Issues In Empirical Research

What a Difference a Day, Week, Month Makes – The Convertible Arbitrage Case Across Economic Environments

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1. Introduction

A considerable amount of academic hedge fund research deals with issues of data dependency, time dependency, and analytical dependency on empirical results. Simple examples of the impact of issues of data dependency include the use of alternative databases and the use of revised data in contrast to actual historical data. Simple examples of time dependency include concentration on specific periods for which results are not representative across different financial or economic periods. Analytical dependency also impacts empirical analysis. Popular software often uses different algorithms in similar analytical processes or simply does not make a particular algorithm available (e.g., lack of robust estimators in Excel based analysis packages). Lastly, issues of data dependency, time dependency, and analytical program dependency are often co-dependent. For instance, the sole availability of monthly returns which may not represent the return process of more frequent investment intervals may prevent researchers from dissecting the time period of analysis into more information specific areas and limit the analytical approaches used for removing or analyzing certain informational impacts (e.g., extreme values). Since many researchers do not have the resources or time to evaluate different data, time, or alternative analytical algorithms, considerable research remains focused on the use of monthly data over long time frames of analysis based on the use of familiar forms of analytical analysis.

In this analysis, we remind investors and researchers alike that there is no simple answer to the data, time horizon, or analytic program dependency. In this analysis, we use a common data source with available daily data. The daily data is then used to create a series of return intervals (e.g., daily, 5-day, 20-day). Over a common time frame, the various return intervals form the basis for a series of empirical comparisons. These empirical comparisons include analysis of common measures of distributional characteristics (annualized return, standard deviation, etc.), as well as simple measures of market (beta) and security time series properties (e.g., autocorrelation). Results indicate similar return and risk measures for the use of daily, 5-day, and 20-day return intervals. However, the choice of the return interval noticeably impacts measures of beta estimation and autocorrelation. Lastly, in contrast to using a general model approach (e.g., robust estimators) to measure the impact of overall data structure on autocorrelation, we simply show the impact of removing a particular time period (e.g., October 2008) on the empirical results. Results indicate that adjusting an extreme data point a day (October 15, 2008), a week (October 13-18, 2008) or a month (October 2008) to a simple assumption of zero has major impact on beta estimation and autocorrelation results. This result has implication on the use of common one size fits all analysis of empirical data as well as the potential benefit of investor or academic decisions on creating data which more accurately represents the period of concern to the investor or academic.

2. Brief Review: Data Availability

Considerable research has analyzed differences in empirical results based on the use of daily, weekly or monthly data. Initial research in the 1960s and 1970s was based primarily on monthly data driven in part by the availability of monthly stock and corporate data in the late 1960s (e.g., Compustat). The increased analysis of daily data in the 1980s was driven by the availability of daily CRSP equity prices and daily data on futures and options. In the

1990s increased availability of tick data increased research on intraday pricing impacts. For fund-based research (mutual funds or hedge funds) most empirical research is still based on monthly data made available through a range of hedge fund and mutual fund data providers (Morningstar, HFR, etc.). Daily data is increasingly available from real-time data providers (e.g., Bloomberg), as well as certain mutual fund and hedge fund data providers but the accessibility of this data for most researchers is limited. As a result, for hedge funds most research continues to be based on the use of monthly data.

The problem of time dependency is linked with the issue of the investment period used in the analysis. The use of longer investment periods (e.g., monthly) in contrast to shorter time periods (e.g., daily) also impacts the type of research conducted, as well as the form that that the research takes. The use of monthly data often results in longer time periods of analysis to ensure that enough data is available to permit the quantitative analysis. The availability of short investment periods permits greater micro period analysis, however, there is a point at which the investment period is so micro (high frequency) that potential problems in the data (e.g., bid ask prices, liquidity) may hide some of the more basic financial relationships. This interaction between time dependency and data (return interval) also impacts how empirical tests are conducted. Certainly the conditional impact of information on asset prices is best measured when that information is closely associated with the measurement period. Considerable research is centered on how best to capture those conditional relationships. Often, how these conditional relationships are analyzed is based in part on the availability of analytical programs to study these relationships. These programs are often designed to reduce the impact of certain data impacts on empirical tests. These tests include various forms of robust estimators. However, most statistically based analytical programs make assumptions as to the consistency of the underlying return processes, often averaging across observations when in fact, it is the unusual observation that may more properly be the focus of the analysis.

3. Data and Methodology

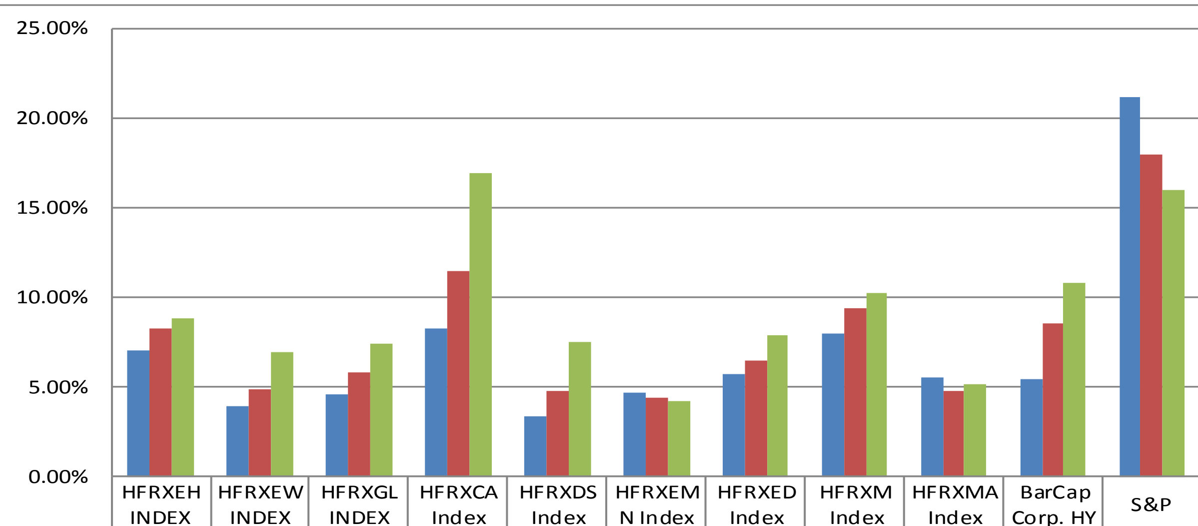
In this analysis, we use a common data source (HFRX Hedge Fund Indices and a set of hybrid mutual funds) with available daily data. In the first part of the analysis, the daily HFRX data is then used to create a series of weekly (5-day), and longer return intervals (20-day) over a common time frame. Over a common investment interval, empirical comparisons are made which include analysis of common measures of distributional characteristics (annualized return, standard deviation, etc.), as well as simple measures of market risk (e.g., beta estimation) and security time series properties (e.g., autocorrelation). In the second part of the analysis, we analyze the impact of a single data point on the estimation of a hedge fund portfolio's autocorrelation. First order autocorrelation has often been used as a basis for measuring potential illiquidity. In this analysis we measure the impact of the use of weekly (5-day), monthly (20-day) data on measured autocorrelation for a set of hybrid mutual funds and HFRX indices. In addition, we illustrate the impact of the adjusting a single data point (day, week, or month) on the measured autocorrelation. The analysis focuses on one strategy , convertible arbitrage, although select results for other strategies are provided in the exhibits. A complete analysis of all strategies can be found at www. INGARM. org.

4. Results

Considerable research has addressed the issue of time and period dependency, and while the conditional nature of the return and risk process is well known, many investors and academics alike continue to rely on published research that has focused on a particular data period, using a particular database, based on a single investment horizon (monthly), and centered on commonly used statistical programs or analytical methodology. A common example of the impact of data dependency on empirical research is the use of daily, weekly or monthly data in the calculation of an asset's standard deviation. In short, if daily or weekly returns were uncorrelated over the period of analysis, then monthly or yearly standard deviations are simple multiples of the measured daily or weekly returns. In short, use of monthly data would provide a basis for a measure of the actual weekly or daily data underlying the monthly measure. If daily or weekly data has a time series pattern that reflects underlying autocorrelation or cross-correlation with other assets then the monthly volatility or beta estimation may not adequately represent the return patterns of shorter time frames or return patterns based on shorter time frames may provide incorrect estimates of various longer term statistical parameters.

Exhibit 1 provides the standard deviations for the period of analysis based on the use of daily, 5-day and 20-day data. In general results show that the standard deviations based on HFRX monthly data are generally higher than those reported for shorter time frames, while for the S&P 500 the reverse is true. These results indicate that return series (at shorter time intervals) may reflect mean reverting processes for the S&P 500. However, they may also reflect some positive autocorrelation patterns within the HFRX daily data.

