Investigation of: “Shopping in the Market-β Mall”*

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Beta [β], the simple regression slope of the returns of the Firm matched with those of the Market is a powerful financial signaling statistic in vogue since the 1960s, and still very much in use by financial analysts and firm decision makers. However, as there are a number of ways that one can obtain a measure of the period Firm-β, this begs the following question: Are there important differences in these various βs? If so, this opens up the possibility of agenda-serving game-driven signaling, and thereby compromises the reliability the β-information. We use the term “Market-β Mall” to indicate the temptation to go shopping for β in order to create a profile that would not be consistent as a Time-Benchmark for a particular firm. We show, clearly, that there are different measured values of β. Given the “adverse” selection

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implications, we suggest a simple way to maintain the reliably of this critical signal—*the period β*.

**Keywords:** β source variation, Data Screening, β-Downloads, β-Consistency

**JEL Classification:** G11, G12, G30, G32

**Introduction**

Despite the fact that the CAPM and the related EMH has fallen into disuse as a factor or variable in the ferreting out the actions of the actors in the market [See: (Grinold, 1993), (Clare and Priestley, 1997) and (Chi-Cheng, Fuller and Chen, 2000)], β, the lynch-pin in the CAPM structure, is still used by Financial Analysts [FA] and Firm decision makers to understand the relative movements of the returns of the firm/portfolio relative to that of the market. This makes sense as the Market β, independent of its CAPM context, is just the slope of the OLS one-stage, two-parameter linear regression [hereafter: β-OLS regression] created as a regression of the dependent variable: the stock market returns of a firm regressed against the independent variable: the time matched returns of the market traditionally surrogated by the S&P 500. Clearly, this relative risk through the return co-variation relative to the return variation—i.e., β is critical market benchmarked information.

Further, at the firm level, β is often a guiding statistic that helps in the development of dividend policy, as well in offering a context for strategic initiatives for market traded firms. In one of the first research articles to address the underlying drivers of β, (Rozef, 1982) posits that firms with high βs establish low dividend payouts because higher βs are an indication of higher operating and financial leverage. This supports the view that dividend payments are “quasi-discretionary-swap” costs in relation to other fixed and therefore unavoidable period costs. Simple put: Dividends are a discretionary hedge against the necessity of entering the long-term capital market where the higher β is a risk signal that may increase the cost of debt
directly in risk-premium or in indenture constrictions limiting management’s project selection menu.

In years subsequent to the Rozeff article, there have been numerous indications that β is created by the firm project selection, which in turn, creates, policy constraints, due to its signaling capability. In this way β both acts and is acted upon dynamically, so that β is both a cause and an effect respecting firm evaluation [and] policy decisions both at the firm and, as indicated above, at the market level. Five works that are highly recommended in support of this idea of the Bi-Action of β are: (Hubbard, Kashyap, and Whited, 1995), (Lusk, Halperin and Yue, 2006), (Brealey, Myers and Allen, 2011: in particular Ch. 9), (Pástor and Veronesi, 2009) and (Ghossoub and Beladi, 2011).

This “Action&Re-action” dynamic creates an interesting and predictable conflict of interest: If it is possible to “shop for” a β that serves a particular firm profiling agenda, and there is no rule or requirement to report the nature of the source of the β reported to the market—i.e., made public, there is a possibility that the reported β information can be gamed and so cannot be relied upon as a realistic and informative firm or market performance statistic. We are calling this possible information asymmetry with its obvious gaming implications: “Shopping in the Market-β Mall” as an indication of the temptation to go shopping for β so as to create a profile that would not be consistent as a Time-Benchmark for a particular firm. Our concern over the possibility of agenda serving selection is reaffirmed in a recent work by (Agrrawal and Waggle, 2011) where the dispersion of β over the various electronic web-links is detailed and underscored by the large number of longstanding sources of EDI-download which can be used in the computation of β a few of which are noted following:

Bloomberg™ [www.bloomberg.com]
Dow-Jones™ [www.dowjones.com]
Interactive Data™ [www.interactivedata.com]
Morningstar™ [www.Morningstar.com]
Standard & Poor’s™ [www.standardandpoors.com]
Thomson-Reuters™ [www.thomsonreuters.com]
Wharton Research Data Service WRDS™ [wrds.wharton.upenn.edu]
This is the point of departure of our study. We provide: (1) information that rationalizes the fact that there is sufficient variability in $\beta$ to encourage agenda-serving selection, and (2) that being the case, we offer, preemptively, a simple system of $\beta$ re-calibrating so as to create benchmarked comparability.

