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## Analysis of Equity $\beta$ Components: New Results and Prospectives in a Low $\beta$ Framework

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### Abstract

*This work aims to exploit the so-called "Beta anomaly" regarding the risk-reward relationship, and set up rules and methodologies in order to build new efficient portfolios. It is well known in literature, and among practitioners, that "Low Beta strategies" generate good performances exploiting alpha opportunities. In this paper we focus on  $\beta$  parameters: we analyze this one and its components (Correlation and Standard Deviation) in order to better understand the drivers and contributions behind the "Low Beta strategies", and eventually exploit them. We perform an extensive empirical analysis on the S&P500 and the relative sectors, covering more than 10 years. In addition we follow Long/Short strategies in building portfolios based on  $\beta$  and their components where we compare results against the benchmark.*

*We also introduce "Walking Beta" approach in order to give a deep and innovative view on the market risk/reward relationship, illustrating different time frames and the evolution of risk parameters.*

**Keywords:** Asset Allocation; Quantitative Portfolio Management; CAPM; Hedge Funds; Correlation; Beta Anomaly.

**JEL Classification:** G11, G12, G14.

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## 1. Introduction

Most of the investing practice rely on the CAPM and the risk-reward relationship which claims that riskier stocks should offer —on average and in the long run—higher returns than less-risky investments (more risk provides more rewards). This is the crucial assumption of the positive relationship between risk and return provided by Sharpe (1964), Litner (1965) and Black (1972, 1993). The risk of the stock is often measured by Beta that shows how much systematic risk - related to the larger economy and common to all investments- the stock bears to. It also means how the stock is sensitive to the news in relation to the market.

On the other hand, a sizeable literature discusses about the mystery of the stock market's "*beta anomaly*": the low  $\beta$  stocks have better performance than the high  $\beta$  ones (a pattern in stock returns that we don't really understand) which conflicts with risk-reward relationship. Up to now, many researches (Cowan and Wilderman, 2011; Asness et al., 2012; Turan et al., 2014; Baker et al., 2016; Cederburg and O'Doherty, 2016) attempt to uncover the reasons for this pattern (beta anomaly). With this work, we aim to explore and analyze part of this phenomenon, filling the gap between the financial literature and the real financial world. In this study we decompose the beta parameter, perhaps the most important variable in a portfolio management framework. Our study finds superior results comparing to the classical beta strategies because we were able to isolate the single beta components and exploit all related characteristics. In a nutshell with our work, we would like to explore how much the CAPM is valuable nowadays in practice and how we can build a rewarding portfolio strategy around the beta parameter, especially if there are some components more valuable than others.

According to Baker et al. (2014) the risk-reward relationship is neither flat nor positive but it is negative: the premium for a higher risk seems to be negative. The empirical tests and research show an equal and, in some cases, better performance from low beta assets rather than high beta ones (Asness et al., 2014). The low beta anomaly is present in the finance world from long time; approximately one century, and is a tool in portfolio management for alpha seekers. Baker and Haugen (2012) summarize the historical evidence of the negative risk-reward relationship. The authors underline that there is no evidence about the fact that high volatility stocks yield higher returns on the long run. They highlight the same anomaly discovered by Haugen and Heins (1972), expanding the analysis to different asset classes.

Haugen and Heins (1972) is one of significant papers that have influenced the mainstream of literature of beta. They were first who documented the Low-Beta

evidence in their study over developed equity markets. Then, Jagannathan and Ma (2003) prove that the minimum variance portfolio has higher returns and lower variance than the benchmark (S&P500 index). Blitz and Van Vilet (2007) rank the stocks by their volatility and observe a remarkable difference between the first and the last decile. Ang et al. (2009) also document that the stocks with high volatility tend to generate very low returns in the American market. Furthermore, they add that high historical idiosyncratic volatility leads to lower realized returns in 23 emerging markets. Equally, Carvalho et al. (2002) show that minimizing variance of the portfolio causes the Sharpe ratio to increase comparing to the Market Cap index.

In turn, Cowan and Wilderman (2011) also find in-line results as of Baker and Haugen (2012) who confirm the persistence of the Low-Beta anomaly. They analyze the American Stock market from 1969 to 2011 and show that the Low Beta stocks over-performed the related index and, in detail, high beta stocks selection, in all the samples tested. The Low Beta selection is characterized not only by lower volatility but also by lower drawdown and better performances than High-Beta stocks.

Zlotnikov et al. (2012), inspired by Cowan and Wilderman (2011), explore extensively the Low-Beta anomaly. They analyze monthly data with a three years investment horizon, from 1920 to 2011, covering not only the US stocks, but also the entire global market.

Lastly, Baker et al. (2014) analyze the US equity market between 1968-2012 and show that the low risk stocks deliver outstanding results outperforming the market with the promised low risk profile. In detail, one dollar invested in the low risk portfolio in 1968, brings back to the investor 81.66\$ in 2012. Whereas, one dollar invested in the high-risk portfolio, brings back to the investor 9.76\$ in 2012. This inverse relationship between risk and reward is also traceable in 31 developed equity market from 1989 to 2012.

To summarize, the  $\beta$  anomaly has rendered classic risk-reward relationship to be questioned. In this paper, the basic objective is to build a long/short equity portfolio (Leibowitz et al., 2009) in a beta neutral framework, trying to modify or adding selection/construction criteria to the method Frazzini and Pedersen (2013), and obtaining a low risk portfolio. After some preliminary analysis, we focus our attention more on the  $\beta$  calculation than optimizing parameters (ie. frequency or time frame sample for prices). We decomposed  $\beta$  formula in 2 components, one is the correlation between the stock and the market; and the second is the volatility ratio between the stock and the market itself.

The remainder of the paper proceeds as follows. *Section 2* introduces the beta decomposition, *Section 3* shows the application of the decomposition to asset allocation, *Section 4* introduces a new proposal to analyze the market and sector beta evolution, *Section 5* concludes.

## 2. The $\beta$ decomposition

In this section we propose the beta decomposition in order to better analyze the *Low Beta anomaly*. We want to explore the  $\beta$  components to improve the efficiency in asset allocation framework, wondering whether we are able to increase the Sharpe Ratio and other relevant parameters.

Let  $R_i$  be the return on single period for a generic stock  $i$ , (with  $i=1, \dots, N$ ) and  $R_M$  the Market return (in the following the subscript  $M$  indicates Market); moreover let  $\mu_i$  and  $\sigma_i$  the average return and standard deviation of  $R_i$ . Thus we can write for the stock  $i$ , the corresponding  $\beta_i$  as:

$$\beta_i = \frac{Cov(R_i, R_M)}{\sigma_M^2}$$

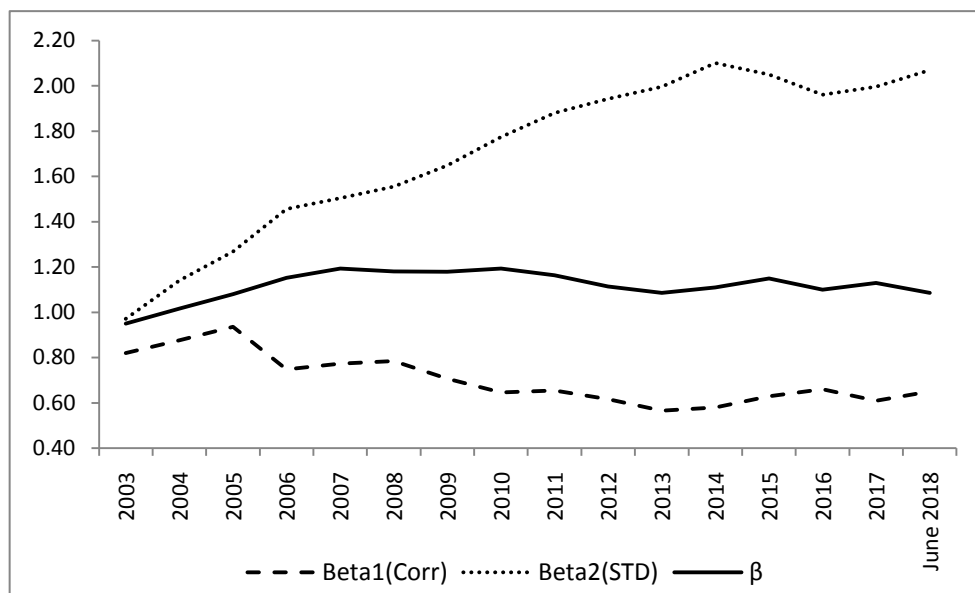
Which can be rearranged as:

$$\beta_i = Corr(R_i, R_M) \frac{\sigma_i}{\sigma_M}$$

These two factors can be highlighted as follows

$$\beta_i = \beta_{i,1} \beta_{i,2}, \quad \beta_{i,1} = Corr(R_i, R_M), \quad \beta_{i,2} = \frac{\sigma_i}{\sigma_M} \quad (1)$$

In the following we indicate with  $\beta_1$  or  $\beta_2$ , the strategies, relying on these two components. To analyze the contributions of the two factors, we compute all these three values for the S&P500 components; we describe sample and methodology in detail in *Sections 3.3 and 3.4*.



