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Article

The Choice of the Time Horizon during Estimation of the Unconditional Stock Beta

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Abstract: The stock beta coefficient literature extensively discusses the proper methods for the estimation of beta as well as its use in asset valuation. However, there are relatively few references with respect to the appropriate time horizon that investors should utilize when evaluating the risk-return relationship of a stock. We examine the appropriate time horizon for beta estimation differentiating our results by sector according to the Industry Classification Benchmark. We employ data from the NYSE and we estimate varying lengths of beta employing data from 30 to 250 trading days. The constructed beta series is then examined for the presence of breaks using the endogenous structural break literature. Results show evidence against the use of betas that employ more than 90 trading days of data provisional to the sector under study.

Keywords: Stock Beta, Endogenous Structural Breaks, Time Horizon

JEL classifications: C10, C22, C59, G12, G19

1. Introduction

Stock beta is used by investors to examine the risk-return relationship, evaluate the return of an asset and compare the relative performance of assets. It is also employed in Capital Budgeting to identify profitable ventures through the Net Present Value (NPV) method which requires the estimation of the Weighted Average Cost of Capital (WACC) and the cost of equity often calculated through the Capital Asset Pricing Model (CAPM).

Despite the fact that the literature has presented substantial methodological advances in the estimation of beta[1], investors often rely on secondary information and simple unconditional 30 to 180 day betas published through the media and through financial services. While those estimates of beta reported usually originate from 7 different sources [7] they also differ substantially [5][2]. Those

[1] Numerous articles have dealt with issues of heteroscedasticity, autocorrelation and the time variation of betas through the estimation of ARCH and GARCH models, GARCH conditional betas, stochastic volatility conditional betas, Kalman Filter approaches, Flexible Least Squares, Markov switching approaches [1, 2, 3, 4, 5]; see Hollstein and Prokopczuk [6] for a recent and comprehensive comparison of market beta estimation techniques.

[2] Some sites such as Bloomberg allows users to specify the period of estimation while other sites such as Compustat and Dow Jones do not.

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differences can, amongst other reasons, be partially attributed to the choice of market index, the calendar period employed and the returns "time horizon".

This article concentrates on determining the appropriate time horizon for the estimation of stock beta which has received little attention in the literature. The time horizon, or period length, refers to how far back we should look at the data to estimate the beta or, simply stated, the number of observations that should be included in the estimation of beta. As the number of observations included in the estimation increases there is a higher probability that significant changes in beta occur. Wrongfully choosing the proper time frame may result in a misrepresentation of the systematic risk which in turn may lead to wrong investment decisions and market inefficiencies.

To discuss the proper time horizon we construct a "time-series" of varying beta-lengths and we examine them for the presence of structural breaks using the methodologies presented by the endogenous structural break literature. If i.e. a structural break on the beta series is observed within 40 trading days and investors employ a longer time horizon beta, then systematic risk will be misrepresented. We employ all 2641 stocks in the NYSE to avoid problems generated by company-specific breaks. Results are broken down by sector using the Industry Classification Benchmark (ICB – ICB1,2,3). While this practice is computationally intensive, it allows an averaging of company-specific events that might not be related to a general sector reaction to market conditions. We employ daily returns data and compare the estimated average sectoral break dates with the most commonly used 30/60/90/120/180 day betas. Our analysis allows us to infer on whether there is a maximum time horizon per sector that investors should employ for their decisions.

2. Literature Review

Beta is reported for investors through a number of financial providers and in its most simple form it is estimated through OLS regression analysis of market returns on the individual stock returns providing unconditional estimates of beta while assuming that they are constant over time.

The estimation of beta with historical data presents itself with a number of problems. One of those problems refers to the choice of interval length i.e., the choice between using daily, weekly, monthly or annual returns for the construction of stock and index returns which may affect the size of the beta. Past research has shown that the simple average of betas tends to increase as the returns interval is lengthened [8]. Further break down suggests that estimates for securities with small (large) market values tend to increase (decrease) as the return measurement interval is lengthened [9, 10].

