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Extracting Portable Alphas From Equity Long-Short Hedge Funds

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Abstract

This paper shows empirically that Equity Long/Short hedge funds have significant alpha to both conventional as well as alternative (hedge fund-like) risk factors utilizing hedge fund data from three major data bases. Following the terminology introduced in Fung and Hsieh (2003a), we call these Equity alternative alphas (or Equity "AAs" for short). Equity AAs are extracted from Equity L/S hedge fund returns by first identifying the systematic risk factors inherent in their strategies. Hedging out these systematic risk factors, the resultant AA return series are empirically shown to be independent of systematic risks during normal as well as stressful conditions in asset markets. This provides collaborative evidence that AA returns are portable across conventional asset-class indices. By modeling the AA return series as GARCH(1,1)-AR(1) processes, it is shown that the unconditional return distributions are normal with time-varying variance free of serial correlations, skewness and kurtosis. Alpha-enhanced equity alternative are constructed admitting higher mean return, better annual returns, and Sharpe ratios to the S&P 500 index over the sample period 1996 to 2002.

1. Introduction

Alternative Investment Strategies ("AIS" for short), in their purest form, are those investment strategies whose returns are not dependent on the behavior of primary asset classes (e.g. stocks and bonds). In other words, AIS are designed to deliver the proverbial "pure alpha." As such, AIS are often also referred to as absolute return strategies—absolute return in the sense that performance is not at the mercy of primary asset classes' performance.

Empirical experience, however, had often proved otherwise. At the worst of times, when primary asset classes are in distress, AIS often experience poor performance. This has attracted skeptics to question whether AIS "alphas" are no more than a redundant bull-market phenomenon. As such, what value it adds to a portfolio of primary asset classes remains unknown.

The range of AIS is wide—from hedge funds to venture capital investments. In this paper, we focus on the more liquid portion of AIS—Equity oriented hedge fund strategies. The reasons for our choice will become apparent as our analysis unfolds. Suffice to say that if a convincing case cannot be made for equity-oriented hedge funds to be included in an institutional portfolio of primary asset classes, then it is doubtful if hedge funds will ever make a meaningful performance difference to large institutional portfolios.

The first known hedge fund was founded by A.W. Jones in 1949. Unlike the typical equity mutual fund, Jones' fund took long and short positions in equities. This style of investing is now called Equity Long/Short ("Equity L/S"), to distinguish it from newer hedge fund styles, such as Global/Macro and Convertible Arbitrage that came along well after Jones' time. The key attributes to this style of trading are—the ability to use short sales, and the ability to use leverage. It is, to-date, the most basic form of alternative strategy to the commonly accepted long-only equity investing.

Even though Equity L/S is one of the oldest hedge fund styles, interest in it has remained strong over the years. As of March 2003, the TASS database has 3,068 hedge funds (excluding funds-of-hedge funds). Roughly 40% are classified as having Equity L/S as the primary investment style. In fact, the next largest style (Managed Futures) has only 15% of the total number of funds. Here, one encounters a major reason for our focus on this particular style of hedge fund strategies. Failure to identify alphas from equity hedge funds will eliminate some 40% of the hedge fund universe from the quest for alternative returns to conventional asset classes.

In this paper we demonstrate that Equity L/S hedge funds can be engineered to offer significant alphas to portfolios of primary asset classes. Following the work of Fung and Hsieh (2002b, 2003a, 2004), alternative alphas (zero beta with respect to conventional asset-class indices as well as alternative systematic risk factors; refer to these as "*AAs*" for short) are extracted from the returns of diversified portfolios of Equity L/S hedge funds. It is shown that these AAs are not sensitive to conventional asset-class indices and alternative risk factors under normal, as well as extreme market conditions. In other words, AAs are *portable* as well as *more than "just a bull market phenomenon."*

However, incorporating AA returns into a conventional asset allocation framework calls for a more detailed analysis of their distributional properties. Since the initial findings of Fung and Hsieh (1997)[1]where hedge fund returns were reported to have fatter tails than those of standard asset classes such as stocks and bonds, different explanations on this phenomenon have been put forward. The evidence thus far points to the observed departure from return normality being a consequence of the nonlinear, option-like nature of hedge fund strategies—see for example Fung and Hsieh (2001) and Agarwal and Naik (2004). However another, less documented, plausible cause of the observed fat-tailed return distribution is that the moments of the return distribution are time-varying. The systematic effect of nonlinear, option-like strategies on the return distribution should be greatly mitigated once the systematic risk factors have been isolated. This in turn implies that the resultant distribution of the AA return series should exhibit much less leptokurtosis.

It is shown in this paper that the fat-tailed behavior of Equity L/S hedge funds returns come primarily from their exposure to the spread between small cap and large cap stocks. Once this exposure is removed from the return series through hedging, kurtosis is reduced dramatically. By modeling the resultant AA return series as a GARCH(1,1)-AR(1) process, we show that each return series is normally distributed with time-varying variance.[2] This conclusion has important implications for portfolio construction and asset allocation strategies. It tells us that the standard mean-variance model applies to alternative Equity L/S alphas despite the reported non-normal return distributions of the underlying hedge fund returns.

The paper is organized as follows. Section 2 describes the data set used and the empirical methodology. AA return series are extracted from Equity L/S hedge funds in Section 3. Section 4 analyzes the distribution properties of these AA return series, while Section 5 puts forth a method for incorporating AAs into a portfolio of conventional assets with minimal disruption to the portfolio's existing risk profile. Concluding remarks are given in Section 6.

2. *Establishing the risk structure of Equity L/S hedge funds: data and methodology*

2a. Data

It is only appropriate to begin our analysis by acknowledging that hedge fund investing is not risk free. More specifically, not only are Equity L/S hedge funds not risk free, they actually exhibit systematic exposure to market risk. In general, Equity L/S hedge funds carry a long bias. The key question is what other systematic risk factors do these strategies carry and is there a significant alpha after adjusting for systematic risks?

[1] Also reported in later studies by other researchers such as Amin and Kat (2003).
[2] Free of skewness and serial correlation.

We begin by introducing terminology. In Fung and Hsieh (2003a, 2004), we introduced the concept of alternative alphas and alternative betas. Defining conventional asset-class indices as the primary risk factors, alternative risk factors are those that lie outside the set of conventional asset-class indices such as stocks and bonds. Typically, they are long/short combinations and sector specializations of conventional asset-class indices such as value to growth spread and small cap stocks. What we need to know is how many risk factors, conventional and alternative, are systematically present in Equity L/S hedge fund returns.

In a related study, Fung and Hsieh (2003b) analyzed individual equity-oriented hedge funds from the three major sources of hedge fund data—Hedge Fund Research ("HFR"), TASS, and Morgan Stanley Capital International ("MSCI"). It was shown that equity-oriented hedge funds have two major exposures—the equity market as a whole (as proxied by the S&P 500 index), and the spread between small cap and large cap stocks (as proxied by the difference between the Wilshire Small Cap 1750 index and the Wilshire Large Cap 750 index). This paper focuses on the property of diversified portfolios of Equity L/S hedge funds constructed from the same data sources—the HFR Equity Hedge index, a comparable, equally weighted Long/Short Equity index constructed from the funds in the TASS database[3], and the MSCI Long Bias (North American) index.

2b. Identification of Common Risk Factors

To identify the common risk in Equity L/S hedge funds, we regress the three indices on the Fama-French (1992) 3-factor model augmented with the Jegadeesh-Titman (1993) momentum factor, as implemented in Cahart (1997). The results are in Tables 1a, b and c.

Insert Table 1a

Table 1a contains the regression results of the HFR Equity Hedge index on the various risk factors. In all regressions, the two most important risk factors are the excess return of the market (Mkt-Rf) and the spread between small cap and large cap stocks (SMB). The spread between high book-to-market and low book-to-market stocks (HML) is not statistically significant in any regression. In addition, the momentum factor (MOM), while statistically significant in the 4-factor regression, does not add substantial explanatory power beyond the 2-factor regression in terms of adjusted R^2. Similar results on the TASS and MSCI indices are reported in Tables 1b and 1c respectively.

[3] This is an equally weighted index of TASS hedge funds that are designated as Long/Short equity hedge funds includes both live and dead funds within the TASS database. The choice of such a construction is to maintain comparability with the other two indices both in terms of the number of funds in the index as well as the index construction method. It is these considerations that precluded the use of the CSFB/Tremont Long/Short equity index, which is both smaller in scope and is value-weighted by construction.

Insert Table 1b, and 1c

To complete the analysis, we check for evidence of market timing ability using the Henriksson and Merton (1981) method of adding absolute values of the regressors (|Mkt-Rf| and |SMB|) to the regressions. Statistical significance of these nonlinear variables would be consistent with the presence of significant market timing strategy in Equity L/S hedge funds. As shown in the last columns of Tables 1a, 1b, and 1c, neither nonlinear factor is statistically significant for all three indices. In light of these findings, we elected to focus our analysis on the 2-factor model (based on factors Mkt-Rf and SMB).[4]

3. *Creating an alternative alpha series for Equity L/S hedge funds*

Having identified the risk structure of Equity L/S hedge funds, two of the Fama-French factors—one primary asset-class risk factor, and one alternative spread risk factor, we can now proceed to neutralize these systematic risk factors to obtain an *alternative alpha* ("AA") return series. For the purpose of this exercise, we consider the three Equity L/S indices as *equity hedge fund portfolios*, or "EHFPs" for short.

The alphas of these portfolios are extracted as follows. For each month, the regression coefficients ("betas") of the previous 24 monthly returns on the two risk factors—the S&P500 index, and the Small-Large spread (measured as the Wilshire Small Cap 1750 index minus the Wilshire Large Cap 750 index[5]) are used as hedge ratios. The monthly returns from a short position in the S&P500 index, and the Small-Large spread, in proportion to the regression coefficients are subtracted from the returns of the EHFP. The resulting return is the "alternative alpha" of the portfolio spanning the period Jan 1996 to December 2002. These return series are respectively denoted as HFR-α, TASS-α, and MSCI-α. Refer to these returns series as the AA return series for short.

Insert Table 2

Table 2 tabulates the annualized AA returns, from 1996 to 2002. On average, these AAs are roughly of the same magnitude as the S&P's average annual return of 10.22%. . However, their standard deviations are much lower and their information ratios are uniformly higher than that of the S&P 500 for the same period. In addition, while the S&P had negative returns in 2000, 2001, and 2002, the annualized AA returns are uniformly positive.

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[4] It shall become obvious why this choice is more than just a preference for simplicity. In extracting alphas from hedge fund returns, certain amount of hedging is required. The more factors a model admits, the more cumbersome will be the attendant hedging process, and at some point, the simulated alphas can become unrealistic propositions.

[5] The choice of the Wilshire indices rather than the academic series from Fama and French is an attempt to move closer to a more readily commercially available data source.

To ensure that the alphas have no linear or nonlinear dependence on the returns of standard benchmarks—an important property of *portability*—we use the method developed in Fung and Hsieh (1997). The monthly returns of eight standard conventional asset-class indices—US equities, non-US equities, emerging market equities, US bonds, non-US bonds, gold, trade-weighted dollar index, and the 1-month Eurodollar deposit rate—are individually sorted from worst to best into quintiles. The average return for each quintile of the asset-class indices and the average of the corresponding months for the respective AA return series are graphed in Figures 1 to 8.

Insert Figures 1-8

The general flat patterns of the AAs indicate that they have little relation to the eight conventional asset-class indices. To complete the analysis, we perform the same check on the dependence of these alphas on the seven hedge fund risk factors (Asset-Based Style factors or "ABS" factors for short) reported in Fung and Hsieh (2004). These ABS factors include two equity-oriented risk factors (S&P500, Small Cap minus Large Cap or "SC-LC"), two bond-oriented risk factors (the change in the 10 year constant Treasury yield, the change in the credit spread as measured by the difference between the Moody's Baa bond yield and the 10 year constant Treasury yield), and three trend-following risk factors (trend following on bonds, trend following on currencies, and trend following on commodities). Figures 9 through 15 show that there is no strong dependence on these seven hedge fund risk factors similar to the pattern observed using conventional asset-class indices.

Insert Figures 9-15

We further check for the dependence of alphas on market volatility. Figure 16 depicts the average alphas for each quintile of the 21-day historical volatility of the S&P500 index. Figure 17 is the corresponding figure for the 21-day historical volatility of the SC-LC factor. There is no strong evidence that alphas are related to market volatility.

Insert Figures 16-17

Figures 18-20 show how the exposures change over time. Figure 18 has the 24-month rolling betas against the S&P500 and SC-LC risk factors for the HFR Equity Hedge Index. Figures 19 and 20 are the corresponding figures for the TASS Equity Long-Short Index and the MSCI Long Bias Index.

Insert Figures 18-20
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4. *Distributional properties of Portable Alternative Alphas*

The results in Section 3 tell us something about the conditional distribution of AAs (conditional on most known risk factors, conventional and alternative). This section completes the analysis by analyzing the unconditional distribution of AAs.