The actual autocorrelations of the HFRX hedge fund indices are shown in Exhibit 2a. Consistent with previous research, the two hedge fund indices with the highest credit risk and lowest potential liquidity reported the highest daily, weekly (5-day), monthly (20-day) positive autocorrelation over the time period. This level of autocorrelation is often regarded as a sign of illiquidity. However, the level of autocorrelation of more frequent return intervals is often much lower than that of longer return intervals. It is difficult to ascribe the high level of autocorrelation evident in monthly data to a lack of liquidity when it is not evident in more frequent time series which underlie the monthly data. The higher level of autocorrelation for 4-week returns may also reflect the lower number of observations and the sensitivity of the results to individual data observations. It is also important to point out the impact of single data periods in cross sectional autocorrelation patterns. In Exhibit 2b, 2c, and 2d, we illustrate the relative first order autocorrelations for the entire period and the period up to August 2008 for daily, weekly and monthly data. Leaving out the period of the credit crisis dramatically changes the autocorrelation statistics, especially for the weekly and monthly data.[1]

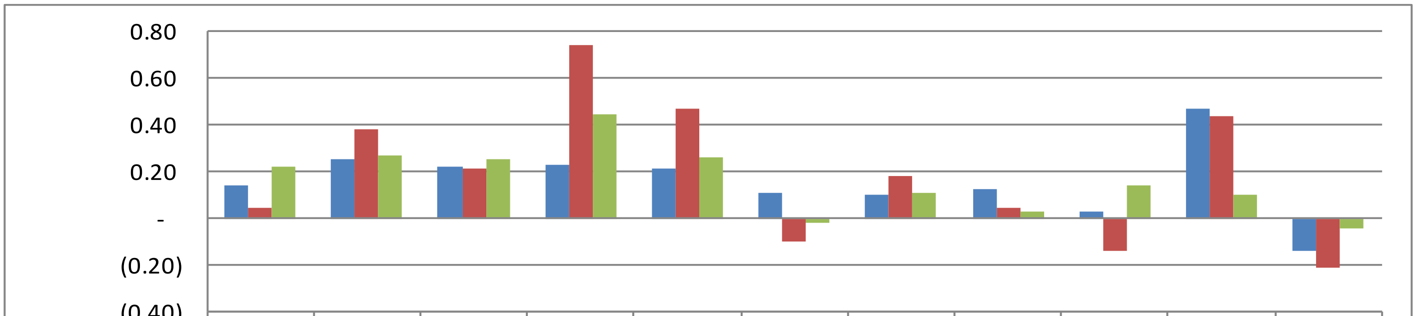


	HFRXEH INDEX	HFRXEW INDEX	HFRXGL INDEX	HFRXCA Index	HFRXDS Index	HFRXEMN Index	HFRXED Index	HFRXM Index	HFRXMA Index	BarCap Corp. HY	S&P
stdev daily	7.09%	3.97%	4.57%	8.27%	3.38%	4.65%	5.72%	7.95%	5.58%	5.48%	21.23%
stdev - weekly	8.32%	4.91%	5.81%	11.50%	4.78%	4.44%	6.48%	9.41%	4.82%	8.53%	18.02%
stdev - monthly	8.82%	6.93%	7.39%	16.97%	7.51%	4.26%	7.89%	10.24%	5.14%	10.79%	16.01%

Exhibit 1 Annual Standard Deviation (Day, Week, 4-Week)

Note: Period of Analysis: 4/2003-2008

Source: HFR



	HFRXEH INDEX	HFRXEW INDEX	HFRXGL INDEX	HFRXCA Index	HFRXDS Index	HFRXEMN Index	HFRXED Index	HFRXM Index	HFRXMA Index	BarCap Corp. HY	S&P
AC - daily	0.14	0.26	0.22	0.23	0.21	0.11	0.10	0.13	0.03	0.47	(0.14)
AC - weekly	0.05	0.38	0.21	0.74	0.47	(0.10)	0.18	0.05	(0.14)	0.44	(0.21)
AC - monthly	0.22	0.27	0.25	0.44	0.26	(0.02)	0.11	0.03	0.14	0.10	(0.05)

Exhibit 2a First Order Autocorrelation (Day, Week, 4-Week)

Notes: Period of Analysis: 4/2003-2008

Source: HFR

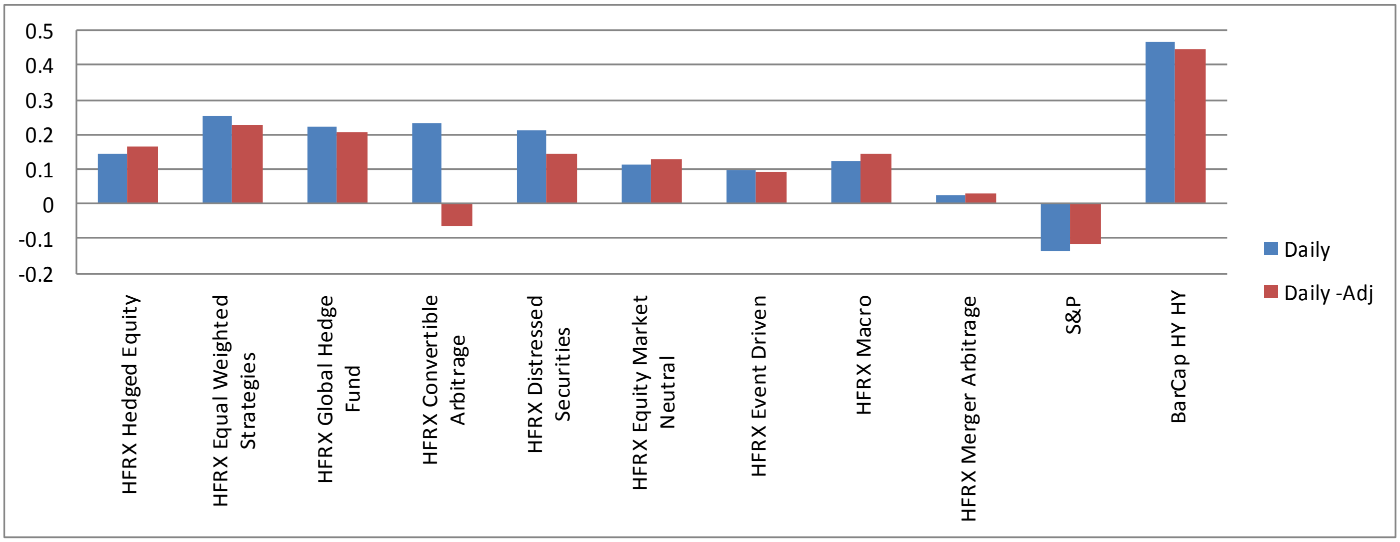


Exhibit 2b First Order Autocorrelation (Daily)

Source: HFR

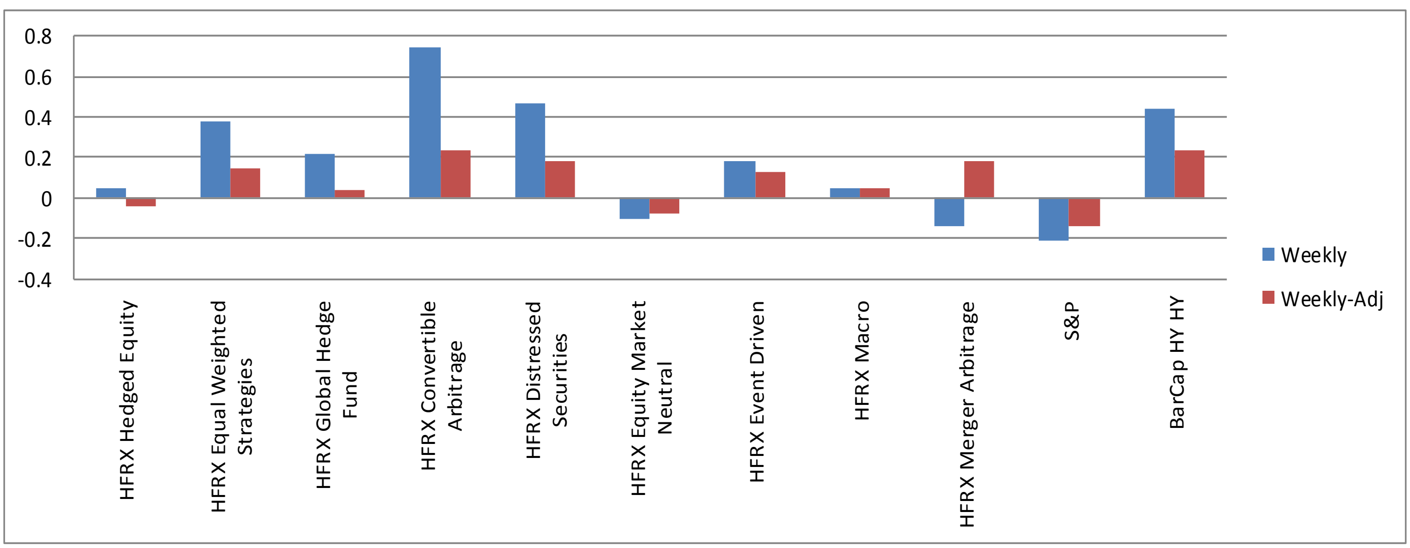


Exhibit 2c First Order Autocorrelation (Weekly)

