Managed Futures
A Composite CTA Performance Review

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Abstract

The data and time dependency of empirical financial research is a common concern to both academics and practitioners. Changes in regulatory, trading and investor environments may result in dramatic changes in the underlying viability of any investment vehicle and/or trading process. This is especially true for managed futures programs for which a single commonly used database does not exist and which often are dynamic in nature and are impacted by changes in trading instruments and underlying markets. As a result, empirical analysis of the potential benefits of Managed Futures (e.g., Commodity Trading Advisors (CTAs)) may be impacted by the period of analysis and the strategy composition of the database or index used to represent the managed futures investment. In this analysis, we conduct a series of empirical tests on CTA indices which are designed to represent the overall return to the reporting universe of CTAs (e.g., composite CTA indices). These tests are similar to those previously conducted on a series of 'composite' hedge fund indices (Schneeweis et. al., 2012). Using major composite CTA indices as a surrogate for CTA portfolios, these tests include cross-sectional and time series analysis. Results reflect the common wisdom that performance results may be dominated by the period of analysis as well as the index and multi-factor regression model used.

Managed Futures Research
A Composite CTA Performance Review

Introduction

During the subprime crisis, managed futures, on average, was one of the few investment vehicles to provide positive returns. However, for many academics and practitioners, managed futures remain a seeming investment anomaly. How can an investment vehicle which trades primarily in futures markets (which are often described as zero sum games) be considered a viable long term asset class? It is not the purpose of this review to detail the economic basis for managed futures trading or the fundamental sources of their return. Over the past thirty years, numerous articles have detailed various economic bases for managed futures investment as well as empirical evidence as to their potential investor benefits (INGARM, 2012). Despite the fact that numerous investment trading firms' "active futures based" proprietary trading operations and numerous public managed futures trading programs have shown themselves to be economically viable, some academic research has questioned the investment benefits of managed futures investment programs (Bhardwaj, Gorton, and Rouwenhorst, 2008).

It is important that research be continually "re-conducted" on any investment area. Changes in regulatory, trading and investor environments may result in dramatic changes in the underlying viability of any investment vehicle and/or trading process. This is especially true for managed futures programs which are often dynamic in nature and are impacted by changes in trading instruments and underlying markets. However, managed futures have traded through many of these dynamic changes. Public managed futures programs began trading in the early-1970s (primarily commodity and currency futures since interest rate futures were introduced primarily in the late-1970s and oil and stock futures did not exist in the mid-1980s). The potential for the time dependency of the profitability of various managed futures programs is further illustrated by the fact that many internationally based futures contracts did not exist until the 1990s. In addition, changes to trading technology, market making, and risk management techniques have the potential for changing the underlying profitability and economic basis of various managed futures programs.

In this analysis we conduct a series of empirical tests on composite CTA indices similar to that previously conducted on a series of hedge fund indices (Schneeweis et. al., 2012). Using major composite CTA indices as a surrogate for CTA portfolios, these tests include cross-sectional and time series analysis of 1) distributional characteristics (e.g., rolling return, rolling standard deviation), 2) measures of relative performance (e.g., rolling correlations), and 3) significance of various trading and/or momentum factors in multivariate regression. Results reflect the common wisdom that findings based on historical data may be dominated by the period of analysis as well as the composition of the portfolio (e.g., CISDM, Barclay or CSFB CTA indices) used. In addition, results show that the relative importance of various market or trading/momentum factors in explaining the return process of the CTA indices is likewise dependent, in part, on the composition of the portfolio, the time period of analysis, and the independent variables used in the regression analysis.

Managed Futures Returns: A Historical Perspective

Similar to other academic research, the questions we ask as to the performance of managed futures are often restricted by the availability of data and the time period of analysis. The rapid increase in equity market research in the 1970s was driven in part by the availability of monthly stock and corporate data in the late-1960s (e.g. Compustat). Futures and options research in the 1970s and 1980s were driven by the availability of futures and option data

(Columbia Center for Futures Markets and Berkeley option data). Similarly, research (and research results) in the managed futures area have been impacted by the availability of managed futures fund returns. In the 1980s the expansion of new contracts and liquidity in futures markets resulted in an increase in the number of new managed futures programs. Managed Account Reports began collecting managed futures and public commodity fund data as well as reporting a series of benchmark indices based on the monthly returns of reporting CTAs. The primary research on managed futures in the 1980s was conducted by Lintner [1983] and Elton, Gruber, and Rentzler [1988, 1989, 1990]. Elton, Gruber and Rentzler's (EGR) research was conducted on Commodity Pools for the period of July 1979 through 1985. Lintner's research was conducted on both managed accounts (15 managers) and commodity pools (8) for the period of July, 1979-1982. EGR's research was critical of the inclusion of commodity pools in an equity portfolio. It is important to note that EGR's studies were criticized in the 1990s (Peters and Warwick ed., [1992, 1997]) for using a breakeven model approach in which the benefits of adding an asset to a stock portfolio was based on time specific correlation of the asset with the stock portfolio as well as the time specific underlying risk free rate. (It is important to point out that EGR state that, in their analysis, fixed income securities were also not attractive additions to stock portfolios in their period of analysis due to the high level of treasury rates impacting the required breakeven return).[1] Most of the research in the 1990s moved away from analysis of

[1] In addition, EGR used assumptions as to the long term correlation and risk free rate in combination with the expected return of publicly traded commodity pools to further reject the economic basis for public commodity funds. In their analysis they estimated the total management, incentive, and fund fees of almost 20%. With such assumptions, public commodity funds would have to earn almost 30% before being added to a portfolio using their estimates of required breakeven. These assumptions as to the fees of public commodity pools were likewise questioned in research conducted in the early 1990s (Irwin et. al., [1993]).

commodity pools, since public commodity pools were formed from a few major CTA players and did not represented the overall industry.

During the first half of the 1990s additional database and benchmark providers entered the market (Barclay and Hedge Fund Research). By the mid-1990s sufficient benchmark data existed for several benchmark providers. Each benchmark provider created indices using a variety of data collection and benchmark reporting. However, by the mid-1990s databases and CTA benchmarks were based on well over 500 CTAs (Edwards et. al., [1999]). Other smaller databases and related CTA benchmarks existed (TASS was based in London and concentrated primarily on European managers). In the late-1990s, CSFB and others worked to increase the size of the CSFB Tremont database resulting in a major increase in managers reported in the CSFB database in early-2000.[2]

In summary, while the CTA index data from CISDM (asset-weighted (AW) for sub-indices and equally-weighted (EW) for the overall index), Barclay and CSFB are not impacted by survivor or backfill bias, the reported number of managers in the 1990s CSFB database (e.g., using the 2002 CSFB database and removing backfill) are well below that reported in the CISDM and Barclay databases. These size differences may result in different sensitivity of the indices to similar market factors. Differences in return, may also exist due to selection bias and/or construction. However, with the dramatic increase in reporting managers to the CSFB database post-2000, the post-2000 benchmarks based on different databases may provide similar results unless there are dramatic differences among the distribution of managers and/or manager styles. Lastly, in the past decade a number of daily CTA benchmark have come into existence.

[2] Several studies (Bhardwaj et al. [2008] and Malkiel [2002] used the CSFB Tremont database and incorrectly assumed that the addition of managers to the CSFB/Tremont database should be considered as backfill when in fact many were simply “additions” from other existing databases. Similarly the CISDM database witnessed two significant increases in reporting funds when the database was purchased by Lyra in 2004 and again in 2007 when the Lyra was sold to Credit Agricole and efforts were made to increase the number of managers reporting.

While not a part of this analysis, the availability of daily data permits additional research which requires daily data to measure the impact of various types of information patterns. In short, by 2010 there exists an almost twenty year history of CTA index returns based on the then reporting managers to each database provider and while database updates of reporting CTA managers contain the traditional concerns of backfill bias and selection bias, the CTA indices (e.g., CISDM and BarclayHedge) do not contain backfill or survivor bias for periods since the early-1990s.[3]

Managed Futures: Data/Index Impact

Unlike equity and fixed income markets, for which a series of commonly used benchmarks exist (e.g., S&P 500, BarCap bond indices) on which most academic research is conducted, for CTAs a variety of databases and their related benchmarks have been used as a basis for academic research. Prior to 2000, three primary CTA databases (CISDM, Barclay, and CFSB) exist for which a series of CTA indices have been published which do not contain backfill or survivor bias.[4] These CTA indices reflect the distribution of reporting CTA managers at the time of the reported index return. As a result, the CTA index returns reflect the distribution of the managers in the 'then existing' underlying database. While various databases may include different managers, the choice of any individual database may have little impact on empirical results as long as the distribution of like managers is similar across the various databases or the number of managers reporting to individual CTA trading sectors is large enough that the law of large numbers dominates the individual differences in reporting mangers. As an alternative to a detailed historical analysis of the individual databases or a diligent combining of the various

[3] The CISDM indices were initially known as the Managed Account Report CTA indices (MAR). Several of the Composite indices were initially created in the late 1980's but have been published continually since the early 1990s. Similarly the Barclay's CTA indices were constructed in the early 1990s and have been published continually since the early 1990's. The CSFB/Tremont indices are reported since 1994.

[4] In addition, at the sub composite strategy level both Barclay and CISDM also provide CTA indices which may be regarded as backfill or survivor bias free. For CISDM at the strategy level, equal weighted non-backfill and survivor free indices exist from 2001 onward.

databases (various private firms have conducted this effort and the research from a common set of firms has been presented on various topics (Schneeweis et. al., [2003], Fund and Hsieh, [2006]), one may compare the relative performance characteristics of the backfill bias and survivor bias free indices which are in essence a portfolio of the then reporting managers at any particular point in time.

Results in Exhibit 1 reflect the performance characteristics of four major CTA indices (Barclay CTA, CISDM AW and EW CTA, and CSFB CTA Index) over the period 1994-2009.[5] Of the major CTA indices, the index with the greatest disparity from the other indices is the CSFB CTA index. The annualized standard deviation (11.8%) of the CSFB managed futures index is over 25% greater than the other three comparison CTA indices (CISDM AW (8.4%), CISDM EW (8.7%), Barclay (7.7%)). In addition, the CSFB index's maximum drawdown (-17.7%) is twice that of the comparison indices (CISDM AW (-8.3%), CISDM EW (-8.7%), Barclay (-7.7%)), and it has the lowest correlation (on average below .90) with the comparison CTA indices (average correlation above .90). As shown in Exhibit 2a-2d, this disparity in descriptive statistics (annualized returns, annualized standard deviation, skewness and kurtosis) was especially true for the period prior to 2000. While in this analysis we have not directly compared the composition of the various CTA indices, as discussed in Aggarwal and Jorion [2009], the CSFB database was essentially reconstructed in 2000 as part of its effort to grow its database. From that period onward the three primary CTA indices reflected databases that were large and diversified enough to reflect the underlying returns of the strategy. For the period prior to 2000, the simple fact is that if the CSFB CTA database reflects the same issues described by

[5] The results of this analysis are for the period 1994-2009. One reason for the restricted data period is that the CISDM asset weighted (AW) index ceased publication in 2010. Since a large part of the previous research was based on the CISDM AW CTA index the analysis used the period 1994-2009. See Appendix 1 for a description of the CTA indices used in this analysis.

Aggarwal and Jorion [2009] for hedge funds, the CSFB CTA index may not capture the returns to the broader set of available CTAs captured by either the CISDM or Barclay CTA indices for the period prior to 2000.

Exhibit 1: Descriptive Performance: 1994-2009

Exhibit 1	Descriptive Performance: 1994-2009			
	Barclay Trader Index CTA	CISDM CTA Asset Weighted Index	CSFB/Tremont Managed Futures Index	CISDM CTA Equal Weighted Index
Annualized Rate of Return	6.05%	7.89%	6.29%	8.51%
Annualized Standard Deviation	7.74%	8.37%	11.79%	8.59%
Info Ratio	0.78	0.94	0.53	0.99
Skewness	0.30	0.24	0.03	0.46
Correlation With: S&P 500	-0.11	-0.10	-0.14	-0.13
Correlation With: Russell 1000	-0.10	-0.08	-0.12	-0.11
Correlation With BarCap Gov.	0.30	0.27	0.27	0.29
Correlation With BarCap HY.	-0.11	-0.12	-0.17	-0.14
Correlation: Barclay Trader Index CTA	1.00	0.94	0.84	0.97
Correlation: CISDM CTA Asset Weighted Inde	0.94	1.00	0.88	0.94
Correlation: CSFB/Tremont Managed Futures	0.84	0.88	1.00	0.85
Correlation: CISDM CTA Equal Weighted Inde	0.97	0.94	0.85	1.00

Cross-sectional results are indicative of a single time frame. Of greater importance is the degree to which these cross-sectional results are reflective of the relative performance in multiple periods of analysis. While Exhibit 1 indicates potential differences in reported risk measures between the CSFB and other CTA benchmarks over the entire period of analysis, results in Exhibits 2a-2d indicate that the CSFB CTA index has a significantly different pattern of annualized return primarily for the period prior to 2000. For example, while the time series patterns of the rolling standard deviations are similar for all of the CTA indices, the CSFB level of standard deviation is consistently higher than those of the CISDM and Barclay while the differences between the CSFB, Barclay and CISDM indices in the levels of reported skewness and kurtosis existed primarily in the pre-2000 period. These differential results for the levels of skewness and kurtosis also generate a higher level of non-normality of the distributions (Exhibit 3) especially for the CSFB in the period prior to the reconstruction of its database around 2000.

Exhibit 2a: CTA Annual Returns

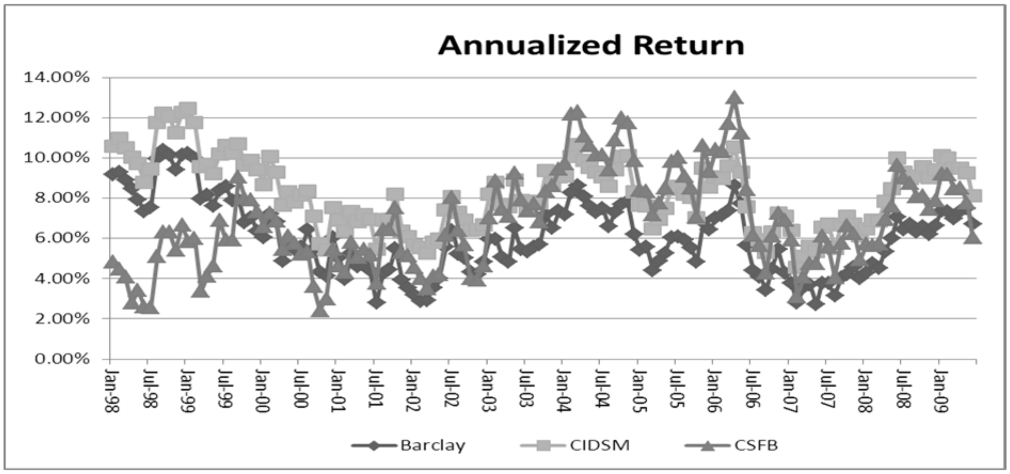


Exhibit 2b: Standard Deviation

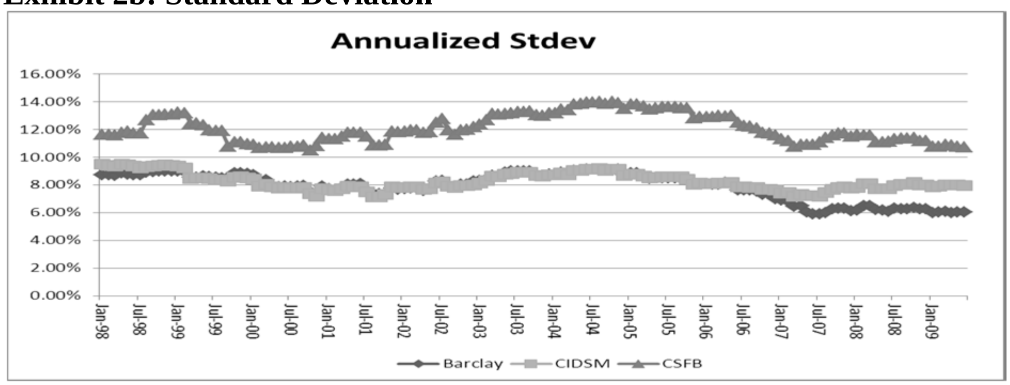


Exhibit 2c: Skewness

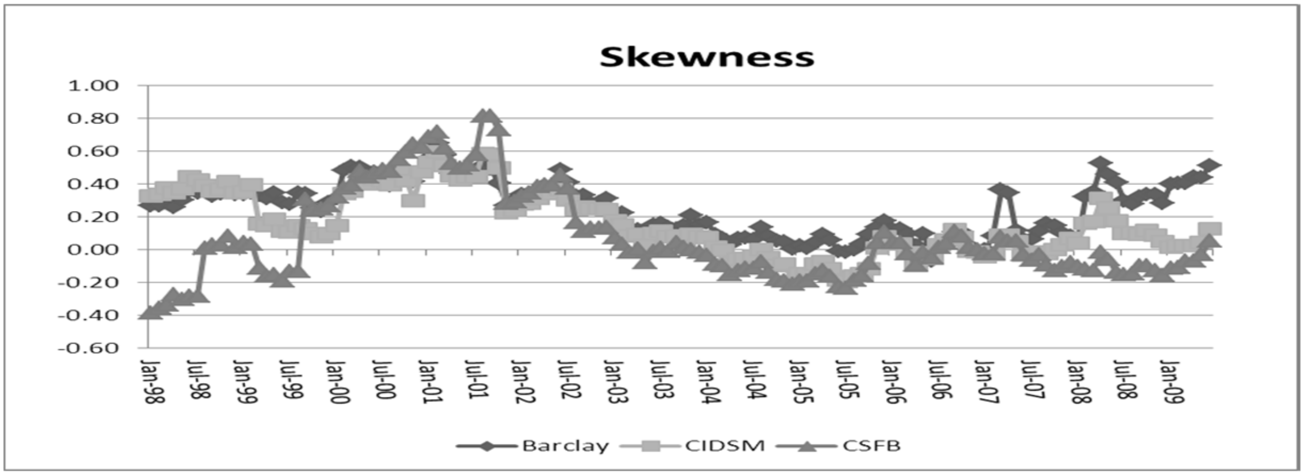


Exhibit 2d: Kurtosis

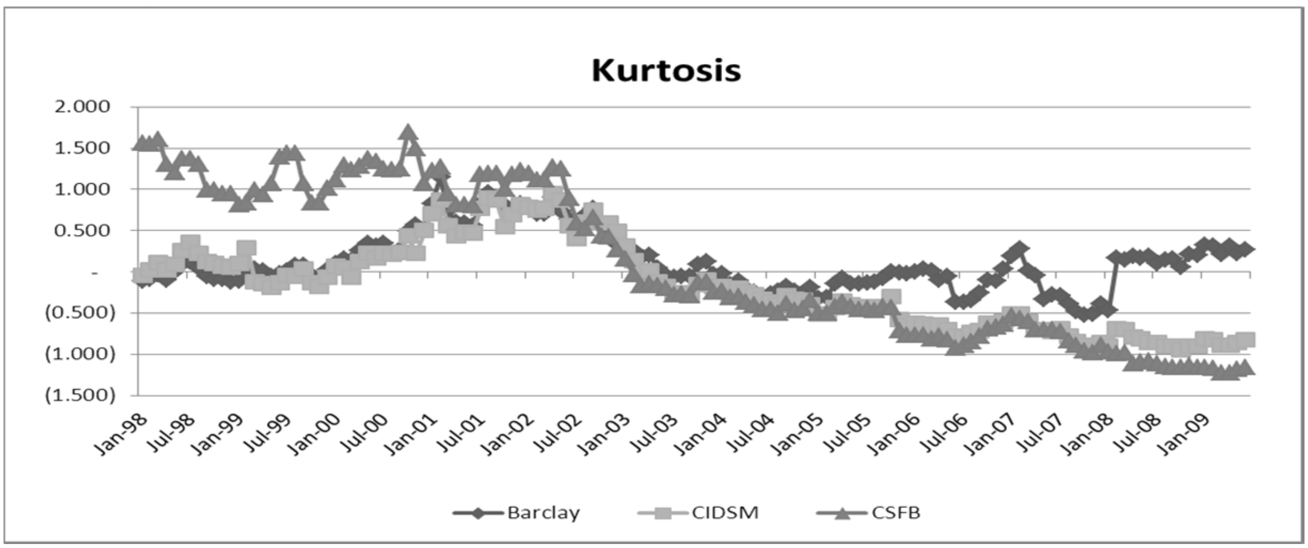
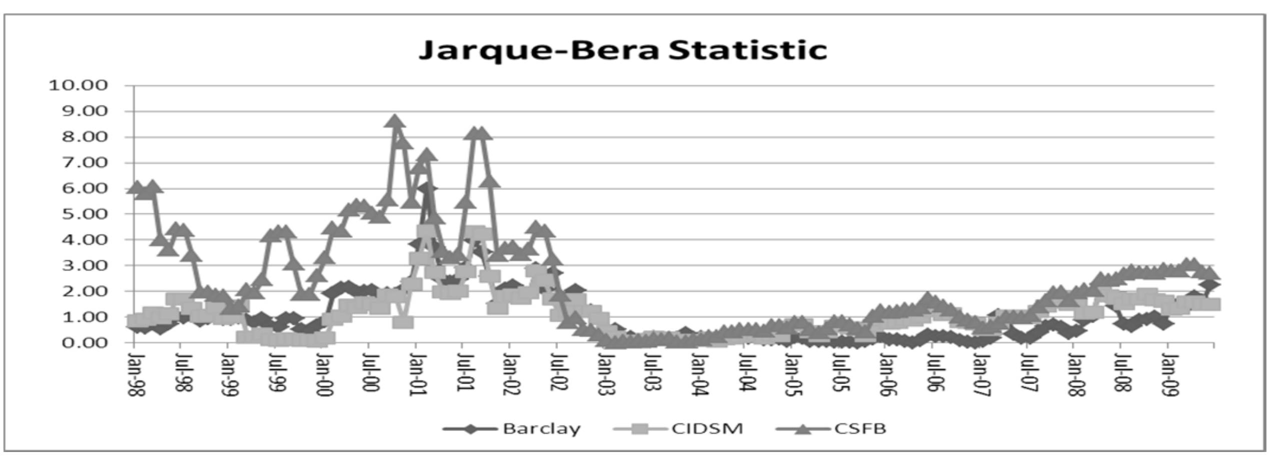


Exhibit 3: Jarque-Bera



Market Factor Correlations

Results presented in the previous section suggest that the CSFB CTA index may have different risk characteristics than the CISDM and Barclay CTA indices especially in the pre-2000 period. In this section we compare the correlation relationships of the various CTA indices with four primary market factors as well as traditionally used passive algorithmic trading factors which are expected to capture the dynamic trading approaches of active CTA managers (Fung and Hsieh PTFS factor returns [1997, 2001] and Spurgin and Schneeweis MFSB trend following returns [1998]).[6] The sources of return to managed futures are uniquely different from traditional stocks, bonds or even hedge funds. For instance, futures, swaps and forward contracts can provide direct exposure to underlying financial and commodity markets but often with greater liquidity and less market impact. Futures and option traders may also easily take short positions or actively allocate assets between long and short positions within the futures/options market trading complex. In addition, options traders may directly trade market/security characteristics, such as price volatility, which underlie the contract. The unique return opportunities to managed futures may also stem from the global nature of futures contracts available for trading and from the broader range of trading strategies. For example, in addition to systematic momentum based trading strategies, managed futures programs may rely on systematic model based trading which focuses on quantitative valuation models as well as more discretionary based trading approaches which place a greater weight on trader judgment of the current conditional factors driving market prices or market volatility.

