

To Beta or Not to Beta

A Comparison of Historical Versus Fundamental Betas for Hedging Market Risk

| July 2007

Jennifer Bender

Fundamental betas provide several conceptual advantages to historical betas--they reflect information on a timelier basis and are less likely to confuse noise for information. This paper revisits the advantages of using fundamental beta for hedging systematic risk in the U.S. Fundamental beta appears to be a more consistent measure for hedging market risk, particularly for investors who care about downside risk and tail risk.

Introduction

Having an accurate measure of a stock or portfolio beta is of paramount importance to any investor interested in identifying market risk whether for hedging a long-only portfolio, creating market-neutral portfolios, or implementing a portable alpha strategy. There are a variety of measures of beta currently in use. MSCI Barra calculates a predicted or fundamental beta based on the variance and covariance estimates derived from its risk models. As the economy and characteristics of individual issuers change, fundamental beta adapts to reflect changing asset characteristics. Factor-model-derived betas also avoid misattributing accidental historical relationships. This article discusses what we know about fundamental beta and its historical counterparts and revisits the advantages of using the former for hedging systematic risk in the U.S.

We find two main results using simulated portfolios over the January 1990 to February 2007 period:

1. **For long-only investors, fundamental betas appear to be a more consistent measure for hedging portfolio performance.** For investors who care only about ex-post beta, the advantages of using fundamental beta may not be so pronounced, but for those who care about volatility reduction and metrics that capture downside risk and tail risk, the gains can be substantial.
2. **For a long-short investor who is industry-neutral, market risk is minimal and may not need to be hedged.** Differences between the hedged and unhedged portfolios are minimal across all metrics.

Though This Be Madness, Yet There is Method In't: What Do We Know About Beta

The basic measure of beta is the covariance of a stock's return with the market return divided by the variance of the market return. Betas can be exponentially weighted to give more weight to recent observations or scaled (Bayesian-adjusted) to some prior estimate like a long-term average. Given the wealth of empirical research on betas and their properties, what do we currently know about beta?

- 1) **Betas appear to be time-varying:** Betas exhibit little stability over time. Evidence on beta-instability in the U.S. is seen in the earliest research: Blume (1971, 1975), Gonedes (1973), Meyers (1973), Levy (1974), Baesel (1974), Bos and Newbold (1984), Gonzalez-Rivera (1997), Groenewold and Fraser (1999), Black and Fraser (2003), Fraser et al (2000).¹
- 2) **Betas are hard to forecast:** Betas show less persistence and predictability than variances and covariances (see Groenewold and Fraser (1999)). This is particularly true of betas constructed with high frequency returns (see Andersen, Bollerslev, Diebold, and Wu (2003)).
- 3) **Betas are less stable for individual securities:** For single securities, betas are noisy. Beta estimates become more stable as portfolio size increases (see Alexander and Chervany (1980)).

Company characteristics, the market, and the risks that exist in the market are continuously changing over time so it is not surprising that betas are time-varying.² What is perhaps surprising is the degree to which beta is more difficult to forecast relative to volatility. Despite these challenges, beta estimates can still be useful approximations, at least for the purposes of assessing and hedging market risk.

What's in a Name? Fundamental Beta Revisited

Fundamental beta moves closer to overcoming these challenges by leveraging the strengths of the multiple-factor model. As the economy and characteristics of individual issuers change, fundamental beta adapts to reflect changing asset characteristics. Moreover, fundamental beta is less susceptible to outliers in the data and because economic logic is used to build the factor structure, it is not limited by purely historical analysis.

Recall that in a factor model framework, the risk of any portfolio is given by:

$$\sigma_p^2 = h_p^T (XFX^T + \Delta)h_p \quad (1)$$

where

h_p = vector of portfolio weights for N assets

X = exposure matrix of N assets to K factors

F = $K \times K$ factor covariance matrix

Δ = $N \times N$ diagonal matrix of specific risk

¹ Additional evidence comes from the conditioning variables literature (see Dybvig and Ross (1985), Hansen and Richard (1987), Ferson, Kandel and Stambaugh (1987), Ferson and Harvey (1991), Jagannathan and Wang (1996), and Wang (2003)) and the financial econometric volatility literature (for a survey, see Anderson, Bollerslev and Diebold (2004)).

² As an example, consider a change in a company's operations such as a major acquisition or a spin-off. Such an event would significantly change the company's risk characteristics but historical beta would only recognize this change slowly over time.