Source: HFR

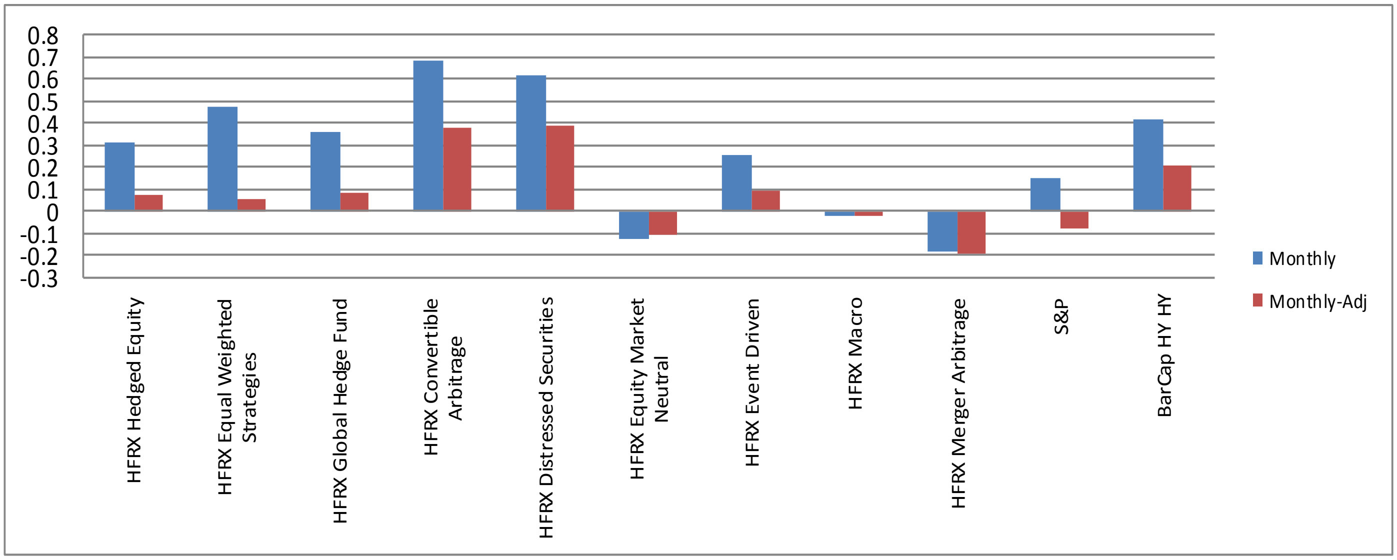
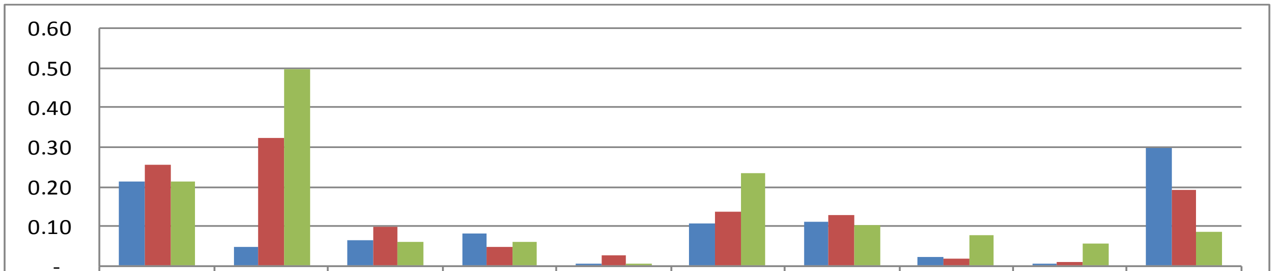


Exhibit 2d First Order Autocorrelation (Monthly)
Source: HFR

Differences in autocorrelation patterns may also be reflected in estimates of various cross-correlation patterns. Previous research has linked stale pricing to significant lagged correlations between the illiquid asset and the corresponding liquid market index. In short a multi-variate regression of the independent variable on the current and lagged values of the S&P 500 may reflect the existence of stale pricing in the HFRX index. Results in Exhibit 3b reflect the autocorrelation in Convertible Arbitrage and Distressed Securities in that the R-Square of the multi-variate regression is higher than that of the simple one factor regression. Results in Exhibit 3a also reflect the autocorrelation pattern in the BarCap U.S. High Yield Corporate indicating that the daily data has a higher autocorrelation than the weekly data which is also higher than the 4-week data. Similarly, the daily data has a higher R-Square difference in the Multi Beta/Single Beta than the weekly and the weekly has a higher R-Square difference than the 4-week. This pattern is more reflective of *ex ante* expectations, that is, daily data should have higher stale price impacts than weekly, and weekly should have higher stale price impacts than monthly. The higher level of R-Square differences for 4-week returns may also reflect the lower number of observations and the sensitivity of the results to individual data observations. It is also important to point out the impact of single data periods in cross sectional R-Square difference patterns. In Exhibit 3b, 3c and 3d, we illustrate the relative R-Square differences for the entire period and the period up to August 2008 for daily, weekly and monthly data. Leaving out the period of the credit crisis dramatically changes the differences in the R-Square statistics, especially for the weekly and monthly data.

5. Time Series Impacts (Autocorrelation)

The cross-sectional results on differential autocorrelation and expanded beta impacts from the use of daily, week, and 4-week return investment periods, indicate a lack of consistency in results. One reason for that lack of consistency across hedge fund styles and traditional assets is the lack of stationarity in the process. In Exhibit 4, the minimum correlation and maximum correlation of the daily, week, and 4-week autocorrelation patterns are shown.



	HFRXCA Index	HFRXDS Index	HFRXED Index	HFRXEH INDEX	HFRXEMN Index	HFRXEW INDEX	HFRXGL INDEX	HFRXM Index	HFRXMA Index	BarCap HY
d	0.21	0.05	0.06	0.08	0.00	0.11	0.11	0.02	0.00	0.30
w	0.26	0.33	0.10	0.05	0.02	0.14	0.13	0.02	0.01	0.19
m	0.21	0.50	0.06	0.06	0.01	0.23	0.10	0.08	0.06	0.09

Exhibit 3a Difference in R-Square (Multi Beta minus Single Beta)

Source: HFR

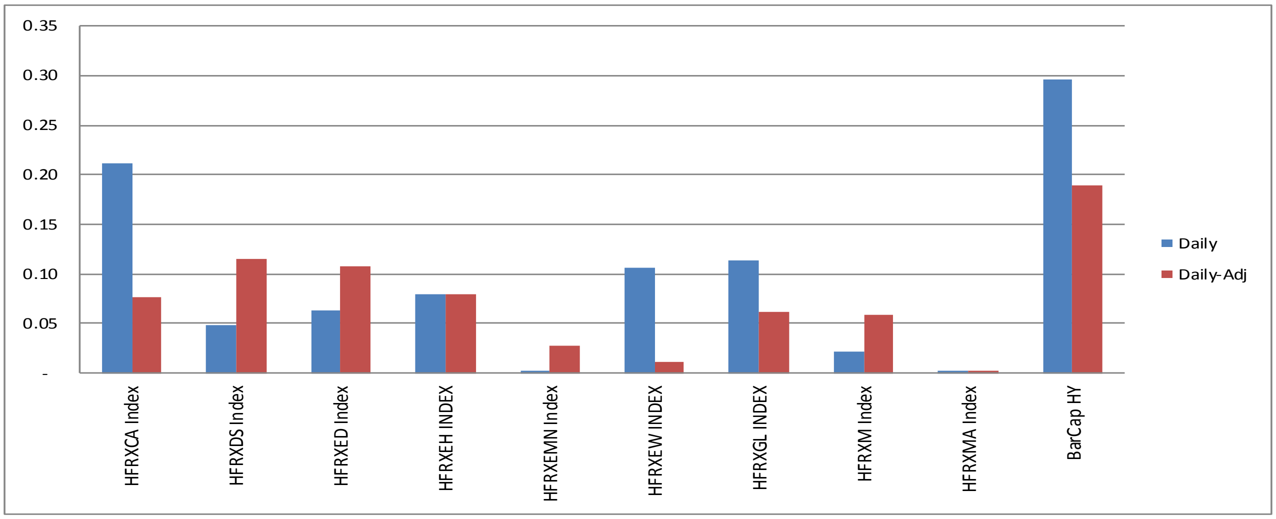


Exhibit 3b Difference in R-Square (Multi Beta minus Single Beta)

