

ETF Betas: A Study of their Estimation Sensitivity to Varying Time Intervals

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As the ETF (Exchange Traded Fund) market grows, new applications for ETFs are continually being designed. Some applications are for traditional long-term investors, while others are for investors with a much shorter time horizon. For example, many portfolio managers are using ETFs as components of a core and satellite investment strategy, with the intent of holding the ETF for an extended investment horizon, while some hedge fund managers are using ETFs in strategies designed to take advantage of a much shorter time horizon and the ability to short on a downtick. For a variety of reasons, such as tax advantage, continuous trading, true NAV pricing, no downtick shorting restrictions, low tracking-error, instant liquidity, segmental exposure, built-in diversification, and low operational and management fees, they have become the choice instrument of trade for professional and hedge fund portfolio managers.

From an analytical standpoint, both of these manager types are likely using beta as a gauge of their systematic portfolio risk, which leads to the important question of how sensitive the beta calculation is to the choices of data frequency (daily or weekly returns) and time interval of estimation (length of estimation window). According to Graham and Harvey [2001] in a survey of industry participants, over 70% of respondents always or almost always look at the traditional CAPM

beta, especially when it comes to assessing the extent of systematic risk in the portfolio.

The purpose of this article is to analyze the impact of data frequency and time interval in the calculation of beta to determine the importance of these variables in the application of ETF strategies. This is an important issue because of the impact the results could have on measuring portfolio metrics such as portfolio beta, net beta for a hedged portfolio, alpha, tracking error, volatility, and idiosyncratic risk. Perhaps more significantly—particularly from the perspective of a portfolio or hedge fund manager—this article provides important new evidence regarding the significance of matching the duration of a risk measure to the duration of the investment time horizon. Additionally, the article provides market betas for some of the most active ETFs in the U.S. equity markets; these were calculated using historical data with time intervals ranging from six months to five years, using both daily and weekly returns.

How stable is the beta calculation for a group of ETFs over different time intervals? Specifically, does it matter if the estimation window length is six months, one year, two years, or five years? What is the impact of frequency of data observation (returns) on stability? Specifically, does it matter if data frequency is daily or weekly? How correlated are index returns across intervals? Does data frequency impact these correlations? Clearly,

the answers to each of these questions have implications for portfolio managers, hedge fund managers, investment advisors, financial engineers, and academic researchers. Variations in trading behavior, holding period, and estimation of risk horizon necessitate that there be some understanding or awareness of the temporal assumptions embedded in beta estimation that are relevant to a particular portfolio's characteristics. The remainder of this article addresses these questions and provides documentation for the impact of these factors on the estimation of beta for ETF applications.

DATA AND LITERATURE

The first ETF was introduced in 1993 (the S&P 500 Spyder—ticker SPY), and by 2001 the total number of ETFs was about 50 with a combined \$79 billion in assets (Poterba and Shoven [2002]). Today that number has exponentially grown to about 300 ETFs with over \$500 billion in assets.

To perform the beta stability tests, a dataset of ETFs was constructed, with return continuity and trading liquidity in mind. In order to be retained in the dataset, the ETF must have at least five years of return data available, from January 2002 to January 2007, and have an average trading volume of at least \$500 million per day. Based on this selection mechanism, 38 ETFs remained in the data set. The S&P 500 continues to be the most prevalent benchmark for portfolio evaluation in the U.S. equity markets and is the index of choice among asset management firms as well as providers of portfolio analytics. Also, it is the choice ETF to short the market, especially for market-neutral hedge fund managers who seek to eliminate systematic market risk from their portfolios and add alpha at the margin, either through stock selection or sector rotation.

$$\text{Alpha } \alpha = \text{Total Return of the Portfolio} - ((\text{Portfolio Beta}) * (\text{Market Return})) \quad (1)$$

We have chosen to calculate market betas using the Standard & Poors SPDR Trust (SPY) as the relevant index. On any given day, it is among the top three most actively traded securities in the U.S. equity market, with an average trading volume of 125 million shares and a current market cap of about \$65 billion.