Similarly, the covariance of a portfolio p with b is given by:

$$\text{cov}(r_p, r_b) = h_p^T (XFX^T + \Delta)h_b \quad (2)$$

Beta takes the usual form:

$$\beta_p = \frac{\text{cov}(r_p, r_b)}{\sigma_b^2} \quad (3)$$

where the portfolio b is a market portfolio proxied by a broad market index like the S&P 500 or the MSCI US Prime Market 750 Index. Substituting (1) and (2) into (3), and separating out the factor and specific terms in the numerator, beta can be written as:

$$\beta_p = \frac{h_p^T XFX^T h_b + h_p^T \Delta h_b}{\sigma_b^2} \quad (4)$$

The first term in the numerator captures the covariance of the portfolio with the market due to their shared common factors. The second term in the numerator captures the specific component. For a single asset³, (4) can be rewritten as:

$$\beta_n = \frac{\sum_{j=1}^K \sum_{k=1}^K x_{n,j} f_{j,k} x_{b,k} + h_{b,n} \sigma_n^2}{\sigma_b^2} \quad (5)$$

where

$x_{n,j}$ = the exposure of an asset n to factor j

$x_{b,k}$ = the market's exposure to factor k

$f_{j,k}$ = the covariance between factors j and k

$h_{b,n}$ = the weight of the asset n in the market

σ_n^2 = the specific variance of the asset n

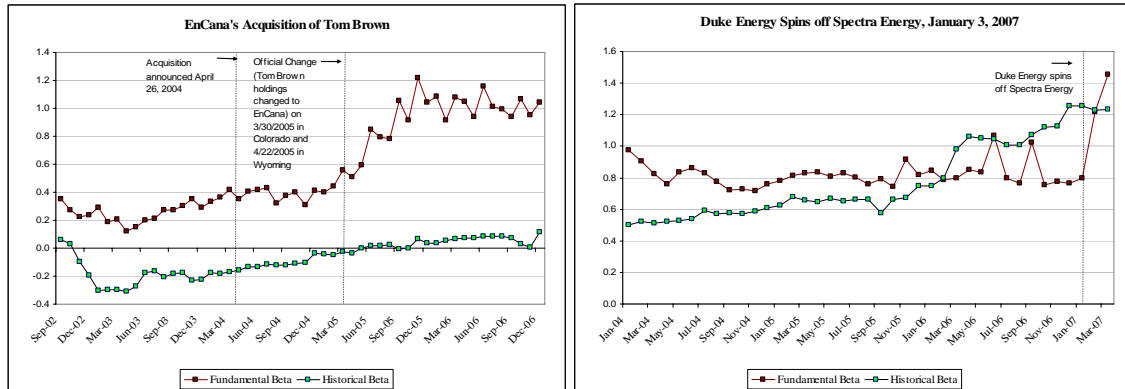
Equation (5) highlights the intuitive appeal of fundamental beta. Since the specific risk term in the numerator is very small (zero if the asset is not in the market index), beta will more accurately reflect systematic risk. In contrast, historical betas for individual stocks are likely dominated by specific risk; historical estimates can easily misattribute one-time comovements between specific returns and the market to systematic comovement.

Moreover, because the exposures are constructed in each month, any changes to a stock's size, industry, exposure to value, growth, momentum, etc. are reflected immediately. Figure 1

³ Note the matrix Δ is diagonal.

illustrates these advantages. During the period in which Canadian-based natural gas company EnCana acquired Tom Brown, EnCana's volatility exposure rose dramatically resulting in higher fundamental beta. Meanwhile, when Duke Energy spun off Spectra Energy, the increase in beta reflected the industry assignment shift (Duke Energy's exposure to Oil Refining went from 0.26 to 0 while its exposure to electrical utilities rose from 0.63 to 0.85 and its exposure to telephones rose from 0.1 to 0.14.).

Figure 1



One final advantage to using fundamental betas relates to implementation. If a market index like the S&P 500 is used as the market return, historical beta ignores the fact that the constituents of the index and/or their weights have changed over time. The longer the history used, the less accurately the estimated beta reflects the current index composition.

All The World's A Stage: Evaluating Beta Performance and Accuracy

Next, we explore the efficacy of using fundamental beta to hedge market risk. It turns out, not surprisingly, that the performance of different types of beta depends on the type of portfolio being hedged and the time period over which the hedge is evaluated. However, several distinct patterns emerge which shed light on the conditions under which beta hedging is effective. The details of the analysis and results are as follows.

Simulated portfolios are constructed, and rebalanced and hedged monthly with S&P 500 futures where the hedge ratio is the beta of the portfolio against the S&P 500. Fundamental betas from our long-horizon and short-horizon (USE3L and USE3S) models are compared against several historical measures of beta: equal-weighted 60-month betas, equal-weighted 250-day betas, exponentially-weighted 250-day betas (with half-lives of 22 days and 180 days), Bayesian adjusted betas⁴, and normalized equal-weighted 250-day betas.⁵ Betas calculated using daily data are adjusted for serial correlation where appropriate.

⁴ Betas can be adjusted to some long-term market or industry average or to some other prior. We build our measure as a weighted linear combination of the time-series equal-weighted 250-day beta of each stock and the cross-sectional cap-weighted average across all stocks for that month. The weights are based on the standard errors.

To evaluate the efficacy of the betas for hedging, we need a metric for performance. The measure most typically used is the ex-post beta between the hedged portfolio returns and the market return which should approximate zero. However, depending on the investor's objective function, metrics that better capture downside risk and non-linear risk may be more appropriate. Cotter and Hanly (2006) propose evaluating hedging performance using volatility of the hedged series, semi-variance (or downside volatility), Value-at-Risk, and conditional Value-at-Risk. Results are calculated for all five types of measures.