Source: HFR

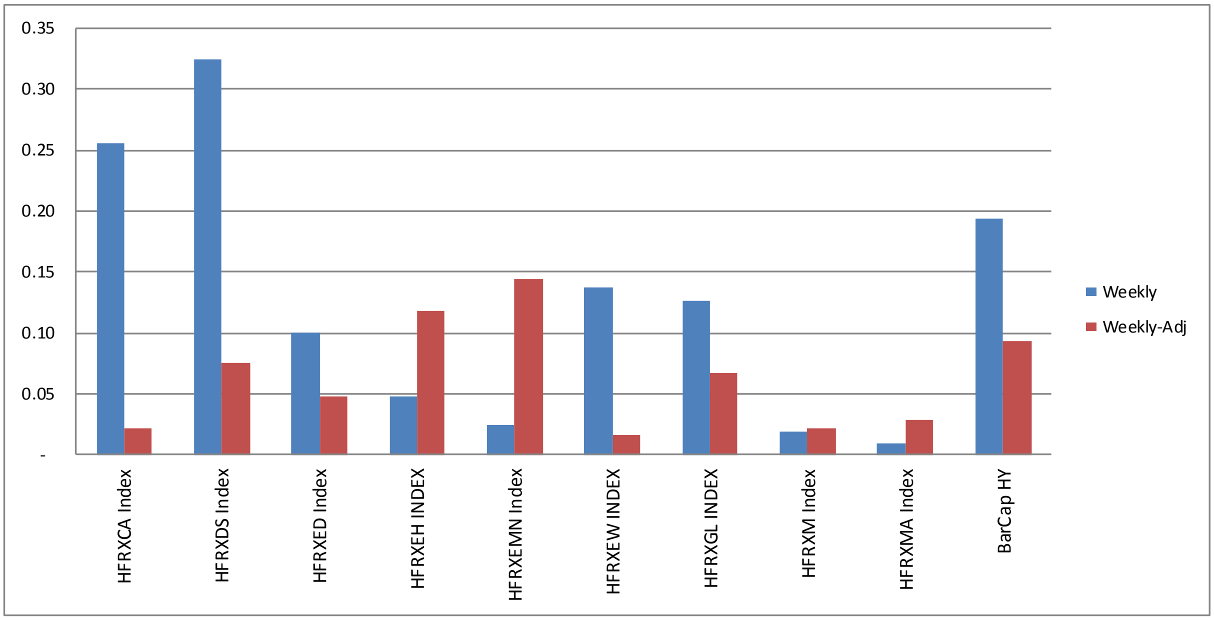


Exhibit 3c Difference in R-Square (Multi Beta minus Single Beta)

Source: HFR

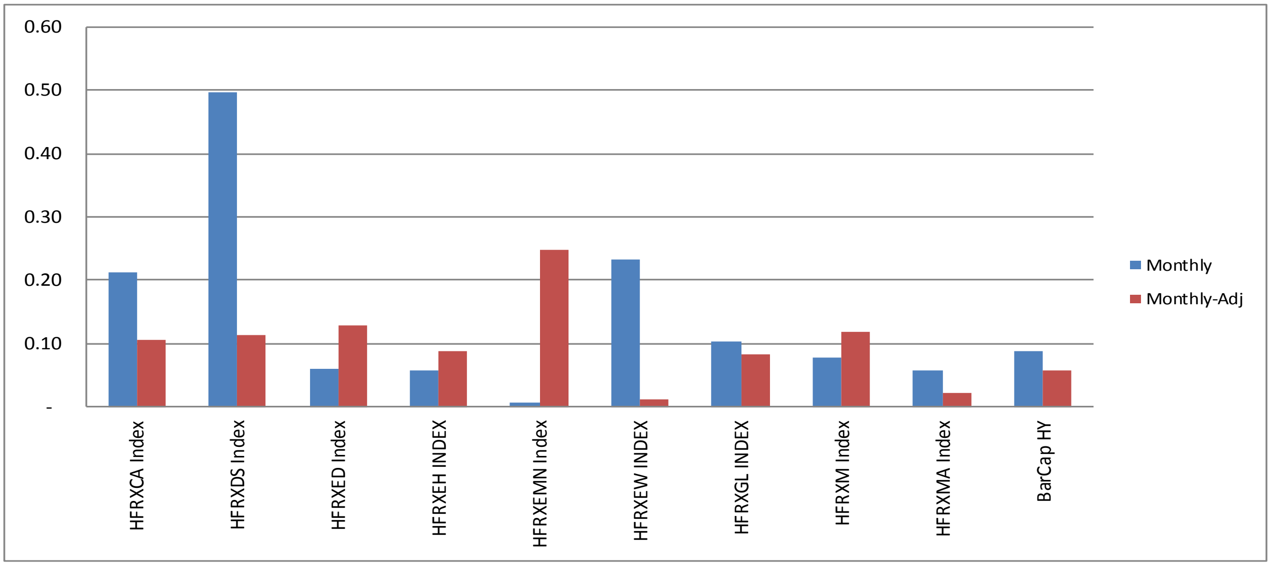


Exhibit 3d Difference in R-Square (Multi Beta minus Single Beta)
Source: HFR

The minimum and maximums for the various strategies (daily, weekly, monthly) are as follows:

- Convertible Arbitrage: Minimum (-.27, -.08, -.42) and Maximum (.24, .42, .73)
- Distressed Securities: Minimum (-.03, -.10, -.02) and Maximum (.30, .59, .72)
- Event Driven: Minimum (-.07, -.31, -.32) and Maximum (.21, .26, .42)
- Equity Hedge: Minimum (-.08, -.31, -.64) and Maximum (.28, .15, .55)
- Equity Mkt Neutral: Minimum (-.04, -.33, -.64) and Maximum (.25, .25, .32)
- EW Strategies: Minimum (-.16, -.23, -.37) and Maximum (.31, .43, .55)
- Global Index: Minimum (-.14, -.28, -.36) and Maximum (.29, .29, .58)
- Macro: Minimum (-.01, -.18, -.52) and Maximum (.32, .28, .27)
- Merger Arbitrage: Minimum (-.16, -.18, -.50) and Maximum (.15, .25, .63)
- BarCap HY: Minimum (-.34, -.26, -.15) and Maximum (.60, .41, .54)
- S&P 500: Minimum (-.22, -.38, -.39) and Maximum (.04, .11, .56)

In Exhibit 5a-5c, the rolling autocorrelations of the HFRX Convertible Arbitrage, S&P 500 and BarCap High Yield indices are shown.

Exhibit 5a indicates that the 4-week return interval for Convertible Arbitrage reports a high autocorrelation pattern at the beginning of the analysis period (near .40), falling to near zero during the middle of the analysis period and then rising again to near .60 for the end of the period of analysis. This pattern is similar to that reported by the weekly (5-day) data series, although the autocorrelation in the weekly data reported lower autocorrelation at the start of the period (.20) and never fell as low as that reported using the monthly data (minimum was near zero). The daily data reported a similar pattern as the weekly and monthly data (autocorrelation fell in the middle of the period and rose in the latter half) however for most of the period the autocorrelation reflected in the use of daily data was less than that reported in the weekly and monthly data series.

The S&P 500 autocorrelation pattern is provided in Exhibit 5b for daily, weekly, and 4-week holding periods. The autocorrelaitons remained low for the daily and weekly series for the entire period. The monthly data autocorrelation remained close to -.20 for the entire period, however for a brief time near the mid-point of the period the correlation rose to near .60 reflecting a similar, although much smaller, rise in the daily and weekly data.