[6] It is not the purpose of this paper to detail the algorithms involved in the creation of the PTFS and MFSB return series. Readers are directed to the initial papers. However, briefly the PTFS is based on the creation of lookback straddles These PTFS factors are constructed based on the article by William Fung & David A. Hsieh, "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," *Review of Financial Studies*, 14 (2001), 313-341. The MFSB are based on a series of short-term, mid-term and long-term trend following benchmarks. For full information on the construction of MFSB indices readers are directed to www.ingarm.org.

It is important to note that many managed futures strategies trade primarily in futures/option markets, which are zero-sum games. If CTAs were only trading against other CTAs, then, one may conclude that managed futures returns are based solely on manager skill. However, academics and practitioners have shown that some spot market players are willing to hedge positions even if they expect spot positions to rise or fall in their favor (e.g., currency and interest rate futures may be traded over time due to government policy to smooth price movements). Managed futures traders offer liquidity to such hedgers and obtain a positive yield (return/risk tradeoff) in return. In short, long term positive expected returns may be consistent with the underlying instruments of CTA strategies. Similarly, in option markets, differences in demand among call and put plays may also provide an excess return to risk tradeoff for individuals who are willing to provide market liquidity.

In short, both academics and practitioners have often suggested that the return and risk opportunities of managed futures are available because the skill-based investment strategies employed by managers do not explicitly attempt to track a traditional stock or bond benchmark/index and managed futures traders are able to offer liquidity or make informational trades which may allow them to maximize long-term returns independent of traditional asset benchmarks. However, as discussed previously, passive algorithm-based managed futures indices exist which represent the return process of active managed futures managers (at least systematic managed futures managers). It is important, therefore, to realize that, while managed futures do not emphasize traditional stock and bond benchmark tracking, this does not mean that CTA return is based solely on manager skill. One can think of managed futures returns as a combination of manager skill and an underlying return to the managed futures strategy or investment style itself. The performance of an individual manager can be measured relative to an active manager based CTA benchmark or a passive algorithmic based investible benchmark. If a manager's performance is measured relative to the passive algorithm-based managed futures index/benchmark, then the differential return may be viewed as the manager's 'alpha' (return in excess of a similar non-manager based replicate portfolio). If a manager's performance is measured relative to an index of other active managers, then the relative performance simply measures the over- or underperformance to that index of manager returns.

An analysis of the correlations of the three CTA composite indices with traditional market factors (S&P 500, Russell 2000, BarCap U.S.Government, and BarCap U.S. High Yield) indicate:

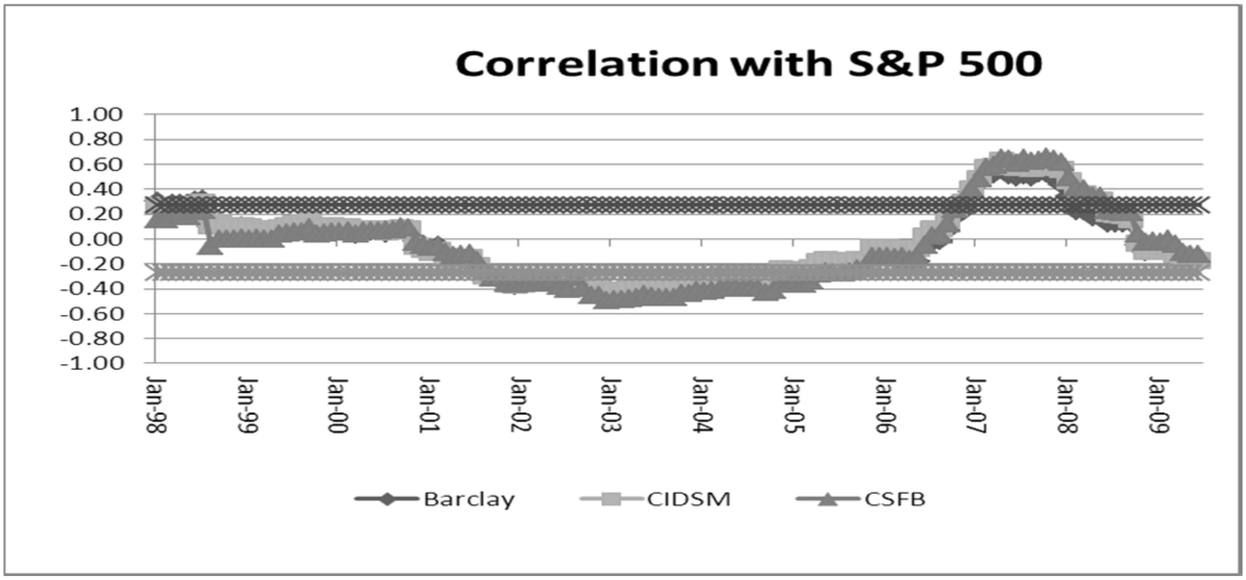
Exhibit 4a - S&P 500 Correlation: For all three reporting CTA indices (Barclay, CISDM, and CSFB) the reported correlation patterns are similar. For most of the period of analysis the correlations were not significantly different from zero and the level of correlation varied dramatically over the period from as high as .60 to as low as -.60. Only for a short time period were the four year rolling correlations significantly negative (2002-2005) or positive (2007).

Exhibit 4b - Russell 2000 Correlation: For all three reporting CTA indices (Barclay, CISDM, and CSFB) the reported correlation patterns are similar to those reported for the S&P 500. For most of the period of analysis the correlations were not significantly different from zero and the level of correlation varied dramatically over the period from as high as .60 to as low as -.40. Only for a short time period were the four year rolling correlations significantly negative (2002-2005) or positive (2007).

Exhibit 4c - BarCap U.S. Gov't Correlation: For all three reporting CTA indices (Barclay, CISDM, and CSFB) the reported correlation patterns are similar, with correlations rising for the first part of the reporting period before beginning to fall in the mid period of the analysis. However for most of the period of analysis the correlations were not significant.

Exhibit 4d - BarCap U.S. Corporate High Yield Correlation: For all three reporting CTA indices (Barclay, CISDM, and CSFB) the reported correlation patterns are similar. For most of the period of analysis, the correlations are not significantly different from zero.

Exhibit 4a: Correlation with S&P 500



*Horizontal Lines Represent Level of Significance

Exhibit 4b: Correlation with Russell 2000

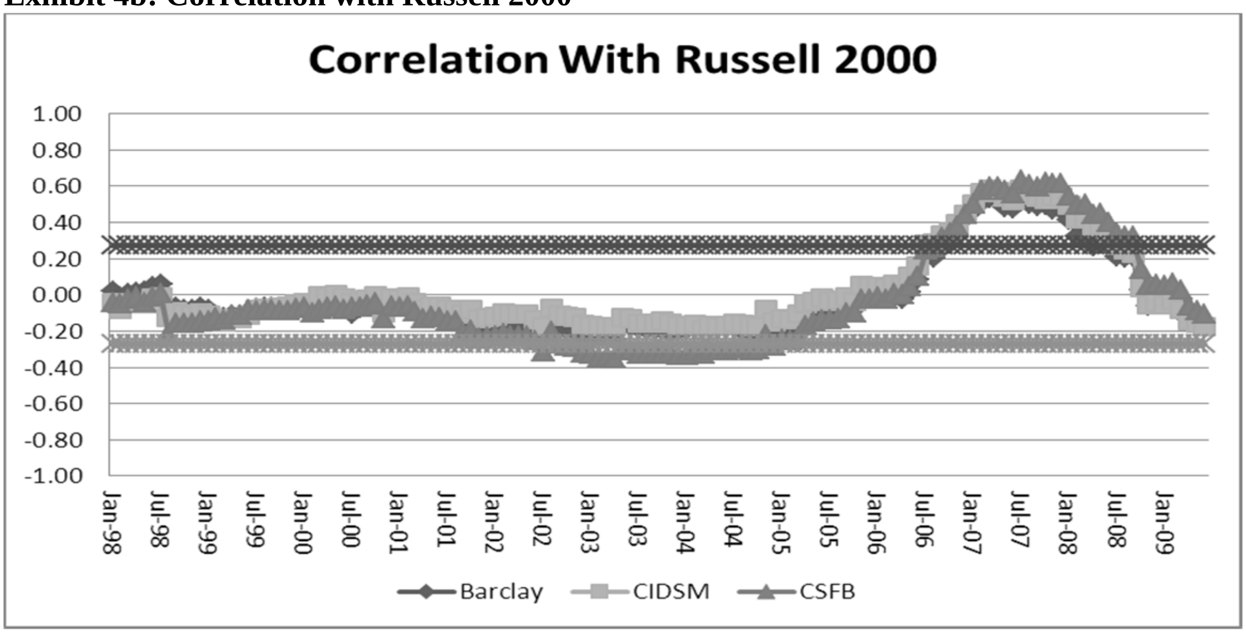


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Exhibit 4c: Correlation with BarCap U.S. Gov't

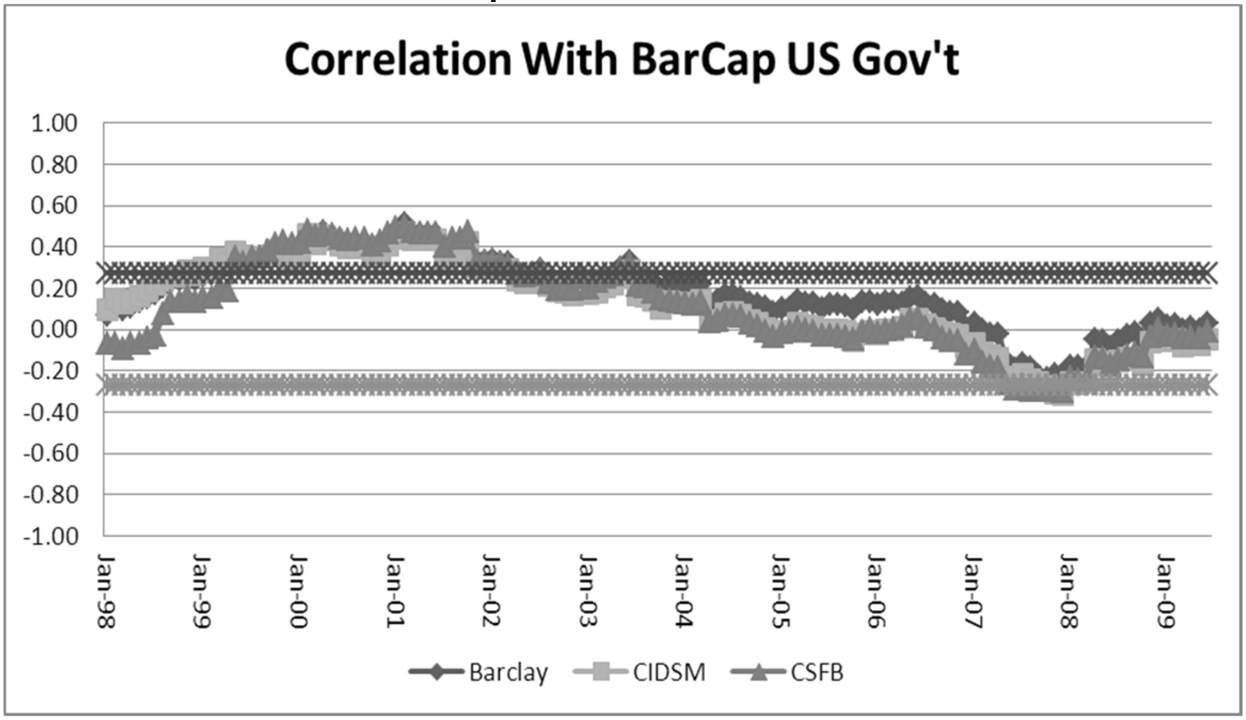

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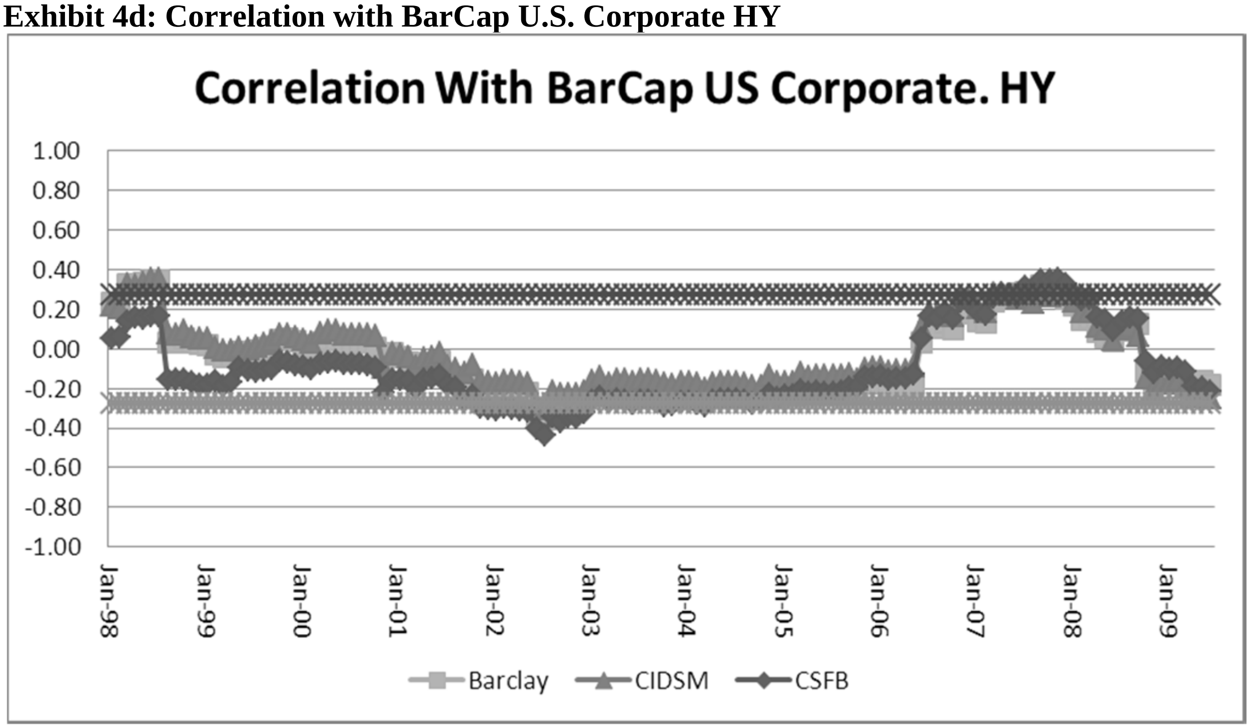
Exhibit 4d: Correlation with BarCap U.S. Corporate HY



*Horizontal Lines Represent Level of Significance

Given the dynamic trading nature of CTAs, the low correlation of CTAs with traditional long bias market factors is not unexpected. Higher correlations are expected between the three CTA composite indices and the dynamic trading (PTFS) and momentum factors (MFSB) factors. Results in Exhibit 5a -5d indicate:

Exhibit 5a - Equity Trading (PTFS) and Momentum (MFSB) Factors: For all three reporting CTA indices (Barclay, CISDM, and CSFB) the reported correlation patterns are similar. For most of the period of analysis the correlations were significantly different from zero although at a relatively low level. The level of correlation remained relatively stable over the period with the correlation varying around .30.

Exhibit 5b - Bond Trading (PTFS) and Momentum (MFSB) Factors: For all three reporting CTA indices (Barclay, CISDM, and CSFB) the reported correlation patterns are similar. For most of the period of analysis the correlations were significant. The level of correlation remained relatively stable over the period with the correlation varying around .60 for the MFSB based momentum factors and at a lower level (.20) for the PTFS factors for much of the central part of the reporting period.

Exhibit 5c - Currency Trading (PTFS) and Momentum (MFSB) Factors: For all three reporting CTA indices (Barclay, CISDM, and CSFB) the reported correlation patterns are similar. For most of the period of analysis the correlations were significant. The level of correlation remained relatively stable over the period, with the correlation varying around .50 for both the MFSB based momentum factors and PTFS trading based factors.

Exhibit 5d - Commodity Trading (PTFS) and Momentum (MFSB) Factors: For all three reporting CTA indices (Barclay, CISDM, and CSFB) the reported correlation patterns are similar. For most of the period of analysis the correlations were significant, although primarily at the start and end of the period of analysis.

