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"Smart Beta strategies may, or may not, outperform the benchmarks: an empirical evidence"

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Firma dello studente

Giorgio Di Vera

Alla mia famiglia.

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Introduction

During the last years, and especially in the aftermath of the global financial crisis, the need of new investment strategies and new approaches in the risk management world, has skyrocket. The focus on the risk component has become fundamental when taking investment decisions and now, more than ever, the trade-off between risk and returns is crucial. Many investors have lost their faith in active management and this has led them to seek more transparent products that are able to provide high liquidity at a more affordable cost.

Also, the psychological aspect of the investors has been affected. They are always more willing to minimize the risk even at the expense of lower performances. For this reason, investors are moving towards passive management strategies. The addition of these new kinds of investments allowed them to have access to a wider range of asset classes with a wider set of investment tools.

However, while active management seek to beat the market by capturing the Alpha, passive investing is aimed at the pure replication of an index. The main objective of an active investor is, indeed, to seek positive Alphas that allow him to achieve an extra return for the same level of risk. However, obtaining very good Alpha values it is not that simple and, often, the high fees and commissions applied by active funds reduce, or even eliminate, the profit. Thus, they started to place their focus on Beta instead of Alpha.

Passive strategies are born to track the market by investing in market-cap indexes such as the S&P500. However, on the contrary of what investors thought until few years ago, these indices do not provide adequate compensation for the risk they entail. For this reason, more and more investors began to look for different forms of investing, such as indexes with different weightings criteria or indexes based on different risk factors. These strategies are half-way between active and passive investing since they offer the benefits of passive investing such as low fees and transparency and, at the same time, they do not simply replicate a benchmark, but they try to outperform it.

The interest in Factor Investing and Smart Beta strategies is growing because of the superiority of their performance with respect to the traditional passive strategies. However, this assumption could be misleading for those who in reality do not know all the risks that make it such. Indeed, although the long-term results confirm their reputation, it is necessary for an investor who is approaching this method, to be fully aware of which sources of risk it is exposed to.

The growth of indexation, but especially that of Smart Beta, is changing the logic of asset allocation of portfolios. The extra return generated by Smart Beta ETFs compared to the market, though, should not lead investors to think that these products are better than traditional ETFs, and to systematically replace them in their portfolios, because each one allows to pursue a different type of strategy, with its pros and cons.

The work is divided into two main parts with the first part being more theoretical and the second one more empirical. First of all, we will touch on the main differences between active and passive investing. We will then focus on the shift from active to passive investment strategies that we are experiencing nowadays and its potential risks. After that, we are going to look at the concept of risk and return and its evolution throughout time, from the MVO until more recent multifactor models, and we are going to explain some analytic measures that will be useful for our empirical analysis in the second part of the paper regarding tail risks, performance evaluation and other core risk-returns measures.

The second chapter will start with a focus on traditional ETFs, what they are and how they work, and then it will move to the central topic of this work: alternative risk premia, factor investing and Smart Beta strategies.

In Chapter 3 we will construct four Smart Beta Indexes, namely Sharpe Ratio Index, Low Volatility Index, Strong Free Cash Flow Index and High Dividend Yield Index. We will explain everything regarding their construction and maintenance such as eligibility criteria, weighting methodology, rules for reconstitutions, periodic rebalances and index changes.

Lastly, in Chapter 4, a time series analysis will be conducted on a testing period that range from December 1999 to May 2020 with a specific focus on particular periods such as Dot Com Bubble, Global Financial Crisis and Covid-19 Pandemic to compare the behavior of these strategies under different market regimes. We will then discuss our statistical findings such as return distribution characteristics, risk-adjusted measures, performances, correlation between the different strategies and their risk-return profiles providing numerical results.

This report explains in detail the operation of a Smart Beta ETF, based on the reference factor, but issuers will not be taken into account, nor the costs related to the purchase, management and sale of ETFs. Moreover, this study could be further improved by modifying the above mentioned strategies to obtain more diversified (e.i. less correlated) portfolios and more complex financial products instead of long-only equity portfolios.

Chapter 1

Passive and active investment strategies

Passive Investing

Passive investing is an investment strategy aimed at maximizing returns by minimizing the buying and selling. Since passive investors limit the amount of buying and selling within their portfolios, it requires a buy-and-hold mentality. Index investing is, perhaps, the most common form of passive investing, whereby investors seek to replicate a representative benchmark, and to hold it over a long-time horizon. The concept behind these strategies is based on two main elements.

The first one is the efficient market hypothesis (EMH). The EMH states that share prices reflect all information available in the market and therefore, consistent Alpha generation is impossible. According to this theory, stocks always trade at their fair values, making it impossible for investors to outperform the overall market through expert stock selection or market timing. The only way through which an investor could obtain higher returns is by taking more risk. The second element is the presence of asymmetric information, which occurs when there is an imbalance of information between different parties of an economic transaction.

Some of the key benefits of passive investing are their ultra-low fees, transparency and tax efficiency. By following an index (which is used as benchmark), indeed, passive managers are able to minimize the costs of stock picking and asset allocation which allows them to ask lower fees than active funds. Moreover, they always have to disclose which assets are included in the index, making all the information fully available to the public. Lastly, the buy-and-hold strategy usually results in small capital gains for the year, which in turn leads to small taxable amounts.

Proponents of active investing would argue that passive strategies are too limited and that they also obtain smaller returns than active investing. Given that these strategies are limited to a specific index or predetermined set of investments, there is little to no variance. Managers are stuck with the stocks that the index they track holds, regardless of how they are doing. Moreover, it is rare that passive funds beat the market, even during times of turmoil, as by definition, they are constructed to track the market. Even if it happens sometimes, they will never reach the big returns that active managers crave, unless the market itself booms.

Active Investing

The goal of active investment strategies is to beat the stock market's average returns and take full advantage of short-term price fluctuations. Usually, in order to obtain higher returns, investors are also exposed to higher risks. The success of these strategies is driven by three main factors:

- asset allocation (the ability to balance risk and reward by choosing portfolio's assets according to an individual's goals, level of risk desired, and investment horizon);
- stock picking (the ability to find undervalued securities that have potential for growth);
- market timing (the ability to move in and out of a financial market or switching between asset classes based on forecasts, following technical indicators or economic data, to gauge the next movements of the market).

The main advantage of active investing is its flexibility. Indeed, active managers are not required to follow a specific index and they can buy those "diamond in the rough" stocks. They are able to exit specific stocks or sectors when the risks become too big or the returns are not satisfying.

Nevertheless, active strategies have also shortcomings. First of all, they are very expensive. Managers usually ask for higher fees because all that active buying and selling triggers transaction costs and they also need to hire analyst teams researching equity picks, which increases salaries' expenses. All those fees can kill a big portion of returns. In addition, there is active risk. Active managers, indeed, are free to make their choices, which could lead to big losses if they turn out to be wrong about their estimates.

However, the passive versus active investment strategies, do not have to be an either/or choice for investors. Combining the two can further diversify a portfolio, reducing the overall risk while increasing returns. It is important to specify, though, that they are not just the returns that matter, but risk-adjusted returns.

Shift from active to passive investing and potential risks

After the global financial crisis of 2008, investors have begun to pay deeper attention to the management and measurement of risk. More and more investors are willing to give up a portion of returns in order to reduce their risk exposure. Over the past couple of decades, indeed, there has been a shift from active to passive investment strategies on a global scale.

This shift has sparked wide-ranging discussions, including claims about effects on industry concentration, asset prices, volatility, price discovery, market liquidity, competition, and corporate governance. The examination of some the repercussions of the active-to-passive shift, has led to the conclusion that some of them reduce risks whilst others increases risks (Anadu, Kruttli et al., 2018).

These changes can be linked to a generalized increase in indexed investing, which may be affecting valuations, returns, volatility and liquidity of various class of financial assets included in the indexes. Some of these effects could have repercussions for financial stability by broadening the impact of market shocks. Researches on indexing effects show that passive investing is pushing up (down) the prices of index constituents when they are added (deleted) from an index.

As Bhattacharya and O'Hara (2017) emphasize, these strategies may lead to pricing distortions. This might happen because purchases and sales of stocks by passive investors are not based on the idiosyncratic characteristics of individual companies or evaluations of company actions or projected changes in value. On the contrary, they buy (and sell) new stocks, at the current market price, when they enter (or exit) their benchmark.

"Academic research estimated an average 9% jump in valuations for stocks newly added to the S&P 500 index, while stocks that are removed suffered an even greater loss in price." (Sueppel, 2017). Active investors pick the stocks based on forecasts and valuations, allocating capital to companies based on them. By doing so, they contribute a service to the market because, theoretically, this process guarantees that observable market prices are in sync with expected present values. For this reason, "price discovery is inhibited by passive investing that impairs the market's ability to determine fair value, and thus allocates funds indiscriminately across companies" (Sueppel, 2017).

Moreover, Bhattacharya and O'Hara (2017) developed also models to explain how inclusion and exclusion of stocks (and more generally of securities), may boost the volatility of underlying assets. Their work ties in with Ben-David, Franzoni, and Moussawi (2017) argument according to which the volatility arising from the trading of these indexes, induces a non-diversifiable source of risk, at least in the short term.

On the other hand, the effects on liquidity is less clear. There may be an increase in asset's liquidity because it becomes easier to trade them as part of an ETF basket[1]. However, the inclusion in these baskets may also crowd out trades of individual assets, which could lead to a decline of the liquidity of assets traded individually.

Particularly relevant for financial stability are the effects on securities' comovement. Indexes, indeed, could cause greater comovement of asset returns and liquidity, which, in turn, could make financial markets more vulnerable to shocks and lead to a broader propagation. Some researchers such as Vijh (1994); Barberis, Shleifer, and Wurgler (2005); and Sullivan and Xiong (2012), have found that when firms are added onto an index, their systematic risk (beta) tend to increase. This "excess comovement" is most likely driven by the simultaneous buying and selling of stocks made by fund managers to replicate an index.

Performance Valuation: Risk and Returns

Every investor, in making his investment choices, focuses on two main factors, and on the relationship between them. These factors are risk and return. An investor is considered rational if his aim is to maximize the returns while keeping the lowest possible risk. The investor allocates the available capital between different assets, having in mind his objective. A portfolio with two or more assets, which are not correlated, allows the investor to reduce his risk exposure through diversification.

To demonstrate that diversification helps reducing portfolio risk, it is sufficient to look at the simplest portfolio possible, with only two assets, A and B. Their variances are respectively σ^2_A and σ^2_B, and the correlation between them is ρ_{AB}. Portfolio variance, then, will be

$$\sigma^2_{Portfolio} = w^2_A \sigma^2_A + w^2_B \sigma^2_B + 2 \; w_A w_B \rho_{AB} \sigma_A \sigma_B$$

where w_A and w_B are the weights of A and B inside the portfolio and $\rho_{AB} \cdot \sigma_A \cdot \sigma_B$ is their covariance. As it is easily observable, if $\rho_{AB} \leq 0$, portfolio variance will be always less than the variance of the two assets taken alone.

[1] What is an ETF and how it works will be explained more in detail in the next Chapter.

Mean variance optimization (MVO)

"Portfolio Selection", an article written by Markowitz in 1952, is a cornerstone of financial literature on portfolio diversification. This model is based on the assumption that investors base their investments on expected returns and risk, intended as standard deviation of returns.

The model is based on the idea that if we consider two portfolios, A and B, such that $\sigma_A \leq \sigma_B$ and $E(r_A) \geq E(r_B)$, then A dominates B. The original Mean-Variance approach seeks the portfolio with the optimal trade-off between return and risk. The main assumptions behind Markowitz model are:

- the investor is risk averse;
- the investor's utility function is concave and increasing;
- the analysis is based on single period model;
- the investor is rational in nature;
- there are no transaction costs and there is perfect competition in the market.

It must be said that, in the real world, the expected returns, volatility and assets correlations cannot be forecasted with high accuracy, and returns have often non-normal distributions. This can make the optimization method based on a return-volatility trade-off inadequate. Extensions of the traditional portfolio theory of Markowitz, include optimization of higher order risks such as tail risk or specific systematic sources of risk.

Mean variance optimization (MVO) is an approximation of a more generic portfolio optimization. It is a second order approximation of the optimization of any utility function. "A utility function quantifies the trade-off between the desired attributes of a portfolio such as high return, and undesirable properties such as high volatility and tail risk" (Kolanovic, 2013).

The goal of this method is to produce a portfolio with the highest Sharpe ratio[2]. Specifically, the utility function that MVO tries to maximize is:

$$\text{Expected Portfolio Return} - \lambda/2 * \text{Expected Portfolio Variance}$$

where λ is a positive value representing the risk aversion factor. The larger the risk aversion factor (λ) is, the more risk averse the investor is. When λ is approximately equal to 0, it means that the investor is risk lover and the optimal portfolio will have 100% of the weight in the

[2] It is a measure of risk-adjusted return of a portfolio. Sharpe Ratio and other ratios will be explained in the next session.

best performing asset without regard to portfolio risk. On the contrary, when λ is very large, MVO will seek the lowest possible risk, without worrying about returns, and this portfolio is also called "Global Minimum Variance" (GMV) portfolio.