The Study Design

The $\beta$ Variants There are two different basic sources for $\beta$: (a) EDT-Downloads from one of the myriad sources, a few of which are mentioned above, and (b) direct computation—i.e., $\beta$-OLS regression—from the firm return series and the match market returns. Within each of these two categories there are a large number of possibilities. To manage the nature of the study, in that it will be sufficient for our purposes to show that $\beta$ has sufficient variability over the various sources so as to open up $\beta$ selection options, we have selected $\beta$ downloads from [CRSP] and selected two computational modes: (a) the usual $\beta$-OLS regression of the value-weighted time series of the firm returns as the response to the returns of the market surrogated by the S&P500 both of which are downloaded from CRSP through WRDS™, and (b) the same time series as in (a) but also screened for outliers as recommended by Lusk, Halperin and Petrov (2011).

The screening is rationalized based upon a research report by Lusk, Halperin and Heilig, 2009 who show that often there are firm market performance profile differences between screened data and its un-screened counterpart. This is, of course, due to the existence of outliers, and to some extent to non-central-fat-tailed distributions, which are outliers of a distributional nature. Also see (Filzmoser, Garrett, and Reimann, 2005) and (Gelpers, Fried and Croux, 2010).

Specifically, for our study, we will use the following three screens to create the Screened Time series: A trimming window with width $[\text{Mean } \pm 2 \times \text{Standard Deviation of the downloaded time series}]$, the BOX-Plot screen due to Tukey which is a window of width $[\text{Median}^{\text{TM}} 1.5 \times \text{IQR}]$ and a relational screen due to (Mahalanobis, 1936) which uses the Mahalanobis-D measure to screen correlation outliers and is set at the 95% CI level which is SAS/JMP-APP default. All statistical, Macro, APP and model testing information is found in (Sall, Creighton and Lehman, 2008). These three
screens were applied only once in the order noted and eliminated, on average, approximately 15% of the data. Details on these screens are found in Lusk, Halperin and Petrov (2011).

The Data Following the design logic of (So and Tang, 2010) and so as to not bias the study to a particular sector, we randomly selected firms often classified as part of: the New Economy [NE], n=23, the Old Economy [OE], n= 15, a group from the Vice-sector—i.e., Drugs, Alcohol and Weapons [Vice], n= 6, and an Other group, n = 14. The condition for inclusion was that the firm had to be continuously traded on the NASDAQ or NYSE exchanges for the 29-year accrual period. We used, as does (Ibbotson, 2009), a rolling contiguous window —i.e., non-overlapping five (5) year time series segments to measure points in the times series for the computation of β. Also being sensitive to the interval estimation issues, in particular relative to smoothing transformations, as discussed by (Brzeszczyński, Gajdka and Schabek, 2011) we selected daily data as the computation interval. This gives then a time series of 25 five-year window measures of β starting in [1980 to 1984] until [2004 to 2008].

Following we will offer the performance information of the sample of 58 randomly selected firms relative to the focus of our study. We will report on the following four Partitions of the Accrued Firm Dataset:

1. Partition I The graphical presentation of the Median and Mean β-values from the β-OLS regression where there are five levels of aggregations: the Macro level, n = 58 and being sensitive to the “heterogeneity factors that are sometime industry specific—i.e., cross-sectional blocking first detailed by Melicher (1974) and followed up by (So and Tang, 2010), there four industry partitions—the Industry level: NE, OE, Vice and Other. In these cases for the graphical presentation there will be six (6) β time series per graph: The Mean and Median β for the Download [β-DL], the Computation without screening [β-C] and the Computation with screening [β-CS] for which we will report the tracking of the Median and Mean βs over the 25 years. This is important visual information and will provide a meaningful context for the statistical testing to follow.

