the orthogonized fund excess returns while x_i is a vector of exogenous variables as shown in Equation (2), the quantile regression model can be written as:

$$\mu_i = x_i^{'}\beta_\phi + \varepsilon_{\varphi\, i} \tag{3}$$

where the ϕ^{th} quantile of $\varepsilon_i = 0$. The underlying assumption of Equation (3) is

$$Quant_\phi(\mu_i \,|x_i) \equiv \inf\left\{\mu : F_i(\mu|x)\phi\right\} = x_i^{'}\beta_\phi \tag{4}$$

where $Quant_\phi(\mu_i\,|x_i)$ is the ϕ^{th} conditional quantile of μ_i given x_i. It should be noted that the median estimator (i.e., ϕ=0.5) is a special case of the quantile regression. The ϕ^{th} regression quantile can be tracked by shifting ϕ between zero and one. To estimate $\hat{\beta}_\phi$, we can minimize

$$\text{Min}\sum_i^n \rho_\phi(\mu_i - x_i^{'}\beta_\phi) \tag{5}$$

where $\rho_\phi(\bullet)$ is the tilted absolute value function and can be defined as

$$\rho_\phi(\varepsilon) = \phi\ \varepsilon \ \text{ if } \varepsilon \geq 0 \text{ or } \rho_\phi(\varepsilon) = (\phi - 1)\varepsilon \ \text{ if } \varepsilon < 0 \text{ [7]} \tag{6}$$

The interior point approach of Karmarkar (1984) is used in the optimization to solve a sequence of quadratic problems. Note that quantile regressions cannot be carried out by simply segmenting the unconditional distribution of the dependent variable into quantiles, and then estimating the covariate effect using OLS method for each subset.

[7] See also Schaeck (2008).

This approach leads to disastrous results, in particular when the data include outliers. In contrast, quantile regressions use all of the data for fitting quantiles.[8]

4. Empirical Results

4.1. Good vs. poor performers: Whole sample

We first estimate Equation (2) by using all funds' data with OLS method, and then apply quantile regression models. Results for both models are reported in Table 4. Column 2 of Table 4 shows the OLS results.[9] On average, hedge funds have a monthly alpha indistinguishable from zero during the period from January 1994 to June 2008. All three Fama-French factors are positive and highly significant. The beta coefficient of MKT (0.2834) suggests hedge funds as a group have relatively low exposure to the equity market risk. Among the five trend-following factors, only PTFSBD (bond trend-following factor) is not statistically significant. The significant risk factors indicate that some of the hedge fund returns are linked to systematic sources.

<<Insert Table 4 here>>

However, as discussed earlier, interpretations based on OLS results are not optimal and have limited informational value because they provide only the value of the conditional mean. Motivated by this concern, we proceed to perform the quantile regression analysis to examine risk factors that differentiate high-performers from low-performers. Columns 3 through 11 exhibit the effects of various risk factors at the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th quantiles of the hedge fund return

[8] See SAS manual, SAS Institute.
[9] To save space, parameters of strategy dummies are not reported.

distribution. It is found that alphas are negative and significant at the 10^{th} ~ 50^{th} quantiles, turning into positive and significant at the 60^{th} quantile and reaching a high of 2.68% at the 90^{th} quantile. These numbers are equivalent to a range of annual alphas from -33.7% to 32.2% from the worst to the best performers. The signs of the risk factor parameters are consistent across quantiles for all risk factors with the only exception of PTFSBD, although we observe different sensitivities. For the PTFSBD risk exposure, the effect on fund performance is negative at the lower-tail of the return distribution, but it increasingly becomes positive toward the higher-tail of the return distribution. The intuition of this result is that at the lower-tail of the distribution funds perform poorly as their returns move in the opposite direction to the bond trend-following strategy. As such, their predominant strategies do not conform well with the bond trend-following factor. On the other hand, at the higher-tail of the distribution, funds perform well as their specific strategies are most likely to be consistent with a general bond trend-following strategy. [10] The insignificant OLS estimate of the PTFSBD, therefore, can be misinterpreted and fails to distinguish the differential impacts of PTFSBD risk factor on high- vs. low-performers. On the other hand, the positive Least Absolute Deviation (LAD) estimator as shown by the result at the 50^{th} quantile, also only reveals half of the story as the effect of PTFSBD on lower performing funds is negative.

[10] Regarding the effect of the bond trend following factor, specific hedge fund strategies should have more explicit positive or negative effects of the factor. For instance, managed futures and global macro strategies are likely to have a positive effect of the bond trend-following factor, because their trading styles are “directional” or “long volatility” in terms of bond markets. On the other hand, “relative value” or “short volatility” type of strategies, such as fixed income arbitrage and event driven, should have a negative effect of the bond trend-following factor. We may also assume that the higher-tail group tends to have an exposure of managed futures or global macro type of strategies, while the lower-tail group is more likely to have an exposure of fixed income arbitrage or event driven type of strategies. Section 5 offers further discussions regarding fund strategies and performance.

While Table 4 reports parameter estimates and their t-statistics, Figure 1 plots these parameter values at various quantiles of the return distribution, which offers a visual inspection of fund performance and strategic differences between good and poor performers. The shaded areas represent estimators within 95% confidence bands. The alphas for various quantiles can be seen in Figure 1(a). As expected, the upward sloping curve indicates poor performing funds tend to be associated with negative alphas and better performing funds generate positive alphas. Figures 1(b) ~ (d) plot the parameters of the Fama-French three factors over various quantiles. The loadings of the first two factors more or less display a u-shaped curve, suggesting that funds at the tails of the return distribution have relatively more exposure to the market risk and size factors. The loading of the value-growth factor, however, is downward sloping, implying that more exposure to a high book-to-market factor leads to lower fund performance. [11]

<<Insert Figure 1 here>>

Similarly, Figure 1(e) plots the exposure of fund returns to the returns of bond trend-following strategy. The shape of this curve resembles the shape of alphas shown in Figure 1(a). That is, funds at the right-tail of the return distribution deliver higher alphas as their portfolios load positively to the bond trend-following factor. On the other hand, funds at the left-tail of the distribution incur negative alphas as their returns load negatively to the bond trend-following returns. Figures 1(f) and 1(h) display upward sloping curves, suggesting that portfolios of good performers have more exposure to these risk factors (namely, currency trend-following and short-term interest rate trend-following returns) than poor/average performers, although the heavier exposure appears

[11] Although both high-tail and low-tail funds appear to have similar exposures to some risk factors, e.g., the size factor, their differential exposures to other risk factors, e.g., PTFSBD and PTFSSTK, would set their performance apart. This is possible because hedge funds operate in multiple asset markets.

to be more likely to enhance returns for good performers. Finally, similar to Figure 1(e), Figure 1(i) also displays an upward sloping curve, implying that high-performers tend to add more exposure to the stock index trend-following risk factor than low-achievers.[12]

4.2. Performance in different market regimes

Conceptually, one may think hedge funds perform well in adverse market conditions because they are "hedged". On the other hand, others may believe that hedge funds usually employ risky strategies with significant amount of leverages, hence are exposed to higher degree of risks in extreme market conditions. Agarwal and Naik (2004) find that a wide range of hedge funds suffer from left tail risk which coincides with market downturns. In this subsection, we further elaborate on hedge fund performance by examining the following three issues: alphas in various market conditions; fund exposures to risk factors in various market conditions; and differences in risk factor loadings across return quantiles. These are important issues in the study of hedge fund performance as suggested by Bollen and Whaley (2009) that nearly 40% of the hedge funds experience shifts in risk exposures. As market conditions play an important role in hedge fund decisions to change strategies, sample partitioning based upon macroeconomic conditions helps reveal the changes in hedge fund strategies and their performance due to strategic decisions, which otherwise are more subtle to detect.

[12] Regarding the effect of the stock index trend-following factor, some hedge fund strategies may have small positive or negative effects. For instance, the equity market neutral strategy should have a small positive effect on the stock index trend factor, and the convertible arbitrage and dedicated short bias strategies may have a negative effect on the factor. On the other hand, similar to the bond trend-following factor, directional or long volatility strategies, such as managed futures and global macro, are likely to have a positive effect on the factor. We may also assume that the lower-tail group tends to have an exposure to equity market neutral, convertible arbitrage, and dedicated short bias strategies, while the higher-tail group is more likely to have an exposure to managed futures and global macro strategies. More discussions about fund strategies are provided in Section 5.

To this end of the analysis, we break down the whole sample as follows: the first subsample runs from January 1994 to March 2000; the second from April 2000 to September 2003; and the third from October 2003 to June 2008. The first subperiod corresponds to the extended economic boom in the US; the second subperiod encompasses the internet bubble period; while the third is the post-internet bubble period. Considering the importance of the global financial crisis, we also focus on the exclusive impact from subprime mortgage woes from January 2007 to June 2008 within the third subperiod.[13] This sample partitioning is based upon the US equity market cycles. The idea is that in spite of the fact that equity market cycles may not be the best guide post to partition samples for hedge funds, which heavily trade instruments beyond the scope of equities, it is often observed that in periods of extreme equity market performances, trading in bonds, derivatives and commodities is also affected. Moreover, equity market performance is widely recognized as a leading indicator that presages general economic conditions. Besides, theoretically hedge funds move their capital in and out of a specific market depending on that market's potential for trading profits.

Figure 2 plots variables in four different markets during the same sample period, including 3-month T-bill yield, Moody's Baa yield, British/US exchange rate, and oil price (OK Cushing). While oil prices exhibit less significant cyclical patterns, all the other three variables show cycles/trend lines similar to that in the equity market. Therefore, one of the research issues that we intend to address is whether and how hedge fund strategies respond to various market cycles.

<<Insert Figure 2 here>>

4.2.1 Pre-internet bubble period

[13] As we indicated earlier, January 2007 is roughly the beginning date of the subprime mortgage problems.

The first subperiod corresponds to the pre-internet bubble period, a period characterized by booming stock markets, low inflation, stable energy prices, and robust economic growth. Results of both the OLS and quantile regressions are reported in Table 5 for comparison. The OLS results show an insignificant alpha, and all Fama-French factors and trend-following factors are statistically significant except for the stock index trend-following factor. On the other hand, similar to the results for the whole sample, a closer look at various quantiles of fund returns reveals a more comprehensive picture. For example, at the lower-tail of the return distribution, fund returns respond to the bond trend-following factor (PTFSBD) negatively, but the loading coefficient becomes significant and positive at the higher-tail of the return distribution. So are the performance responses to the PTFS on stock index. Clearly, the insignificant parameter for the PTFSSTK in the OLS result is the consequence of offsetting factor loadings between higher-tail and lower-tail of the return distribution. The differences in risk factor loadings between good and poor fund performance can be attributed to a successful or unsuccessful implementation of the bond/stock trend-following strategy, which cannot be revealed by the conditional means estimated by the OLS regression.

<<Insert Table 5 here>>

4.2.2 Internet bubble period

While we have analyzed hedge fund performance during a long span of booming economy, it is more revealing to examine their performance and strategic behaviors during the period of stock market bubbles. Table 6 reports our findings. The OLS results show an insignificant alpha of -0.11%. The S&P500, however, lost more than 30% during the same period. OLS results also indicate that hedge fund returns are not significantly exposed to the bond, commodity and stock index trend-following risk factors.

Again, quantile regressions capture some interesting hidden information across a spectrum of strategies. For example, quantile regressions point out that PTFSSTK parameters are negative and significant for the left-tail of the fund return distribution, yet positive and significant for the right-tail of the distribution. This finding contrasts with the OLS result of an insignificantly positive stock index trend-following factor (PTFSSTK). Obviously, during the market bubble period, poorly performing funds' returns are negatively related to stock index trend-following returns, while funds with superior performance can attribute their success to their ability in following the stock index trend. Our results regarding the left-tail distribution echo the finding in Brunnermeier and Nagel (2004) that hedge funds were heavily invested in technology stocks during the internet bubble period. Predicting stock trend correctly (incorrectly) during this subperiod helps to contribute to a fund's relative superior (poor) performance.

<<Insert Table 6 here>>

4.2.3 Post internet bubble period

Table 7 summarizes the results for this more recent subperiod. Although the OLS alpha during this market recovery period is also insignificant, the dispersion of alphas across quantiles is less dramatic compared to the bubble period. There is also strong evidence that hedge funds follow trends in the bond, commodity, and stock markets, as the parameters for PTFSBD, PTFSCOM, and PTFSSTK are mostly positive and significant across all return quantiles. Since this is a period of skyrocketing commodity prices, good performing funds appear to load more heavily on the PTFSCOM.[14] As for the foreign exchange risk factor, poor performers tend to load negatively and significantly on foreign currency trend-following returns, while good performers' returns load positively and significantly on this risk factor.

<<Insert Table 7 here>>

4.2.4 Subprime mortgage crisis period

Since the above third subperiod incorporates the most recent subprime mortgage woes, we create another unique subsample that starts from January 2007 in order to zero in on the ability of hedge funds to weather such a financial storm and disclose how their trading behaviors differ across the performance distribution.[15] As can be seen in Table 8, the OLS results reveal some noticeable differences from previous subperiods. For example, fund returns load negatively on the SMB, HML, PTFSBD, PTFSFX, PTFSIR, and PTFSSTK risk factors as these parameters all carry negative signs. Returns load positively only on two risk factors – MKT and PTFSCOM. PTFSSTK is not statistically significant in the OLS model, but this does not tell any story for funds at the tail distribution. Columns 3 through 11 display quantile regression parameter estimates. Specifically, parameters of PTFSBD are significant and negative across all return

[14] Besides direct investment in derivatives or physical commodities, hedge funds also actively take on indirect commodity exposures; e.g. long-short managers invest in equities or corporate debts of commodity producers; emerging market players trade currencies and sovereign debts in commodity exporting countries.
[15] Although the subprime mortgage woes surfaced in early 2007, the most serious damage to the equity and credit markets started after the bankruptcy of Lehman Brothers which occurred in mid-September of 2008. Our data end in June 2008. Anecdotal evidence, however, indicates that 2008 is a bad year for the hedge fund industry. The Wall Street Journal reports that through November 2008, long-short funds were down 26%, and funds investing in emerging markets dropped 30%. Nevertheless, short managers were up 32%, and global macro funds, which follow trends in currencies and bonds managed to gain 5%. (The Wall Street Journal, January 2, 2009, p. R7)

quantiles. This finding suggests that during this period, regardless of winners or losers, bond trading strategies of these hedge funds actually run counter to the bond trend-following risk factor. This unusual phenomenon is also observed for the foreign currency trend-following returns (PTFSFX). The poor performers, nevertheless, load more heavily on PTFSFX than good performers. The only trend-following return factor that is consistently and positively correlated with fund performance is commodity trend-following returns. Recall from Figure 2 that this is a period with skyrocketing energy and commodity prices. It is not surprising that most funds are significantly exposed to the PTFSCOM risk factor during this unique time period.