It was noted in Fung and Hsieh (1997) that hedge fund returns tend to have excess kurtosis, or fat-tailed distributions—an observation that has since been confirmed by other researchers such as Amin and Kat (2003). Although there is no single conclusive theory as to why this occurs, one sufficient condition seems most likely. Suppose that the strategies used by most hedge fund managers are nonlinear, option-liked in character. This will certainly lead to observed returns from hedge funds to depart from normality. Thus far, theoretical models of hedge fund strategies proposed in Fung and Hsieh (2001), Mitchel and Pulvino (2001), and Agarwal and Naik (2004) have all point to option-like characteristics. While these are sufficient conditions for certain hedge fund strategies to exhibit non-normal return distributions, they are not necessary conditions for all hedge funds return to exhibit systematic departure from normality. Certainly, up to the time of writing, no theoretical option-like model of Equity L/S strategies has been put forward. Our empirical results have not confirmed option-like market timing characteristics from Equity L/S hedge funds—at least not at the level of a diversified portfolio of such strategies. Yet Table 3 shows that the three EHFPs all have excess kurtosis (that are statistically different from zero).

Insert Table 3

As the primary interest of this paper is on the series of AA returns extracted from the EHFPs, it is important to know whether leptokurtic return behavior survives the alpha extraction process. Table 3 shows that a substantial part of the observed excess kurtosis in the EHFPs' returns is due to exposures to the systematic risk factors. Although the S&P has virtually no excess kurtosis the alternative risk factor, the SC-LC factor, exhibits a high degree of excess kurtosis. However when we reach the level of the AA series, where exposures to the two systematic risk factors have been removed, the resulting returns exhibit substantially less excess kurtosis.

Next we examine the other source of observed leptokurtic return behavior—the possibility of time-varying moments of the return distribution. A frequent cause of kurtosis in financial time series is time-varying volatility, as shown in the pioneering work of Engle (1982) and Bollerslev (1986). To investigate this, we fit GARCH(1,1)-AR(1) models to the alphas of the three portfolios using the following specification:

$$u_t = c + \rho\, u_{t-1} + (h_t)^{1/2} e_t\,,\ \ e_t \sim N(0,h_t)$$

$$h_t = s + a\,(e_{t-1})^2 + b\, h_{t-1}$$

In the first equation, the u's are the AA return series from the three EHFPs. In this specification, there is a constant term, c. A first-order autoregressive term, $u_{t-1,}$ to capture any serial correlation that may potentially arise from infrequent trading of the securities in the underlying hedge fund portfolios. The error term, e_t, is assumed to be normally distributed with zero mean and variance h_t following the standard GARCH(1,1) process specified by the second equation.

Insert Table 4

Table 4 reports the maximum likelihood estimates using the same procedure as in Hsieh (1988). Several results are worthy of note. One, the serial correlation of the AA series is small—the coefficients are between 0.15 and 0.24—and are not statistically different from zero. Fung and Hsieh (2002b) asserted that the reported lagged dependency between hedge fund returns and the S&P 500 index returns in Asness, Krail and Liew (2001) could be due the choice of benchmark rather than purported measurement error. Based on the GARCH(1,1)-AR(1) model of the AA returns series with explicitly identified systematic risk factors, the results in Table 4 provide direct evidence that the AA return series are indeed serial correlation free as asserted in Fung and Hsieh (2002b).

Two, although four of the six GARCH(1,1) coefficients are not statistically different from zero, the joint test on the lack of GARCH(1,1) indicates that it is present in the TASS AA return series, and are also likely in the HFR and MSCI AA return series.

Third, the kurtosis of the standardized residuals is no longer statistically different from zero. Fourth, the insignificant kurtosis in the standardized residuals together with the lack of skewness is consistent with the proposition that the AA return series are normally distributed, with time-varying variances.

These results on the distributional property of the AA return series lead to the comforting conclusion that standard mean-variance analysis can be applied to AAs extracted from EHFPs. However, an explicit model of the time-varying variance process needs to be constructed.[6]

5. *The role of Portable Alternative Alphas in a conventional asset-class portfolio*

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[6] The theory and empirical construct for such a model is well beyond the scope of this paper, nonetheless, it remains an important area for future research.

One way to add value utilizing portable alphas is to create an alpha-enhanced alternative to conventional equity investments. This section reports the results of one such approach.[7]

In extracting the AA return series from the EHFPs, two overlay transactions were taken—a short position on the S&P 500 index to mitigate the persistent directional exposure to the equity market in general, and a short position on the spread between small cap and large cap stocks. However, if one proxies the Small Cap exposure by the Russell 2000 index[8] and the large cap exposure the S&P 500 index, then the net hedging transactions amount to a net short positions on the S&P 500 index as well as the Russell 2000 index. This has generally been the case since the beta of the EHFP returns to the S&P 500 index tended to be larger than the beta to the Small Cap/Large Cap spread factor.

To create an alpha-enhanced conventional passive equity investment (say the S&P 500 index) synthetically, all one needs to do is to replace the existing cash investment in the S&P 500 index by its futures contract equivalent, and invest the capital released into Equity L/S hedge funds on a hedged basis –hedged against the two systematic risk factors so as to extract the AA returns described in the previous sections. Refer to these as the *alternative alpha portfolio*(s) ("AA" portfolio(s) for short, one for each of the three hedge fund indices, HFR, TASS and MSCI).

Insert Table 5

Table 5 shows the annual returns of the three AA portfolios. Each has an average return that is higher than the S&P 500 index. The annual return in each year from 1996 until 2002 is superior to that of the S&P for all three portable alpha portfolios. By design, all three AA portfolios have returns that are highly correlated to the S&P500 index with similar return standard deviations. However, all three AA portfolios have better Sharpe ratios than the S&P 500 index.

Lastly, we note that the returns of the AA portfolios do not have excess kurtosis and no significant skewness. In contrast, over this sample period, the distribution of the S&P 500 index's monthly return has a statistically significant skewness to the left. Interestingly, one could argue that these AA portfolios are more amenable to conventional mean-variance asset allocation models than the S&P 500 index.

The results in Section 3 showed that AAs are uncorrelated (during both normal and stressful markets) to most conventional asset-class indices; the same replication

[7] An approach that combines the hedged EHFPs, the S&P 500 index futures and the Russell 2000 index to generate alpha-enhanced equity alternatives.

[8] The Russell 2000 index is by far a more practicable candidate for short sale transactions than the Wilshire indices as both futures contracts and ETFs exist mimicking the Russell 2000. We note also that the returns of the Russell 2000 index are highly correlated to the Wilshire Small Cap 1750 index that we used in constructing the AA returns series.

procedure used here can be applied to other conventional asset-class indices to create alpha-enhanced alternatives. Alpha-enhanced alternatives that offer better risk-adjusted returns without the baggage of nonlinear return distributions that are often reported on hedge fund investments.

6. *Concluding Remarks*

Unlike long-only equity mutual funds, equity hedge funds are a mixture of alpha and beta bets. However, hedge fund risks are known to differ from conventional asset-class risks. Consequently, to extract the alpha returns from Equity L/S hedge funds necessitated the identification of both conventional as well as alternative risk factors. Although we are able to show that diversified portfolios of Equity L/S hedge funds can be adequately modeled using a simple 2-factor model, it must be noted that less diversified indices such as CSFB/Tremont's Long/Short Equity index's returns can exhibit less well conditioned return characteristics, as the 2-factor model can only capture 66.5% of return variation in terms of adjusted R^2. The precise process through which diversification simplifies the return generation process is still unknown with hedge fund returns.[9] Research to-date points to nonlinear factors at work driving the performance of hedge fund strategies.

Against this background, we analyzed the distributional properties of the AA return series extracted from EHFPs using the 2-factor model. Conditional on the outcomes of eight conventional asset classes, the AA return series display no abnormal behavior. These results are interpreted to support the state-independent nature as well as portability of AAs. What remains to be done is to see how these AA return series can be incorporated into conventional asset allocation models. Since, conventional asset allocation models tend to rely on a mean-variance framework, we proceeded to analyze the unconditional return distribution of the AA return series.

Modeling the AA return series as a GARCH(1,1)-AR(1) process we are able to show that these return series are normally distributed with time-varying variance. This allows us to create alpha-enhanced equity alternatives (alternative alpha portfolios or "AA portfolios" for short; one for each of the three databases) to the S&P500 index's returns using Sharpe ratios as performance criteria. Over the sample period 1996-2002, these AA portfolios are highly correlated to the S&P 500 index but outperformed the S&P 500 index each year for all seven years. The AA portfolios have higher mean returns and better Sharpe ratios compared to the S&P 500 index. To what extent similar alpha-enhanced portfolios can be constructed relative to other asset-class indices remains a subject for future research; thus far, the framework and empirical results established here provide a promising start.

[9] Or to what extent the index construction method of the CSFB/Tremont index impeded the process of diversification is also unclear.

Table 1a
Regression Of HFR Equity Hedge Index on 4-Factor Model
1994-2002

	2-Factor	3-Factor	4-Factor	Nonlinear
Intercept	**0.0102**	**0.0103**	**0.0091**	**0.0076**
	0.0011	*0.0012*	*0.0011*	*0.0022*
Mkt-RF	**0.4383**	**0.4385**	**0.4721**	**0.4426**
	0.0270	*0.0300*	*0.0273*	*0.0307*
SMB	**0.2646**	**0.2648**	**0.2496**	**0.2545**
	0.0412	*0.0399*	*0.0373*	*0.0350*
HML		0.0006	0.0232	
		0.0458	*0.0389*	
MOM			**0.0851**	
			0.0236	
|Mkt-Rf|				0.0191
				0.0519
|SMB|				0.0602
				0.0488
R^2	0.8109	0.8109	0.8374	0.8156
Adjusted R^2	0.8073	0.8055	0.8312	0.8084

(Heteroskedasticity-consistent standard errors in italics. Coefficients in bold are statistically significant at the 1% level)
Two-factor model: Rm-Rf and SMB from Fama-French (1992).
Three-factor model: Rm-Rf, SMB, and HML from Fama-French (1992).
Four-factor model: Rm-Rf, SMB, and HML from Fama-French (1992), and MOM from Carhart (1997).

Table 1b
Regression Of TASS Long/Short Equity Funds Average on 4-Factor Model
1994-2002

	2-Factor	3-Factor	4-Factor	Nonlinear
Intercept	**0.0114**	**0.0113**	**0.0102**	**0.0073**
	0.0011	*0.0012*	*0.0011*	*0.0020*
Mkt-RF	**0.4990**	**0.4891**	**0.5193**	**0.5066**
	0.0256	*0.0296*	*0.0268*	*0.0290*
SMB	**0.2882**	**0.2790**	**0.2653**	**0.2788**
	0.0409	*0.0394*	*0.0365*	*0.0309*
HML		-0.0222	-0.0019	
		0.0444	*0.0388*	
MOM			**0.0765**	
			0.0259	
|Mkt-Rf|				0.0445
				0.0498
|SMB|				0.0632
				0.0442
R^2	0.8582	0.8586	0.8765	0.8639
Adjusted R^2	0.8555	0.8545	0.8717	0.8586

(Heteroskedasticity-consistent standard errors in italics. Coefficients in bold are statistically significant at the 1% level)
Two-factor model: Rm-Rf and SMB from Fama-French (1992).
Three-factor model: Rm-Rf, SMB, and HML from Fama-French (1992).
Four-factor model: Rm-Rf, SMB, and HML from Fama-French (1992), and MOM from Carhart (1997).

Table 1c
Regression Of MSCI Long Bias Fund Averages on 4-Factor Model
1994-2002

	2-Factor	3-Factor	4-Factor	Nonlinear
Intercept	**0.0110**	**0.0105**	**0.0097**	**0.0078**
	0.0012	*0.0012*	*0.0011*	*0.0025*
Mkt-RF	**0.5803**	**0.6193**	**0.6431**	**0.5848**
	0.0279	*0.0311*	*0.0289*	*0.0294*
SMB	**0.3023**	**0.3386**	**0.3278**	**0.2875**
	0.0511	*0.0463*	*0.0424*	*0.0404*
HML		0.0876	**0.1036**	
		0.0416	*0.0353*	
MOM			**0.0603**	
			0.0248	
|Mkt-Rf|				0.0142
				0.0490
|SMB|				0.0843
				0.0620
R^2	0.8670	0.8720	0.8808	0.8725
Adjusted R^2	0.8644	0.8683	0.8761	0.8676

(Heteroskedasticity-consistent standard errors in italics. Coefficients in bold are statistically significant at the 1% level.)
Two-factor model: Rm-Rf and SMB from Fama-French (1992).
Three-factor model: Rm-Rf, SMB, and HML from Fama-French (1992).
Four-factor model: Rm-Rf, SMB, and HML from Fama-French (1992), and MOM from Carhart (1997).