Exhibit 5a: Correlation with Equity Based Trading and Momentum Factors

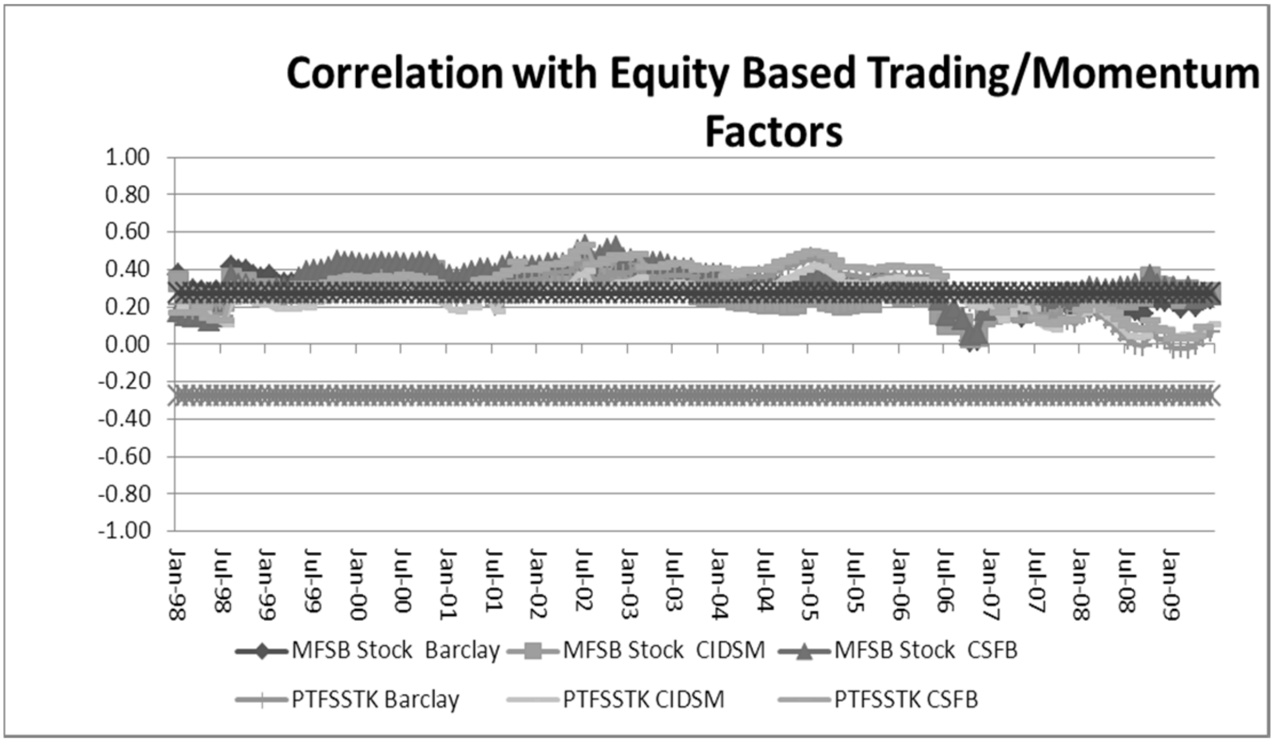


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Exhibit 5b: Correlation with Bond Based Trading and Momentum Factors

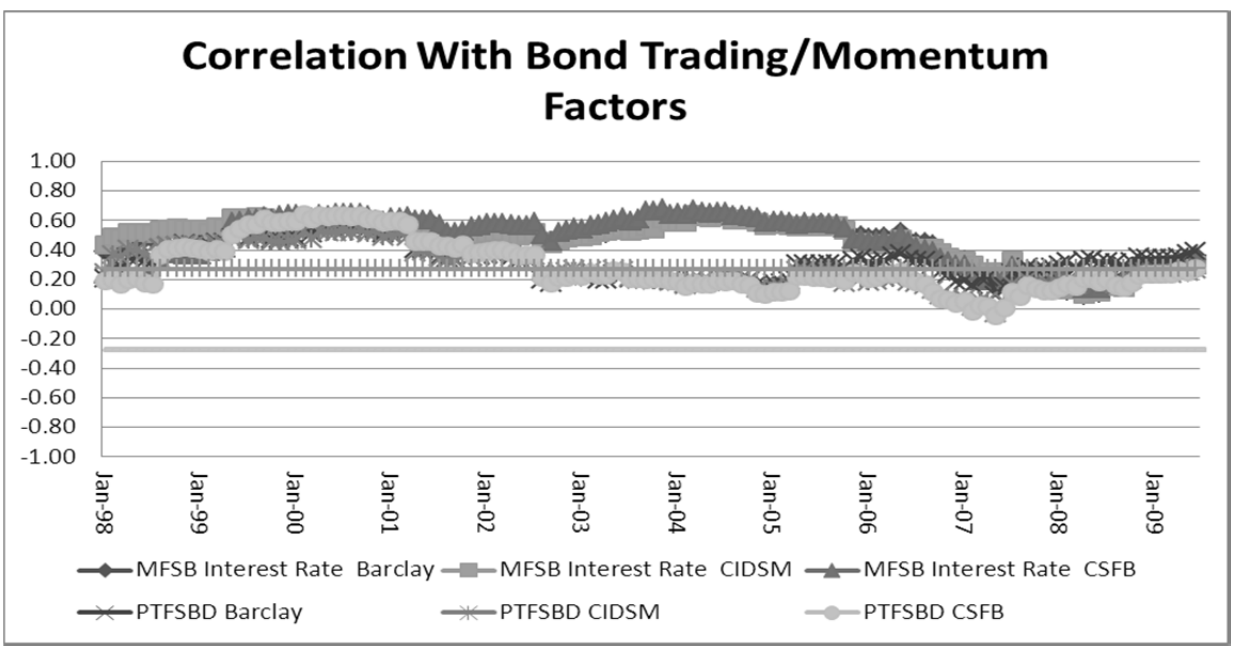

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Exhibit 5c: Correlation with Currency Based Trading and Momentum Factors

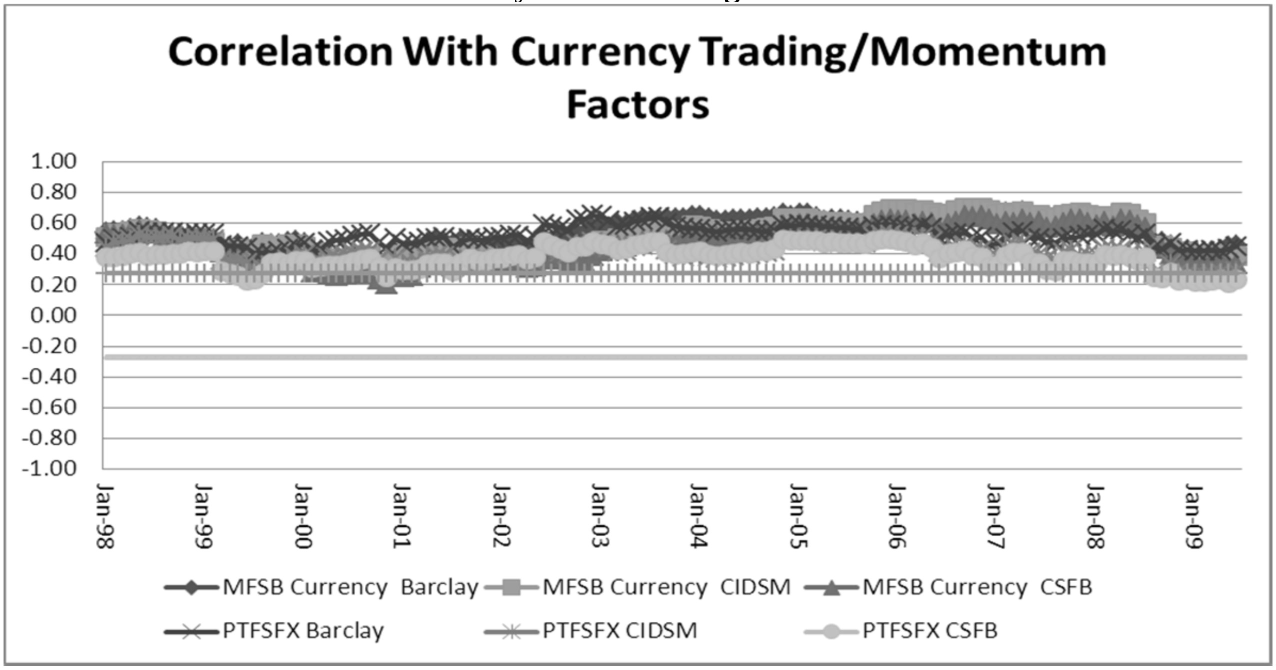

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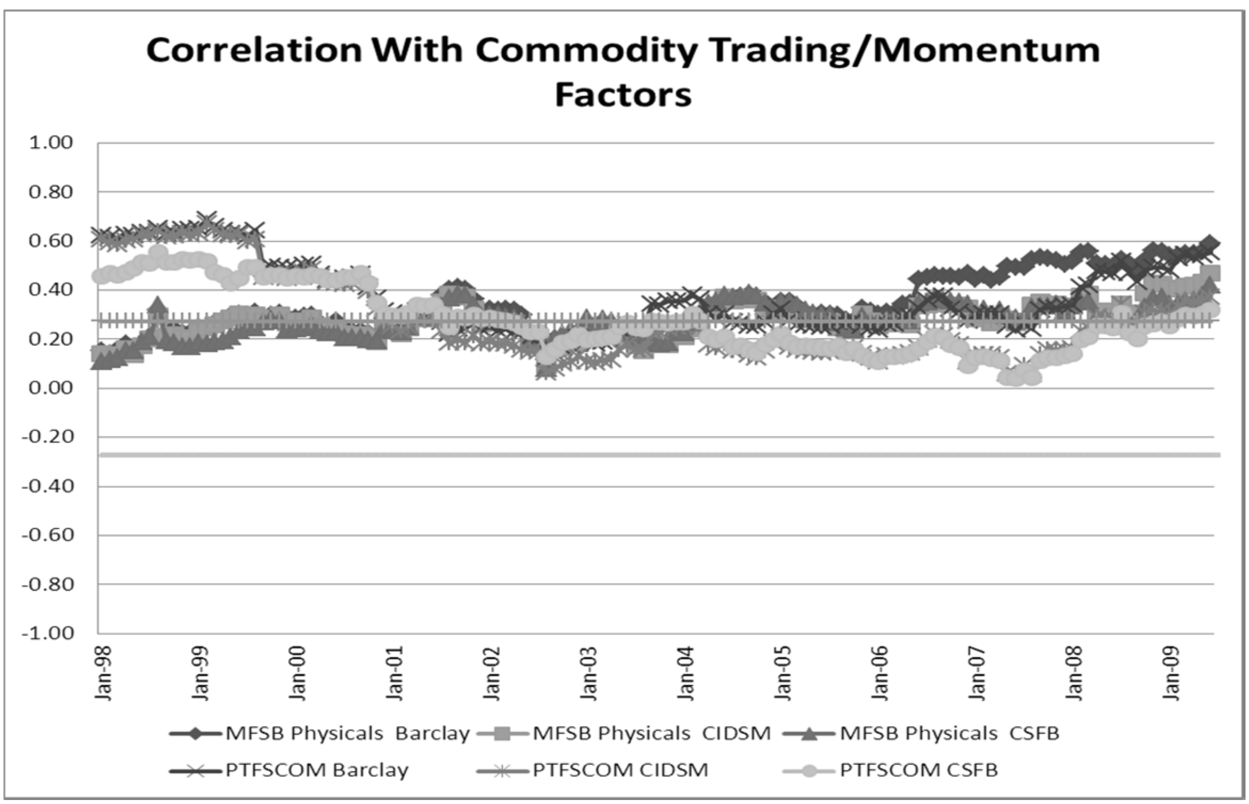
Exhibit 5d: Correlation with Commodity Based Trading and Momentum Factors



*Horizontal Lines Represent Level of Significance

Managed Futures: Return Estimation

In the previous section, the benefits of CTAs as additions to an existing stock and bond portfolio was determined primarily by the statistical properties of the standalone CTA indices and a stock and bond portfolio. The actual market or risk factors driving CTA return are a subject of debate. In the mid-1990s academic analysis (Schneeweis et al., [1998]) on CTA returns used a basic multivariate model in which the independent variables included long positions in fundamental market factors (S&P 500, BarCap U. S. Corporate Aggregate Bond index, Currencies (USDX Currency), and Commodities (GSCI Commodity Index) and absolute value of similar asset returns to capture the ability of CTAs to profit in both up and down markets). As an alternative to the use of absolute values to capture the potential for up and down markets, in the mid-1990s Fung and Hsieh ([1998], [2006]) replaced the use of absolute values with a dynamic lookback straddle. The use of the dynamic trading factors captures the return pattern of a trend following CTA. By the end of the 1990s addition research on CTAs concentrated on creating tradable indices which replicate the underlying trading process (Jaeger [2002], Schneeweis and Spurgin [1998], Spurgin [1999], INGARM [2010]).

The use of market factor 'long bias' factor models, as well as multivariate models which include variables which attempt to capture various dynamic trading processes have become commonplace in alternative investment management research. The multi-factor models are as follows:

Model 1 (Trad): Traditional Four Factor Model (S&P 500, Russell 2000, BarCap U.S. Government and Corporate High Yield).

Model 2 (PTFS): Traditional Four Factor Model (S&P 500, Russell 2000, BarCap U.S. Government and Corporate High Yield) plus Fung and Hsieh four dynamic trading PTFS factors (Equity, Fixed Income, Currency and Commodities).

Model 3 (MFSB): Traditional Four Factor Model (S&P 500, Russell 2000, BarCap U.S. Government and Corporate High Yield) plus four momentum factors (Equity, Fixed Income, Currency and Commodities) based on the Schneeweis and Spurgin (1998) and Spurgin (1999) futures based trend following momentum factors.

Model 4 (ABS): Traditional Four Factor Model (S&P 500, Russell 2000, BarCap U.S. Government and Corporate High Yield) plus Schneeweis and Spurgin (1998) four absolute value factors (Equity, Fixed Income, Currency and Commodities).

Model 5 (FF): Traditional Three Factor Fama-French Equity Factors (Market Factor Excess Return, SMB, HML).

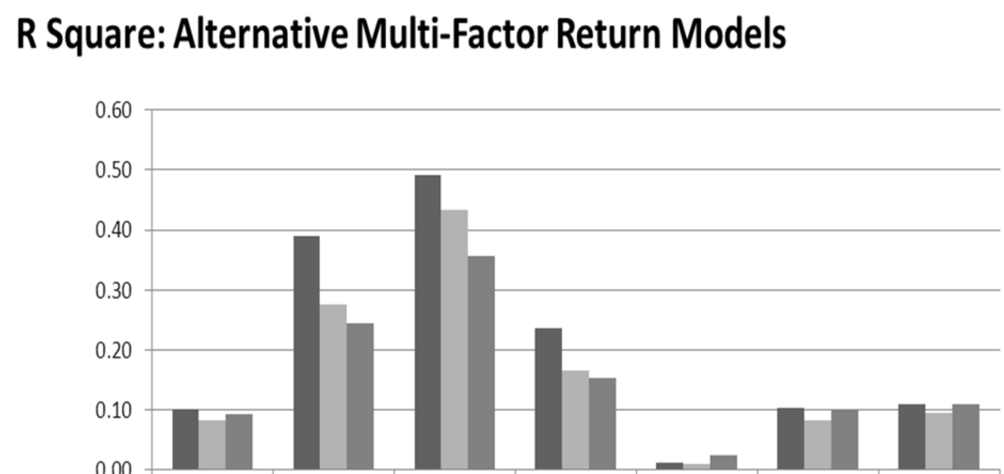
Model 6 (FF/FI): Traditional Three Factor Fama-French Equity Factors (Market Factor Excess Return, SMB, HML) plus Fixed Income Factors (BarCap U.S. Government and Corporate High Yield).

Model 7 (FF ADJ): Traditional Three Factor Fama-French Equity Factors (Market Factor Excess Return, SMB, HML) plus Fixed Income Factors (BarCap U.S. Government and Corporate High Yield) plus Equity Momentum Factor (French, 2010).

What is less common is the analysis of the application of these various model approaches across various databases or representative indices. In this section, we emphasize the impact of a typical four traditional factor/four dynamic trading and momentum based regression model on the analysis of the comparison CTA indices. In Exhibit 6, the T-Stats of each of the factors in a traditional four factor and eight factor model as well as their associated R-Square are presented for each of the three CTA indices. Results show that over the entire period of analysis, the eight factor model dominates the four factor model in terms of reported R-Square. In Exhibit 7a and 7b we provide the cross-sectional T-Stats and R-Square for each of the 8 Factor models (PTFS and MFSB based). In general, the T-Stats of the intercept of the MFSB based eight factor regression are less than those of the PTFS based eight factor regression. This reflects, in part, the higher R-Square of the MFSB based regression relative to that of the PTFS based regression. The differences in T-Stats and R-Square of the MFSB and PTFS regression models are shown in

Exhibit 7c. As shown in Exhibit 7c, the MFSB also reported generally higher T-Stats for the Bond and Currency factors. Of greater interest is the relative performance of the three indices with the MFSB and PTFS based regression models over varying four year rolling time periods.

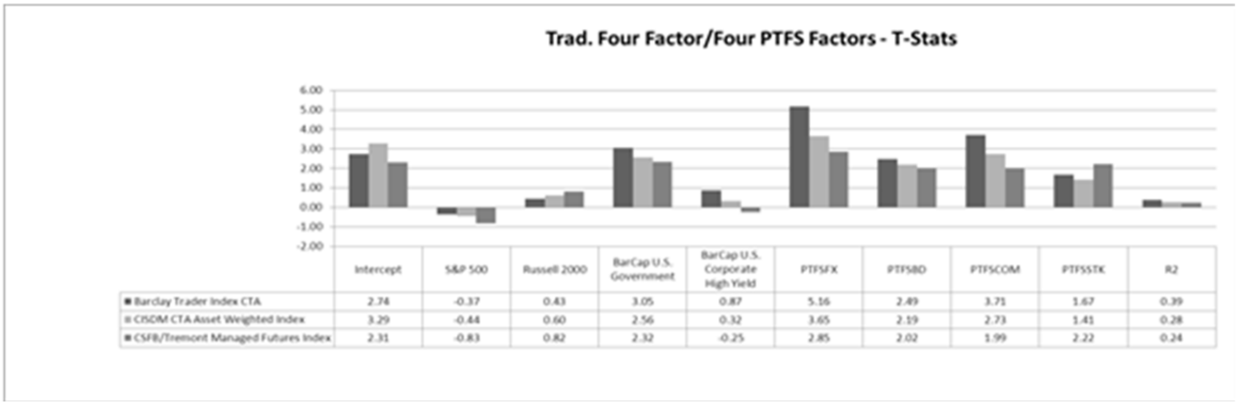
Exhibit 6: Factor Regression Model



	Trad	PTFS	MFSB	ABS	FF	FF/FI	FF ADJ
Barclay Trader Index CTA	0.10	0.39	0.49	0.24	0.01	0.10	0.11
CISDM CTA Asset Weighted Index	0.08	0.28	0.43	0.17	0.01	0.08	0.10
CSFB/Tremont Managed Futures Index	0.09	0.24	0.36	0.15	0.02	0.10	0.11

Period of Analysis: 1994-6/2009

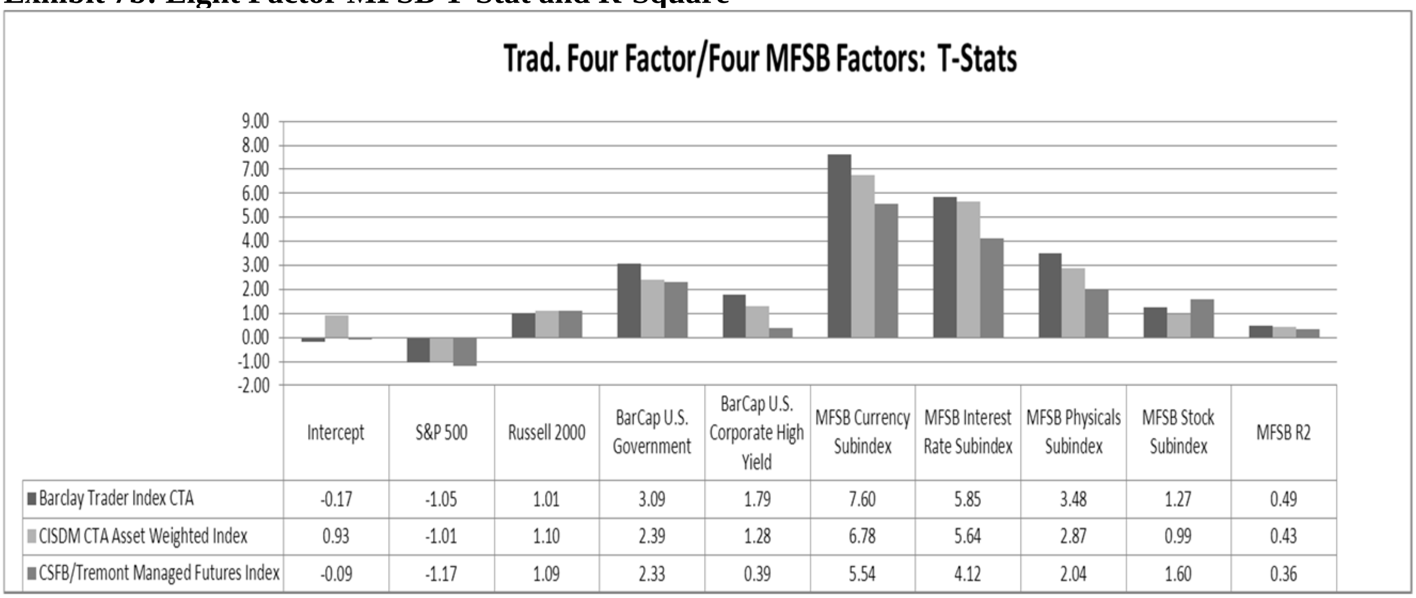
Exhibit 7a: Eight Factor PTFS T-Stat and R-Square



	Intercept	S&P 500	Russell 2000	BarCap U.S. Government	BarCap U.S. Corporate High Yield	PTFSFX	PTFSBD	PTFSCOM	PTFSSTK	R2
Barclay Trader Index CTA	2.74	-0.37	0.43	3.05	0.87	5.16	2.49	3.71	1.67	0.39
CISDM CTA Asset Weighted Index	3.29	-0.44	0.60	2.56	0.32	3.65	2.19	2.73	1.41	0.28
CSFB/Tremont Managed Futures Index	2.31	-0.83	0.82	2.32	-0.25	2.85	2.02	1.99	2.22	0.24

Period of Analysis: 1994-6/2009

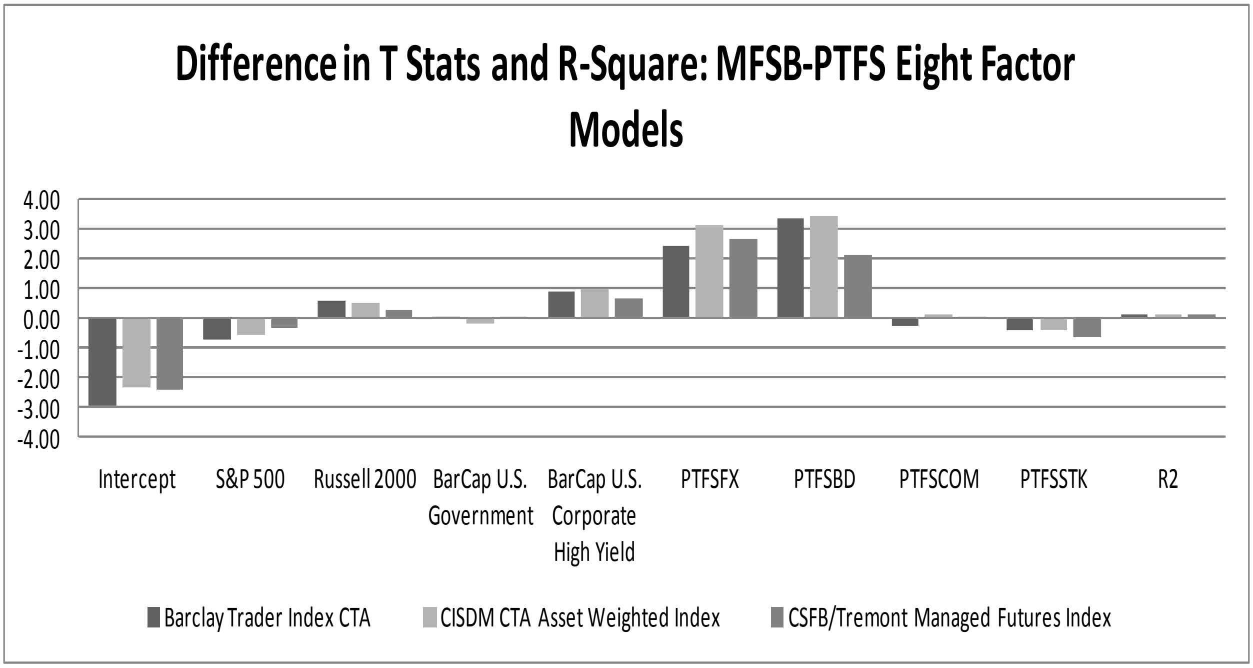
Exhibit 7b: Eight Factor MFSB T-Stat and R-Square



	Intercept	S&P 500	Russell 2000	BarCap U.S. Government	BarCap U.S. Corporate High Yield	MFSB Currency Subindex	MFSB Interest Rate Subindex	MFSB Physicals Subindex	MFSB Stock Subindex	MFSB R2
Barclay Trader Index CTA	-0.17	-1.05	1.01	3.09	1.79	7.60	5.85	3.48	1.27	0.49
CISDM CTA Asset Weighted Index	0.93	-1.01	1.10	2.39	1.28	6.78	5.64	2.87	0.99	0.43
CSFB/Tremont Managed Futures Index	-0.09	-1.17	1.09	2.33	0.39	5.54	4.12	2.04	1.60	0.36

Period of Analysis: 1994-6/2009

Exhibit 7c: Differences in T-Stat and R-Square: MFSB-PTFS Regression Models



Period of Analysis: 1994-6/2009

In Exhibits 8 through Exhibit 17 results are based on four year rolling regressions using monthly returns. The time varying T-stats of the various independent regression factors are presented. Results in Exhibit 8 though Exhibit 17 show:

Exhibit 8a and 8b: R-Square: The R-Square for both the PTFS and MSFB regressions were above .5 for most of the period of analysis. However, for the period prior to 2000, the CSFB CTA index had the lowest R-Square in both regression models. Lastly, as discussed later, the R-Squares of the MFSB based regressions generally dominated those of the PTFS based regressions.