<<Insert Table 8 here>>

4.2.5 Comparison of risk factor loadings over market cycles

Although it is suspected that hedge funds switch strategies depending on anticipated economic conditions, empirical evidence supporting this conjecture is rather scant. Results based upon quantile regressions presented in Tables 5 – 8 above are useful to enhance our understanding of this matter. To better contrast various hedge fund strategies over different market cycles, in this subsection we turn to the findings of main interest by plotting the quantile regression parameters for various risk factors over different market cycles. To save space, we report diagrams for selected risk factors only. Figure 3 plots the quantile regression parameters for SMB risk factor. Differences in this risk factor loading over quantiles can be seen from the four panels which correspond to four market cycles in our sample. In brief, fund returns load positively during and before the internet bubble periods, but load negatively in the post-bubble periods, with tail-performers exhibiting more sensitivity to the size factor. Note that although both good and poor performers load more heavily on the size factor, SMB is only one of the many existing risk factors. Other risk factors such as HML would help discriminate good from poor fund performance.

<<Insert Figure 3 here>>

The parameter estimates of HML over different subsamples are reported in Figure 4. In Panel (a) the parameter estimates of HML decrease persistently from low to high quantiles. That is, lower return funds appear to be correlated with more exposure to value-stock returns than higher return funds during these economic boom years. In a bull market, value-stock strategies tend to be defeated by growth-stock strategies. On the other hand, during the internet bubble period, good performers load more heavily on the value-growth risk factor. The upward sloping pattern is also observed during the onset of financial crisis (Panel (d)) although most of the loadings are negative. This suggests that funds adopting a value-stock strategy (high book-to-market) perform relatively better during the turbulent years.

<<Insert Figure 4 here>>

Figure 5 demonstrates the quantile regression parameter plots for the bond trend-following strategy (PTFSBD). In Figure 5(a), the estimated PTFSBD parameters indicate that high-performance funds respond positively to the trend-following strategies in bonds, while low-performance funds respond negatively. In other words, good achievers have significant exposures to the bond trend-following risk factor during the pre-bubble period. In contrast, the negative sloping curve in Panel (c) implies that well performing funds are less exposed to the returns of bond trend-following risk factor than poorly performing funds in the post-bubble period, during which Baa yield declines significantly.

<<Insert Figure 5 here>>

Fund exposures to the commodity trend-following risk factor are shown in Figure 6. Panel (a) suggests that during the pre-bubble period, low-performance funds are more responsive to commodity trend-following returns than high performance funds. Specifically, in the pre-internet bubble period, funds which are most active in commodity trading (e.g., managed futures) and which have a significant commodity exposure, fail to produce excess returns. It should be noted that the general inflation rate during this subperiod is very low, which can be seen from the almost trendless crude oil prices during this period in Figure 2. In a sharp contrast, during the post-bubble periods (Panels (c) and (d)) good performing funds load more heavily on commodity trend-following strategies. During this period, there is a long-term bull trend in several commodity markets and trend-following hedge fund managers may have taken full advantage of these market movements.

<<Insert Figure 6 here>>

Figure 7 presents the estimated parameters for the foreign currency trend-following strategy (PTFSFX). During the post-bubble periods (Panels (c) and (d)), as represented by “carry-trade strategies”, currency trades are known to be one of the most popular investment strategies in the hedge fund community. The higher-tail group may have well enjoyed the successful trading in the currency markets. As shown in Figure 2, the US dollar has weakened significantly during this subperiod.

<<Insert Figure 7 here>>

Finally, Figure 8 shows the estimated quantile parameters for the short-term interest rate trend-following strategy. During the internet bubble period (Panel (b)), poorly performing funds load negatively to the PTFSIR risk factor, while funds with superior performance can attribute their success to their ability in following the PTFSIR trend. This subperiod has witnessed the post 9.11 recession and an expansionary monetary policy, which generated a solid downward trend in interest rates. During this period, 3-month T-bill rates declined from over 6% to less than 1% (see Figure 2). The higher-tail group may have benefited from timing those monetary trends.

<<Insert Figure 8 here>>

4.3. Quantile regression results of fund strategies and market cycles

By this point, we have controlled for fund strategies by using strategy dummies. However, funds adopting different strategies may respond to risk factors differently over market cycles. In this subsection, we report some quantile regression results of the effect of fund strategies on the risk exposure over different market cycles. To save space, we show only two subperiods (internet bubble vs. post-internet bubble) and two quantiles (15^{th} vs. 90^{th}) to illustrate distinctive effects.[16] To this end, the original regression model (Equation (2)) is expanded to include fund strategies and some variables capturing the interaction between fund strategies and risk factors in addition to the systematic risk factors. The "interaction dummy" variables thus measure the effect of fund strategy on the loadings of risk factors. For example, Event_HML measures the effect of the value-growth risk factor given the event-driven strategy being adopted. The purposes of this kind of analysis are threefold: to examine if and how a fund's exposure to various risk factors differ across market cycles given a specific fund strategy; to contrast the loadings

[16] Other results are available from the authors upon request.

of risk factors across return distribution quantiles given the fund strategy; and to show the differences in the loadings of risk factors across fund strategies given the market cycle. Results are reported in Table 9.

<<Insert Table 9 here>>

Since there are 90 parameters for each equation, we select only a few examples to demonstrate our findings. First, given the fund strategy, a fund's exposure to various risk factors is found to differ across market cycles. For example, the only significant factor loading for the event-driven strategy during the bubble period at the 15th quantile return distribution is Event_HML. However, Event_HML, Event_PTFSFX, Event_PTFSIR, and Event_PTFSCOM are all statistically significant during the post-bubble period.[17] Therefore, given the stated fund strategy, a fund's ex post trading strategies indeed change dynamically depending on macro-economic conditions. Estimates based upon a single-regime framework may thus lead to inappropriate inferences regarding fund strategic behavior and performance.

Second, given the fund strategy, a fund's exposure to risk factors is also found to differ across return distribution quantiles. That is, under the same macro-economic condition and stated fund strategy, exposures to risk factors vary greatly between good and bad performers. For example, during the post-bubble period, managed futures strategy has a positive and significant Managed_SMB coefficient at the lower-tail return distribution, while the exposure to the same risk factor becomes negative and significant at the higher-tail return distribution, implying that different levels of exposure to the same

[17] Event driven strategy is traditionally characterized as active-value-up strategy and its main focus is asset-rich companies (or low market-to-book ratio stocks). However, in recent years, its focus has expanded and covered not only corporate events but also macro events such as commodity boom and credit deterioration. The result confirms this style shift.

risk factor can attribute to the differential fund performances even if the fund stated strategy is the same.

Third, fund strategy determines exposures to various risk factors. For example, dedicated short strategy has significant and negative large exposure to market excess returns (Dedicatedshort_MKT) irrespective of market conditions and return distributions.[18] Conversely, emerging market strategy has positive and significant exposure to market excess returns (Emerging_MKT) irrespective of market conditions and return distributions.[19] On the other hand, the exposure to the market excess return for the event-driven strategy (Event_MKT), however, is barely existent. Based upon these findings, we conclude that fund trading strategy varies over market cycles and across performance distributions, impacting loadings of risk factors, and thus fund performance.

4.4. Summary of alphas by quantiles and by sample periods

We have analyzed hedge fund performance and their exposure to the systematic risk factors across return distributions and under different strategies as well as market regimes in the previous subsections. In this subsection, we summarize the central results on alphas in Table 10 and Figure 9. Our results show that irrespective of market regimes, the lowest four quantiles (10^{th}, 20^{th}, 30^{th}, and 40^{th}) exhibit negative alphas (i.e. inferior performance) in all market regimes and this pattern does not seem to be altered in any significant way by the market conditions. The median (50^{th}) quantile (i.e., LAD estimator) has negative alphas, but is significant only in the post internet bubble period.

[18] Short bias strategy is characterized as put option like strategy. The result reveals that short players steadily maintain their short equity exposure with great perseverance in both bull and bear market cycles.

[19] Emerging market strategy often invests in a heavily long biased equity portfolio. This is due to managers' perspective on the solid expansion of emerging economies. However, the shortage of short instruments in the emerging market is a practical hurdle for enhancement of their short portfolios.

Figure 9 shows that the differential performance between good and bad performers is most evident during the financial crisis period, while such difference is the smallest during the pre-internet bubble period.

<<Insert Table 10 and Figure 9 here>>

5. Robustness Check

Although in prior analyses we've taken into account unobservable firm fixed effect and observable fund strategies, in this section we check the result robustness by considering other fund characteristics. These additional fund characteristics include management fees, incentive fees, lockup periods, redemption notice, and age of the fund. Both OLS and quantile regression results are reported.

Table 11 reports OLS results for various sample periods and market cycles. A few observations are worth noting. First, with few exceptions, coefficients of all systematic risk factors remain highly significant even after the inclusion of fund characteristics. In effect, the magnitude of the coefficients of systematic risk factors show little change from the results reported in Tables 4 – 8. This confirms the notion that generally fund performance consists of two components: systematic component and fund-specific component. Although hedge funds may be "hedged", they are still exposed to systematic risks and their returns load on these risk factors. Second, fund characteristics are sporadically significant only, and the age of a fund appears to be negatively related to the fund performance. Third, portfolio strategy dummy variables indicate that, compared with the reference strategy (i.e., "other"), long-short strategy performs poorer during internet bubble and financial crisis periods;[20] and convertible arbitrage strategy performs poorly for most of the sample periods except for the bubble period. It is interesting to note that dedicated short bias strategy performs better than the reference category only during the period of financial stress.[21]

<<Insert Table 11 here>>

Table 12 reports quantile regression results for the whole sample with fund characteristics. First, the loadings for systematic risk factors show little changes from those reported in Tables 4 – 8. Thus, our earlier findings are robust to the inclusion of observable fund characteristics. Second, although none of the fund characteristics coefficients is significant in the OLS regression (see Column 2 of Table 11 or Column 2 of Table 12), quantile regressions reveal a different story. For example, management fee, incentive fee, lockup period, and fund age load negatively for funds at the lower tail of the return distribution, but positively for the good performing funds at the right tail. On the other hand, redemption notice loads positively for the poor performing funds, but negatively for the better performing funds.

<<Insert Table 12 here>>

6. Conclusions

We study hedge fund performance and their exposure to systematic risk factors over different market cycles using a sample of 1,821 hedge funds from January 1994 to June 2008. Since hedge funds employ a wide variety of trading strategies and financial

[20] Known among hedge fund insiders, long-short managers are not good at constructing short equity portfolios. The result reveals their weakness in an environment of market stress.

[21] Short bias strategy, which is mostly composed of short equity positions, is frequently characterized as put option like strategy. The result reveals the unique edge of the strategy in the crisis period.

instruments, we model fund returns using both the Fama-French three-factor model and Fung and Hsieh's five non-linear trend-following factors. To take into account potential firm fixed effect and momentum/reversal effect, we orthogonize fund returns with these unobservable/observable factors in the first stage of the modeling. Orthogonized fund returns then are used in the second stage analysis. Fund performance over various market cycles is analyzed using a quantile regression approach, as traditional regression model only provide estimates of the conditional means or conditional medians, and it offers little insight into whether and how funds in the tails of the return distribution change strategies.

Our findings indicate that hedge funds are exposed to systematic risk factors. Quantile regression results successfully capture and reveal that high-achievers and low-achievers respond to risk factors differently. These differences vary substantially depending on market conditions. For example, good performers tend to have less exposure to the commodity trend-following risk factor during the pre-internet bubble period, but add significantly more exposure to the same risk factor during the post-internet bubble period. Conversely, good performers are found to have larger exposure to the bond trend-following risk factor during the pre-internet bubble period, but such exposure to the same risk factor declines during the post-internet bubble period. Hedge funds, therefore, are greatly affected by systematic risk factors and the success (failure) of a fund partially depends on its ability to efficiently manage these risk exposures. The extent of fund exposure to risk factors thus heavily depends on prevailing market regimes; its ability to choose an appropriate amount of exposure to the right risk factors separates superior from poor performers. We provide robust evidence that funds switch between different strategies based upon their expectations and their abilities to do so would determine their ultimate performance. However, minimizing fund exposures to systematic risk factors by means of hedging does not always lead to good results. This finding resonates with the argument of Bollen and Whaley (2009) that hedge funds shift strategies.

Furthermore, we also investigate the impact of stated fund strategy on fund performance and risk factor loadings. Our analyses yield insights regarding several important observations on hedge funds. It is found that the loadings of risk factors differ significantly across market cycles given the fund strategy; loadings of risk factors also vary greatly across return distribution quantiles given the fund strategy; and there are differences in the loadings of risk factors across fund strategies given the market cycle and the sampling period.

Studying fund performance at the tails of the return distribution using quantile regressions allows us to achieve a much better understanding of hedge fund trading strategies under various market regimes. Our findings are interesting and informative from the perspectives of both investors and regulators, because hedge funds rarely reveal their trading strategies except for the broad classification purpose.

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Table 1. Descriptive Statistics for All Funds

This table reports descriptive statistics of raw returns and fund characteristics. Funds must have consecutive returns of 36 months or longer to be included. Age is measured in years; Management Fee and Incentive Fee in percentages; Lockup period in months; Redemption Notice in days; and Standard Deviation in percentages.