**Figure 1.**  $\beta$ ,  $\beta_1$  and  $\beta_2$  average values, on annual basis, for the components of the S&P500

Figure 1 displays the time evolutions of the  $\beta$  and its components given by (1) for the stocks listed in the reference index. The  $\beta$ s are computed on a 104-weeks basis, sliding window: our analysis cover more than 180 months.

Interestingly, the "classical"  $\beta$  (meaning the Beta coming from CAPM theory) is pretty stable and increase modestly during 2007/2009 (till Lehman default) and decrease in the next years; indeed the two components show very different behaviors. While  $\beta_1$ , the parameter related to correlation, shows a decreasing trend (only in 2008 during the crisis we have a small inversion), the  $\beta_2$ , associated to the standard deviation ratio, shows an upward stable trend.

Moreover, computing some trivial statistical analysis and in particular the skewness of the  $\beta$ s' distributions, we note that the "classical"  $\beta$  is rather symmetric (as we can expect). Instead, we found that  $\beta_1$  and  $\beta_2$  are negative (-0.65) and positive (+1.1) skewed respectively. These differences in skewness are even stronger if we consider the single years rather than the aggregate average.

### 3. Portfolio Construction for $\beta$ strategies

As mentioned in section 1, shows several anomalies may question the validity of CAPM. We want to explore more in details the "Low-Beta" one: in essence empirical evidences exhibit SML flatter than the theory predicts and, in some

cases, the slope is even negative. Our aim is to study this risk/reward distortion in order to generate alpha in risk-adjusted terms, building portfolios based on  $\beta$  (Frazzini et al., 2014). Moreover, as original part, we use the  $\beta$  decomposition to give more insight about market behavior. For our analysis the first step is to calculate the Beta parameter following the CAPM and elaborate some basic math and statistic as described below.

In detail, once the  $\beta$ s are computed, the further steps are:

- ✓ Divide the stock sample in quartiles using  $\beta$  as discriminant;
- ✓ Compose two portfolios: the Long portfolio (**L**) with the stocks belonging to the first quartile (*lowest  $\beta$  stocks*) and the Short portfolio (**H**) with the stocks belonging to the fourth one (*highest  $\beta$  stocks*);
- ✓ Calculate the single stock weight in each portfolio using its  $\beta$ ;
- ✓ Normalize the weight ( $\beta$  standardization) in order to have market neutral exposure (ie.the stocks weights for each portfolio summing to 1)

Worth to remember that the overall strategy includes the Long and the Short portfolio, consequently, by construction, is  $\beta$ -neutral (Hurd, 2001; Jacobs and Levy, 2005): obviously the total performance will be the difference between 2 components (Long and Short) and then we are able to calculate the alpha produced by different level of Beta. In an original way we extend the analysis to  $\beta$  components,  $\beta_1$  and  $\beta_2$ , comparing finally two possible strategies.

A point to clarify is how to compute the weights on the basis of the  $\beta$ s and its components. The  **$\beta$ -weighted strategy** (hereinafter BW) produces: (i) in the high  $\beta$  portfolio (**H**, the short leg) large weights for the stocks with a higher  $\beta$ ; (ii) in the low  $\beta$  portfolio (**L**, the long leg) large weights for the stocks with a low  $\beta$ .

In detail for the high beta portfolio (H), the first step is to calculate the raw weight for stock  $i$  as:

$$\omega_{i,H}^* = \frac{\hat{\beta}_{i,H}}{\sum_i^n \hat{\beta}_{i,H}}$$

Then, once the raw weights are computed, we obtain the raw portfolio beta  $\hat{\beta}_{BH}$  as:

$$\beta_{BH} = \sum_{i=1}^n \hat{\beta}_{i,H} \omega_{i,H}^* \quad (2)$$

And now we are able to normalize the portfolio H ( $\beta_{BH} = 1$ ), using normalized weights  $\omega_{i,H}$ .

$$\omega_{i,H} = \frac{\omega_{i,H}^*}{\hat{\beta}_{BH}} \quad (3)$$

The latest formula is the final weight for the stock  $i$  in portfolio H.

For the low beta portfolio (L) we use for the weights the reciprocal of the  $\beta$ s: that's because lower  $\beta$  is better and has to drive the larger weight. Re-arranging the previous formula for single raw weights we have:

$$\omega_{i,L}^* = \frac{\hat{\beta}_{i,L}^{-1}}{\sum_{i=1}^n \hat{\beta}_{i,L}^{-1}}$$

Following the same steps described before we have the raw portfolio beta  $\hat{\beta}_{BL}$  and then the normalized weights  $\omega_{i,L}$ , leading again to a portfolio L with unitary beta.

We remark that the raw weights in the H portfolio are larger than the standardized ones,  $\omega_{i,H}^* > \omega_{i,H}$ , because they are standardized respect to a factor greater than 1,  $\hat{\beta}_{BL} > 1$ . Conversely, the raw weights in the L portfolio are smaller than the standardized ones,  $\omega_{i,L}^* < \omega_{i,L}$ . Definitely we need to leverage for set up the strategy. With these weights the strategy is Beta neutral.

Now we are able to calculate the L and H portfolio returns, and in turn the overall strategy performance. Defining  $r_s$  as the  $i$ -th stock weekly return, the monthly return is:

$$R_i^* = \prod_{h=1}^k (1 + r_i) - 1$$

where  $k$  is the number of weeks in a given month. Summing up the two portfolios' returns are:

$$R_p = \sum_{i=1}^n R_i^* \omega_{ip}, \quad p \in (H, L)$$

Finally, the monthly return  $R_s$  of the strategy is the difference between the long side and the short side returns:

$$R_s = R_L - R_H$$

We apply this procedure not only for  $\beta$  portfolio but also to build portfolios using  $\beta_1$  and the  $\beta_2$  components, obtained from the decomposition (1). We name the strategies:  **$\beta_1$  Corr** and  **$\beta_2$  Std**.

### 3.1. Data of Portfolios

We consider weekly observations from 2003 to June 2018 of the S&P 500 Index and its constituents, paying attention to survivorship bias and other statistical issues.

The time series are obtained from a well-known data-provider platform: unfortunately, the platform does not provide the historical S&P 500 index composition and, as well documented, the index members can vary each months. Therefore, we are using a sample composed by the companies currently listed and we had verified that this subset is a good approximation, with very low tracking error and minimal difference in terms of sector distribution and performance. Consequently we're going back to 2001 and our data-set was reduced progressively; furthermore we have excluded the companies included in S&P500 after the 01/01/2016, because we need almost 104 week to compute  $\beta$ s, following some traditional conventions. Iterating this procedure backward, for each year, the stocks inserted to substitute the de-listed ones have been removed from the sample. Finally, we end up with 487 stocks sample in 2018, which progressively shrink until a sample of 428 in 2003.

In addition, it is worth to note that no *survivorship-bias*<sup>1</sup> effect is present, because we ascertain that the de-listed stocks belong to the central quartiles, so they would not enter the portfolios H and L.

We utilize the historical returns time series, including dividends (ie. Total Return approach). Data are adjusted to manage the possible mismatch between weeks, months and years.

### 3.2. Performance of Portfolios

This section presents the performance of the strategies based on the BW portfolio described in *Section 3* using  $\beta_1$ Corr and  $\beta_2$ Std. The analysis range on the entire period 2003-2018 and on the smaller one (ie. 2005-2018), applying two different methods in order to avoid some distortion that can affect portfolio construction and results: *Iteration* and *Winsorization* (see *Section 3.4*). We have to introduce these corrections, because the  $\beta$  computation provides in some cases

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<sup>1</sup> It is a bias that occurs when the individuals survived from a selection procedure are considered. The results are distorted because the data of who failed are not taken into account. This bias was defined for the first time in the active funds framework. In fact, it was clear that the unsuccessful funds were closed or merged and so de-listed from the index. If we compute the average return based on the survivor funds, it is higher than the expected return.