We examine the following types of portfolios: long-only portfolios formed randomly and based on various attributes (i.e., size, volatility, beta, etc.); long-only portfolios with industry and style biases; long-short industry-neutral portfolios; and long-short portfolios with asymmetric industry bias. We form portfolios of various sizes (e.g., 10, 20, 50, 100, 200 stocks) equal-weighted and cap-weighted. All names are pulled from the estimation universe for the USE3 models, which consist of roughly the 2,000 largest cap names in the U.S. Performance of the hedged portfolios is evaluated over the period January 1990 to February 2007. We report average metrics over the various portfolios below. For the ex post beta metric, mean absolute deviation may be in fact a more relevant measure; here, the results are qualitatively similar to those using the average and are available upon request.

Two distinct patterns emerge from our results:

(1) For long-only investors, fundamental betas appear to be a more consistent measure for hedging portfolio performance.

While all betas do a reasonably good job at hedging market risk, fundamental beta does at least as well if not better across all metrics. For investors who care only about ex-post beta, the advantages of using fundamental beta are not as pronounced, but for those who care about volatility reduction and metrics that capture downside risk and tail risk, the gains can be substantial.

Looking first at ex-post betas, fundamental beta does consistently well in all portfolios, as do 60-month historical betas whereas daily-data derived historical betas yield suboptimal results in all cases. Ex-post betas range between and -0.07 and 0.09 across portfolios of all size with the best hedges falling between -0.02 and 0.02.

Turning to the remaining four metrics, fundamental beta exhibits consistently better results—the volatility of the hedged portfolios is consistently lower for these portfolios, and losses in the tail are smaller. One subset of our results (randomly generated portfolios with $n = 50$ stocks, and style/industry portfolios) is shown in Tables 1A and 1B.

⁵ Because historical betas are on average more cross-sectionally dispersed than fundamental betas, we normalize them to have the same mean and standard deviation as fundamental beta to examine whether this adjustment has an impact.

Table 1A: Hedging Performance for Long-Only Well-Diversified Portfolios

Hedging Performance Results: Randomly Constructed Portfolios, Long-Only, N = 50
Average Metrics Across 100 Portfolios
Period of Evaluation: January 1990 - February 2007 Monthly

	Unhedged	Hedged (USE3S Beta)	Hedged (Historical 60-Mth Beta)	Hedged (Historical 360-Day Beta Eq Wgtd)	Hedged (Historical 360-Day Beta Exp. Wgtd, Half-life = 22 Days)	Hedged (Historical 360-Day Beta Exp. Wgtd, Half-life = 180 Days)	Hedged (Bayesian-adj. USE3S Beta)
Ex Post Beta	0.99	-0.01	-0.02	0.02	0.02	0.02	0.03
Downside Ex Post Beta*	0.98	-0.02	-0.02	0.03	0.03	0.03	0.03
Volatility (Stdev Annualized)	17.04%	9.78%	10.00%	9.83%	9.83%	9.83%	9.84%
Downside Volatility (Stdev Ann)*	14.33%	10.02%	10.03%	10.24%	10.06%	10.06%	10.06%
VAR (95th Percentile)	0.075	0.044	0.044	0.045	0.044	0.044	0.044
VAR (99th Percentile)	0.131	0.072	0.074	0.072	0.072	0.072	0.072
Conditional VAR (95th Percentile)	0.108	0.062	0.064	0.061	0.062	0.062	0.062
Conditional VAR (99th Percentile)	0.154	0.088	0.092	0.087	0.088	0.088	0.088

* Computed using months w hen S&P 500 market return is negative.

** VAR expressed as \$ per one dollar investment.

Table 1B: Hedging Performance for Long-Only Concentrated Portfolios

Hedging Performance Results: Style and Industry, Long-Only
Average Metrics Across 79 Portfolios (24 Style Portfolios, 55 Industry Portfolios)
Period of Evaluation: January 1990 - February 2007 Monthly

	Unhedged	Hedged (USE3S Beta)	Hedged (Historical 60-Mth Beta)	Hedged (Historical 360-Day Beta Eq Wgtd)	Hedged (Historical 360-Day Beta Exp. Wgtd, Half-life = 22 Days)	Hedged (Historical 360-Day Beta Exp. Wgtd, Half-life = 180 Days)	Hedged (Bayesian-adj. USE3S Beta)
Ex Post Beta	1.06	0.01	-0.01	0.10	0.10	0.10	0.11
Downside Ex Post Beta*	0.67	0.01	0.03	0.10	0.10	0.11	0.07
Volatility (Stdev Annualized)	21.85%	15.36%	15.68%	15.56%	15.56%	15.56%	15.61%
Downside Volatility (Stdev Ann)*	19.31%	15.78%	15.83%	16.14%	15.84%	15.84%	15.84%
VAR (95th Percentile)	0.096	0.069	0.070	0.069	0.069	0.069	0.069
VAR (99th Percentile)	0.158	0.105	0.108	0.107	0.107	0.107	0.107
Conditional VAR (95th Percentile)	0.133	0.092	0.094	0.097	0.093	0.093	0.098
Conditional VAR (99th Percentile)	0.179	0.122	0.128	0.134	0.124	0.124	0.137

* Computed using months w hen S&P 500 market return is negative.