	No. of Funds	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
Return	1821	0.0103	0.0066	-0.0145	0.0558	1.575	5.129
Age	1821	8.1109	4.2365	3	39	1.486	3.461
Management Fee	1809	0.0164	0.0070	0	0.07	1.484	8.481
Incentive Fee	1809	0.1817	0.0583	0	0.5	-1.605	5.051
Lockup	1686	4.1174	7.0843	0	90	2.662	15.886
Redemption Notice	1686	37.2058	27.916	0	180	1.374	3.743
Standard Deviation	1821	0.0353	0.0243	0.0002	0.1606	1.463	2.540

Table 2. Descriptive Statistics of Fund Returns

This table reports descriptive statistics for fund raw returns based upon all individual observations. The whole sample is also partitioned into three subperiods and one sub-subperiod. Subperiod 01/1994-03/2000 corresponds to the years of economic booms; subperiod 04/2000 – 09/2003 corresponds to the years of Internet bubbles; subperiod 10/2003 – 06/2008 corresponds to the years of post-internet bubble market recovery. Sub-subperiod 01/2007 – 06/2008 is the period characterized by subprime woes.

	No. of Returns	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Whole Sample	169484	0.0106	0.0453	-0.4986	0.6475
01/1994-03/2000	29079	0.0159	0.0628	-0.4986	0.6475
04/2000- 09/2003	42985	0.0099	0.0483	-0.4110	0.6081
10/2003-06/2008	97470	0.0094	0.0372	-0.4609	0.6227
01/2007- 06/2008	29844	0.0068	0.0425	-0.4587	0.4229

Table 3. Descriptive Statistics by Strategies

This table reports fund return statistics based upon stated fund strategy.

Strategy	No. of Return Observations	Mean Return	Standard Deviation	Mean/STD
Convertible Arbitrage	62	0.0073	0.0036	2.0419
Dedicated Short Bias	10	0.0031	0.0039	0.7986
Event Driven	230	0.0092	0.0050	1.8324
Emerging Market	159	0.0165	0.0098	1.6933
Equity Market Neutral	128	0.0071	0.0041	1.7586
Fixed Income Arbitrage	100	0.0055	0.0043	1.2912
Global Macro	88	0.0100	0.0069	1.4476
Long/Short Equity	704	0.0113	0.0061	1.8464
Managed Futures	163	0.0105	0.0062	1.6912
Other	178	0.0088	0.0054	1.6314

Table 4. Quantile Regression Analysis of Fund Performance (Whole Sample)

This table reports OLS and quantile regression results for the whole sample. Alpha measures the fund performance; MKT is the market excess return; SMB is the Fama-French small-minus-big risk factor; HML is the high-minus-low risk factor; PTFSBD is the Fung and Hsieh's bond trend-following factor; PTFSFX is the currency trend-following factor; PTFSCOM is the commodity trend-following factor; PTFSIR is the short-term interest rate trend-following factor; and PTFSSTK is the stock trend-following factor. T-statistics are reported in the parentheses. ** denotes statistical significance at the 1% levels.

	OLS	Quantile Regression								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Alpha	-0.00005 (-0.15)	-0.0281 (-60.6)**	-0.0156 (-56.3)**	-0.0089 (-38.4)**	-0.0041 (-21.5)**	-0.0005 (-2.57)**	0.0033 (17.3)**	0.0078 (34.2)**	0.0137 (44.3)**	0.0268 (53.8)**
MKT	0.2834 (84.5)**	0.3391 (76.9)**	0.2655 (100.7)**	0.2249 (102.8)**	0.1984 (109.2)**	0.186 (108.8)**	0.1841 (101.1)**	0.1903 (88.3)**	0.2113 (71.7)**	0.2488 (52.6)**
SMB	15.085 (42.2)**	14.432 (30.7)**	11.3327 (40.3)**	10.138 (43.4)**	9.3827 (48.4)**	9.2888 (50.9)**	9.3853 (48.3)**	10.236 (44.5)**	11.311 (35.9)**	14.870 (29.5)**
HML	8.4489 (19.5)**	13.256 (23.2)**	10.762 (31.5)**	9.688 (34.2)**	8.6648 (36.8)**	8.0428 (36.3)**	7.7248 (32.7)**	7.5042 (26.8)**	7.4585 (19.5)**	7.2599 (11.9)**
PTFSBD	0.0014 (1.55)	-0.0205 (-17.6)**	-0.0099 (-14.3)**	-0.0049 (-8.4)**	-0.0018 (-3.8)*	0.0011 (2.36)**	0.0037 (7.74)**	0.0076 (13.3)**	0.0122 (15.7)**	0.0258 (20.6)**
PTFSFX	0.0083 (12.3)**	0.0048 (5.43)**	0.0027 (5.01)**	0.0024 (5.4)**	0.0026 (7.2)**	0.0031 (9.09)**	0.0042 (11.4)**	0.0051 (11.8)**	0.0074 (12.5)**	0.0119 (12.5)**
PTFSCOM	0.0219 (26.4)**	0.0201 (18.4)**	0.0151 (23.2)**	0.0122 (22.5)**	0.0108 (23.9)**	0.0102 (23.9)**	0.0106 (23.5)**	0.0125 (23.4)**	0.0149 (20.3)**	0.0186 (15.8)**
PTFSIR	-0.0125 (-31.6)**	-0.0168 (-32.3)**	-0.0135 (-43.4)**	-0.0108 (-41.5)**	-0.0095 (-44.1)**	-0.0085 (-42.1)**	-0.0079 (-36.8)**	-0.008 (-31.3)**	-0.0080 (-23.1)**	-0.0085 (-15.1)**
PTFSSTK	0.0180 (19.3)**	0.0056 (4.54)**	0.0081 (11.0)**	0.0093 (15.3)**	0.0112 (22.1)**	0.0126 (26.5)**	0.0156 (30.8)**	0.0190 (31.6)**	0.0238 (29.0)**	0.0278 (21.1)**
Strategy Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. Quantile Regression Analysis of Fund Performance (Pre-03/2000 Period)

This table reports OLS and quantile regression results for the pre-internet bubble period. Alpha measures the fund performance; MKT is the market excess return; SMB is the Fama-French small-minus-big risk factor; HML is the high-minus-low risk factor; PTFSBD is the Fung and Hsieh's bond trend-following factor; PTFSFX is the currency trend-following factor; PTFSCOM is the commodity trend-following factor; PTFSIR is the short-term interest rate trend-following factor; and PTFSSTK is the stock trend-following factor. T-statistics are reported in the parentheses. ** denotes significance at the 1% level.

	OLS	Quantile Regression								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Alpha	-0.0016 (-1.46)	-0.0317 (-24.7)**	-0.0173 (-21.9)**	-0.0097 (-15.8)**	-0.0047 (-8.8)**	-0.0005 (-1.05)	0.0038 (7.06)**	0.0089 (13.1)**	0.0171 (19.6)**	0.0296 (22.1)**
MKT	0.3745 (33.8)**	0.420 (33.4)**	0.3294 (42.7)**	0.2735 (45.6)**	0.2427 (46.6)**	0.2375 (46.8)**	0.2312 (44.1)**	0.2357 (35.6)**	0.2613 (30.6)**	0.3066 (23.3)**
SMB	20.423 (20.2)**	18.426 (16.0)**	13.809 (19.6)**	12.287 (22.4)**	11.320 (23.8)**	11.973 (25.8)**	12.047 (25.1)**	12.774 (21.1)**	14.106 (18.1)**	16.438 (13.7)**
HML	11.482 (7.2)**	24.869 (13.7)**	16.943 (15.2)**	12.906 (14.9)**	10.044 (13.4)**	9.308 (12.7)**	6.962 (9.2)**	4.1035 (4.3)**	1.1162 (0.9)	-7.5204 (-3.9)*
PTFSBD	0.0132 (4.7)**	-0.0379 (-11.9)**	-0.0176 (-8.9)**	-0.0101 (-6.6)**	-0.0045 (-3.4)**	0.0009 (0.73)	0.0073 (5.48)**	0.0157 (9.4)**	0.0272 (12.6)**	0.0499 (14.9)**
PTFSFX	0.0114 (5.2)**	0.0064 (2.56)**	0.0059 (3.85)**	0.0054 (4.5)**	0.0042 (4.0)**	0.0040 (3.91)**	0.0048 (4.5)**	0.0063 (4.8)**	0.0100 (5.8)**	0.0140 (5.3)**
PTFSCOM	0.0137 (4.9)**	0.0204 (6.5)**	0.0147 (7.6)**	0.0118 (7.8)**	0.0091 (7.0)**	0.0078 (6.1)**	0.0069 (5.3)**	0.0051 (3.1)**	0.0033 (1.6)	0.0012 (0.38)
PTFSIR	-0.0187 (-8.7)**	-0.0147 (-6.0)**	-0.012 (-8.0)**	-0.0104 (-8.9)**	-0.0096 (-9.4)**	-0.0097 (-9.8)**	-0.011 (-10.7)**	-0.0134 (-10.4)**	-0.0159 (-9.6)**	-0.0189 (-7.4)**
PTFSSTK	0.0024 (0.8)	-0.0162 (-4.8)**	-0.0091 (-4.4)**	-0.0070 (-4.3)**	-0.0027 (-1.91)	0.0015 (1.11)	0.0061 (4.4)**	0.0114 (6.4)**	0.0162 (7.1)**	0.018 (5.1)**
Strategy Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Quantile Regression Analysis of Fund Performance (04/2000 – 09/2003 Period)

This table reports OLS and quantile regression results for the internet bubble period. Alpha measures the fund performance; MKT is the market excess return; SMB is the Fama-French small-minus-big risk factor; HML is the high-minus-low risk factor; PTFSBD is the Fung and Hsieh's bond trend-following factor; PTFSFX is the currency trend-following factor; PTFSCOM is the commodity trend-following factor; PTFSIR is the short-term interest rate trend-following factor; and PTFSSTK is the stock trend-following factor. T-statistics are reported in the parentheses. ** denotes significance at the 1% level.

	OLS	**Quantile Regression**								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Alpha	-0.0011 (-1.44)	-0.0298 (-28.4)**	-0.0166 (-25.5)**	-0.0093 (-19.5)**	-0.0044 (-10.7)**	-0.0008 (2.12)	0.0029 (7.2)**	0.0072 (14.8)**	0.0133 (20.2)**	0.027 (23.5)**
MKT	0.2084 (32.1)**	0.2383 (26.8)**	0.1726 (31.4)**	0.1346 (33.4)**	0.1203 (34.9)**	0.1149 (34.7)**	0.1211 (35.9)**	0.148 (35.9)**	0.1952 (35.0)**	0.2633 (27.1)**
SMB	14.354 (18.8)**	17.181 (16.5)**	11.654 (18.0)**	9.2448 (19.5)**	8.1990 (20.2)**	8.058 (20.7)**	8.713 (21.9)**	9.480 (19.6)**	10.507 (16.0)**	14.357 (12.6)**
HML	8.250 (10.7)**	6.6942 (6.3)**	5.0767 (7.7)**	4.7702 (9.9)**	4.989 (12.1)**	4.9218 (12.5)**	5.628 (14.0)**	7.6038 (15.5)**	9.929 (14.9)**	12.225 (10.6)**
PTFSBD	0.0006 (0.4)	-0.0016 (-0.7)	-0.0014 (-1.02)	-0.0013 (-1.23)	-0.0003 (-0.4)	0.0014 (1.67)	0.0018 (2.06)*	0.0038 (3.7)**	0.0052 (3.7)**	0.0039 (1.6)
PTFSFX	0.0165 (11.0)**	0.0224 (10.9)**	0.0179 (14.1)**	0.0132 (14.2)**	0.0099 (12.5)**	0.0088 (11.6)**	0.0075 (9.64)**	0.0070 (7.4)**	0.0099 (7.7)**	0.0106 (4.7)**
PTFSCOM	0.0023 (0.95)	-0.0054 (-1.66)	-0.0044 (-2.18)	-0.0022 (-1.48)	-0.0012 (-0.95)	-0.0008 (-0.63)	0.0004 (0.3)	0.0012 (0.78)	-0.0002 (-0.07)	0.001 (0.3)
PTFSIR	0.0045 (3.07)**	-0.0084 (-4.2)**	-0.0032 (-2.56)**	-0.0024 (-2.65)**	-0.0014 (-1.77)	0.0005 (0.67)	0.0020 (2.60)**	0.0043 (4.6)**	0.0091 (7.2)**	0.0158 (7.2)**
PTFSSTK	0.0015 (0.65)	-0.0165 (-5.2)**	-0.0145 (-7.3)**	-0.0076 (-5.3)**	-0.0021 (-1.7)	-0.0004 (-0.37)	0.0043 (3.6)**	0.009 (6.1)**	0.0129 (6.4)**	0.0179 (5.1)**
Strategy Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Quantile Regression Analysis of Fund Performance (Post 09/2003 Period)

This table reports OLS and quantile regression results for the post-internet bubble period. Alpha measures the fund performance; MKT is the market excess return; SMB is the Fama-French small-minus-big risk factor; HML is the high-minus-low risk factor; PTFSBD is the Fung and Hsieh's bond trend-following factor; PTFSFX is the currency trend-following factor; PTFSCOM is the commodity trend-following factor; PTFSIR is the short-term interest rate trend-following factor; and PTFSSTK is the stock trend-following factor. T-statistics are reported in the parentheses. ** denote significance at the 1% level.