Table 2
Annual Alphas of the Equity Hedge Fund Portfolios
1996-2002

Year	S&P	HFR-α	TASS-α	MSCI-α
1996	22.96%	13.43%	14.82%	0.71%
1997	33.36%	13.34%	9.39%	6.89%
1998	28.58%	15.48%	13.51%	9.40%
1999	21.04%	30.46%	33.27%	27.29%
2000	-9.11%	8.79%	8.52%	14.03%
2001	-11.88%	0.79%	2.76%	6.34%
2002	-22.10%	3.76%	6.28%	4.66%
Average	**10.22%**	**11.48%**	**12.65%**	**9.35%**
Std Dev	16.24%	5.41%	9.97%	5.09%
Average/ Std Dev	0.629	2.122	1.269	1.837

(Averages in bold are statistically significant at the 1% level.)
S&P: Standard and Poors 500 index.
HFR-α: alpha of HFR Equity Hedge Index.
TASS-α: alpha of the equally-weighted average of TASS Long/Short Equity Funds.
MSCI-α: alpha of MSCI Long Bias (North American) Index.

Table 3
Excess Kurtosis of Hedge Fund Portfolios
Jan 1994 – Dec 2002

Ex Kurtosis	S&P	SC-LC	HFR	TASS	MSCI
Raw Returns	0.169	**4.046**	**1.451**	**2.905**	**1.043**
Alphas			**1.011**	0.888	**1.184**

(Coefficients in bold are statistically significant at the 1% level.)
S&P: Standard and Poors 500 index.
HFR: HFR Equity Hedge Index.
TASS: Equally-weighted average of TASS Long/Short Equity funds.
MSCI: MSCI Long Bias (North American) Index.

Table 4
GARCH(1,1)-AR(1) Model of Alphas

	HFR-α	TASS-α	MSCI-α
c	**0.007998**	**0.006398**	0.004866
	0.002335	*0.001255*	*0.002233*
ρ	0.155580	**0.236075**	0.232230
	0.128093	*0.084019*	*0.127301*
s	0.000095	**0.000005**	0.000040
	0.000087	*0.000002*	*0.000044*
a	0.153903	0.028006	0.111228
	0.123220	*0.034218*	*0.109217*
b	0.442002	**0.949146**	**0.694664**
	0.392391	*0.041245*	*0.276933*
χ^2 Test of a=0 & b=0	3.36	18.65	4.42
p-value	0.1861	0.0000	0.1096
Standardized Residuals:			
Ex. Kurtosis	0.617	0.888	0.627
Skewness	0.262	0.228	0.180

(Coefficients in bold are statistically significant at the 1% level. Standard errors are in italics.)
HFR-α: HFR Equity Hedge Index alphas.
TASS-α: Equally-weighted average of TASS Long/Short Equity funds alphas.
MSCI-α: MSCI Long Bias (North American) Index alphas.

GARCH(1,1)-AR(1) model of alphas:

$$u_t = c + \rho\, u_{t-1} + (h_t)^{1/2} e_t$$

$$h_t = s + a\,(e_{t-1})^2 + b\, h_{t-1}$$

Table 5
Return of the Portable Alpha Portfolios
1996-2002

Year	S&P	HFR-F	TASS-F	MSCI-F
1996	22.96%	36.92%	39.1%	24.25%
1997	33.36%	46.75%	42.5%	40.79%
1998	28.58%	45.42%	45.0%	40.73%
1999	21.04%	54.08%	58.6%	52.33%
2000	-9.11%	-2.56%	-2.2%	2.84%
2001	-11.88%	-12.50%	-10.8%	-7.43%
2002	-22.10%	-20.56%	-18.4%	-19.86%
Average	10.22%	17.79%	18.60%	16.78%
Std Dev	16.24%	18.89%	18.36%	18.42%
Corr w/ S&P	1.000	0.949	0.951	0.948
Ex. Kurtosis	0.169	-0.055	-0.346	0.324
Skewness	**-0.601**	-0.254	-0.156	-0.114
Sharpe Ratio	0.355	0.401	0.770	0.911

(Excess kurtosis and skewness coefficients in bold are statistically significant at the 1% level.)
S&P: Standard and Poors 500 index.
HFR-F: HFR Equity Hedge Index plus futures.
TASS-F: Equally-weighted average of TASS Long/Short Equity funds plus futures.
MSCI-F: MSCI Long Bias (North American) Index plus futures.
Sharpe ratio: (Average Return – Risk Free Return)/Standard Deviation, where the risk free return is the average return of the 3 month Treasury bill from 1996 until 2002.

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Figure 1. Alphas in Different Quintiles of USEQ