"unusual results", too low, too high and sometimes negative. For this reason, we follow Damodaran (2012) and introduce the  $\beta$  revision<sup>2</sup> as described below:

$$\tilde{\beta}_i = \frac{1}{3} + \frac{2}{3}\hat{\beta}_i$$

### 3.3. Iteration: Floor value 0.1

The first correction method is based on iteration<sup>3</sup>. As a preliminary analysis, we test different *floors* for the  $\beta$  values. After a very simple statistical tests and analysis, we determine that the appropriate level is equal to 0.1. This value is a good trade-off between the preservation of the data results and practical issues, allowing us to build a portfolio with realistic weights.

We apply the BW strategy and report some metrics for returns in the period 2003-2018 in table 1. In addition we show year-by-year performance of the portfolios.

In terms of total return, we notice that both strategies *outperform* the S&P500 index: but if  $\beta_1$  *Corr* was very good doubling the mark, the  $\beta_2$  *Std* delivered an impressive result, with an annual CAGR above 29% vs 6% of the index. Furthermore on the positive side we remark a small maximum drawdown for our Beta' strategies. Finally, another interesting result is that the standard deviation of  $\beta_2$  *Std* has value similar to index: as a direct consequence, the traditional metrics, like Sharpe Ratio, Sortino and Information Ratio, used to grade strategy goodness, are outstanding. We notice that, in terms of kurtosis and skewness, we have satisfactory results too and, in relative terms, better than the benchmark.

Summarizing, we can conclude that the  $\beta_2$  *Std strategy* presents better results than both the benchmark and the  $\beta_1$  *Corr*. We can, therefore, argue that these methods capture a lot of the useful part of the "Low Beta anomaly" and point to the fact that the well-known beta strategies, are not optimized for the

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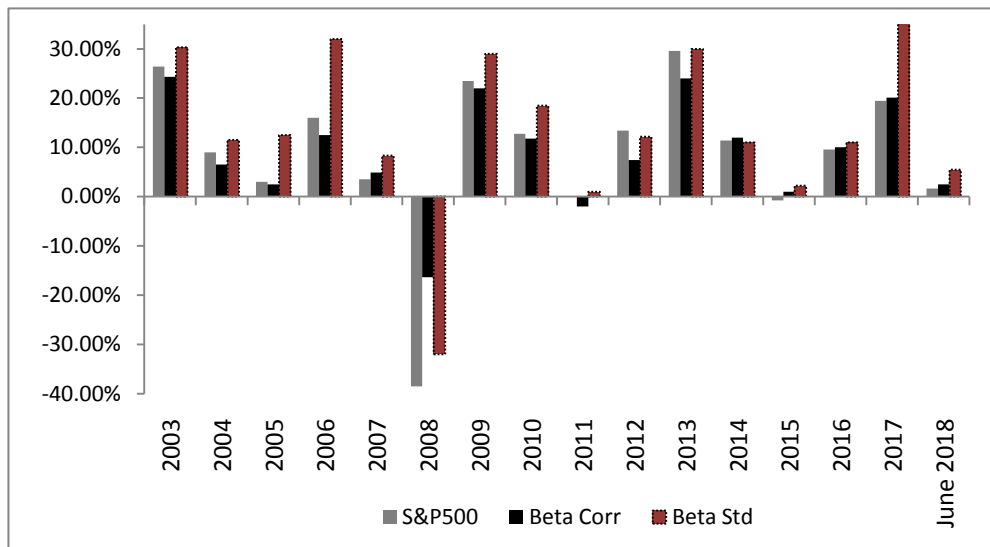
<sup>2</sup> We would like to avoid this "artificial" correction to preserve more adherences with market information, but we need iteration and winsorization to have more reliable data and realistic weights. We are aware about the controversy about too low or negative  $\beta$ , but this discussion is beyond the scope of this paper.

<sup>3</sup> With the iteration process, we try different floor values starting from 0.05 until 0.25. We choose the 0.1 value because provide us a good trade-off between the preservation of the data and realistic portfolio weights. Moreover, the 0.1 floor value provides us the highest Sharpe ratio.

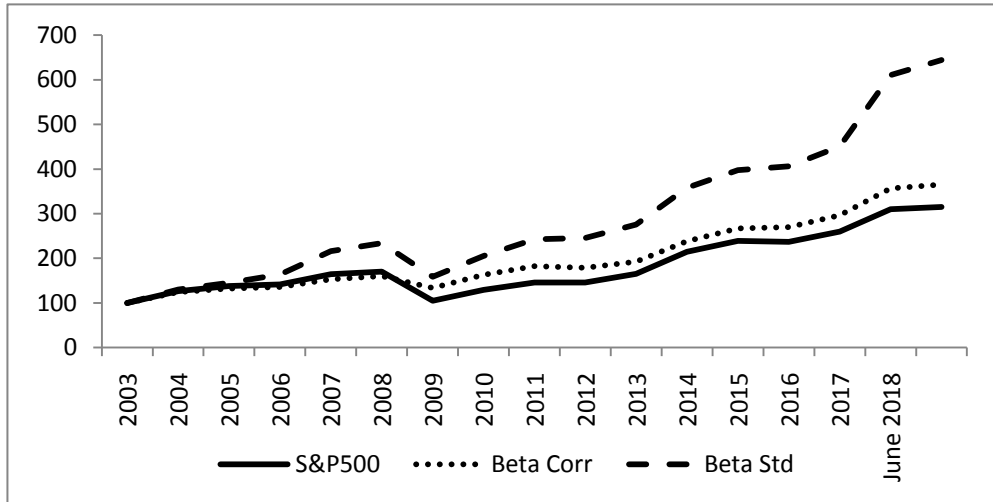
components which "cast-down" the performance, and this may be a clear evidence. The alpha generation is impressive.

**Table 1.** Strategy results over the period 2003-2018

Statistics	$\beta_1$ Corr	$\beta_2$ Std	S&P500
Arithmetic Monthly Average	0.72%	2.03%	0.52%
Annualized Average Return	9.20%	28.80	5.84%
Standard Deviation	3.20%	5.85%	2.45%
Annualized Standard Deviation	16.50%	27.58	17.50
Turnover	3.63%	3.12%	
Kurtosis	0.25	2.75	3.85
Skewness	-0.31	-0.32	-0.65
Maximum	18.59%	13.50	13.58
Minimum	-15.57%	-	-
Maximum Drawdown	-44.46%	-	-
Range	34.16%	32.49	33.72
Sum	73.94%	195.85	56.30
Compound Return	125.37%	401.08	110.3
Information Ratio	0.30	1.12	
Sharpe Ratio	0.13	0.25	0.05
Sortino Ratio	0.15	0.19	0.04



**Figure 2.** Returns vs S&P500



**Figure 3.** Performance of Portfolios during 2003- 2018

### 3.4. Winsorization Value 95% Results

This section presents the results using winsorization<sup>4</sup>. In that case we have different thresholds: 99%-1%, 97.5%-2.5%, 95%-5%, 92.5%-7.5%. One advantage of winsorization is that one helps to take into account the non-normality of the return distribution. Moreover, in our opinion, winsorization is more robust than iteration, because it relies on normalization of the beta coefficients. After some analysis we select the 95%-5% thresholds because we can build reasonable portfolio in terms of weights, with minimal change from raw beta calculations.