An exhaustive literature survey revealed no article on the topic of beta stability for ETFs. The techniques used

in this article make reference to the beta stability in the stock market research of Gooding and O'Malley [1977] where they outline tests for beta stationarity and implement a correlation testing technique. The time interval tests follow the methodology developed in Theobald [1981]. Past research has focused on the stability of the betas using individual stocks or portfolios of individual stocks. Fabozzi and Francis [1978]; Sundar [1980]; Bos and Newbold [1984]; and Collins, Ledolter, and Rayburn [1987] all found a lack of beta stability for individual stocks. Collins, Ledolter, and Rayburn [1987]; and Gregory-Allen, Impson, and Karafiath [1994] found beta instability in some portfolios as well. This article seeks to add to this literature by testing for beta stability, or lack thereof, in ETFs. Additionally, the article provides market betas for the 38 most active ETFs in the U.S. equity markets over different estimation windows (intervals) and return frequencies.

RESULTS: BETA DISPERSION TESTS

The OLS beta for individual securities is estimated with the standard market model, with additional specifications with respect to a time interval of L and a window-length of estimation T.

$$r_i = \alpha_i + \beta_i r_M + e_i \quad (2)$$

$$r_{iLT} = \alpha_{iL} + \beta_{iL} r_{MLT} + e_{iLT} \quad (3)$$

where: r_i is the return on security i , r_M is the return on the market, r_f is the risk-free rate of return, β_i is the calculated beta coefficient, α_i is the intercept term, and e_i is the residual term.

Exhibit 1 identifies the 38 ETFs that meet our liquidity and trading history criterion and provides estimates for beta for time intervals of six months, one year, two years, three years, four years, and five years for each ETF. Betas are also calculated using both daily and weekly data. For ease of reference, betas greater than 1.25 are in bold while those less than 0.75 are in *italics*. This exhibit is intended as a ready reference for the reader or practitioner to see the differential impact of varying interval lengths and return frequencies on the value of the estimated betas. Exhibit 2 presents summary statistics from the information in Exhibit 1 and provides summary evidence that on a time interval basis there is not a substantial difference

EXHIBIT 1

Selected ETF Beta Values Using Daily and Weekly Data

Betas were calculated using historical data with time intervals ranging from six months to five years using both daily and weekly returns. The S&P 500 SPDR Trust ETF, SPY, was used as a proxy for the market index.