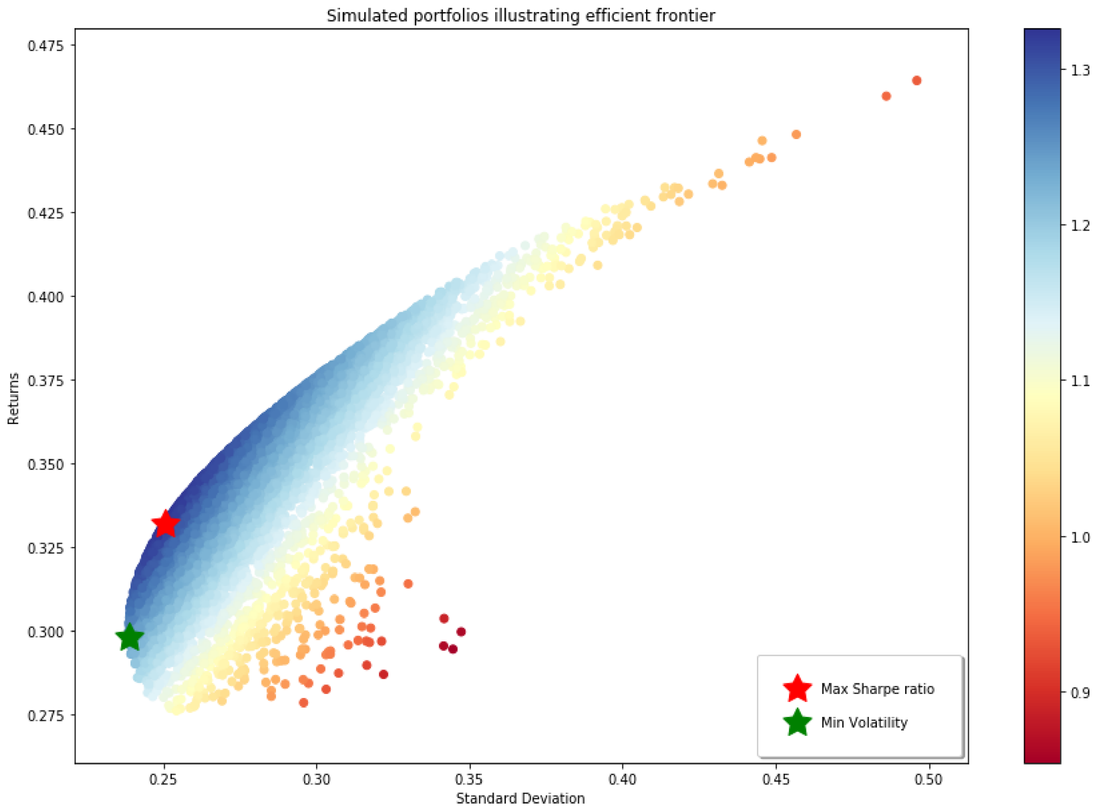


Figure 1. Source: author's elaboration. Model constructed with Python (see Appendix). "MVO Portfolio".

According to the mean-variance principle, the lower branch of the above hyperbole contains all the inefficient portfolios because they are dominated by those in the upper branch (e.i. the efficient frontier). The optimal portfolio is on the efficient frontier and it depends on the individual utility function and risk aversion. The efficient frontier is the set of optimal portfolios that have the highest expected return for a given level of risk or the lowest level of risk for a given expected return. Portfolios that lie below the efficient frontier are sub-optimal.

The optimal portfolio can be found by maximizing the Sharpe Ratio which means, finding the steepest Capital Allocation Line (CAL), the line which makes up the allocation between a risk-free asset and a risky portfolio for an investor. Therefore, the point in which the utility function is maximized is where the efficient frontier and the CAL are tangent. This model, however, take into consideration only portfolios composed by risky assets and it also assume that the risk aversion of investors is homogeneous, making a comparison between individuals impossible.

Tobin (1958) removes the latter assumption and, in addition, he introduced the possibility of investing in risk-free assets. In this way, the expected return will be a linear combination of risky return (R_m) and risk-free return (R_f): $R_p = (1\text{-}X)R_f + XR_m$, where X is the portion of wealth invested in the risky assets and (1 - X) is the portion of wealth invested in the risk-free assets.

Putting together all possible combinations of risk-free and risky assets, one of these combinations dominates the others. This portfolio is called Market Portfolio[3], and it is the tangent point between the line which has the intercept equal to r_f and the efficient frontier. The market portfolio is perfectly diversified and therefore, it is exposed only to systematic risk. Combinations of risk-free assets and market portfolios form the capital market line (CML), whose equations is:

$$E(r_P) = r_f + \frac{E(r_m)-r_f}{\sigma_m} \cdot \sigma_P$$

The Capital Market Line (CML) is a special case of the CAL in which the risky portfolio is the market portfolio. Its slope is the Sharpe Ratio. The CML identify all efficient portfolios, which are exposed to systematic risk. On the contrary of specific risk, systematic risk is non-diversifiable and it can be defined as:

$$\sigma_p = \rho_{i,m} \cdot \sigma_i$$

where $\rho_{i,m}$ is the correlation between the yields of the security (or portfolio of securities) and the yields of the market portfolio. Therefore, the CML will be:

$$E(r_P) = r_f + \frac{E(r_m) - r_f}{\sigma_m} \cdot \rho_{i,m} \cdot \sigma_i$$

Setting $(\rho_{i,m} \cdot \sigma_i)/\sigma_m = \beta$, that equation becomes $E(r_p) = r_f + \beta[E(r_m) - r_f]$, which is known as security market line (SML).

The SML equation is at the base of the Capital Asset Pricing Model (CAPM), created in the early 1960s by Sharpe, Treynor, Lintner and Mossin. The CAPM implies that the market portfolio is mean-variance optimal (MVO) portfolio and all investors should allocate between market portfolio, as it has the highest Sharpe Ratio, and risk-free asset.

[3] The market portfolio contains all assets available in the market, weighted proportionately to their market value.

Capital Asset Pricing Model (CAPM)

The CAPM measures the relationship between the expected return of an asset and its riskiness. In the CAPM, the risk being measured is the market risk and it is represented by the β. However, the assumptions of this model are that all investors:

- aim to maximize economic utilities (asset quantities are given and fixed);
- are rational and risk-averse;
- are broadly diversified across a range of investments;
- are price takers, i.e. they cannot influence prices;
- can lend and borrow unlimited amounts at the risk-free rate;
- trade without transaction or taxation costs;
- deal with securities that are all highly divisible into small parcels (all assets are perfectly divisible and liquid);
- have homogeneous expectations;
- assume all information is available at the same time to all investors (Arnold, Glen, 2005).

In the context of CAPM, the risk of a single asset (i) for an investor corresponds to the risk that this asset adds to the market portfolio (m). This additional risk is measured by the covariance (Cov) of the asset (i) with the market portfolio (m). However, since the Cov is not a standardized measure, it is difficult to determine the riskiness. For this reason, the covariance between each asset and the market portfolio, is divided for the variance of the market portfolio.

$$\boldsymbol{\beta} = \frac{\boldsymbol{Cov_{im}}}{\boldsymbol{Var_m}} = \frac{\boldsymbol{\sigma_{im}}}{\boldsymbol{\sigma^2{}_m}}$$

The Beta is a measure of the "sensitivity" of a security or an investment portfolio to movements in the overall market.

- Beta = 1 (Cov = Var): the asset has the exact same volatility of the market.
- Beta > 1 (Cov > Var): the asset is more volatile than the market.
- Beta < 1 (Cov < Var): the asset is less risky than the market. Its volatility is s lower than the market's volatility.
- Beta = 0 (Cov = 0): regardless of which way the market moves, the value of the asset remains unchanged. In other words, it is risk-free.

– Beta < 0 (Cov < 0): indicate an inverse relation to the market.

Therefore, the expected return of an asset (i) will be a function of risk-free rate, β and market risk premium:

$$E(R_i) = R_f + \beta_i \underbrace{[E(R_m) - R_f]}_{\text{Market Risk Premium}}$$

The security market line (and the CAPM) represents the relationship between return and risk. Thus, if an asset has a higher (lower) return than the SML, investors will deal with an undervalued (overvalued) stock. The purchase (sale) of undervalued (overvalued) assets will increase (decrease) the prices and lower (increase) the returns, restoring the CAPM equilibrium.

To better explain this phenomenon, Sharpe suggested also another relationship, that is:

$$E(r_i)=\alpha_i + \beta_i \cdot r_{mkt} + \varepsilon_i$$

where α_i is the measure of asset-specific risk, β_i the measure of systematic risk, r_{mkt} the market risk premium and ε_i is a random variable resulting from regression. In this equation the specific risk is considered as remunerable, unlike the original CAPM.

To summarize, the main limitations of the CAPM are:

– unrealistic assumptions;
– it is not always easy to estimate the parameters of the model;
– it considers only the systematic risk and not the specific risk.

Arbitrage Pricing Theory (APT)

Given the limitations of the CAPM, in the 1976, a new model was developed by Ross: the Arbitrage Pricing Theory (APT). This model is based on the assumption that investors benefit from arbitrage opportunities. Unlike the CAPM, which is based on the assumption that the market is perfectly efficient, the APT assumes that the market sometimes misprices securities.

Therefore, if two portfolios have the same risk exposure but offer different expected returns, investors will buy the portfolio with higher expected return. In this way, they will drive up the price, and thus lower the expected return, restoring the equilibrium with the other portfolio and moving back securities to their fair value.

The APT, as well as other models, distinguishes a company specific risk from systematic risk (market risk). The difference is in how the latter is measured. According to the APT, market risk is affected by several macroeconomic variables such as GDP, interest rate, inflation, etc. and it measures the sensitivity of investments to changes in these macroeconomic variables (each one of them with a different beta).

Therefore, the beta measures the sensitivity of the activity to the variation of each macroeconomic variable (called "factor"). As already said, diversification helps eliminating the specific risk, and therefore, according to the APT, the expected return of a portfolio will derive from the market risk alone.

Thus, the expected return of a portfolio is a linear function of beta and it can be defined as:

$$E(R)= R_f + \beta_1[E(R_1)-R_f] + \beta_2[E(R_2)-R_f] + \ldots + \beta_n[E(R_n)-R_f]$$

R_f = expected return of a portfolio with a beta = 0 (risk-free), $E(R_j)$ = expected return of a portfolio with a beta = 1 with respect to factor, $[E(R_j)-R_f]$ = risk premium associated with macroeconomic variable j (factor j).

The APT requires the estimation of the beta and of the risk premium for each factor. In order to estimate them, it is necessary to make the factorial analysis on historical returns, which allows to find also the "number" of variables that have affected the historical data. The limitation of the APT, however, is that it is able to identify only the "number" of variables that determine the expected return, but it fails to establish "which ones" determine it (Damodaran, 2015).

Multifactorial risk-return models

The APT is one of the first multifactorial risk-return models. Such models try to identify "which" are the macroeconomic variables that concretely generate systematic risk in order to determine the sensitivity of the expected returns relatively to the relevant macroeconomic variables. The main way of doing this is to analyze the time series of the factors (to see their behavior over time) and to compare them with the time series of the different macroeconomic variables, to check if these variables are actually correlated over time with the factors identified by the factor analysis. The issue with these models, however, is that both the number and the identity of the relevant economics factors may vary over time.

Empirical models based on regression

The models seen until now start from the concept of market risk and then, they try to characterize it through economic models, whose parameters are obtained by analyzing the historical data. Regression models, on the other hand, start from the statistical data (e.i. from the distribution of historical returns) and then, they to go back to come up with a risk-return model. In particular, these models try to explain the investment returns analyzing them over long periods of time and analyzing the characteristics of such investments (for example company size, multiples of the share price, etc.). In practice, these are regression models based on specific company's variables and historical returns.

Fama and French in "The cross section of expected returns" (1992), indeed, analyzed individual stock returns between 1962 and 1990 and they concluded that the "Beta" of the CAPM, did not explain much about the returns. Therefore, they tried to find more specific variables that could have explained such returns and they found out two main variables: market capitalization and P/B ratio. These findings led to the birth of "value" factor and "size" factor, which are highly used in factor investing and which will be discussed more in detail later on.

In 1993, Fama and French came up with a tree-factors model that suggests that much of the variation in average returns is related to the market, size, and B/M (book-to-market equity ratio) factors. However, available evidence also suggested that much of the variation in average returns related to profitability and investment is left unexplained by this three-factor model.

These findings led to the creation of a more sophisticated model that added profitability and investment factors to the previous model. Fama and French (2014), found out that this new five-factor model explains between 71% and 94% of the cross-section variance of expected returns. Therefore, by adding those two factors, they improved their previous work and they demonstrated that it performs better than the tree-factors model, even though it fails to capture the low average returns on small stocks.

In the last two decades, researchers, through the use of empirical models, have begun to seek constantly new and better approximations of risk. They found out many variables that may explain excess returns such as: earning momentum, price momentum, low liquidity, etc. These models have been a big step forward toward the correction of expected returns in order to reflect market reality and to lay the foundations for new ways of investing. Therefore, they deviate from traditional risk and return models as they take a pragmatic perspective in order to study the risk-return relationship in the real world.

Risk-Return Analytics

In order to analyze the risk-return relationship and the historical return distributions of any investment, usually investors include simple performance statistics, as well as risk metrics such as standard deviation (volatility), skewness of returns, and tail risk (kurtosis). Additionally, performance ratios such as Sharpe, Sortino, Treynor, Calmar and other ratios are taken into consideration, as well as factor correlations. For completeness, and in order to better understand these analytic measures which will also be used for an empirical analysis in the next chapter, they are going to be explained in the session below.

For a time series observation of total returns $\boldsymbol{R} = (r_1, \dots, r_T)'$ with N observations per annum and the corresponding time series of risk-free rates $\boldsymbol{R}_f$, $\boldsymbol{R}_e = \boldsymbol{R} - \boldsymbol{R}_f = (r_1^e, \dots, r_T^e)'$ is the excess return. In addition, $\boldsymbol{S}_R = (S_1, \dots, S_T)^T$ with $S_t = \prod_{i=1}^{t}(1+r_i)$ is the net asset value (NAV) for the return series $\boldsymbol{R}$.

Core Risk-Return Analytics

Annual Return:

$$\text{Annual Return} = (\text{Ending Value} / \text{Initial Value})^{(1 / \text{No. of Years})} - 1$$

The term "annual return" refers to the return earned from an investment over a given period of time and as such, it is expressed as the time-weighted annual percentage. In other words, it represents the increase (or decrease) in value of an investment. The percentage used when reporting the historical return (such as the three-, five-, and 10-years), measures the money made (or lost) and therefore, it is a helpful guide for measuring a long-term performance. The rate of annual return is measured against the initial amount of the investment and represents a geometric mean rather than a simple arithmetic mean.

Annualized compounded return (CAGR):

$$\boldsymbol{g_R} = \left[\prod_{i=1}^{T}(1 + r_i)\right]^{\frac{N}{T}} - \mathbf{1} = (S_T)^{\frac{N}{T}} - 1$$

Compounded annual growth rate (CAGR) is the rate of return of an investment, assuming that the profits (such as dividends or interests) were reinvested at the end of each year of the investment's lifespan. It essentially describes the rate at which an investment would have grown if it had grown the same rate every year and the profits were reinvested at the end of each year. Even if this sort of performance is unlikely, CAGR can be used to compare alternative investments more easily. It can also be rewritten in a simpler way as:

$$\text{CAGR} = (\text{Ending Value}/\text{Beginning Value})^{1/n} - 1$$

Annualized standard deviation (StDev):

$$\boldsymbol{\sigma_R} = \sqrt{N \frac{\sum_{i=1}^{T}(r_i - \bar{r})^2}{T-1}}$$

where $\bar{r}$ is the arithmetic average of returns. The standard deviation is the square root of variance and as such, it is never negative. It measures the average deviations of a return series from its mean, that is the dispersion of a dataset relative to its mean. The more volatile is an asset, the higher the standard deviation. However, it is highly impacted by outliers.