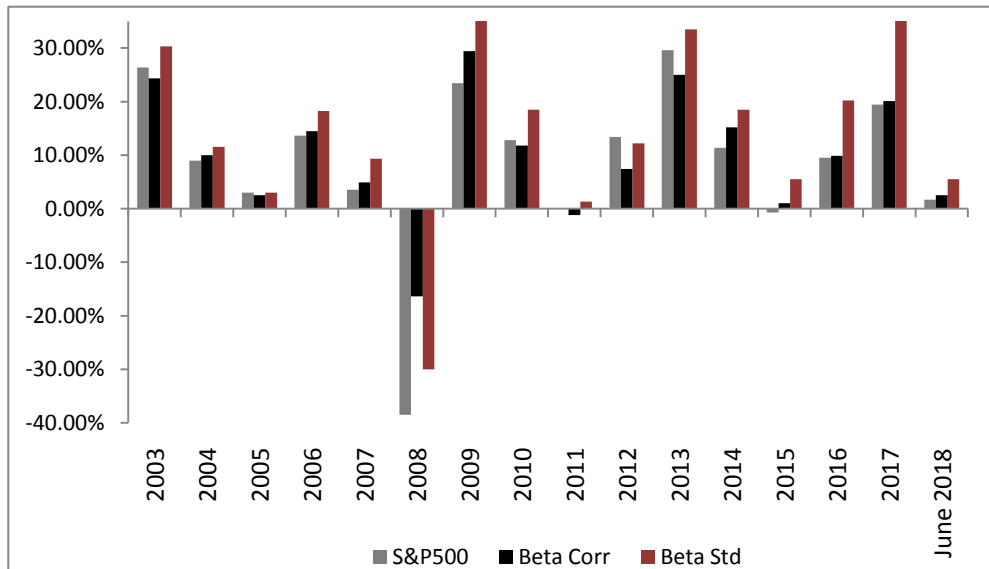
As seen before, even with this method, the strategy  $\beta_2 Std$  presents better results in terms of risk-adjusted performance than the others (see Table 2).

At a glance, in terms of returns,  $\beta_2 Std$  winsorization delivers higher returns and better risk-adjusted indicators (Sharpe and Sortino) than  $\beta_2 Std$  iteration. Considering the other indicators, we can conclude that  $\beta_2 Std$  winsorization returns are more volatile than the one by  $\beta_2 Std$  iteration with a wider range, but a smaller maximum drawdown.

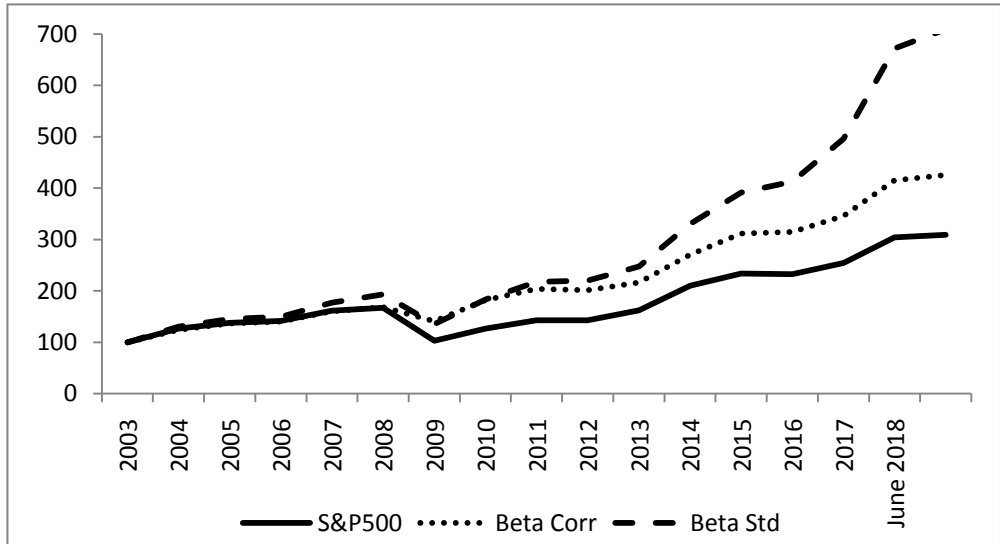
<sup>4</sup> Statistical procedure for artificially customize a random variable distribution. This aims to limit the extreme values effect on the distribution.

**Table 2.** 95%-5% Threshold statistics 2003-2018

Statistics	$\beta_1$ Corr	$\beta_2$ Std	S&P500
Arithmetic Monthly Average	0.75%	2.55%	0.52%
Annualized Average Return	9.18%	38.60	5.84%
Standard Deviation	3.37%	4.42%	2.45%
Annualized Standard Deviation	16.86%	24.56	17.50
Turnover	3.25%	2.78%	
Kurtosis	4.65	6.66	3.85
Skewness	-0.45	1.22	-0.65
Maximum	10.37%	58.37	13.58
Minimum	-23.34%	-	-
Maximum Drawdown	-17.34%	-	-
Range	33.71%	101.7	33.72
Sum	77.80%	285.4	56.30
Compound Return	133.30	442.5	110.30
Information Ratio	-0.01	1.22	
Sharpe Ratio	0.05	0.75	0.05
Sortino Ratio	0.08	0.83	0.04



**Figure 4.** Returns vs S&P500



**Figure 5.** 95%-5% Winsorization Returns Graph

Summing up, we see that the  $\beta_2 Std$  presents better results both in terms of absolute returns and of Sharpe Ratio/Information Ratio with respect to  $\beta_1 Corr$ . Worth to mention that  $\beta_1 Corr$  presents results more similar to the benchmark, but exhibits lower risk level.

It is interestingly at this point to notice that we explored different cases in terms of time frame, extending the procedure at sector level, finding similar results. This means that our finding about “Low Beta anomalies” is persistent or, if you prefer, we find strategies able to generate pure alpha starting from classical CAPM.

### 3.5. Sector Exposition and Sector Portfolios

Asness et al. (2014) show that low risk investments are not driven by certain *Sector-Bet* and the returns are not due to the *Value-Effect*. In their work they also illustrate how the *Industry-Neutral* strategy is better than the *Pure-Industry Bet* and the *Regular strategy*.

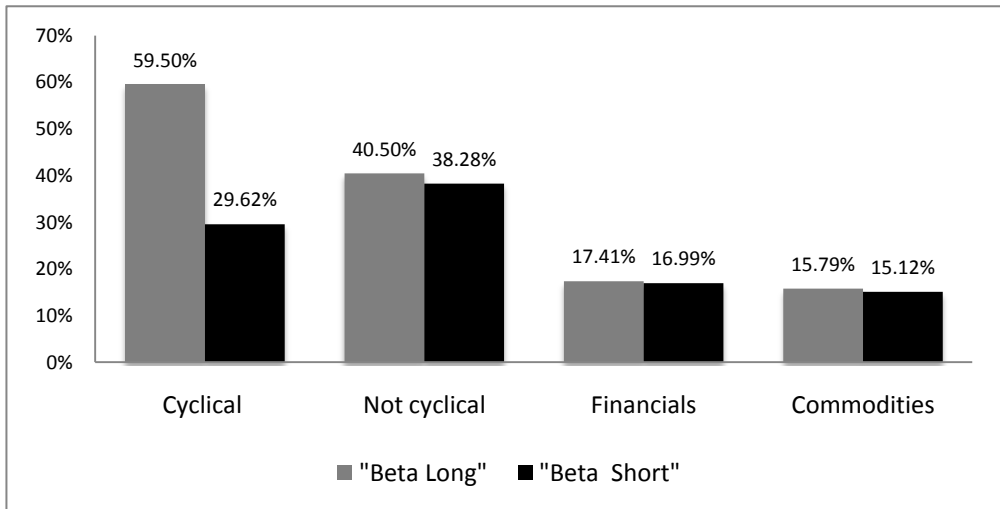
On the basis of this evidence, we group the stocks into 4 sectors, following the *Global Industry Classification Standard (GICS)*<sup>5</sup>:

<sup>5</sup> We are referring to the first GICS level

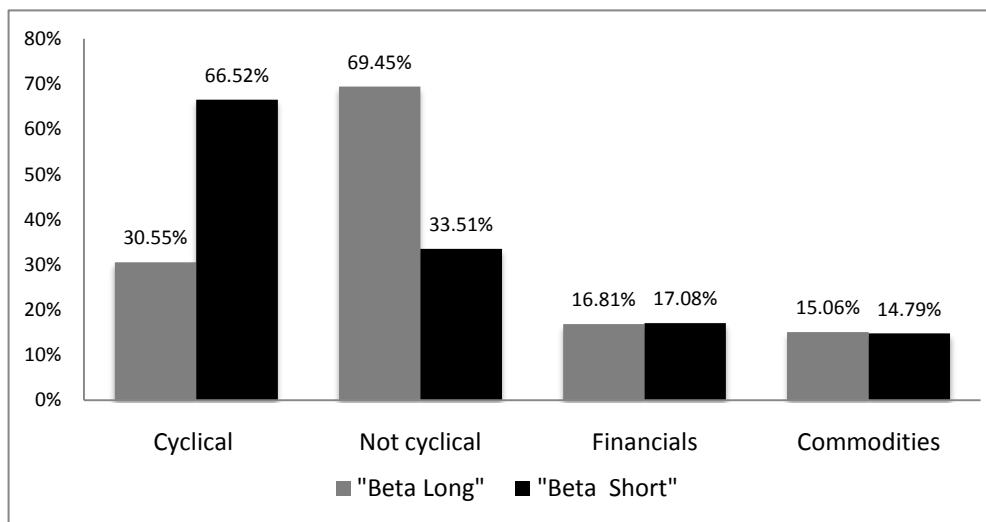
- **Cyclical:** Consumer Discretionary, Industrial and Information Technology;
- **Not-Cyclical:** Consumer Staples, Healthcare, Utilities, Telecommunication services;
- **Financials**
- **Commodities:** Energy and Materials