ETF	Daily Data						Weekly Data					
	6 mo.	1 yr	2 yr	3 yr	4 yr	5 yr	6 mo.	1 yr	2 yr	3 yr	4 yr	5 yr
DIA	0.88	0.92	0.93	0.92	0.93	0.94	0.97	0.97	0.93	0.92	0.96	0.92
EFA	1.05	1.19	1.02	1.03	0.92	0.82	1.07	1.33	1.15	1.12	0.99	0.86
EWA	1.02	0.92	0.83	0.85	<i>0.6</i>	<i>0.52</i>	1.01	1.21	1.02	0.99	0.75	<i>0.63</i>
EWG	1.2	1.39	1.17	1.18	1.17	1.13	1.16	1.6	1.36	1.37	1.35	1.24
EWH	1.27	1.19	0.98	1.04	0.99	0.83	1.25	1.15	0.89	1.05	0.98	0.79
EWJ	1.15	1.39	1.17	1.22	1.03	0.8	1.1	1.51	1.24	1.22	1.03	<i>0.73</i>
EWM	0.75	<i>0.74</i>	<i>0.57</i>	<i>0.67</i>	<i>0.5</i>	<i>0.33</i>	<i>0.37</i>	<i>0.7</i>	<i>0.53</i>	<i>0.61</i>	<i>0.43</i>	<i>0.42</i>
EWS	1.09	1.09	0.88	0.95	0.95	<i>0.69</i>	0.8	1.17	0.87	0.99	1.04	0.83
EWT	1.5	1.58	1.24	1.4	1.31	1.14	1.3	1.88	1.52	1.64	1.32	1.17
EWV	2.16	2.21	1.67	1.49	1.09	0.87	1.93	2.18	1.97	1.78	1.39	1.07
EWY	1.45	1.67	1.45	1.43	1.28	1.06	1.67	2.05	1.76	1.82	1.66	1.29
EWZ	2.12	2.63	2.13	1.96	1.44	1.03	2.13	2.61	2.21	2.17	1.79	1.4
IBB	1.39	1.36	1.24	1.39	1.33	1.26	1.64	1.49	1.37	1.39	1.37	1.3
IJR	1.68	1.49	1.37	1.36	1.17	0.99	1.68	1.53	1.5	1.43	1.25	1.09
IVV	0.98	0.99	0.99	0.99	0.99	0.99	0.98	0.99	1	1	0.99	0.99
IWD	0.84	0.93	0.97	0.96	0.97	0.94	0.89	0.97	0.98	0.97	0.97	0.96
IWF	1.16	1.04	0.98	1	1.02	1.02	1.15	1.07	1.04	1.02	1.02	1.03
IWM	1.76	1.64	1.48	1.46	1.26	1.06	1.82	1.64	1.61	1.55	1.35	1.15
IWN	1.65	1.56	1.41	1.37	1.17	0.97	1.66	1.51	1.48	1.41	1.23	1.04
IWO	1.9	1.73	1.53	1.54	1.35	1.15	2.05	1.81	1.74	1.68	1.47	1.28
IYR	0.94	0.92	0.98	0.89	<i>0.7</i>	<i>0.48</i>	1.13	1.04	1.15	0.93	<i>0.72</i>	<i>0.57</i>
MDY	1.4	1.28	1.17	1.15	1.04	0.97	1.48	1.39	1.32	1.26	1.12	1.05
OEF	0.87	0.86	0.88	0.89	0.94	0.98	0.88	0.88	0.87	0.89	0.94	0.97
OIH	1.4	1.6	1.46	1.21	0.85	0.94	1.75	1.67	1.67	1.37	0.89	0.94
PPH	<i>0.65</i>	<i>0.7</i>	<i>0.66</i>	<i>0.71</i>	0.78	0.82	0.78	<i>0.55</i>	<i>0.5</i>	<i>0.58</i>	<i>0.65</i>	<i>0.74</i>
QQQQ	1.63	1.34	1.21	1.26	1.28	1.33	1.45	1.4	1.4	1.37	1.33	1.43
RTH	1.26	0.94	1	0.99	1.01	0.93	0.98	1.01	1.06	1.03	1.04	0.96
SMH	1.93	1.59	1.39	1.48	1.55	1.67	2.12	1.52	1.6	1.65	1.72	1.83
SPY	1	1	1	1	1	1	1	1	1	1	1	1
XLB	1.14	1.36	1.28	1.25	1.12	0.98	1.11	1.46	1.43	1.4	1.22	1
XLE	1.02	1.28	1.34	1.13	0.84	0.83	1	1.31	1.41	1.17	0.8	0.78
XLF	1	0.99	0.99	0.98	1.02	1.06	0.96	0.96	0.95	0.97	1.02	1.08
XLI	1.05	0.99	0.98	1	0.98	0.97	1.07	1.07	0.99	1.03	1.03	1
XLK	1.39	1.17	1.06	1.12	1.2	1.31	1.23	1.26	1.24	1.26	1.31	1.43
XLP	<i>0.61</i>	<i>0.61</i>	<i>0.66</i>	<i>0.65</i>	<i>0.65</i>	<i>0.58</i>	<i>0.41</i>	<i>0.51</i>	<i>0.53</i>	<i>0.52</i>	<i>0.59</i>	<i>0.58</i>
XLU	<i>0.32</i>	<i>0.61</i>	0.8	<i>0.71</i>	<i>0.67</i>	0.76	<i>0.47</i>	<i>0.56</i>	<i>0.65</i>	<i>0.66</i>	<i>0.71</i>	0.76
XLV	<i>0.67</i>	<i>0.69</i>	<i>0.7</i>	0.76	0.78	0.78	<i>0.69</i>	<i>0.54</i>	<i>0.57</i>	<i>0.64</i>	<i>0.67</i>	<i>0.67</i>
XLY	1.18	0.99	1.03	1.03	1.06	1	1.14	1.05	1.11	1.09	1.13	1.04

*Betas >1.25 are in **bold**, betas <0.75 are in *italics*.