	OLS	Quantile Regression								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Alpha	-0.0003 (-0.87)	-0.0239 (-45.1)**	-0.0138 (-39.3)**	-0.008 (-29.3)**	-0.0042 (-17.9)**	-0.0009 (-3.95)**	0.0024 (9.9)**	0.0061 (22.4)**	0.0109 (30.7)**	0.0219 (37.6)**
MKT	0.3995 (73.7)**	0.5079 (69.5)**	0.3942 (81.7)**	0.3346 (88.7)**	0.2893 (89.9)**	0.2642 (85.9)**	0.2594 (77.4)**	0.2603 (69.2)**	0.2758 (56.1)**	0.3027 (37.8)**
SMB	5.0212 (7.5)**	5.4563 (6.1)**	6.712 (11.3)**	5.9737 (12.9)**	5.9274 (15.0)**	5.5708 (14.8)**	4.4416 (10.8)**	4.304 (9.3)**	3.7474 (6.2)**	5.6379 (5.7)**
HML	4.1939 (5.8)**	6.3948 (6.6)**	6.760 (10.5)**	7.1823 (14.3)**	6.9807 (16.3)**	7.2198 (17.6)**	6.4337 (14.4)**	6.1842 (12.3)**	6.679 (10.2)**	6.925 (6.5)**
PTFSBD	0.0046 (3.1)**	0.0169 (8.5)**	0.0152 (11.6)**	0.0115 (11.2)**	0.0075 (8.6)**	0.0051 (6.1)**	0.0024 (2.7)**	0.0003 (0.34)	-0.0024 (-1.79)	-0.0063 (-2.9)**
PTFSFX	0.0048 (6.4)**	-0.0085 (-8.3)**	-0.0052 (-7.7)**	-0.0029 (-5.6)**	-0.0014 (-3.2)**	0.0003 (0.7)	0.0027 (5.7)**	0.0047 (8.9)**	0.0078 (11.4)**	0.0167 (14.9)**
PTFSCOM	0.0282 (32.8)**	0.0144 (12.5)**	0.0123 (16.0)**	0.0112 (18.8)**	0.0112 (22.0)**	0.0125 (25.7)**	0.0145 (27.3)**	0.0184 (30.8)**	0.0237 (30.5)**	0.0347 (27.3)**
PTFSIR	-0.0135 (-37.2)**	-0.0210 (-43.1)**	-0.0159 (-49.5)**	-0.0121 (-47.9)**	-0.0103 (-48.2)**	-0.0089 (-43.6)**	-0.0082 (-36.6)**	-0.0076 (-30.4)**	-0.0071 (-21.5)**	-0.0073 (-13.8)**
PTFSSTK	0.0238 (22.5)**	0.0203 (14.2)**	0.0167 (17.6)**	0.0147 (19.8)**	0.0146 (23.1)**	0.0148 (24.6)**	0.0168 (25.6)**	0.0200 (27.1)**	0.0244 (25.3)**	0.0308 (19.6)**
Strategy Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Quantile Regression Analysis of Fund Performance (Post 12/2006 Period)

This table reports OLS and quantile regression results for the subprime mortgage crisis period. Alpha measures the fund performance; MKT is the market excess return; SMB is the Fama-French small-minus-big risk factor; HML is the high-minus-low risk factor; PTFSBD is the Fung and Hsieh's bond trend-following factor; PTFSFX is the currency trend-following factor; PTFSCOM is the commodity trend-following factor; PTFSIR is the short-term interest rate trend-following factor; and PTFSSTK is the stock trend-following factor. T-statistics are reported in the parentheses. ** denotes significance at the 1% level.

	OLS	Quantile Regression								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Alpha	-0.0003 (-0.33)	-0.0249 (-23.8)**	-0.0142 (-20.8)**	-0.0087 (-15.7)**	-0.0048 (-10.4)**	-0.0011 (-2.3)	0.0023 (4.9)**	0.0064 (11.5)**	0.0120 (16.9)**	0.0236 (21.4)**
MKT	0.2472 (21.3)**	0.2783 (18.4)**	0.2381 (24.1)**	0.2190 (27.2)**	0.2052 (30.6)**	0.2033 (28.7)**	0.213 (32.1)**	0.2278 (28.3)**	0.2417 (23.5)**	0.2741 (17.2)**
SMB	-13.905 (-4.9)**	-17.548 (-4.7)**	-14.32 (-5.9)**	-9.962 (-5.08)**	-9.836 (-6.03)**	-9.349 (-5.4)**	-12.187 (-7.5)**	-14.465 (-7.4)**	-19.579 (-7.8)**	-28.066 (-7.2)**
HML	-16.597 (-7.6)**	-39.484 (-13.9)**	-19.684 (-10.6)**	-12.897 (-8.5)**	-8.391 (-6.7)**	-6.882 (-5.2)**	-2.1576 (-1.72)	2.1053 (1.39)	1.1251 (0.58)	-5.569 (-1.85)
PTFSBD	-0.0424 (-12.8)**	-0.0467 (-10.8)**	-0.0387 (-13.7)**	-0.0423 (-18.3)**	-0.0353 (-18.4)**	-0.0308 (-15.1)**	-0.0297 (-15.6)**	-0.0262 (-11.4)**	-0.0236 (-8.0)**	-0.0244 (-5.3)**
PTFSFX	-0.0478 (-13.3)**	-0.1185 (-24.9)**	-0.0823 (-26.6)**	-0.0623 (-24.7)**	-0.0475 (-22.6)**	-0.0355 (-15.9)**	-0.0266 (-12.8)**	-0.0202 (-8.0)**	-0.0129 (-4.0)**	-0.0033 (-0.7)
PTFSCOM	0.0629 (31.6)**	0.0253 (9.7)**	0.0307 (17.9)**	0.0346 (24.8)**	0.0383 (33.0)**	0.0406 (33.1)**	0.0458 (39.9)**	0.0515 (36.9)**	0.0577 (32.4)**	0.0846 (30.7)**
PTFSIR	-0.0159 (-35.1)**	-0.0217 (-36.7)**	-0.0167 (-43.4)**	-0.0133 (-42.5)**	-0.0119 (-45.6)**	-0.0112 (-40.5)**	-0.0106 (-40.9)**	-0.0099 (-31.7)**	-0.0100 (-24.5)**	-0.0119 (-19.1)**
PTFSSTK	-0.0009 (-0.33)	-0.0495 (-13.9)**	-0.0316 (-13.7)**	-0.0226 (-11.9)**	-0.012 (-7.7)**	-0.0023 (-1.4)	0.0055 (3.5)**	0.0133 (7.0)**	0.0234 (9.7)**	0.0390 (10.4)**
Strategy Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Quantile Regression Analysis of Fund Strategy over Market Cycles

This table reports quantile regression results for the bubble and post-bubble periods. Alpha measures the fund performance; MKT is the market excess return; SMB is the Fama-French small-minus-big risk factor; HML is the high-minus-low risk factor; PTFSBD is the Fung and Hsieh's bond trend-following factor; PTFSFX is the currency trend-following factor; PTFSCOM is the commodity trend-following factor; PTFSIR is the short-term interest rate trend-following factor; and PTFSSTK is the stock trend-following factor. Event, Long Short, Equity Neutral, Convertible, Fixed Income, Dedicated Short, Emerging, and Global are hedge fund strategy dummy variables. The product of fund strategy and risk factor (e.g., Event_MKT) represent interaction dummy variables. T-statistics are omitted to save space. ** denotes significance at the 1% level.

	15^{th} Quantile		90^{th} Quantile	
	Bubble Period	**Post-Bubble**	**Bubble Period**	**Post-Bubble**
Alpha	-0.0186**	-0.0173**	0.0258**	0.0224**
MKT	0.1720**	0.3363**	0.1912**	0.2782**
SMB	9.0267**	2.6001	11.4516**	1.0185
HML	-0.3247	7.2044**	6.9830	-3.6775
PTFSBD	0.0025	0.0038	0.0148	-0.0083
PTFSFX	0.0099*	-0.0003	0.0136	0.0152**
PTFSCOM	-0.0000	0.0128**	0.0034	0.0376**
PTFSIR	-0.0000	-0.0169**	0.0069	-0.0079**
PTFSSTK	-0.0040	0.0207**	0.0220	0.0342**
Event	0.0014	0.0030**	-0.0040	-0.0074**
Long short	-0.0201**	-0.0089**	0.0188**	0.0099**
Equity Neutral	-0.0006	0.0011	0.0001	-0.0042**
Convertible	0.0065**	0.0025*	0.0009	-0.0121**
Fixed Income	0.0103**	0.0042**	-0.0051	-0.0060**
Dedicated Short	-0.0156**	-0.0012	0.0124	0.0024
Emerging	-0.0275**	-0.0149**	0.0270**	0.0203**
Managed	-0.0375**	-0.0202**	0.0446**	0.0335**
Global	-0.0151**	-0.0120**	0.0254**	0.0145**
Event_MKT	-0.0314	0.0265	0.0240	-0.0107
Event_SMB	2.4489	4.7320	0.0396	8.6792
Event_HML	9.6347**	7.7626**	4.2125	13.7681**
Event_PTFSBD	-0.0054	0.0053	-0.0260**	0.0025
Event_PTFSFX	-0.0053	-0.0094**	-0.0014	-0.0090
Event_PTFSCOM	0.0019	-0.0107**	-0.0107	-0.0257**
Event_PTFSIR	-0.0062	0.0072**	-0.0050	0.0027
Event_PTFSSTK	-0.0114	-0.0078	-0.0085	-0.0179**
Longshort_MKT	0.2046**	0.2579**	0.2479**	0.1363**
Longshort_SMB	9.7726**	10.6909**	10.4785**	16.5697**
Longshort_HML	9.7554**	-6.9235**	12.2943**	2.6160
Longshort_PTFSBD	0.0040	0.0122	-0.0195	-0.0062
Longshort_PTFSFX	0.0111	-0.0115**	-0.0211**	0.0001
Longshort_PTFSCOM	0.0079	0.0065	-0.0088	0.0074
Longshort_PTFSIR	-0.0074	-0.0048**	0.0246**	-0.0027
Longshort_PTFSSTK	-0.0075	0.0038	-0.0058	0.0031
Equityneutral_MKT	-0.1051**	-0.1960**	-0.1959**	-0.2568**
Equityneutral_SMB	1.3714	-1.5801	-3.1064	4.8222
Equityneutral_HML	3.6925	1.5342	-7.7006	2.8477
Equityneutral_PTFSBD	-0.0130	-0.0100	-0.0227	0.0085
Equityneutral_PTFSFX	0.0109	-0.0051	0.0024	-0.0159**
Equityneutral_PTFSCOM	-0.0067	-0.0146**	-0.0249	-0.0181**
Equityneutral_PTFSIR	0.0032	0.0094**	0.0112	0.0098**
Equityneutral_PTFSSTK	0.0078	-0.0228**	-0.0213	-0.0186**
Convertible_MKT	-0.0968**	-0.0770	-0.0977	-0.1690**

Convertible_SMB	-6.8533	5.7733	-1.3086	7.2008
Convertible_HML	-6.1454	1.2148	-7.3254	20.2515**
Convertible_PTFSBD	-0.0109	0.0098	-0.0321	-0.0129
Convertible_PTFSFX	0.0084	-0.0131**	0.0020	-0.0165**
Convertible_PTFSCOM	-0.0248	-0.0135**	-0.0070	-0.0148
Convertible_PTFSIR	-0.0087	0.0099**	-0.0097	0.0080**
Convertible_PTFSSTK	-0.0116	0.0006	-0.0237	-0.0237**
Fixedincome_MKT	-0.1913**	-0.1389**	-0.1652**	-0.2214**
Fixedincome_SMB	-8.5469	-8.184	-4.8029	-8.4980
Fixedincome_HML	-1.7418	13.216**	-9.4961	-0.0156
Fixedincome_PTFSBD	-0.0137	-0.0070	-0.0197	0.0136
Fixedincome_PTFSFX	-0.0025	-0.0065	0.0063	-0.0118
Fixedincome_PTFSCOM	-0.0215	-0.0131**	-0.0002	-0.0250**
Fixedincome_PTFSIR	-0.0056	0.0058**	-0.0089	0.0051
Fixedincome_PTFSSTK	0.0172	-0.0152**	-0.0112	-0.0119
Dedicatedshort_MKT	-1.0987**	-1.3244**	-1.1751**	-1.2419**
Dedicatedshort_SMB	-18.6041	-29.9311**	-39.8273**	-26.0881
Dedicatedshort_HML	11.6576	2.2597	24.2249	13.9979
Dedicatedshort_PTFSBD	-0.0084	0.0162	-0.0087	-0.0169
Dedicatedshort_PTFSFX	-0.0030	-0.0094	0.0031	0.0032
Dedicatedshort_PTFSCOM	-0.1020**	-0.0184	-0.1240**	-0.0168
Dedicatedshort_PTFSIR	-0.0132	0.0178**	-0.0013	0.0145*
Dedicatedshort_PTFSSTK	0.0092	-0.0212	-0.0351	-0.0182
Emerging_MKT	0.3776**	0.4099**	0.3700**	0.3305**
Emerging_SMB	24.0242**	-10.0859**	23.9335**	-7.2282
Emerging_HML	11.2976**	-15.1801**	4.2703	20.2947**
Emerging_PTFSBD	-0.0124	-0.0012	-0.0275**	0.0076
Emerging_PTFSFX	0.0044	-0.0032	-0.0324**	0.0016
Emerging_PTFSCOM	-0.0062	0.0162**	-0.0026	0.0420**
Emerging_PTFSIR	0.0029	-0.0139**	0.0268**	-0.0194**
Emerging_PTFSSTK	-0.0265**	0.0146**	-0.0344	0.0249**
Managed_MKT	-0.4541**	0.1892**	-0.1486**	0.2535**
Managed_SMB	10.6011**	9.1454**	-21.4332**	-17.3722**
Managed_HML	7.5670	-1.3965	-3.8919	15.8329**
Managed_PTFSBD	0.0139	0.0631**	0.0563**	0.0779**
Managed_PTFSFX	0.0486**	0.0363**	0.0928**	0.0374**
Managed_PTFSCOM	0.0421**	0.0340**	0.0190	0.0667**
Managed_PTFSIR	0.0076	0.0001	-0.0032	-0.0034
Managed_PTFSSTK	-0.0314**	-0.0016	0.0866**	0.0216**
Global_MKT	-0.0236	0.1419**	0.0838	0.1298**
Global_SMB	4.0019	-9.5645**	13.1974	-9.2179
Global_HML	5.3382	5.7837	13.5107	9.0584
Global_PTFSBD	-0.0126	-0.0014	-0.0056	0.0404**
Global_PTFSFX	0.0080	0.0165**	0.0425**	0.0135
Global_PTFSCOM	0.0140	0.0118	-0.0175	0.0117
Global_PTFSIR	-0.0106	-0.0049	0.0159	0.0057
Global_PTFSSTK	0.0099	0.0058	0.0270	0.0153

Table 10. Alphas by Quantiles and by Sample Periods

This table summarizes the Alphas across return distribution quantiles and across market cycles.