Annualized downside deviation (DownDev):

$$\boldsymbol{D\sigma_R}(R_{\text{Target}}) = \sqrt{N \frac{\sum_{i=1}^{T}\left[\min(r_i - R_{\text{Target}}, 0)\right]^2}{T}}$$

where R_{Target} is so-called target return (Minimum Acceptable Return). In the calculation of the downside standard deviation, also referred to as downside risk, on the contrary of the traditional standard deviation, the sum is restricted to those returns that are less than the R_{Target}. It focuses on returns that fall below a threshold. As we will see, the downside risk is used also in the calculation of Sortino Ratio. While Standard deviation treats all deviations from the average, whether positive or negative, as the same, this measure allows investors to focus more on the negative divergences rather than positive ones.

Annualized Covariance (CoVar):

$$\textbf{CoVar}_{R,X} = \frac{N}{T-1}\sum_{i=1}^{T}(r_i - \bar{r})(x_i - \bar{x})$$

It measures the relationship between two assets, determining if they tend to move with or against each other. It could help determine what assets to include in the portfolio by picking assets that complement each other in order to reduce the overall portfolio risk. A limitation, though, is that the Covariance alone does not allow to determine the strength of such relationship. Moreover, since it uses historical returns, there will not be certainty about the future, it can only try to predict how they might perform relative to each other.

Together with covariance, in order to have a better understanding of the strength of the relationship between two assets, investors need to study also their correlation. The covariance, indeed, is not easy to interpret, since it takes values between $-\infty$ and $+\infty$. Thus, usually it is more convenient to use the Pearson correlation coefficient, which is a standardized covariance, and it takes values between -1 and $+1$.

Correlation (Corr):

$$\mathbf{Correl}_{R,X} = \frac{\mathbf{CoVar}_{R,X}}{\sigma_R \sigma_X}$$

By dividing the Covariance between both variables for the product of the assets' standard deviations, it provides an additional information about the degree of dependency of the two assets. In other word, the degree to which they move together. In the case of $\rho_{RX} = 1$, the two assets move perfectly together, in the case $\rho_{RX} = -1$, they move in the exact opposite direction and when $\rho_{RX} = 0$, they move in random directions from each other. All the possible numbers in between, represents different levels of comovement.

Correlation risk is especially critical in risk management as an increase in the correlation of asset returns increases the risk of financial loss. However, the Pearson correlation coefficient capture only the linear dependence. Therefore, if it gives a value of 0, it tells us that the variables are uncorrelated, but this does not mean that the variables are independent. It fails to capture nonlinear relationships, and financial variables, which are the variables we are interested in, are mostly nonlinear (Meissner, 2014).

Tail Risk Analytics

In reality, asset returns tend to deviate from the Gaussian (normal) distribution. They tend to be (Allen, Boudoukh, Saunders, 2004):

– Fat-tailed: A fat-tailed distribution is characterized by having heavier tails. In other words, the tails simply look fatter than the normal distribution. As the tails have more bulk, the probability of extreme events is higher compared to the normal.
– Skewed: A skewed distribution is asymmetric, both on the right or on the left. The first one is also known as positive skew. In this kind of distribution there are very few high values, while data points cluster mainly on the left side. The second one is the opposite case.
– Unstable: Unstable parameter values are the result of varying market conditions, and they may have effect on volatility or on other variables of the distribution which may vary over time.

Skewness (Skew) & Kurtosis (Kurt):

$$\textbf{Skew} = \sum_{i=1}^{T}\left(\frac{r_i - \bar{r}}{s_R}\right)^3 \qquad \textbf{Kurt} = \sum_{i=1}^{T}\left(\frac{r_i - \bar{r}}{s_R}\right)^4$$

where $s_R = \sigma_R / \sqrt{N}$ is the (unannualized) standard deviation of the returns.

As already mentioned above, a distribution has "fatter tails" than the normal distribution if it has a similar mean and variance, but different probability mass at the extreme tails of the probability distribution. The phenomenon of fat tails poses a severe problem in risk management. Risk measurement, indeed, is focused mainly on extreme events and normal distribution seems to fail precisely where investors need it to work best.

Thus, the normality assumption is only strictly appropriate when working with a symmetric (i.e. zero-skew) distribution with a kurtosis of 3. If the skewness is far from being 0 and/or the Kurtosis is much greater than 3, then the normality assumption is inappropriate and the mean–variance framework can produce misleading estimates of risk.

CoSkewness (CoSkew) & CoKurtosis (CoKurt):

$$\textbf{CoSkew} = \sum_{i=1}^{T}\frac{(r_i - \bar{r})(x_i - \bar{x})^2}{s_R s_X^2} \qquad \textbf{CoKurt} = \sum_{i=1}^{T}\frac{(r_i - \bar{r})(x_i - \bar{x})^3}{s_R s_X^3}$$

The Co-Skewness and Co-Kurtosis statistics are measured relative to a particular benchmark to assess the systematic exposure to skew and tail risks. These two additional multivariate higher moments are important in asset allocation process and portfolio management. Indeed, they allow portfolio managers to test the same portfolio under different compositions, in order to eliminate some allocations in badly performing securities which may cause, for example, more pronounced negative coskewness.

Assets with negative coskewness, indeed, will tend to undergo extreme negative deviations at the same time. Assets with high levels of cokurtosis, instead, will tend to undergo extreme positive and negative deviations at the same time (Pawel, 2013).

Drawdown (DD):

$$\mathbf{DD}_{\boldsymbol{R}}(t_1, t_2) = \frac{S_{t_2}}{\mathrm{HWM}(t_1, t_2)} - 1, \text{where } \mathrm{HWM}(t_1, t_2) = \max_{t_1 \le t \le t_2} S_t$$

A drawdown is a peak-to-trough decline during a specific period. It is a measure of how much the investment has gone down from a previous relative maximum or absolute maximum, before fully recover. Any financial strategy, even if profitable, is subject to a more or less extended and prolonged level of drawdown. Morevoer, it is important to take into consideration not only how down it has gone, but also the time it takes to recover.

Value at Risk (VaR):

$$\boldsymbol{VaR} = -q_p$$

the VaR is defined contingent on two arbitrarily chosen parameters: a confidence level α (where $p = 1 - \alpha$), which indicates the likelihood of obtaining an outcome no worse than the VaR estimated; and a holding (or horizon) period, which is the period of time until portfolio profit or loss are measured, and which might be a day, a week, a month, or whatever. To give a practical example, 1-day 95% VaR is the maximum expected loss over the next 1 day with 95% probability or, in other words, there is 5% probability to have a loss greater than that, in the next one day.

The VaR is simply the negative of the q_p quantile of the P/L distribution (or return distribution). In other words, when we are faced with a more general (non-normal) distribution in the real world, the assumptions made about the distribution are less restricted. Our focus is on the left tail of that distribution (that is the worst p% of outcomes), which brings us back to the VaR. One of the main limitations of VaR is that if a tail event occurs, investors do expect to lose more than the VaR, but the VaR itself gives us no indication of how much that might be.

Performance Evaluation Analytics

Alpha:

$$\boldsymbol{R_e = \alpha + \beta_1 f_1 + \cdots + + \beta_n f_n + \varepsilon}$$

where f_1, ... , f_n are n systematic excess return factors and ε is a white noise error term. The estimation of $\boldsymbol{\alpha}$ is a measure of portfolio performance after adjusting for systematic factors such as the Fama-French five factors. It represents the ability of a strategy to beat the market.

The estimated β_1, ... , β_n are the Betas, which measure the relative sensitivity of portfolio excess returns to each factor (after controlling for other factors). Alpha is often considered the "active return" on an investment. An alpha of 0 would indicate that a portfolio is generating returns only as result of general movement in the market, that means it is perfectly tracking a benchmark index, without adding any value.

To accurately analyze the performance of a portfolio, an investor should look not only at its overall return, but also at the level of risk involved, in order to determine if the investment's return compensates properly for the risk it takes. For this reason, instead of the common $\boldsymbol{\alpha}$, sometimes investors look at Jensen's alpha, which is a risk-adjusted performance measure.

$$\boldsymbol{\alpha}_J = R_p - (R_f + \beta_p(R_m - R_f))$$

It basically compares the excess returns earned by the portfolio to the returns suggested by the CAPM model. Jensen's alpha tries to explain whether a portfolio has performed better or worse than a market-related investment. If Jensen's alpha is significant and positive, it means that the portfolio generates returns on top of what would be expected based on factors alone (Jensen, 1968). In other words, the excess returns derive from stock picking and active portfolio management. When comparing different strategies, investors should choose the one with higher alpha since this implies greater reward for the same level of risk.

Sharpe Ratio (SR):

$$\boldsymbol{Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}}$$

Introduced by William Sharpe in 1966, the Sharpe Ratio is the grandfather of all risk measures. It is calculated dividing the excess return of a portfolio above the risk-free rate by its standard deviation. As already said, a rational investor will look for high return and low variability. The higher the Sharpe ratio the better the combined performance of risk and return. It provides information on how much excess return (risk premium) the fund is able to generate for each unit of risk (volatility).

Unlike Sharpe Ratio, Treynor and Sortino ratios do not consider total risk.

$$\textit{Treynor Ratio} = \frac{R_p - R_f}{\beta i} \qquad \textit{Sortino Ratio} = \frac{R_p - R_f}{\sigma_{p-negative}}$$

The first one measures the differential between portfolio return and risk-free return in terms of systematic risk (β). Although it is well known, it is less frequently used because it ignores specific risk. If a portfolio is fully diversified and therefore, it is subject only to systematic risk, theoretically Treynor Ratio and Sharpe Ratio will give the same result.

The second one measures the same differential in terms of unit of downside risk. Therefore, the concept of risk in Sortino Ratio refers only to the possibility of achieving an extra-negative return, while the cases in which the extra-return is positive are not considered. "Portfolio managers will not be penalized for upside variability but will be penalized for variability below the minimum target return" (Bacon, 2009).

In addition to the previous three ratios, there is a fourth one which differs from the others because it takes into consideration no longer the risk-free return, but that of the benchmark. It is called Information Ratio (IR) and its denominator is the Tracking Error[4].

$$\textit{Information Ratio} = \frac{R_p - R_b}{\sigma_{(R_p - R_b)}}$$

The information Ratio measures the return of an investment strategy compared to the benchmark. It is a risk-adjusted measure of performance, as well as Sharpe Ratio. The key difference, though, is in the definition of excess return. While in the Sharpe Ratio it is defined as the return above the risk-free rate, in the Information Ratio it is the return in excess of a relevant benchmark index (Israelsen, 2004).

The IR is often used as a measure of the productivity of an active manager and his ability to generate excess returns relative to a benchmark. According to Grinold and his "Fundamental

[4] Tracking Error describes the volatility of a fund's returns compared to a benchmark. It will be described more in detail in the next chapter.

Law of Active Management", the performance will depend both on the manager's skill, and on how often that skill is put to use.

$$IR = IC * \text{sqrt}(\text{Breadth})$$

Where IC is the Information Coefficient which represents his skills and it is defined as the correlation of ex-ante forecasts with realized return, and Breadth is the extent to which he applies his skill, which is defined as the number of independent signals he derives (e.i. the number of forecasts he makes over a time horizon).

Thus, at any given level of risk, an active manager can either seek to improve his productivity by increasing the number of independent bets he makes (an increase in Breadth), or he can improve his skill (an improvement in IC). However, important drawbacks are:

- the formula was derived in the absence of transaction costs, which significantly distort the two parameters;
- it defines the expected IR of a single manager or strategy in isolation, and in doing so, it ignores essential portfolio considerations;
- IC cannot be estimated a priori.

Calmar Ratio:

$$\textit{Calmar Ratio} = \frac{\textit{Annualized}(R_p)}{\textit{MaxDD}_p}$$

Calmar ratio, also known as Drawdown ratio, was developed in 1991 by Terry Young. It uses the maximum drawdown as the only measure of risk. A maximum drawdown is a measure of the portfolio's maximum loss from its peak value over a specific period of time. The higher the Calmar ratio, the better the portfolio performed on a risk-adjusted basis.

It is on average more understandable and it usually considers a time frame of three years (even if it is updated monthly) which makes it more reliable than other gauges with shorter time frames because it tends to be less more affected by natural market volatility. However, given that it only focuses on drawdown, it ignores general volatility and therefore, it is less statistically significant and useful (Kenton, 2020).

Upside capture ratio & Downside capture ratio:

$$\textit{Upside Capture Ratio} = \frac{\left[\prod_{i,R_b^m \geq 0}\left(1 + R_p^m\right)\right]^{\frac{12}{N}} - 1}{\left[\prod_{i,R_b^m \geq 0}\left(1 + R_b^m\right)\right]^{\frac{12}{N}} - 1} \qquad \textit{Downside Capture Ratio} = \frac{\left[\prod_{i,R_b^m \leq 0}\left(1 + R_p^m\right)\right]^{\frac{12}{N}} - 1}{\left[\prod_{i,R_b^m \leq 0}\left(1 + R_b^m\right)\right]^{\frac{12}{N}} - 1}$$ [5]

where R_b^m is the benchmark return, R_p^m is the portfolio return, and N is the number of up (or down) periods.

Upside capture ratios for funds, or investments in general, are calculated by taking the fund's monthly return during months when the benchmark had a positive return and dividing it by the benchmark return during that same month. Downside capture ratios are calculated by taking the fund's monthly return during the periods of negative benchmark performance and dividing it by the benchmark return.

They offer a quite straightforward way of evaluating and monitoring historical performances (during both up and down of the markets) and conducting due diligence on possible additions to your portfolio. These statistics determine whether a given fund has outperformed the market during periods of market strength and weakness, and if so, by how much. Indeed, an upside capture ratio over 100 indicates a fund has generally outperformed the benchmark during periods of positive returns for the benchmark. Meanwhile, a downside capture ratio of less than 100 indicates that a fund has lost less than its benchmark in periods when the benchmark has been in the red (Pak, 2011).

[5] Multiplied by 100.

Chapter 2

ETF

ETF is the acronym for Exchange Traded Fund. These funds are traded on Stock Exchanges as any other share and they are built to track a specific benchmark, through a totally passive strategy. ETFs are able to increase diversification and reduce risk exposure while improving transparency of information.

In most of the cases, fees are calculated on a daily basis as a percentage of the total assets under management. Given the passive nature of these investment strategies, the costs associated with them are usually pretty low, between 0.2% and 0.9%. If, for example, the operating costs were equal to 0.50% per year, every day 0.00137% (0.50%:365) of the value of the assets under management would be deducted from the fund and collected by the management company of the ETF.