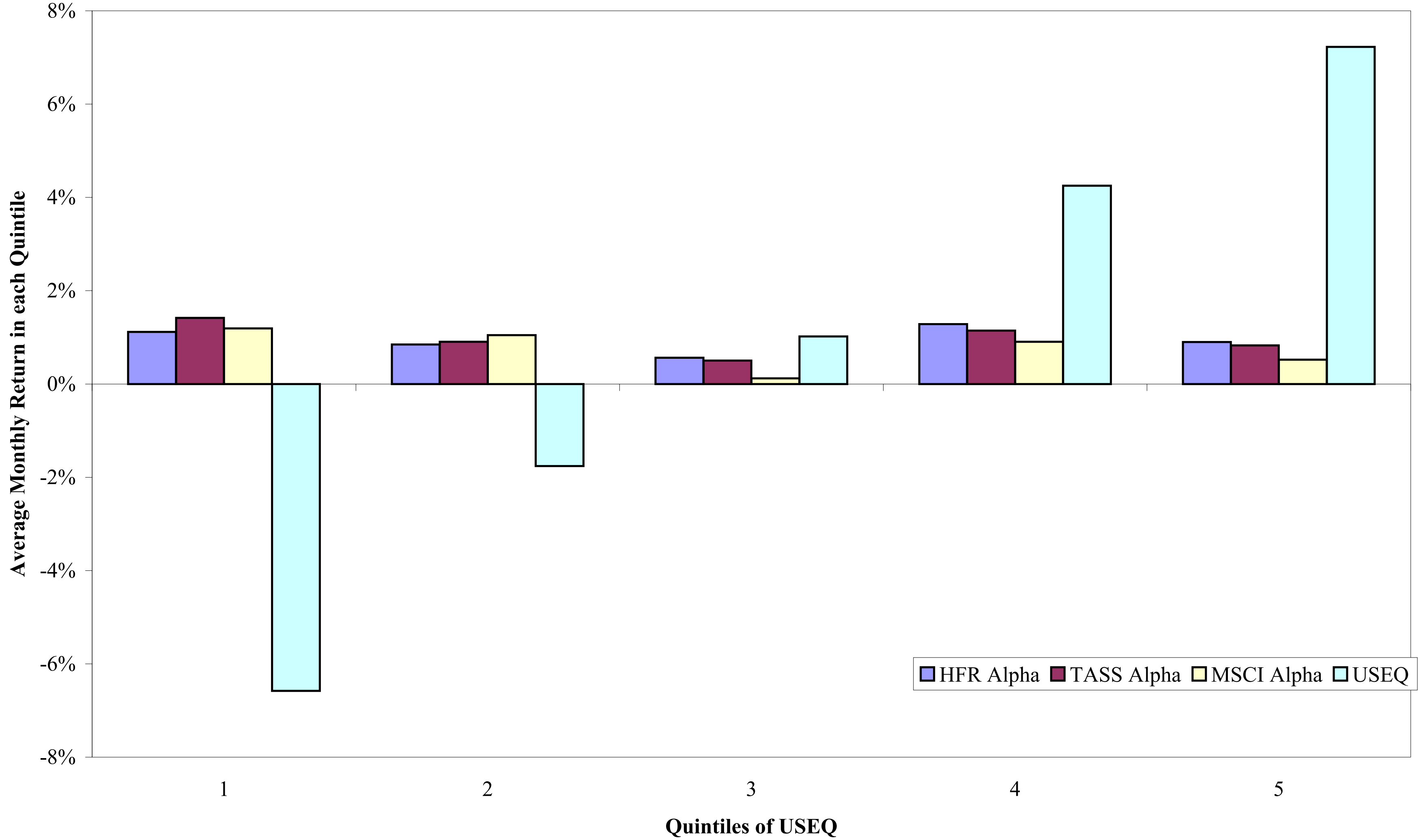

Figure 2. Alphas in Different Quintiles of NUSEQ

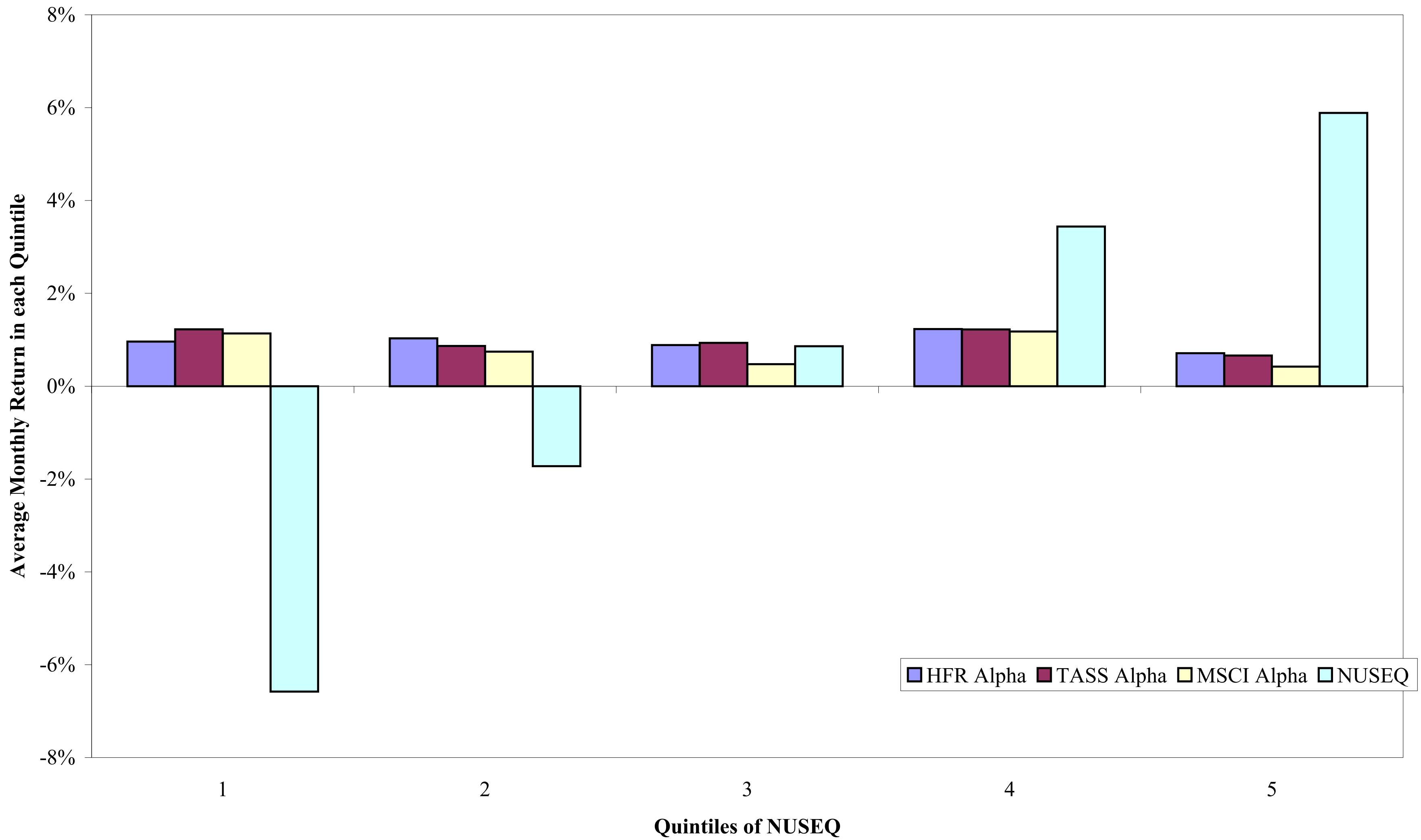

Figure 3. Alphas in Different Quintiles of IFC

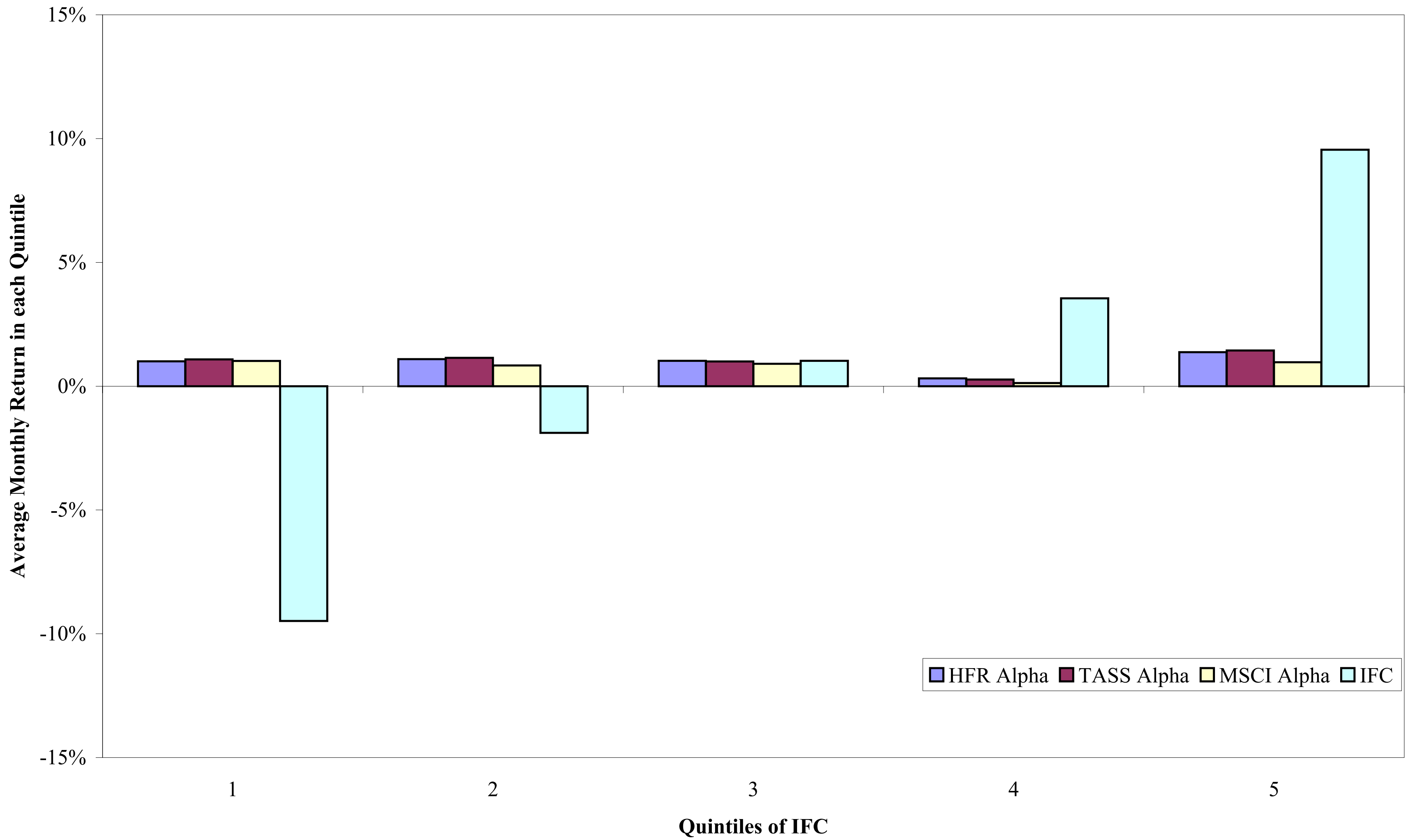

Figure 4. Alphas in Different Quintiles of USBD

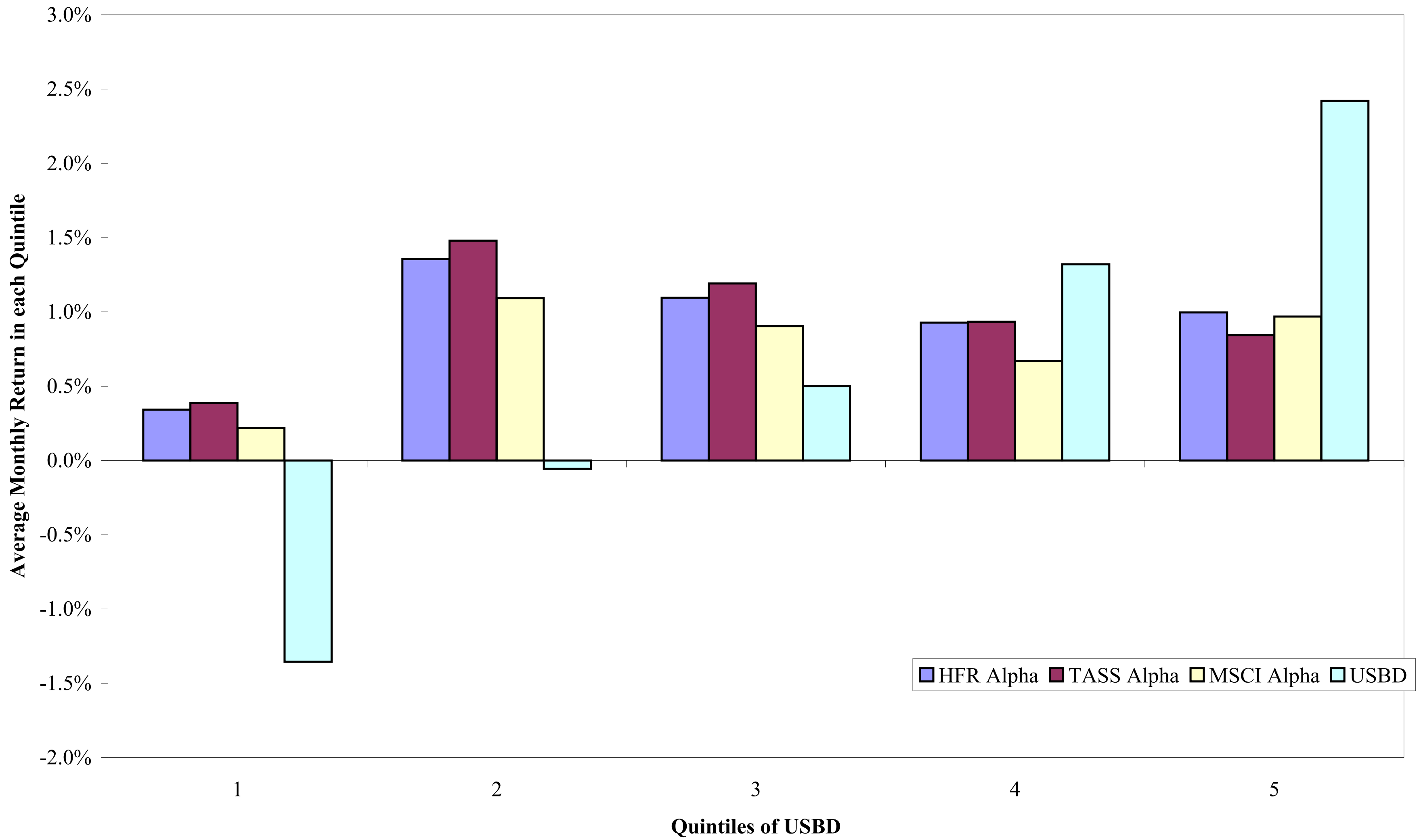

Figure 5. Alphas in Different Quintiles of NUSBD

