Fundamental Indexation in Europe: new evidence

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ABSTRACT

A fundamental index weights each listed company using several metrics of its "economic footprint" such as book value, income, revenues and dividends. We analyze the risk-return profile of these alternative indexes in comparison with a traditional cap-weighted index focusing on European equity markets during a 14-year observation period (1999-2013). As in previous studies, we show that the greatest benefit of the fundamental indexation is detected during the Internet bubble burst, when stock prices significantly deviated from their fundamentals. By focusing on the most recent financial crises, the Global financial crisis and the EU sovereign debt crisis, we exhibit that fundamental indexes underperform the cap-weighted index. We also compare the performance of the two methodologies relying on the degree of overlap between their compositions. Finally, through factor analysis, we attempt to optimize the construction of fundamental Composite Index focusing on the weighting scheme for the four underlying metrics.

Keywords: Fundamental indexation; Index design; Fama and French model; Financial crises

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1. Introduction

Since the 60's, the insights stemming from the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966) led to consider the market portfolio (a basket of securities based on a market-capitalization weighting scheme) as the mean-variance optimal portfolio. The market portfolio is thus considered the most desirable benchmark in asset management, being the most representative of the overall markets, easily replicable and designed following objective rules. As a consequence, the most popular stock market indexes are weighted proportionally to their market cap, aiming to get closer to the fair value of each stock (and, therefore, of the overall market) that otherwise cannot be exactly represented (Roll's critique). However, over time, there have been many empirical evidences suggesting the need to debate the hypothesis behind the cap-weighting efficiency. In particular, during certain phases of the market, securities prices tend to deviate from their intrinsic values creating a mispricing. Consistently, Cap-Weighted (CW) portfolios are desirable when the Efficient Market Hypothesis (Malkiel and Fama, 1970) is verified, that is when the market capitalization of a firm is a good indicator of its true worth and reflective of the firm's representativeness in the reference market.

A broader empirical literature, however, provides evidence that market prices can be easily influenced by speculation as well as by many other factors not fully explained by firm's fundamentals. In practice, tracking those indexes means to increase the portfolio's weight of overpriced securities (thus overweighting the ones with a lower upside potential) as well as to underweight undervalued stocks. Consequently, a growing number of alternative index construction methodologies have been proposed in order to provide a response to the criticisms highlighted (Amenc et al., 2011).

Among these, the methodology developed by Arnott et al. (2005) suggests the creation of fundamental indexes based on companies accounting data rather than their market capitalization. These authors argue that Fundamental Indexation (FI) tends to overcome the above mentioned portfolio misallocation caused by the so-called "noise trading" of irrational investors[1], consequently leading to portfolios that have a better risk-return profile when compared to the related CW Indexes. In particular, they design Fundamental Weighted (FW) Indexes focusing on long-term averages of six fundamental measures (employment, sales, revenues, book value, operating income and dividends) aimed to capture the intrinsic value of the stocks. Their analysis is based on a

[1] The theme of the resistance to the noise of this new methodology is reprised and analyzed more in-depth by many different authors, leading to the birth of the Noisy Market Hypothesis (Siegel, 2006). This new theory moves again from the sub-optimality of the cap-weighted portfolios and is, according to Siegel, due to prices which can be influenced by speculators and momentum traders, as well as by insiders and institutions that often buy and sell stocks for reasons unrelated to fundamental value, such as for diversification, liquidity and taxes.

sample of 1,000 US stocks, over the period from 1962 to 2004, and provides evidence of a yearly average excess return of the FW Index over the S&P500 Index equal to 1.91%, associated with a similar risk profile.

Thereafter, other studies provide evidence of the FI superiority, focusing on different equity markets. For example, Hemminki and Puttonen (2008), analyzing the FW version of the DJ Euro Stoxx50 Index from 1996 to 2006, show an annual excess return equal to 1.74% (for the same risk). Stotz et al. (2010) examine the DJ Euro Stoxx 600 Index between 1993 and 2007 determining an annual excess return of 1.90%, again showing the same standard deviation. Furthermore, the extra returns are confirmed by a broader literature based on several equity markets in different observation periods: the German market between 1988 and 2007 (Mihm and Locarek-Junge, 2010); the Portuguese market in the period 1995-2012 (Ribeiro, 2013); the European market between 1992 and 2007 (Houwer and Plantinga, 2009); the Emerging markets between 1996 and 2010 (Hsieh, 2013) and between 1994 and 2009 (Arnott and Shepherd, 2010), the South African market from 1996 to 2009 (Ferreira and Krige, 2011); the Australian market from 1985 to 2010 (Basu and Forbes, 2013); the global equity markets (MSCI World and FTSE World Indexes) between 1988 and 2005 (Shimizu and Tamura, 2005) and from 1982 to 2008 (Walkshäusl and Lobe, 2010). The advantage of the FI on the US market has been recently verified by Chen et al. (2015), over the period 1962-2009, showing FW indexes' excess returns of 28.26% and 46.14% with respect to the DJ Industrial Average Index and the Russell 1000 Index, respectively.

Further studies focus on the analysis of the risk-return profile of fundamental indexes based on an alternative index construction methodology with respect to Arnott et al. (2005). For example, Neukirch (2008) overcomes the criticisms arising from the use of back-testing methodology, designing FW portfolios of Exchange Traded Funds where weights are defined in an ex-ante perspective. Moreover, Blitz et al. (2010) aim to verify if the positive results of the FI are influenced by the timing of index rebalancing and to demonstrate that the best results are achieved when rebalancing is made in March rather than in January, while a reweighting in September offers the worst performance.

Another strand of research argues that FI is merely a variant of a value strategy (Asness, 2006) and the excess returns can be explained by the well-known value premium rather than by the pricing noise in the stock markets (and the related cap drag). Lakonishok et al. (1994) argue that value strategies yield higher returns exploiting the suboptimal behavior of the typical investor and not because are riskier. Furthermore, still concerning the investment style, other authors consider FI as an active investment style or, at least, a quasi-active strategy (Ginis and Schoenfeld, 2006), which is in contrast with the idea of its proponents who consider FI as a passive strategy. More in detail, FI is largely considered as an active strategy that favours value stocks (Perold, 2007). A further criticism, which is common to all the alternative strategies to the CW, is based on the higher transaction costs that must be incurred.

These criticisms about the FI clash with the mentioned results prevailing in literature that demonstrate the superiority of FW Indexes in different markets and on different time horizons. In particular, the highest extra return of FW Indexes is recorded during the Internet bubble burst as demonstrated by Arnott et al. (2005) which show an annual average over performance equal to 9.44% in the period 2000-2004. Therefore, we think it is not a mere coincidence that FI was established in 2005, in order to overcome the anomalies occurred during that speculative bubble where stock prices were completely unrelated from their fundamentals.

This study aims firstly to test whether the properties of FI are verified, focusing on an alternative European stock market index with respect to previous studies, the Bloomberg European 500 (BE500) Index. We construct FW Indexes following the original methodology proposed by its founders and focusing on the 500 largest stocks of the Euro Area. In the index construction, we have chosen to rebalance the constituents twice a year considering only the information disclosed at the time of the reweighting (adopting, therefore, the same rules of the BE500). This means that we design FW Indexes in the perspective of an asset manager, avoiding any possible look-head bias. We analyze the FW Indexes in several sub-periods such as bull and bear market phases and during the latest financial crises. In particular, the analysis focuses on the time window between 1999 and 2013, a period characterized by three of the toughest worldwide financial crises: the Internet bubble burst (2000-2001), the Global financial crisis (2007-2008) and the European sovereign debt crisis (2010-2011). Furthermore, we analyze the performance of the two indexes in relation to the degree of overlap between their compositions. Finally, we intend to verify, through the factor analysis, whether it is possible to optimize the fundamental measures' weights in the FW Composite Index.

Our results confirm the higher risk-return profile of the FW Indexes over the entire time horizon even if, generally, this is not a statistically significant result. In particular, we have a single significant over performance concentrated during the Internet bubble, where we also find out that a large part of the excess return between the two methodologies can be explained by the style bias. Moreover, dividing the observation period in bear and bull markets, we show that CW outperform FW during bull markets while, in the case of bear markets, we do not observe substantial differences in performance. We also highlight that the outperformance of the FW Indexes is statistically significant only when the cumulative difference in constituents' weights of the two indexes is under 40%. When the difference is higher, the results are not univocal and the difference between the performances of the indexes is rather volatile. Finally, we show that the divergence in the composition of the two indexes narrows after an outperformance of the FW over the CW, on a semiannual basis.

The remainder of the paper is organized as follows. Section two describes the data set and the methodology; section three presents the results and the factor analysis; a final section concludes.

2. Methodology

Our study aims at comparing the FW and CW Index construction methodologies, focusing on the equity market of the Euro area during the period between July 1999 and June 2013 (14 years). We create several FW portfolios using a sample of the top 500 stocks of the Eurozone, being the constituents of our benchmark, the Bloomberg European 500 (BE500) Index. The BE500 Index is weighted by free-float market capitalization and reviewed on a semi-annual basis. The dataset used in our analysis is provided by Bloomberg Finance L.P. and includes: the list and the relative weights of the BE500 Index constituents and several selected accounting measures for each component[2] besides their stock prices and their total returns (gross dividends). The frequency of the data collection is semi-annual. In accordance with the methodology designed by Arnott et al. (2005), we adopt the following fundamental measures which are closely related to the company size: 1) book value (BV); 2) trailing five-year average operating income (INC); 3) trailing five-year average revenue (REV); 4) trailing five-year average gross sales (SAL); 5) trailing five-year average gross dividends (DIV); 6) total employment (EMP). In particular, we calculate trailing five-year measures when we deal with measures published more frequently in interim records (REV, SAL, DIV and INC), in order to consider a full business cycle of the firms (Campbell and Shiller, 1988).