EXHIBIT 2

Summary Statistics on the Average Beta from 38 ETFs

Betas for the 38 ETFs were averaged to generate summary data. Betas were calculated using both daily and weekly returns over a time interval ranging from six months to five years. Note that for both daily and weekly return frequencies the average beta declines as the time interval increases. The standard deviation declines with the average.

Daily Data						
Return Interval	Valid N	Mean	Harmonic Mean	Lower Quartile	Upper Quartile	Standard Deviation
6 month	38	1.22	1.06	0.98	1.45	0.42
1 year	38	1.23	1.10	0.93	1.49	0.43
2 year	38	1.12	1.04	0.97	1.34	0.31
3 year	38	1.12	1.05	0.95	1.36	0.28
4 year	38	1.02	0.96	0.92	1.17	0.24
5 year	38	0.94	0.87	0.82	1.06	0.24
Weekly Data						
6 month	38	1.22	1.03	0.97	1.64	0.46
1 year	38	1.28	1.10	0.99	1.52	0.46
2 year	38	1.20	1.05	0.95	1.48	0.40
3 year	38	1.18	1.06	0.97	1.40	0.37
4 year	38	1.09	0.99	0.94	1.32	0.31
5 year	38	1.00	0.92	0.79	1.15	0.28

between the betas generated from daily data relative to the results using weekly data. Exhibit 2 also demonstrates that, on average, beta tends to decrease and converge toward one as the estimation window increases; in other words, there is an inverse relationship between interval length and average beta values. The results stand even when the mean is replaced by the harmonic mean, which assigns lesser weights to extreme values. It is also interesting to note that the standard deviation of the set of betas for a particular interval length and frequency combination declines as the estimation window gets larger. This observation has important implications for hedge fund managers maintaining a beta-neutral portfolio, who have to factor in the effects of volatile betas estimated over shorter durations. The effect is persistent across both daily and weekly frequencies. It is also pertinent to managers charged with generating alpha, since lower betas tend to produce higher risk-adjusted alphas and can affect their annual compensation, which is often a function of the risk-adjusted alpha they deliver.

Exhibit 3 presents the results of a formal test for the differences between the mean beta estimates using daily and weekly data for each time interval by applying a paired t-test. In this exhibit, p-values are presented for the difference in means assuming the unequal variance t-test.

The exhibit is designed to investigate the differential impact of using daily and weekly return frequency in beta estimation. The results indicate that the frequency of returns is not as important as the length of the interval window, since the means are not significantly different for all congruent interval periods. Exhibit 3 also provides evidence that both hedge fund managers and portfolio managers alike should be aware of—that there is a significant difference between the betas derived from short and long duration time intervals.

Exhibit 4 tests for differences in variance between the average betas calculated using daily and weekly observations. At the 5% level of significance, variance between the average betas calculated with the daily and weekly frequencies are not significantly different. It should be noted that variances are significantly different at the 10% level of significance for time intervals between two and four years. There is also evidence to suggest that the lower standard deviation for longer time intervals is significantly different from the higher standard deviation found in shorter time intervals. This indicates further support for managers to make sure they match the time interval used to generate beta with their expected investment horizon. Hedge fund managers with short-term, beta-neutral strategies could be particularly vulnerable to these issues.

EXHIBIT 3

p-values from Difference in Means Tests for Daily and Weekly Betas

The difference in means test assuming unequal variances produces the following p-values when comparing the average betas found in Exhibit 2. Daily data are displayed in column form and weekly data in row form. For the same time interval, means are not significantly different using daily or weekly data. The mean beta is significantly different when comparing long duration with short duration time interval based betas, suggesting beta stability issues.

Daily \ Weekly	6 month	1 year	2 year	3 year	4 year	5 year
6 month	0.9511	0.6018	0.8074	0.6480	0.1085	0.0085
1 year	0.9406	0.6126	0.7972	0.6390	0.1071	0.0085
2 year	0.2844	0.0894	0.3382	0.4388	0.6228	0.0813
3 year	0.2479	0.0724	0.2937	0.3858	0.6584	0.0791
4 year	0.0245	0.0042	0.0240	0.0312	0.3406	0.6892
5 year	0.0019	0.0002	0.0014	0.0016	0.0312	0.3521

*Values in **bold** are significant at the $p < 0.05$ level.