By purchasing an ETF, investors can take a real time position on the market, for a price that perfectly reflect the market value of the benchmark at that given point in time. These funds are passively managed in the sense that they replicate exactly the composition and the weights of the index they are tracking. For this reason, they also will obtain the exact same returns. The aim of a traditional ETF is to replicate a benchmark, not to beat it. The only exception is if the reference currency is other than the trading currency. In this case the returns may be different in consequence of devaluation/revaluation of such currency.

Thanks to a particular mechanism referred to as creation/redemption in kind, the price on the Stock Exchange is constantly aligned to the official value of the ETF, the NAV (Net Asset Value). The ETF creation and redemption mechanism is used by market makers to help reconcile the difference between NAV and market values, preventing the trading of an ETF at a discount or premium.

Market makers are authorized participants (AP) that have the right to create and redeem shares of an exchange traded fund (ETF). Through their work, they increase transparency of markets and improve liquidity of ETFs (Chen, 2020). AP are responsible for acquiring the securities that an ETF wants to hold and deliver them. When a divergence between NAV and market values occurs, authorized participants will make a risk-free profit by exploiting the arbitrage opportunity.

Through ETFs investors can obtain a broad diversification. As a matter of fact, investing in an ETF means taking a position in an index, which contains a huge basket of securities. Moreover, investors can benefit from periodical proceeds. Dividends and/or interest that an ETF matures, indeed, are distributed periodically to the investors or permanently capitalized in the assets of the ETF. Either way, the investor will benefit from them.

There are many ETFs alternatives available to investors but each one of them belongs to one of the two broader categories: synthetic and physical. Depending on the designation of an ETF to either one or the other category, risk exposure, potential returns, maturation dates and fees will be all directly affected.

Physical ETFs are the most traditional form of ETF, born in the early 90s. This type of fund follows as closely as possible its benchmark and it actually acquires and holds the underlying securities.

Synthetic ETFs, introduced at the beginning of the new century, have the same primary objective of physical ETFs. However, instead of directly buying the securities in question, they use derivative products to implement their methodology. The primary derivative used in synthetic ETFs are the Swaps contracts.

After stipulating the agreement, the fund provides the money, and the counterparty, in turn, gives back to the ETF the total returns of the benchmark (net of all the costs related to the Swap agreement). In this way, "the synthetic ETF is able to track an index or security(s) without actually owning any of the assets involved." (Aramonte S., Caglio C., Tuzun T., 2017). Moreover, to protect investors against default risk, most of the times these ETFs are collateralized.

Structured and Active ETFs

Inside the broad category of ETFs, a first division can be made based on the kind of assets they invest in such as Equity, Fixed-Income, Commodity, Currency and Real Estate. In addition, particular ETFs invest in specific geographic areas or specific industries. In recent years, though, new kind of ETFs, that are worth dwelling on, are born. They are Structured and Active ETFs.

Structured ETFs are not aimed at the simple replication of an index. They take long/short positions on the reference index. The three main types are: ETF Leveraged, ETF short and ETFs covered.

- ETFs Leveraged amplify the index results through "lever" mechanisms, participating in a more than proportional manner in the performance of an index. Basically, they bet on a positive market trend for the near future.
- ETFs short allows investors to participate inversely in the movements of the reference market by short selling the basket underlying the ETF. In this case, investors bet on a negative performance of the benchmark.
- ETFs covered invest in the benchmark index by taking long and short positions (through the use of options) simultaneously. In this way, they usually are less risky than a standard ETF.

Structured ETFs have the advantage of improving the performance of each strategy with respect to a standard ETF. Indeed, these funds allow to access more complex investment strategies by joining the benefits of a passive strategy with those of a more active and dynamic management.

The most recent entrants in the world of ETFs are the Active ETFs. By their nature, ETFs are born as completely passive strategies, however, new types of ETFs are emerging. They seek to reach a higher performance than the benchmark itself while keeping some of the benefits of passive investing such as lower fees. Active ETFs select a specific set of components from the benchmark based on either companies' data (dividends, revenues, P/E, etc.) or deterministic and mathematical models, and invest on them.

Tracking Error

As already mentioned, the aim of ETFs is to replicate an index. Therefore, in order to evaluate the ability of doing so, investors may want to look at the so called "tracking error". The tracking error tells investors how much the ETF's performance diverges from the performance of the index used as benchmark. It indicated that the ETF did not replicate the index as effectively as intended, creating an unexpected profit or loss.

$$\text{Tracking Error} = \text{Standard Deviation of } (P - B)$$

where P is portfolio return and B is benchmark return.

There are many factors that affect the Tracking Error. First of all, the net asset value (NAV) of an index fund tends to be lower than the benchmark itself because of fees and commissions. For this reason, a high total expense ratio[6] (and more specifically Management expense ratios) could lead to a quite significant divergence of the two performances.

Other factors are related to mismatches between the assets included in the index with those included in the fund, or also differences in weighting. Investors may encounter difficulties in finding all the underlying assets of an index because some of them could be highly illiquid. Moreover, being able to respond rapidly to changes is critical. Every index is subject to rebalancing and reconstitution periodically and an ETF must be able to adapt to these changes as quickly as possible, otherwise the Tracking Error will skyrocket.

Illiquid securities can also have a negative impact on tracking error for an additional reason. Indeed, when securities are thinly traded, prices could differe significantly from market price when the fund buys or sells such securities, because of larger bid-ask spreads. Finally, the level of volatility for an index can also affect the tracking error.

The size of an ETF Tracking Error also depends on the type of fund. “Sector, international and dividend ETFs tend to have higher absolute tracking errors; broad-based equity and bond ETFs tend to have lower ones.” (Chen, 2020).

Factor investing and Alternative Risk Premia

The main task for fund managers is to deliver stable and positive returns. The low yield market environment that the financial world is experiencing in the aftermath of the 2008 global crisis, is forcing investors into more risky assets if they want to achieve higher yields.

At the same time, investors have increased their awareness regarding the importance of a good financial risk management and the task of reducing portfolio risk has become equivalent to looking for new alpha opportunities.

Aimed at reducing portfolio correlations, investors are moving away from traditional assets towards “alternative” assets. These assets, called “alternative risk factors”, seek to access new sources of risk premia.

[6] TER= Total fund assets/Total fund costs

The concept of alternative risk premia is an extension of the simpler factor investing, which consists in building long-only equity portfolios. Indeed, they also involve equities, rates, credit, currencies and commodities and correspond to long/short portfolios. The two main characteristic of these factors are the ability to capture non-traditional source of premia and the low correlation between them, which can help reducing portfolio volatility and tail risk.

The terms “factor investing” and “alternative risk premia” describe active and index-based investment strategies that give investors exposure to one or more factors. These strategies are implemented through rules-based methodologies that use factor selection and/or alternative weighting with the aim of outperform a benchmark or reduce portfolio risk, or both.

What makes a risk factor a good risk factor, is the presence of a strong economic rationale behind it explaining the source of that risk premia. Indeed, they are designed to exploit specific market inefficiencies such as irrational behaviors of market participants, supply/demand friction or change in market micro structure. For this reason, investors have to fully understand the source of these risk premia, together with their lifecycles and limitations of each one of them (Stoneberg and Smith, 2019).

“The most common mistakes in designing risk factors are related to an in-sample bias in the determination of parameters.” (Kolanovic, 2013). These in-sample biases can range from statistical mistakes to failures due to trading rules. Trading rules, indeed, need to be updated and correct as markets evolve. Otherwise a risk factor, who performed well in the past, will look good in a backtest but will perform poorly in the future.

A deep understanding of the lifecycle of these factors is fundamental because as markets change, new factors will emerge while others will weaken or disappear. Each factor behaves differently in different market regimes. “Given that risk factors have lifecycles, investors need to constantly research and test new factors, as well as evaluate the effectiveness of old ones.” (Kolanovic, 2013).

The growing interest in alternative risk premia is due to the fact that they are generally unrelated to broader macro fundamentals and consequently, they could provide diversification benefits when included in a portfolio (Reid and Van Der Zwan, 2019).

It is important to note that alternative risk premia should not be confused with “alpha”, which is the idiosyncratic component of the returns. Portfolio returns can be seen as the combination of market beta and alpha. As investors learned more about these “new” sources of risk premia, part of the old alpha could be attributed to these risk factors, leaving the “true alpha” limited to idiosyncratic returns.

While traditional risk premia have a risk/return profile quite straightforward to understand, the behavior of alternative risk premia is more complex and heterogenous. As Thierry Roncalli highlights in his paper “Alternative Risk Premia: What Do We Know?” (2017), they cover two main categories of strategies: skewness risk premia and market anomalies.

Skewness risk premia can be considered ‘pure’ risk premia, meaning that they reward systematic (non-diversifiable) risks in bad times. Market anomalies, instead, are related to strategies that have performed well in the past, but this performance can only be explained by behavioral theories, not by the existence of a risk premium.

As a result, statistical properties are different between one factor and another. These considerations are particularly important because “some investors see portfolios of alternative risk premia as all-weather strategies. However, this is not the case in reality. “(Roncalli, 2017).

Therefore, identifying alternative risk premia cannot be reduced to backtesting a strategy and performing a statistical analysis of past performance (Cochrane, 2011). To create a viable systematic strategy, two core elements are the selection of risk factors and the choice of weighting methodology.

There is no unique taxonomy and the task of identifying alternative risk premia is not easy because there is no consensus between investors. The main factor styles could be classified as: carry, growth, liquidity, low beta, momentum, quality, size, value, volatility, but this list is certainly not exhaustive. Additionally, factors can be designated across different asset classes (equities, credit, currency, commodity, volatility) and geographic regions (Americas, Europe, Developed Asia, Emerging Markets and Frontier Markets).

On the other hand, weights of factors can be selected to minimize portfolio volatility, maximize Sharpe ratio or diversification, equalize risk contribution from each factor, or implement an investor’s specific views on risk and returns. Once the factor relative weights are determined, overall portfolio risk can be managed by dynamically allocating risk between the factor portfolio and risk-free asset.

Classification of Risk Factors

As mentioned above, there is no unique way of classifying risk factors. In an idealized word, they should be independent, deliver positive risk premia and be able to explain the risk of any systematic strategy. In the real world, although they have low correlation, this is almost never zero. In addition, they can occasionally suffer from draw-downs and lead to negative risk premia. Finally, they constantly evolve as new market inefficiencies come into existence, creating the need for adding or removing factors. For this reason, the aim of the following list of factors will only give an overall view of some of the main factors in use today.

Value

Value strategies are designed to buy assets that are undervalued (cheap) and sell those that are overvalued (expensive) according to a specific valuation model chosen by the investor. Basu (1983) was the first one to argue that low P/E stocks generates higher returns relative to high P/E stocks. Therefore, a value strategy seeks to capture excess returns to attractively priced assets.

This strategy is based on the concept of mean reversion of asset prices to their fair-value anchors. The premise is that prices move away from 'fair value' by either behavioral effects (over-reaction, herding) or liquidity effects (temporary market impact, long term supply/demand friction) only temporarily, but they will come back to their fair value.

The derivation of asset fair values is based on economic and fundamental indicators. In fixed income, currencies and commodities, the main indicators are the capital account balance, level and changes in economic activity, inflation and fund flows. In equities and credit, investors often rely on corporate metrics such as book value, cash flows, earnings and levels of debt.[7]

Momentum

Jegadeesh and Titman (1993) found that buying past winners and selling past losers is highly profitable. Momentum strategy ranks securities relative to peers using relative strength methodology to identify the strongest and weakest investment trends. This strategy consists in "chase winners and sell losers" (Reid and Van Der Zwan, 2019).

[7] This list is not exhaustive, and it is subject to the discretion of the investors.

This is in contrast with the hypothesis of efficient markets which state that past performances alone do not predict future performances. In fact, it has been observed that asset prices trend. "Reasons for this momentum effect can be found in investors' behavior, supply and demand friction, positive feedback loops between risk assets and the economy, and even in the market microstructure" (Kolanovic, 2013).

The behavioral reason behind this effect can be explained by under-reactions and over-reactions of investors to market news. Indeed, they react with different speeds and often what happens is that, after an initial under-reaction, investors base their choices on past behaviors and therefore, they create price momentum. In addition, the so called "psychology of fear and greed" often causes investors to continue selling losing assets and buying winning assets.

Microstructure effects and behavioral patterns are often closely related as investors look for investments in products and strategies that mimic their behavioral biases. Fundamental causes are, instead, positive feedback loops between risk assets and the economy. These loops derive from the fact that a stronger economy boosts equities, which increase the overall wealth in the system that in turn boost spending and investing, boosting equities even more and so on. Since the production cycle is often slow to adjust to demand trends, a mismatch of asset supply and demand cycles may happen and lag increased demand from a booming economy. Consequently, persistent shortages of supply can lead to an upward price momentum.

Quality

Sloan (1996) found that stock prices do not fully reflect information. For this reason, this kind of strategies seek to capture excess returns justified by indicators of quality as defined by profitability, quality of earnings, operational efficiency and managerial strength. Quality factor seek to include in a portfolio those stocks with good and stable fundamentals. In order to classify a stock as a quality stock, investors look at several variables.

To analyze the profitability, they may consider measures such as ROE (Return on Equity), ROA (Return on Asset) and FCF (Free Cash Flow). To analyze liquidity, leverage and efficiency, they may look at variations in leverage, variations in number of shares and turnover. However, these are only few of the metrics that an investor could use. Indeed, depending on the investment manager, quality can mean gross profitability, return on invested capital, growth, stability of earnings, high payout rates, low volatility or other measures.

To summarize, as Assness and Frazzini (2013) state, investing in quality stocks means investing in safe, profitable, expanding and well-managed companies.

Size

Banz, back in 1981, was the first to find out that mid-cap and small-cap stocks generally outperformed large-cap stocks. These higher returns can be explained by two main reasons. First of all, small-cap stocks are usually riskier than large-cap stocks given that they are less liquid and more susceptible to changing business cycles, defaults and volatility. Second of all, they are usually more likely to grow. Nevertheless, the fact that this kind of stocks tends to be more volatile and illiquid given that the volumes exchanged in the market are not that big, is a huge drawback. However, as Asness (2015) shows in one of his studies, there are also high quality small-cap stocks, with good fundamentals and low volatility.

Low volatility

Haugen and Helns (1972) showed that low volatility stocks realized extra risk-adjusted returns. Later on, in 2011, Baker, Bradley and Wurgler came up with the concept of the low volatility anomaly which confirms the previous theory.