** VAR expressed as \$ per one dollar investment.

For randomly generated portfolios, we find that hedging performance is fairly uniform across portfolios. On the other hand, if an investor takes systematic bets, hedging performance can vary dramatically across the type of bet and the time period in question. Certain portfolios such as those with a bias towards high trading activity or low momentum are more difficult to hedge no matter which beta is used. Other portfolios such as high growth, small cap, high volatility, and low yield portfolios exhibit a wide variation in ex post betas in different subperiods. This appears to be confined to extremely concentrated portfolios (e.g., those consisting of the top or bottom deciles of style-biased stocks as measured by their exposures) since it does not appear to be true of portfolios formed using second and third deciles.

Turning to our subperiod results, we find that overall, hedging performance is good for these well-diversified portfolios across all sizes. However, one interesting result stands out: during 2000-

2001, the 60-month historical beta (which performed at least as well as fundamental beta over the whole time period) performed particularly poorly for hedging. The ex-post betas for the former range between -0.08 and -0.06 during this two-year period compared to ex-post betas of 0.01-0.03 for the latter. Fundamental beta may be particularly better suited to capturing systematic comovement during turbulent market periods. Table 2 illustrates this point.

Table 2: Ex-post Betas for Long-Only Diversified Portfolios, 2000-2001

Hedging Performance Results: Randomly Constructed Portfolios, Long-Only, Of Varying Size
Average Ex Post Beta Across 100 Portfolios
Period of Evaluation: January 2000 - December 2001 Monthly

	Unhedged	Hedged (USE3S Beta)	Hedged (Historical 60-Mth Beta)	Hedged (Historical 360-Day Beta Eq1 Wghtd)	Hedged (Historical 360-Day Beta Exp. Wghtd, Half-life = 22 Days)	Hedged (Historical 360-Day Beta Exp. Wghtd, Half-life = 180 Days)	Hedged (Bayesian-adj. USE3S Beta)
N = 10	1.00	0.03	-0.06	0.09	0.09	0.09	0.10
N = 20	1.02	0.03	-0.03	0.08	0.08	0.08	0.09
N = 50	1.01	0.01	-0.08	0.04	0.04	0.04	0.05
N = 100	1.03	0.02	-0.06	0.05	0.05	0.05	0.06
N = 200	1.03	0.02	-0.06	0.05	0.05	0.05	0.06

Lastly, what is the impact of portfolio size or diversification on hedging performance? As evidenced in Table 2, ex post betas in fact vary little across portfolios of different size even though volatility diversifies away quickly as we expect. The hedging efficacy of fundamental beta changes very little relatively as the number of names in the portfolio is increased.

(2) For a long-short investor who is industry-neutral, market risk is minimal and may not need to be hedged.

Long-short investors, who have moderate to significant biases in their net portfolios, experience similar hedging results as long-only investors in the previous section. Tests using randomly generated long and short portfolios and long-short portfolios with asymmetric bets confirm that fundamental beta continues to be consistently better over a wide range of portfolios. However, for long-short industry-neutral investors, an interesting result emerges. We find that the impact of hedging is in itself minimal and that the differences between the hedged and unhedged portfolios are quite small across all metrics considered.

To test whether the choice of beta type matters for hedging long-short industry-neutral portfolios, if at all, we construct 100 long-short pairs for each industry. Most stocks are assigned to one and only one industry; therefore by offsetting a short position with a long position for each Barra industry, we create 100 industry-neutral pairs by shorting an equal dollar amount for every long position. The resulting portfolios contain little market risk as measured by ex-post betas as seen in Table 3.

Table 3: Hedging Performance Results for Long-Short Industry-Neutral Portfolios

Hedging Performance Results: Industry Neutral Portfolios, Long-Short							
<i>Average Metrics Across 55 Portfolios (Each Portfolio Contains 100 Industry Pairs)</i>							
<i>Period of Evaluation: January 1990 - February 2007 Monthly</i>							
	Unhedged	Hedged (USE3S Beta)	Hedged (Historical 60-Mth Beta)	Hedged (Historical 360-Day Beta Eq Wgtd)	Hedged (Historical 360-Day Beta Exp. Wgtd, Half-life = 22 Days)	Hedged (Historical 360-Day Beta Exp. Wgtd, Half-life = 180 Days)	Hedged (Bayesian-adj. USE3S Beta)
Ex Post Beta	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Downside Ex Post Beta*	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Volatility (Stdev Annualized)	5.30%	5.28%	6.07%	5.29%	5.29%	5.29%	5.29%
Downside Volatility (Stdev Ann)*	5.37%	5.33%	5.52%	5.33%	5.33%	5.33%	5.33%
VAR (95th Percentile)	0.024	0.024	0.025	0.024	0.024	0.024	0.024
VAR (99th Percentile)	0.038	0.038	0.039	0.038	0.038	0.038	0.038
Conditional VAR (95th Percentile)	0.033	0.033	0.035	0.033	0.033	0.033	0.033
Conditional VAR (99th Percentile)	0.047	0.047	0.049	0.047	0.047	0.047	0.047

* Computed using months when S&P 500 market return is negative.