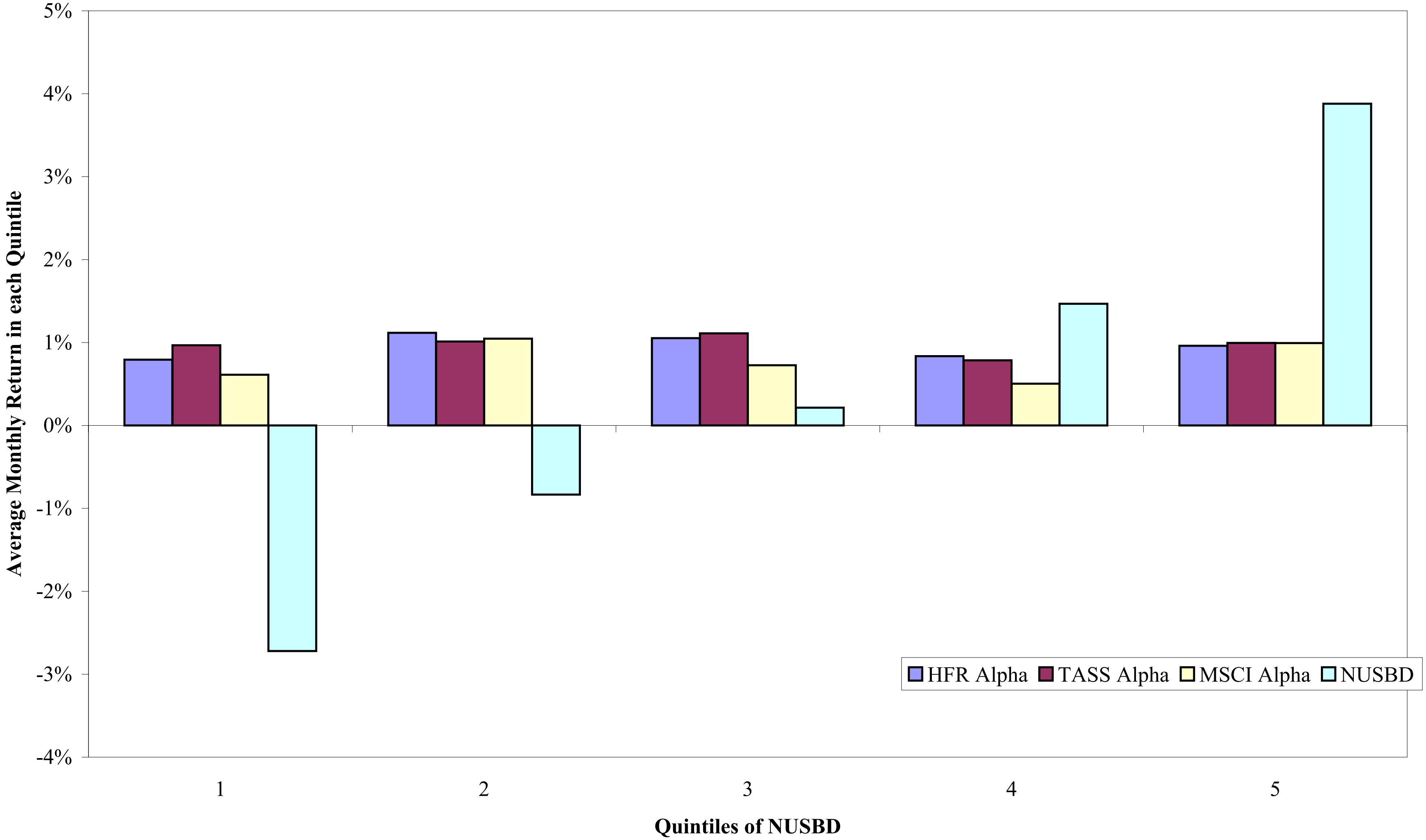

Figure 6. Alphas in Different Quintiles of ED1M

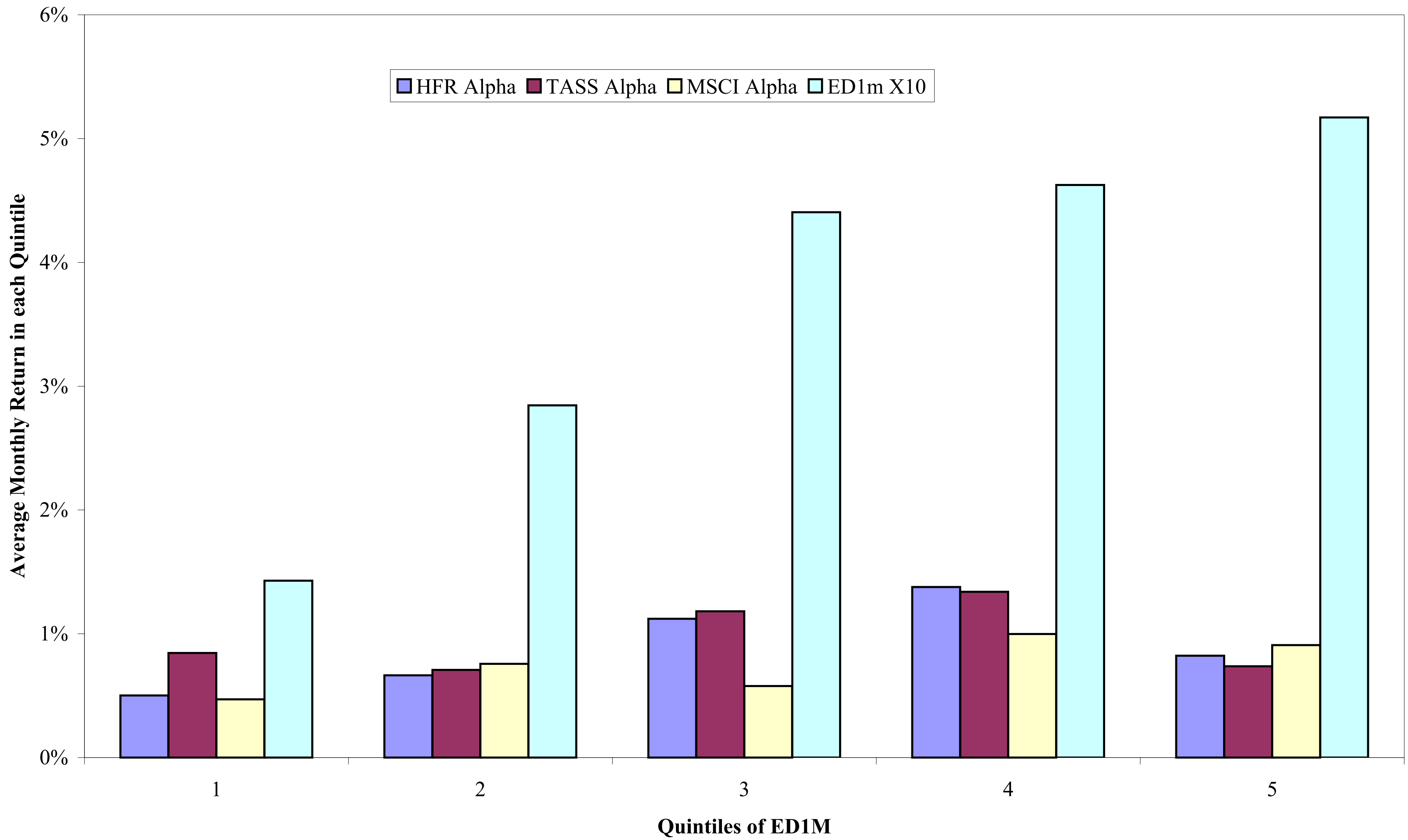

Figure 7. Alphas in Different Quintiles of Gold

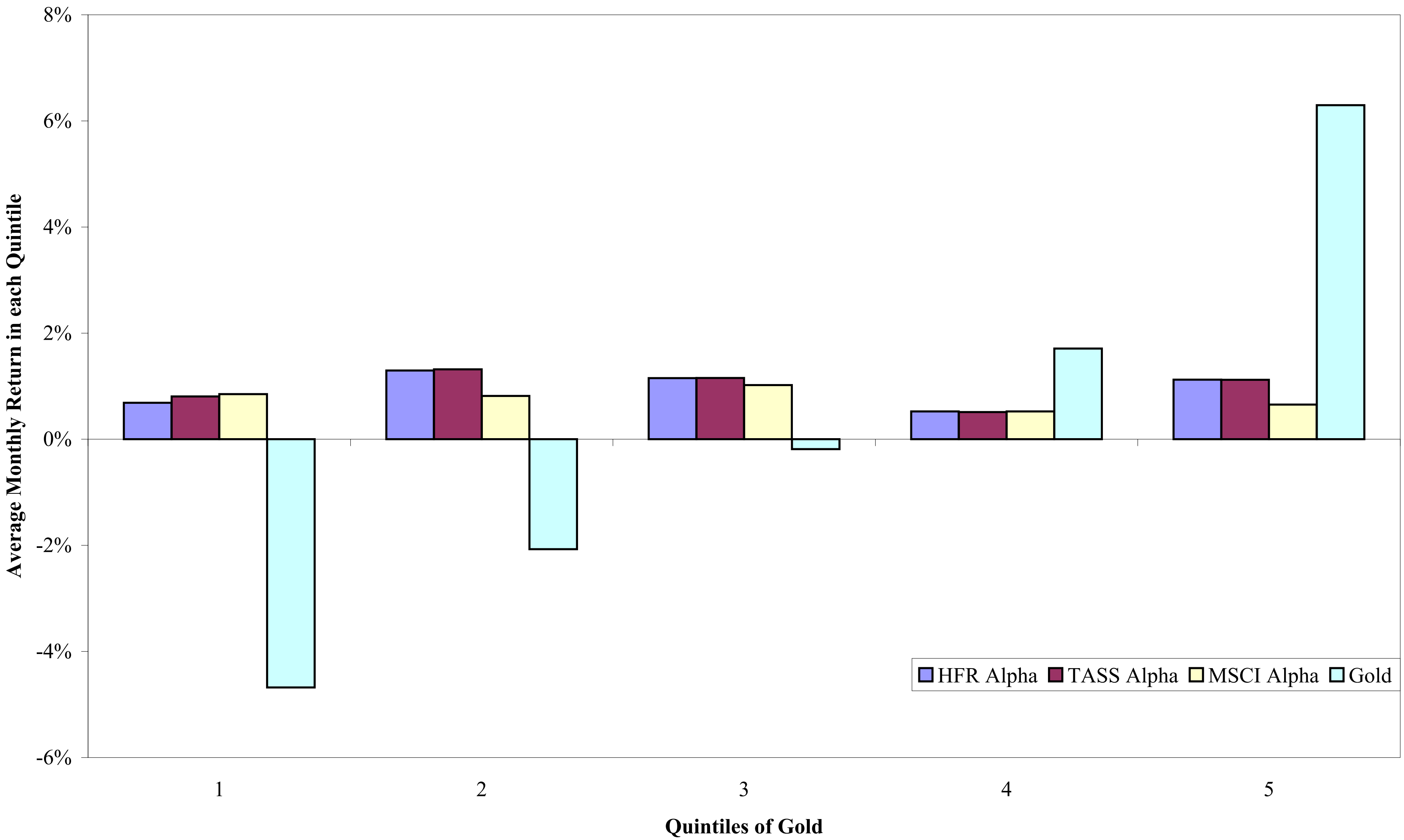

Figure 8. Alphas in Different Quintiles of DOLLR

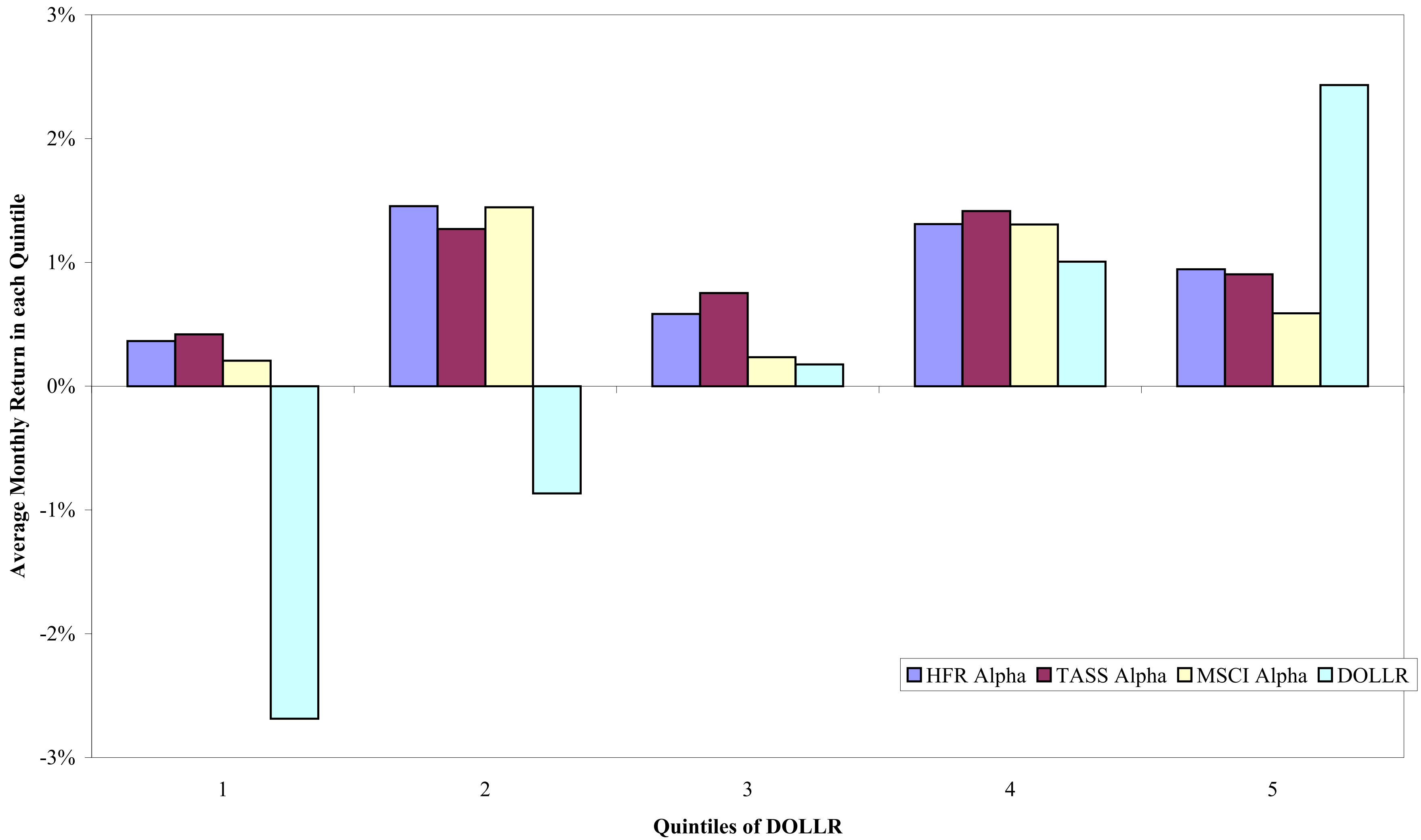

Figure 9. Alphas in Different Quintiles of S&P 500

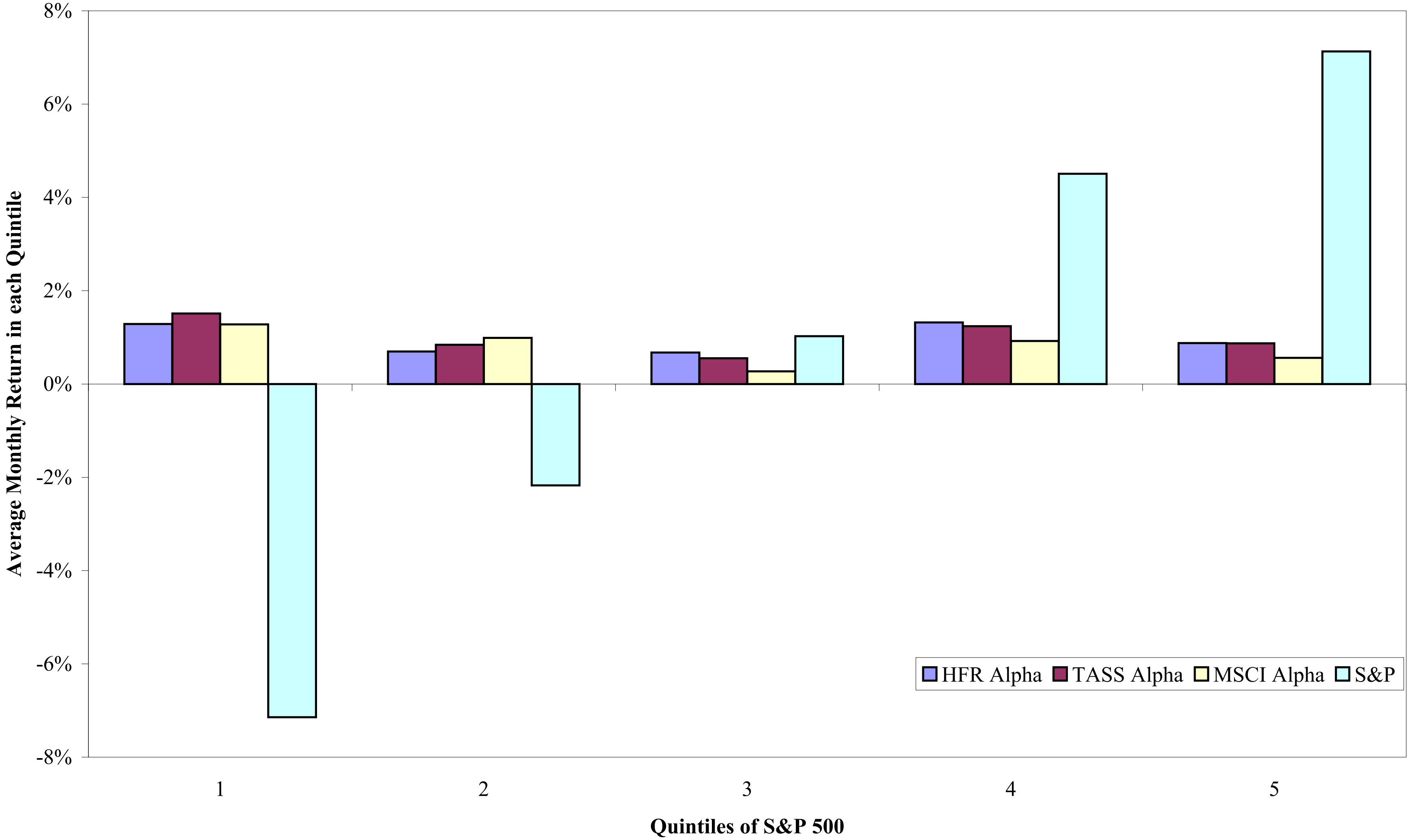