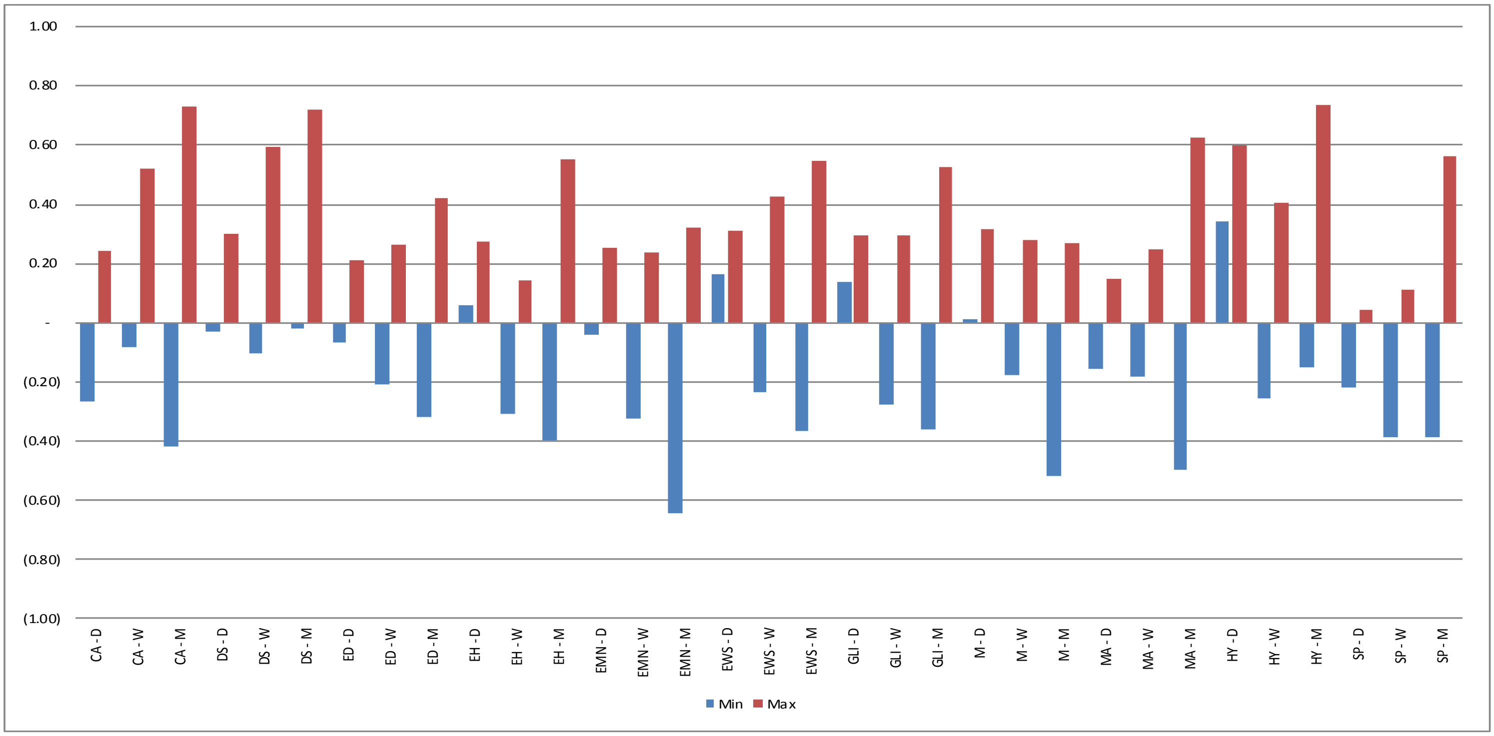


Exhibit 4 Autocorrelation Patterns by Investment Period (Day, Week, 4-Week)
Source: HFR

Exhibit 5c provides autocorrelations for BarCap HY. The autocorrelation pattern for daily data remains high (between .40 and .60) for the entire period while the monthly and weekly data rose together in the middle of the period, fell briefly in late 2007 and rose again at the end of the period.

6. Beta Estimation

The cross-sectional results on differential autocorrelation and expanded beta impacts from the use of daily, weekly, and 4-week holding investment period indicate a lack of consistency in results. One reason for that lack of consistency across hedge fund styles and traditional assets is the lack of stationarity in the process. In Exhibit 6, we show the minimum and maximum of the difference in R-Square by investment period. Results show a dramatic increase in the difference as we move from daily data to monthly data. The minimum and maximums for the various strategies (daily, weekly, monthly) are as follows:

- Convertible Arbitrage: Minimum (.01, .02, .01) and Maximum (.36, .37, .56)
- Distressed Securities: Minimum (.01, .02, .20) and Maximum (.07, .52, .73)
- Event Driven: Minimum (.04, .03, .01) and Maximum (.10, .12, .48)
- Equity Hedge: Minimum (.03, .01, .02) and Maximum (.16, .07, .41)
- Equity Mkt Neutral: Minimum (.00, .01, .01) and Maximum (.09, .14, .48)
- EW Strategies: Minimum (.09, .03, .06) and Maximum (.18, .32, .68)
- Global Index: Minimum (.08, .02, .04) and Maximum (.19, .22, .52)
- Macro: Minimum (.01, .02, .09) and Maximum (.19, .17, .58)
- Merger Arbitrage: Minimum (.00, .01, .04) and Maximum (.03, .20, .54)
- BarCap HY: Minimum (.07, .03, .01) and Maximum (.42, .30, .61)

In Exhibit 7, the difference between the multi-beta R-Square and the single beta R-Square of the HFRX Convertible Arbitrage index is shown. Results show that the 4-week return interval reports the highest difference in R-Square pattern at the beginning of the analysis period(near .60), falling to near zero, rising again to near .60 , falling again

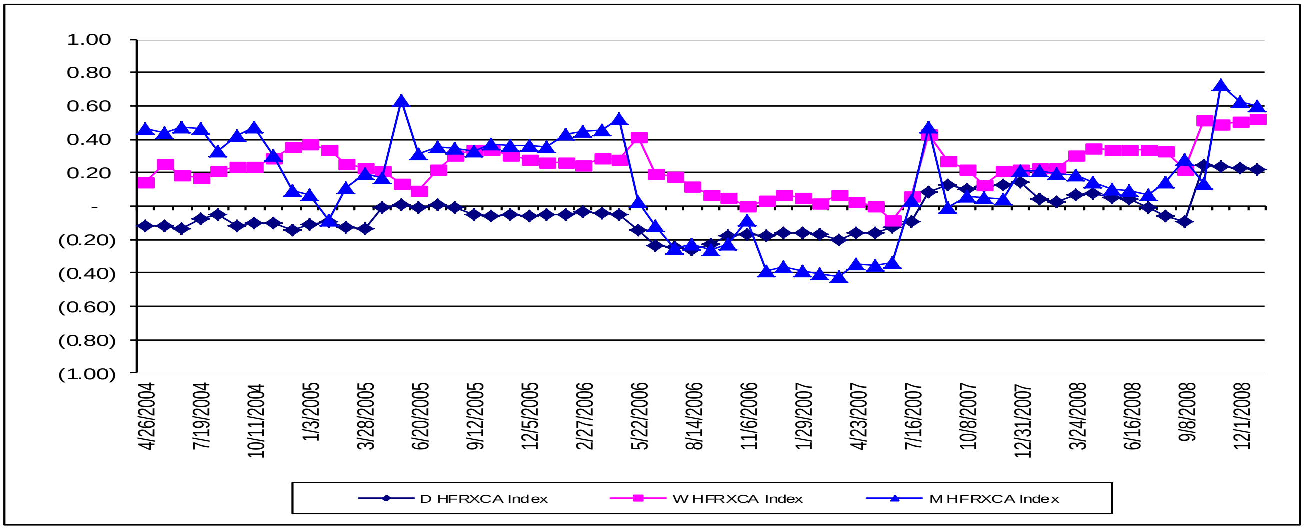


Exhibit 5a Convertible Arbitrage: First Order Autocorrelation (Daily, 5-Day, 20-Day)