We firstly construct six FW indexes based on the aforementioned measures. We decided to rebalance these indexes twice each year, at the beginning of January and July[3], aimed to implement a reweighting methodology closer to the operational needs of asset managers. In reference to the symbols used by Stotz et al. (2010), the weight of a stock i in a FW Index, at time t ($x_{i,t}^{\mathrm{FW}}$), is defined as:

$$x_{i,t}^{\mathrm{FW}} = \frac{\mathrm{F_{i,t\text{-}1y}}}{\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{F_{i,t\text{-}1y}}} \qquad (1)$$

[2] Since 1996. The data start in 1996 in order to calculate, for some fundamentals, a trailing five-year average.

[3] In particular, the fundamental metrics available on annual basis (BV and EMP) are kept constant in the two consecutive rebalancing dates that occur between the publications of financial statements; for the data published more frequently (INC, SAL, DIV, REV) we use the updated values provided by Bloomberg on January and July, depending on the timing of rebalancing.

where $F_{i,t-1y}$ is the metric of the stock *i* shown in the financial statement of the fiscal year preceding time *t,* (t-1y).

Moreover, we design a Composite (COMP) Index, which is composed equally weighting four of the six measures mentioned (BV, REV, INC and DIV)[4], meaning that the weight of the stock *i* in the COMP Index ($x_{i,t}^{\text{COMP}}$) is calculated as follows:

$$x_{i,t}^{\text{COMP}} = {}^{1}\!/_{4} \cdot \left(x_{i,t}^{\text{BV}} + x_{i,t}^{\text{REV}} + x_{i,t}^{\text{INC}} + x_{i,t}^{\text{DIV}}\right) \tag{2}$$

It is important to highlight that the COMP portfolio merely includes the stocks whose four fundamental measures are available at the rebalancing date, meaning that its number of constituents is steadily lower than that of the BE500 Index. In order to preserve the highest number of constituents, we construct a further index, namely Partial Composite (PC), which includes with respect to the COMP, even the stocks for which only two or three fundamentals are available. The difference in the number of components between the PC and the COMP Indexes is, on average, equal to 27 stocks (Max = 42; Min = 16). The full description of the number of components of each mentioned Index is presented in Appendix A.

Furthermore, we construct a benchmark portfolio (Reference Index) for each FW Index (BV, REV, SAL, DIV INC, EMPL, COMP, PC) being composed of the same constituents of the corresponding FW Index but constructed using the CW methodology.

Finally, we calculate the monthly total return for each index $\text{R}_{\text{t}\to t+1m}^{\text{Index}}$ as follows:

$$\text{R}_{\text{t}\to t+1m}^{\text{Index}} = \left(\sum_{i=1}^{N} x_{i,t} \cdot \text{R}_{i,t\to t+1m}\right) \tag{3}$$

where $\text{R}_{i,t\to t+1m}$ is the monthly total return of the stock *i* and $x_{i,t}$ is the stock's weight in *t*.

In order to measure the extra returns of the FW Indexes we also calculate the Jensen's alpha, based on the CAPM and defined as the difference between a portfolio's excess return over the risk-free rate and the return explained by the market model:

$$R_t^{FW} - R_t^{F} = \propto_{JEN} + b \cdot (R_t^{CW} - R_t^{F}) + \varepsilon_t \tag{4}$$

where $\propto_{JEN}$ is the Jensen's alpha, $R_t^{FW}$is the return of the FW Index (the Composite), $R_t^{CW}$is the return of the Reference CW Index and R_t^{F} is the return on a risk-free asset. $\propto_{JEN}$ provides an estimate of the risk-adjusted return, assuming that *b* is an appropriate measure for the systematic risk. The standard errors for the time series are consistent both in the case of heteroscedasticity and in the case of serial autocorrelation of residuals (Newey-West standard errors).

[4] As discussed in Arnott et al. (2005), EMP and SAL are excluded from the Composite index: the first because the information is often unavailable, the latter because SAL and REV are closely related and, therefore, redundant.

Since the consensus in academic finance and among practitioners is that the simple one-factor model is not properly effective in capturing the cross section of expected stock returns (Amenc et al. 2009), we perform the Fama-French (1992) three-factor regression analysis. The aim is to verify if the difference in performance between FW and CW portfolios could be explained by common risk factors, such as value and small-cap exposures. Thus, we run the following regression:

$$R_t^{FW} - R_t^F = \alpha + b \cdot (R_t^{CW} - R_t^F) + s \cdot SMB_t + h \cdot HML_t + \varepsilon_t \qquad (5)$$

where R_t^{FW} is the return of a FW Index, R_t^{CW} is the return of its Reference Index, R_t^F is the return on a risk-free asset, SMB is the small-cap factor and HML is the value factor. In particular, SMB is a portfolio that is long small cap stocks and short large stocks while HML is a portfolio that is long high book-to-price stocks (value stocks) and short low book-to-price stocks (growth stocks). In our analysis, the small-cap factor is measured by means of the excess return of the S&P Small Cap Eurozone TR Index over the DJ Euro Stoxx 50 TR Index while the value factor is measured as the excess return of the S&P Eurozone Value TR Index over the S&P Eurozone Growth TR Index.

3. Results

3.1 FI: a first comparison on asset allocation

As already mentioned, likewise the CW approach, FW Indexes favour large cap stocks, as the selected fundamental measures are proxies of the investable securities size and, therefore, highly correlated with the stock market capitalization. It follows that, in terms of liquidity and investment capacity of the constituents, the two methodologies are comparable as well as in terms of low index turnover. Unlike the CW method, however, FW portfolios do not take into account the level of the equity prices, thus avoiding overweighting overestimated stocks and underweighting undervalued stocks. In particular, the FW methodology favours value stocks, omitting young companies as well as growth stocks.

Figure 1 shows the dynamics of the concentration of FW and CW Indexes (COMP versus its Reference portfolio) on their 20 largest constituents. The Reference portfolio registers a sum of the top 20 stocks weights ranging between 26% and 39% during the observation period, whereas for the COMP this sum ranges between 27% and 31%. This means that the FW Index concentration level on the top stocks is lower and more stable with respect to its comparable CW version[5].

[5] Observing the other fundamental Indexes, however, only INC and DIV show a higher concentration than the comparable CW Indexes during the period.

<< INSERT FIGURE 1 ABOUT HERE >>

Focusing on the sectorial allocation, we analyse the portfolios following the sectorial classification provided by Bloomberg: Financial, Industrial, Communications, Basic Materials, Utilities, Consumer Cyclical, Consumer Non-Cyclical, Energy, Diversified and Technology. Figure 2 shows the different dynamics of the sector composition of the two COMP Indexes. The FW Index presents a more stable sectorial allocation than its CW version. This evidence, according to Arnott et al. (2005), refers to the weaker anchorage of the FW methodology to the investors' preferences. In other words, FI allows better reflecting the regular growth of real economy with a gradual change in the sectorial allocations.

<< INSERT FIGURE 2 ABOUT HERE >>

Figure 3 shows the difference of each sector weights in the two COMP Indexes (FW minus CW) highlighting: 1) the constant underweight of the IT sectors (Technology and Communications) in the FW Index due to its structural underweight of growth stocks; 2) the constant underweight of Consumer Non-Cyclical in the FW Index due to the size effect (in other words, being the consumer staples the highest market capitalizations, FI attenuates their weights with respect to the CW methodology; 3) the constant overweight of value sectors (such as Energy and Financials) in the FW Index.

<< INSERT FIGURE 3 ABOUT HERE >>

Finally, we focus on the degree of overlap between the two COMP Indexes. Figure 4 shows the dynamics of cumulative difference between the weights of each constituent: the sum of weight differences ranges between 32% and 63%, whereas the lowest level of overlap occurs during the Internet bubble burst.

<< INSERT FIGURE 4 ABOUT HERE >>

3.2 Risk-Adjusted Performance analysis

Figure 5 shows the Indexes dynamics during the observation period. It should not surprise the constant alignment between Reference and BE500 Indexes, as both are CW: the only difference lies is in the number of components as the COMP Reference omits all the stocks that do not present all the measures required by its FW version.

<< INSERT FIGURE 5 ABOUT HERE >>

Table 1 shows the results of the Risk-Adjusted Performance analysis for each portfolio during the 14 years between 1999 and 2013.

<< INSERT TABLE 1 ABOUT HERE >>

Among the FW Indexes considered, the best performer is INC, showing a cumulative total return of 112.58% and an annualized rate of return of 5.53% (the others range from 3.99% for DIV and 4.67% for COMP). Each Index outperforms its CW version: the annualized excess returns range from 1.34% (SAL) to 3.11% (INC); COMP and PC outperform their Reference portfolios by 1.46% and 1.52% respectively. These statistics confirm the results of previous studies which focused on the European stock market, showing the outperformance of the FW over the related CW Indexes of nearly 2% (Hemminki and Puttonen, 2008; Houwer and Plantinga, 2009; Stotz et al., 2010).

Moving to the risk profile, the standard deviation registered by the Reference Index (16.45%) is the lowest with respect to all the other portfolios (ranging from 16.74% to 19.32%). Focusing on the parameter beta, the recorded values are in the range 0.96 – 1.09, revealing a similar risk attitude for all the indexes represented. The Jensen's alpha expresses the incremental return of a portfolio over the market return: all the FW indexes show positive coefficients, which means that the excess returns are not fully explained by a higher level of risk but, at least partially, by portfolio composition (i.e. stock picking ability). The Calmar ratio relates the average returns of the index for each year and the measure of maximum drawdown recorded during the period considered. The lower the result (as in the case of Reference), the worse the performance registered, adjusted by the risk. Conversely, the higher this value, as in the case of the FW Indexes (particularly the COMP), the better the risk-return profile of the portfolio. The advantage of a fundamental approach is also confirmed by other statistics: Sharpe, Ω, Sortino and Kappa. In particular, Ω (calculated as the ratio between the average of portfolio returns exceeding a certain threshold rate, and the average of portfolio returns not exceeding the same threshold) registers, for both the FW and CW indexes, values greater than one: this indicates an overall positive performance during the period and, even in this case, INC assumes the highest value. Finally, we focus on the Tracking Error Volatility (TEV) and the Information Ratio (IR) being the measures used in portfolio management to identify an active management style. TEV registers values relatively low while IR range between 0.3 and 0.8: these values, according to the metric used by Grinold and Kahn (1995), are associated with a rating of "good" or "very good" in judging the performance of an active asset manager.