Exhibit 9a and 9b: Intercept: The T-Stats for the intercept for both the PTFS and the MSFB regressions were rarely significant over the period of analysis. Only in the very last part of the analysis period were the T-Stast consistently greater than two.

Exhibit 10a and 10b: S&P 500: The T-Stats for the S&P 500 for both the PTFS and the MSFB regressions were rarely significant over the period of analysis. Moreover, the pattern of the T-Stats were similar for the two regression based approaches.

Exhibit 11a and 11b: Russell 2000: The T-Stats for the Russell 2000 for both the PTFS and the MSFB regressions were rarely significant over the period of analysis. Moreover, the pattern on T-Stats differed in that the MFSB based regressions exhibited higher T-Stats for the latter part of the period of analysis.

Exhibit 12a and 12b: BarCap U.S. Gov't: In contrast to the other market factors, the T-Stats for the BarCap U.S. Gov't factor were significant and the patterns similar for both regression forms (PTFS and MFSB) for most of the period of analysis.

Exhibit 13a and 13b: BarCap U.S. Corporate High Yield: In contrast to the other bond market factor (BarCap U.S. Gov't), the T-Stats for the BarCap U.S. Corporate High Yield factor were not significant for both regression forms (PTFS and MFSB) for most of the period of analysis.

Exhibit 14a and 14b: PTFS and MFSB Bond: Results indicate that the T-Stats of the trading (PTFS) and momentum (MFSB) bond factors were significant for both the PTFS and MFSB based regression models. Of the two regression models and two bond trading/momentum factors, the MFSB bond factor had the highest T-Stat over the period of analysis. These results indicate a greater consistency of the MFSB based approach, making it superior to one based on the PTFS factors.

Exhibit 15a and 15b: PTFS and MFSB Currency: Results indicate that the T-Stats of the trading (PTFS) and momentum (MFSB) currency factors were significant for both the PTFS and

MFSB based regression models. Of the two regression models and two bond trading/momentum factors, the MFSB bond factor had the highest T-Stat over the period of analysis. These results further indicate a greater consistency between the MFSB strategy based factor approach, than one based on a general factor approach (e.g., lookback straddles).

Exhibit 16a and 16b: PTFS and MFSB Stock: Results indicate that the T-Stats of the trading (PTFS) and momentum (MFSB) stock factors were not significant for both the PTFS and MFSB based regression models. Of the two regression models and two equity trading/momentum factors, the MFSB stock factor had the lowest T-Stat over the period of analysis. It is important to note, that for each of the four MFSB momentum factors analyzed, the MFSB based process seems to be weakest in capturing the momentum patterns of equity. In short, if unique momentum models were optimized for each market factor, results may not directly reflect those used in this analysis.

Exhibit 17a and 17b: PTFS and MFSB Commodity: Results indicate that the T-Stats of the trading (PTFS) and momentum (MFSB) commodity factors were not significant for both the PTFS and MFSB based regression models at the start and end of the period. Of the two regression models and two bond trading/momentum factors, the MFSB commodity factor generally had the highest T-Stat over the period of analysis.

Exhibit 8a Eight Factor PTFS R-Square

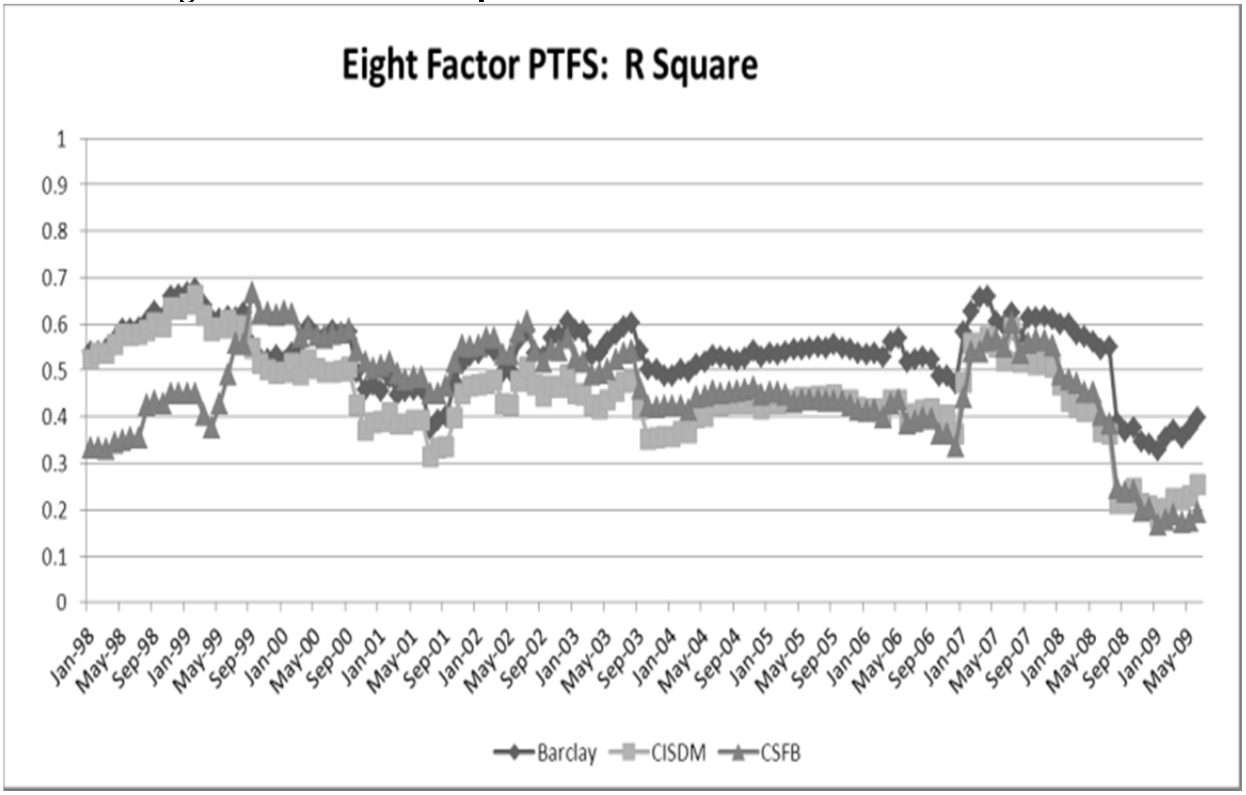


Exhibit 8b: Eight Factor MFSB R-Square

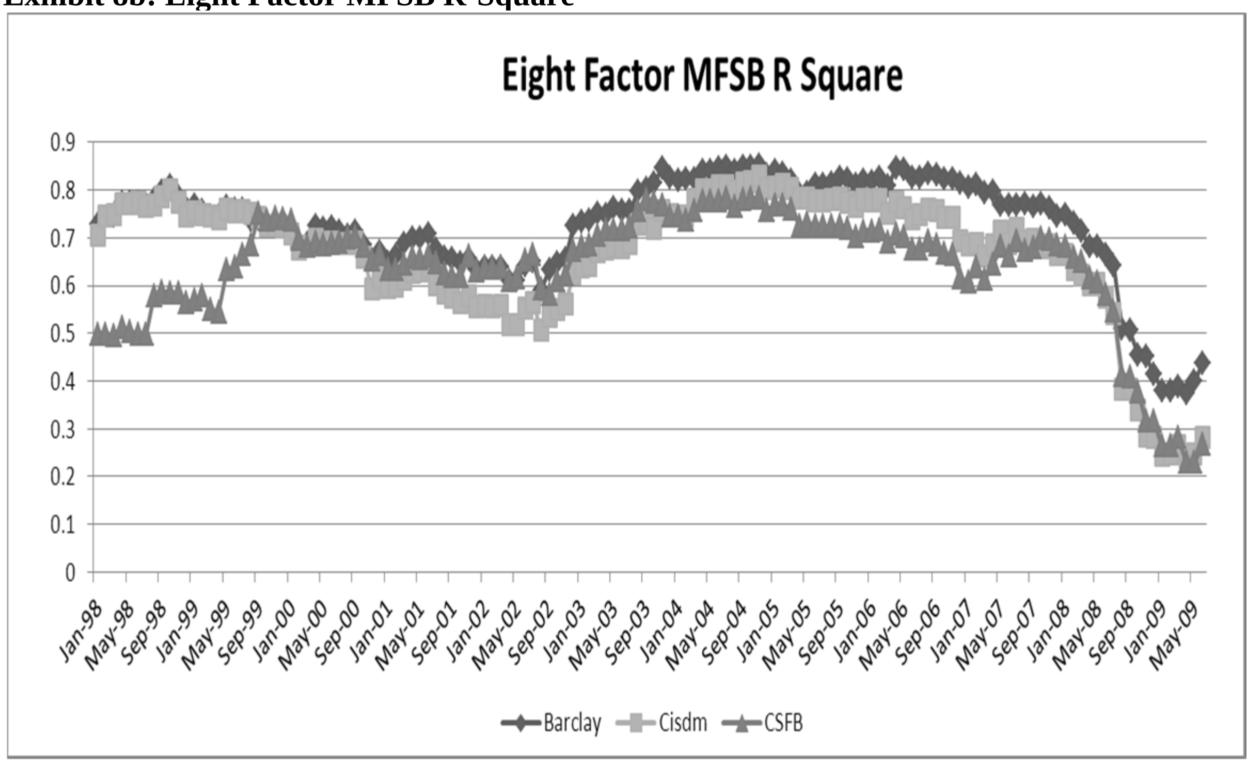
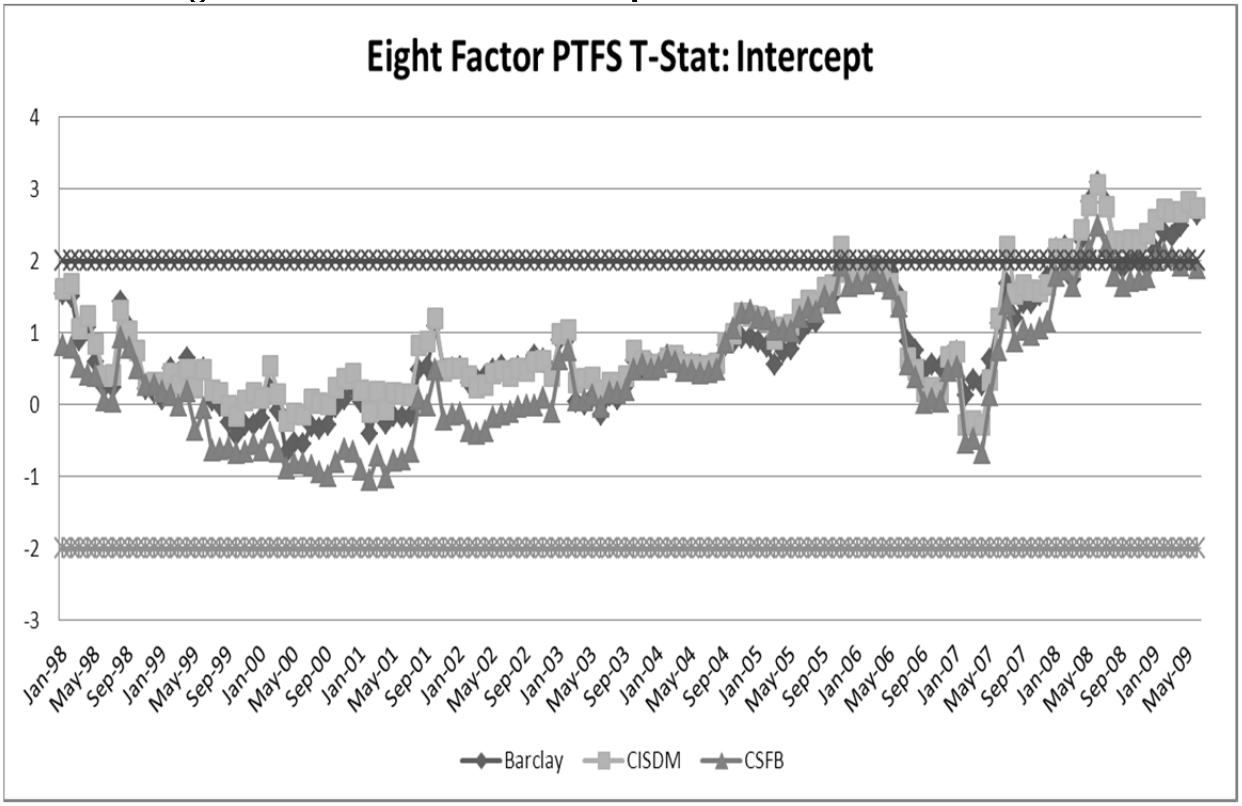
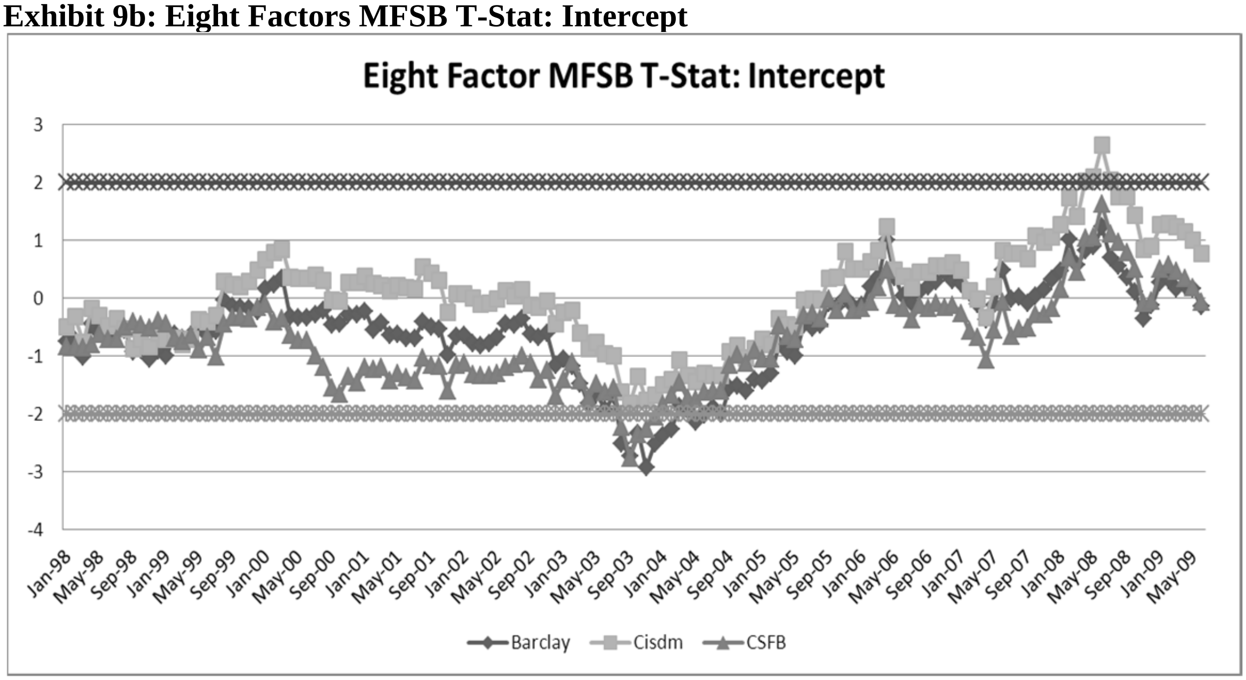


Exhibit 9a: Eight Factor PTFS T-Stat: Intercept



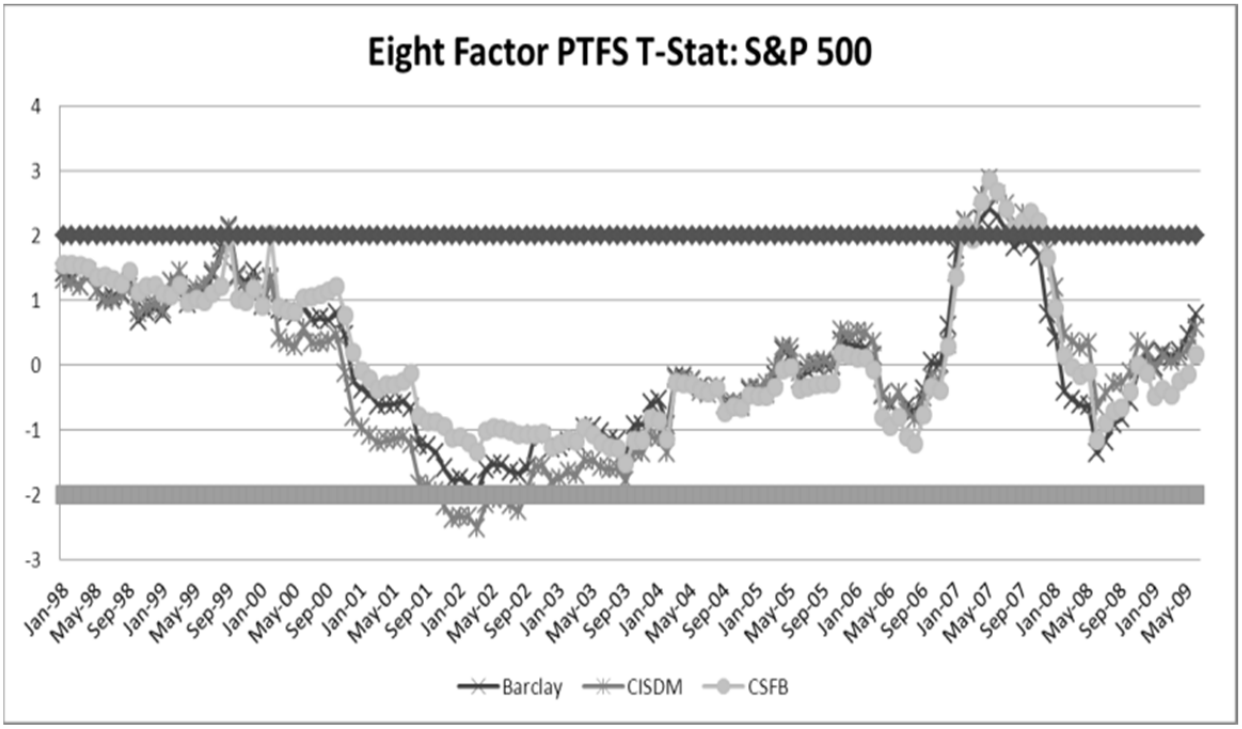
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 9b: Eight Factors MFSB T-Stat: Intercept