First of all, we analyze the composition of the portfolios produced by the  $\beta_1$  *Corr* and  $\beta_2$  *Std* strategies obtained on the whole sample (see Figures 6 and 7). This analysis deserves few remarks. Considering the average sector exposition, the  $\beta_1$  *Corr* strategy has an over-exposure to cyclical sector and a small over-exposure to not-cyclical sector, whereas the  $\beta_2$  *Std* strategy has a different picture with an over-exposure on not-cyclical sector on long side and an over-exposure to cyclical sector in the short side. This is, probably, the principal source of delta performance.

Considering larger aggregate for the number of sectors, the  $\beta_1$  *Corr* strategy presents an over-exposure on the long side for the cyclical sector, and a similar situation for both the sides on the not-cyclical sector. Whereas, the  $\beta_2$  *Std* strategy presents overexposure on the long side for no-cyclical sector and the same amount of exposure, but in the short side, for the cyclical sector.



**Figure 6.**  $\beta_1$  *Corr* Sector exposition values



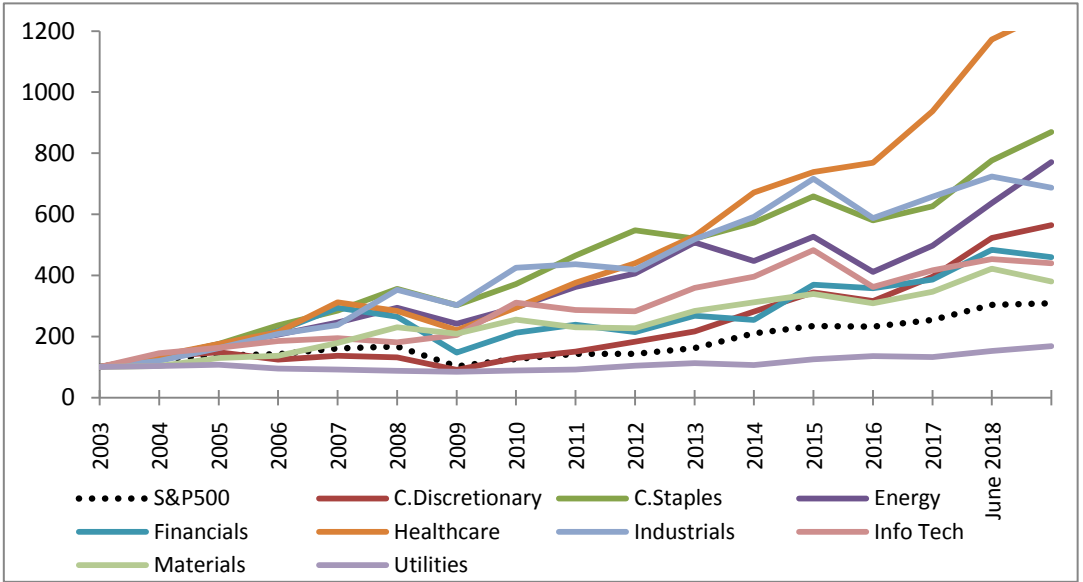
**Figure 7.**  $\beta_2$  Std Sector exposition values

We extend our analysis applying the  $\beta_1$  Corr and  $\beta_2$  Std strategies to each sector, for every month, generating more than 2000 portfolios.

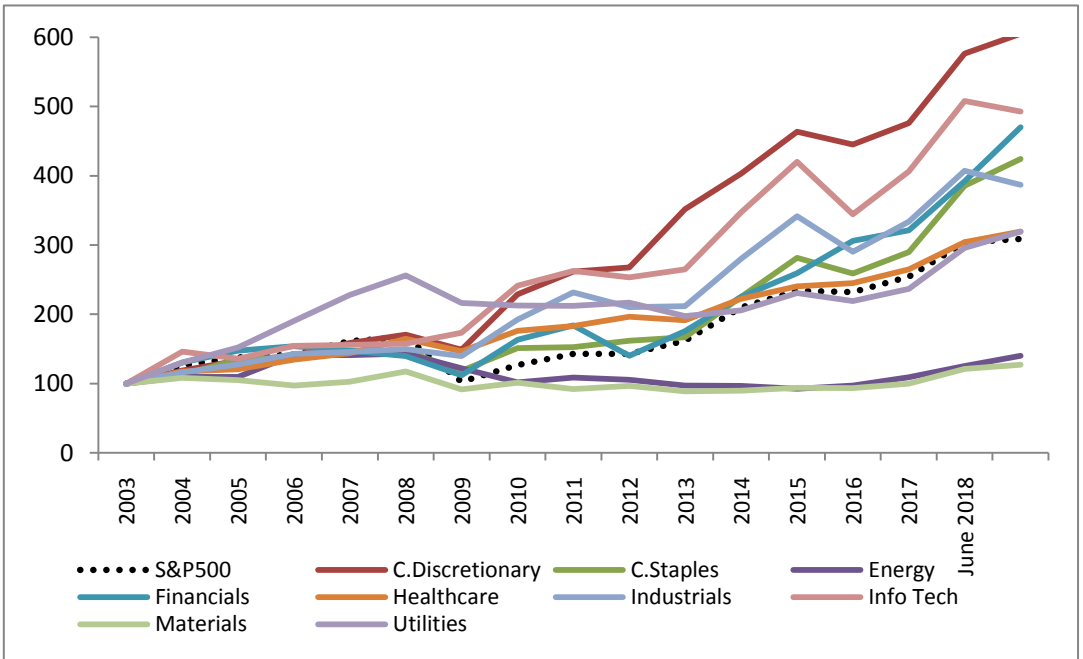
We slightly modify the procedure, computing the stocks'  $\beta$ s respect to the Sector index and not the whole one. Then, applying (1) we obtain the  $\beta_1$  and  $\beta_2$  parameters calculated against each sector. Then the portfolios are built following the procedure described in Section 3 and the returns for each month are computed accordingly. In order to overcome the distortion due to extremely high or low beta values, we apply a winsorization with threshold 95%-5%.

#### 4. New views on $\beta$ : Dispersion level in sectors and "Walking Value"

In this paragraph, we extend the results of Beta's strategies using the 9 GICS sectors (ie. Utilities, Materials, Infotech, Industrials, Healthcare, Financials, Energy, Consumer Staples and Consumer Discretionary), adding new calculations and views, in order to confirm the previous finding and eventually improve our research. First of all, we notice that the relations between the market and the sector  $\beta$ s, can also be analyzed considering the time dimension. The time dimension characteristic arises from stocks singularity in terms of structure and features. For this reason for a generic stock  $i$  we can calculate Beta and its components against market and Sector. Figures 9 and 10 display the performances of the  $\beta_1$  Corr and  $\beta_2$  Std strategies compared to the S&P500 returns.