Figure 10. Alphas in Different Quintiles of SC-LC

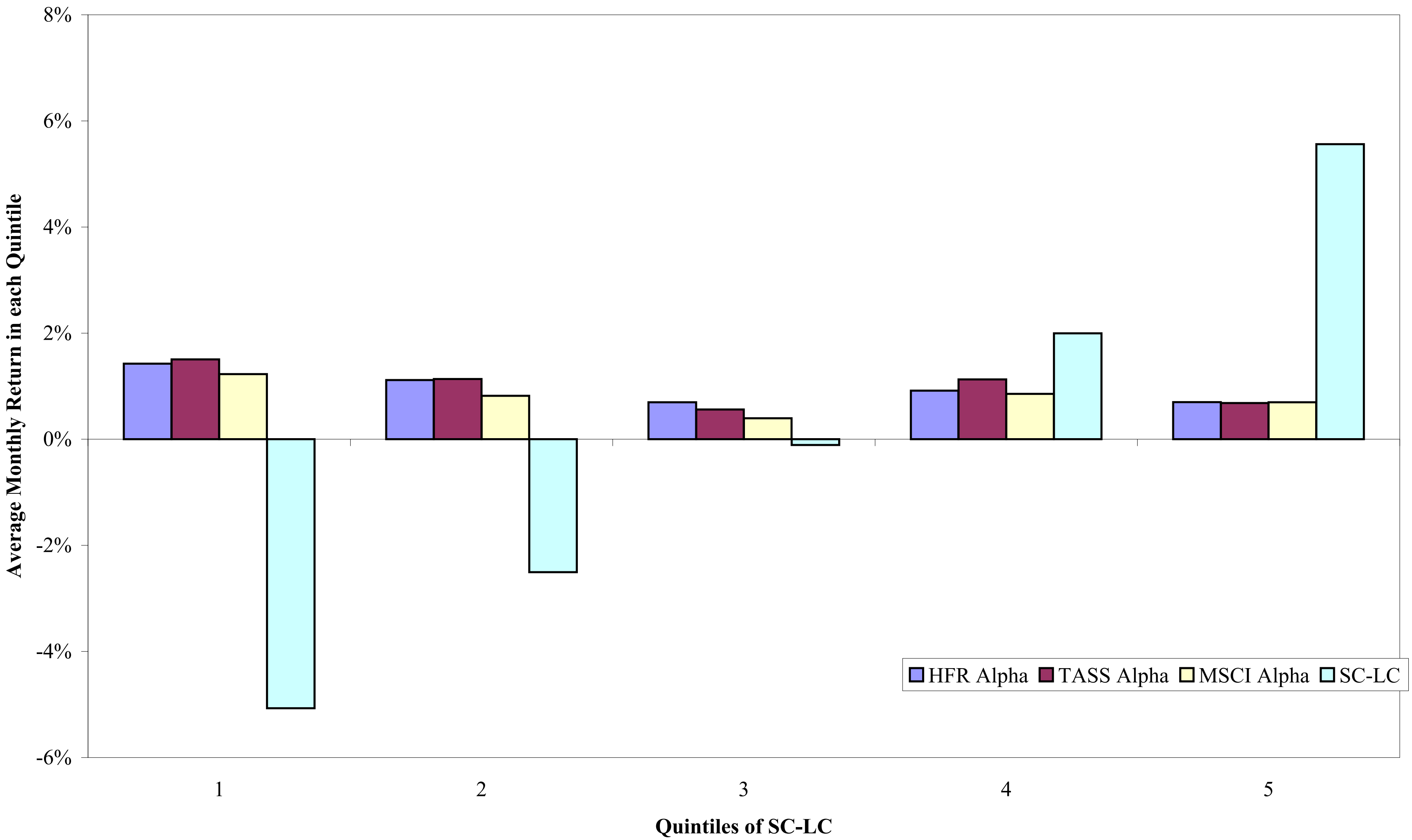

Figure 11. Alphas in Different Quintiles of 10Y Yield Change

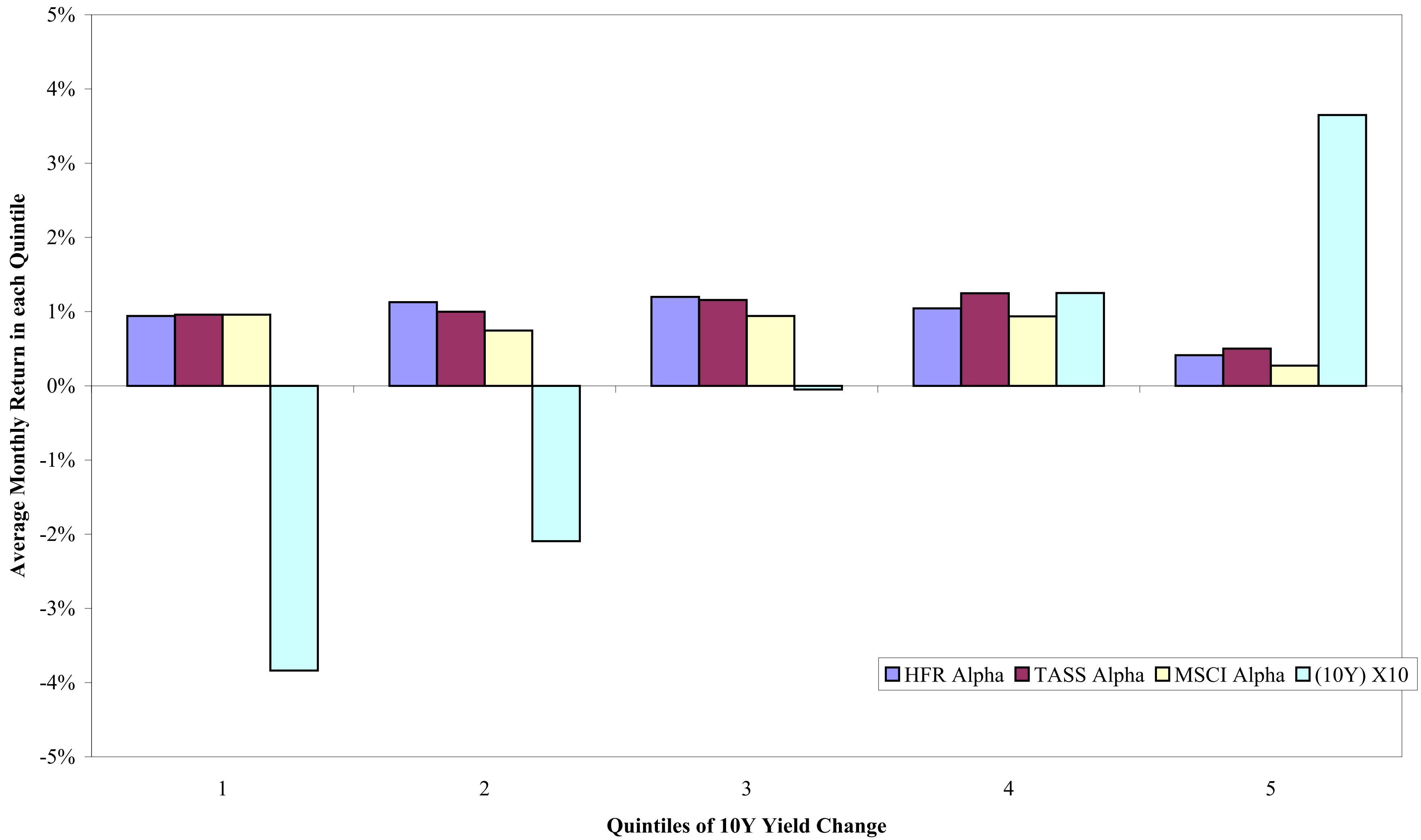

Figure 12. Alphas in Different Quintiles of Credit Spread Change

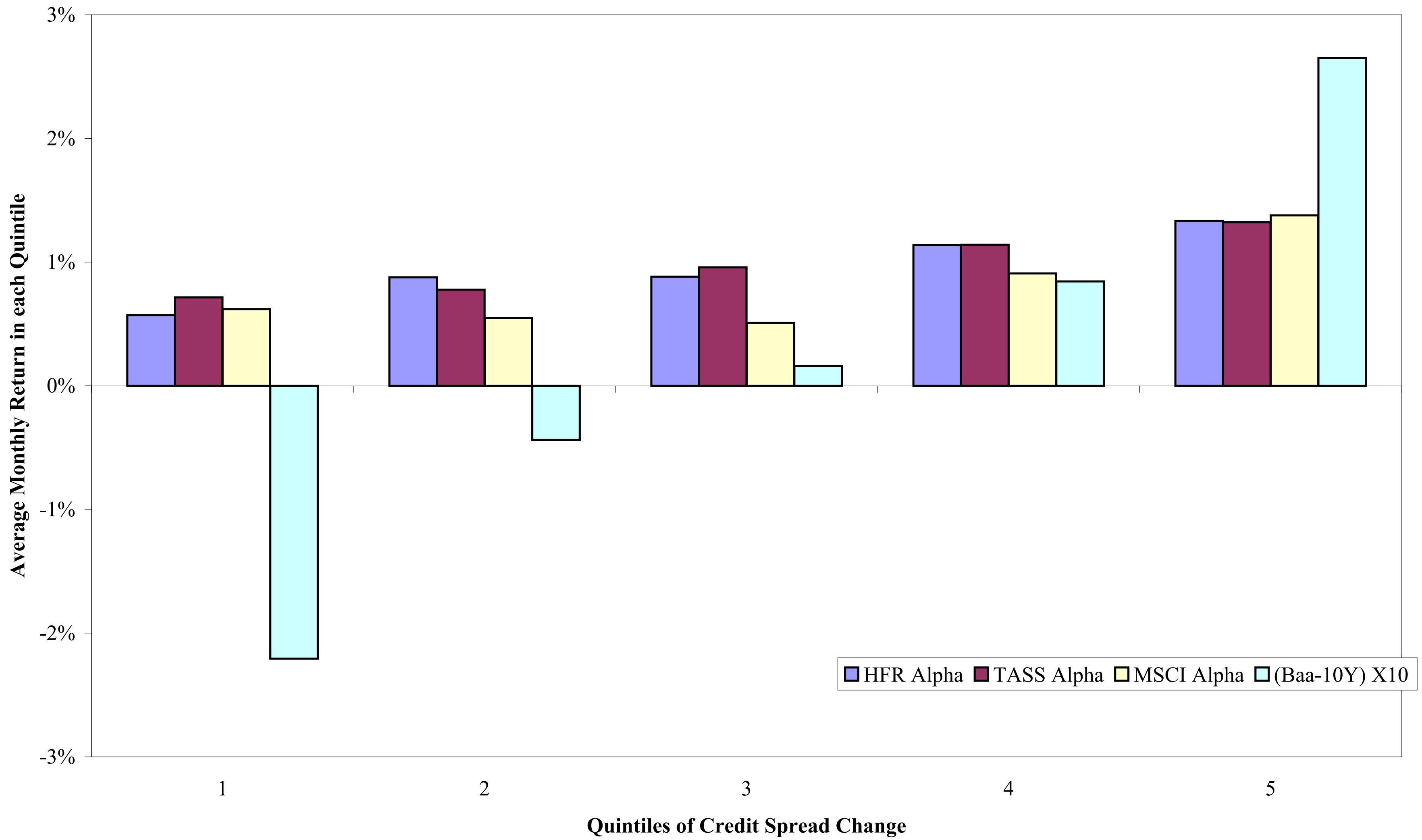

Figure 13. Alphas in Different Quintiles of Trend Following in Bonds