Quantile	Whole Sample	Pre-03/2000	03/2000-09/2003	Post-09/2003	Post-12/2006
0.1	-0.0281	-0.0317	-0.0298	-0.0239	-0.0249
0.2	-0.0156	-0.0173	-0.0166	-0.0138	-0.0142
0.3	-0.0089	-0.0097	-0.0093	-0.0080	-0.0087
0.4	-0.0041	-0.0047	-0.0044	-0.0042	-0.0048
0.5	-0.0005	-0.0005	-0.0008	-0.0009	-0.0011
0.6	0.0033	0.0038	0.0029	0.0024	0.0023
0.7	0.0078	0.0089	0.0072	0.0061	0.0064
0.8	0.0137	0.0171	0.0133	0.0109	0.0120
0.9	0.0268	0.0296	0.0270	0.0219	0.0236

Table 11. OLS Regression Analysis with Fund Characteristics

This table reports OLS regression results with fund characteristics and strategies. Alpha measures the fund performance; MKT is the market excess return; SMB is the Fama-French small-minus-big risk factor; HML is the high-minus-low risk factor; PTFSBD is the Fung and Hsieh's bond trend-following factor; PTFSFX is the currency trend-following factor; PTFSCOM is the commodity trend-following factor; PTFSIR is the short-term interest rate trend-following factor; and PTFSSTK is the stock trend-following factor. T-statistics are reported in the parentheses. ** denotes significance at the 1% level.

	Whole Sample	Pre-03/2000	03/2000-09/2003	Post-09/2003	Post-12/2006
Alpha	-0.0002	0.0015	0.0003	0.0009	-0.0018
	(-0.34)	(0.62)	(0.18)	(1.46)	(-1.3)
MKT	0.2834	0.3746	0.2075	0.3998	0.247
	(84.5)**	(33.8)**	(31.9)**	(73.8)**	(21.3)**
SMB	15.085	20.494	14.41	5.0227	-13.9
	(42.2)**	(20.3)**	(18.9)**	(7.6)**	(-4.9)**
HML	8.448	11.822	8.407	4.245	-16.59
	(19.5)**	(7.4)**	(10.9)**	(5.9)**	(-7.6)**
PTFSBD	0.0013	0.0127	0.0006	0.0045	-0.0424
	(1.48)	(4.52)**	(0.37)	(3.1)**	(-12.8)**
PTFSFX	0.0083	0.0113	0.0164	0.0048	-0.0478
	(12.3)**	(5.1)**	(10.9)**	(6.4)**	(-13.3)**
PTFSCOM	0.0219	0.0134	0.0016	0.0282	0.0629
	(26.4)**	(4.8)**	(0.69)	(32.8)**	(31.6)**
PTFSIR	-0.0125	-0.018	0.0050	-0.0135	-0.0159
	(-31.5)**	(-8.4)**	(3.42)**	(-37.2)**	(-35.1)**
PTFSSTK	0.0180	0.0029	0.0009	0.0237	-0.0009
	(19.3)**	(0.99)	(0.41)	(22.3)**	(-0.33)
Management	0.0005	0.0086	0.0441	0.017	0.931
fee	(0.03)	(0.16)	(1.25)	(0.97)	(2.52)
Incentive fee	0.0007	0.0143	0.0046	-0.0067	-0.0002
	(0.4)	(2.04)*	(1.09)	(3.3)**	(-0.05)
Lockup	-0.0000	-0.0001	0.0001	-0.0000	-0.0000
	(-0.12)	(-1.0)	(2.57)**	(-1.76)	(-1.25)
Redemption	-0.0000	-0.0000	-0.0000	0.0000	-0.0000
	(-0.27)	(-1.02)	(-0.3)	(1.36)	(-0.7)
Age	0.000	-0.0003	-0.0003	-0.0001	0.0000
	(0.34)	(-3.3)**	(-4.5)**	(-3.1)**	(0.7)
Event	-0.0001	0.0002	0.0001	-0.0002	-0.0041
	(-0.13)	(0.13)	(0.13)	(-0.34)	(-3.73)**
Longshort	-0.0002	0.0048	-0.0025	-0.0005	-0.0035
	(-0.54)	(3.64)**	(-2.97)**	(-1.2)	(-3.8)**
Equityneutral	-0.0001	0.0013	0.0009	-0.0007	0.0001
	(-0.12)	(0.63)	(0.77)	(-1.2)	(0.07)
Convertible	0.0000	-0.0007	0.0043	-0.0026	-0.0046
	(0.01)	(-0.3)	(3.28)**	(-3.7)**	(-3.0)**
Fixed income	-0.0001	-0.004	0.0024	-0.0004	-0.0023
	(-0.12)	(-1.77)	(1.8)	(-0.7)	(-1.7)
Dedicatedshort	0.0006	-0.0105	0.0154	-0.0018	0.0127
	(0.44)	(2.9)**	(5.9)**	(-1.23)	(3.86)**
Emerging	-0.0001	0.0010	-0.0023	0.0004	-0.0043
	(-0.12)	(0.6)	(-2.1)	(0.64)	(-3.76)**
Managed	0.0001	-0.0027	0.0026	0.0008	0.0052
	(0.12)	(-1.6)	(2.36)	(0.15)	(4.4)**
Global	0.0001	-0.0012	0.0009	-0.0003	0.0022
	(0.15)	(-0.5)	(0.7)	(-0.44)	(1.56)

Table 12. Quantile Regression Analysis with Fund Characteristics (Whole Sample)

This table reports quantile regression results with fund characteristics and strategies. Alpha measures the fund performance; MKT is the market excess return; SMB is the Fama-French small-minus-big risk factor; HML is the high-minus-low risk factor; PTFSBD is the Fung and Hsieh's bond trend-following factor; PTFSFX is the currency trend-following factor; PTFSCOM is the commodity trend-following factor; PTFSIR is the short-term interest rate trend-following factor; and PTFSSTK is the stock trend-following factor. T-statistics are reported in the parentheses. ** denotes significance at the 1% level.

	OLS	Quantile Regression								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Alpha	-0.0002 (-0.34)	-0.0178 (-20.46)**	-0.0080 (-15.8)**	-0.0037 (-8.9)**	-0.0014 (-4.02)**	0.0002 (0.68)	0.0021 (5.9)**	0.0041 (9.8)**	0.0071 (13.0)**	0.0142 (15.7)**
MKT	0.2834 (84.5)**	0.3333 (70.7)**	0.2628 (95.4)**	0.2223 (98.8)**	0.1969 (103.9)**	0.1843 (104.8)**	0.1834 (97.5)**	0.1901 (84.0)**	0.2094 (71.4)**	0.2455 (50.4)**
SMB	15.085 (42.2)**	14.363 (28.6)**	11.368 (38.7)**	9.964 (41.5)**	9.3748 (46.4)**	9.2662 (49.4)**	9.4159 (46.9)**	10.234 (42.4)**	11.142 (35.6)**	14.201 (27.3)**
HML	8.4489 (19.5)**	12.987 (21.3)**	10.680 (29.9)**	9.521 (32.7)**	8.6907 (35.4)**	8.1247 (35.7)**	7.869 (32.3)**	7.815 (26.7)**	7.4649 (19.7)**	6.9520 (11.0)**
PTFSBD	0.0013 (1.48)	-0.018 (-14.4)**	-0.0082 (-11.2)**	-0.0041 (-6.8)**	-0.0016 (-3.1)**	0.0009 (1.96)	0.0031 (6.1)**	0.0062 (10.2)**	0.0101 (12.9)**	0.0221 (17.0)**
PTFSFX	0.0083 (12.3)**	0.0045 (4.7)**	0.0023 (4.14)**	0.0022 (4.9)**	0.0025 (6.6)**	0.0031 (8.7)**	0.0044 (11.7)**	0.0055 (12.2)**	0.0079 (13.4)**	0.0126 (12.9)**
PTFSCOM	0.0219 (26.4)**	0.0203 (17.3)**	0.0152 (22.2)**	0.0128 (22.9)**	0.0113 (23.9)**	0.0107 (24.5)**	0.0114 (24.5)**	0.0134 (23.8)**	0.0163 (22.4)**	0.0199 (16.4)**
PTFSIR	-0.0125 (-31.5)**	-0.0171 (-30.6)**	-0.0135 (-41.4)**	-0.0109 (-40.8)**	-0.0096 (-42.7)**	-0.0085 (-40.9)**	-0.0078 (-35.0)**	-0.008 (-28.9)**	-0.0080 (-22.9)**	-0.0086 (-14.9)**

Table 12. Quantile Regression Analysis with Fund Characteristics (Continued)

	OLS	Quantile Regression								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
PTFSSTK	0.0180 (19.3)**	0.0050 (3.84)**	0.0086 (11.2)**	0.0099 (15.8)**	0.0113 (21.4)**	0.0126 (25.8)**	0.0157 (29.9)**	0.0194 (30.7)**	0.0246 (30.1)**	0.0281 (20.7)**
Management fee	0.0005 (0.03)	-0.1261 (-5.45)**	-0.1025 (-7.6)**	-0.0622 (-5.6)**	-0.0206 (-2.22)*	0.0169 (1.96)	0.0556 (6.0)**	0.0856 (7.7)**	0.1174 (8.2)**	0.1500 (6.3)**
Incentive fee	0.0007 (0.38)	-0.0373 (-13.4)**	-0.0236 (-14.5)**	-0.0165 (-12.5)**	-0.0102 (-9.16)**	-0.0047 (-4.54)**	0.0011 (0.98)	0.0083 (6.2)**	0.0189 (10.9)**	0.0421 (14.6)**
Lockup	-0.0000 (-0.12)	-0.0001 (-4.82)**	-0.0001 (-6.6)**	-0.0001 (-5.0)**	-0.0000 (-2.46)	-0.0000 (-0.45)	0.0000 (1.83)	0.0000 (2.9)**	0.0001 (4.7)**	0.0001 (3.7)**
Redemption	-0.0000 (-0.27)	0.0001 (8.79)**	0.0000 (9.31)**	0.0000 (6.98)**	0.0000 (4.31)**	0.0000 (0.31)	-0.0000 (-3.7)**	-0.0000 (6.2)**	-0.0000 (-7.8)**	-0.0001 (-8.35)**
Age	0.000 (0.34)	-0.0005 (-13.6)**	-0.0003 (-16.7)**	-0.0002 (-13.9)**	-0.0001 (-9.30)**	-0.0000 (-2.46)	0.0001 (4.3)**	0.0002 (10.0)**	0.0003 (15.3)**	0.0006 (16.2)**
Strategy Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