The choice of interval length also has an impact on the standard errors of the estimates. Betas based on daily returns provide smaller standard errors than betas based on longer interval returns, however, high frequency data is also more likely to create error heteroscedasticity problems resulting in inefficiency of the estimates [11]. To deal with contradictory evidence, Levy et. al. [12], who associate the interval length with the holding period, assert that the interval length employed for the estimation of beta employed should match the investor's holding period[3].

While the choice of the time interval in the estimation of unconditional betas has received adequate attention in the literature, articles discussing the choice of the time horizon are limited. As the number of observations that are employed in the estimation of beta increases - i.e. as the estimation period increases - the estimate of beta improves in terms of precision. Yet increases in the period length compromise the validity of the results as firm-specific structural breaks might be present as a direct cause of recapitalization, acquired divisions, spin-off divisions or changes in product mix leading to changes in the beta [13].

Theobald [14] was one of the first to tackle this issue and concluded that increasing the length of the estimation period results in the reduction of sampling fluctuations. However, a higher estimation period also implies an increased probability of betas having changed so that optimal data

[3] Other studies that have concentrated on the impact of the choice of interval length on the estimation of beta and the resulting effect on the estimates of beta include Altman et. al.[15], Baesel [16], Roenfeldt et. al. [17], Smith [18], Alexander and Chervany [19].

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length involves a trade-off between these two opposing forces. Daves et. al. [13] incorporated in his study the effect on beta of differing both interval length and the estimation period. Their conclusions with respect to interval length are concrete however, their results do not provide adequate evidence for the proper estimation period. They examined eight different periods for estimation that vary from 1 to 8 years and found that although longer periods result in a tighter error for the estimate of beta they also result in a higher probability that there is a significant change in the beta. Longer estimation periods are more likely to bias the estimates. Their results favor the use of up to a 3-year beta. Within this time frame, beta estimates capture a large percentage of the maximum possible reduction in the standard error.

Contributing to the literature on the time horizon of beta we examine the presence of significant changes in the beta and the proper time-horizon for the estimations separating our results by industry using ICB classifications[4]. We employ daily data as it uses more detailed information about the variability of the stock price and the index [8] and provides smaller standard errors for the estimates [13]. More important however, is the fact that the daily returns data is one of the main tools employed by investors and provided by financial services which is relevant to the motivation of this study.

3. Data and Methodology

Daily data for 2641 stocks from the NYSE was downloaded using the Metastock software for the period of September 1, 2011 to August 31, 2012. A second data set from September 1, 2006 to August 31, 2007 was employed to compare and contrast the results. For the market index we used the S&P500. The data downloaded was adjusted for stock splits and dividends.

Beta can be estimated through either the market model or the excess return model [22]. We estimate beta by using simple returns such that,

$$R_{s,t,i} = a_{s,t} + \beta_{s,t} R^{m}_{t,i} + e_{s,t,i} \tag{1}$$

where R^s represents the daily return on stock s, $s = 1, \ldots, 2641$ for all the stocks in the NYSE, R^m represents the daily return on the market, t represents the length of the beta included in the regression where t ranges from a minimum of 30 daily observations to 223 daily observations and i represents the i^{th} observation $\forall\, i = 1, \ldots, 252$ [5]. Returns on stocks and the market are estimated in continuous time using logarithmic differences of daily returns[6].

For every one of the stocks in our data we obtain a vector of 223 observations that represent betas of different length, from 30-day beta to 252-day beta. We thus construct a "time-series" for each one of the securities that allows us to examine how beta evolves as more information is included in the estimation[7].

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[4] Past research has concentrated on the differences in beta amongst sectors. Rosenberg [20] noted that companies active in the Agriculture and Utilities industry show lower levels of betas while companies in the Electronics, Air transport and Securities higher. Liu [21] found that Real Estate shows high values of time varying betas.

[5] 252 daily observations were downloaded minus the 30 most recent observations allow for the estimation of 30-day betas all the way to 252 day betas.