Source: HFR

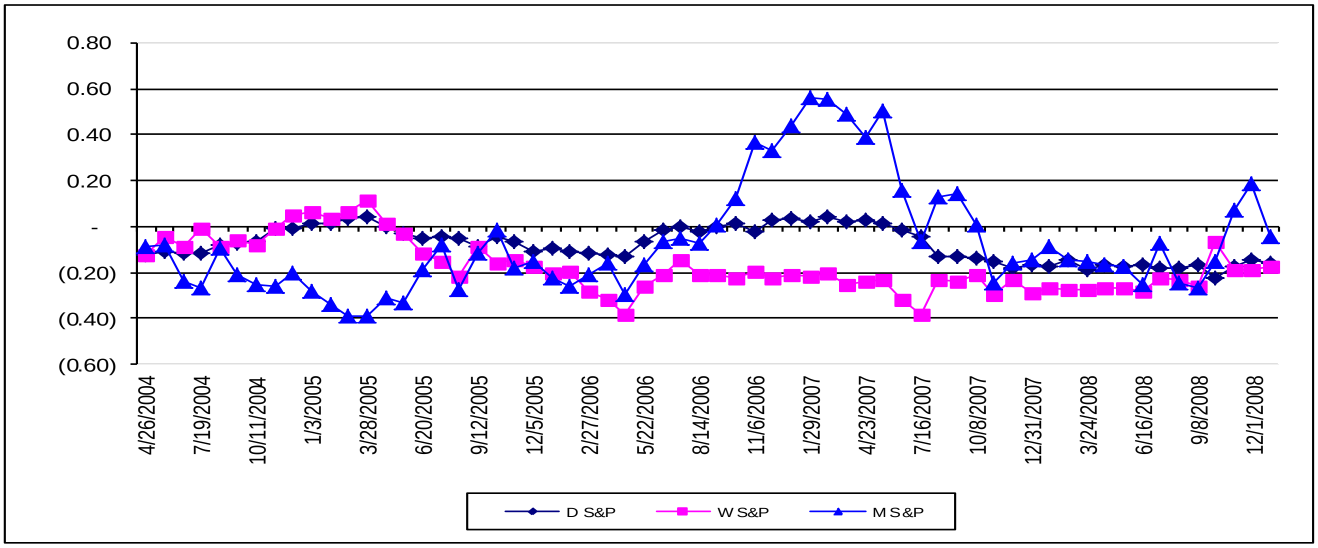


Exhibit 5b S&P 500: First Order Autocorrelation (Daily, 5-Day, 20-Day)

Source: Morningstar

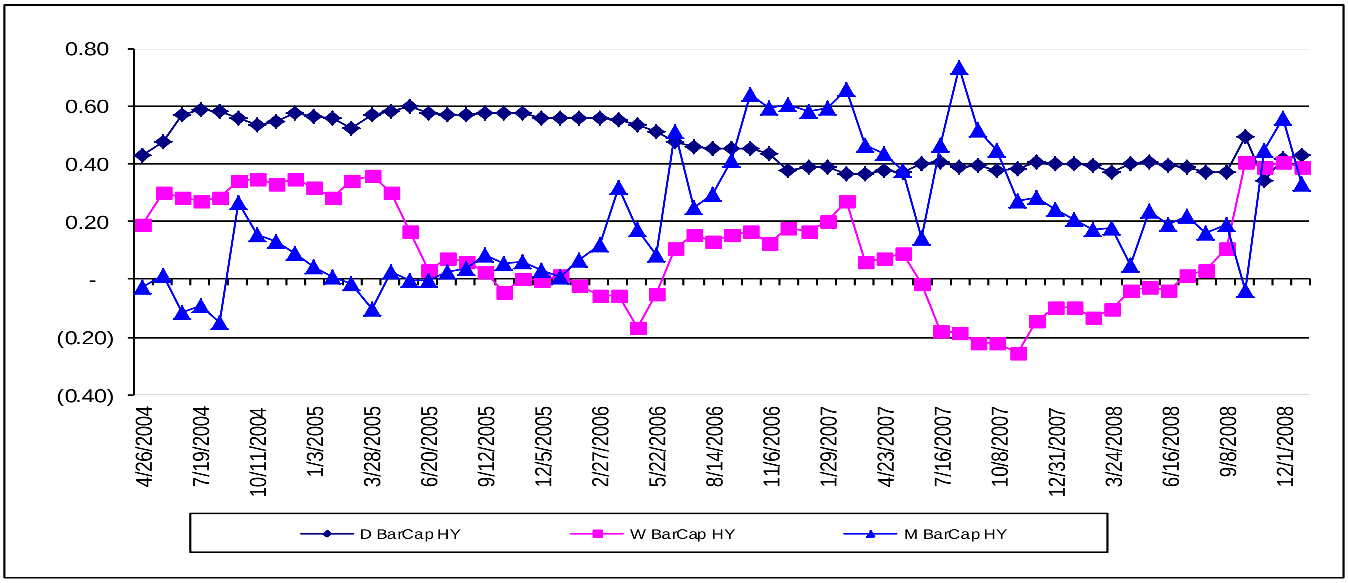
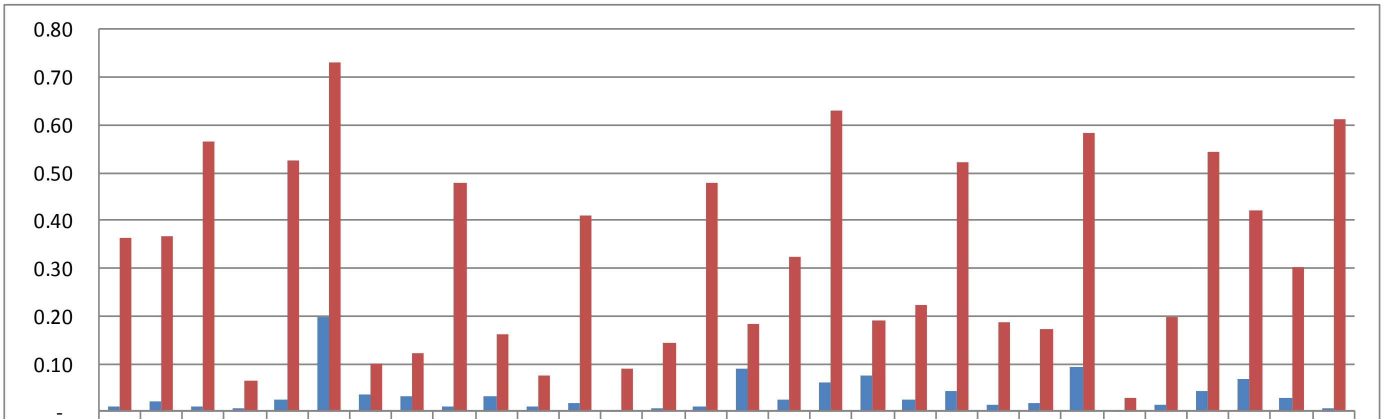


Exhibit 5c BarCap HY: First Order Autocorrelation (Daily, 5-Day, 20-Day)

Source: Morningstar



	CA D	CA W	CA M	DS D	DS W	DS M	ED D	ED W	ED M	EH D	EH W	EH M	EMN D	EMN W	EMN M	EWS D	EWS W	EWS M	GLI D	GLI W	GLI M	M D	M W	M M	MA D	MA W	MA M	HY D	HY W	HY M
Min	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max	0.3	0.3	0.5	0.0	0.5	0.7	0.1	0.1	0.4	0.1	0.0	0.4	0.0	0.1	0.4	0.1	0.3	0.6	0.1	0.2	0.5	0.1	0.1	0.5	0.0	0.2	0.5	0.4	0.3	0.6

Exhibit 6 Minimum and Maximum Difference in R-Square (Daily, 5-Day, 20-Day)

Source: HFR

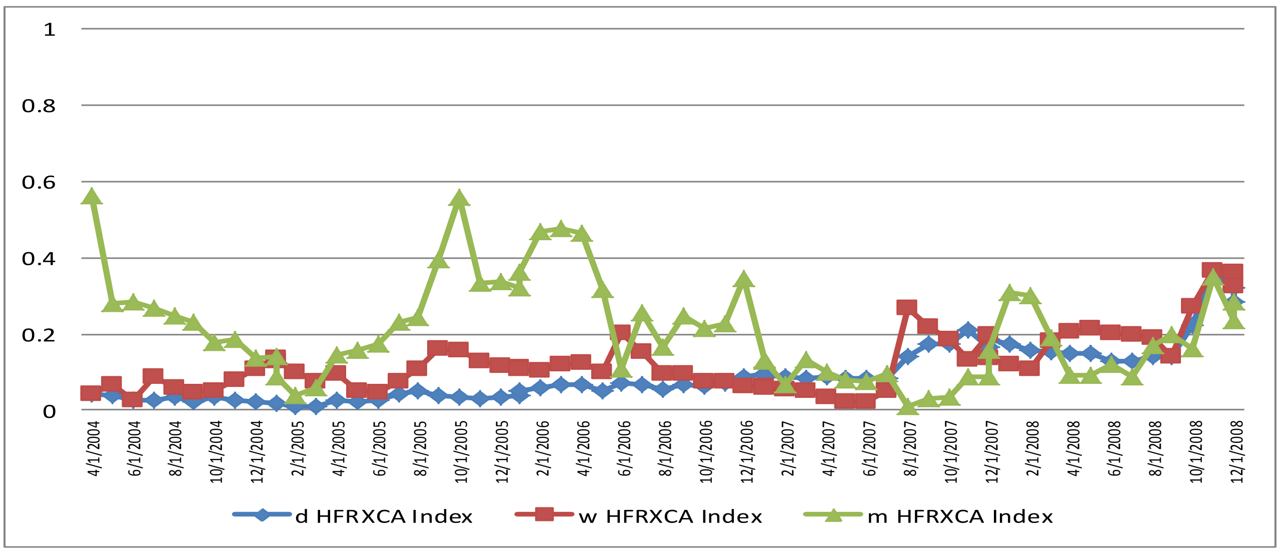


Exhibit 7 Convertible Arbitrage: R-Square Difference (Multi Beta- Single Beta)