** VAR expressed as \$ per one dollar investment.

By all metrics, layering a hedging policy on top of industry-neutral portfolios adds little in value. This result is not unsurprising -- in the Barra risk framework, industry risk captures a large portion of systematic risk; therefore we would expect portfolios which are industry neutral to have little systematic risk.

To summarize, fundamental betas appear to be a more consistent measure for hedging portfolio performance. The performance advantage is stronger in down-markets and during extreme negative movements. One point deserves additional consideration. Of all the historical beta measures tested, historical 60-month betas by far exhibited the best hedging efficiency. Shorter-term estimates like the betas based on daily historical data with varying half-lives fail to outperform the long-term beta. Andersen, Bollerslev, Diebold, and Wu (2003) suggest that "time varying betas may do more harm than good when estimated from daily data, even if the true underlying betas display significant short memory dynamics: it may not be possible to estimate reliably the persistence or predictability in individual realized betas, so good in-sample fits may be spurious artifacts of data mining." Continued investigation in the properties of historical betas based on short-term data is necessary.

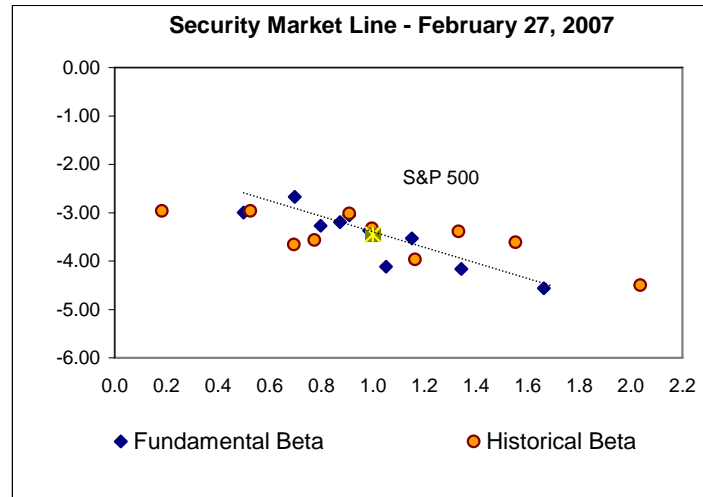
Off Expectation Fails, and Most Off There: A Closer Look at Beta Performance During Extreme Down-market Events

In this last section, we discuss in more detail the accuracy of forecast betas during large negative market movements. Our previous results regarding hedging performance indicate that fundamental beta does a better job hedging portfolios both when the market is down and when the stocks in the portfolio experience extreme negative returns. Rosenberg (1985) proposes a simple alternative that analyzes beta prediction over market swings. After identifying market upswings and downswings, cumulative performance of beta factor portfolios (high-beta minus low-beta stocks) is calculated over the swings; the returns of these portfolios should be negative in downswings and positive in upswings.

In a similar spirit, we look at the 3.47% drop in the S&P 500 on February 27, 2007. We plot forecast betas against returns on that day for cap-weighted deciles of stocks ranked by beta. The

highest beta group is expected to have the most negative return on that day and the lowest beta group is expected to have the least negative return that day. (The historical beta used in this example is the 60-month historical beta since this was found to have the best hedging properties of the various historical measures considered in the previous section.)

Figure 2: Security Market Line – February 27, 2007



The relationship between forecast beta and realized return is closer for fundamental betas with the R-squares equal to 0.79 and 0.61 for fundamental and historical betas, respectively. In Table 9, we show R-squares for the beta-return relationship for all days since January 1, 1980 in which the S&P 500 suffered a greater than 4% drop.

Table 4: The Relationship Between Beta and Realized Return on Extreme Down-market Days

Correspondence Between Beta Decile Portfolios and Realized Returns			
Days When the S&P 500 Return Fell Below -4%, 1980-2006			
Date	S&P Market Return	Adjusted R2 for Historical Beta Deciles	Adjusted R2 for Fundamental Beta Deciles
9/11/1986	-4.81%	0.89	0.99
10/16/1987	-5.16%	0.93	1.00
10/19/1987	-20.47%	0.92	1.00
10/26/1987	-8.28%	0.95	1.00
11/30/1987	-4.18%	0.98	0.99
1/8/1988	-6.77%	1.00	0.97
4/14/1988	-4.35%	0.98	0.99
10/13/1989	-6.13%	0.97	0.99
10/27/1997	-6.72%	0.75	0.99
8/31/1998	-6.78%	0.67	0.99
4/14/2000	-5.70%	0.54	0.99
3/12/2001	-4.32%	0.73	0.99
9/17/2001	-4.88%	0.73	0.90
9/3/2002	-4.15%	0.81	0.98

The reported R-squares on these days in which the S&P 500 suffered a 4% loss or greater are consistently higher for deciles ranked using fundamental betas. In particular, R-squares on August 31, 1998 and April 14, 2000 reflect a weak relationship between forecast betas using historical data and realized returns. Overall, a portfolio hedged with fundamental betas during the past two decades would have remained more immune to market risk when it mattered.