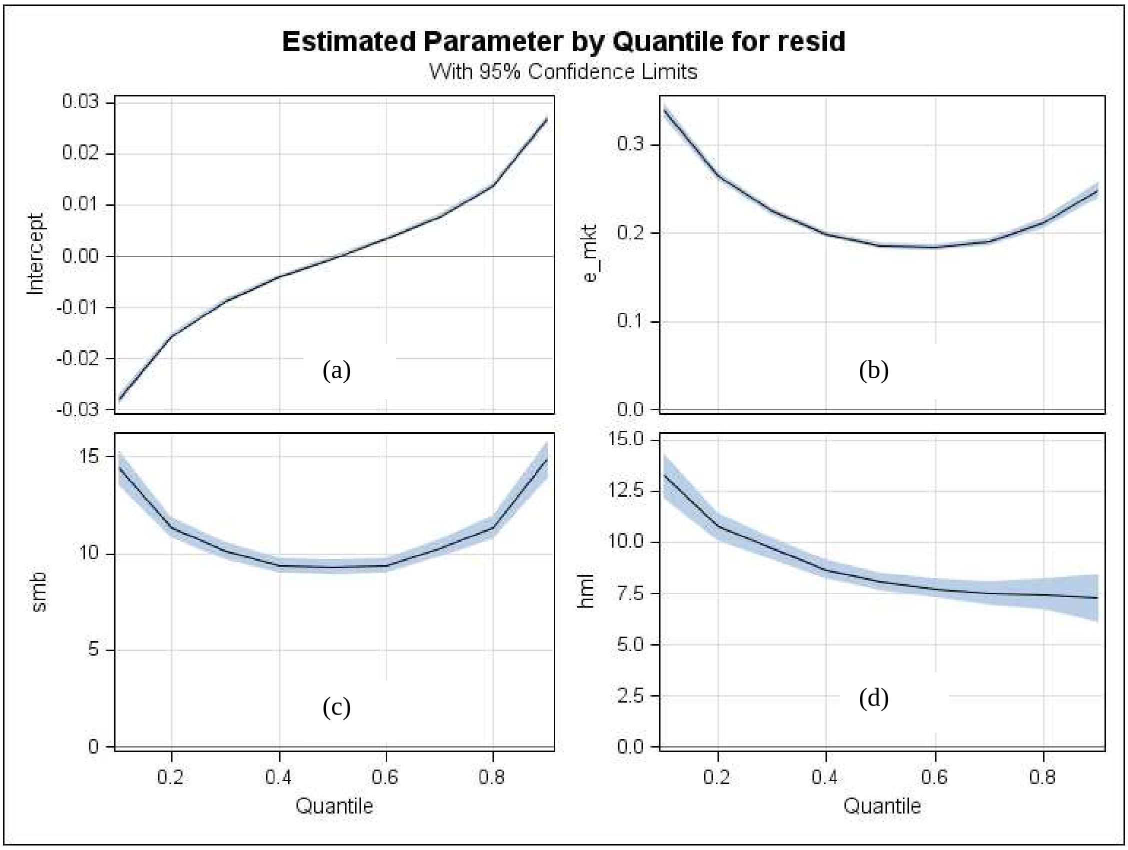
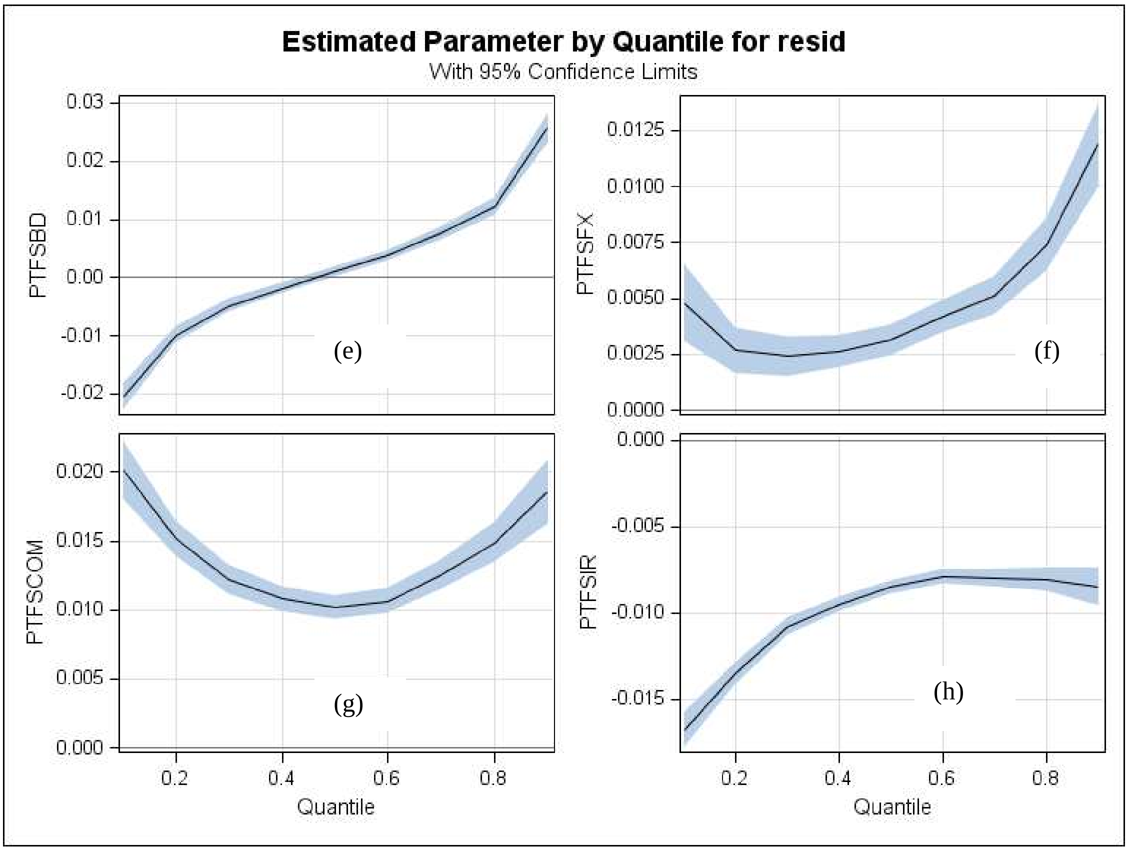


Figure 1. Quantile regression plots for the whole sample. resid is the fund's orthogonized excess return, intercept is the fund alpha, e_mkt is the excess market return, and smb and hml are the Fama-French size and value-growth returns.



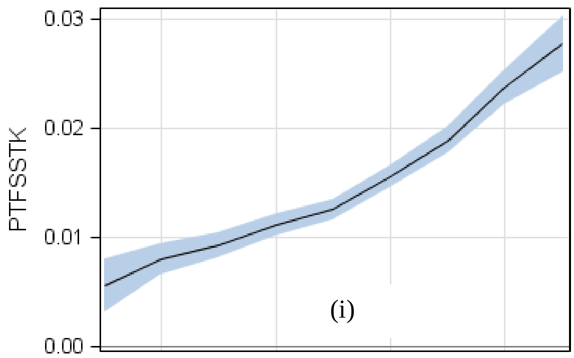
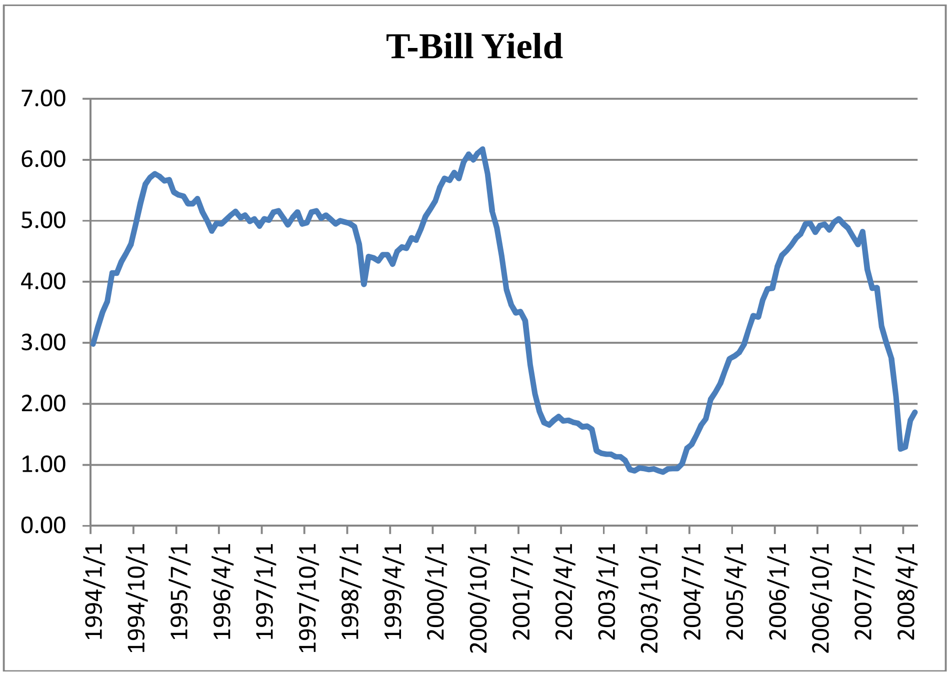


Figure 1 (continued). Quantile regression plots for the whole sample. PTFSBD is bond trend following factor, PTFSFX is currency trend following factor, PTFSCOM is commodity trend following factor, PTFSIR is short-term interest rate trend following factor, and PTFSSTK is stock index trend following factor.


T-Bill Yield
7.00
6.00
5.00
4.00
3.00
2.00
1.00
0.00
1994/1/1
1994/10/1
1995/7/1
1996/4/1
1997/1/1
1997/10/1
1998/7/1
1999/4/1
2000/1/1
2000/10/1
2001/7/1
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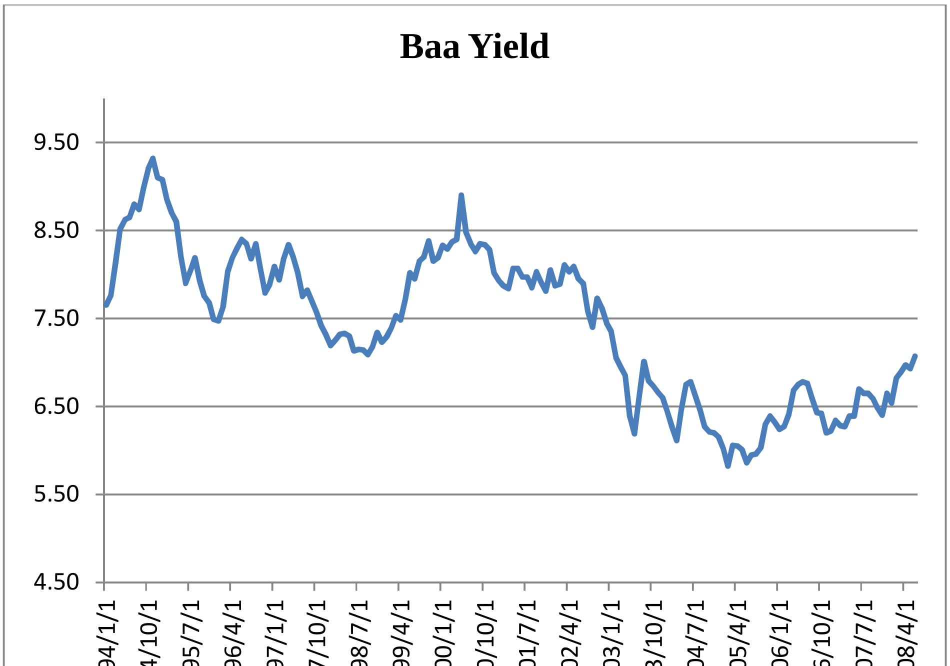
2007/7/1
2008/4/1


Baa Yield
9.50
8.50
7.50
6.50
5.50
4.50
1994/1/1
1994/10/1
1995/7/1
1996/4/1
1997/1/1
1997/10/1
1998/7/1
1999/4/1
2000/1/1
2000/10/1
2001/7/1
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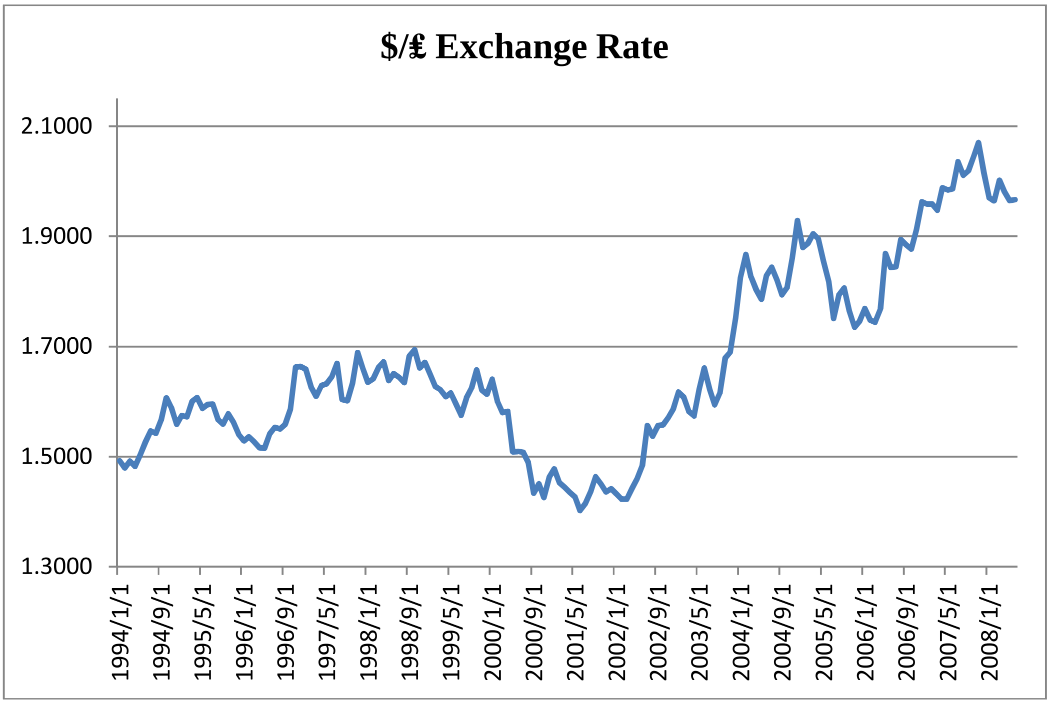
2007/7/1
2008/4/1