To further investigate the short-term duration versus long-term duration beta estimation issue, paired t-tests were conducted to test for the difference in mean beta observation across the time intervals for each frequency—in other words, separate tests for both daily and weekly betas. Exhibit 5 provides the p-values from these tests. These results provide further evidence that there is a significant difference between the average beta generated from shorter duration and longer duration time intervals, even when controlled for return frequency. For example, notice that there is a significant difference between the mean betas calculated over a six-month to three-year time interval and the mean betas calculated over a five-year

time interval. The results are qualitatively similar for both daily and weekly frequencies, providing further evidence that the time interval of estimation (window length) is the driving factor in the variability of beta estimates.

RESULTS: CORRELATION TESTS

Exhibit 6 presents a correlation matrix that measures the cross-correlations of betas between various permutations of intervals and frequencies. It is interesting to note that the same time interval returns are highly correlated, ranging from 0.94 to 0.98 (shaded cells within the correlation matrix, in the top right quadrant), for

EXHIBIT 4

p-values from Difference in Variance F-tests

The difference in variance F-tests produces the following p-values when comparing the variances of the average betas found in Exhibit 2. Daily data are displayed in column form and weekly data in row form. For the same time interval (shaded cells), variances are not significantly different at the 5% level using daily or weekly data (although they are close in the 2–4 year intervals). The variances are significantly different when comparing longer duration and shorter duration time intervals (bold values), suggesting beta stability issues.

Daily \ Weekly	6 month	1 year	2 year	3 year	4 year	5 year
6 month	0.3157	0.2836	0.3969	0.2202	0.0340	0.0071
1 year	0.3349	0.3019	0.3765	0.2048	0.0303	0.0061
2 year	0.0113	0.0089	0.0597	0.1463	0.4957	0.2547
3 year	0.0024	0.0018	0.0180	0.0538	0.2905	0.4612
4 year	0.0000	0.0000	0.0008	0.0038	0.0509	0.1600
5 year	0.0001	0.0000	0.0014	0.0063	0.0725	0.2079

*Values in **bold** are significant at the $p < 0.05$ level.

EXHIBIT 5

p-values from Difference in Means Tests

The difference in means tests assuming unequal variances produces the following p-values when comparing the average betas found in Exhibit 2. Daily betas are compared at the top of the exhibit and weekly betas at the bottom of the exhibit. The mean beta is significantly different when comparing long duration and short duration time interval based betas, even when controlled for return frequency, suggesting inter-temporal beta instability.

	p-values of Daily Data					
	6 month	1 year	2 year	3 year	4 year	5 year
6 month	1.0000					
1 year	0.9888	1.0000				
2 year	0.2302	0.2268	1.0000			
3 year	0.1952	0.1924	0.9425	1.0000		
4 year	0.0139	0.0139	0.1346	0.1328	1.0000	
5 year	0.0008	0.0008	0.0077	0.0062	0.1502	1.0000
	p-values of Weekly Data					
	6 month	1 year	2 year	3 year	4 year	5 year
6 month	1.0000					
1 year	0.5748	1.0000				
2 year	0.8641	0.4458	1.0000			
3 year	0.7104	0.3271	0.9350	1.0000		
4 year	0.1454	0.0383	0.1685	0.2233	1.0000	
5 year	0.0153	0.0026	0.0146	0.0189	0.2156	1.0000

daily and weekly return frequencies, thus providing further support for frequency being a less important factor than the time interval for estimating beta. The importance of time interval choice is highlighted by the substantial differences in correlation between interval return sets. For example, the correlation between returns using the six-month, daily interval and the one-year, daily interval is 0.91, while the correlation with the five-year, daily interval is only 0.57 (all correlations are significant at a p-value of 0.05). The correlations of pairs where the interval lengths vary by two years or more are generally below 0.75, indicating that there are substantial differences in the estimated betas, depending on estimation interval variation. This indicates that short duration betas are quite different from long duration betas, a result that should be factored in during portfolio formation and risk estimation. Failure to do so could result in modeling errors in portfolio reallocation, risk assessment, and performance measurement. In addition, short-term portfolio rebalancing could occur at sub-optimal levels due to the use of improper betas, potentially resulting in higher levels of tracking error.