A common assumption in finance, indeed, is that increasing a portfolio's risk exposure should generate a higher return. In contrast, the low volatility anomaly refers to the observation that historically, portfolios of lower-volatility stocks produced higher risk-adjusted returns than portfolios with high-volatility stocks.

Low volatility factor utilizes volatility rankings while seeking to minimize the impacts of market fluctuations. This strategy is used especially during market crises, when investors seek safer assets. In times of macro-economic uncertainty, indeed, both realized and implied volatility tend to rise, and investors need to limit unforeseeable fluctuations.

Moreover, there is usually high correlation between volatilities since the drivers are often common to different asset classes. Volatility tends to persist in a regime for long periods of time, while transitions to a different regime are quick and difficult to predict. For this reason, the performance of these strategies tends to be more affected by tail events, rather than day to day volatility.

Carry

These strategies are designed to take advantage of the outperformance of higher yielding assets over lower yielding assets. Usually they involve holding long positions in higher yielding assets and short selling lower yielding assets. These opportunities usually derive from mispricing of asset yields. Although they are adopted across a wide range of asset classes, they are more popular across currencies and fixed income while they are not common in Equity risk factor investing. The closest strategies for carry are income and dividend base risk factors.

Dividend yield

This is a measure of how much a company returns to its shareholders on an annual basis. Companies characterized as high dividend tend to issue higher annual payouts. Historically, dividend yield factor has been assimilated to a value strategy as high yield often implies low growth or reflects a recent price decline. During the financial crisis of 2008, it started to be considered more like a quality factor and nowadays, an increasing number of investors treat dividend yield as a standalone factor.

While investors often focus on short-term price fluctuation, it is important to note that dividends account for a significant part of the equity premium, over the long-term. High dividend stocks tend to be related to more mature firms which are usually also less risky. Several studies show that investing in stocks which pay high dividend not only reduces volatility, but it also produces higher than average returns.

Factor Correlations

Over the last years, the correlation between traditional asset classes reached historical highs and it has been also quite volatile. As we already discussed above, one of the main advantages of risk factors, is that they show low correlation levels. From portfolio theory, volatility of the portfolio goes up as correlation among the assets goes up. This means that diversification works best with low correlations, and it does not work as well with assets that are highly correlated.

However, it has been noticed that, especially during times of stress, correlations between assets tend to increase. This means that when there are market declines, they happen across many different asset classes, even across those that have had low correlations historically.

This phenomenon is called "correlation breakdown" (Nurtaza, 2020) and it gives rise to portfolio downside tail risk.

The correlation structure of risk factors should be a key input for factor selection. It is important to keep in mind that it may also vary under different market regimes such as volatility, growth, inflation. Although the ability of a factor to generate risk premia can be analyzed for each factor separately, in order to understand the diversification value of a factor, one needs to analyze the factor's relationship to other factors in a portfolio.

Understanding factor correlations is essential, however, it may happen that investor do not ask for an ideal set of orthogonal risk factors. It is possible, indeed, to construct an orthogonal set of new factors, and some investors may prefer to do so.

A common approach to designing independent factors is Principal Component Analysis (PCA). This technique takes the original time series and re-weights them to create new uncorrelated (orthogonal) factors, which will be linear combinations of the original factors. The first principal component is the one that explains the largest portion of data variance (it is the 'vector' corresponding to the highest 'eigenvalue' of the diagonalized covariance matrix). The second principal component by design has zero correlation to the first principal component and explains the second largest portion of data variability, and so on.

Given that investors usually use only the top principal components to conduct their analysis, they may exclude the less volatile but potentially more important risk premium sources. Furthermore, sometimes the principal components could be falsely regarded as independent factors, which may lead to misunderstanding and misjudgment when the original risk sources are significantly non-normal.

Alternative weighting methodologies

Introduced by Sharpe in his "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk" (1994), the CAPM (Capital Asset Pricing Model) is the foundation for a number of index models, especially the capitalization-weighted indexes. This model assigns to cap-weighted portfolios the best trade off in terms of risk and returns.

The market capitalization of each stock is determined by taking the share price and multiplying it by the number of shares outstanding and the weight of a company in the index is equal to the market cap of that company divided by the total market cap of all the companies in the index. In this way, a company's weight within the index and its contribution to the overall performance is proportional to its size.

They are constructed to measure the characteristics and performances of specific markets. It provides a broad benchmark with which the market can be compared, promotes diversification and is relatively cheap to track. The problem with this methodology is that if securities do not trade at their fair values (which happens often), every stock that is overvalued will be overweighted, while those that are undervalued will be underweighted. Historical performance suggests that returns are in fact impacted by the choice of weighting methodology employed.

Despite the fact that this methodology is still commonly used, more and more alternative weighting methodologies have been used over the last years. In alternatively-weighted indexes, constituents' weights are determined independently of market capitalizations. They are targeted to specific objectives as reducing risk or improving diversification. The use of alternative weighting approaches attempts to address and overcome the main shortcomings of capitalization-weighted indexes such as (Zanutto, 2011):

- risk of concentration. Given that bigger companies have more weight in the index, they will affect more the overall performance, endanger a diversified index;
- risk of mispricing. The assets underlying the index can be mispriced (it is well known that they not always trade at their fair value) and consequently, also the index will be mispriced by construction;
- risk of a bubble bursting. Adding shares just based on market capitalization could mean adding overvalued stocks and assigning them a larger weighting, the purchase of these stocks could increase even further the price and the market capitalization, leading to a stock market bubble.

As mentioned in the previous session, academic research has shown how performance can largely be explained by some common characteristics (factors) such as size, value, price momentum, quality, and volatility. Alternative weighting mechanisms are designed to capture the performance of these factors. The aim of these indexes is to offer more focused exposures to factors than their market cap-weighted counterparts.

Equally-Weighted (EW)

Equally-Weighted (EW) indexes avoid overweighting companies with large market capitalization, reaching on average higher Sharpe ratios. This methodology holds an equal dollar amount of each component, so they all have the same weight within the index. The weights are a direct function of the number of companies in the index (e.g. if the index has 500 components, each one of them will have a weight of 0.2%).

Equal-weight indexes must be rebalanced periodically and the goal is maintain all the weights equals while keeping index turnover to a minimum. During the rebalancing process, shares of stocks with good performances in the previous period will be sold and those that performed poorly will be bought in order to keep the equal weight.

Looking at some equal-weighted indexes such as Standard & Poor's 500 Equal-Weight Index (EWI), we can see that it had superior long-term performance with respect to the S&P 500, except during periods of high volatility such as between 2019 and 2020. The reason is that longer periods are more favorable for small/mid-cap stocks, and indeed, the S&P 500 EWI has a greater exposure toward small-cap stocks with respect to the S&P 500 which gives more weight to larger companies. However, during times of crises, mid-cap and small-cap stocks are risker than large-cap stocks because of higher volatility, higher liquidity risk, higher probability of default.

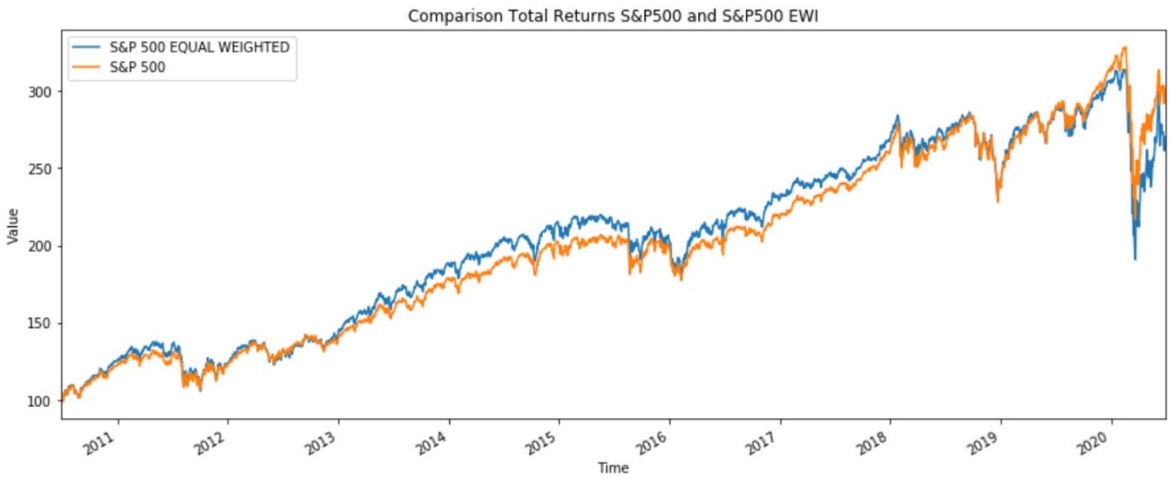


Figure 2. Source: author's elaboration. "Comparison Total Return S&P500 and S&P500 EWI".

Moreover, volatility tends to be higher in the S&P 500 EWI versus the S&P 500. According to a fact sheet released by S&P Dow Jones Indices, the annualized standard deviations of the past five years was 15.51% for the S&P EWI versus 13.65% for the S&P 500. This reflects the fact that smaller-cap stocks are generally more volatile than larger companies.

This difference in levels of volatility between small and large corporations is observed because large companies are usually more mature, stable and well-established firms.

Fundamental Indexing

A fundamental index attempts to go beyond these simpler approaches by selecting and weighting component stocks based on financial metrics such as sales, cash flow, earnings, revenues and dividends. They seem to occupy a middle ground between market-cap weighted and equal-weight indexes. “They tend to track somewhat closer to market-cap weighted index performance over time while avoiding those indexes' large-cap bias and vulnerability to momentum-driven markets.” (White, 2019).

Arnott, Hsu, and Philip Moore in a paper named “Fundamental Indexation” (2005), show that the fundamentals-weighted, consistently provide higher returns and lower risks than the traditional cap-weighted indexes while retaining many of the benefits of traditional indexing.

The argument behind fundamentally weighted indexes is that the price of a stock does not always represents the company’s true value. Prices are often influenced by a variety of factors such as speculations, momentum trading, buying and selling of stocks by institutions for tax purposes. Rob Arnott, Jason Hsu, and Phillip Moore in a study conducted in 2005, showed that fundamentally weighted indexes outperformed the S&P 500 by approximately 2% per year for the 43 years of the study. 2% per year is quite significant considering that, when compounded, it doubles the size of an investor's portfolio in 35 years (Wagner, 2019).

Based on some research conducted by Rob Arnott, chairman of Research Affiliates, by periodically rebalancing the weights based on the new and updated data, this kind of indexes will tend to have lower price/earnings ratio (P/E ratio) and less volatility than market-cap weighted indexes. Moreover, data also suggests that they usually overweight value stocks and underweight growth stocks. Listed below there are few examples of fundamental indexing:

- Dividends Weighted: this methodology ignores market capitalization and allocates weights base on cash dividends paid out. Therefore, companies who pay out more dividends have more weight.

- Earnings Weighted: this methodology determines companies’ weights based on reported earnings. Companies with higher earnings will account for a greater portion of the index. In this way, investors avoid potentially risky growth companies that have negative earnings, but at the same time, they are biased toward value stocks.

- Revenues Weighted: while dividend and earnings-weighted methodologies may bring to a value bias, revenue-weighted approach attempt to be more balanced, giving more weight to growth stocks. The drawback of this strategy is that revenues can be easily manipulated to meet shareholder expectations, modifying the real value of the assets.

Smart Beta Strategies

Also known as Alternative beta or Strategic beta, the concept of Smart beta has been around for decades even though the interest in these strategies has spiked in the last years. More and more investors are using alternative weighting and factors to pursue investment performance and/or help manage portfolio risk. Throughout the years, investors have tried to identify the sources of risk premia (e.i. the factors) explaining the excess return, in order to generate alpha. These new ways of capturing yield and mitigating risk are changing how risk is measured and returns are achieved.

While traditional beta is known as "market risk", the portion of excess return, positive or negative, is represented by the "alpha". Since these factors have been increasingly understood, identified, extracted and repackaged in a systematic way in order to invest in them, "traditional alpha" has become "smart beta". The goal of Smart beta methodologies is to make risk factors available, while providing different risk/return characteristics than the broad market.

Smart beta is something hybrid. The idea behind Smart Beta is to gain greater exposure to specific investment factors in a transparent, rules-based approach. However, Smart Beta strategies and factor investing are two different things. First of all, with the traditional factoring investing approach there is greater exposure to stock-specific risk. Indeed, risks inherent in the traditional factor approach have not been necessarily diversified away. For this reason, Eric Shirbini, global product specialist at ERI Scientific Beta, call Smart beta "smart factor" as they "identify all the stocks to include in a particular factor-based index, but use a diversification-based weighting scheme. That's what had been missing in the market".

Smart beta strategies lie between active and passive methodologies. Given their rules-driven nature, they may be seen as passive, however, they do not passively follow an index, but they seek exposure to factors. Therefore, the question now is if, with the growth of Smart Beta, investors will replace market-cap indexes or if they will replace active management.

Investors recognize that cap-weighted investments have several limitations and they are aware that Smart Beta does, at least in part, what active managers do. Moreover, they face lower cost, lower governance, and they need less oversight. Traditional fund managers charge high fees for their skills and ability of judgment. The quants are demonstrating that when these managers outperform, the excess return is often driven by factors that can be identified and commoditized.

This process started in 1970s, when investors started to realize that what was thought to be an outperformance deriving from active management, was instead identifiable with market factors. In other words, those excess returns did not derive from a good active management, but from the securities themselves.

Through Smart Beta, managers are able to actively choose the factors they want to invest in, while enjoying an index-like implementation. In this way they will have active-like returns and index-like costs, transparency and liquidity.

In determining a strategy, investors need to have in mind individual beliefs, objectives, tolerance for risk and time horizon. Smart Beta strategies have the potential for generating attractive long-term risk-adjusted performance. Indeed, they are able to improve Sharpe ratios without overpaying. However, integrating smart beta strategies within a broader portfolio requires an ongoing analysis and review and for this reason, even strategies based on the same factor, such as low volatility, can have huge differences in the way they are constructed and in performances.

Smart Beta strategies are usually used together with passive and active allocation strategies in a portfolio. Kal Ghayur, an Asset Manager from Goldman Sachs, says that the recommended allocation range between 20% and 40%, sometimes it could be more. This percentage depends on investment goals, philosophy and many other factors.