[6] The excess return specification would estimate $R^{s}_{t,i} - R^{f}_{i} = a_{s,t} + \beta_{s,t}\left(R^{m}_{t,i} - R^{f}_{i}\right) + e_{s,t,i}$ Where additionally to equation 1, R^{f}_{i} represents the risk free rate in period i. In the return-level specification of equation 1, alpha (α) represents the constant return earned whereas in the excess-return specification of equation 2, the α-coefficient represents the constant return of the security in excess of the risk free rate.

[7] Average t-day betas were estimated for the whole sample of 2641 stocks in the NYSE and were found to be very close to 1.

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On these 2641 constructed series of betas we employ the methodology presented by Zivot and Andrews [23] to examine for structural breaks and the stationarity of the series. The investigation of a time series' stationarity usually precedes the estimation of a model, especially when this is based on Ordinary Least Squares (OLS) method. This is ought to the fact that some basic hypothesis of the general linear model concerning the error term (especially that of homoskedasticity), are not satisfied when one or more of the time series used are non-stationarity. As a result, the OLS estimated coefficients will not be the best of all linear and unbiased estimators of the true values of models coefficients. Moreover the results of the estimation could be characterized as spurious, even though the high and statistically significant value of the coefficient of determination may indicate an estimated model that explains a big proportion of the variability of the model's endogenous variable. The determination of a series stationarity is also very important in the context of univariate statistical analysis, concerning the specification of the functional form of a series evolution through time and the use of it in order to estimate its future magnitude.

A second issue that has to be taken into account is related to the nature of a series' non-stationarity, that is, whether the trend component of the series is deterministic or stochastic. In the first case where the trend component is deterministic, the examined series is characterized as a trend stationary process and its stationarity is achieved after determining the functional form of the time trend and removing the later from the data. The remainder constitutes the series' stationary cyclical component that is associated with economic cycles. On the other hand if the trend component is stochastic then the examined series is characterized as a difference stationary process. In this case the series' stationarity may be attained after determining the number of its unit roots and differencing its level on the basis of the detected number of unit roots.

A time series can be examined for the presence of a unit root graphically with a correlogram. The rapid (slow) geometrical convergence of the graph of the autocorrelation function towards zero is indicative of a stationary (non-stationary) process. The results of this methodology may, however, turn out to be quite questionable. For example, when we examine a nearly integrated time series, i.e. a time series which converges to its long-run equilibrium value very slowly, its slow decay autocorrelation function may lead to the false conclusion that the considered time series is non-stationary.

Procedures which might be used to determine the presence of a unit root in a time series, are the ones proposed by Dickey and Fuller [24, 25], Kwiatkowski et al. [26] and Phillips and Perron [27] who drew a unit root test using non-parametric statistical methods. Various Dickey-Fuller and Phillips-Perron test statistics are biased toward the acceptance of the unit root null in the presence of structural breaks, i.e. structural breaks reduce the power of the unit root test. Therefore, Perron [28, 29, 30, 31], Zivot and Andrews [23], Banerjee et. al. [32], Perron and Vogelsang [33, 34, 35] have developed tests, in the context of which the significance of the unit root null is tested, allowing for a break in a time series and choosing the break date either exogenously or endogenously.

Using the Zivot and Andrews [23] methodology, the investigations for a unit root in the time series $\{Y_t\}_{t=1}^{T}$ involves the (OLS) estimation of the following three models:

$$A \text{ (break in level)} : Y_t = \mu + \beta t + \theta DU_t + aY_{t-1} + \sum_{i=1}^{k} c_i \Delta Y_{t-i} + u_t \tag{2}$$

$$B \text{ (break in trend)} : Y_t = \mu + \beta t + d\, DT_t + a\, Y_{t-1} + \sum_{i=1}^{k} c_i \Delta Y_{t-i} + u_t \tag{3}$$

$$C \text{ (break in level \& trend)} : Y_t = \mu + \beta t + \theta\, DU_t + d\, DT_t + a\, Y_{t-1} + \sum_{i=1}^{k} c_i \Delta Y_{t-i} + u_t \tag{4}$$

where Δ is the difference operator, t is a simple time trend, DU is a level dummy variable where $DU_t = 0(1)$ if $t \le T_B\ (t > T_B)$, DT is a slope dummy where $DT_t = 0\,(t - T_B)$

if $t \le T_B$ ($t > T_B$), $1 < T_B < T$ with T: the number of used observations & T_B : the point in time where the structural break occurs.