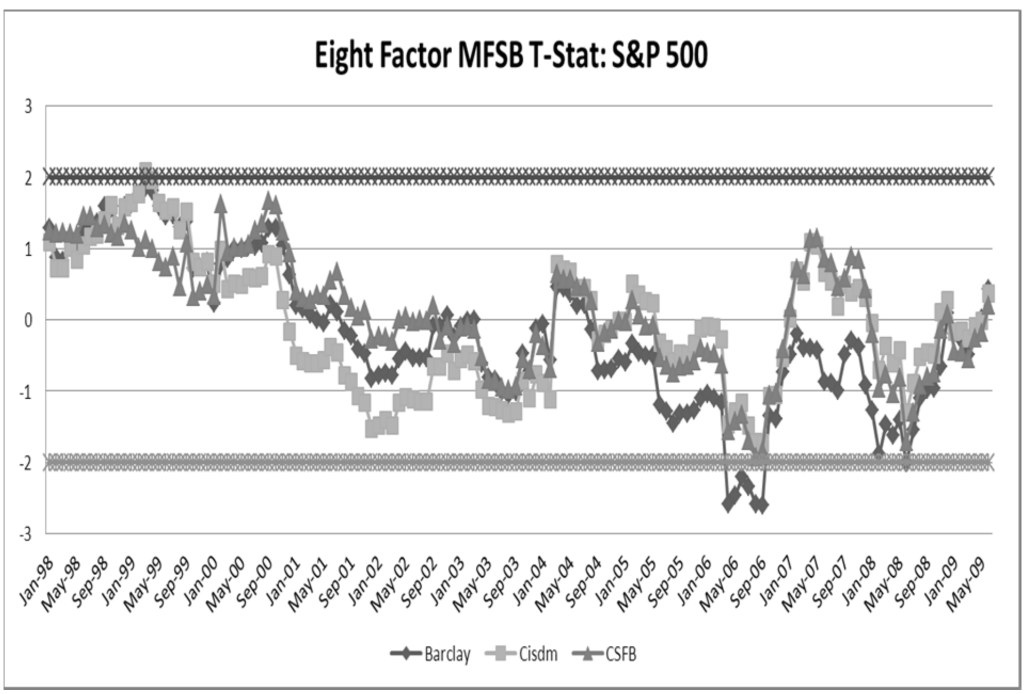
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 10a: Eight Factor PTFS T-Stat: S&P 500



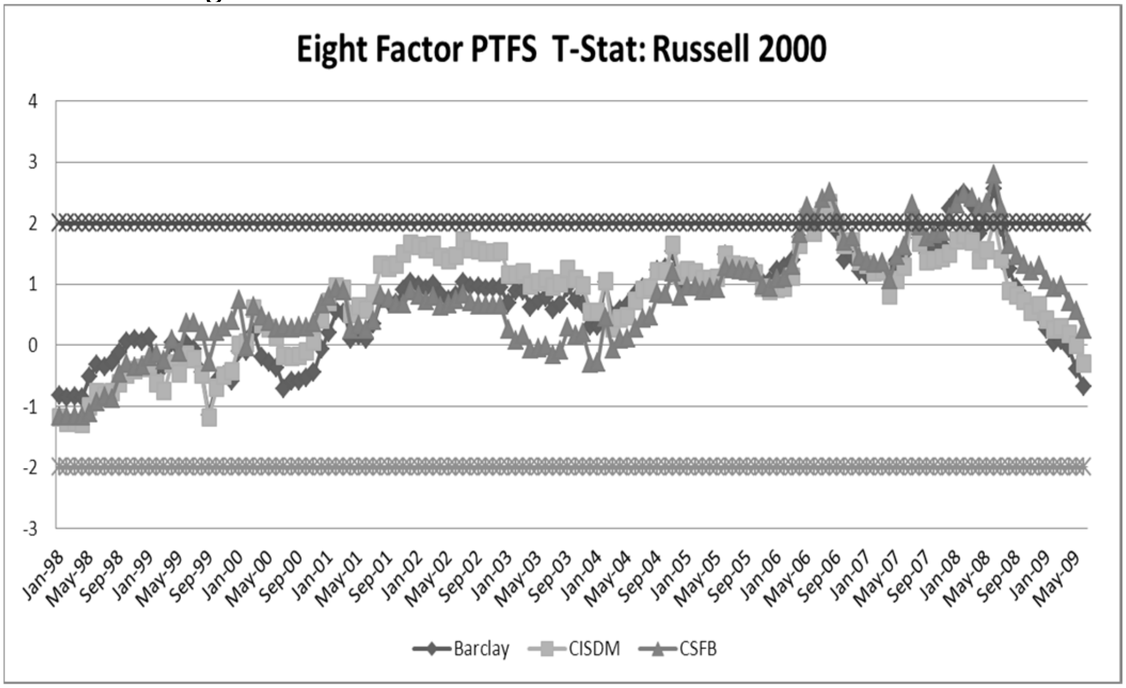
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 10b: Eight Factor MFSB T-Stat: S&P 500



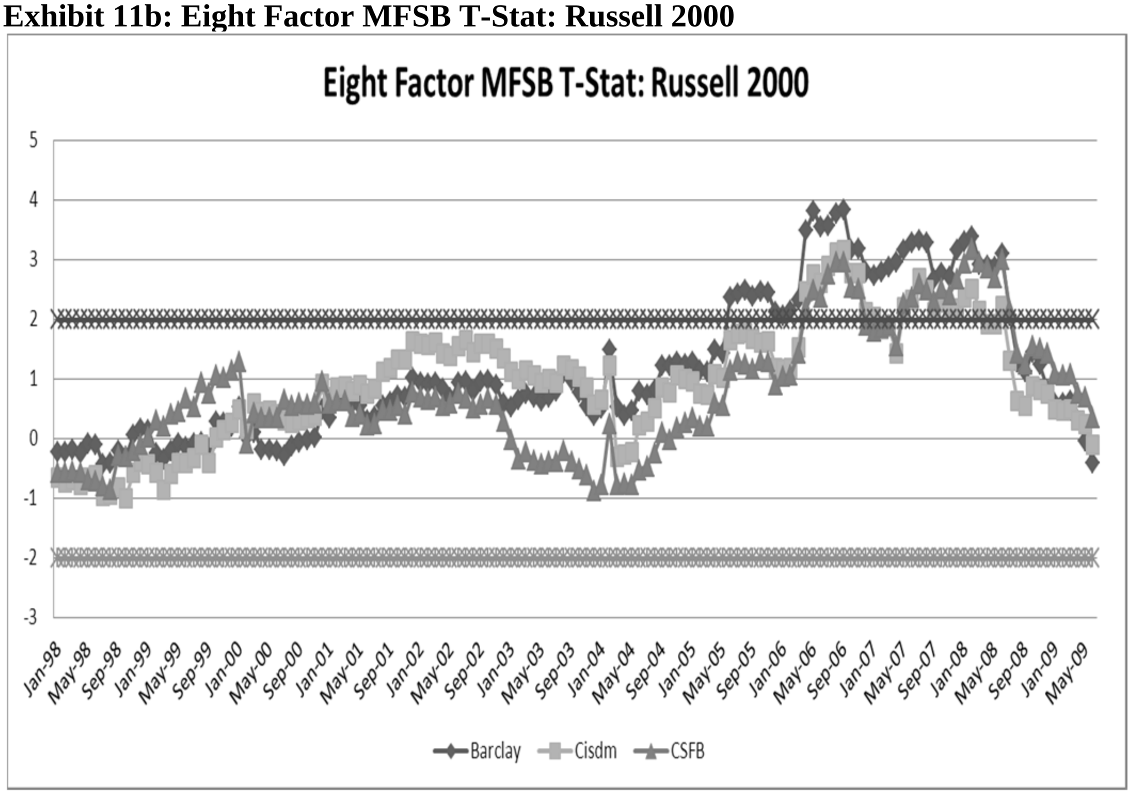
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 11a: Eight Factor PTFS T-Stat: Russell 2000



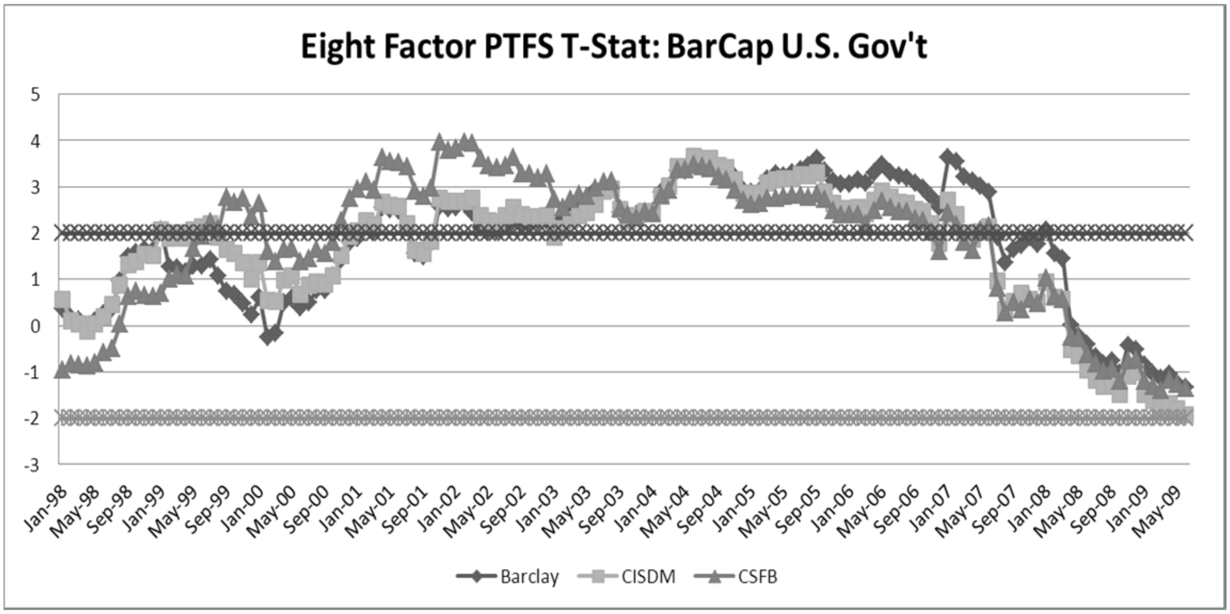
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 11b: Eight Factor MFSB T-Stat: Russell 2000



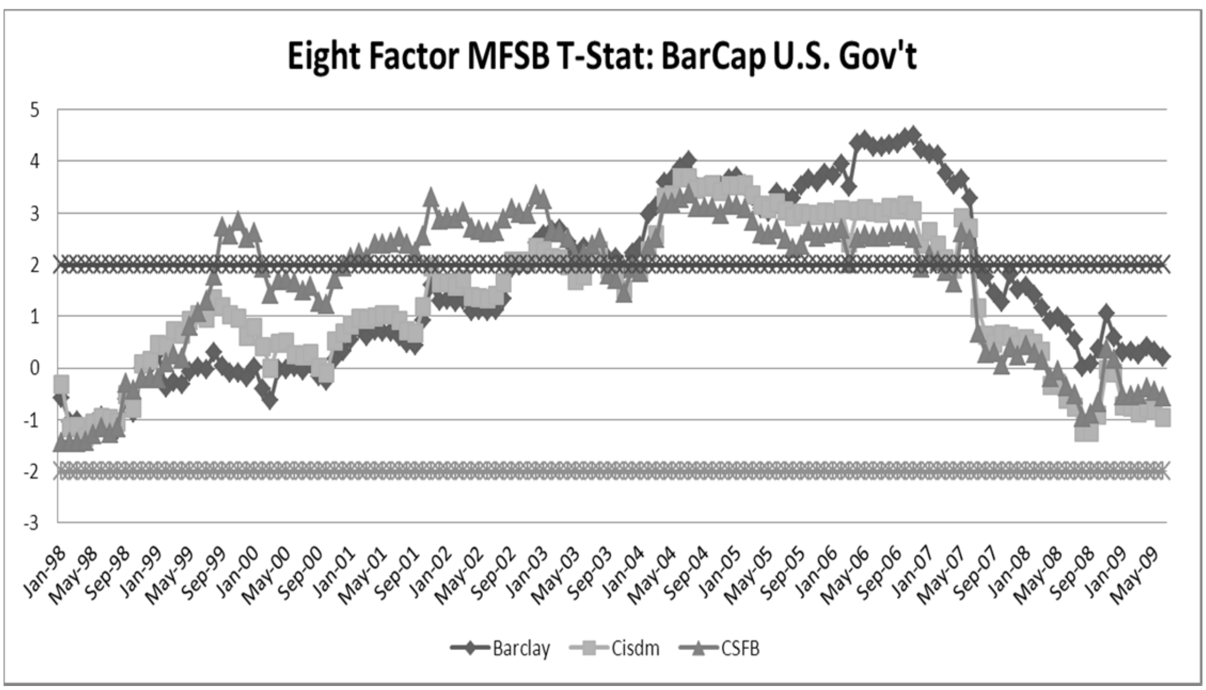
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 12a: Eight Factor PTFS T-Stat: BarCap U.S. Govt



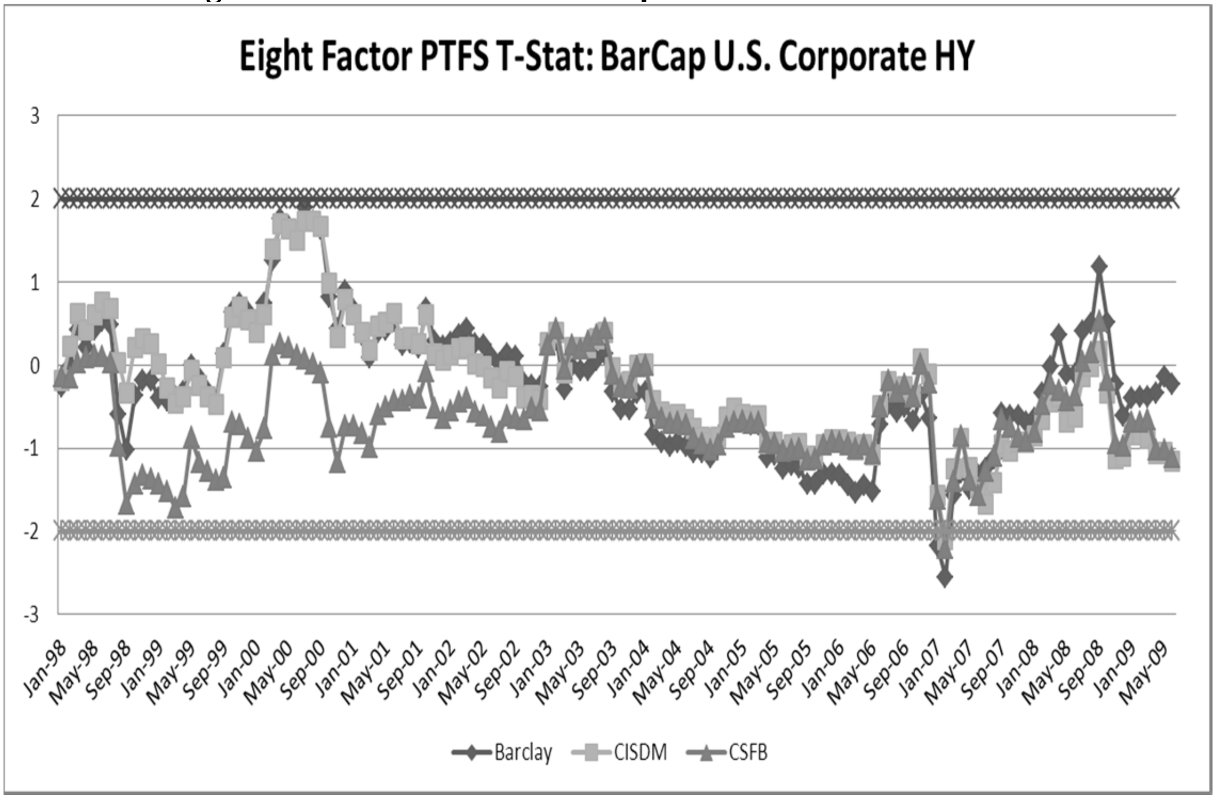
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 12b: Eight Factor MFSB T-Stat: BarCap U.S. Govt



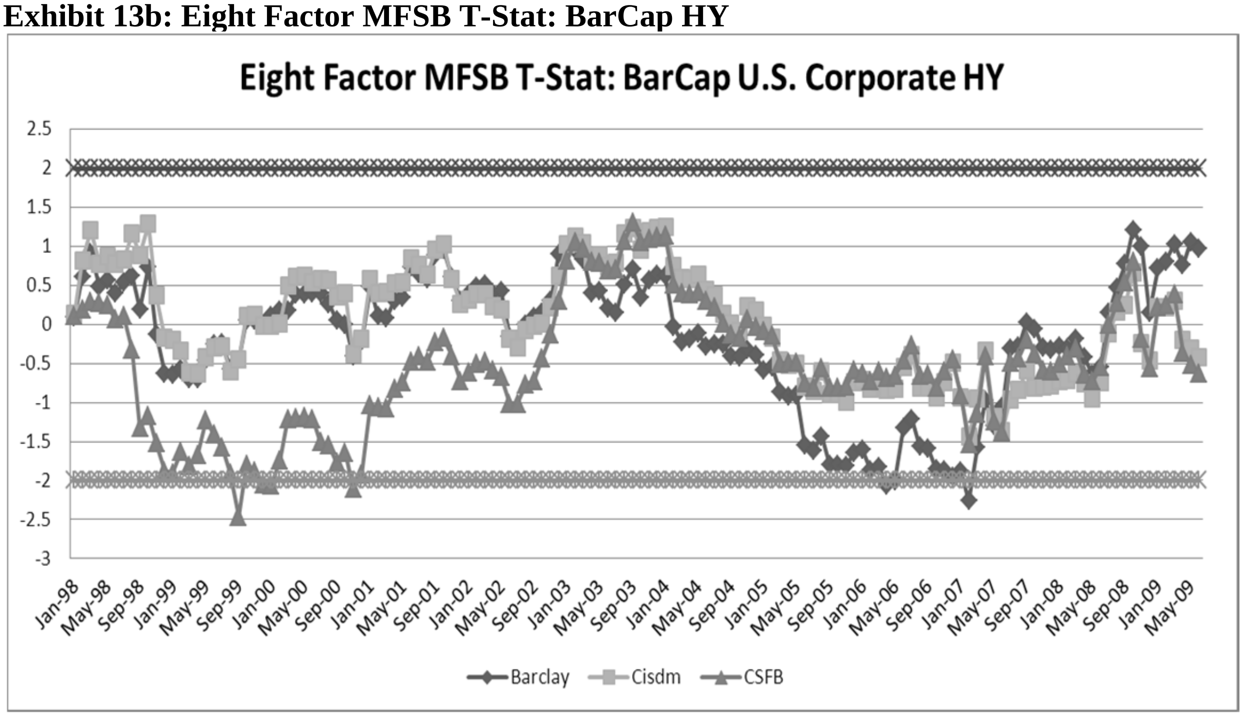
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 13a: Eight Factor PTFS T-Stat: BarCap HY



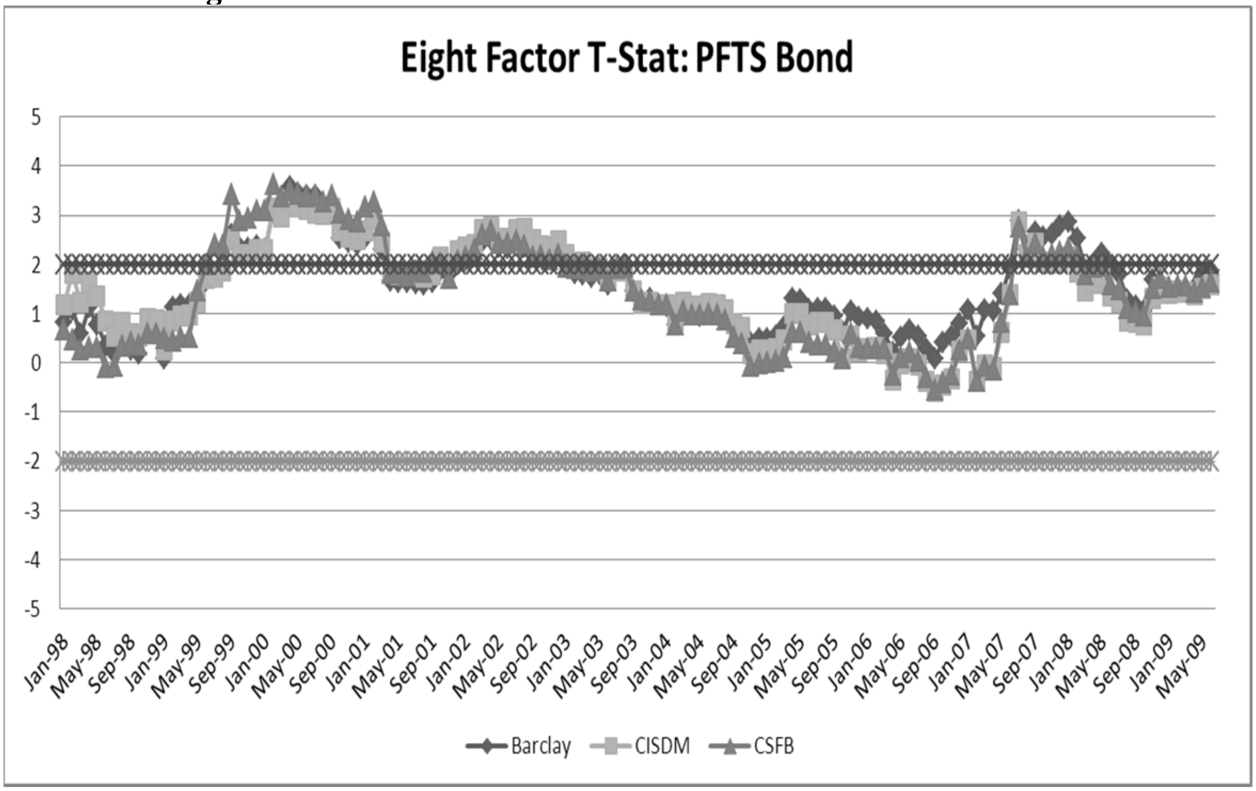
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 13b: Eight Factor MFSB T-Stat: BarCap HY