2. Partition II The Time Series Structure of the tracked β as follows: (i) The Macro-level—i.e., over all 58 firms, (ii) by Industry: NE, OE,
Vice and Other, and also for each of the 58 individual firm. This is valuable information respecting the structure of the underlings as a generating process. The idea here is simply: If the track of $\beta$ at the Macro, Industry and Firm for the Median, Mean over the three measures: the $\beta$-DL, $\beta$-C and $\beta$-CS did not exhibit time-related structure this would negate the interest in benchmarking $\beta$ by its historical profile and so is a critical aspect of the study. Also as a validation of the accrued dataset, we will examine the event character of the tracked time series. Following on the early work of Rosenberg and Guy (1976) that considered differential detachment of the market beta, our validation hypothesis is that during the Internet Bubble Build Up—1992 to 1999—there will be a difference between the tracked $\beta$s for the NE compared to the OE&Vice&Other taken together. Focusing on the NE relative to the other industry groupings follows from the reporting of Pástor &Veronesi (2009), Ghossoub & Beladi (2011) and Phillips, Wu & Yu (2011) who detail the selective reasons for the sector factors in the Bubble Period and support the test that the NE will be more connected to the market during the bubble period as the NE is the “tech”-sector being fueled by the Internet, whereas the other three sectors will be relatively detached from the market as they are not in sync with the tech-sector that is driving the market during the Bubble Period. This detachment should mean that the OE&Vice&Other aggregation should experience a dip in $\beta$ relative to the NE sector. If we do not find this typical characterization this would again call into question the generalization of our results.

3. Partition III The nature of the Differences between the various measure of $\beta$ at the Macro and Industry level viewed statistically controlling for time-period as this is a panel dataset. This is the aspect of the study that addresses the question: Are there differences in $\beta$ that would rationalize concern about agenda serving selections? In other words, if the Null was the characterization, meaning that there were in fact no differences in $\beta$, the temptation to shop for $\beta$ would, of course, not obtain and no
monitoring for control actions preemptive or otherwise would be needed.

4. Partition IV The Harmon-Factor Structure of the relationships of the six measures of $\beta$. If all of the measures exhibit a high degree of correlation association as is the case reported by (Ibottoson: Morningstar, 2009) relative to the use of various market proxies, then this would be of interest. This is an exploratory aspect of the study.

These then are the four performance areas for the study that we will use to judge and provide information regarding “Shopping in the “Market-$\beta$ Mall”.

Examination of the Validation Expectation

To provide a context for the graphical and the time series examination of the tracked $\beta$ over the accrual period, we first will examine the validation hypothesis.

Validation Information The simplest test is to determine if the relative reduction in $\beta$ for the firms from the NE sector was smaller than for the comparison sector groupings: OE, Vice and Other. Here we proffer an expectation using the previously cited work of (Pástor and Veronesi, 2009), (Ghossoub and Beladi, 2011) and (Phillips, Wu and Yu, 2011) and anticipate a larger dip $\beta$ or detachment of the Firm from the Market resulting in a mollification of $\beta$ to the NULL of no association for the OE, Vice and Other than for the NE as argued above. To test this we created two datasets:

(i) the Bubble Period: [1996 to 2002]. We will be indexing back from these terminal dates for five years—i.e., the five year period 1992 to 1996 inclusive and moving contiguously forward as a five year rolling window to 2002 resulting in seven-five year windows, and
(ii) non-Bubble Time Periods consisting of the other 18 five-year sub-widows in the accrual period [1984 to 2008].
For these partitions, we used all three measures of β irrespective of whether they were from the Download or from the Computations of β as there is no reason to condition the dip in β relative to the source. We created the ratio of β measured during the Bubble Period to the Median of β of the Non-Bubble Period. This forms the relative ratio of β during the Bubble Period compared to the Non-Bubble Time Period as the benchmark. One can then directly test the relative detachment hypothesis by observing the difference in the ratios between the NE sector and the OE, Vice and Other sectors. The inference information is contained in Table 1 following.