The determination of the lag parameter k ensures that the residuals are not correlated. Its value is endogenously determined following the general to specific recursive procedure [29]. We examine the significance of the lag coefficient c_i for a maximum k of 14. The parameter k could be estimated using Schwert's [36] rule that suggests that $k_{\max} = \operatorname{int}\left[12\left(\frac{T+1}{100}\right)^{1/4}\right]$ for T>100 which in our case implies that kmax=14.

The t-statistic $T_{\hat{c}_{k^{\max}}} = \frac{\hat{c}_{k^{\max}}}{s.e.(\hat{c}_{k^{\max}})}$ is examined as compared to the value 1.64 in absolute terms. If $\left|T_{\hat{c}_{k^{\max}}}\right| < 1.64$ then $k \ne k^{\max}$ and the procedure was repeated by decreasing the length of the lag by 1 such that $k = k^{\max} - 1$. We continued this procedure until $\left|T_{\hat{c}_{k^{\max}}}\right| \ge 1.64$ or until all lags are eliminated at k = 0.

After the selection of the lag length parameter k, say k^*, the equations (2) to (4) are estimated using the OLS. method for all potential break dates T_B, assuming that $2 < T_B < T - 1$. The date for which the estimated value of the t – statistic $T_{\hat{a}} = (\hat{a} - 1)/s.e.(a)$ was minimized, and for which the probability of rejecting the unit root null was maximized, is considered to be the endogenously determined break date of the examined series. In the context of the performed unit root test, the statistical significance of the unit root null without a break in series is tested against the alternative of a break – stationary process.

In this article we employ only the third model for our estimations. Sen [37] argues that if we employ model A when in reality the break occurs by a model such as C, in other words if the break is related to the slope dummy then we lose power of the test. If on the other hand we employ model C yet the true break occurs according to model A then we have only minor losses in power. Additional limitations to our estimation are due to the fact that we include a trend in the specification of model C. When there is no trend in the data, the power of the test for the null hypothesis is reduced as the addition of a trend variable increases hypothesis testing critical values whereas when the series does include a trend and a trend component is not added in the specification we might lose explanatory power of the model [38].

The resulting combinations of break dates are examined for differences amongst groups in the NYSE as defined by first, second and third level ICB categories similar to past approaches by Mergner and Bulla [1]. A full description of the categories can be found in the NYSE Website.

4. Results

We examine the differences in the average break dates starting with level 1 ICB groups presented in Table 1[8]. Columns 2-5 show the results for the first set of data that spans from 2011 to 2012 while columns 6-9 for the period 2006-2007. In column 2 we see the number of NYSE stocks that fall in the respective category. The average break date for each category produced is presented next (column 3) together with the respective standard deviation (column 4). I.e. for the 143 companies that are listed in the "Basic Materials" category for the 2011-2012 data, the average break date occurs after 101 daily observations with a standard deviation of 54.2 days. To assist in the interpretation and since the standard deviation is a relatively large number, column 5 presents the percentage of NYSE

[8] Only 2324 out of 2641 stocks in the NYSE were included in the analysis as some lacked an ICB classification match and some exhibited negative betas when few observations were included in the regression.

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stocks within each category where we observe a break with a beta employing up to 60 trading days of information. For the first category 14% of the stocks exhibited a beta series with structural breaks within 60 trading days. For the 2006-2007 data (columns 6-9) 117 stocks fall in the first category of Basic Materials and the average break date is now 113 with a lower standard deviation.