**Figure 8.** Beta 1 Corr Strategy vs S&P500



**Figure 9.** Beta 2 STD Strategy vs S&P500



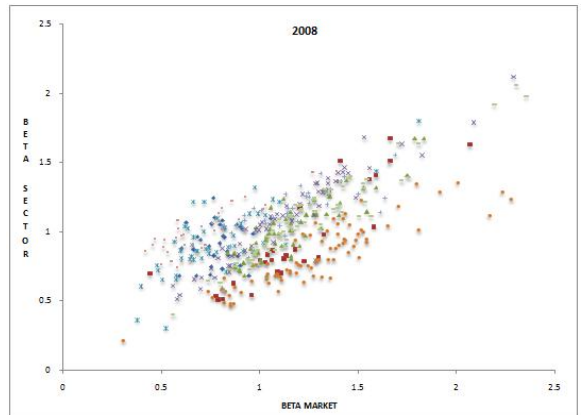
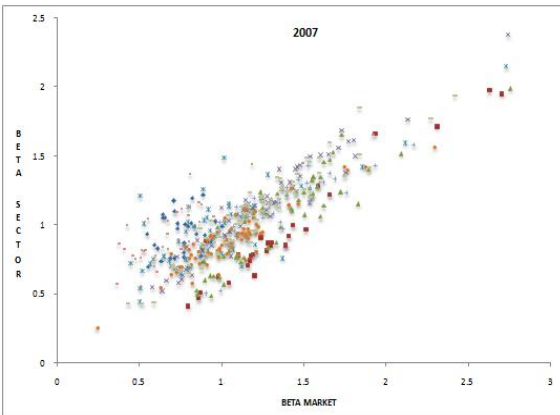
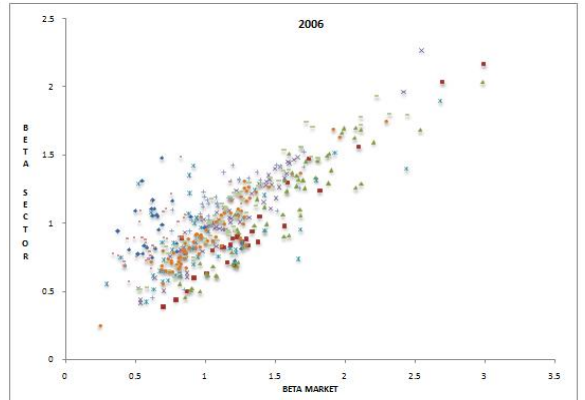
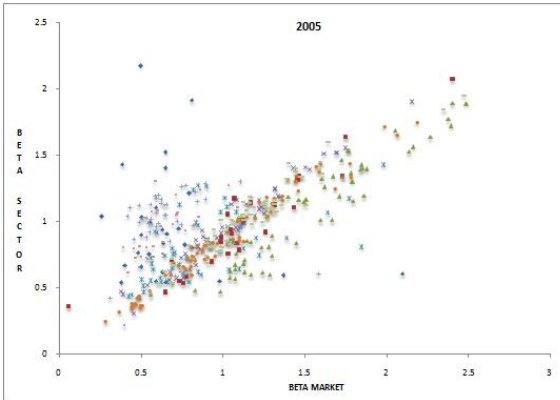
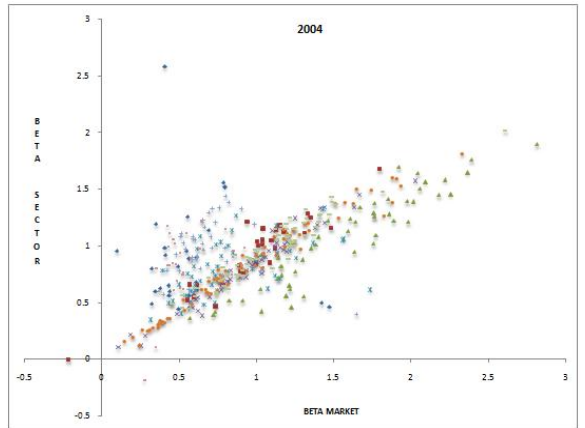
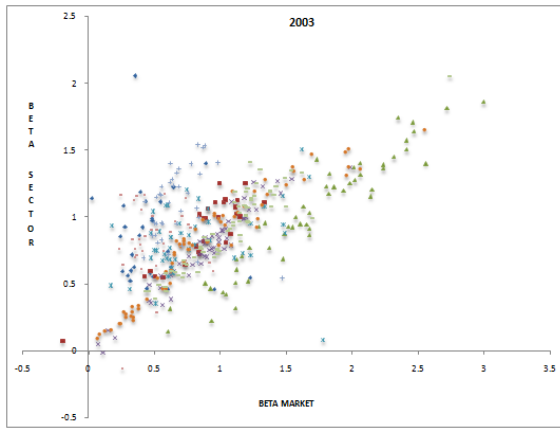
Starting from that, we can calculate  $\beta_{i,M}$  and  $\beta_{i,S}$  the Market Beta and the Sector Beta respectively and we present a graphical representation of the joint evolution of these parameters, providing 2 different types of analysis:

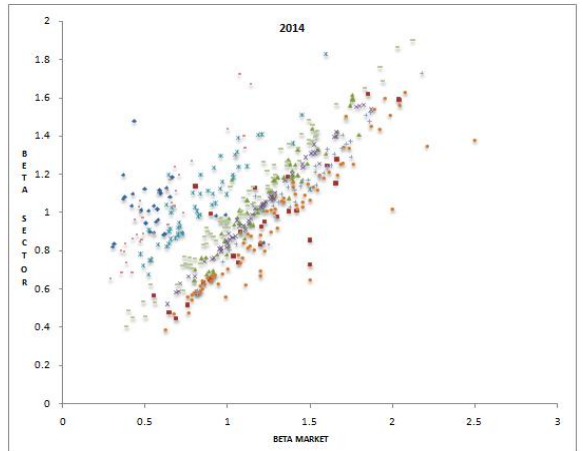
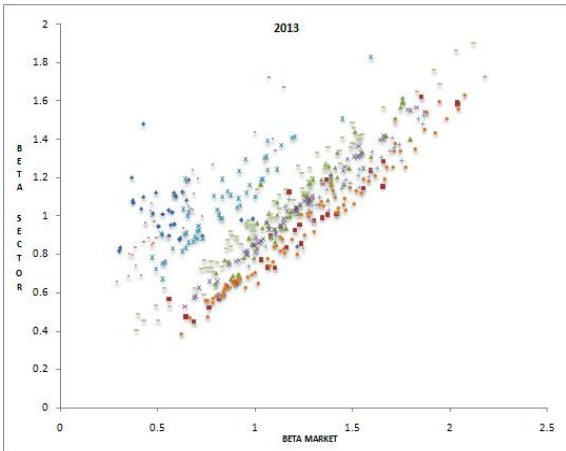
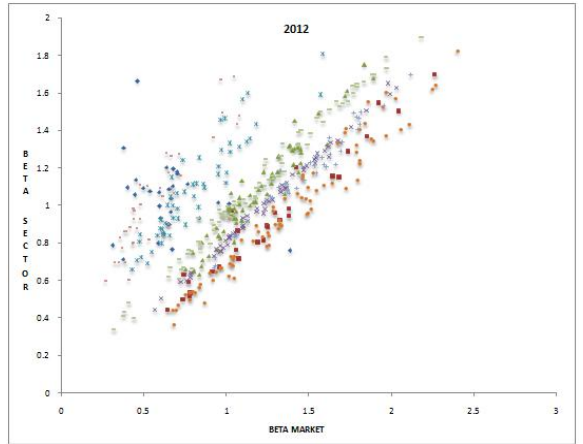
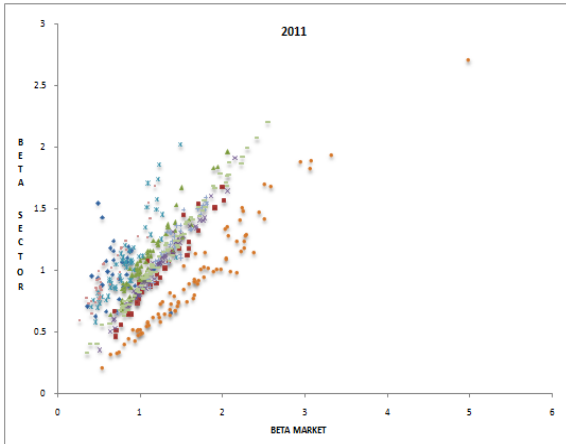
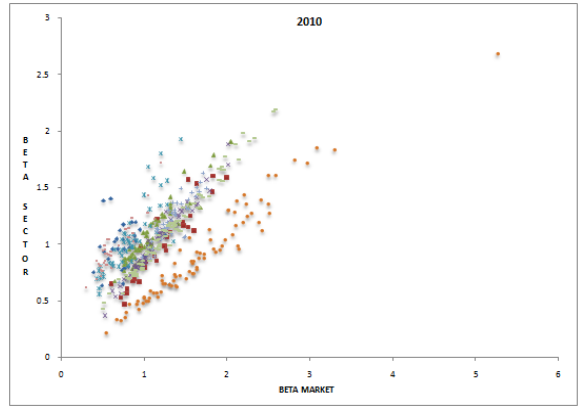
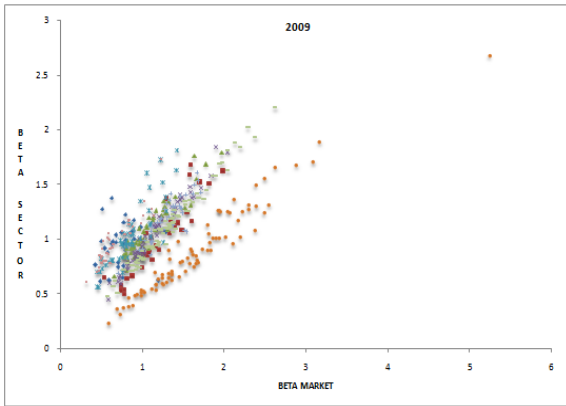
- I. *Dispersion within Years*: we display a scatter plot using our panel of stocks. On x-axis we have the Market Beta and on y-axis the Sector Beta; each sector has a different color. The idea is to check the dispersions among sectors and with an innovative visualization about market structure. We repeat the graph to visualize the differences and the evolution among years (Figure 10).
- II. *Walking value*: we calculate for each sector the "average normalized  $\beta$ ", respect to both the market and the sector; in this way we have for each sector  $S$  a pairs  $(\mathfrak{B}_{tM}, \mathfrak{B}_{tS})$ , where  $\mathfrak{B}_{tM}$  the annual average of the market beta for the year  $t$  and