3.3 Transaction costs

We estimate the rebalancing costs that must be incurred when a FW strategy is implemented. These costs are directly related to the turnover of the FW portfolios that is, on average, equal to 12.8 %[6]. This statistic is higher if compared to the turnover calculated by Houwer and Plantinga (2009) for the European equity market Indexes (between 7% and 8%) and, at the same time, lower than the 15% - 30% range calculated by Dash et al. (2010) for the US equity Indexes. If we assume negotiation fees equal to 10 bps for stock trading, the average transaction costs are limited to nearly 1 bps per year. Furthermore, aiming to repeat the exercise provided by Arnott et al. (2005), we estimate what should be the level of trading fees able to balance the excess return registered by FW Indexes. In our case, this threshold is equal to 14%.

3.4 CAPM and the Fama-French three-factor model

Table 2 shows the results of the CAPM and Fama-French three-factor regression analyses. Panel A refers to the one-factor model results. Our findings highlight that FW portfolios have a positive coefficient but it is not significantly different from zero, except for INC. The alpha generated by FW Indexes range between 13 and 25 bps per month, among which COMP generates an extra return of 12 bps per month.

<< INSERT TABLE 2 ABOUT HERE >>

Panel B shows the results of the three-factor model, which takes into account the exposure to value and small cap factors. The exposure to the value premium (coefficient *h*) is positive and significant for each index. Looking at the exposure to the small-cap factor (SMB), the coefficient *s* is positive and statistically significant only for EMPL (but lower than *h*). In the case of COMP, *s* is negative and not significant.

These results confirm that the FI tilts towards value securities. This means that, when the style factor is considered in the regression model, abnormal returns are considerably lower than when the one-factor model is applied: in the case of COMP Index, on average, the monthly alpha is less than 1 bp per month, compared to 12 bps. Our findings confirm the prevailing view in

[6] The detailed data of turnover for all FW indexes are the following: 13.69% (EMPL); 13.71% (BV); 11.50% (SAL); 11.18% (REV); 12.99% (INC); 14.53% (DIV); 12.65% (COMP); 12.17% (CP).

literature, namely that the strong value tilt accounts for most of the outperformance of FW portfolios.

3.5 FI during bull and bear markets

As in Arnott et al. (2005), we proceed with the comparison of the indexes during periods of bull and bear markets, defining as a bull market a 20% of upside from the previous low and as a bear market a 20% decline from the previous high. The authors' results reveal an outperformance of the FW indexes both during bull and bear markets of 55 bps and 640 bps, respectively. Our results, presented in Table 3, do not confirm this evidence showing an underperformance of the FW Indexes during bull markets and a slight over/under performance during bear markets, depending on which FW index is examined. In particular, in case of bull markets the Reference Index shows a consistent over performance of 352 bps with respect to the average of the FW Indexes and of 56 bps in the case of bear markets. Focusing on the comparison between the Composite and the Reference Indexes, our results show an underperformance (363 bps) only in case of bull markets while we record an outperformance of 84 bps in case of bear markets.

<< INSERT TABLE 3 ABOUT HERE >>

3.6 FI during financial crisis

We continue the analysis of FW Indexes focusing on the three latest financial crises, periods characterized by a sharp decline of European equity markets, and we calculate the maximum drawdown recorded. We refer to these financial crises as follows: Internet bubble burst (28/04/00-31/03/03), Global financial crisis (31/05/07-27/02/09) and European sovereign debt crisis (29/04/11-30/09/11). The aim is to verify whether the FW methodology is able to mitigate the losses during market downturns as widely claimed in literature. Table 4 shows interesting results.

<< INSERT TABLE 4 ABOUT HERE >>

Not surprisingly, we register a strong outperformance of FW Indexes over their Reference portfolios during the Internet bubble burst (in the 10% - 21% range). It is worth remembering that the collapse of the TMT stocks has demonstrated the need to prevent the vicious circle, which led portfolio managers to keep buying stocks already overvalued because of the growing weight of these securities in their benchmarks.

Less predictable is instead the result obtained by analysing the two following financial crises that have occurred. During both the Global financial crisis and the European Sovereign debt crisis, the FW Indexes underperform their benchmark. Focusing on the Composite Index, the underperformance is in the 144 - 283 bps range. The underperformance of FI during the Global Financial crisis is confirmed by Chen et al. (2015) on the US equity market: their analysis shows a return of the FW Index of -58.39% with respect to the -49.75% of the Russell 1000 Index over the period November 2007 – February 2009. Chen et al. argue that the poor performance of the FI is due to the overweight position in the financial sector (value stocks) whose stock prices had dropped sharply. It is worth noting that, among the fundamental indexes, INC is confirmed to be the best performer.

Table 5 exhibits the outcomes of the one-factor and three-factor regression models related to the three financial crises. The results in Panel A reconfirm the significance of the outperformance of FI during the Internet Bubble Burst. During the Global Financial Crisis, however, the performance difference between the two indexes appears not significant while, during the European sovereign debt crisis, the underperformance of FI is significant at 5% level. Panel B shows the results of FF model. Focusing on the Internet Bubble Burst, we show a positive coefficient α, statistically significant at 5% level. Both the beta coefficient and the value factor are highly significant: in particular, b is equal to 1.0798, while h is equal to 0.5174. The small-cap factor s is positive but not significant. These results indicate that the excess return of the Composite Index versus the Reference index is only partially explained by the aforementioned tilt value attributed to the fundamental methodology. Even during the second financial crisis the coefficients b (1.0245) and h (0.2785) are highly significant. Finally, focusing on the European Sovereign debt crisis, we find rather different results. In this case, α is negative and significant at 5% level; the beta coefficient is highly significant and slightly lower than 1; the coefficient s is negative and significant at the 10% level; the value factor h is not statistically significant. Although based on few observations, these latter results lead interesting considerations. They suggest that, during the last financial crisis, the value factor did not contribute to explain the performance of the FW Index, while the size factor has registered a negative effect.

<< INSERT TABLE 5 ABOUT HERE >>

3.7 FI: the stock's fundamental abnormal weights

Our last analyses focus on the observation of the dynamics of the two indexes' composition. Moved by this purpose, we define 'fundamental abnormal weight' the difference between the stock's fundamental index weight and the stock's market index weight. Going back to the graph of

Figure 4 we note that the degree of overlap between the two indexes is rather different during the observation period. In particular, a smaller degree of divergence in the composition of the two indices is detected in the central period. Therefore, we arbitrarily choose a threshold of 40% to divide the observation period into three parts: the first (June 1999 – December 2003) and the third (January 2009 – July 2013) are characterized by a level of imbalances exceeding 40% while the second (January 2004 – December 2008), by a level below the threshold. From the observation of sectorial differences, visible from the graph of Figure 3, we can also notice a greater similarity in the composition of the two indexes during the central period. In this case, we choose a threshold of 45% to distinguish the following three periods (where the second is characterized by a level of sectorial imbalances lower than the threshold): I. June 1999 – December 2002; II. January 2003 – July 2010; III. August 2010 – July 2013. Our purpose is to test the difference in performance of the two indexes in periods when the degree of similarity in their composition is different. Thus, we calculate the average monthly difference between the performances of the two indexes (FW-CW) and test the statistical significance. Table 6 presents the results. Whether we choose to divide the period, basing on the sum of the weights difference of individual stocks, or on the weights difference at the sectorial level, the results indicate a positive and statistically significant over performance of the FW index only in the intermediate period, meaning that the composition of the two indexes is mostly similar. One possible interpretation of this result may be that periods of strong differences in the composition of the two indexes are the result of irrational movements of the markets, where prices deviate from the stocks' fundamentals.

<< INSERT TABLE 6 ABOUT HERE >>

Finally, we observe the evolution of the difference between the compositions of the two indexes after each semi-annual rebalancing date of the FW Index. By relating the change in the overlap level of the two indexes (deriving from rebalancing) to the FW extra return (FW-CW) of the previous six months, we verify that each outperformance of the FW index corresponds to a decrease in the difference between the composition of the two indexes (after rebalancing), and vice versa. Figure 6 shows this inverse relationship ($R^2 = 0.75$). This evidence reveals that, when market rewards the best stocks (from a fundamental perspective), the gap in the composition of the two indexes tends to narrow, as the weight of best stocks will have risen in the price sensitive CW Index. On the other hand, an underperformance of the FW index is followed by a widening difference between the two indexes.

<< INSERT FIGURE 6 ABOUT HERE >>

3.8 FI: an attempt of optimization

The Composite Index summarizes four accounting data (BV, REV, INC, DIV) and is calculated as an equally weighted average of the constituents of these indexes. The choice of this specific index links to its representativeness of the entire category of fundamental indexes and to its function of synthesis, which helps correcting any possible distortion in corporate and performance evaluation. Theoretically, this could be thought as an implicit assumption of no correlation between the four accounting variables or even a lack of consideration of the relationships between them. In fact, we think that the arithmetic mean, while helping to reduce potential evaluation errors residing in each single FW index, constitutes also a simplification that could lead to deviate from the search for an indexing methodology that better mirrors the movements of real economy.