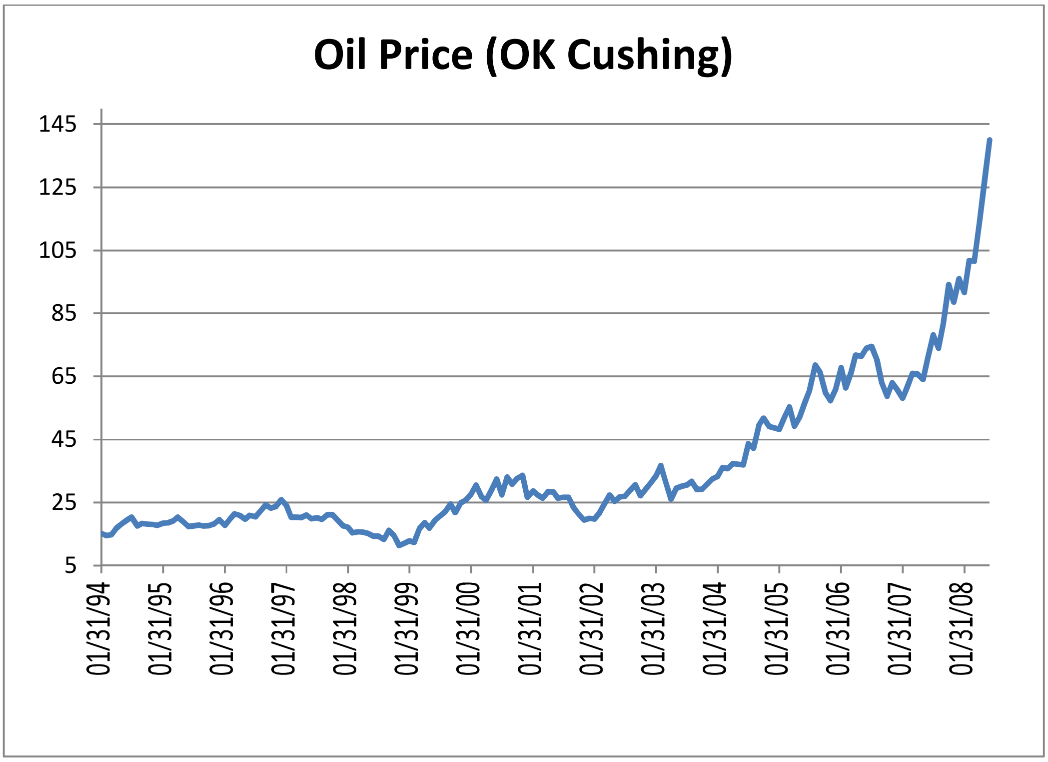
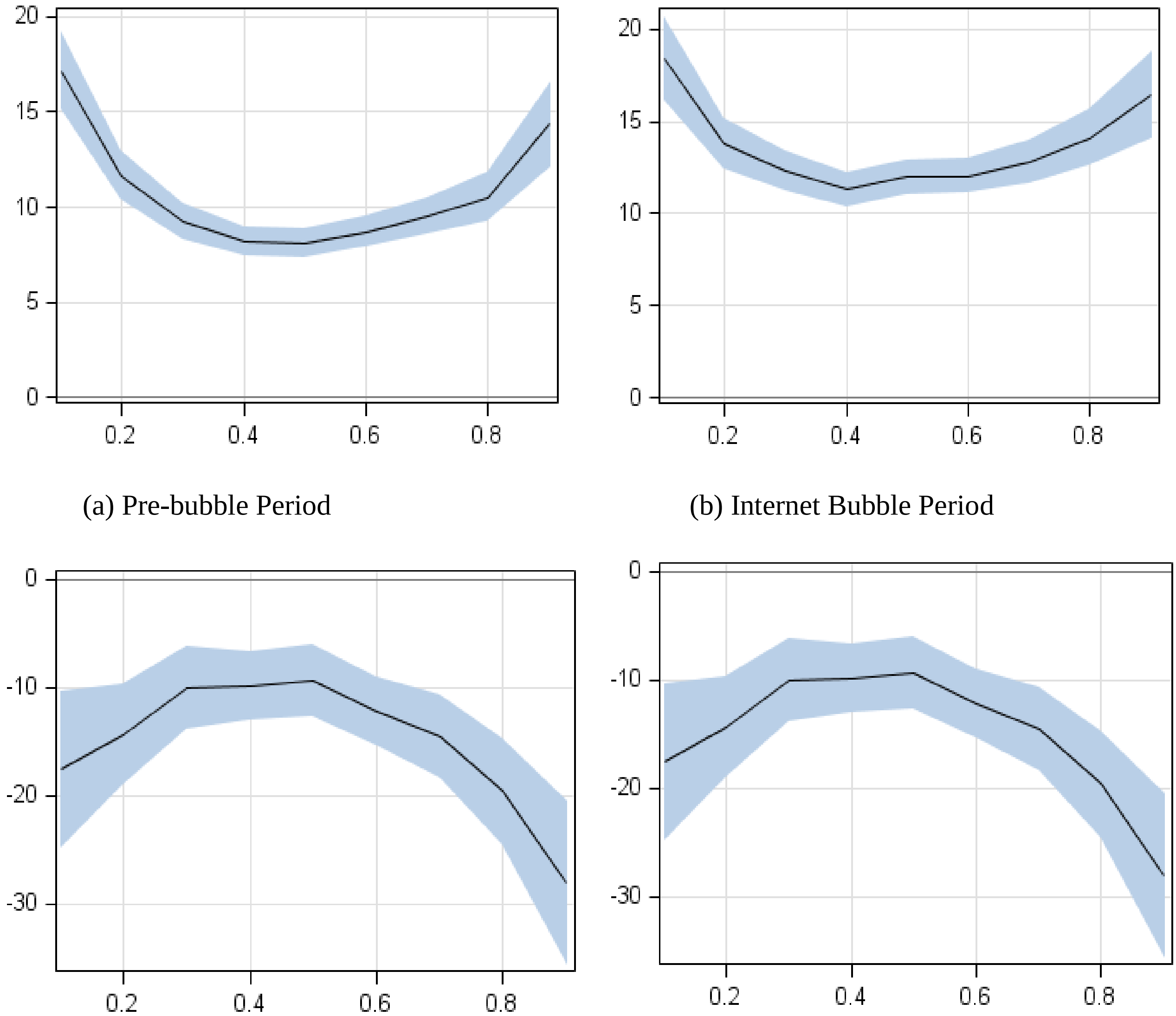


Figure 2. Plots of T-Bill yield, Moody's Baa yield, US/UK exchange rate, and oil price during the whole sample period.



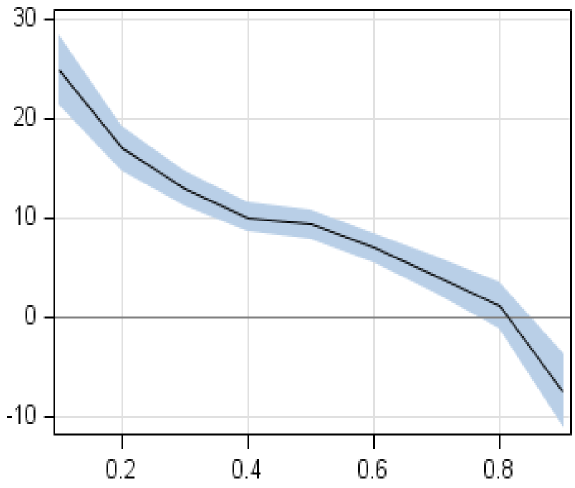
(a) Pre-bubble Period

(b) Internet Bubble Period

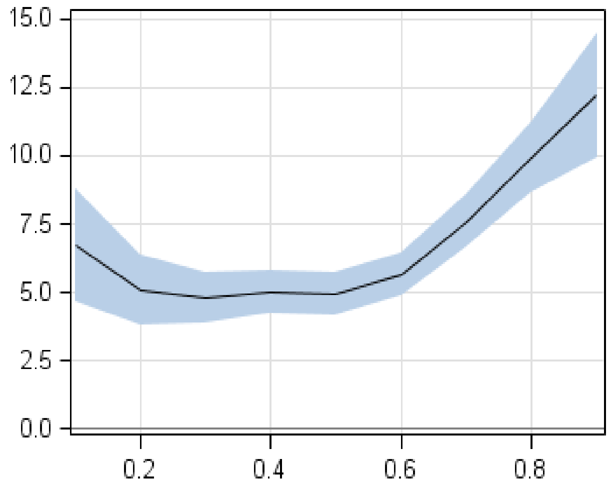
(c) Post-bubble Period

(d) Financial Crisis Period

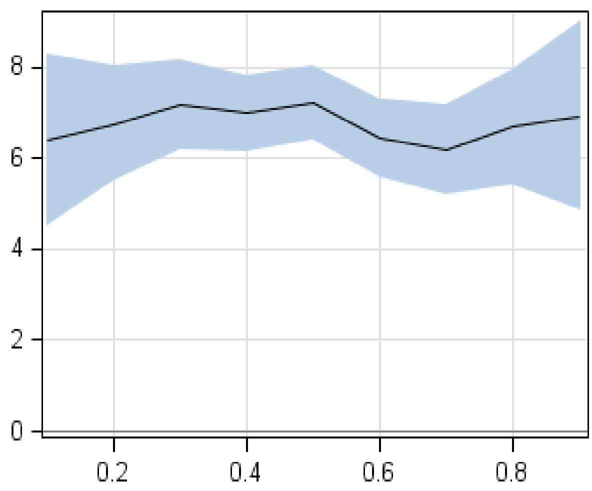
Figure 3. Quantile regression plots for the Fama-French size factor (SMB).



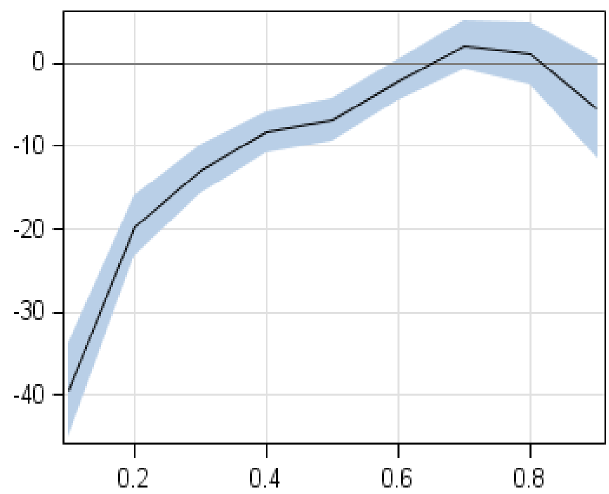
(a) Pre-bubble Period



(b) Internet Bubble Period

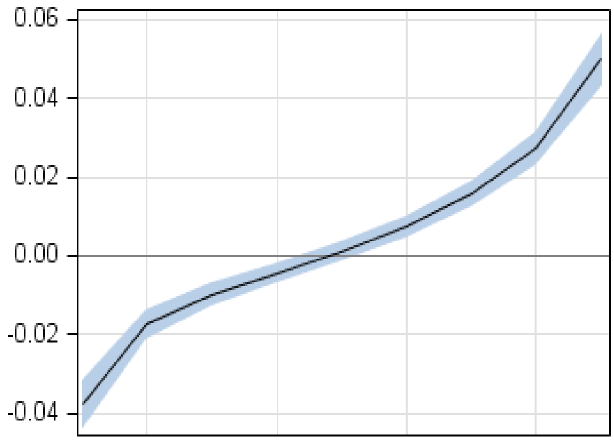


(c) Post-bubble Period

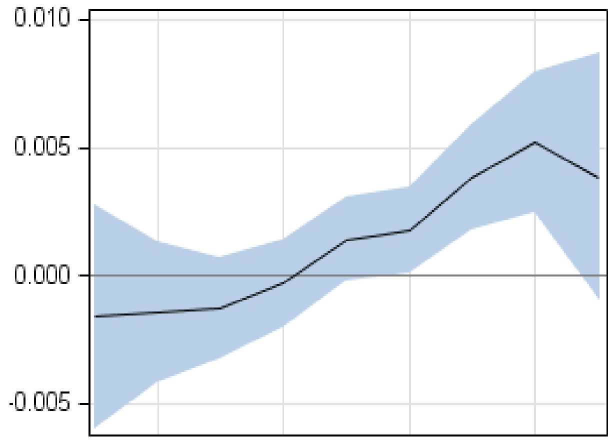


(d) Financial Crisis Period

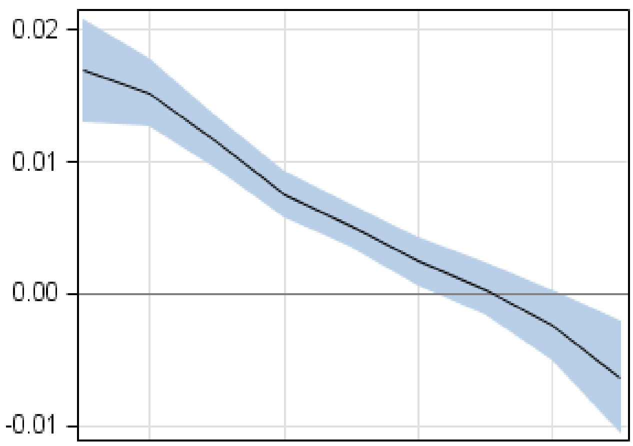
Figure 4. Quantile regression plots for the Fama-French value-growth factor (HML).



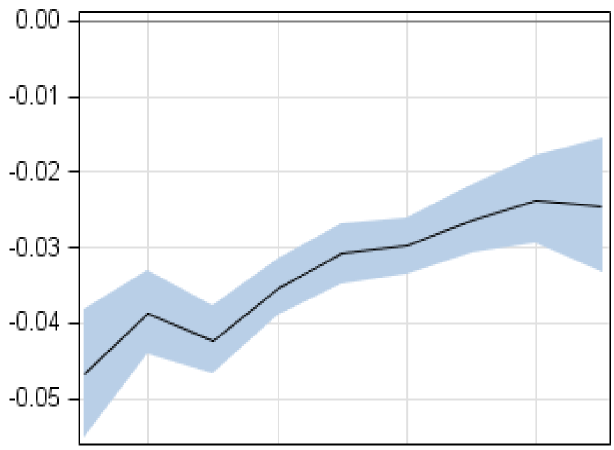
(a) Pre-bubble Period



(b) Internet Bubble Period

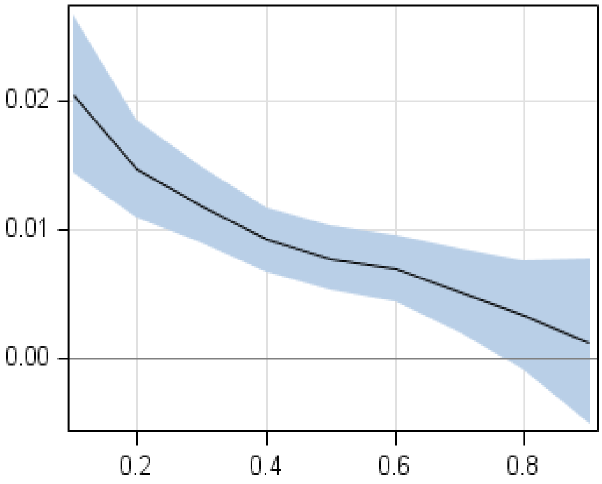


(c) Post-bubble Period

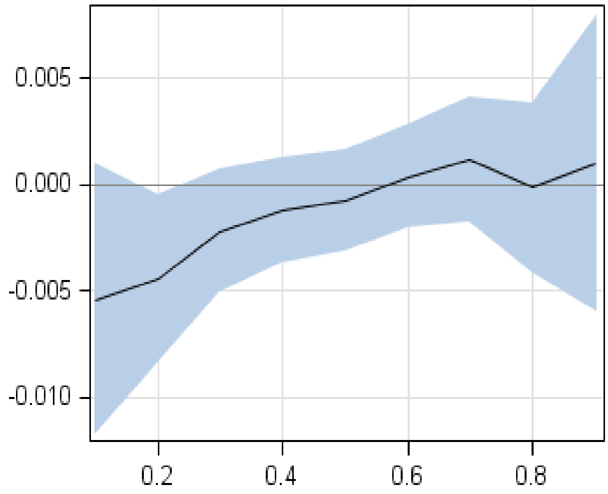


(d) Financial Crisis Period

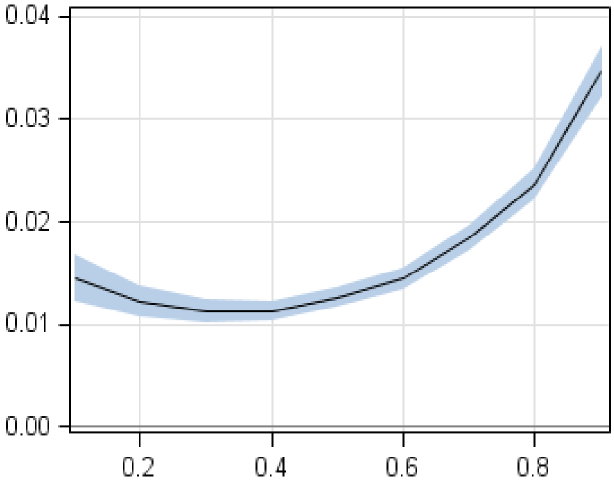
Figure 5. Quantile regression plots for the bond trend-following strategy (PTFSBD).