These strategies are added into a portfolio mainly because they provide two additional levels of diversification. First of all, he argues that "individual factor portfolios have unique risk-return characteristics, which result in low or negative pair- wise correlations […] and they are designed to provide an opportunity to realize significant risk reduction as well as return enhancement benefit". Second, by allocating them, investors add an additional layer of diversification.

These indexes are systematically rebalanced at pre-determined time frames using pre-defined construction rules. Securities are added or removed to maintain the market exposure to the specific factor(s) on which the index is based. According to the objective nature of these strategies, they stick to the rules and therefore, they will be rebalanced regardless of market sentiment.

Investors can choose to invest in a single factor or to combine multiple factors. There are some popular combinations such as value, quality and low volatility. This combination, for example, theoretically creates a portfolio with undervalued stocks with low volatility and higher-than-average quality. This "three-factor" approach also helps to neutralize cyclical variations and potential drawdowns due to factors' lifecycle.

When investing in a multi-factor strategy, timing and pricing are still important, but it becomes easier to implement the strategy in different points during the market cycles. Understanding and forecasting market conditions over time is crucial in order to analyze how the factors will be impacted and to choose which ones are best to invest in, in that specific point in time.

These strategies are not short-term strategies. Investors need to think more long-term and they have to consider at least one complete cycle. During factors' lifecycle there can be periods of significant underperformance but the risk-return profile is usually compelling in the long term. Moreover, by investing in multiple factors relative drawdowns are reduced because factors move differently in different market regimes, so the idea is to combine them to neutralize the negative trends.

Smart Beta ETFs

As Invesco argued in "Understanding smart beta", "through smart beta ETFs, investors have the ability to express market views, fine-tune exposures or diversify through core and satellite positions in pursuit of building better investment portfolios". As we have already said, Smart Beta ETFs base their strategies on indexes constructed upon predetermined rules and formulaic construction in order to access to a variety of risk factors.

Smart beta ETFs are investment tools that track smart beta indexes. Before them, investors did not have access to this kind of investments since it is not possible to directly invest in indexes. Moreover, advancements in technology made it possible for individual investors to access different factors of the market, even from home computers and mobile phones (Draper, 2016).

Beyond Equities

Although smart beta is usually discussed in the context of equities, it also has equal applications in fixed income and other asset classes, and it works in pretty much the same way. A fixed income index, for example, exposes investors to the most indebted issuers, which could be corporations, governments, or other entities. A smart beta strategy can weight credits by fundamental factors, such as GDP growth for sovereign debt. Concentration risk is an issue here as well, and potential losses can be triggered through defaults.

This kind of indexes are capable of performing well even in a scenario with rising rates and/or rising in the percentage of defaults in the world of credit.

After realizing which factors drive the returns, additional factors, such as underlying volatility or pricing volatility, can be built in as well. "It's the same process of asset allocation, but through a risk-factor lens" explains Sara Shores, managing director and head of strategic beta at BlackRock. A parent index could be customized to reduce downside credit risk for example underweighting or eliminating downgraded securities or those with the highest risk of default. Other techniques involve sorting issuers by their spreads or their sensitivity to interest rates (e.i. duration).

Other versions focus on rewarded risk factors, the drivers of return that underlie each asset class. Risk factors include macro factors like interest rates, inflation, credit, political, liquidity and economic risk. To create a strategy based on diversification by risk factors, investors need to identify which combination of asset classes gives the best exposure to each.

To summarize, in the financial world "good ideas are constantly repackaged as something new. Smart Beta is the latest example. It takes well-established, quantitative investing styles, or factors, and implements them in a simple, transparent manner, at lower fees than what we've seen in the past." (C. S. Asness, J. M. Liew, 2014).

While typically smart beta is thought as single-style, long-only equity strategies, many investors are migrating toward multi- style, long/short, multi-asset portfolios.

Single Factor Within a Single Asset Class (Long-Only)

Most Smart Beta funds today are still long-only equity strategies focused on one investment style or factor. These Smart Beta indexes are the most straightforward, they take long positions on stocks only. The difference with a traditional S&P500 is that these stocks are selected for having certain characteristic (such as low volatility or high dividends or low P/E, etc.) and they are not market-cap weighted.

Multiple Factors Within a Single Asset Class (Long-Only)

It has been demonstrated, however, that combining more than one factor at the time can bring to long-run, hypothetical excess returns with low correlation to traditional markets over multiple decades, in multiple geographies and asset classes.

Asness and Liew (2014) considered three investment styles together: Value, Momentum and Profitability. They showed the worst three-year hypothetical excess returns for each style along with the hypothetical performance for the other two styles during that same period. In each case, the worst performance for any one style is mitigated by the other two.

But how can investors combine them? There are two main ways. To invest separately in single-style funds a la carte (e.g., a value fund, a momentum fund, etc.), or to invest in a single fund that integrates multiple styles simultaneously. The second approach is naturally more efficient because of:

- lower transactions costs: these funds are able to net different style signals before trading, avoiding needless turnover;
- interaction benefits: a stock that may not be attractive in separate, single-style funds, might be among the most attractive when viewed across multiple styles, because of the interactions with other stocks;
- maintaining active risk: combining different separate single-style funds into a unique fund can lower “active risk” because drawdowns of a style will tend to partly be offset by the others.

Multiple Factors Within Multiple Asset Classes (Long/Short)

When implementing a long/ short Smart Beta strategy, we are moving away from "traditional" Smart Beta, which are usually long-only strategies, towards the so called "alternative risk premia" that we discussed in the previous session. In contrast to simpler form of Smart Beta, these long/short implementations generally use derivatives and leverage. However, it is really just Smart Beta where investors are going long the "smart" part and short the part that you consider less profitable, or even worthless.

Style premia, such as those analyzed above (value, momentum, etc.), can be found also in other asset classes such as bonds, currencies and commodities. Data suggest that many of the styles that work for predicting stock returns also work in other asset classes. In a study conducted by Clifford S. Asness and John M. Liew in 2014 using simulations from 1990–2013, it has been showed that there is a significant benefit from combining style premia and implementing them across multiple asset classes.

Risks

As in anything, there are risks involved with investing in Smart Beta ETFs, including possible loss of money. Even though index-based ETFs are not actively managed, they are subject, together with actively managed ETFs, to risks similar to stocks, including those related to short selling and margin maintenance. Moreover, as discussed in the previous session, the fund's return may not always match the return of the index.

These strategies seek to outperform a benchmark or reduce portfolio risk, or both, in active or passive vehicles. However, it might happen that Smart beta strategies underperform cap-weighted benchmarks and increase portfolio risk. It is not guaranteed, indeed, that an investment strategy will outperform or achieve its investment objectives as well as low volatility is not assured.

Smart Beta strategies are growing so fast that some economists, such as Scott Bauguess (SEC's chief economist), start to be worried. Through their automated investment strategies, they risk increasing the fragility of the market. The main risk is that a loop of behaviors, based on certain market trends, could happen, all without the intervention of human judgment. The same that happened on the Black Monday in 1987, during which Wall Street lost 22% in one day. This shows how automated trading programs may intensify the pressure on sales (or purchases). Moreover, several Smart Beta, in times of market stress, replace high-volatility assets with low-volatility assets, increasing even further the market instability.

Marro (2017) gave a concrete example of how automated "smart beta" strategies can contribute to market fragility. There are many ETFs today which invest in Low-Volatility stocks of the S&P500. Given that during the last years volatility was at historic lows, now those indexes give more weight to Tech companies. What would happen with a return of volatility? Most likely, the ETFs will start selling all those assets, in a complete automated manner, causing the so called “herding effect”.

Chapter 3

An Empirical Analysis on four Smart Beta Indexes

In the next session, four different Smart Beta Indexes will be implemented and explained. In order to understand how they are constructed and how they work, a description of their functioning and maintenance will be given before analyzing their performances over time. They take their cue from some of the “factors” described in chapter 2, with the aim of capturing risk premia in order to beat the market.

All four portfolios are long-only equity portfolios composed by stocks selected according to specific criteria which will be explained in detail below. The starting universe from which they are screened is composed by the 500 largest companies listed on stock exchanges in the United States. The four strategies in question are:

- Sharpe Ratio Index (SRI): It is a portfolio of large-capitalization stocks listed on US stock exchanges that have been screened for having the highest Sharpe Ratio as of the last business day of the second month of each calendar quarter. Its methodology selects five stocks in each one of the ten GICS sectors.
- Low Volatility Index (LVI): It is a portfolio of large-capitalization stocks listed on US stock exchanges that have been screened for low daily price volatility. Its methodology selects five stocks in each one of the ten GICS sectors.
- Strong Free Cash Flow Index (SFCFI): Focuses on companies with strong Free Cash Flow characteristics. Free Cash Flow is a powerful financial metric that incorporates a more comprehensive view of a company’s financial profile, including Capital Expenditures and Working Capital needs. As it will be explained more in details in the next session, it serves as fair, impartial and transparent measures of the performance of companies using the financial and business characteristics identified in their methodologies.
- High Dividend Yield Index (HDYI): It is a portfolio of large-capitalization stocks listed on US stock exchanges that have been screened for offering high dividend yields as of the last trading day of November. Its methodology selects five stocks in each one of the ten GICS sectors.

Selecting stocks from different sectors is a way of ensuring diversification across sectors and to limit the exposure to potential shocks happening in a specific sector. The ten GICS (The Global Industry Classification Standard) sectors (“the sectors”) taken into consideration are:

- Materials;
- Industrials;
- Consumer Discretionary;
- Consumer Staples;
- Health Care;
- Financials;
- Information Technology;
- Communication Services;
- Utilities. [8]

These indexes are entirely rules-based, which means:

⇒ they depend on a clearly defined rules-based methodology: this rules-based approach allows to avoid the substantial costs associated with human stock pickers and human capital in general;

⇒ no discretion is exercised in compiling the Indexes. The rules-book contains all the essential information and they are available to the public. Therefore, they need to be followed without exceptions;

⇒ pre-defined screening protocol assures a consistent, transparent and arms-length compilation process.

Benchmark Indexes

The Benchmark Indexes that will be used, are designed to provide accurate coverage of publicly listed US stocks that represent over 98% of the market capitalization of the US market and therefore, they can be assimilated with the overall market. All Benchmarks involved are weighted based on float market capitalization and they include an index constituted by the 500 largest US stocks (which will be called SN500) and an index constituted by the 1000 largest US stocks (which will be called SN1000).

The starting universe from which the stocks of the Benchmarks are retrieved, is formed by the largest-cap stocks domiciled in the US. However, certain stocks domiciled in countries other than the US are also included in the universe, provided the US is the principal place of business for these stocks and their primary stock exchange listing is in the US.

[8] The full list of GICS sectors include also Real Estate, which is not considered in the indexes' construction here.

Eligibility for inclusion in the starting universe (from which the stocks will be screened to be included in the Smart Beta Indexes) is determined based on the company's full market capitalization and buffers of 10% are applied to the eligibility criteria at each reconstitution for current constituents of the benchmark. Accordingly, stocks must fall below the following thresholds to be dropped from the Benchmarks.

Each of the Benchmarks has a value at inception of 1000 on their inception date, which is set to be 31st December 1999. This will facilitate the comparison between the different strategies and will make it easier to visualize the differences and similarities over their lifetime. Thus, all the indexes (both Benchmarks and Smart Beta) are back-tested starting from that date, in order to evaluate the performances over these last two decades.

The Indexes are reconstituted semi-annually on the third Fridays of June and December and are rebalanced quarterly on the third Friday of the last month of each calendar quarter. The selection criteria for the SN500 and the SN1000 include requirements for primary exchange listing, minimum market capitalization, minimum average daily trading volume, and other factors.

Eligibility Criteria and Weighting

Individual securities to be included in the indexes are screened and selected based on four different ranking systems depending on the risk factor that each index is exposed to. In all four Indexes the stocks are 100% domiciled in the US (a comprehensive list of all the components of each index can be found in the Appendix).

Sharpe Ratio Index

It includes stocks with the highest Sharpe Ratios as of the last business day of the second month of each calendar quarter. Sharpe Ratio is computed based on the 3-month average of a stock's outperformance of the risk-free rate divided by the 3- month daily standard deviation of the stock's price returns. Despite the fact that its methodology selects five stocks in each one of the ten GICS sectors, the distributions between the sectors can vary slightly due to index changes between two consecutive reconstitution dates (the same applies to High Dividend Yield Index and Low Volatility Index).

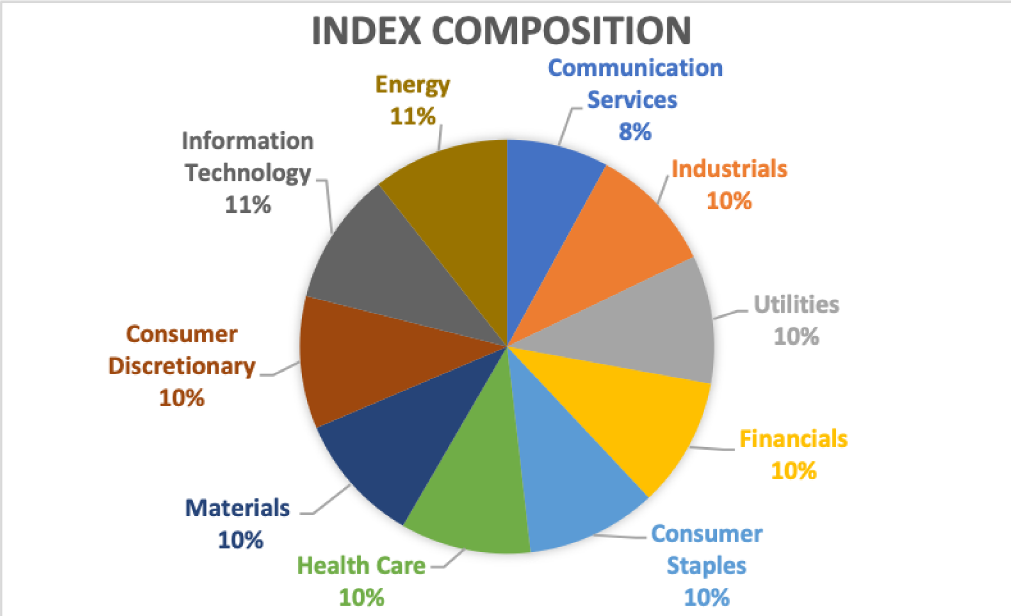


Figure 3. Source: author's elaboration. "Snapshot of Sharpe Ratio Index as at 31/03/2020".