For that reason, in this section, we employ the factor analysis to explore which actually are the relationships between the four accounting metrics (BV, REV, INC, DIV). In this way, it will be possible to assign new coefficients to each fundamental metric, when calculating the weights for the Composite Index. This should guarantee a more realistic picture of each company because it is fairly intuitive to think the four fundamental measures as tied together, although less intuitive is quantifying the strength of these bonds[7]. In other words, for all of the issuers included in the index, we want coefficients (one for each of the four accounting variables) to take into account that there may be changes in correlations between metrics over time and over different data sets. Then, instead of a standardized calculation methodology, we will define a weighting scheme that varies over time according both to the reporting period and to the specific data set. We use the factor analysis that is a statistical method of multivariate analysis whose goal is to synthesize the information included in a set of correlated variables, trying to determine a number of latent dimensions (factors), which are not directly observable. Therefore, the general purpose is to determine one or more factors, each one representative of a linear combination of the original variables: that is to say that a limited number of independent components are found and identified as to represent the proportion of variance in common among the variables[8].

A potential step further in the analysis involves the calculation of factor scores: these are standardized scores associated to the original variables for each of the factors identified by the

[7] For instance, except in special circumstances, a firm who achieved a high level of revenues in a given year will record higher earnings, which, in turn, might be paid out as dividends or retained as reserves within the firm.

[8] The general rule of thumb is that, if the absolute value of the standardized loading is greater than 0.3, the variable is relevant for the particular factor so it can be considered: the variable with the highest loading will be the most significant relatively to the factor considered.

analysis[9]. The common goal is, once identified the number of factors underlying a data set, to use the information about the factors in subsequent analyses (Gorsuch, 1983). The common principle behind all these calculation methods (especially valid for refined ones) is to obtain factors as linear combinations of the original variables (X_1,…, X_p), which consider both shared variance and error term variance:

$$F_1 = c_{1,1} \cdot X_1 + \ldots + c_{1,i} \cdot X_i + \ldots + c_{1,p} \cdot X_p \tag{6}$$

where $c_{k,i}$ is the factor score coefficient which represents the weight of the i-th standardized variable in determining the single factor F_1. It is worth highlighting how similar the weights definitions are for a generic factor and for the COMP Index itself; in fact, the latter is a linear combination of accounting variables:

$$x_{i,t}^{\mathrm{COMP}} = \alpha_t \cdot x_{i,t}^{\mathrm{BV}} + \beta_t \cdot x_{i,t}^{\mathrm{REV}} + \gamma_t \cdot x_{i,t}^{\mathrm{INC}} + \delta_t \cdot x_{i,t}^{\mathrm{DIV}} \tag{7}$$

where all four coefficients of the original model $(\alpha_t, \beta_t, \gamma_t, \delta_t)$ always assume the same standard value of 0.25 and $x_{i,t}$ represents the weight of the i-th firm for each fundamental index at time t.
The analogy with the expression (6) is now apparent thus, very simply, our optimization aims at obtaining, date by date, different values for each of the four coefficients used in calculating $x_{i,t}^{\mathrm{COMP}}$. Unlike originally intended by Arnott et al. (2005), these coefficients become unknown variables instead of constants: our inputs are semiannual time series of the normalized weights (i.e. varying between 0 and 1) we computed and assigned to each constituent firm when calculating BV, REV, INC and DIV indexes.

From some preliminary testing, we decide to employ the factor analysis with maximum likelihood extraction, using the first factor as cut-off threshold. This choice of a single factor has been confirmed either by scree test, by Kaiser criterion and by the portion of variance explained, in all cases close to (or exceeding) the 70% threshold. Moreover, this would still be the only choice consistent with the target of the optimization, given the ideal overlap between the first factor extracted and the COMP Index itself.

We summarize in Table 7, first four columns, the unrotated factor loadings taken from the factor matrix extracted. These are the correlations between observed variables and the single factor, for the unrotated solution, so their possible values range from -1 to +1.

<< INSERT TABLE 7 ABOUT HERE >>

[9] Concretely, many are the possibilities to compute these factor scores, among which the two main classes are refined (e.g. multiple regression, Bartlett's approach and Anderson-Rubin method) and non-refined methods (e.g. sum scores).

Statistical significance is generally high for all dates as shown by the eigenvalues associated with the individual factors, all greater than one. The high levels of total variance explained, indirectly, confirm this significance[10]. There is no need of rotation and even forcing it, loadings do not change. The results in the table show very high correlations between the four sizes and the factor, which in turn, according to transitive property, indicate high correlation between the variables themselves.

The next step is to focus on the obtainment of factor scores, cause they are necessary as proxies for the coefficients $(\alpha_t, \beta_t, \gamma_t, \delta_t)$ in the calculation of the optimized Composite Index. As already hinted, there are different ways to create factor scores: which method to use depends on many issues such as the goal of the project, the nature of the work, and even issues such as researches' knowledge of methodology, statistical techniques, and software (DiStefano et al., 2009). The most common refined methods use standardized information to create standardized factor scores. Generally, these methods are preferable because aim at maximizing validity (by producing factor scores highly correlated with a given factor) and obtaining unbiased estimates of the true factor scores (Gorsuch, 1983). In addition, they attempt to preserve the relationships among factors. In particular, the multiple regression method may seem the most appropriate technique for our optimization because of its two additional advantages of taking into account correlation among observed variables (as well as correlation among factors and correlation between factors and observed variables) and to use its underlying model to virtually produce optimal factor scores. Major risks of this procedure are that scores could be not univocal, could be biased or correlated. However, the most important matter concerns its application to our optimization model, since the definition of standardized score implies that the mean of all factor scores will be zero[11]. To overcome all these issues, our proposal is to use a non-refined approach, such as the "weighted sum score" method. In general, non-refined factor scores are thought to be more stable across samples than refined methods (Grice and Harris, 1998). This advantage means that the obtained results do not heavily depend on the particular sample used even if, as a drawback, the method may produce scores that are correlated (Glass and Maguire, 1966).

In order to preserve the information extracted by factor analysis about the relationships among the accounting variables, we decide to approximate coefficients on the basis of factor loadings. Consistent with this, for convenience, we suppose hypothetically identical (unitary) items for all fundamental metrics, so that new coefficients $(\alpha_t, \beta_t, \gamma_t, \delta_t)$ are calculated by first summing

[10] Minimum values recorded for it over our time horizon belong to first two dates but, in general, the level is high enough to ensure the validity of the analysis, with a maximum of 86.5%.

[11] Indeed, this entails the presence of both positive and negative scores but it is not permissible given the subsequent use of such scores as weighting coefficients for the fundamental weights composing the COMP: we cannot consider negative weights, being them equivalent to short positions.

all four factor loadings at each date and then dividing each one by the corresponding total. As a result, at each date, we will get four coefficient values whose sum is equal to unity; these could also be easily expressed in percentage, therefore fostering their use both in the construction of a new Composite (COMPAF) and in the comparison with the original COMP (from now COMPRIF).

Results are presented in Table 6, from the sixth to the ninth column: it emerges clearly that, except in few cases, there are not very large deviations from the 25% of the original COMPRIF. A first explanation to this result could be that the correlation coefficient between the accounting variables tends to zero, meaning that it is not possible to operate any synthesis. A different interpretation of the same results, much appropriate in our case, is that of very high correlations between fundamental metrics: for this reason, the equally weighted average would be redundant. This second explanation could then be translated into the practical suggestion to use just one of the four fundamental indexes underpinning the Composite.

For our data set, the resulting coefficients are not far from the original ones, leading to construct two indices (COMPRIF and COMPAF) whose performances are virtually coincident (see Table 8). There is just a slight superiority, potentially random, in the overall results of the former over the latter.

<< INSERT TABLE 8 ABOUT HERE >>

In general, however, according to the main risk-adjusted performance measures, the original COMP Index emerges as preferable when compared to the optimized one. In any case, we do not think this does affect the merits of the methodology we proposed as factor analysis is closely linked to both data set and period examined. On the contrary, having obtained similar results for the two Composites seems to reinforce the goodness of our idea because it shows that increasing realism does not sacrifice profitability. Nevertheless, the methodology we propose lends itself to be improved and applied to different studies and data sets, with respect to which we do not exclude wider differences between ex-ante and ex-post factor analysis coefficients. Accordingly, there could be wider differences in the performances of the two COMP indexes. If the trends here recorded were confirmed for all the weighting coefficients, we might expect greater coefficients for INC and DIV weights, gradually decreasing when moving toward BV and REV. If that would happen, then we would like to draw conclusions similar to those of Siegel (2006) according to which 'dividends are the only fundamental variable that is completely objective, transparent and unable to be manipulated'. Otherwise, but similarly, if other empirical studies would detect the persistence of a substantial equivalence between the weighting coefficients of COMPRIF and COMPAF, we would not refuse the hypothesis of using only one fundamental metric instead of the current four.

3 Conclusions

In this paper we analyze the risk-return profile of fundamental based indexes that weight each listed company using several metrics of its "economic footprint" such as book value, income, revenues and dividends. We focus on the Euro equity market following the research methodology proposed by Arnott et al. (2005). We confirm the superiority of the FI, during the overall period, only in the case of the fundamental index based on the firm's income. In the other cases the over-performance is not statistically significant. Focusing on the three financial crises occurred on the time interval 1999-2013, we confirm the superiority of the fundamental indexation during the Internet bubble burst, when overvalued stocks realigned towards their fundamentals. During the other financial crises, the fundamental indexes underperform the CW index as well as during bull market phases while we do not have univocal results for the bear market phases. Observing the performance of the FI during sub periods characterized by a different level of overlap between the compositions of the two indexes, we show a statistically significant outperformance only when the two indexes are more similar. Moreover, we find an inverse relation between the change in the overlap level of the two indexes (deriving from the rebalancing) and the FW extra return registered in the previous six months.

Finally, we attempt to optimize the construction of the fundamental Composite Index, being composed by the indexes related to four metrics, equally weighted. We show that the high correlation of these metrics would permit to focus only on one of these metrics, simplifying the index construction process, its maintenance and diminishing its costs.