Summary

Our subset of metrics highlights just a piece of the puzzle. Reflecting the range of objectives investors may have, a number of measures that capture hedging effectiveness have been recently proposed. Patton (2004) for instance introduces metrics, which reflect the fact that risk averse investors prefer negative correlation with market returns in down-markets and positive correlation in up-markets and other investors may only want to ensure that when market volatility increases, their portfolio volatility does not also increase. These issues underscore the importance of how we actually define a successful hedge.

Fundamental betas provide several advantages to historical betas which make them conceptually more effective for hedging since the more noise embedded in beta estimates, the greater the loss of efficiency when hedging. The results of our tests indicate that while the advantages of using fundamental beta may not be so pronounced for investors who care only about ex-post beta, they do appear to matter for those who care about volatility reduction and minimizing downside loss. Overall, fundamental betas appear to be a more consistent measure for hedging market risk across different metrics of hedging effectiveness.

References

Alexander, G. J., and N. L. Chervary (1980), "On the Estimation and Stability of Beta", *Journal of Financial Quantitative Analysis*, Vol. 15, No. 1, pp. 123-137.

Andersen, T., Bollerslev, T. and F. X. Diebold (2004), "Parametric and Nonparametric Volatility Measurement", in L.P. Hansen and Y. Ait-Sahalia, *Handbook of Financial Econometrics*. Amsterdam: North-Holland.

Andersen, Bollerslev, Diebold, and Wu (2003), "Realized Beta: Persistence and Predictability", PIER Working Paper Archive 04-018, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania, Revised March 2004.

Baesel, J. B. (1974), "On The Assessment of Risk: Some Further Considerations," *Journal of Finance*, Vol. 29, No. 5, pp. 1491-1494.

Black, A. and P. Fraser (2003), "Are Stock Prices Too Volatile and Returns Too High? A Reassessment of the Empirical Evidences Using a Dynamic Version of the CAPM", *ICFA Journal of Applied Finance*.

Blume, M. E.(1971), "On the Assessment of Risk", *Journal of Finance*, Vol. 26, No.1, pp. 1-10.

Blume, M. E. (1975), "Betas and Their Regression Tendencies", *Journal of Finance*, Vol. 30, No. 3, pp. 785-795.

Bos, T. and P. Newbold (1984), "An Empirical Investigation of the Possibility of Stochastic Systematic Risk in the Market Model", *Journal of Business*, Vol. 57, No. 1, pp. 34-41.

Cotter, J. and J. Hanly (2006), "Re-evaluating Hedging Performance", *Journal of Futures Markets*, Vol. 26, Issue 7 , pp. 677 – 702.

Dybvig, P.H. and S. A. Ross (1985), "Differential Information and Performance Measurement Using a Security Market Line," *Journal of Finance*, Vol. 40, pp. 383-400.

Ferson, W. and C. R. Harvey (1991), "The Variation of Economic Risk Premiums", *Journal of Political Economy*, Vol. 99, pp. 385-415.

Ferson, W., Kandel, S. and R. F. Stambaugh (1987), "Tests of Asset Pricing with Time-Varying Expected Risk Premiums and Market Betas", *Journal of Finance*, Vol. 42, pp. 201-220.

Fraser, P., F. Hamelink, M. Hoesli, and B. Macgregor (2000), "Time-Varying Betas and the Cross-Sectional Return-Risk Relation: Evidence from the U.K.", Working Paper, University of Aberdeen.

Gonedes, N. J. (1973), "Evidence on the Information Content of Accounting Numbers: Accounting-based and Market-based Estimates of Systematic Risk", *Journal of Financial and Quantitative Analysis*, Vol. 8, No. 3, pp. 407-443.

Gonzalez-Rivera, G. (1997), "The Pricing of Time-Varying Beta", *Empirical Economics*, Vol. 22, No. 3, pp. 345-363.

Groenewold, N. and P. Fraser (1999), "Time-Varying Estimates of CAPM Betas", *Mathematics and Computers in Simulation*, Vol. 48, pp. 531-539.

Groenewold, N. and P. Fraser (2000), "Forecasting Beta: How Well Does the 'Five-Year Rule of Thumb' Do?", *Journal of Business Finance & Accounting*, Vol. 27, No. 7-8, pp. 953-982(30).

Hansen, L. P. and S. F. Richard (1987), "The Role of Conditioning Information in Deducing Testable Restrictings Implied by Dynamic Asset Pricing Models," *Econometrica*, Vol. 55, pp. 587-613.

Jagannathan, R. and Z. Wang (1996), "The Conditional CAPM and the Cross Section of Expected Returns", *Journal of Finance*, Vol. 51, pp. 3-53.

Levy, R.A. (1974), "On the Short-Term Stationarity of Beta Coefficients", *Financial Analysts Journal*, Vol. 27, pp. 55-62.

Meyers, S. C. (1973), "The Stationarity Problem in the Use of the Market Model of Security Price Behavior", *Accounting Review*, Vol. 48, No. 2, pp. 318-322.