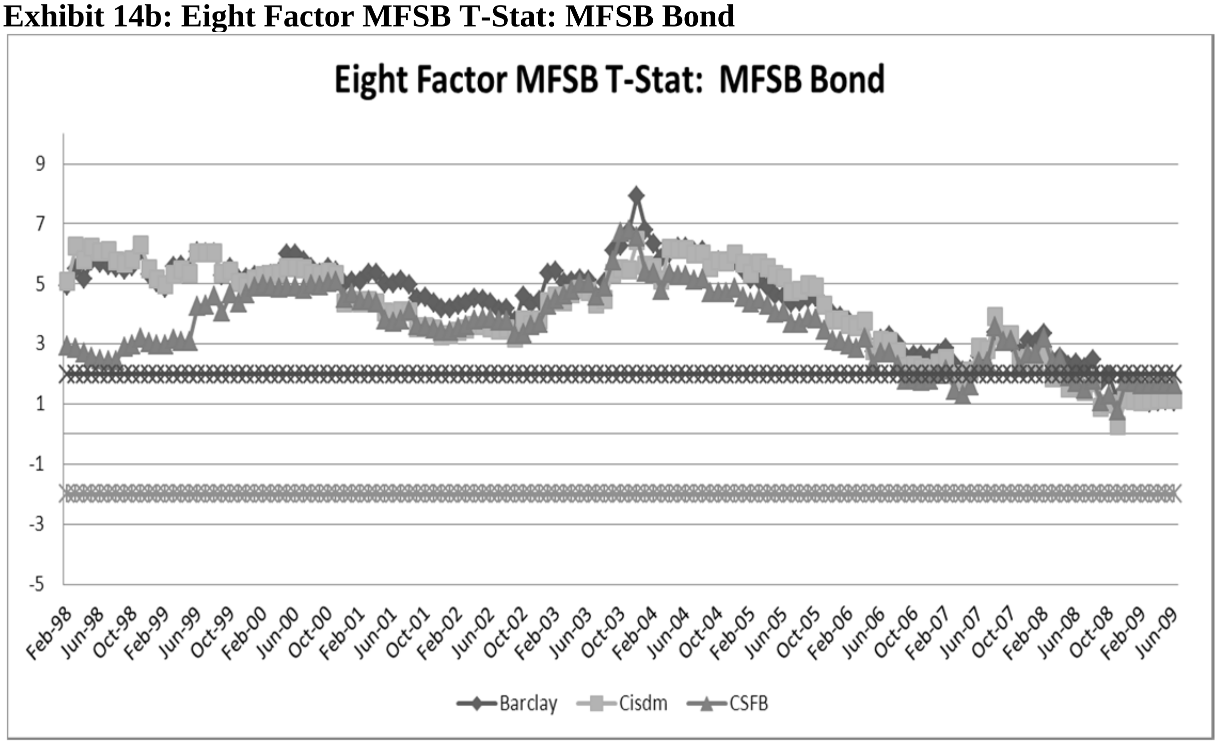
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 14a: Eight Factor PTFS T-Stat: PTFS Bond



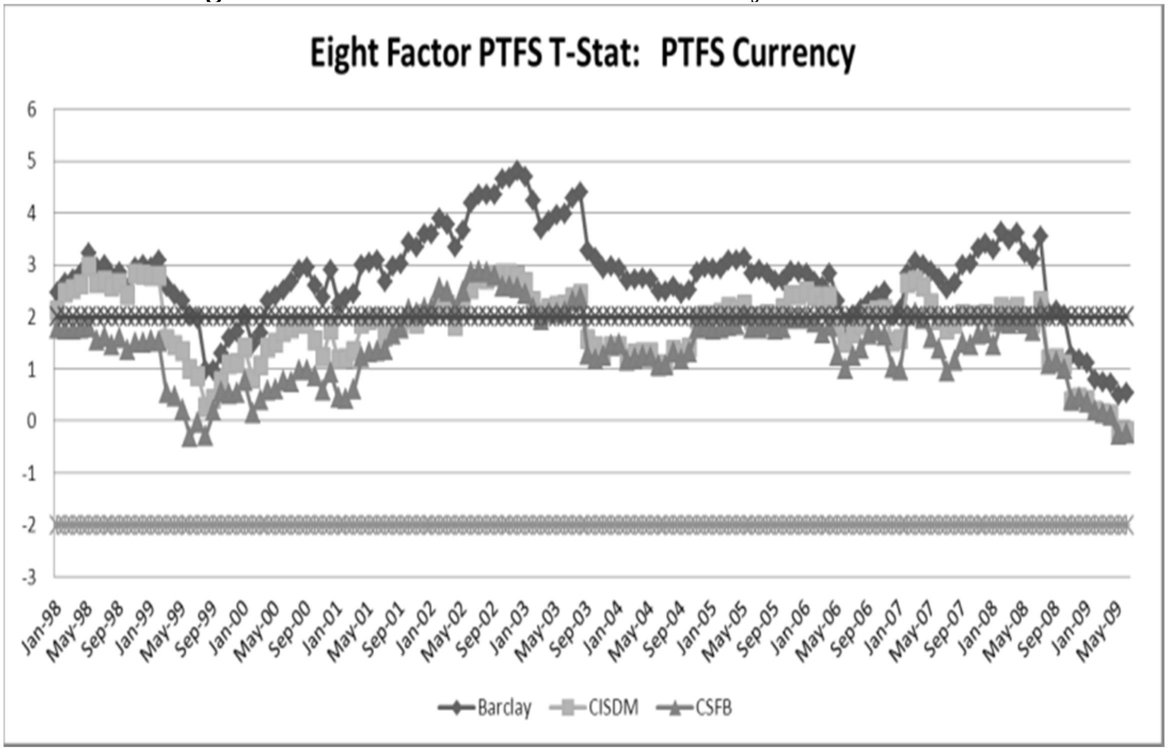
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 14b: Eight Factor MFSB T-Stat: MFSB Bond



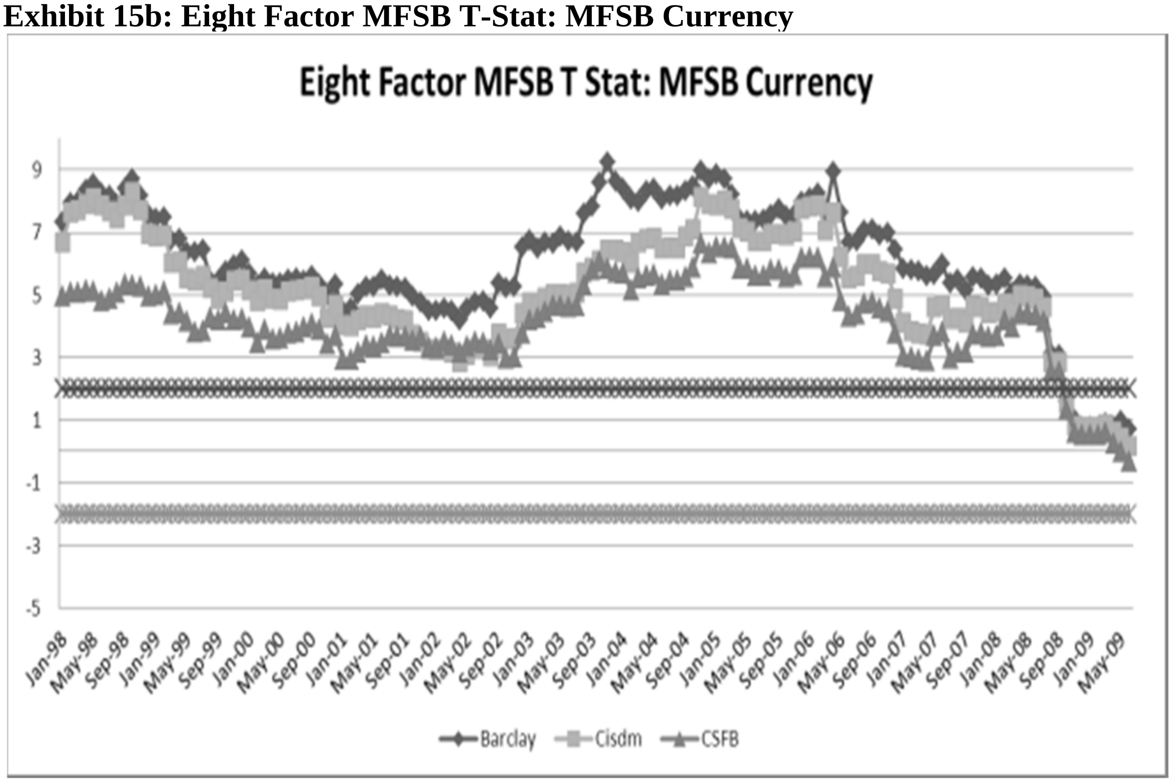
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 15a: Eight Factor PTFS T-Stat: PFTS Currency



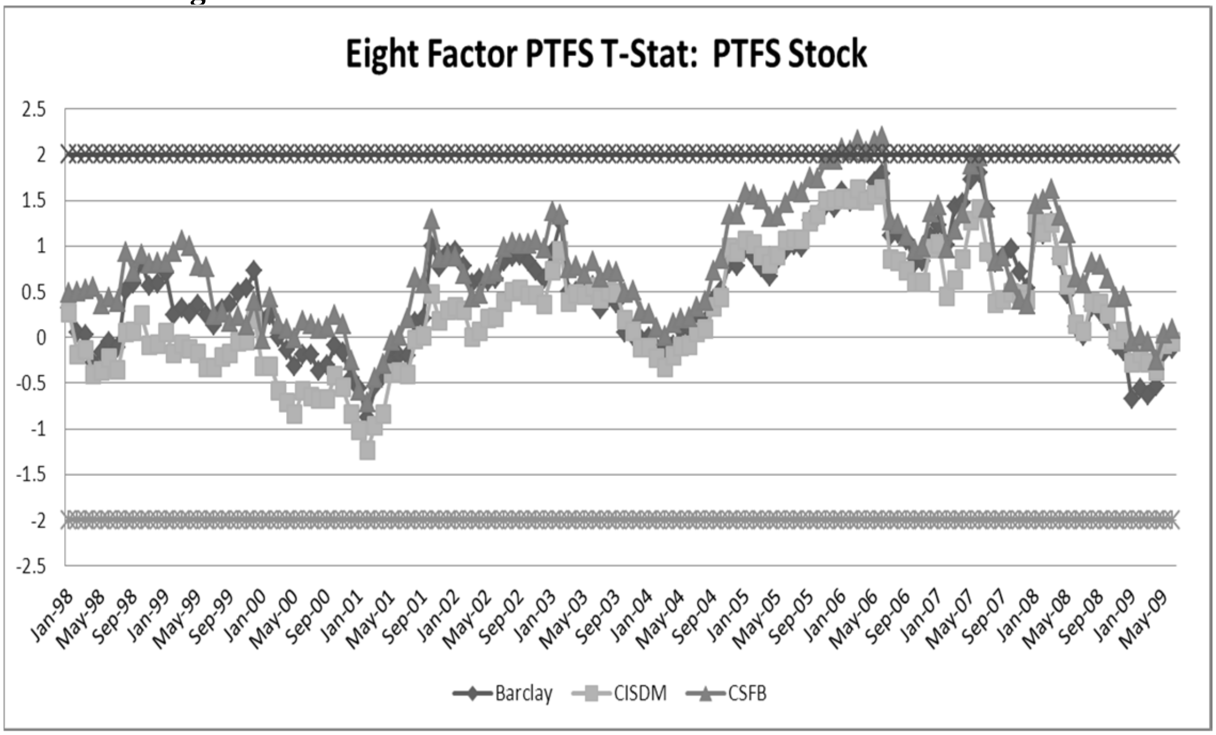
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 15b: Eight Factor MFSB T-Stat: MFSB Currency



*Horizontal Lines Represent Two Standard Errors From Zero

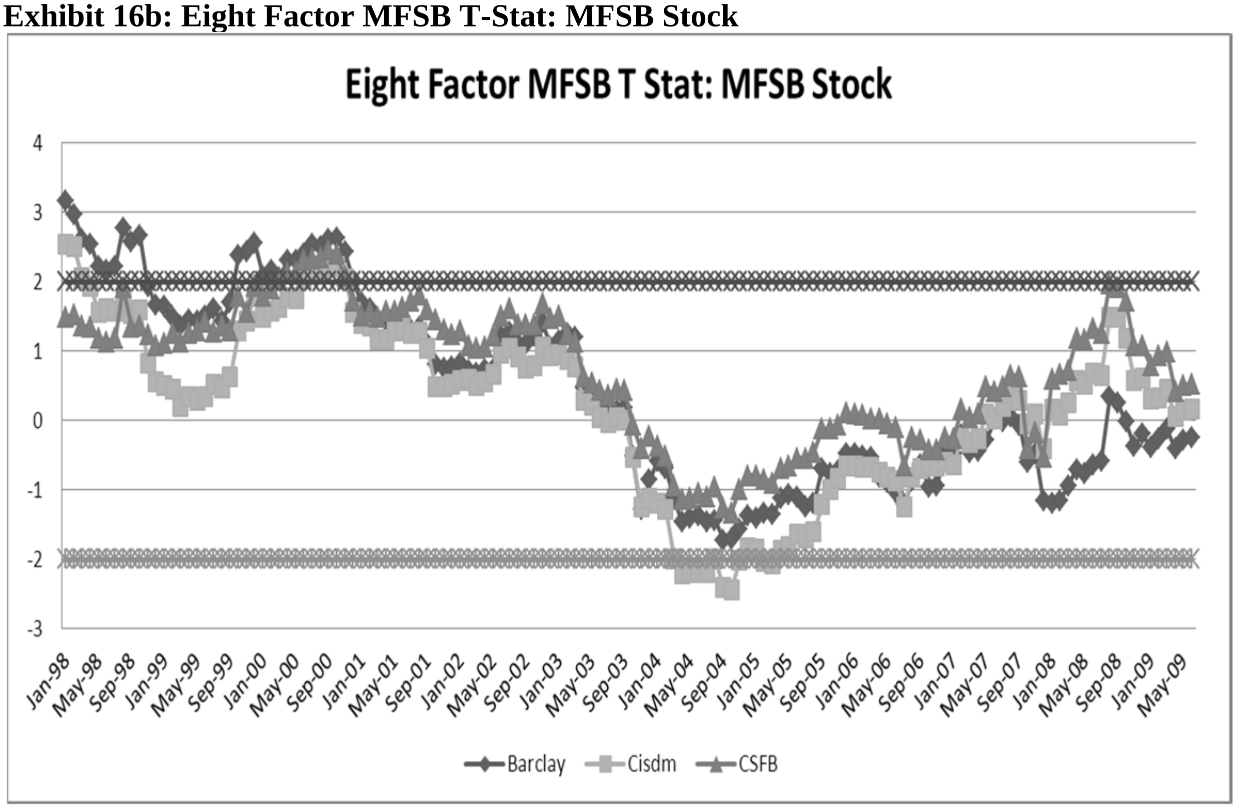
Exhibit 16a: Eight Factor PTFS T-Stat: PTFS Stock



h

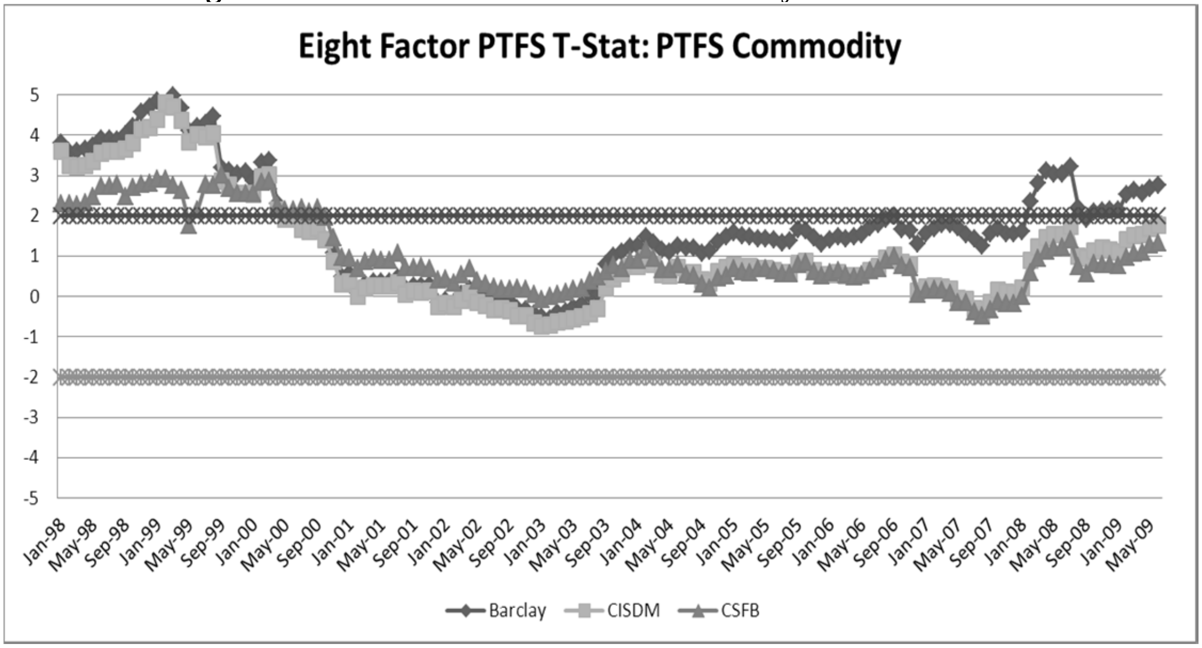
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 16b: Eight Factor MFSB T-Stat: MFSB Stock



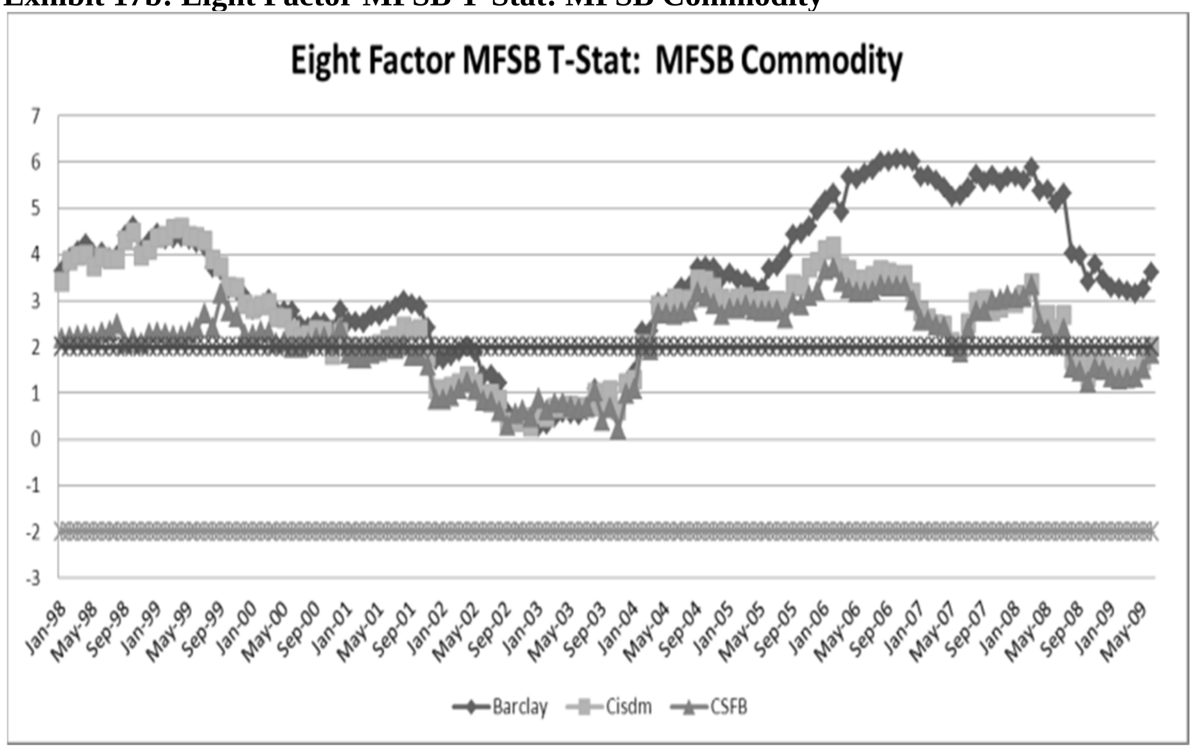
*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 17a: Eight Factor PTFS T-Stat: PTFS Commodity



*Horizontal Lines Represent Two Standard Errors From Zero

Exhibit 17b: Eight Factor MFSB T-Stat: MFSB Commodity



*Horizontal Lines Represent Two Standard Errors From Zero

Managed Futures: Comparison Regression Models

Questions remain, however, as to the importance of the two multi-factor regression models used in the analysis in explaining CTA return. In Exhibit 18, the four year rolling R-Square of the various multi-factor regression models on the CISDM CTA AW index are shown. While the MFSB based regression model remains the dominant regression format, the relative superiority of the model varies over time. Of greater importance is the use of a four year rolling analysis when reviewing the T-Stats of the MFSB and PTFS factors. The results in Exhibits 19a and 19b are based on four year rolling regressions on monthly returns. The four year moving T-Stats of each of the four MFBS factors and four PF factors are provided and the dynamic nature of the significance of the various factors are illustrated. Results show the potential impact of the period of analysis on assessing particular trading approaches, however, the T-Stats of the MFSB factors (interest rate and currency) remain the dominant factors in the MFSB regression but the relative significance of these factors in the PTFS regressions vary dramatically over time.