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Figure 1

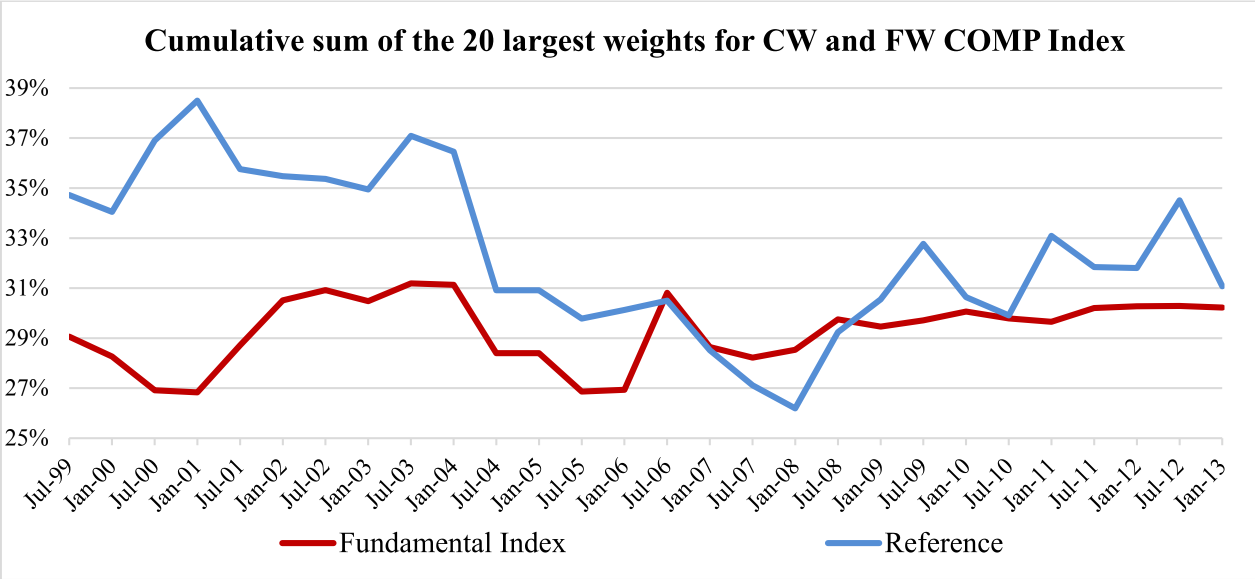

Cumulative sum of the 20 largest weights for CW and FW COMP Index
39%
37%
35%
33%
31%
29%
27%
25%
Jul-99
Jan-00
Jul-00
Jan-01
Jul-01
Jan-02
Jul-02
Jan-03
Jul-03
Jan-04
Jul-04
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
Jan-08
Jul-08
Jan-09
Jul-09
Jan-10
Jul-10
Jan-11
Jul-11
Jan-12
Jul-12
Jan-13
Fundamental Index
Reference

Figure 2

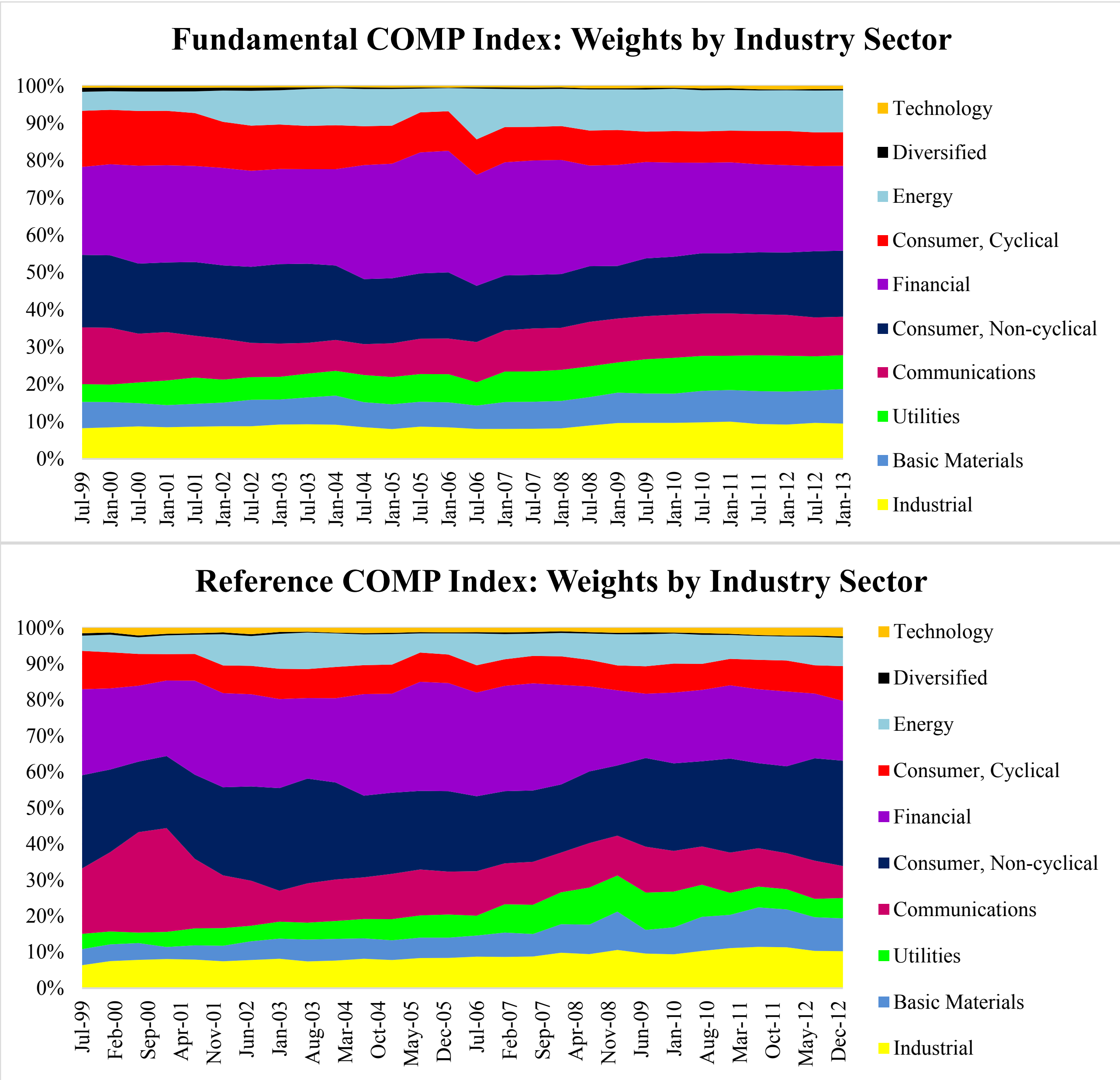

Fundamental COMP Index: Weights by Industry Sector
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Jul-99
Jan-00
Jul-00
Jan-01
Jul-01
Jan-02
Jul-02
Jan-03
Jul-03
Jan-04
Jul-04
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
Jan-08
Jul-08
Jan-09
Jul-09
Jan-10
Jul-10
Jan-11
Jul-11
Jan-12
Jul-12
Jan-13
Technology
Diversified
Energy
Consumer, Cyclical
Financial
Consumer, Non-cyclical
Communications
Utilities
Basic Materials
Industrial
Reference COMP Index: Weights by Industry Sector
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Jul-99
Feb-00
Sep-00
Apr-01
Nov-01
Jun-02
Jan-03
Aug-03
Mar-04
Oct-04
May-05
Dec-05
Jul-06
Feb-07
Sep-07
Apr-08
Nov-08
Jun-09
Jan-10
Aug-10
Mar-11
Oct-11
May-12
Dec-12
Technology
Diversified
Energy
Consumer, Cyclical
Financial
Consumer, Non-cyclical
Communications
Utilities
Basic Materials
Industrial