Source: HFR

to zero and rising near the end of the period of analysis. This pattern is similar to that reported by the weekly (5-day) data series, although the difference in R-Square in the weekly data reported was lower at the start of the period (.20) and never fell as low as that reported using the monthly data. The daily data reported a similar pattern to the weekly and monthly data. (The difference in R-Square fell in the middle of the period and rose in the latter half, however for most of the period the difference in R-Square reflected in the use of daily data was less than those reported in the weekly and monthly data series.)

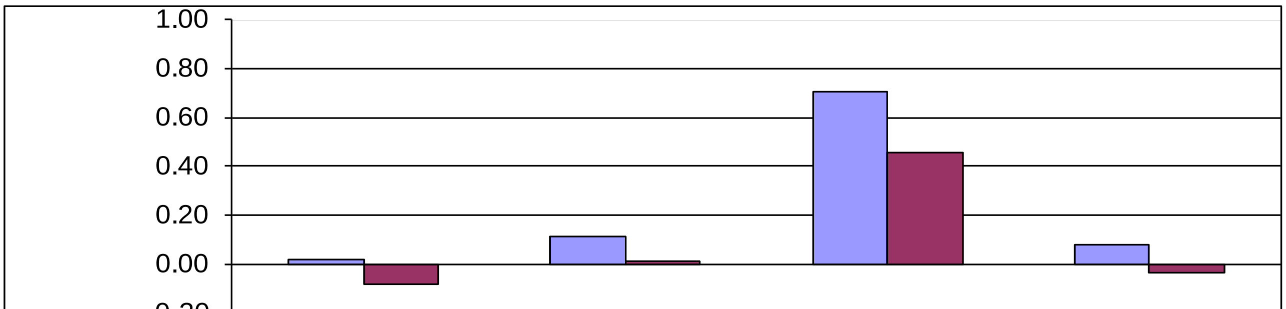
7. Data Point Impacts

Previous sections have shown the variability in autocorrelation patterns due to varying time periods and varying investment intervals. The rapid changes in autocorrelation patterns may be due in part to a single data point impacting 4-week data analysis more than weekly data. In the final part of the analysis, we analyze the impact of a single data point on the estimation of hedge fund portfolio's autocorrelation. First order autocorrelation has often been used as a basis for measuring potential illiquidity. In this analysis we measure the impact of the use of weekly and monthly data on measured autocorrelation for a set of hybrid mutual funds and the HFRX Convertible Arbitrage Index. In addition, we measure the impact of adjusting a single data point (day, week, or month) on the measured autocorrelation. In Exhibit 8 we show the impact on cross sectional autocorrelation of putting a zero return in place of October 2008 and the week ending October 15.

As shown in Exhibits 8, the autocorrelation of the HFRX CA Index as well as the Hybrid CA mutual funds is greater for monthly data than weekly data. As important, the autocorrelation is greater in the hedge fund index than in the comparison hybrid mutual fund portfolio. This is consistent with greater liquidity and fewer stale price impacts in mutual funds than hedge funds. However, results also show dramatic reduction in autocorrelation from the simple reduction of the large negative return in October 2008 to an assumed zero return for both the weekly and monthly data and for both the HFRX index as well as the hybrid mutual fund data.

8. Autocorrelation: Rolling

Previous sections have shown the variability in autocorrelation patterns varying investment intervals, as well as the impact of a single data point on the estimation of hedge fund portfolio's autocorrelation. First-order autocorrelation has often been used as a basis for measuring potential illiquidity. In this analysis we measure the impact of the use of weekly, monthly data on measured autocorrelation for the HFRX Convertible Arbitrage index. In addition, we



	Calamos Convertible Fund	Columbia Convertible Securities Fund	HFRX Convertible Arb	CA Portfolio
Full-Weekly	0.02	0.12	0.70	0.08
ADJ-Weekly	-0.09	0.01	0.45	-0.04

Exhibit 8 Convertible Arbitrage Autocorrelation: Weekly (Adjusted and Unadjusted)

Source: HFR, Morningstar

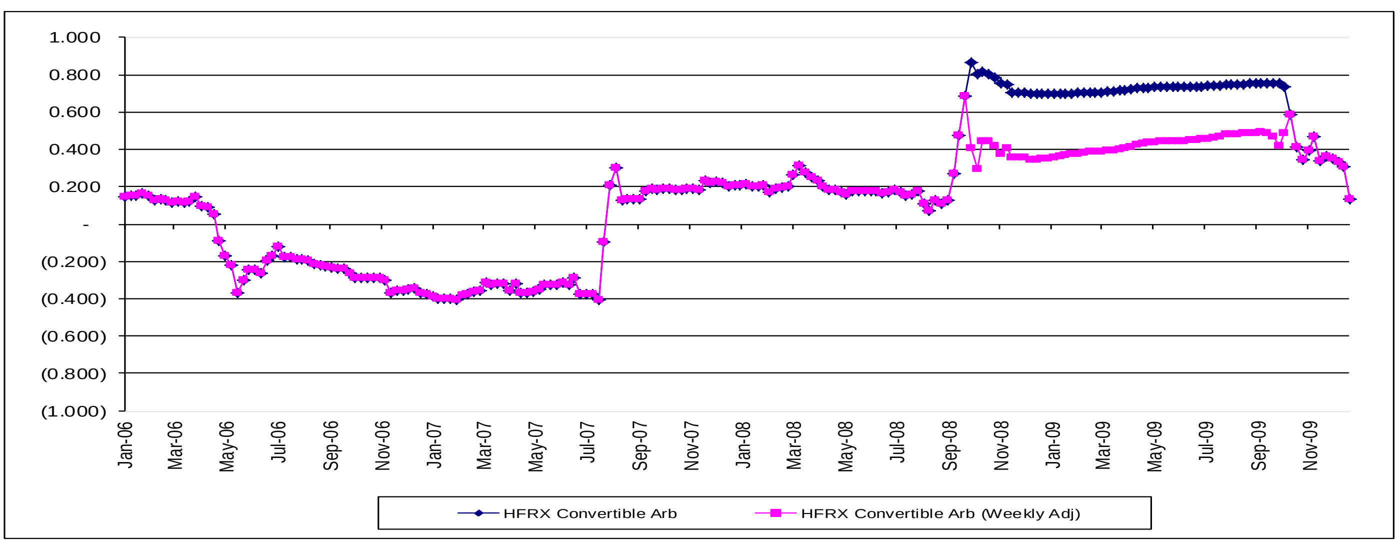


Exhibit 9a Convertible Arbitrage HF Rolling Autocorrelation - Weekly (Adj and Unadjusted)