Low Volatility Index

It includes stocks with the lowest daily price volatility over the previous year. Volatilities are updated quarterly on the last business day of the second month of each calendar quarter and the revised volatilities are applied on the quarterly reconstitutions. Volatilities are calculated using the following methodology. Daily standard deviation is calculated using the following formula:

$$\sigma = \frac{\Sigma\sqrt{(x-\mu)^2}}{n-1}$$

where n = number of observations. The daily standard deviation is then annualized by multiplying it by the square root of 252.

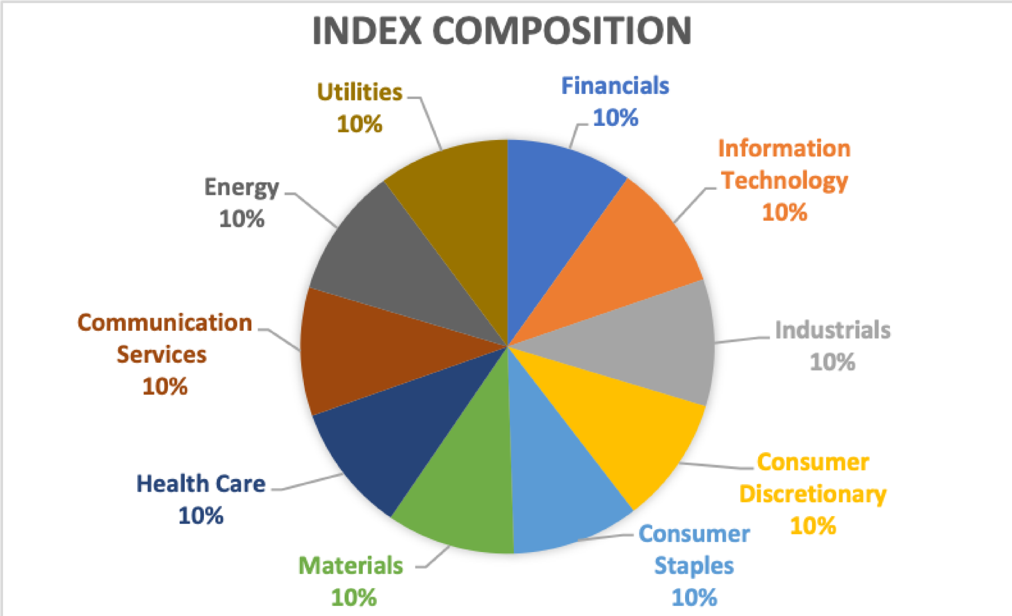


Figure 4. Source: author's elaboration. "Snapshot of Low Volatility Index as at 31/03/2020".

Strong Free Cash Flow Index

It includes stocks with the highest Free Cash Flows (FCF). FCF that can be taken directly from any publicly-traded company's Cash Flow Statement and it is equal to Cash Flow from Operating Activities less Capital Expenditures. Free Cash Flow is a particularly important metric in today's market environment because investors overall are concerned about a potential recession, high levels of corporate debt, and how they can generate income in a low (or now negative) interest rate environment.

Free Cash Flow is not only the fundamental element for why any investor would want to be a shareholder in a company (i.e. to receive cash distributions from that company), but also stands-out as being very difficult to paint a "rosier" picture of financial performance compared to reality. In contrast, all other common measures of financial performance can indeed "overestimate" a company's financial profile.

Free Cash Flow is a powerful and comprehensive measure of a company's profitability, while many other common financial metrics exclude key elements of a company's financial profile. For example:

a) Income: does not take into consideration Working Capital requirements of a business and can obscure Capital Expenditure needs; also, Net Income can be unfairly depressed by non-cash charges;

b) EBITDA: excludes interest expense, Working Capital needs, Capital Expenditures, and income taxes.

Investing in companies with only the most favorable Free Cash Flow characteristics is therefore a way to avoid potential pitfalls with elevated levels of corporate debt, since these companies are much less likely to encounter cash flow crunches.

When governments start to issue debt at negative interest rates (e.i. it promises to repay less money than the principal at maturity), it is natural for investors to start looking for yield via dividends from publicly-traded companies.

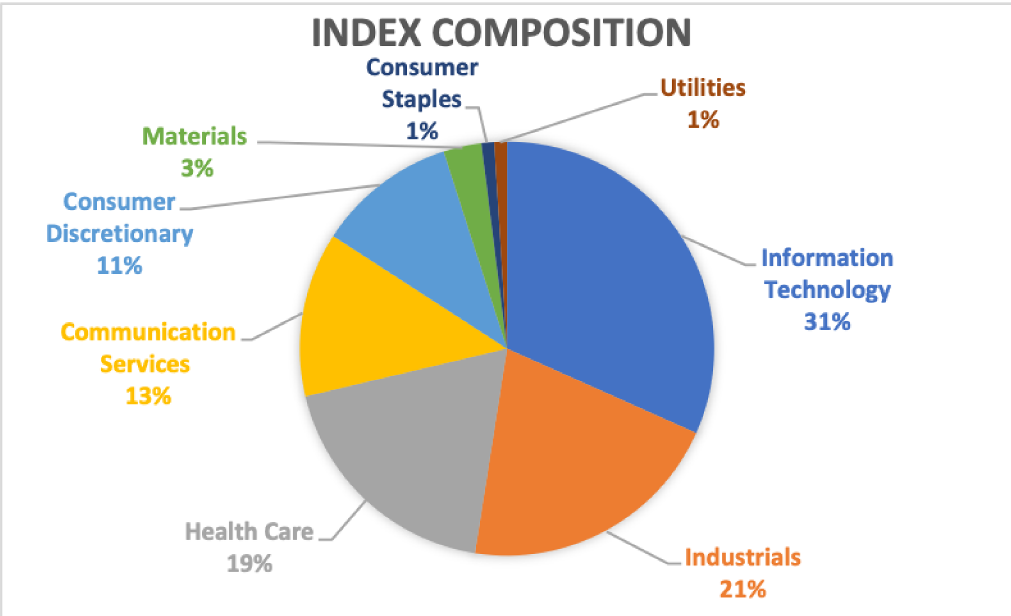


Figure 5. Source: author's elaboration. "Snapshot of Strong Free Cash Flow Index as at 31/03/2020".

High Dividend Yield Index

It includes stocks with the highest dividend yields as of the last trading day of November. Only stocks that have paid a dividend in each of the previous four calendar quarters and that are current constituents of the S&P 500 as of the last trading day of the second month of each calendar quarter ("the snapshot date") are eligible for inclusion in the index.

The Dividend Yield of a stock is obviously a natural metric to consider in identifying opportunities using this investment approach. However, Dividend Yield can be a misleading metric:

a) Low Dividend Yields can present an opportunity for yield-focused investors if a company is able to raise the amount of excess cash they distribute to shareholder via dividends. In this way, Dividend Yield may ignore additional upside that could be available from companies that have strong Free Cash Flow generation. At the same time, a low Dividend Yield could indicate that a company is very richly valued, if there is not much upside to the current dividend payout.

b) Companies that have high Dividend Yields could be quite attractive, but also could be a risky proposition. Often companies trade at high Dividend Yields because the market is skeptical that the business fundamentals will be able to sustain the current dividend payout.

Unlike other high dividend yield indexes, this Index will not include any qualitative screens, such as dividend growth, dividend consistency and coverage ratio. The indexes are based entirely on dividend yield, making them the only pure play dividend indexes available.

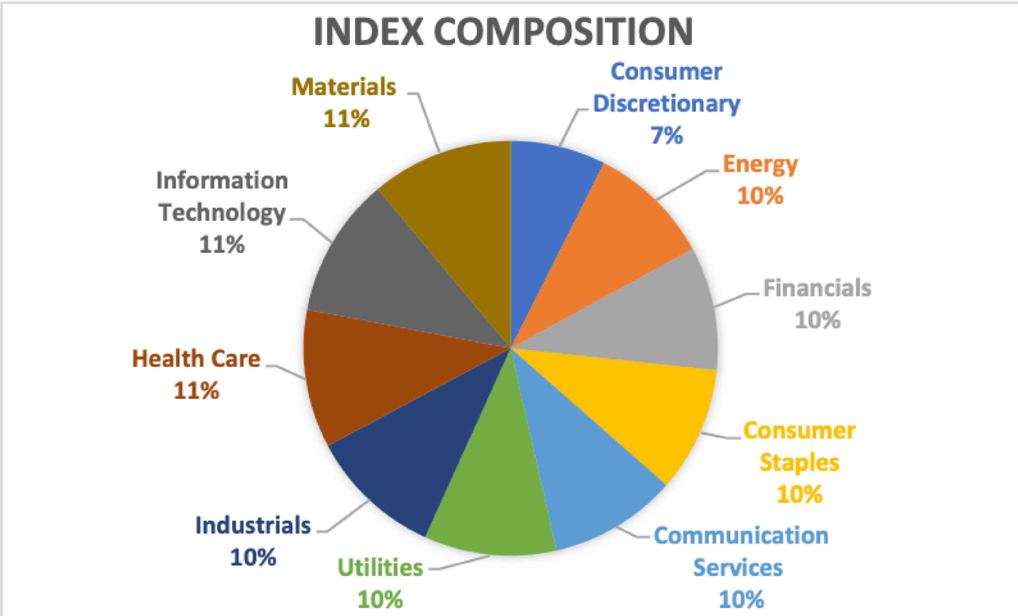


Figure 6. Source: author's elaboration. "Snapshot of High Dividend Yield Index as at 31/03/2020".

GICS sector classifications are updated quarterly as of the last trading day of the month prior to the rebalancing month. All stocks selected for inclusion in the indexes are equally weighted. As seen in the previous chapter, this methodology avoids momentum bias and domination by mega-cap stocks, while maintaining high correlation to the relevant benchmark. Share weights will be based on prices as of the close of trading on the second Friday of the rebalancing month ("The Record Date").

Rules for Reconstitutions, Rebalances, and Index Changes

Index Changes

The Indexes are rebalanced quarterly at the close of trading on the third Friday of the last month of each calendar quarter. Index changes take place at each rebalancing date except in the event of certain corporate actions, such as mergers, acquisitions, and delistings. In such cases, the change is applied on the effective date of the action, unless otherwise determined. Share increases and decreases are reflected on the rebalancing date. The Indexes are reconstituted quarterly on the third Friday of last month of each calendar quarter.

Additions and Deletions

Additions and deletions to the Indexes are made 1) at the close of trading on the quarterly reconstitution date and 2) in the event of the deletion of a constituent stock due to a corporate action. When a stock is deleted, a replacement will be added on the next rebalancing date.

Deletions are made at any time, in the event a stock is liquidated, de-listed, files for bankruptcy, is acquired, or merges with another stock. Upon deletion, the weight of the removed stock is reallocated proportionately to the remaining constituents. Additions are made only upon the effective date of the quarterly rebalancing.

If a stock is deleted from the universe from which it derives (SN500 or SN1000), the stock will be deleted from the index on the date of the next rebalancing. If a stock is deleted after the snapshot date for additions and deletions pursuant to quarterly rebalancings but before the rebalancing date, the stock will be deleted from the index and a replacement stock will be chosen.

Ongoing Maintenance

In addition to the scheduled quarterly reviews, the Indexes are reviewed on an ongoing basis. Changes in index composition and related weight adjustments are necessary whenever there are extraordinary events such as liquidations, conversions, delistings, bankruptcies, mergers or takeovers involving index components. In these cases, each event will be taken into account on its effective date.

- **Changes of Eligible Securities.** In the event that a component no longer meets the eligibility requirements described herein, it will be removed from the index on the effective date of the next rebalancing.
- **Changes of Sector Classification.** Stocks are eligible for inclusion in a specific Index based on their inclusion in an applicable sector. Mergers, takeovers, and spin-offs, may cause a stock to lose its eligibility. In such a circumstance, the stock will be deleted from the index on the effective date of the next rebalancing. A stock's classification may also require an immediate change as the result of a special event such as a merger, takeover or spin-off.
- **Mergers.** If two index constituents merge, their component positions will be replaced by the surviving stock immediately, and the weight of the removed stock will be redistributed to all the remaining constituents on a proportional basis. If an index constituent merges with a non-component stock, it will be removed from the index and its weight will be redistributed to all the remaining constituents on a proportional basis.
- **Takeovers.** If an index component is taken over by another component stock, the former will be removed from the index immediately upon completion of the takeover and the weight of the removed stock will be reallocated proportionately to the remaining constituents in the index. If an index component is taken over by a non-component stock, it will be removed from the index and its weight will be redistributed to all the remaining constituents on a proportional basis.
- **Spin-Offs.** In the event of a spin-off, the spun-off company's stock will be sold on the effective date of the spin-off and the proceeds will be reinvested directly back into the parent organization.
- **Conversions.** If an index component is converted to a non-eligible financial security, it will be deleted from the index and the weight of the removed stock will be reallocated proportionately to the remaining constituents in the index.
- **Share Offerings and Share Buy-Backs.** All Share Offerings and Buybacks that result in an increase or decrease of a constituent stock's shares outstanding will be implemented at the quarterly rebalancing.
- **Rights Offerings.** Rights will be executed, provided the rights are "in the money." The costs associated with exercising the rights will be derived proportionately from the remaining constituents in the index.

- **Removal of Stocks Due to Delisting, Bankruptcy or Extreme Financial Distress.** If an index constituent is de-listed by its primary market, or is in bankruptcy proceedings, it will be removed from the index.
- **Pricing of Stocks in Extreme Financial Distress for Index Maintenance.** When a stock is suspended from trading due to financial distress and subsequently de-listed by its primary market prior to resumption of trading, the Calculation Agent will use the best-available alternate pricing source to determine the value at which the stock should be removed from the index.

Calculation and Adjustments

Real-time stock prices are provided by Reuters. The latest trading price (close price) is used for index calculation. Corporate actions are sourced from public news services, regulatory filings, data vendors and Bloomberg Terminal. The constituent stocks themselves may be used as an additional source.

Index Formula

The index is calculated using a Laspeyres formula[9]. This formula is used for the calculation of both the total return index and the price index. The difference between the two is that the divisor D_t is different. A Laspeyres price index is computed by taking the ratio of the total cost of purchasing a specified basket of securities at current prices to the cost of that same basket at base-period prices and multiplying it by 100, which is considered to be the Base Index Value.

$$Index_t = \frac{\sum_{i=1}^{n}(p_{it} * q_{it})}{\left(C_t \sum_{i=1}^{n}(p_{io} * q_{io})\right)} * Base\ Index\ Value = \frac{M_t}{B_t} * Base\ Index\ Value$$

The above-mentioned formula can be simplified as: $Index_t = M_t / D_t$

Where:

$D_t = B_t /$ base index value = divisor at time (t)

n = the number of stocks in the index

[9] This formula is not the only one used in the market, other formulas such as Paasche Price Index or Fisher Price Index are also commonly used.

p_{i0} = the closing price of stock i at the base date

q_{i0} = the number of shares of stock i at the base date

p_{it} = the price of stock i at time (t)

q_{it} = the number of shares of stock i at time (t)

C_t = the adjustment factor for the base date market capitalization

t = the time the index is computed

M_t = market capitalization of the index at time (t)

B_t = adjusted base date market capitalization of the index at time (t)

The main advantages are that it is quite straightforward to use and understand, cheap to implement and the quantities for future years do not need to be calculated since only base year quantities are used. What keeps on changing is the value of the numerator that is affected by changes of prices from one period to another (Armknecht and Silver, 2012).