Figure 3

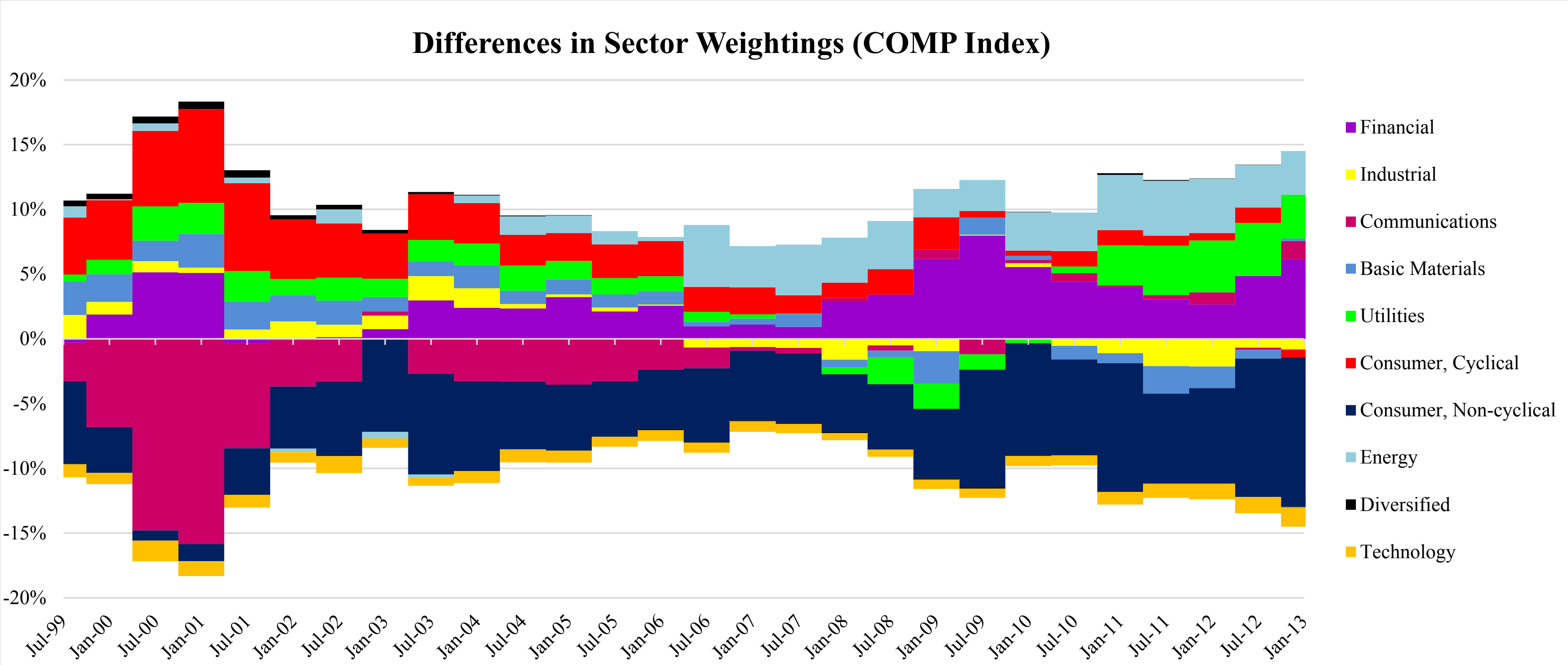
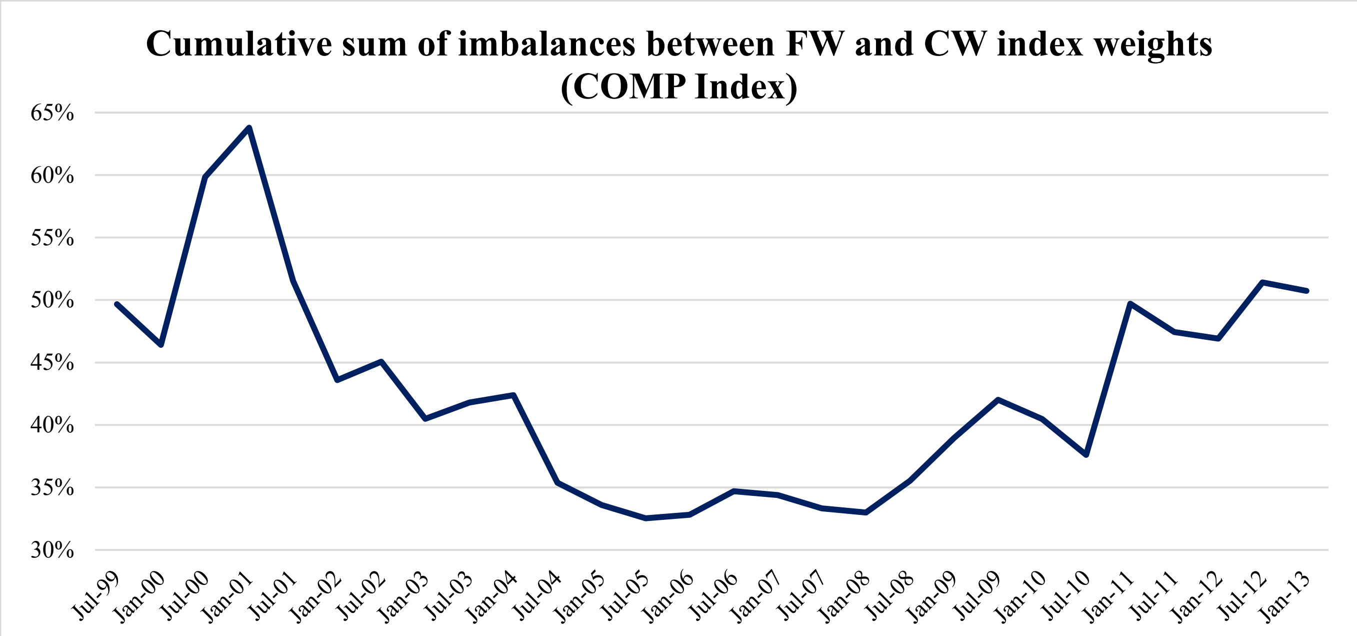

Differences in Sector Weightings (COMP Index)
20%
15%
10%
5%
0%
-5%
-10%
-15%
-20%
Jul-99
Jan-00
Jul-00
Jan-01
Jul-01
Jan-02
Jul-02
Jan-03
Jul-03
Jan-04
Jul-04
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
Jan-08
Jul-08
Jan-09
Jul-09
Jan-10
Jul-10
Jan-11
Jul-11
Jan-12
Jul-12
Jan-13
Financial
Industrial
Communications
Basic Materials
Utilities
Consumer, Cyclical
Consumer, Non-cyclical
Energy
Diversified
Technology

Figure 4


Cumulative sum of imbalances between FW and CW index weights (COMP Index)
65%
60%
55%
50%
45%
40%
35%
30%
Jul-99
Jan-00
Jul-00
Jan-01
Jul-01
Jan-02
Jul-02
Jan-03
Jul-03
Jan-04
Jul-04
Jan-05
Jul-05
Jan-06
Jul-06
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Jul-07
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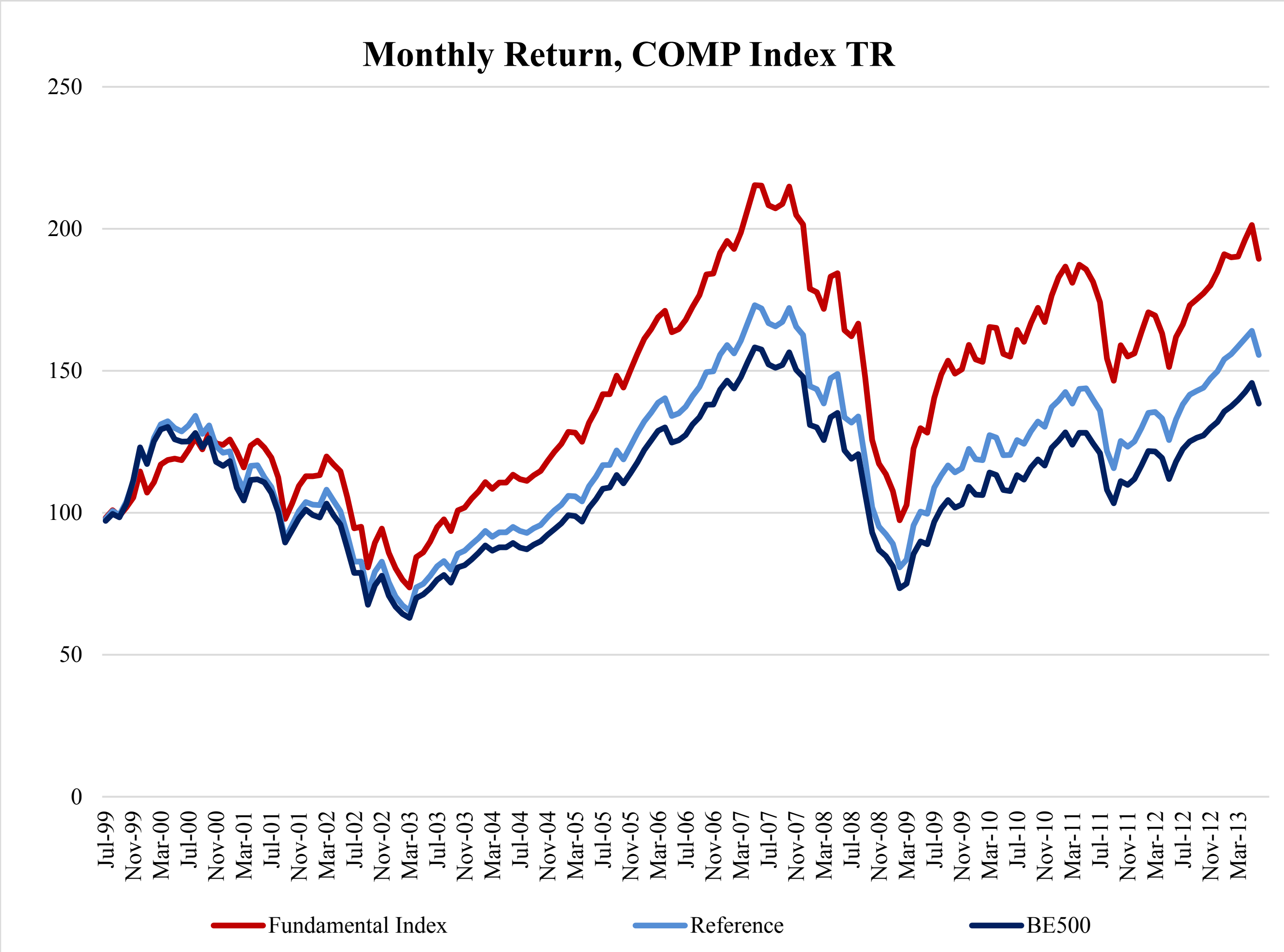
Jan-12
Jul-12
Jan-13

Figure 5



Monthly Return, COMP Index TR
250
200
150
100
50
0
Jul-99
Nov-99
Mar-00
Jul-00
Nov-00
Mar-01
Jul-01
Nov-01
Mar-02
Jul-02
Nov-02
Mar-03
Jul-03
Nov-03
Mar-04
Jul-04
Nov-04
Mar-05
Jul-05
Nov-05
Mar-06
Jul-06
Nov-06
Mar-07
Jul-07
Nov-07
Mar-08
Jul-08
Nov-08
Mar-09
Jul-09
Nov-09
Mar-10
Jul-10
Nov-10
Mar-11
Jul-11
Nov-11
Mar-12
Jul-12
Nov-12
Mar-13
Fundamental Index
Reference
BE500