Source: HFR

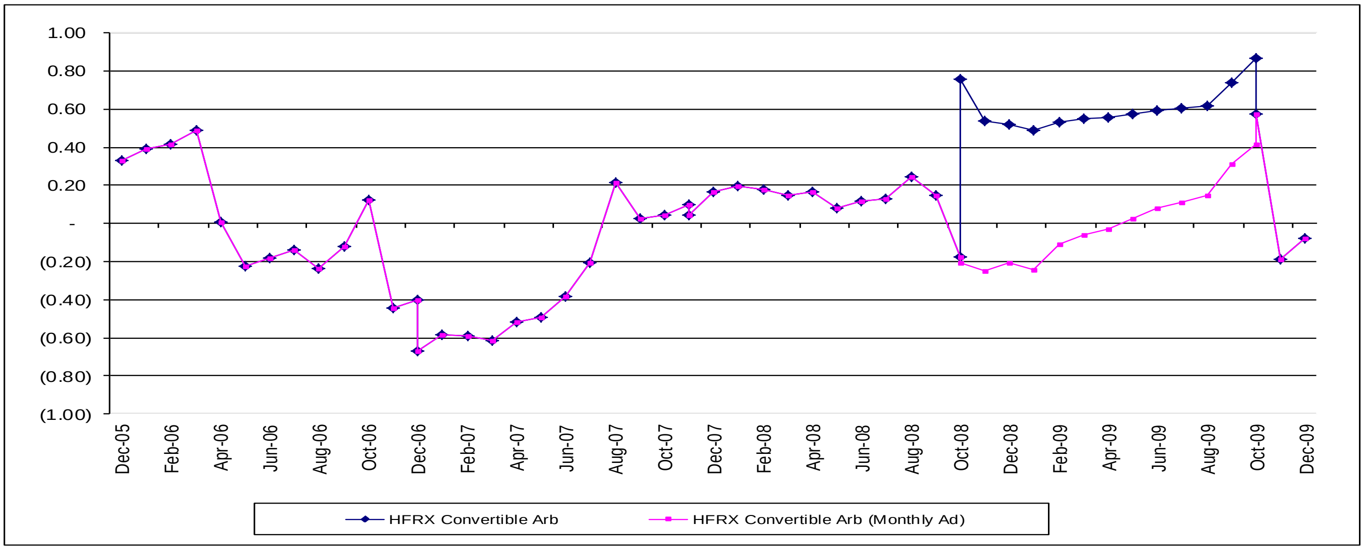


Exhibit 9b Convertible Arbitrage HF Autocorrelation (Rolling) - Monthly (Adj. and Unadjusted)

Source: HFR

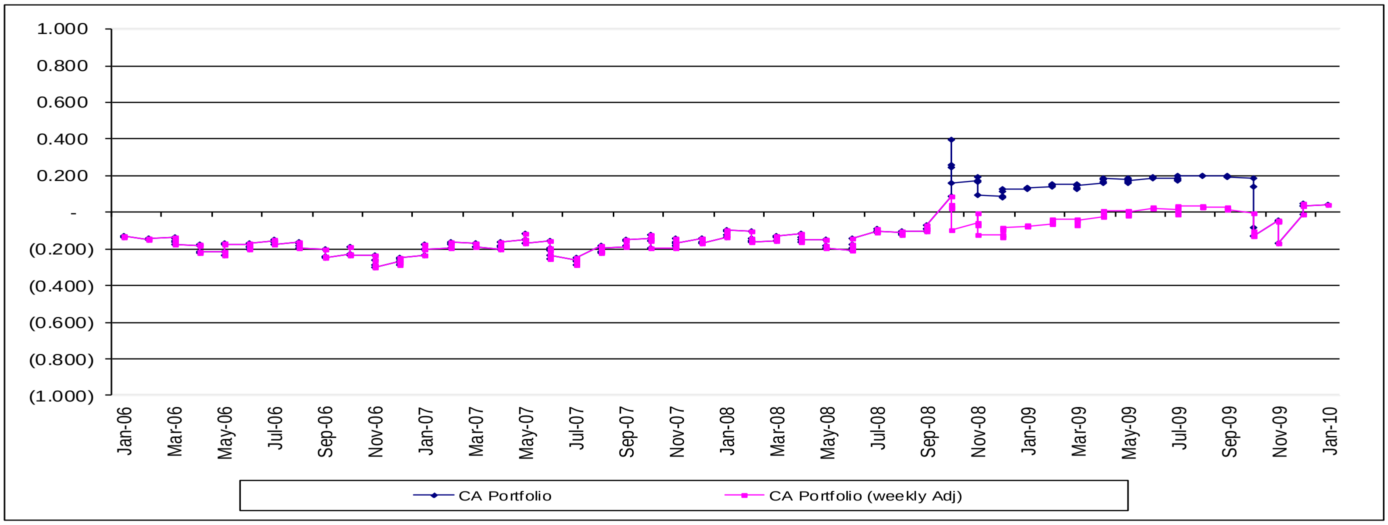


Exhibit 9c Convertible Arbitrage Mutual Fund Rolling Autocorrelation - Weekly (Adj and Unadjusted)

Source: Morningstar

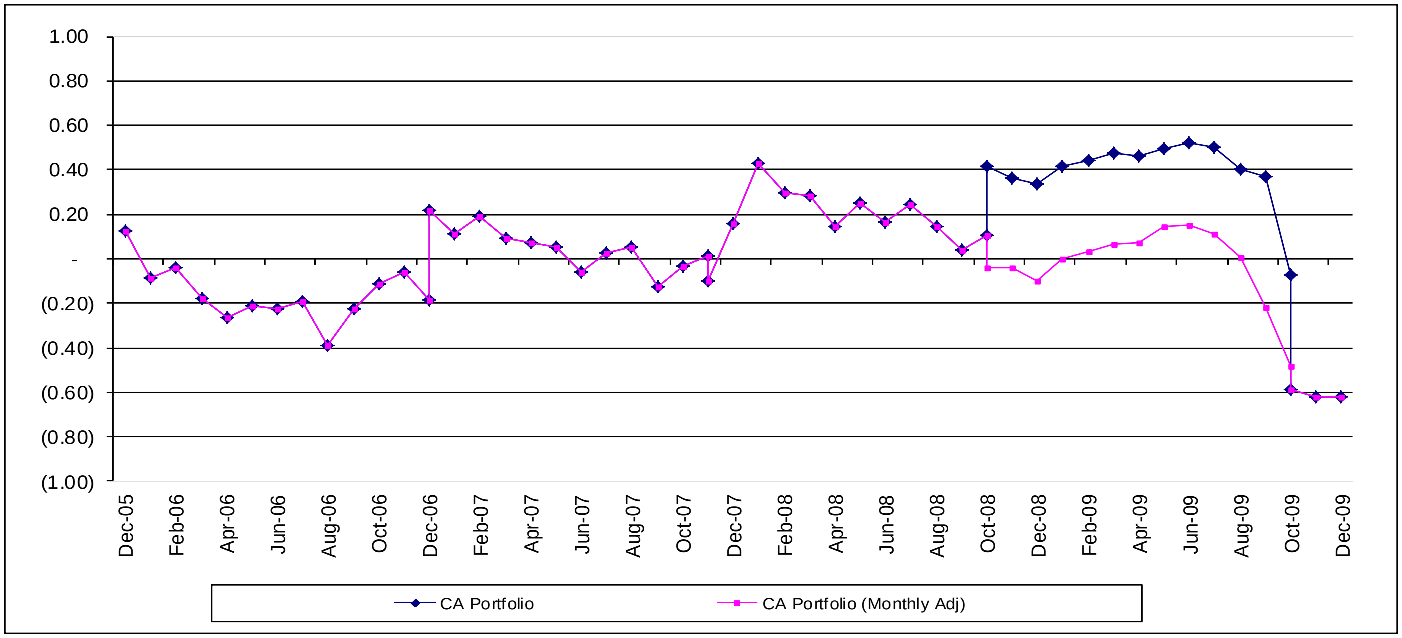


Exhibit 9d Convertible Arbitrage Mutual Fund Autocorrelation (Rolling) - Monthly (Adj. and Unadjusted)

Source: Morning Star

measure the impact of the adjusting a single data point (week, or month) on the measured autocorrelation. In Exhibits 9a to 9d we show the impact on rolling autocorrelation of putting a zero return in place of October 2009 and the week ending October 15.

As indicated Exhibit 9a and 9b, the cross sectional autocorrelation for convertible arbitrage (unadjusted) was near .60 for the HFRX Convertible Arbitrage index for late-2008 to late-2009. In these Exhibits the autocorrelation over the period is often negative and rarely rises above .40 (this is especially true after adjusting the data for the October crash).

9. Conclusions

The results of this analysis suggest that the choice of time interval (daily, weekly, or monthly) may potentially have a larger impact on beta and autocorrelation estimation than on return and standard deviation estimation. Furthermore, the removal of a single data point was shown to have a significant impact on beta and autocorrelation estimates. While this analysis does not define an "ideal" time interval or treatment of outliers, it does suggest that researchers should be aware that these choices may significantly impact their results.

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[1] The sensitivity of the results to individual observations may also be reflected in the time series pattern of autocorrelations. If an individual observation impacts reported autocorrelation its removal in a rolling regression may result in a drop in reported autocorrelation.

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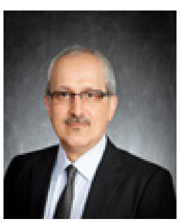

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