Patton, A. (2004), "Are 'Market Neutral' Hedge Funds Really Market Neutral?", *EFA 2004 Maastricht Meetings Paper No. 2691*.

Rosenberg, B. (1985), "Prediction of Common Stock Betas", *Journal of Portfolio Management*, Winter.

Wang, K. Q. (2003), "Asset Pricing with Conditioning Information: A New Test", *Journal of Finance*, Vol. 58, pp. 161-196.

Appendix

Table A1: Descriptive Statistics: Cross Sectional

Cross Sectional Descriptive Statistics: Average Across All Months						
	USE3S Beta	Historical 60-Mth Beta	Historical 360-Day Beta Eq Wgtd	Historical 360-Day Beta Exp. Wgtd, Half-life = 22 Days	Historical 360-Day Beta Exp. Wgtd, Half-life = 180 Days	Bayesian-adj. USE3S Beta
Jan 1990 - Feb 2007						
Mean/Standard Deviation	1.02 / 0.44	1.04 / 1.03	0.94 / 0.43	0.94 / 0.56	0.94 / 0.44	0.93 / 0.36
Min/Max	-0.37 / 2.66	-14.27 / 13.52	-0.39 / 2.71	-1.12 / 3.54	-0.4 / 2.73	-0.07 / 2.08
By Subperiod						
Jan 1990 - Dec 1995						
Mean/Standard Deviation	1.03 / 0.41	1.09 / 0.81	0.93 / 0.44	0.91 / 0.63	0.93 / 0.45	0.91 / 0.34
Min/Max	-0.62 / 2.41	-17.22 / 8.72	-0.68 / 2.82	-1.67 / 3.99	-0.71 / 2.85	-0.15 / 1.97
Jan 1996 - Dec 1999						
Mean/Standard Deviation	0.91 / 0.38	0.97 / 1.33	0.81 / 0.37	0.78 / 0.48	0.81 / 0.38	0.82 / 0.31
Min/Max	-0.41 / 2.4	-32.37 / 15.84	-0.28 / 2.61	-0.81 / 3.2	-0.3 / 2.59	0.01 / 1.83
Jan 2000 - Dec 2001						
Mean/Standard Deviation	0.99 / 0.56	1.04 / 1.21	0.88 / 0.51	0.93 / 0.62	0.89 / 0.52	0.88 / 0.45
Min/Max	-0.53 / 2.86	-2.79 / 26.18	-0.21 / 2.64	-0.65 / 3.29	-0.21 / 2.66	-0.1 / 2.24
Jan 2002 - Feb 2007						
Mean/Standard Deviation	1.1 / 0.48	1.04 / 0.98	1.07 / 0.44	1.09 / 0.53	1.07 / 0.44	1.05 / 0.39
Min/Max	0.01 / 3.07	-1.47 / 12.41	-0.22 / 2.7	-0.89 / 3.37	-0.2 / 2.71	-0.03 / 2.33

Table A2: Descriptive Statistics: Time Series

Time Series Descriptive Statistics: Average Across All Estimation Universe Stocks						
	USE3S Beta	Historical 60-Mth Beta	Historical 360-Day Beta Eq Wgtd	Historical 360-Day Beta Exp. Wgtd, Half-life = 22 Days	Historical 360-Day Beta Exp. Wgtd, Half-life = 180 Days	Bayesian-adj. USE3S Beta
All Cap (Jan 1990 - Feb 2007)						
Mean/Standard Deviation	1.09 / 0.22	1.14 / 0.36	0.97 / 0.26	0.98 / 0.47	0.98 / 0.27	0.96 / 0.21
Min/Max	0.71 / 1.57	0.53 / 1.77	0.52 / 1.47	-0.02 / 2.04	0.5 / 1.5	0.59 / 1.37
Skewness/Kurtosis	0.28 / -0.01	-0.01 / 0.09	0.09 / -0.29	0.11 / 0.38	0.1 / -0.27	0.09 / -0.35

Table A3: Time Series Correlations Between Fundamental and Historical Beta

Average Time Series Correlations Across Betas, Jan 1990 to Feb 2007						
	USE3S Beta	Historical 60-Mth Beta	Historical 360-Day Beta Eq. Wgtd	360-Day Beta Exp. Wgtd, Half-life = 22 Days	Historical 360-Day Beta Exp. Wgtd, Half-life = 180 Days	Bayesian-adj. USE3S Beta
USE3S Beta	1.00					
Historical 60-Mth Beta	0.29	1.00				
Historical 360-Day Beta Eq. Wgtd	0.37	0.17	1.00			
Historical 360-Day Beta Exp. Wgtd, Half-life = 22 Days	0.28	0.09	0.53	1.00		
Historical 360-Day Beta Exp. Wgtd, Half-life = 180 Days	0.39	0.17	0.95	0.69	1.00	
Bayesian-adj. USE3S Beta	0.37	0.17	0.98	0.52	0.93	1.00

Contact Information

clientservice@mscibarra.com

Americas

Americas	1.888.588.4567 (toll free)
Atlanta	+ 1.404.949.4529
Boston	+ 1.617.856.8716
Chicago	+ 1.312.706.4999
Montreal	+ 1.514.847.7506
New York	+ 1.212.762.5790
San Francisco	+ 1.415.576.2323
Sao Paulo	+ 55.11.3048.6080
Toronto	+ 1.416.943.8390