Table 1. Average Break Dates by 1st Level ICB Categories

		2012				2006			
	1	2	3	4	5	6	7	8	9
	Category	Number of Stocks	Av. break	Av. std	Perc. < 60	Number of Stocks	Av. break	Av. std	Perc. < 60
1	Basic Materials[2,6,10]	143	101	54.2	14.0%	117	113	44.5	19.7%
2	Consumer Goods[3,5,7,9,10]	203	115	61.8	19.2%	151	115	41.3	15.9%
3	Consumer Services[2,6,10]	224	102	54.0	21.4%	184	113	40.9	13.0%
4	Financials[6,10]	887	106	55.8	20.6%	829	112	39.9	14.8%
5	Health Care[2,,6,10]	105	100	51.1	27.6%	95	107	40.5	15.8%
6	Industrials[1,3,4,5,7,9,10]	356	113	57.4	18.8%	322	107	44.6	22.7%
7	Oil & Gas[2,4,6,10]	168	97	54.4	28.6%	143	100	43.6	14.7%
8	Technology[10]	88	110	60.2	26.1%	76	109	42.2	19.7%
9	Telecommunications[6,10]	50	96	49.4	24.0%	46	111	43.6	21.7%
10	Utilities[1 through 9]	100	131	61.5	20.0%	90	104	40.0	8.9%

Using first level ICB categories most of stock's beta series presented a break date once 90 trading days of information were included in the estimations. This presents strong evidence in favor of the use of betas that employ less than 60 days of information, some evidence against the use of betas that employ between 60-90 days of information (due to the high standard deviation[9]) and strong evidence against the use of betas with more than 120 days of information as significant changes in the average beta-series seem to appear. Despite the average break date implied by the analysis, the reader should be cautious of the high standard deviation; Column 5 helps us analyze this in more detail. For Basic Materials, the average break date that appears after 101 days of information suggests 14% of the stocks in the category exhibit a break date of less than 60 trading days. The maximum percentage appears in the Oil & Gas category with 28.6% of the stocks showing a break date of less than 60 trading days. For these stocks even the use of the 60 day beta could result in miscalculation of the systematic risk, the expected returns, and the investment decisions[10].

Additionally, when we examine the average break date among the groups we find that there are significant differences at a=0.05 level between categories. These are highlighted with the superscript on column 1 and are estimated only for the 2012 data. For example Basic Materials differ significantly with Consumer Goods category, Industrials and Utilities. These differences present an interesting contrast with the results by Rosenberg [20] and Liu [21] who found differences in beta levels amongst different categories of companies.

Comparing columns 6-9 (for 2006-2007) with columns 2-5 (for 2011-2012) we observe that during the period prior to the Global Financial Crisis (GFC) the beta-series where more stable as both the average break date is higher for most of the categories and the standard deviation was also lower. The main exception occurs in the Utilities category that seems to present a much higher average break date as compared to the pre-GFC period.

[9] The large standard deviation suggests that there are numerous stocks in each category both on the upper and the lower side of the average. This, however, represents the main reason that we took all of the stocks in NYSE so as to allow company specific events to average out which allows us to glimpse at the sectoral averages.

[10] We would therefore need to look at ICB2-3-4 categories for more detailed information. Moreover, about 40% of the stocks in each category are non-stationary at the 1% level, 50% at the 5% level and 60% at the 10% level of significance.

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Second and third ICB level categories are shortly presented with the help of Tables 2 and 3[11]. With ICB2 we see that there is more differentiation that becomes apparent in terms of the average break date. Utilities, and Personal & Household Goods exhibit the most significant differences with rest of the sectors showing more stable beta series with break dates at a longer time horizon, reflecting different sector responses to economy wide fluctuations and beta stability. On the other hand Telecommunications, Oil and Gas, Media, Food and Beverages and Basic Resources have significantly lower levels of break dates. Within category significant differences are only observed between categories 2b and 2c. Average break dates for the pre-GFC period are observed at a longer time horizon with the exception of Industrials and Utilities.