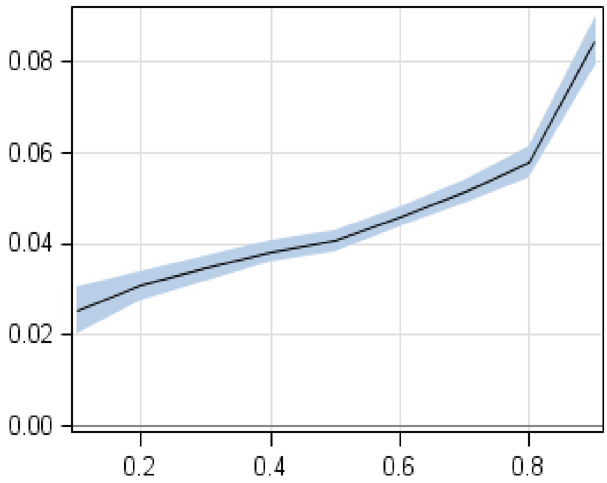
(a) Pre-bubble Period



(b) Internet Bubble Period

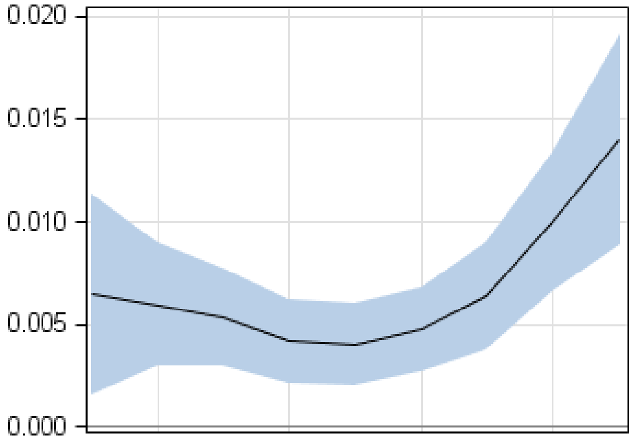


(c) Post-bubble Period

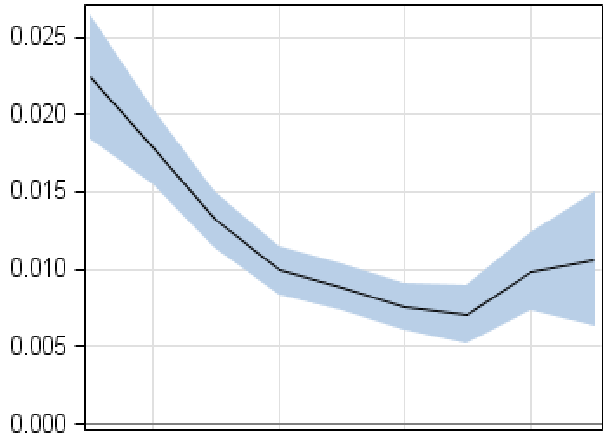


(d) Financial Crisis Period

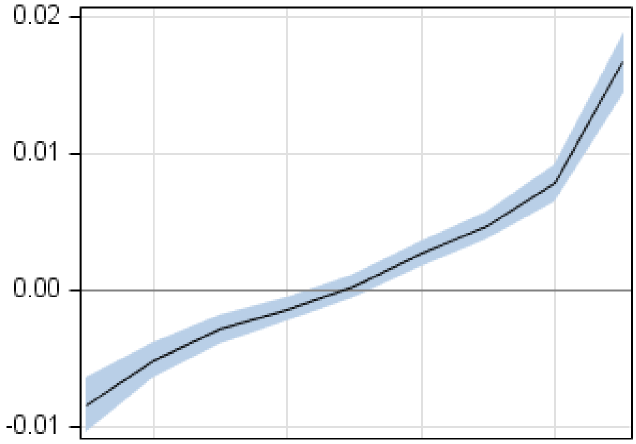
Figure 6. Quantile regression plots for the commodity trend-following strategy (PTFSCOM).



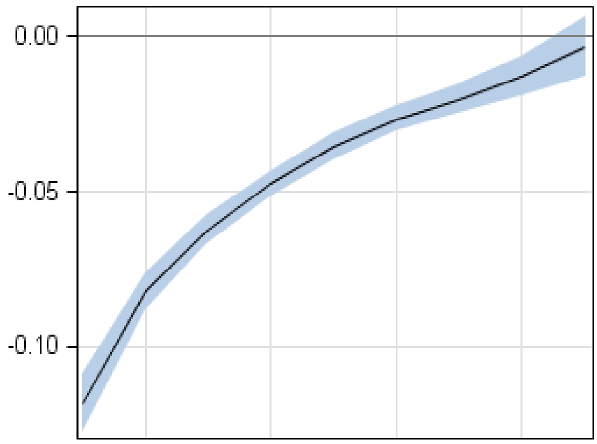
(a) Pre-bubble Period



(b) Internet Bubble Period

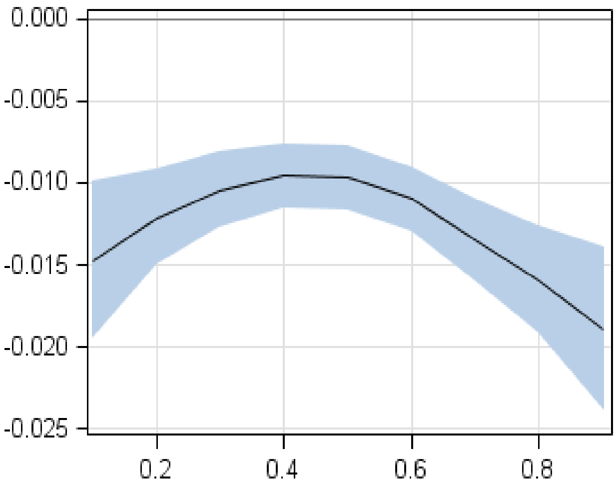


(c) Post-bubble Period

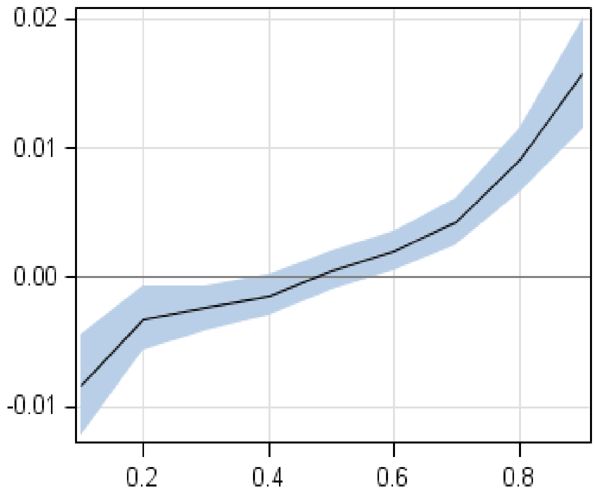


(d) Financial Crisis Period

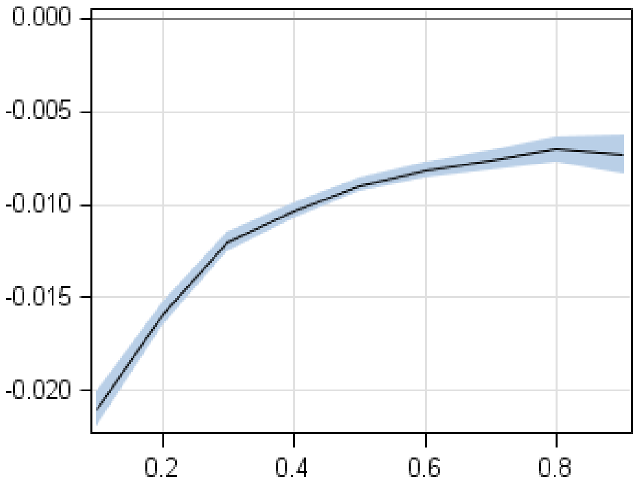
Figure 7. Quantile regression plots for the foreign currency trend-following strategy (PTFSFX).



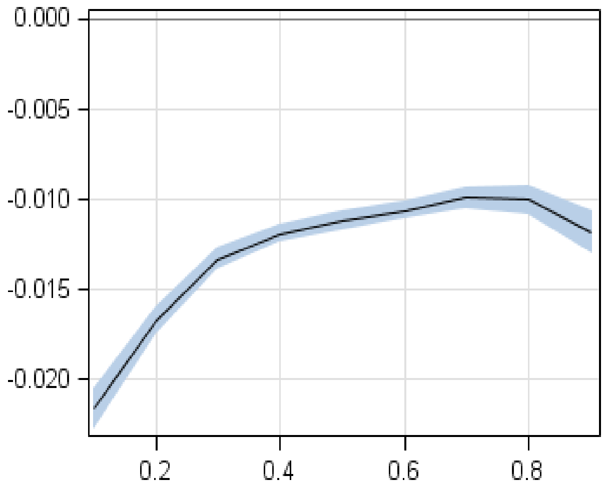
(a) Pre-bubble Period



(b) Internet Bubble Period



(c) Post-bubble Period



(d) Financial Crisis Period

Figure 8. Quantile regression plots for the interest rate trend-following strategy (PTFSIR).

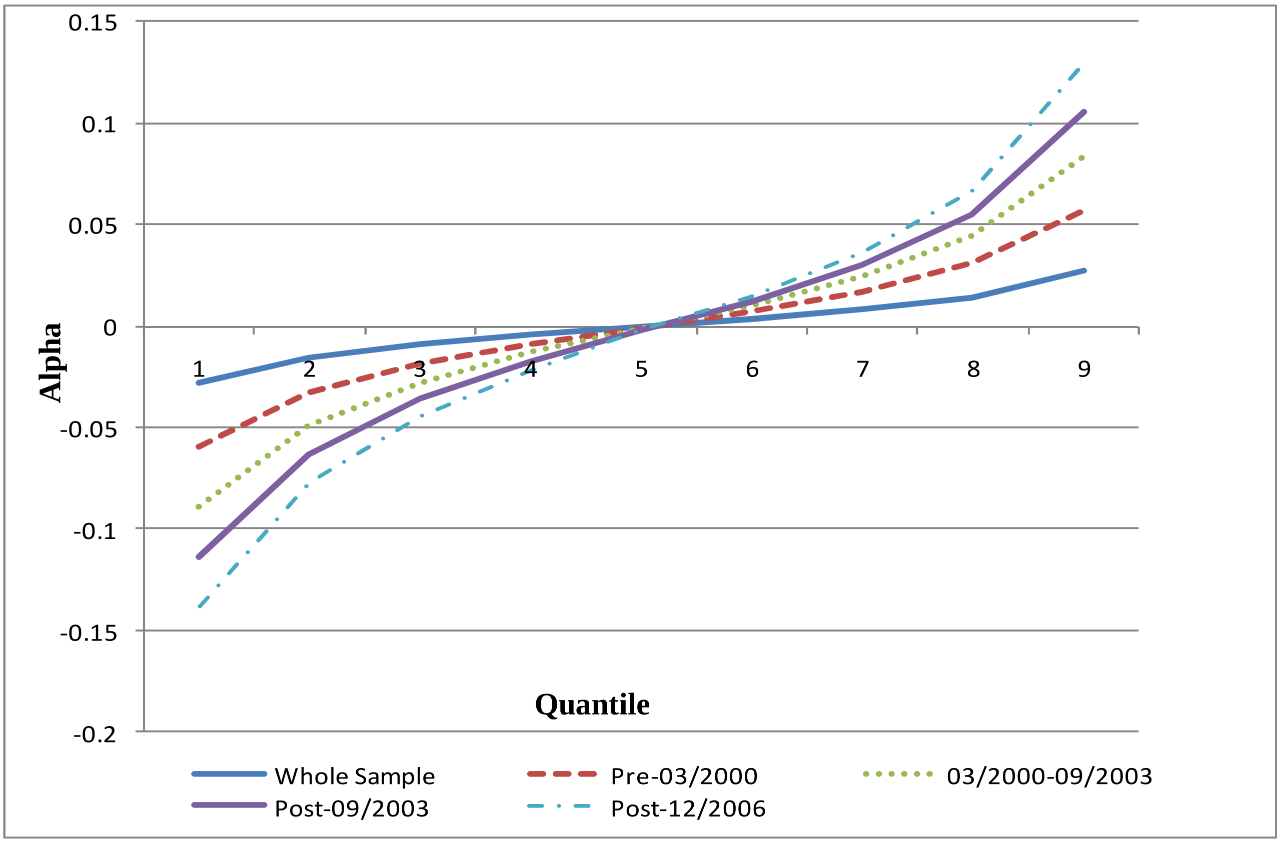


Figure 9. Alphas by quantiles and by sample periods.