Table 1: All Three Measure of β taken together for the NE contrasted with the OE, Vice and Other groups for the Bubble Period

<table>
<thead>
<tr>
<th>Test Groupings</th>
<th>Test:</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bubble</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Median : Mean</td>
<td></td>
</tr>
<tr>
<td>NE</td>
<td>0.91 : 0.96</td>
<td>-</td>
</tr>
<tr>
<td>OE &amp; Vice &amp; Other</td>
<td>0.69 : 0.72</td>
<td>&lt;0.0001 : &lt;.0.0001</td>
</tr>
</tbody>
</table>

The inference is clear; relative to the relative changes the NE dipped around 10% or so to around 91% in Median ratio terms while the β values for the OE&Vice&Other group dipped around 30% or so to 69% in Median ratio terms. These changes were statistically different in both the Non-parametric test [Median Test, noted as M-Test] and the ANOVA Parametric t-test at a p-value < 0.0001 providing conclusive evidence for rejecting the Null that there was a similar relative dip in the NE and the OE&Vice&Other in the Bubble Period in favor of support for the expectation that the dip or detachment in the NE sector would be less.

To follow up on the next obvious question: if one does not aggregate over the three measures of β, do we observe that the NE outside of the Bubble Period has more associational contact with Market—i.e., is closer to 1.0—compared to the other three groups: OE, Vice and Other? Here we are examining the question: Is it the case that blocking on: (i) the β download [β-DL], (ii) the β-computation directly from the Firm and S&P500 returns
[β-C], and (iii) the Screened commutation [β-CS] that for the NE β is higher compared to the other three groups taken together as was the validating expectation? The results of this contrast are presented following in Table 2.

<table>
<thead>
<tr>
<th>β Groupings</th>
<th>NE vs. [OE &amp;Vice &amp;Other] Medians : Means</th>
<th>95% CI</th>
<th>p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>β-DL</td>
<td>1.07:1.05 vs. 0.77:0.77</td>
<td>[1.02 to 1.09] &amp; [0.74 to 0.80]</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>β-C</td>
<td>0.92:0.91 vs. 0.65:0.65</td>
<td>[0.88 to 0.95] &amp; [0.63 to 0.68]</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>β-CS</td>
<td>0.80:0.79 vs. 0.52:0.56</td>
<td>[0.76 to 0.83] &amp; [0.53 to 0.58]</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

The fact that again the NE tests higher than the benchmark and in this case is closer to 1.0—the market β—validates the expectation that the NE is more in contact or in sync with the market compared to the other groups [OE, Vice and Other] in that the β-values in all three cases are statistically significantly higher than for three combined groups.

Therefore in summary, testing (i) the relative market dip during the Bubble Period [Table I] and (ii) the contact with the market outside the Bubble Period [Table II], we find that firms in our sample follow the sector expectations offered a-priori and, in this sense, we offer these results as a validation of the generalizability of our study. The implication is that we can use this validated dataset to draw an inference relative to the question: Does there seem to be different β “shopping” possibilities? We now address the question by examining the four Partitions.

Partition I: The graphical presentations of β for the aggregated time series

To provide a meaningful and instructive visual of the variation in β, we offer the following figures as the context for the statistical analysis that
we will use in addressing the principal research question: Is it possible to shop for the \( \beta \) that will serve a firm agenda? Consider now Figures 1-5.

**Figure 1:** Macro—All the Firms Together, \( n = 58 \)

![Figure 1: Macro—All the Firms Together, n = 58](image)

**Figure 2:** New Economy [NE], \( n = 23 \)

![Figure 2: New Economy [NE], n = 23](image)
Figure 3: Old Economy [OE], n = 15

Figure 4: Vice, n = 6

Figure 5: Other, n = 14
As is clear from these figures, there are: (1) zones of systematic $\beta$ detachment as between the three $\beta$-sources [$\beta$-DL, $\beta$-C and $\beta$-CS] as one observes the cross-section over the five summary graphs, (2) the average $\beta$-values over the six computation measures sometimes appear to be different blocking on various time periods and also appear to be different on an inter-grouping basis—i.e., over time, and (3) rarely does there seem to be a meaningful difference between the Median and the Mean characterization of $\beta$ controlling for source.