Table 2. Average Break Dates by 2nd Level ICB Categories

			2012				2006			
			2	3	4	5	6	7	8	9
	ICB	**ICB2**	**Number of Stocks**	**Av. break**	**Av. std**	**Perc. < 60**	**Number of Stocks**	**Av. break**	**Av. std**	**Perc. < 60**
1a	Basic Materials	Basic Resources	79	96	47.5	20%	65	113	43.3	23%
1b		Chemicals	64	109	61.1	6%	52	112	46.2	15%
2a	Consumer Goods	Automobiles & Parts	34	112	62.0	9%	23	114	39.6	13%
2b		Food & Beverage	51	99	54.5	22%	39	116	40.4	15%
2c		Personal & Household Goods	118	122	63.9	21%	89	114	42.5	17%
3a	Consumer Services	Media	64	97	49.6	28%	41	115	39.6	7%
3b		Retail	96	103	55.0	18%	82	115	39.9	10%
3c		Travel & Leisure	64	104	57.3	20%	61	107	43.3	21%
4a	Financials	Banks	124	110	55.9	19%	103	121	39.4	14%
4b		Financial Services	672	104	54.9	20%	647	109	39.8	15%
4c		Insurance	91	115	60.9	24%	79	118	39.4	13%
5	Health Care	Health Care	105	100	51.1	28%	95	107	40.5	16%
6a	Industrials	Construction & Materials	52	108	58.4	15%	51	100	41.5	29%
6b		Industrial Goods & Services	304	114	57.3	19%	271	109	45.0	21%
7	Oil and Gas	Oil & Gas	168	97	54.4	29%	143	100	43.6	15%
8	Technology	Technology	88	110	60.2	26%	76	109	42.2	20%
9	Telecommunications	Telecommunications	50	96	49.4	24%	46	111	43.6	22%
10	Utilities	Utilities	100	131	61.5	20%	90	104	40.0	9%

Similar to the conclusions from ICB1 analysis results suggest that there are substantial group differences that would direct us towards the use of different length beta for ICB2 sub-categories to account for the significant changes in the beta. There is strong evidence for the use of up to 60 day betas, some evidence against the use of betas that employ between 60 and 90 trading days of information and strong evidence against the use of any beta that employs more than 90 days of information.

Table 3 presents ICB3 results where we now see ample differentiation in the average break date between categories. Using ICBS3 there is again strong evidence for the use of up to 60 day beta for most of the categories, similar to the results implied when we employed the ICB1 and ICB2. There are some categories where the average break dates are now somewhat smaller.

[11] 4th level ICB categories are available upon request only, as the great number of categories and the few number of observations in many of these categories prevents us from either effectively discussing the results within the limits of an article or reaching useful conclusions.

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Table 3. Average Break Dates by 3rd Level ICB Categories