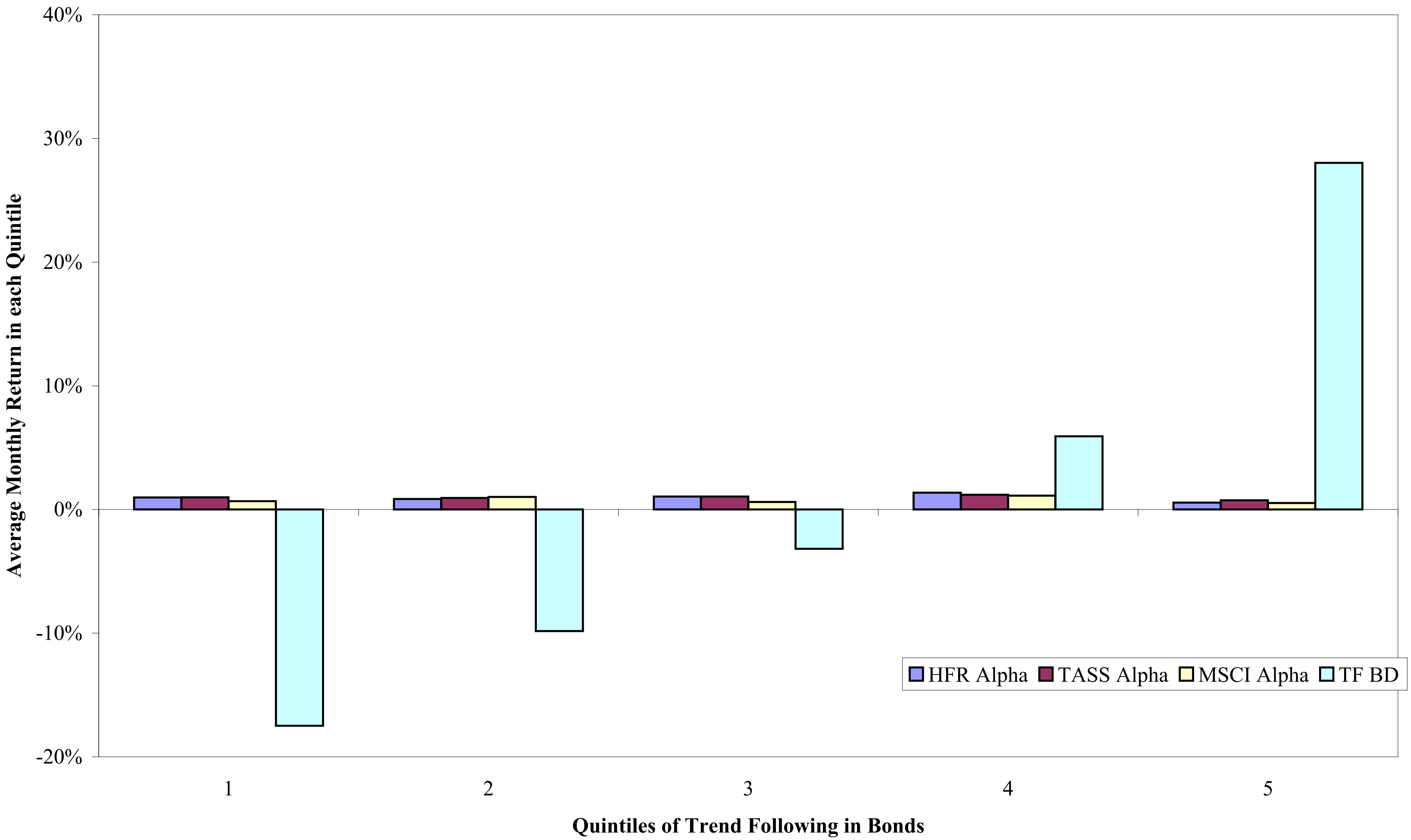

Figure 14. Alphas in Different Quintiles of Trend Following in Currencies

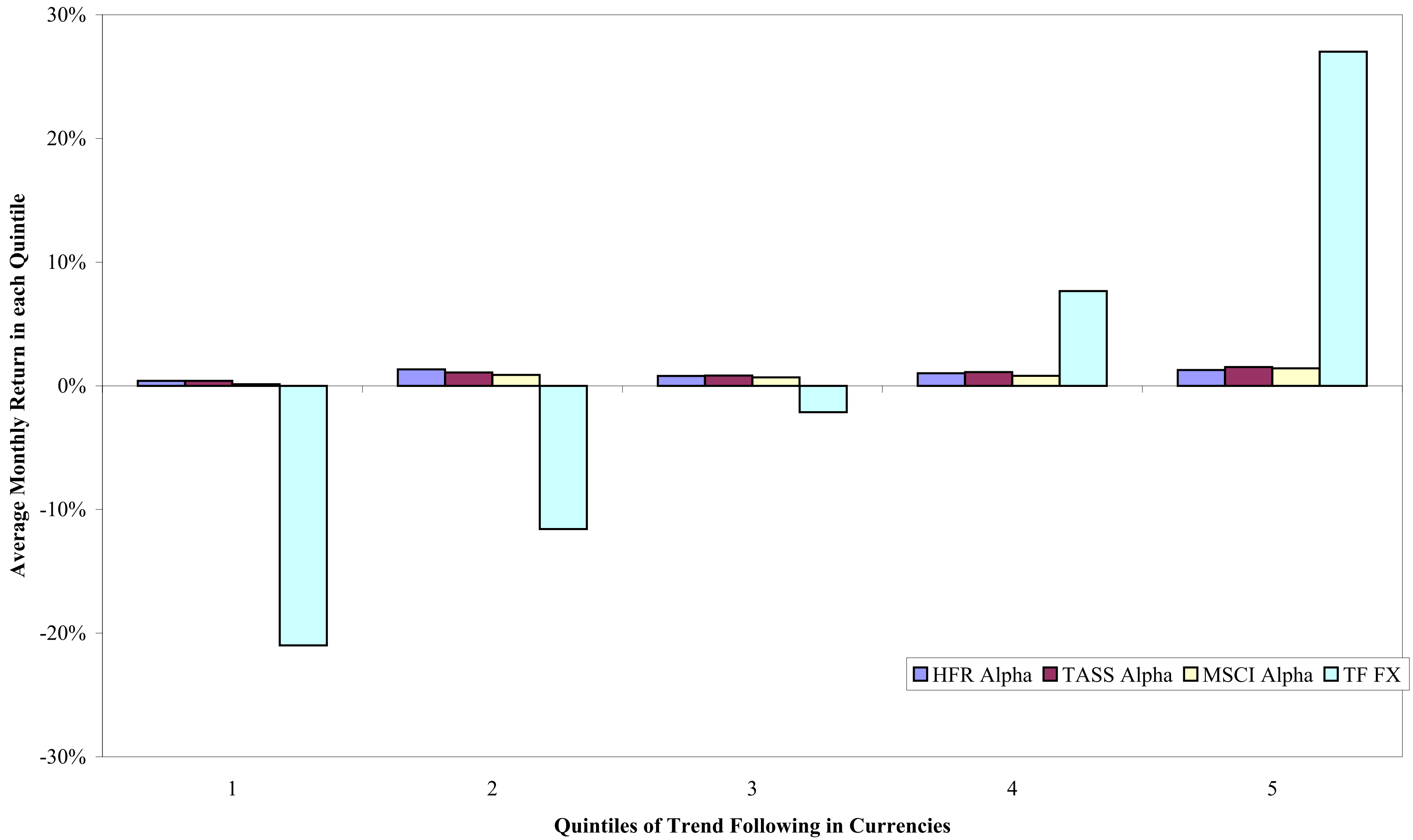

Figure 15. Alphas in Different Quintiles of Trend Following in Commodities

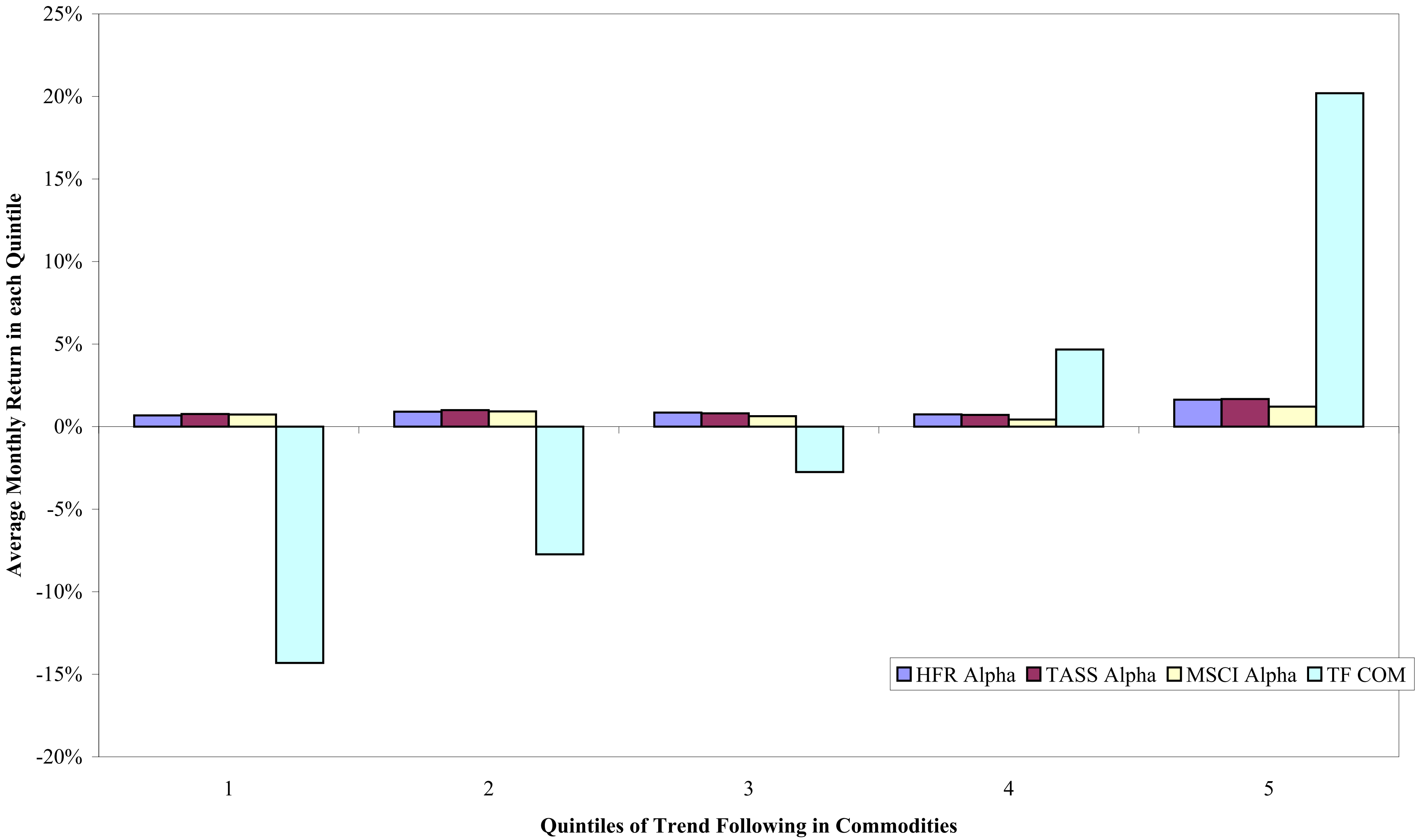

Figure 16. Alphas in Different Quintiles of S&P Historical Volatility

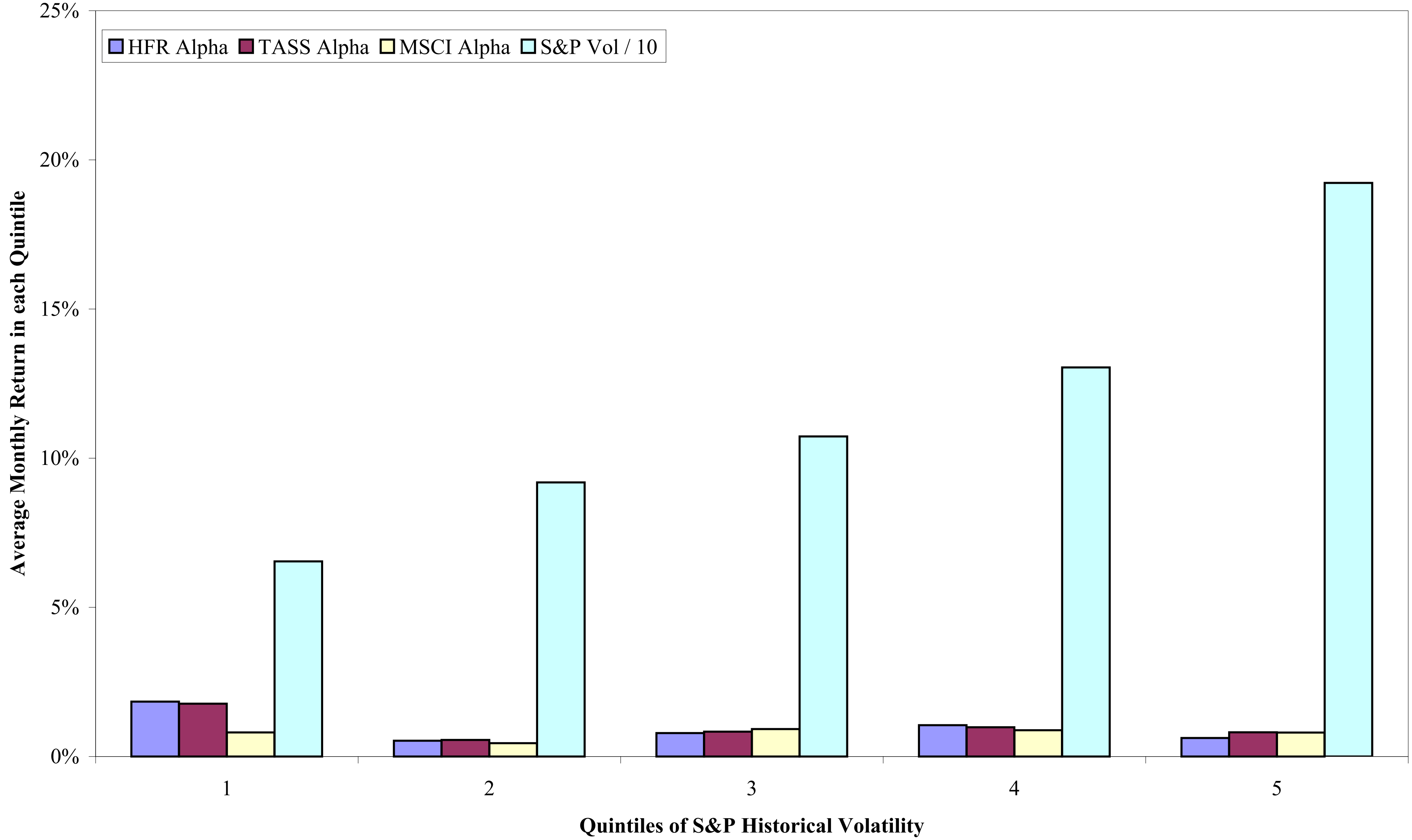