The changing relative importance of the use of the MFSB and PTFS factors are illustrated in Exhibits 20a and 20b. In Exhibit 20a, the time series of the difference between the multi-factor MFSB based R-Square and the multi-factor PTFS based R-Square is presented. Over the approximately twelve year reporting period (1998-6/2009) the R-Square for the MFSB based multi-factor model was higher than the R-Square of the PTFS based model in all periods with a minimum difference of .05 and a maximum of .40. As shown in Exhibit 20b, similar differences exist between the reported T-Stats of comparable factors of the MFSB and PTFS models. Again, the MFSB T-Stats generally dominate those of the PTFS (For interested readers, the differential T-Stats and R-Squares for the three CTA indices for the MFSB and PTFS regression models are given in Appendix I.).

Exhibit 18: CISDM CTA Regression Models: R-Squares

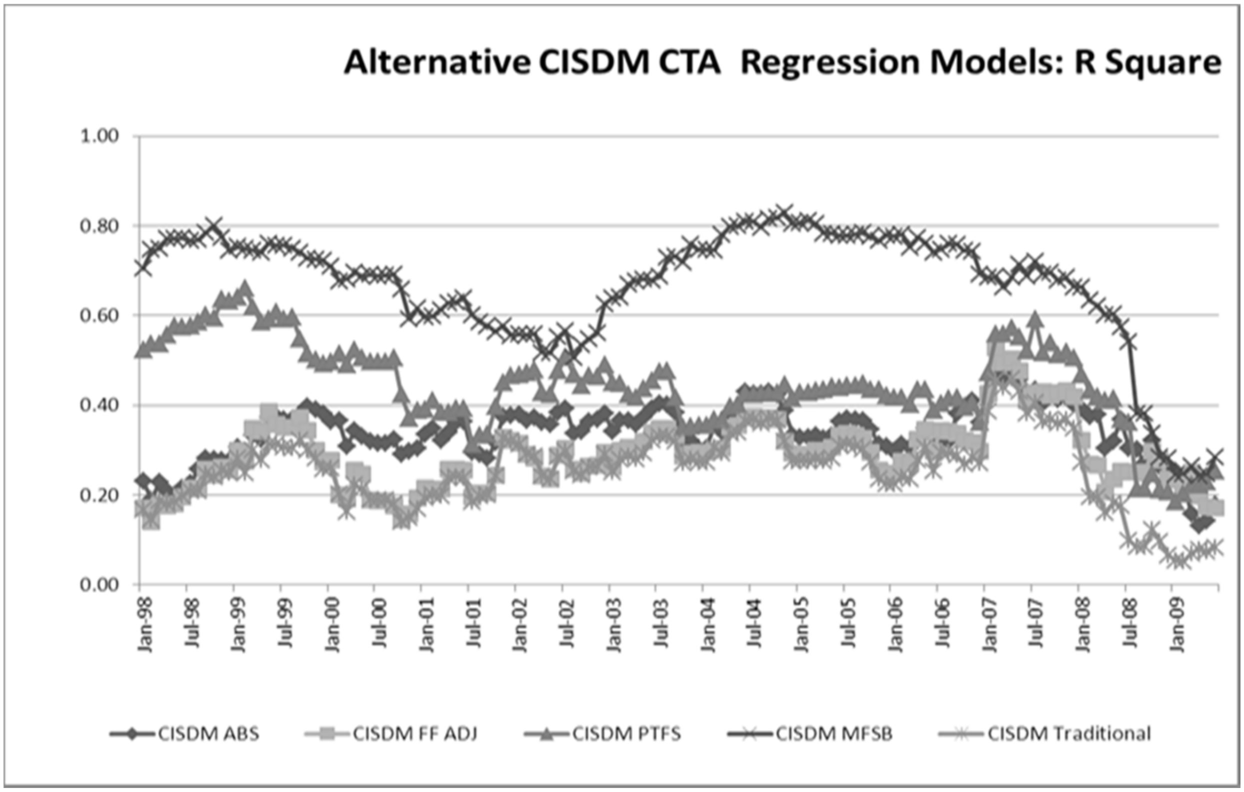


Exhibit 19a: MFSB: T-Stats

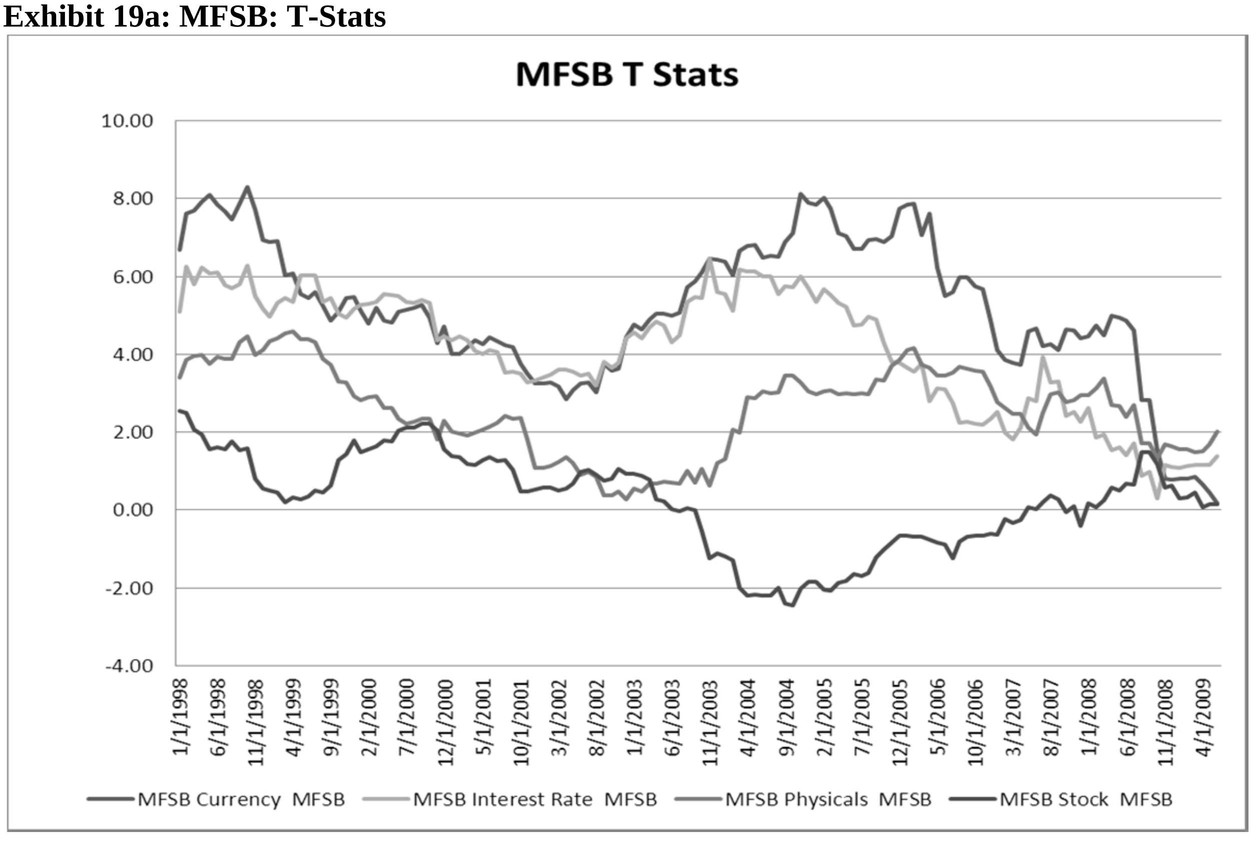


Exhibit 19b: PTFS - T-Stats

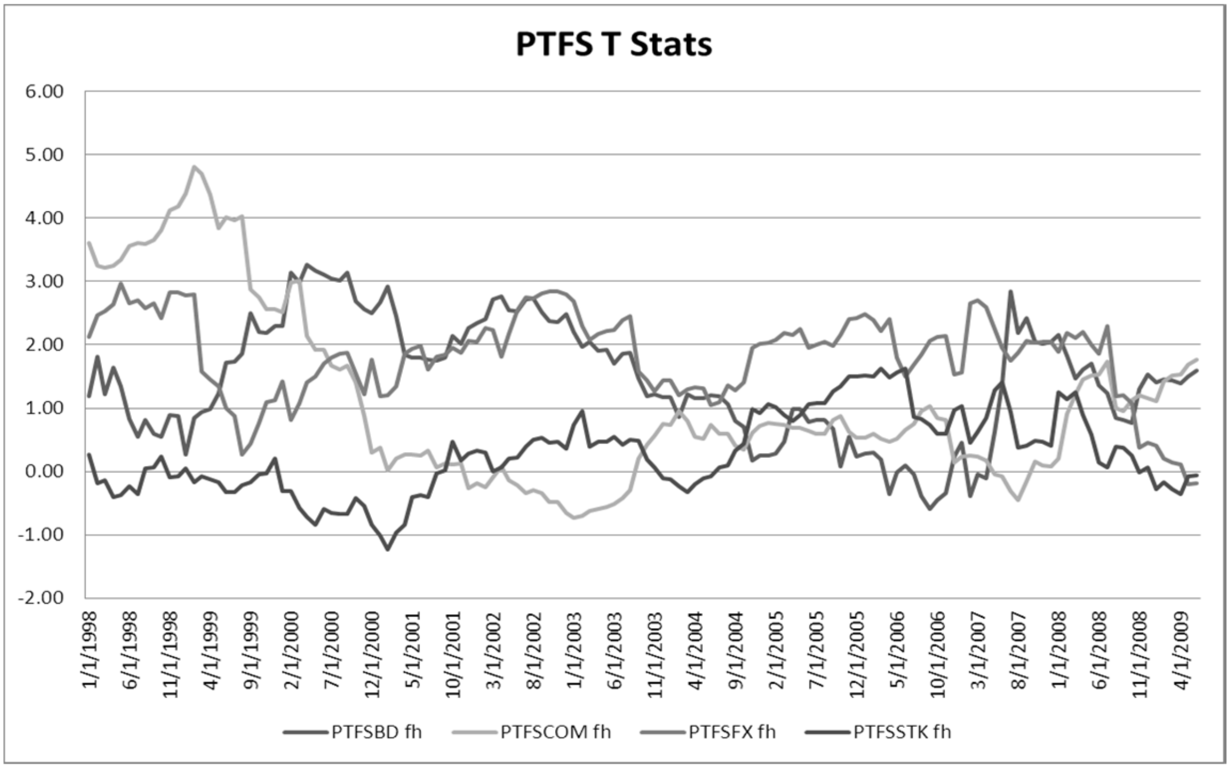


Exhibit 20a: Differences in MFSB and PTFS R-Squares

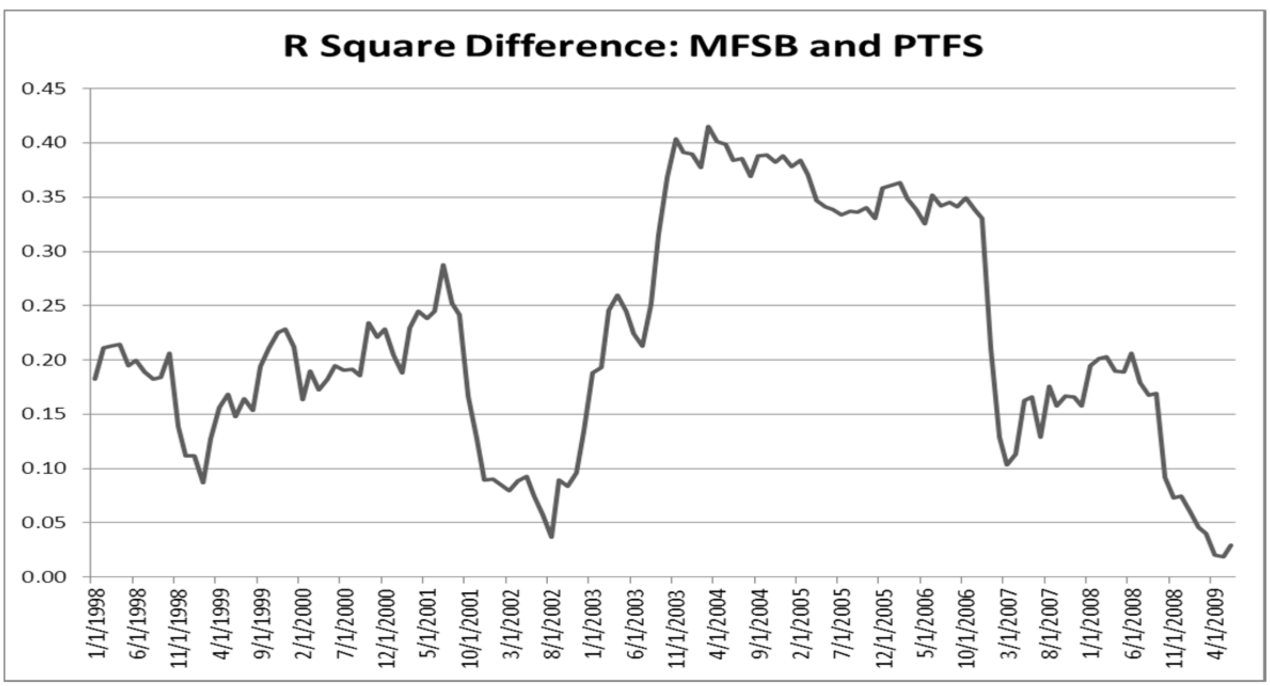
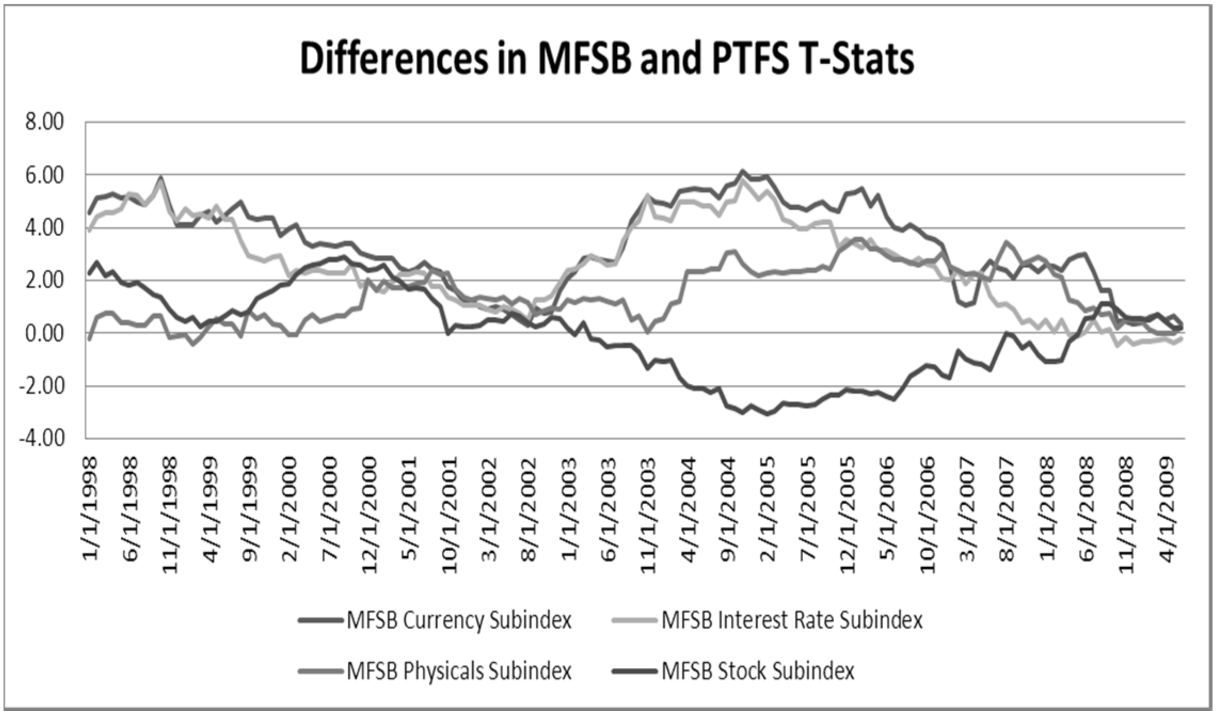


Exhibit 20b: Differences in MFSB and PTFS T-Stats



Conclusion

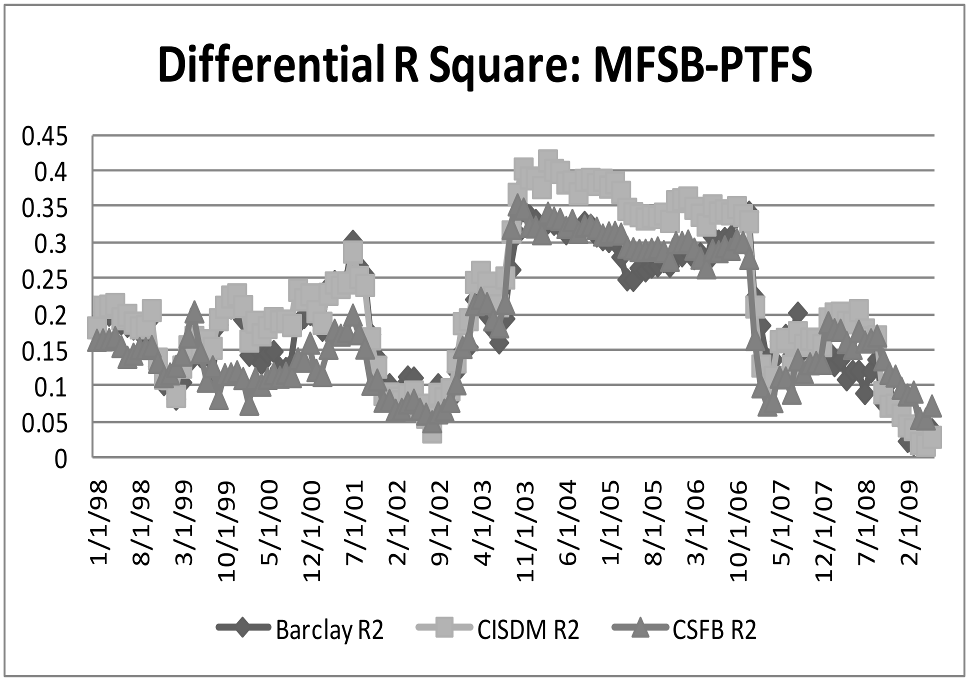
Results of this analysis remind us of the importance that research be continually "re-conducted" on any investment area. Changes in regulatory, trading and investor environments may result in dramatic changes in the underlying viability of any investment vehicle and/or trading process. This is especially true for managed futures programs which often are dynamic in nature and are impacted by changes in trading instruments and underlying markets. However, managed futures programs have traded through many of these dynamic changes.

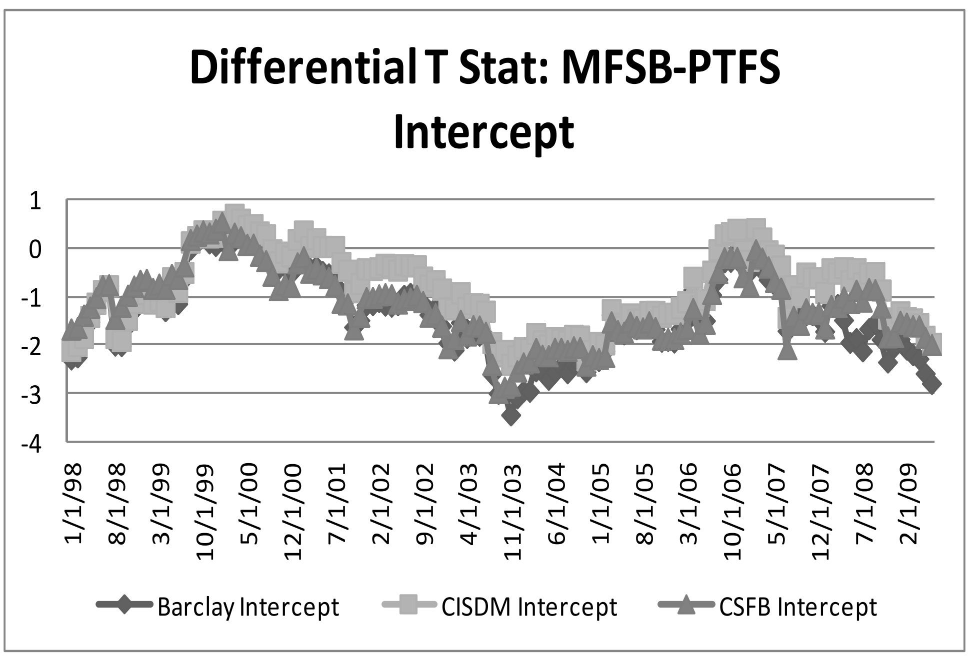
Results indicate the importance of understanding the underlying characteristics of the CTA strategy or data used to represent that strategy. CTA trading strategies have changed dramatically over time and the indices used to represent those composite portfolio returns have likewise provided a time varying absolute and relative return and risk performance. As important, the data sources used to capture these return processes have their own dynamic in terms of when and how they were created. In this analysis, for the period prior to 2000, questions may exist as to the relative performance characteristics of the CSFB CTA index in comparison to the Barclay and CISDM CTA indices.