			2012				2006			
			2	3	4	5	2	3	4	5
	ICB2	ICB3	Num. of Stocks	Av. break	Av. std	Perc. < 60	Num. of Stocks	Av. break	Av. std	Perc. < 60
1a	Basic Resources	Forestry & Paper	14	109	57.1	21%	11	81	42.2	64%
1b		Industrial Metals	36	100	54.3	28%	28	113	40.0	18%
1c		Mining	29	84	28.9	10%	26	127	41.3	12%
2	Chemicals	Chemicals	64	109	61.1	6%	52	112	46.2	15%
3	Automobiles & Parts	Automobiles & Parts	34	112	62.0	9%	23	114	39.6	13%
4a	Food and Beverages	Beverages	7	120	69.3	14%	7	140	7.2	0%
4b		Food Producers	44	96	52.0	23%	32	110	42.8	19%
5a	Personal and Household Goods	Household Goods	57	110	58.6	23%	44	116	42.7	18%
5b		Leisure Goods	22	136	67.8	27%	15	116	40.0	7%
5c		Personal Goods	31	141	66.1	10%	24	111	45.4	17%
5d		Tobacco	8	103	66.2	38%	6	112	45.5	33%
6	Media	Media	64	97	49.6	28%	41	115	39.6	7%
7a	Retail	Food & Drug Retailers	10	112	55.4	10%	8	130	17.7	0%
7b		General Retailers	86	102	55.1	19%	74	114	41.3	11%
8	Travel & Leisure	Travel & Leisure	64	104	57.3	20%	61	107	43.3	21%
9	Banks	Banks	124	110	55.9	19%	103	121	39.4	14%
10a	Financial Services	Equity Investment Instruments	379	103	51.5	21%	405	112	39.5	13%
10b		General Financial	126	109	58.1	23%	116	108	41.7	18%
10c		Nonequity Investment Instrumen	6	142	67.2	17%	3	122	31.7	0%
10d		Real Estate	161	102	59.5	16%	123	103	38.9	22%
11a	Insurance	Life Insurance	35	109	59.0	20%	28	106	38.3	18%
11b		Nonlife Insurance	56	119	62.2	27%	51	124	38.7	10%
12a	Health Care	Health Care Equipment & Servic	78	99	48.7	26%	68	107	38.1	15%
12b		Pharmaceuticals & Biotechnolog	27	103	58.6	33%	27	105	46.8	19%
13	Construction and Materials	Construction & Materials	52	108	58.4	15%	51	100	41.5	29%
14a	Industrial Goods and Services	Aerospace & Defense	26	111	51.7	12%	28	116	42.1	14%
14b		Electronic & Electrical Equipm	51	114	63.8	25%	44	110	48.0	20%
14c		General Industrials	36	115	55.6	25%	35	106	39.9	23%
14d		Industrial Engineering	59	119	60.0	15%	59	110	43.2	19%
14e		Industrial Transportation	55	120	57.3	20%	41	95	42.0	29%
14f		Support Services	77	107	54.0	18%	64	114	49.8	22%
15a	Oil and Gas	Alternative Energy	1	64		0%	1	128		0%
15b		Oil & Gas Producers	116	91	52.2	33%	96	101	45.3	16%
15c		Oil Equipment, Services & Dist	51	111	57.5	20%	46	98	40.4	13%
16a	Technology	Software & Computer Services	42	113	60.6	19%	35	99	37.1	20%
16b		Technology Hardware & Equipmen	46	107	60.3	33%	41	117	44.9	20%
17a	Telecommunications	Fixed Line Telecommunications	28	110	57.0	21%	25	111	40.6	20%
17b		Mobile Telecommunications	22	79	30.7	27%	21	111	47.9	24%
18a	Utilities	Electricity	66	132	60.0	15%	54	99	41.0	11%
18b		Gas, Water & Multiutilities	34	128	65.1	29%	36	110	38.1	6%

Post GFC stability in the beta series is now apparent in the Forestry and Paper category, Leisure goods, Personal Goods, Non-Equity Investment Instruments, Life Insurance, Construction and

Materials, General Industrials, Industrial Transportation, Oil Equipment Services and distribution, Software and Computer Services, Electricity and Gas, Water and Industrials.

5. Conclusions

We constructed time series of the beta values for each one of the stocks in the NYSE for the period of September 1, 2011 to August 31, 2012 and for the period September 1, 2006 to August 31, 2007. The constructed series were examined for endogenous structural breaks using model C from the Zivot and Andrews [23] method. The objective of the paper was to examine the break dates inferred by our analysis for each ICB category and discuss the use of the maximum time horizon for the estimation of the beta.

Results were examined by looking at the average break in each ICB category at all levels of categorization. Our results for both data sets in our analysis support that the 120 and 180 day beta commonly used will, in most cases, miscommunicate the level of systematic risk to investors as this time horizon is adequate for substantial changes to affect most of the companies' beta. The use of up to 90 day betas seems to be appropriate for the estimation of the systematic risk of a stock allowing however, for some differentiation of this conclusion with respect to certain categories where both a high standard deviation is observed as well as a large percentage of stocks that present a break in the beta series within 60 trading days.

Future research is centered in examining the robustness of the series to more chronological data as well as dealing with the problems created by heteroscedasticity and autocorrelation issues in the estimation procedures. Moreover, a dynamic version of the method can be implemented to account for changes in the patterns due to economy wide changes. A dynamic examination of break dates will better reflect economy wide events that may cause changes in the suggested time horizon of the beta for specific sectors. One of the problems with implementing such methods is the estimation time required for this computationally intensive process.

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