**Partition II The Tukey/Wilcoxon Detachment Table for the Macro dataset**

To further elucidate these visual zones of detachment and similarities, consider now the statistical mean $\beta$-comparisons for the Macro $\beta$ [Figure 1] tracking using the Wilcoxon overall p-value as the measure of detachment. See Table III. In the p-value column we have indicated the Tukey HSD Multiple Comparison Test [MCT], $\alpha = 0.05$ differences. We give first the Wilcoxon non-directional p-value followed by the number of HSD differences. For example, 0.02[2] means that the overall Wilcoxon p-value is 0.02 indicating that there is likely to be differences among the $\beta$ measured from the three sources: $\beta$-DL, $\beta$-C and $\beta$-CS and that there are two (2) MCT differences at the 0.05 detection level: one of which is always the smallest and the largest $\beta$-value and one of the other possible combinations. A “[1]” indicates that the only MCT difference was the largest from the smallest, while a “[3]” indicates that all three were HSD different.

<table>
<thead>
<tr>
<th>Year</th>
<th>$\beta$-DL</th>
<th>$\beta$-C</th>
<th>$\beta$-CS</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984</td>
<td>0.97</td>
<td>0.79</td>
<td>0.57</td>
<td>0.02[2]</td>
</tr>
<tr>
<td>1985</td>
<td>1.04</td>
<td>0.83</td>
<td>0.64</td>
<td>0.06[2]</td>
</tr>
<tr>
<td>1986</td>
<td>0.95</td>
<td>0.84</td>
<td>0.70</td>
<td>0.01[1]</td>
</tr>
<tr>
<td>1987</td>
<td>0.98</td>
<td>0.76</td>
<td>0.56</td>
<td>0.003[1]</td>
</tr>
<tr>
<td>1988</td>
<td>0.96</td>
<td>0.74</td>
<td>0.55</td>
<td>0.02[3]</td>
</tr>
</tbody>
</table>
As an example regarding reading the information of Table 3, for 1990 the three measures for $\beta$ are: $\beta$-DL = 0.95, $\beta$-C = 0.75 and $\beta$-CS = 0.52 and all three test to be statistically distinct using the Tukey HSD MCT.

Table 3 Results: For the Macro dataset there are only four (4) time periods for which there are no Tukey-HSD MCT differences. This is a representative table of the results for the industry groupings: NE, OE, Vice and Other, where we find that more than 85% of the time there is $\beta$-detachment between the Downloaded $\beta$ and the Screened $\beta$. Finally, in Table 3, the Bubble Period years 1996 to 2002 have been bolded. Here we see,
statistically, the evidence of the relative dip that was tested above and displayed in Figures 1-5. In summary, the statistical results, which are also visually evident from Figure 1, are clear: At the aggregate or the portfolio level, there is evidence that various \( \beta \) values exist controlling for time period as the Null is rejected in 21 of the 25 test cases suggesting strongly that there are sufficient variations in \( \beta \) to provide the context for shopping for the \( \beta \) that serves the “agenda du jour”. To say this result in another way, for the Macro-level, the results of which also extend to the four industry groupings, there is strong statistical evidence that one can reject the Null hypothesis that there is no difference in the values of \( \beta \) over the three sources: \( \beta \)-DL, \( \beta \)-C and \( \beta \)-CS, providing support for the belief that there is source variation in \( \beta \) further indicating that agenda serving possibilities exist.

**Partition III The Time series characterization of the \( \beta \)-tracked time series**

We tested for time series structure in the various series as presented in Figures 1 through 5, and also in the three series for each firm, \( n = 174 \) of the \( \beta \)-tracked series. We are interested in ascertaining if there is structure, presumably autocorrelation, as the underlying generating process. If this is found to be the case, it will provide a way to calibrate one series from the information in the other series as Transfer functions—the simplest being the OLS regression. If we determine that there is likely to be structure that can be modeled, as opposed to noise as the generating process, then we will be able to use the related structure to suggest a way to create consistent benchmarking information that can be used to address, and so to control, the agenda serving gaming that could occur.