Figure 17. Alphas in Different Quintiles of SC-LC Historical Volatility

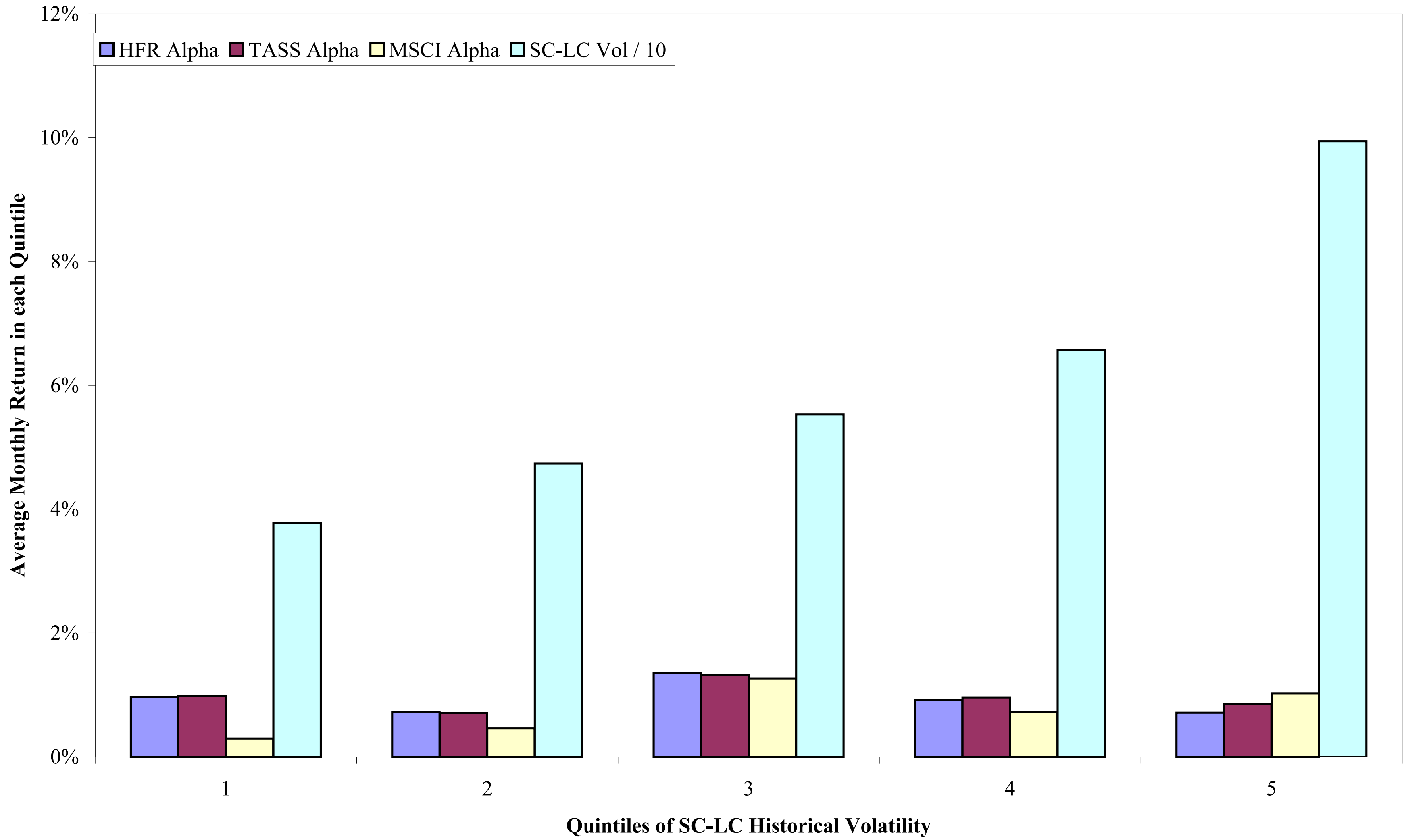

Figure 18. 24-Month Rolling Betas: HFR Equity Hedge

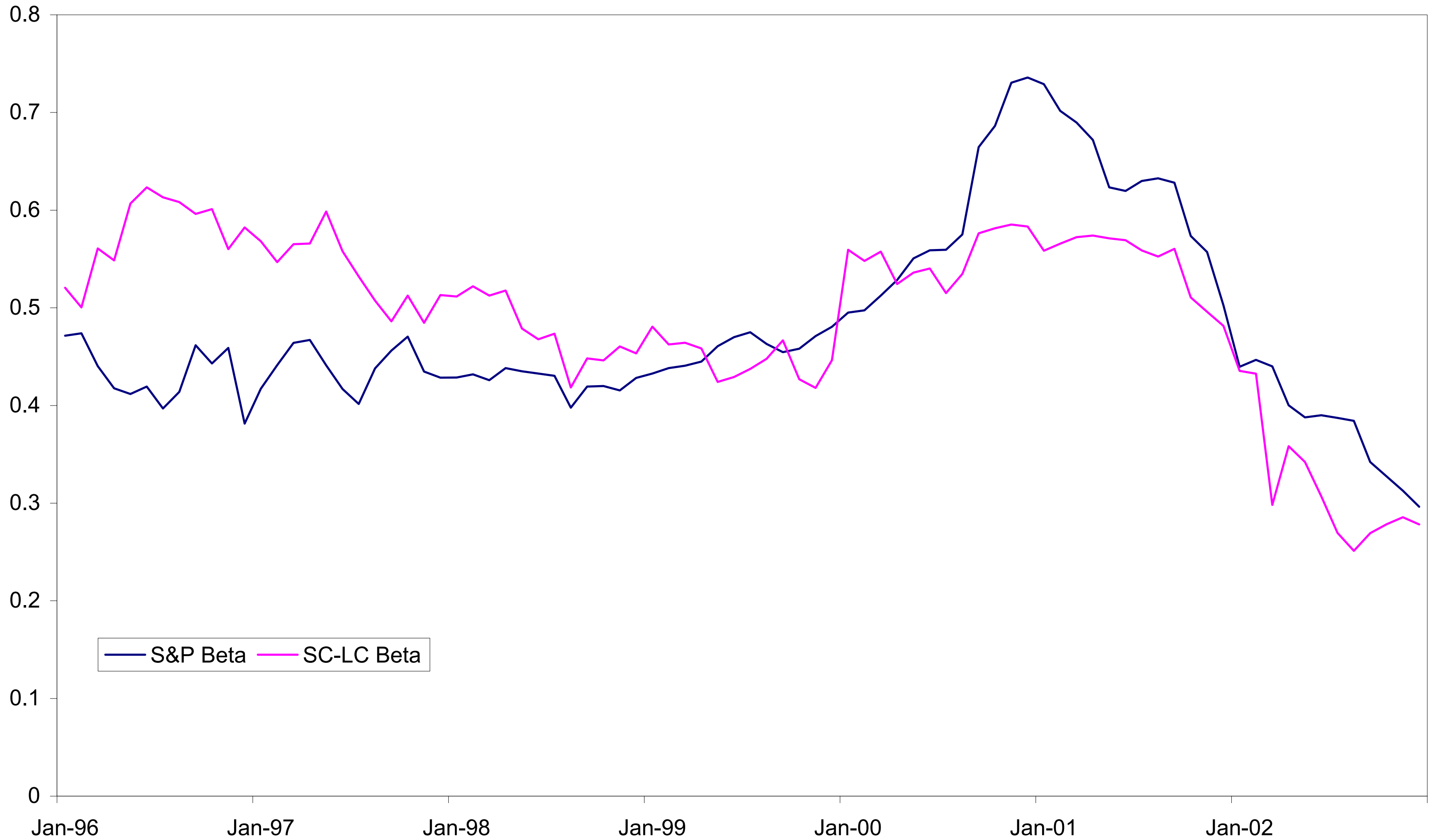

Figure 19. 24-Month Rolling Betas: CTI Equity Long-Short

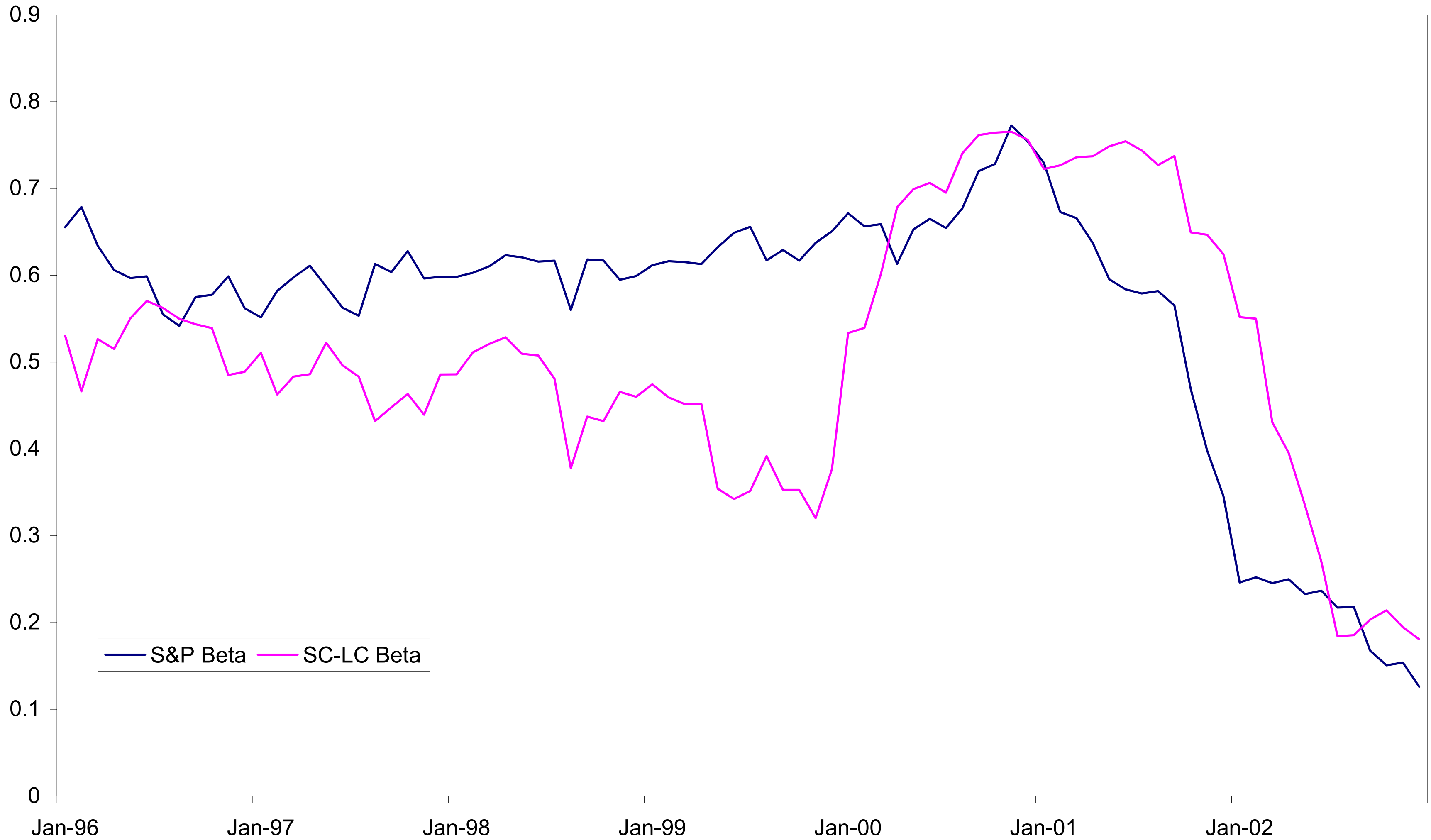

Figure 20. 24-Month Rolling Betas: MSCI Long Bias