Figure 6

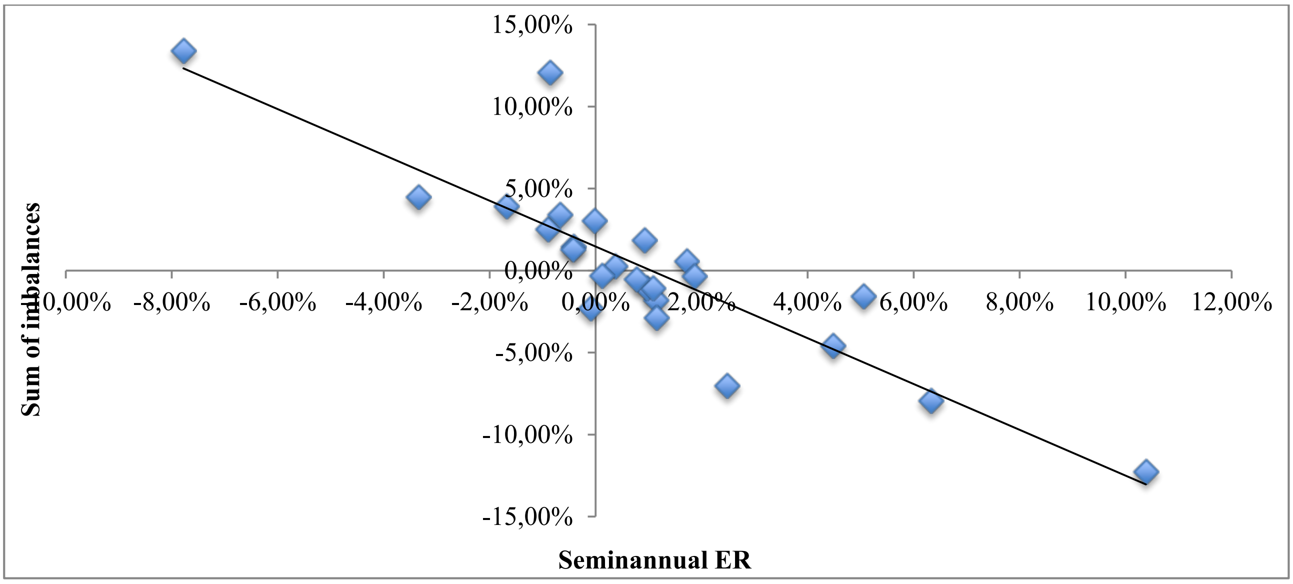

15,00%
10,00%
5,00%
0,00%
-5,00%
-10,00%
-15,00%
-10,00%
-8,00%
-6,00%
-4,00%
-2,00%
0,00%
2,00%
4,00%
6,00%
8,00%
10,00%
12,00%
Sum of imbalances
Seminannual ER

Table 1

Index	Cumulative Return	Geom. Return (yearly)	ER vs Reference	St. Dev. (yearly)	Beta	Alpha	R2	Calmar	Sharpe	Omega	Sortino	Kappa	Treynor	TEV	IR	t-value for ER	
BE500	38.45%	2.35%	-	16.24%	-	-	-	-	-	-	-	-	-	-	-	-	
Employment	82.88%	4.41%	2.22%	18.77%	1.06	2.42%	0.93	0.079	5.66%	1.19	0.094	0.195	0.0029	4.93%	0.48	1,88	*
Book Value	79.05%	4.25%	1.59%	18.90%	1.09	1.76%	0.95	0.074	5.40%	1.19	0.093	0.186	0.0027	4.49%	0.41	1,59	
Sales	74.50%	4.06%	1.34%	19.32%	1.09	1.56%	0.93	0.071	5.15%	1.18	0.087	0.178	0.0026	5.46%	0.29	1,17	
Revenues	73.43%	4.01%	1.58%	19.23%	1.10	1.84%	0.93	0.071	5.08%	1.18	0.086	0.176	0.0026	5.43%	0.34	1,36	
Income	112.58%	5.53%	3.11%	16.81%	0.97	3.07%	0.95	0.104	7.56%	1.26	0.124	0.257	0.0038	3.80%	0.78	2,94	***
Dividends	73.00%	3.99%	1.67%	16.74%	0.96	1.67%	0.93	0.073	5.02%	1.18	0.087	0.178	0.0025	4.46%	0.34	1,35	
Composite	**89.43%**	**4.67%**	**1.46%**	**17.59%**	**1.05**	**1.52%**	**0.96**	**0.085**	**6.09%**	**1.21**	**0.102**	**0.209**	**0.003**	**3.76%**	**0.41**	**1,60**	
Partial Composite	75.07%	4.08%	1.52%	17.97%	1.04	1.62%	0.95	0.073	5.15%	1.18	0.089	0.179	0.0026	3.98%	0.4	1,58	
Reference	**55.58%**	**3.21%**	**-**	**16.45%**	**1**	**-**	**1**	**0.06**	**3.70%**	**1.14**	**0.068**	**0.138**	**0.0018**	**-**	**-**	-	

Table 2

HAC SE bandwidth 4 (Bartlett kernel)	α		b		s		h		No. Observations
Panel A: One-factor model									
COMP	0.0012574		1.04418	***					168
t-value	*1.1341*		*35.987*						
PC	0.0013429		1.04256	***					168
t-value	*1.161*		*32.261*						
EMPL	0.0019943		1.06250	***					168
t-value	*1.3879*		*29.234*						
BV	0.0014581		1.09323	***					168
t-value	*1.3697*		*28.638*						
SAL	0.0012977		1.08536	***					168
t-value	*0.8746*		*25.668*						
REV	0.0015231		1.09844	***					168
t-value	*1.0001*		*25.89*						
INC	0.0025240	**	0.97208	***					168
t-value	*2.0711*		*33.058*						
DIV	0.0013822		0.96041	***					168
t-value	*0.9909*		*26.423*						
Panel B: Three-factor model									
COMP	0.0005766		1.03572	***	-0.00264279		0.528087	***	168
t-value	*1.0296*		*80.777*		*-0.1391*		*14.4093*		
PC	0.0006057		1.03860	***	-0.00309768		0.564345	***	168
t-value	*1.0456*		*77.645*		*-0.1472*		*15.5226*		
EMPL	0.0007617		1.06818	***	0.11458100	***	0.581296	***	168
t-value	*0.8919*		*48.449*		*4.2265*		*10.7362*		
BV	0.0008029		1.08788	***	-0.00195067		0.501257	***	168
t-value	*1.1162*		*48.998*		*-0.0603*		*7.7255*		
SAL	0.0003079		1.08214	***	0.00350755		0.733578	***	168
t-value	*0.3838*		*49.122*		*0.1141*		*14.8563*		
REV	0.0005594		1.09404	***	0.00261589		0.717038	***	168
t-value	*0.7057*		*49.172*		*0.0869*		*14.0295*		
INC	0.0018566	***	0.96851	***	-0.00368382		0.513175	***	168
t-value	*3.1798*		*82.844*		*-0.1823*		*8.9612*		
DIV	0.0006372		0.95687	***	-0.02747240		0.640804	***	168
t-value	*1.0988*		*77.327*		*-1.3084*		*11.6233*		

* Statistically significant at the 10 percent level; ** Statistically significant at the 5 percent level

*** Statistically significant at the 1 percent level

Table 3

	Bull markets			Bear markets		
	Geometric Return	Volatility	Sharpe Ratio	Geometric Return	Volatility	Sharpe Ratio
BE500	29.55%	13.27%	1.95	-25.63%	19.51%	-1.61
Reference	30.93%	13.00%	2.05	-24.80%	20.19%	-1.49
Composite	27.30%	14.02%	1.77	-23.96%	21.38%	-1.36
P. Composite	27.35%	14.06%	1.76	-25.42%	21.53%	-1.44
Employment	27.67%	14.47%	1.69	-26.37%	22.73%	-1.43
Book Value	29.75%	14.24%	1.92	-27.04%	22.52%	-1.46
Sales	27.67%	14.84%	1.68	-26.75%	23.29%	-1.42
Revenues	27.07%	14.95%	1.65	-26.70%	23.21%	-1.42
Income	27.50%	13.76%	1.83	-21.84%	20.70%	-1.27
Dividends	24.78%	13.70%	1.70	-23.45%	19.80%	-1.45
Av (ex Comp.)	27.41%	14.33%	1.74	-25.36%	22.04%	-1.41

Table 4

FW Indexes	*Internet Bubble burst (28.04.00 – 31.03.03)*		*Global financial crisis (31.05.07 – 27.02.09)*		*EU Sovereign debt crisis (29.04.11 – 30.09.11)*	
	Geom. Return	ER vs Reference	Geom. Return	ER vs Reference	Geom. Return	ER vs Reference
Employment	-42.77%	12.27%	-55.93%	-1.66%	-23.72%	-3.62%
Book Value	-41.62%	10.25%	-57.56%	-3.33%	-24.66%	-4.48%
Sales	-41.48%	11.09%	-56.98%	-2.72%	-24.82%	-4.74%
Revenues	-41.16%	12.47%	-56.87%	-2.90%	-24.87%	-4.74%
Income	-32.06%	21.57%	-52.89%	1.08%	-20.62%	-0.47%
Dividends	-34.76%	20.60%	-54.70%	-1.20%	-20.29%	-0.41%
Composite	-37.83%	12.65%	-54.78%	-1.44%	-21.80%	-2.38%
P. Composite	-40.17%	13.35%	-55.54%	-1.77%	-22.74%	-2.83%