Europe, Middle East & Africa

Amsterdam	+ 31.20.462.1382
Cape Town	+ 27.21.683.3245
Frankfurt	+ 49.69.2166.5325
Geneva	+ 41.22.817.9800
London	+ 44.20.7618.2222
Madrid	+ 34.91.700.7275
Milan	+ 39.027.633.5429
Paris	0800.91.59.17 (toll free)
Zurich	+ 41.1.220.9300

Asia Pacific

China Netcom	10800.852.1032 (toll free)
China Telecom	10800.152.1032 (toll free)
Hong Kong	+ 852.2848.7333
Singapore	+ 65.6834.6777
Sydney	+ 61.2.9220.9333
Tokyo	+ 813.5424.5470

www.mscibarra.com

Notice and Disclaimer

- This document and all of the information contained in it, including without limitation all text, data, graphs, charts (collectively, the "Information") is the property of Morgan Stanley Capital International Inc. ("MSCI"), Barra, Inc. ("Barra"), or their affiliates (including without limitation Financial Engineering Associates, Inc.) (alone or with one or more of them, "MSCI Barra"), or their direct or indirect suppliers or any third party involved in the making or compiling of the Information (collectively, the "MSCI Barra Parties"), as applicable, and is provided for informational purposes only. The Information may not be reproduced or redisseminated in whole or in part without prior written permission from MSCI or Barra, as applicable.
- **The Information may not be used to verify or correct other data, to create indices, risk models or analytics, or in connection with issuing, offering, sponsoring, managing or marketing any securities, portfolios, financial products or other investment vehicles based on, linked to, tracking or otherwise derived from any MSCI or Barra product or data.**
- **Historical data and analysis should not be taken as an indication or guarantee of any future performance, analysis, forecast or prediction.**
- **None of the Information constitutes an offer to sell (or a solicitation of an offer to buy), or a promotion or recommendation of, any security, financial product or other investment vehicle or any trading strategy, and none of the MSCI Barra Parties endorses, approves or otherwise expresses any opinion regarding any issuer, securities, financial products or instruments or trading strategies. None of the Information, MSCI Barra indices, models or other products or services is intended to constitute investment advice or a recommendation to make (or refrain from making) any kind of investment decision and may not be relied on as such.**
- The user of the Information assumes the entire risk of any use it may make or permit to be made of the Information.
- NONE OF THE MSCI BARRA PARTIES MAKES ANY EXPRESS OR IMPLIED WARRANTIES OR REPRESENTATIONS WITH RESPECT TO THE INFORMATION (OR THE RESULTS TO BE OBTAINED BY THE USE THEREOF), AND TO THE MAXIMUM EXTENT PERMITTED BY LAW, MSCI AND BARRA, EACH ON THEIR BEHALF AND ON THE BEHALF OF EACH MSCI BARRA PARTY, HEREBY EXPRESSLY DISCLAIMS ALL IMPLIED WARRANTIES (INCLUDING, WITHOUT LIMITATION, ANY IMPLIED WARRANTIES OF ORIGINALITY, ACCURACY, TIMELINESS, NON-INFRINGEMENT, COMPLETENESS, MERCHANTABILITY AND FITNESS FOR A PARTICULAR PURPOSE) WITH RESPECT TO ANY OF THE INFORMATION.
- Without limiting any of the foregoing and to the maximum extent permitted by law, in no event shall any of the MSCI Barra Parties have any liability regarding any of the Information for any direct, indirect, special, punitive, consequential (including lost profits) or any other damages even if notified of the possibility of such damages. The foregoing shall not exclude or limit any liability that may not by applicable law be excluded or limited.
- Any use of or access to products, services or information of MSCI or Barra or their subsidiaries requires a license from MSCI or Barra, or their subsidiaries, as applicable. MSCI, Barra, MSCI Barra, EAFE, Aegis, Cosmos, BarraOne, and all other MSCI and Barra product names are the trademarks, registered trademarks, or service marks of MSCI, Barra or their affiliates, in the United States and other jurisdictions. The Global Industry Classification Standard (GICS) was developed by and is the exclusive property of MSCI and Standard & Poor's. "Global Industry Classification Standard (GICS)" is a service mark of MSCI and Standard & Poor's.
- The governing law applicable to these provisions is the substantive law of the State of New York without regard to its conflict or choice of law principles

© 2007 MSCI Barra. All rights reserved.

About MSCI Barra

MSCI Barra develops and maintains equity, fixed income, multi-asset class, REIT and hedge fund indices that serve as benchmarks for an estimated USD 3 trillion on a worldwide basis. MSCI Barra's risk models and analytics products help the world's largest investors analyze, measure and manage portfolio and firm-wide investment risk. MSCI Barra is headquartered in New York, with research and commercial offices around the world. Morgan Stanley, a global financial services firm and a market leader in securities, asset management, and credit services, is the majority shareholder of MSCI Barra, and Capital Group International, Inc. is the minority shareholder.