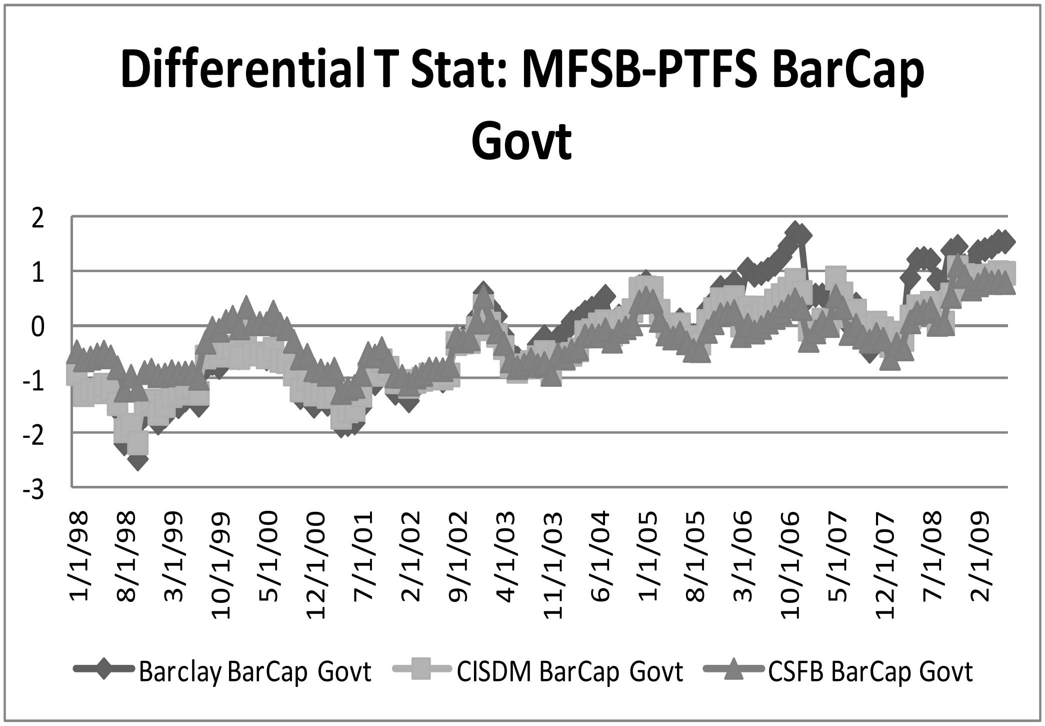
In addition, the various models used to capture the return variability of CTA indices likewise have their own dynamic. While a number of models contain variables which attempt to capture the dynamic trading process of CTAs, those models which use more direct trading based approaches to capture the underlying return process rather than simply attempting to capture ex post return processes are shown to provide an additional advantage in describing the return process.

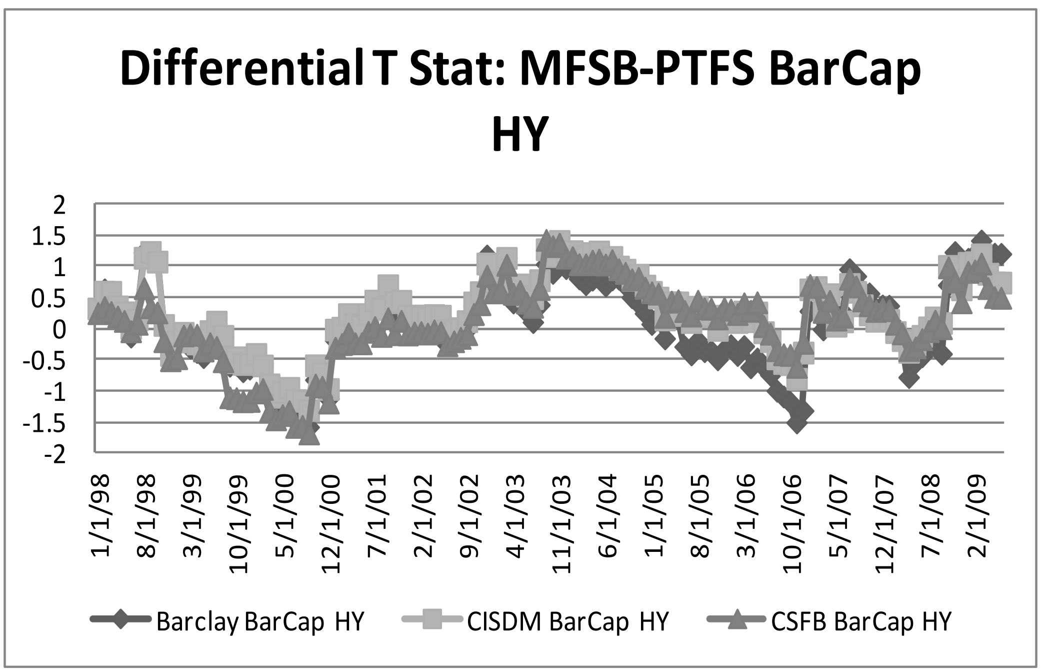
Lastly, in this analysis a four year investment period is used to present much of the analysis. This is consistent with the period used in a principal part of existing academic research; however, investors are cautioned that such averaging may hide some of the dynamics of the comparison asset return process. As more discrete periods of analysis are used, the periods of relative CTA benefit are more dynamic and time specific.

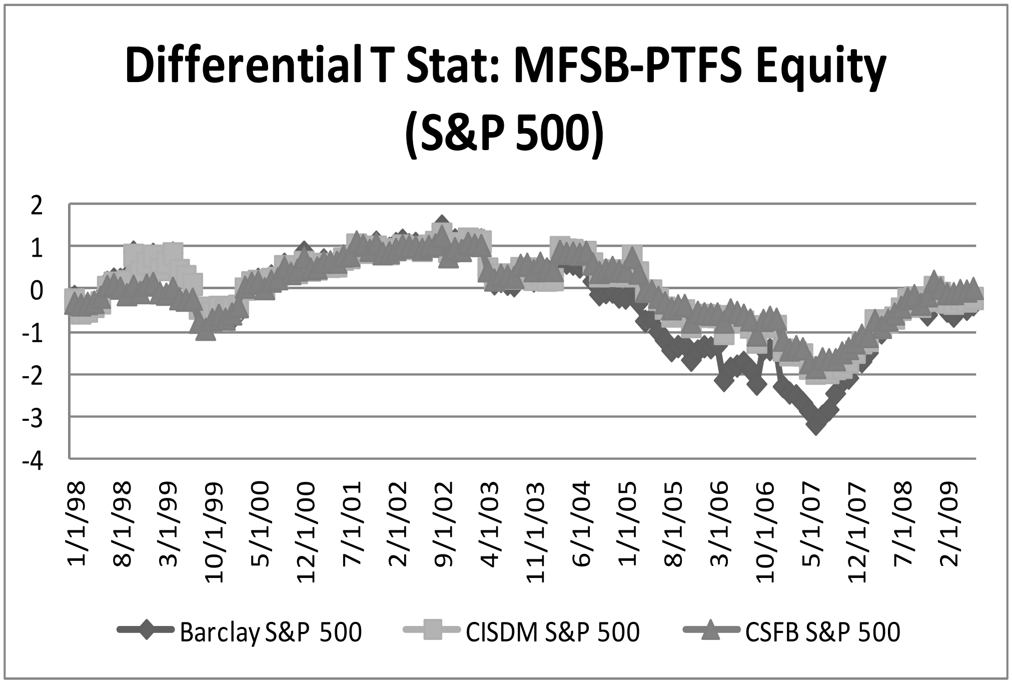
Appendix I: Differential T-Stats and R-Square (MFBS-PTFS)

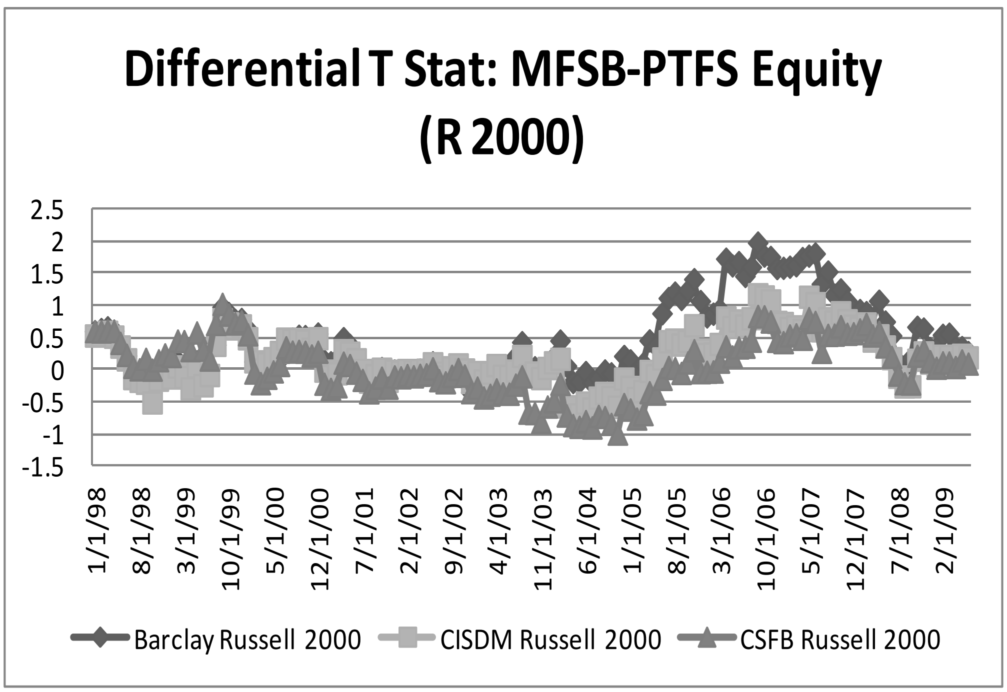


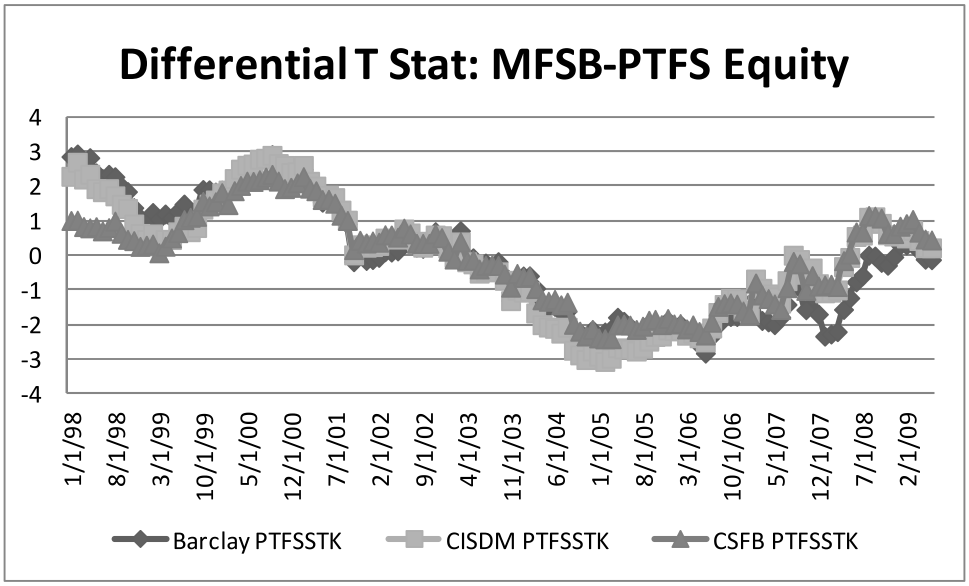


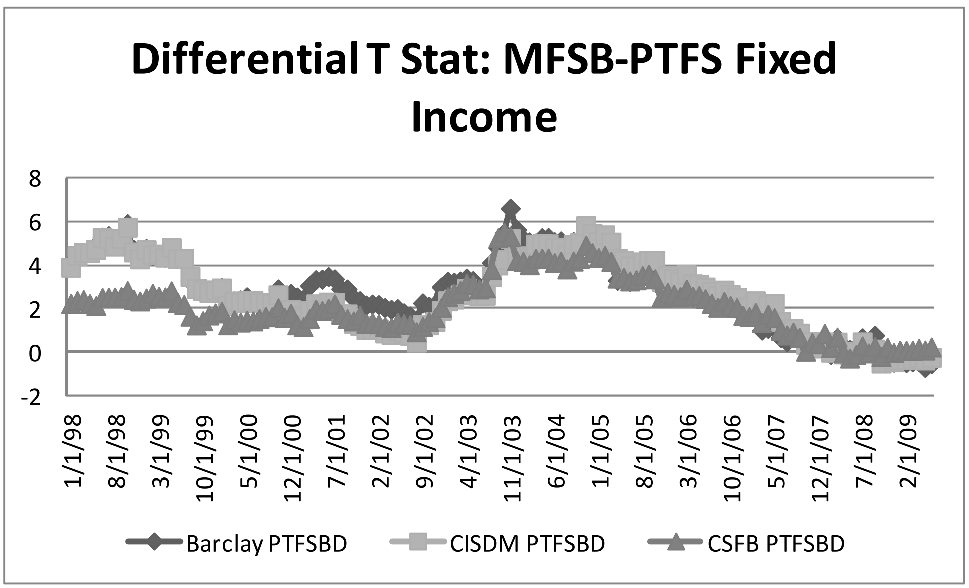

Differential T Stat: MFSB-PTFS BarCap Govt
2
1
0
-1
-2
-3
1/1/98
8/1/98
3/1/99
10/1/99
5/1/00
12/1/00
7/1/01
2/1/02
9/1/02
4/1/03
11/1/03
6/1/04
1/1/05
8/1/05
3/1/06
10/1/06
5/1/07
12/1/07
7/1/08
2/1/09
Barclay BarCap Govt
CISDM BarCap Govt
CSFB BarCap Govt

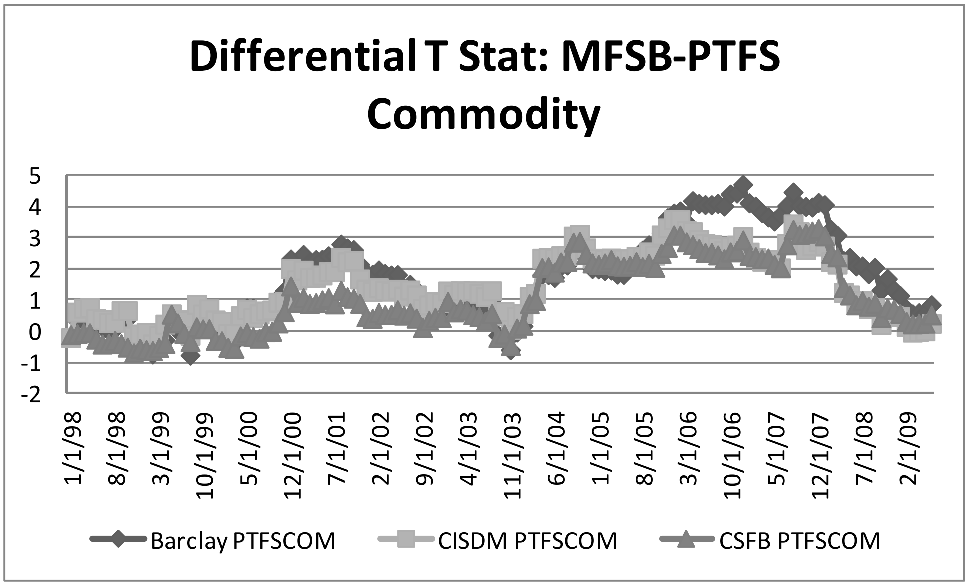

Differential T Stat: MFSB-PTFS BarCap HY
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
1/1/98
8/1/98
3/1/99
10/1/99
5/1/00
12/1/00
7/1/01
2/1/02
9/1/02
4/1/03
11/1/03
6/1/04
1/1/05
8/1/05
3/1/06
10/1/06
5/1/07
12/1/07
7/1/08
2/1/09
Barclay BarCap HY
CISDM BarCap HY
CSFB BarCap HY

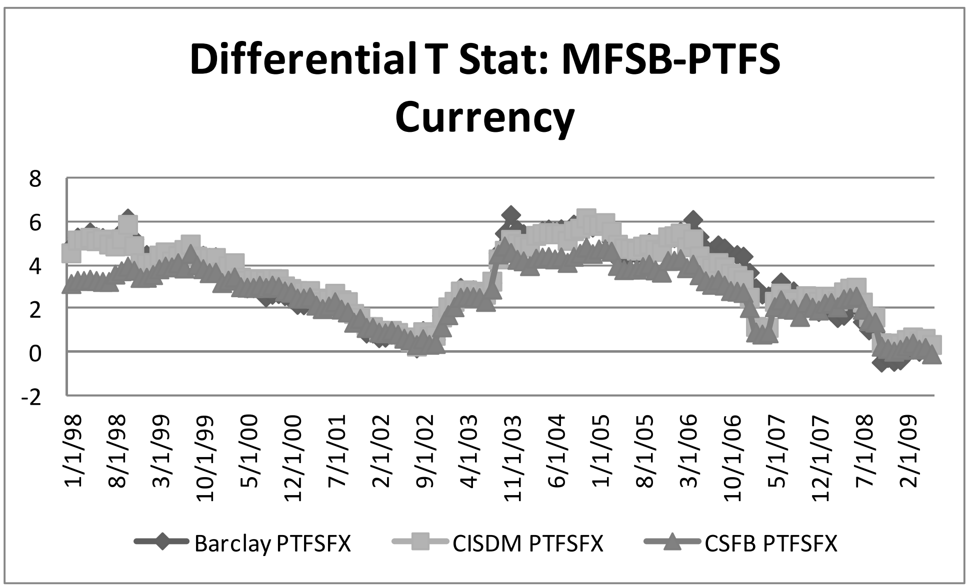

Differential T Stat: MFSB-PTFS Equity (S&P 500)
2
1
0
-1
-2
-3
-4
1/1/98
8/1/98
3/1/99
10/1/99
5/1/00
12/1/00
7/1/01
2/1/02
9/1/02
4/1/03
11/1/03
6/1/04
1/1/05
8/1/05
3/1/06
10/1/06
5/1/07
12/1/07
7/1/08
2/1/09
Barclay S&P 500
CISDM S&P 500
CSFB S&P 500


Differential T Stat: MFSB-PTFS Equity (R 2000)
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
1/1/98
8/1/98
3/1/99
10/1/99
5/1/00
12/1/00
7/1/01
2/1/02
9/1/02
4/1/03
11/1/03
6/1/04
1/1/05
8/1/05
3/1/06
10/1/06
5/1/07
12/1/07
7/1/08
2/1/09
Barclay Russell 2000
CISDM Russell 2000
CSFB Russell 2000


Differential T Stat: MFSB-PTFS Equity
4
3
2
1
0
-1
-2
-3
-4
1/1/98
8/1/98
3/1/99
10/1/99
5/1/00
12/1/00
7/1/01
2/1/02
9/1/02
4/1/03
11/1/03
6/1/04
1/1/05
8/1/05
3/1/06
10/1/06
5/1/07
12/1/07
7/1/08
2/1/09
Barclay PTFSSTK
CISDM PTFSSTK
CSFB PTFSSTK


Differential T Stat: MFSB-PTFS Fixed Income
8
6
4
2
0
-2
1/1/98
8/1/98
3/1/99
10/1/99
5/1/00
12/1/00
7/1/01
2/1/02
9/1/02
4/1/03
11/1/03
6/1/04
1/1/05
8/1/05
3/1/06
10/1/06
5/1/07
12/1/07
7/1/08
2/1/09
Barclay PTFSBD
CISDM PTFSBD
CSFB PTFSBD


Differential T Stat: MFSB-PTFS
Commodity
5
4
3
2
1
0
-1
-2
1/1/98
8/1/98
3/1/99
10/1/99
5/1/00
12/1/00
7/1/01
2/1/02
9/1/02
4/1/03
11/1/03
6/1/04
1/1/05
8/1/05
3/1/06
10/1/06
5/1/07
12/1/07
7/1/08
2/1/09
Barclay PTFSCOM
CISDM PTFSCOM
CSFB PTFSCOM


Differential T Stat: MFSB-PTFS
Currency
8
6
4
2
0
-2
1/1/98
8/1/98
3/1/99
10/1/99
5/1/00
12/1/00
7/1/01
2/1/02
9/1/02
4/1/03
11/1/03
6/1/04
1/1/05
8/1/05
3/1/06
10/1/06
5/1/07
12/1/07
7/1/08
2/1/09
Barclay PTFSFX
CISDM PTFSFX
CSFB PTFSFX

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