Results The time series analysis produces statistical results that are clear and follow the visual information regarding structure of the generating process which is unarguably autoregressive. Specifically, the two-parameter linear exponential smoothing model offered by Holt as programmed in SAS/JMP v.9 fits all of these mean/median time series, as presented in Figures 1 to 5, over the three \( \beta \)-measures: (i) DownLoad [\( \beta \)-DL], (ii) Computation [\( \beta \)-C] and (iii) Computation: Screening Modification [\( \beta \)-CS]. We used the Fisher’s Kappa [FK] test of structure in the spectral range of the
residuals as the criteria of an adequate fit. Specifically, we set the FK screening test as: a FK p-value < 0.05 as rejection of the Null of no residual structure. For all of the series in Figures 1 to 5 the FK p-value for the Holt residuals was > 0.05 indicating an adequate fit for the Holt model. Further we tested the 174 individual time series [58 x 3] and found that in all but three cases of the 174 series the Fisher’s Kappa residual p-values > 0.05 indicating that the Null of no-residual structure could not be rejected—i.e., the Holt fit left no structure in the spectra that could be modeled. As the Holt model, which also is an ARIMA/Box-Jenkins (0,2,2), is the richest characterization of a dynamic autoregressive process—i.e., level as well as slope time-related modifications, one may interpret this Holt fitting information as conclusive evidence both of structure and of structure characterized as an autoregressive generating process. Also see (Box, Jenkins and Reinsel, 1994).

**Partition IV The Factor Structure**

As related exploratory information, we conducted the Standard Harmon Factor Analysis on the six variables for each of the five β-tracking situations. The following Macro analysis is typical of the factor results for the Macro and the Sectors:

**Principal Components: on Correlations**

<table>
<thead>
<tr>
<th>Number</th>
<th>Eigenvalue</th>
<th>Factor Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.6359</td>
<td>60.598</td>
</tr>
<tr>
<td>2</td>
<td>1.9675</td>
<td>32.792</td>
</tr>
<tr>
<td>3</td>
<td>0.2326</td>
<td>3.877</td>
</tr>
</tbody>
</table>

Rotated Factor Loading [Using the Harmon eigenvalue rule of rotating on the number of eigenvalues > 1.0] produces the following factor Two Structure:

<table>
<thead>
<tr>
<th>β-DL Mean</th>
<th>Factor 1</th>
<th>Factor 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>C Mean</td>
<td>0.910077</td>
<td>0.991735</td>
</tr>
<tr>
<td>β-DL Median</td>
<td>0.128298</td>
<td>-0.12140</td>
</tr>
<tr>
<td>β-C Mean</td>
<td>0.915773</td>
<td>-0.12140</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>β-C Median</td>
<td>0.812493</td>
<td>-0.241862</td>
</tr>
<tr>
<td>β-CS Mean</td>
<td>0.992456</td>
<td>0.122567</td>
</tr>
<tr>
<td>β-CS Median</td>
<td>0.926400</td>
<td>0.112871</td>
</tr>
</tbody>
</table>

Using the Harmon variable loading rule of $\sqrt{.5}$ – these variables are bolded above – we see the important information that the two central tendencies [Mean & Median] of β from the download [β-DL] exhibit correlation and define a Factor and the Computations whether screened or not [β-C and β-CS] define a different Factor. This suggests that the central tendency computations, whether screened or not, are associated, and are different from the basis of the computation used to compute the β that were downloaded. This is also a related validity check, in that the β computation used by the β-Download source is founded on (Scholes and Williams, 1977), a three-period moving-average smoothing model which differs from the OLS standard used by (Sharpe, 1964), (Lintner, 1965) and (Mossin, 1966) who “first” offered β as the firm OLS regression response linkage to the market. These Factor Results do offer as a possible future investigation following on the work of Clare and Priestley (1997): What is the inference jeopardy(ies)/effects in moving away from the standard OLS definition of β? It is interesting also that the Median and Mean β download is the measure that drives the detachment p-values from Table III as the β-DL magnitudes are uniformly higher when there is detachment. This β-variable detachment should pique research interest in the future investigations of the inference effects of modeling variation—e.g., the Scholes and Williams smoothing model compared to the Standard OLS regression.

Summary Points of the Principal Question and Related Information

1. From Table III and the related discussion, we find that indeed there statistically distinct selection possibilities for β.

2. As an indication from the factor results, we find the possibility that models other than the standard OLS regression may produce differences in the magnitude of β controlling for the dataset.
3. From all of the Figures, 1 through 5, there is clear evidence that the time track of $\beta$ is being generated by a structural model, and that model is functionally autocorrelation in nature. This has an implication regarding the ability to translate the information from one time series to another. In fact, this is the basis of the CAPM model where we compute $\beta$ as the systematic reaction of the firm return series given the market return series both of which are usually autocorrelation in nature. The systematic nature of the $\beta$-time series as we find them in Figures 1 through 5 will be important for creating benchmarking information.