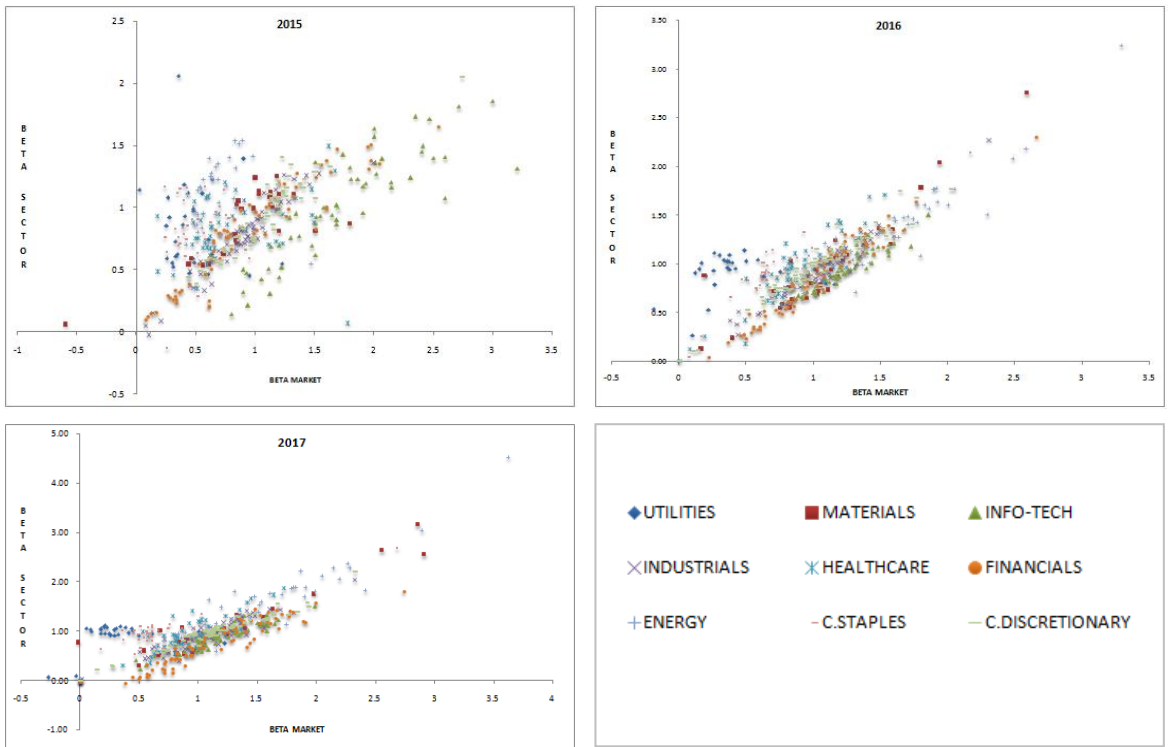
$$\mathfrak{B}_{tS} = \frac{1}{N} \sum_i^N \widehat{\beta}_{i,S} \quad (4)$$

where  $\widehat{\beta}_{i,S}$  is the annual average for the year  $t$  of the  $i$ -th constituents of sector  $S$ . The normalization comes from a Z-score procedure.

Focusing on the figure 10, "*Dispersion within Years*": as a general remark, from 2003 to 2017, we can see an interesting path in the market shape. The pre-crisis years (2003-2006) present a linear shape explained by the different sectors characteristics; probably, we explain this behavior as a *normal-rotation* among sectors. From 2007 something changes, and the cloud becomes looser around the line as the crisis approaches. We point out that this shape shows an increase in terms of risk (we name this path as *alert-situation*): on the economic side we can observe stocks valuations flip and, in general, the market becomes unstable with volatility spikes. In 2007 and 2008, all sectors present the maximum degree of dispersion, with values in the interval 0.5-2.0. The 2008/2009 storm now affects the global markets. After the *alert-situation*, the market seems to gain some degree of stabilization and the cloud reverts back to a linear shape: we name this period as *cover-situation*.