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Table 5

HAC SE bandwidth 4 (Bartlett kernel)	α		b		s		h		No. Obs.
Panel A: One-factor model									
Internet Bubble Burst (28/04/2000 – 31/03/2003)									
COMP	0.00714	***	1.0269	***					36
t-value	*3.875*		*23.10*						
Global Financial Crisis (31/05/2007 – 27/02/2009)									
COMP	0.00035		1.0441	***					22
t-value	*0.269*		*100.70*						
European Sovereign debt crisis (29/04/2011 – 30/09/2011)									
COMP	-0.0043	**	1.0243	***					6
t-value	*-3.636*		*59.30*						
Panel B: Three-factor model									
Internet Bubble Burst (28/04/2000 – 31/03/2003)									
COMP	0.0027	**	1.0798	***	0.0315		0.5174	***	36
t-value	*2.353*		*54.889*		*0.693*		*12.163*		
Global Financial Crisis (31/05/2007 – 27/02/2009)									
COMP	0.0014		1.0245	***	-0.0018		0.2785	***	22
t-value	*1.3625*		*108.557*		*-0.0731*		*6.131*		
European Sovereign debt crisis (29/04/2011 – 30/09/2011)									
COMP	-0.0059	**	0.9931	***	-0.2531	*	-0.4251		6
t-value	*-4.586*		*55.478*		*-4.242*		*-2.0243*		

* Statistically significant at the 10 percent level; ** Statistically significant at the 5 percent level
*** Statistically significant at the 1 percent level

Table 6

Sub-Periods	Av. ER (FW-CW)	St.dev	t	No.obs
Stock's weights differences (threshold = 40%)				
I. June 1999 – December 2003	0.31%	1.43%	1.61	54
II. January 2004 – December 2008	0.08%	0.33%	1.77*	60
III. January 2009 – June 2013	0.02%	1.22%	0.12	54
Sector's weights differences (threshold = 45%)				
I. June 1999 – December 2002	0.30%	1.57%	1.24	42
II. January 2003 – July 2010	0.18%	0.77%	2.23**	91
III. August 2010 – June 2013	-0.19%	1.05%	-1.05	35

* Statistically significant at the 10 percent level; ** Statistically significant at the 5 percent level
*** Statistically significant at the 1 percent level

Table 7

	Factor loadings				New fundamental coefficients				Significance
	FBV	**FREV**	**FINC**	**FDIV**	**PBV**	**PREV**	**PINC**	**PDIV**	**σ^2 explained**
05/07/1999	0.383	0.734	0.958	0.886	0.129	0.248	0.324	0.299	66.77%
03/01/2000	0.387	0.732	0.957	0.89	0.13	0.247	0.323	0.3	66.85%
03/07/2000	0.835	0.793	0.923	0.804	0.249	0.236	0.275	0.24	77.77%
08/01/2001	0.834	0.788	0.925	0.81	0.249	0.235	0.276	0.241	77.89%
02/07/2001	0.829	0.771	0.914	0.857	0.246	0.229	0.271	0.254	78.45%
07/01/2002	0.835	0.793	0.919	0.87	0.244	0.232	0.269	0.255	79.96%
01/07/2002	0.855	0.807	0.883	0.858	0.251	0.237	0.259	0.252	79.28%
06/01/2003	0.837	0.804	0.891	0.86	0.247	0.237	0.263	0.254	79.02%
07/07/2003	0.844	0.804	0.871	0.855	0.25	0.238	0.258	0.253	78.38%
05/01/2004	0.857	0.803	0.864	0.857	0.253	0.238	0.256	0.253	78.59%
05/07/2004	0.844	0.795	0.893	0.882	0.247	0.233	0.262	0.259	79.72%
03/01/2005	0.841	0.79	0.894	0.879	0.247	0.232	0.263	0.258	79.43%
04/07/2005	0.845	0.739	0.944	0.891	0.247	0.216	0.276	0.261	80.14%
02/01/2006	0.846	0.742	0.943	0.891	0.247	0.217	0.276	0.26	80.27%
03/07/2006	0.841	0.844	0.97	0.939	0.234	0.235	0.27	0.261	85.83%
08/01/2007	0.83	0.811	0.961	0.919	0.236	0.23	0.273	0.261	83.42%
02/07/2007	0.856	0.831	0.967	0.924	0.239	0.232	0.27	0.258	85.14%
07/01/2008	0.859	0.831	0.967	0.928	0.24	0.232	0.27	0.259	85.36%
07/07/2008	0.884	0.839	0.943	0.942	0.245	0.233	0.261	0.261	86.10%
05/01/2009	0.885	0.837	0.942	0.941	0.245	0.232	0.261	0.261	86.01%
06/07/2009	0.87	0.824	0.936	0.954	0.243	0.23	0.261	0.266	85.40%
04/01/2010	0.872	0.836	0.939	0.953	0.242	0.232	0.261	0.265	85.96%
05/07/2010	0.885	0.834	0.927	0.946	0.246	0.232	0.258	0.263	85.67%
03/01/2011	0.886	0.834	0.927	0.947	0.247	0.232	0.258	0.263	85.72%
04/07/2011	0.875	0.843	0.955	0.936	0.243	0.234	0.265	0.259	86.36%
02/01/2012	0.876	0.843	0.955	0.936	0.243	0.234	0.265	0.259	86.42%
02/07/2012	0.852	0.837	0.953	0.93	0.239	0.234	0.267	0.26	85.24%
07/01/2013	0.851	0.824	0.954	0.929	0.239	0.232	0.268	0.261	84.83%

Table 8

INDEX	*Cumulative Return*	*Annualised Average Rate*	*Excess Return*	*Annualised St. Dev.*	*Beta*	*Alpha*	*R2*	*Calmar*	*Sharpe*	*Omega*	*Sortino*	*Kappa*	*Treynor*	*TEV*	*IR*	*Average Ptf Turnover*	*Max drawdown*
COMPRIF	89.42%	4.67%	1.46%	17.62%	1.047	1.52%	0.96	0.0852	0.0608	1.208	0.101	0.208	0.00295	3.76%	0.411	12.63%	-54.80%
COMPAF	88.78%	4.64%	1.44%	17.57%	1.045	1.49%	0.96	0.0848	0.0605	1.206	0.1	0.206	0.00294	3.74%	0.405	12.70%	-54.73%

Appendix A

Data Set Characteristics

		Stocks with available accounting metrics								Stocks with a zero FI weight (in %)					
Date	**Comp. BE500**	**EMPL**	**SAL**	**BV**	**REV**	**INC**	**DIV**	**PC**	**COMP**	**EMPL**	**SAL**	**BV**	**REV**	**INC**	**DIV**
5/7/99	546	471	454	473	510	510	442	409	393	0.00%	0.00%	1.69%	0.00%	1.37%	2.26%
3/1/00	560	482	458	491	524	524	443	414	397	0.00%	0.00%	1.63%	0.00%	1.91%	2.48%
3/7/00	563	473	451	476	530	530	459	413	396	0.00%	0.00%	1.26%	0.00%	2.64%	2.83%
8/1/01	551	473	449	477	518	518	449	414	397	0.00%	0.00%	1.26%	0.00%	2.32%	2.00%
2/7/01	562	495	475	487	535	535	465	422	380	0.00%	0.00%	1.85%	0.00%	6.54%	6.24%
7/1/02	515	467	440	466	490	490	426	404	365	0.00%	0.00%	2.15%	0.00%	5.71%	5.87%
1/7/02	514	444	447	456	488	488	427	398	360	0.00%	0.00%	2.41%	0.00%	4.92%	5.39%
6/1/03	512	449	449	463	484	484	426	405	369	0.00%	0.00%	1.94%	0.00%	3.93%	4.69%
7/7/03	508	431	443	445	480	480	424	390	354	0.00%	0.00%	1.57%	0.00%	5.42%	4.25%
5/1/04	495	426	435	442	470	470	407	382	354	0.00%	0.00%	1.36%	0.00%	4.47%	2.70%
5/7/04	500	440	448	453	476	476	448	429	401	0.00%	0.00%	1.32%	0.00%	4.41%	2.68%
3/1/05	500	449	450	460	475	475	448	436	403	0.00%	0.00%	1.30%	0.00%	5.26%	3.35%
4/7/05	500	444	447	453	476	476	467	444	419	0.00%	0.00%	0.88%	0.00%	3.78%	2.36%
2/1/06	500	449	452	458	476	476	463	446	424	0.00%	0.00%	0.87%	0.00%	3.57%	2.16%
3/7/06	500	443	450	452	477	477	466	444	423	0.00%	0.00%	1.11%	0.00%	2.10%	2.36%
8/1/07	499	445	451	461	477	477	468	453	428	0.00%	0.00%	1.30%	0.00%	1.89%	2.78%
2/7/07	501	449	454	457	482	482	474	450	432	0.00%	0.00%	1.31%	0.00%	1.24%	2.32%
7/1/08	501	454	451	461	480	480	473	455	430	0.00%	0.00%	1.08%	0.00%	1.46%	3.38%
7/7/08	501	460	456	463	480	480	477	460	434	0.00%	0.00%	2.38%	0.00%	1.67%	2.94%
5/1/09	501	467	462	473	479	479	470	464	437	0.00%	0.00%	1.69%	0.00%	1.88%	3.62%
6/7/09	501	456	457	459	483	483	475	451	427	0.00%	0.00%	0.22%	0.00%	2.48%	3.37%
4/1/10	501	470	469	472	485	485	473	460	440	0.00%	0.00%	0.21%	0.00%	1.65%	2.75%
5/7/10	500	469	471	474	485	484	472	462	441	0.00%	0.00%	0.63%	0.00%	2.69%	2.54%
3/1/11	500	472	474	477	485	484	474	467	450	0.00%	0.00%	0.63%	0.00%	1.86%	1.69%
4/7/11	499	475	468	474	483	482	476	469	437	0.00%	0.21%	1.90%	0.21%	3.73%	2.10%
2/1/12	500	475	470	478	484	483	477	472	442	0.00%	0.21%	1.88%	0.21%	3.11%	2.10%
2/7/12	499	474	472	479	485	485	480	474	443	0.00%	0.21%	1.46%	0.21%	4.12%	2.29%
7/1/13	499	474	472	480	484	484	479	475	445	0.00%	0.21%	1.67%	0.21%	3.51%	2.51%
Average	512	460	456	466	489	488	458	438	411	0.00%	0.03%	1.39%	0.03%	3.20%	3.07%