POTENTIAL APPLICATIONS FOR THE INVESTMENT COMMUNITY

This article presents what it considers the first analysis of time-dependent factors that influence the stability of beta in the ETF market. Study results indicate that the calculated betas for ETFs are quite dependent on the choice of time interval used in their calculation. In addition, daily and weekly return collection frequencies are analyzed, and the results indicate that return frequency does not significantly affect the beta estimate, as long as the estimation intervals are similar or overlapping. These results have implications for investors, portfolio managers, and hedge fund managers, who intrinsically assume beta stability and stationarity in measuring portfolio metrics such as aggregate beta, net beta for a hedged portfolio, alpha, tracking error, volatility, and idiosyncratic risk.

The quantitative community in the U.S. asset management industry primarily uses vendor-supplied betas that are based on a 60-month return calculation (monthly frequency and a 60 month window-length of estimation period). The authors think there may be a legacy issue here, borne out of computational and data limitations

EXHIBIT 6

Interval Window and Frequency Correlation Matrix

The correlation matrix below measures the cross-correlations of betas between various permutations of intervals and frequencies. It is interesting to note that the same time interval returns are highly correlated, ranging from 0.94 to 0.98 (shaded cells), for daily and weekly return frequencies, thus providing further support for frequency being a less important factor than time interval for estimating beta. The importance of time interval is highlighted by the substantial differences in correlation between interval return sets. For example, the correlation between returns using the six-month daily interval and the one-year daily interval is 0.91, while the correlation with the five-year daily interval is 0.57. The exhibit indicates that the calculated betas for ETFs are quite dependent on the choice of time interval used in their calculation and that return frequency does not significantly affect the beta estimate, as long as the estimation intervals are similar or overlapping.

	Daily 6 mo.	Daily 1 yr	Daily 2 yr	Daily 3 yr	Daily 4 yr	Daily 5 yr	Weekly 6 mo.	Weekly 1 yr	Weekly 2 yr	Weekly 3 yr	Weekly 4 yr	Weekly 5 yr
D - 6 mo.	1	0.91	0.88	0.92	0.8	0.57	0.94	0.88	0.90	0.92	0.85	0.72
D - 1 year		1	0.97	0.96	0.73	0.44	0.88	0.97	0.95	0.96	0.82	0.61
D - 2 year			1	0.96	0.74	0.50	0.90	0.93	0.97	0.95	0.82	0.64
D - 3 year				1	0.87	0.61	0.92	0.94	0.95	0.98	0.91	0.74
D - 4 year					1	0.87	0.80	0.72	0.74	0.84	0.96	0.93
D - 5 year						1	0.62	0.43	0.51	0.59	0.78	0.95
W - 6 mo.							1.00	0.86	0.91	0.91	0.84	0.74
W - 1 year								1.00	0.96	0.97	0.83	0.61
W - 2 year									1.00	0.97	0.84	0.67
W - 3 year										1.00	0.92	0.75
W - 4 year											1.00	0.91
W - 5 year												1.00

*All correlations significant at $p < 0.05$ level (95% level of significance).

Values in **bold are < 0.75 in magnitude.

years ago when beta first started getting deployed *en masse* in industrial portfolio evaluation.¹ In particular, there appears to be no justification for employing a 60-month beta, based on a monthly interval to indicate a one-day or one-week portfolio systematic risk. We also believe that with the growth of the market-neutral hedge fund industry, the need for daily portfolio rebalancing will necessitate the use of differing interval betas, with a drift toward higher frequency information and thus shorter intervals. Indeed, the results of this article suggest that investment firms following short time horizon strategies might be well served to calibrate the length of the beta estimation window with the duration of the underlying investments.

ENDNOTE

¹Thus the birth of processed financial information providers such as BARRA, Berkeley, 1975, and Vestek Systems, San Francisco, 1983.

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