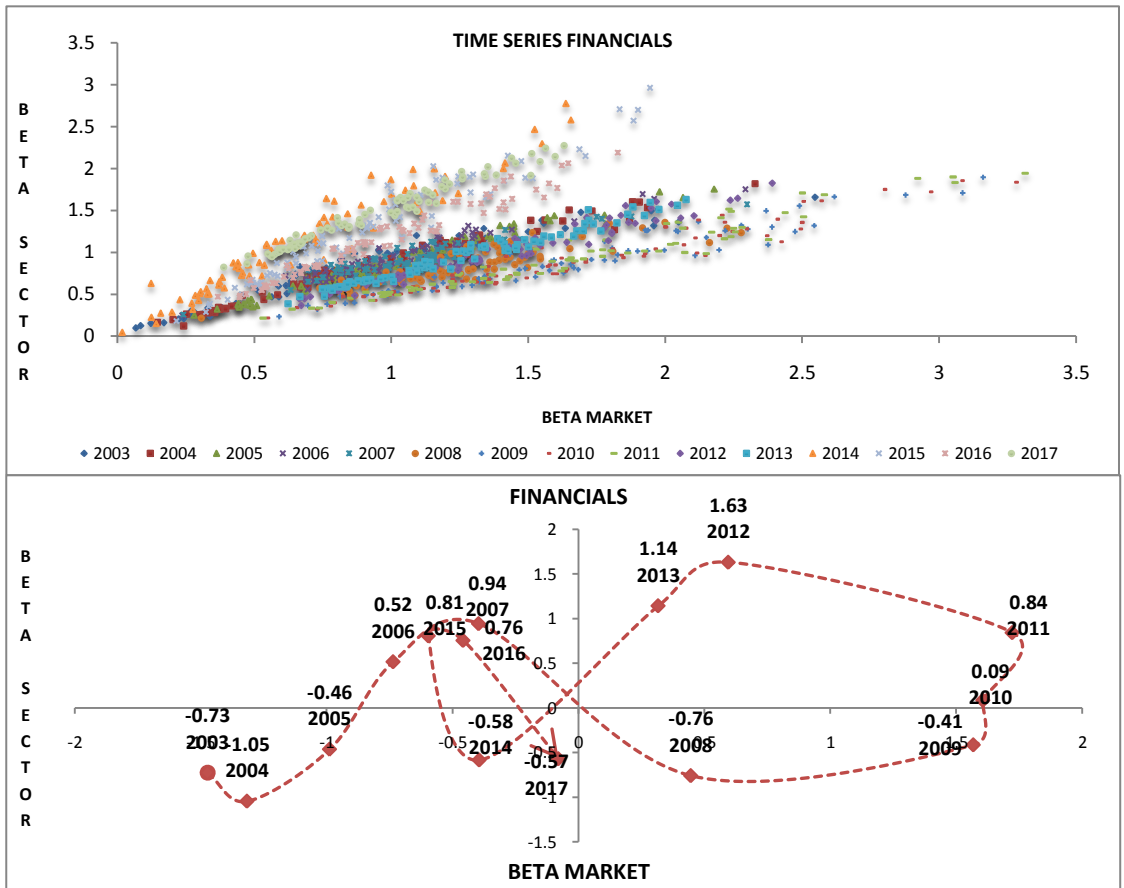




**Figure 10.** Beta Sector vs Beta Market from 2003 to 2017

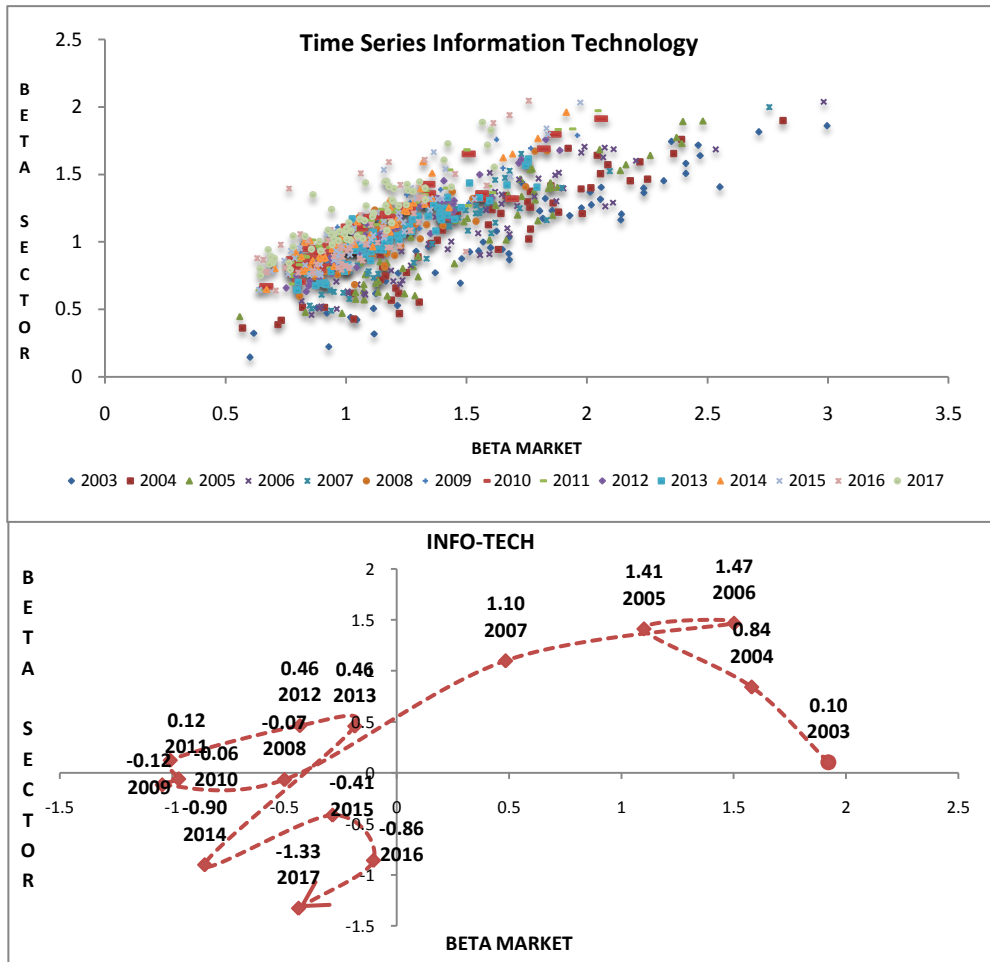
Now consider the figures 11-12 in which we present our second original analysis, the “Walking value”: the idea is to represent the evolution of the Sector Beta /MarketBeta interaction. Here, we present the results for Financial and Info-Tech Sectors, but we performed the analysis for all GICS sectors.

In these graphs below, we are able to check the Beta dispersion within sector and market and, in this way, we can figure out the risk entity within the sector and the risk direction changes. To clarify our statements, we mean that a movement to the right (left) represents a higher (lower) level of dispersion versus the overall market. On the contrary, a movement to the top (bottom) represents a higher (lower) level of dispersion versus the reference sector. From 2003 to 2017, we can figure out: (i) how the beta is changed in each sector, (ii) where the beta is gone (we are facing more risk with respect to the market now than in 2003). In conclusion, this analysis allows us to study the single sector story from the beta point of view, and to perform a cross-sector analysis and eventually exploit some mispriced situations.



**Figure 11.** Financials Beta Dispersion and Financial Walking Beta

Above graphs presents valuable information. The **Financial** sector is the one more "under the lights" given its central role in the recent financial crisis. As expected, we have a high grade of dispersion related to the market beta, and the lowest point is during 2008. About the direction, we move from the left-hand side of the graph to the right-hand side, and after a brief period of dispersion against the sector, now the trend is again toward the market dispersion. A higher sector dispersion degree means a higher sector risk due to the related sector stocks interconnection. In distresses periods the degree of correlation within assets tends to be higher, this is consistent with the 2008 financial crises of which the financial sector was the "main actor".



**Figure 12.** Info-Tech Beta Dispersion and Financial Walking Beta

The *Info-Tech* sector shows always a discrete level of dispersion against the overall market, with a remarkable infra-sectorial dispersion at the beginning. Nowadays, the Beta is lower than the starting point, underlying the sector relevance today and, probably, a mispricing. Furthermore a higher market dispersion degree means a higher sector risk due to external factor with respect to the related sector. In the particular case, the higher degree of dispersion versus the overall market is due to other sector related to the Tech as for example key suppliers or customers.

## 5. Conclusion

The hypothesis behind the most important model in the modern finance, the CAPM, seems to be too far from the market reality. Surely, the CAPM remains a pillar for market analysis, but we have to remark that some of its features are even in contrast with the observed risk-reward relationship, deserving driving more deep analysis (Fama and French, 2004). With this purpose, we decided to focus on the analysis of the risk market parameter (ie. The  $\beta$ ).

It is well known that we can write the  $\beta$  formula as a product of two components (Fama and French, 2003): First, correlation between stock and reference market; Second, standard deviation ratio between stock and market. With these elements, we are able to assess the impact of each factor on the overall beta, in order to well understand the dynamics behind the  $\beta$  behavior. Our work evidences that the Standard Deviation component plays a central role in low risk strategies, deserving better results. In order to have "realistic" portfolios, we propose some solutions to avoid "strange" results coming from improbable weights, particularly when we have to manage very low or negative  $\beta$  values. The first solution is quite trivial and takes into account a floor value selected by an iteration process; the second one is based on *winsorization* thresholds. We have good results in both the ways, but in terms of risk-adjusted performance, the *winsorization* process presents more outperforming results emphasizing low risk strategies. We expand our work running strategies at sector level, introducing a new view and gaining interesting insights about the market behavior. In essence, we find the low  $\beta$  strategies are yielding good performances at sector level too. The consequential step to these results is to put in relation the market  $\beta$  with the sector  $\beta$ . Here, we find some interesting relations, which allow us to reinforce the Low Beta anomaly presence and allow us to exploit the opportunity to generate alpha. We provide two types of analysis: the first one compares the market  $\beta$  with the sector  $\beta$ , analyzing different years in order to see a general evolution a static framework about market movements. It is interesting how this analysis highlights some sector behavior, like in the Financial sector, where we can see different Beta dispersion in the recent events (i.e. the 2008 financial crisis). The second analysis is about sector exposure in comparison with market: for a single sector we are able to detect the relation between the market  $\beta$  and the sector  $\beta$  over the time; we call that "*the walking Beta*". The results show some interesting evidence: it is possible to remark that different sector movements in terms of risk and risk-path along time reflect a concern or a trend in place. A movement due to the market  $\beta$ , is a hint of a general risk change, a movement due to the sector  $\beta$ , is a hint of the specific sector risk change. The reported plots are maps providing a new version of risk: they compare and show a link within market and sectors.

With our work we improve the most used beta strategies, widely embodied in smart-beta ETFs. Our intuition can explain, and limit the damages, of the beta-related strategies in stressed periods; at the same time, the performances can be enhanced in normal or bull periods. The idea to consider the beta components instead of the overall beta, allows to isolate the part that could cast-down the performance (i.e. the correlation), and thus allows to transform this component from a "badwill" into a "goodwill" building ad hoc strategy. Macroeconomic and external factors disable the classic beta strategies, and cannot be detected looking at the overall beta.

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