Given these results, it certainly seems that the possibility of shopping for $\beta$ exists. Given the long and troubling list of firms that have not only manipulated data to enhance their performance profile, but have indeed fabricated data, one should expect that firms will try to game the information set, and to shop for the $\beta$ that serves their agenda. The next section addresses possible pre-emptive actions that may take the gaming out of selecting this important performance statistic.

**Suggestions for refining the market information relative to the possibility of $\beta$-shopping**

From the information presented above, we conclude that agenda serving selection behavior can be expected. The next question is: What is a reasonable way to deal with this “information asymmetry” created by firm manipulation of their performance profile in shopping for a $\beta$ that sends the “right” signal? Fortunately, there is precedent in how to deal with such performance profile gaming. This is essentially the same problem that has been faced by the Public Accountants in their role as certifying “agents” in assuring of the reported results of performance of firms. According to the AICPA, the rule setting organization for Certified Public Accountants in the USA, one of the basic principles in the Assurance Audit under AS 5 of the PCAOB, the licensing agency created under Sarbanes-Oxley: 2002 [SOX], is the consistent application of the accounting principles in reporting the results of operations of the firm. This is called the Consistency Principle. It simply says that: Management cannot change Accounting Principles to
create the firm performance profile that serves their purposes. For example, assume that in prior years management used FIFO to determine cost of goods sold during which time prices happened to be rising; then prices started to fall and so to maintain the favorable gross margin projection compared to previous years, management changed to LIFO. This switch in costing from FIFO to LIFO would create a “Consistency Exception” which must be addressed by the CPA in certifying the current financials. We call this the AICPA version of consistency monitoring; we offer that such “consistency” monitoring should be a part of the reporting in the Financial Market place. Specifically, we propose:

*If the firm reports their period Market-β, then they must provide full disclosure as to its source and computation.*

With such disclosure and the fact, as demonstrated above, that time series of tracked β usually have autocorrelation structure that will allow the creation of information from one time series to aid in understanding of other time series—i.e., Summary Point 3 above, consistency benchmarking of β can be done. To illustrate this idea consider the following scenario:

Assume that a firm uses Non-screened data to compute β; for 2010 the β-value reported was $\beta = 0.8839$. This year, 2011, management computes/projects that the value of β will be 0.9173. However, assume that management in 2011 wants to show a “better” relative-to-market-risk compared to 2010. So they re-compute β using Screened return data; this recalculation gives a β of 0.8234 for 2011. In this case, by changing from Non-screened return data to Screened return data management “creates” a relative reduction in risk compared to 2010 of 6.9% \[\left(\frac{0.8839 - 0.8234}{0.8839}\right)\]. Had management consistently used Non-screened data there would have been a relative increase of risk of 3.8% \[\left(\frac{0.8839 - 0.9173}{0.8839}\right)\]. This we label as a β-consistency exception.

Under our proposal of full disclosure, in 2011 the firm will be required to indicate that they used Screened data, and of course the nature of the screening, to compute the 2011 value of β of 0.8234. With this simple disclosure and the fact that β follows a structured time path [summary point 3] one can determine or estimate the correct benchmarking of β for 2011
relative to 2010 and therefore have reliable benchmarking information—i.e., the goal of making the consistency adjustment. There are two separate ways to deal with this β-consistency exception: Re-calculation and Re-estimation.

Re-calculation The simplest way to create a consistent benchmark for β follows the AICPA model where the β-information is part of the assurance audit. In this case, the auditors are charged with requiring management to report consistent β information. So management can use Screened data for 2010 and 2011 and report those results OR they can use, for 2010 and 2011, Non-screen data and report those results. They just cannot mix Non-screened and Screened return data because it creates the β-consistency exception. If they used Screened return data for both years, they would show essentially β-values of 0.7934 and 0.8234 for 2010 and 2011 respectively. These would yield an increase of risk of approximately 3.8% \((0.7934 - 0.8234)/0.7934\). Or they can use the Non-screened data in which case the values of β reported would be 0.8839 and 0.9173 also yielding the relative risk increase of 3.8% as shown above. Either would satisfy the β-consistency principle as we arrive at the same information; relative risk between 2010 and 2011 increased by 3.8%. We call this the AICPA version of the consistency benchmarking. However, if there were no requirement to certify the consistency of the firm reported β-value and assuming that the Screened firm return data is not publically available which is the likely case, then we recommend using the Blume Conversion. (Blume, 1971)

Re-estimation The Blume Conversion is an OLS two-parameter linear regression of the two series at issue to create information from one series in order to re-calibrate the performance statistic of the other series. This assumes that a group such as Bloomberg or Ibbtson has run Blume regressions or has time series information on some aggregate Macro or Industry data for (i) Average Downloads, (2) Aggregate Screened Data and (3) Aggregate Non-screened Data. From this information or data one may produced a set of conversion formulae. There will be a number of conversions formulae for the three-β calculations; in fact, there will be six in total—\(3C_2 \times 2\).

For example, let us assume that for the data reported in Table III above that we run a Blume Regression on the Macro Screened Data [β-CS] as the Independent Series and the Macro Non-Screened data as the Response Variable. The results of that regression are in Table 4:
Table 4: Blume Conversion Non-Screened from Screened Return Data

<table>
<thead>
<tr>
<th>Blume Regression</th>
<th>Conversion Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta-C ) vs ( \beta-CS )</td>
<td>( \beta)-Conversion(( \beta-C )) = 0.36 + 0.64 x ( \beta-CS )</td>
</tr>
</tbody>
</table>

This regression relationship is relevant as the two time series are structure-driven as indicated in summary point 3; additionally the intercept [0.36] and slope [0.64] are both statistically significant at \( p < 0.0001 \) suggesting a strong rejection of the Null of no association. Using the conversion formula in Table 4, for the value of \( \beta-CS = 0.8234 \) we produce an aggregate estimate of \( \beta \) from the Non-screened series [\( \beta-C \)] of 0.8870: [0.36 + 0.64 x 0.8234]. This then is a reasonable correction of the \( \beta \) reported information. Specifically, management wanted to present as their 2011 market \( \beta \) a value of 0.8234, which looks like a reduction in market relative risk of 6.9%. However, the actual change in the market-\( \beta \) was an increase of 3.8% as indicated above. Now using the Blume consistency correction, we find that the 2011 reported value of \( \beta = 0.8234 \) from the Screened data produces a converted value of \( \beta = 0.8870 \) for the Non-Screened data which gives an estimated increase of 3% in relative risk compared to management’s attempt to game the market information by merely switching to a new scale by screening the return data and suggest that market risk decreased by 6.9%. Therefore, either by re-calculation or re-estimation more realistic and so reliable information obtains.

Conclusion and Summary

We have suggested that the issue of agenda serving \( \beta \)-selection can be tempting, pervasive and endemic as \( \beta \) is a critical signal to the market. See (Kryzanowski and Rahman, 2008) and (Au & Shapiro, 2010). We suggest that this is the time to be pro-active in offering a way to refine the quality of market related risk information. We have seen the dire consequence of ignoring clear signals of possible problems as the “clear conflict of interest” created by Public Accountants providing Consulting Services and Auditing and Assurance Services. This was a “time-bomb” just waiting to go off and went ignored by the AICPA, the SEC, as well as the Investment Banking
community. This time bomb of course finally went off in the Houston office of the Arthur Anderson, LLP, the flagship of the Public Accounting community, crashing “overnight” the largest Public Accounting LLP. The point here is that pro-action was needed; it does little good to wait for problems to appear and then to be re-active in trying to correct them.

In this regard, relative to the problem of firms shopping for a β that serves their agenda to the detriment of the market to “truly” understand what is the firm’s market relative risk, we have offered a simple proposal:

**If the firm reports their period Market-β, then they must provide full disclosure as to its source and computation.**

This requirement of full disclosure provides the possibility to make the benchmark conversions where it is the case that there is a β-consistency exception. To this end then, if there is a formal requirement that is part of the AICPA audit rules then such β conversion will be accomplished as a re-calculation—i.e., as part of the certification audit. If there is no requirement to use the Audit as the consistency conversion of β, then the Blume re-estimation conversion can be used. In either case better market information is the result of the pre-emptive action of requiring consistent β information.

References