Dividend payments are not taken into account in the price indexes, whereas dividend payments are reinvested in the index constituents of the total return index on a proportional basis, but further details will be provided below. The adjustment protects the indexes from the effects of changes in index composition and the impact of corporate actions. See the “Adjustments for Corporate Actions” subsection below for details.

Changes in the index market capitalization due to changes in the composition (additions, deletions or replacements), weighting following quarterly reviews, corporate actions (mergers, or special cash or stock distributions of other stocks) result in a divisor change to maintain the index’s continuity. By adjusting the divisor, the index value retains its continuity before and after the event. For rights offerings, the rights will be priced during the subscription period, not before or after. Alternatively, they may start be priced after the ex-date and before the subscription period, under the condition that the rights are priced daily.

Divisor Adjustments

Corporate actions affect the share capital of component stocks and therefore trigger increases or decreases in the index. To avoid distortion, the divisor of the index is adjusted accordingly.

The following formulae will be used for divisor adjustments (note that they are not necessary for stock splits, since adjusted price = closing price * A / B new number of shares = old number of shares *B/A).

$$D_{t+1} = D_t * \left(\frac{\sum(p_{it} * q_{it}) \mp \Delta MC_{t+1}}{\sum(p_{it} * q_{it})}\right)$$

where:

D_t = divisor at time (t)

D_{t+1} = divisor at time ($t+1$)

P_{it} = stock price of stock i at time (t)

Q_{it} = the number of shares of stock i at time (t)

ΔMC_{t+1} = add new components' market capitalization and adjusted market capitalization

An index divisor may decrease (▼) or increase (▲) or keep constant (■) when corporate actions occur for a component stock. All the effects that corporate actions may have on the divisor and how to calculate their impact is showed in the following table.

Assuming shareholders receive "B" new shares for every "A" share held for the following corporate actions:

▼	CASH DIVIDEND (applied for total return index only)	adjusted price = closing price - dividend announced by the stock
■	SPECIAL CASH DIVIDEND:	adjusted price per share = closing price – special dividend amount adjusted shares = closing index market capitalization / adjusted price per share

■	SPIN-OFF	adjusted price per share = closing price per share – spinoff value adjusted shares = closing index market capitalization / adjusted price per share
■	SPLIT AND REVERSE SPLIT	adjusted price = closing price * A / B new number of shares = old number of shares * B / A
■	RIGHTS OFFERING	adjusted price = (closing price * A + subscription price * B) / (A + B) new number of shares = old number of shares * (A + B) / A
■	STOCK DIVIDEND	adjusted price = closing price * A / (A + B) new number of shares = old number of shares * (A + B) / A
▼	STOCK DIVIDEND OF A DIFFERENT STOCK SECURITY	adjusted price =(closing price * A - price of the different stock security * B)/A
▲	COMBINATION STOCK DISTRIBUTION (DIVIDEND OR SPLIT) AND RIGHTS OFFERING	Shareholders receive B new shares from the distribution and C new shares from the rights offering for every A shares held: If rights are applicable after stock distribution (one action applicable to other): adjusted price = [closing price * A + subscription price * C * (1 + B / A)] / [(A + B) * (1 + C / A)] new number of shares = old number of shares * [(A + B) * (1 + C / A)] / A If stock distribution is applicable after rights (one action applicable to other): adjusted price = [closing price * A + subscription price * C] / [(A + C) * (1 + B / A)] new number of shares = old number of shares * [(A + C) * (1 + B / A)]
▲	STOCK DISTRIBUTION AND RIGHTS	adjusted price = [closing price * A + subscription price * C] / [A + B + C] new number of shares = old number of shares * [A + B + C]

Price Return Index or Total Return Index?

Smart Beta ETFs, as well as other kinds of ETFs and investment funds in general, generate returns by two means: capital gains or losses due to appreciation or depreciation in the price of the of the asset (e.g., stock, bond, mutual fund unit) and income that may be generated (e.g., interest, dividends, coupons).

The Price Return Index, which has been the only one taken into consideration for gauging performance for many years, captures only the capital appreciation aspect of index constituents, and ignores the second component. It is calculated simply as the difference in value between the two periods divided by the beginning value. When talking about “returns on indexes” most referenced tend to be price return, especially when referring to changes over shorter time intervals, such as days or weeks.

However, since most assets have other cash flows during their lives (such as dividends), price return is usually a misleading representation of an investment’s return. Total Return Index, instead, has been introduced to make things transparent and credible. It includes both sources of profit to determine returns, or, more precisely, it adds to the price return also the income generated from the securities in the index.

The Total Return Index is based on the assumption that all dividends (or source of revenues in general) are reinvested into the index. The return of a total return index will always be higher price return index’s returns. This is a quite straightforward consideration, given that in the Total Return Index includes the additional payouts by way of dividends.

Morningstar’s research shows that 69% of large-cap funds outperformed the S&P BSE 100 PRI over the last five years but when compared with the S&P BSE 100 TRI, the percentage of large-cap funds outperforming the index comes down to 52% (Kapadia, 2018). This clearly demonstrate that the “dividends” part of returns can really make the difference in a fund’s performance and it needs to be considered. For this reason, comparison of an investment to alternatives or benchmarks should always be done on a total return basis (Rogers, 2017).

Looking at the performance of the four Smart Beta Indexes during the last ten years (2010-2020), it is clear that depending on the kind of strategy we are dealing with, there will be more or less discrepancy between price returns and total returns. The red line represents the Total Return Index and the white line the Price Return Index.

As we would expect, in the High Dividend Yield Index the difference between price returns and total returns is bigger than in any other strategy. This happens because this index is composed by companies with high dividend yield and therefore, including (or not including) the dividends payments in the return calculations makes a huge difference.

On the contrary, in the Strong Free Cash Flow Index the difference is minimal. In fact, this is in contrast with the assumption that companies with sufficient cash have better opportunities to maintain and expand their business while paying out persistent or growing dividends. Therefore, this (almost) overlapping between price return and total returns means that probably these companies are reinvesting inside the company, paying off debt, buying back stocks, or expanding the business instead of distributing large dividends.

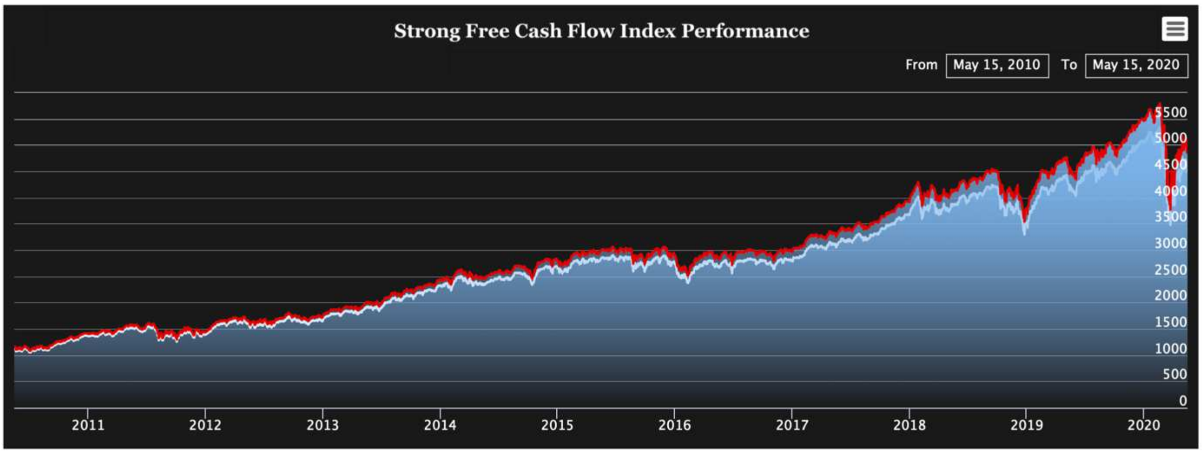


Figure 7. Source: author’s elaboration. “Total Return and Price Return of Strong Free Cash Flow Index”.

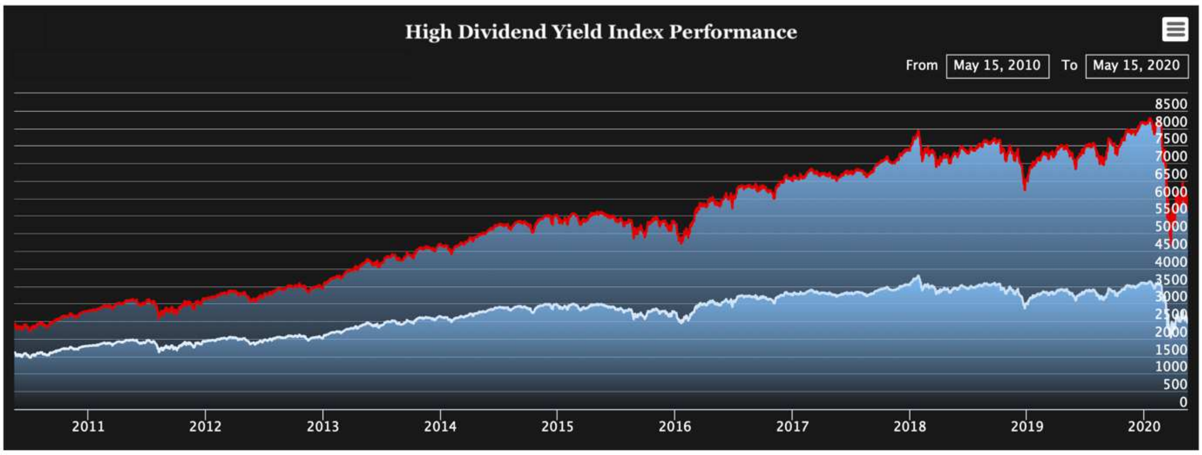


Figure 8. Source: author’s elaboration. “Total Return and Price Return of High Dividend Yield Index”.

Regarding the Sharpe Ratio Index and the Low Volatility Index, there is nothing particular to note except that we can further confirm what the theory suggests, namely that the Total Return Index is always higher than the Price Return Index.

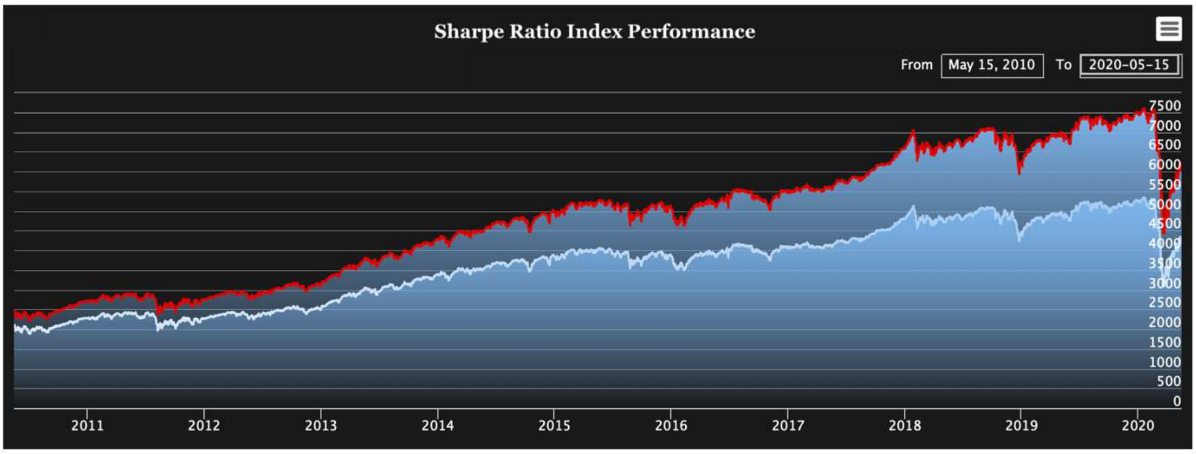


Figure 9. Source: author's elaboration. "Total Return and Price Return of Sharpe Ratio Index".

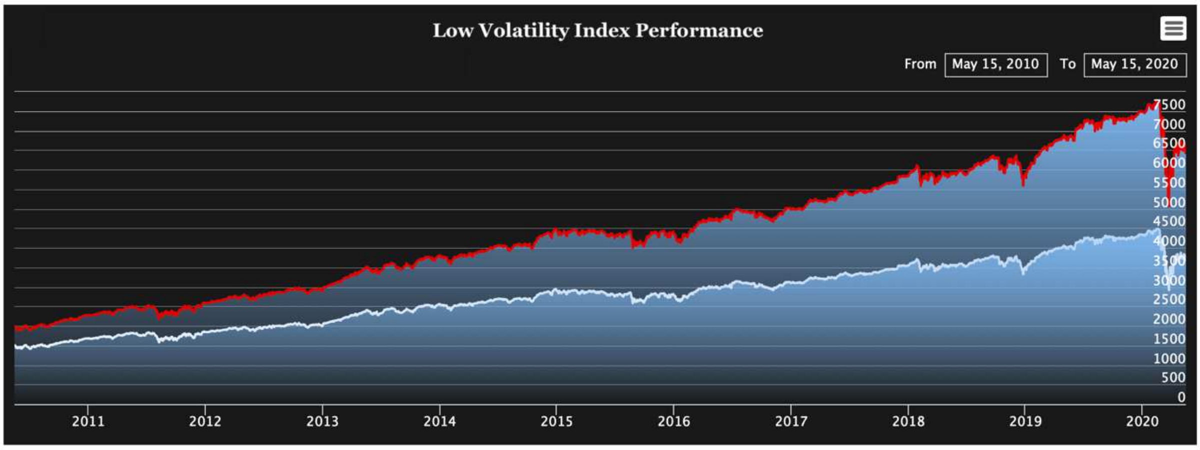


Figure 10. Source: author's elaboration. "Total Return and Price Return of Low Volatility Index".

Chapter 4

Time Series Analysis

In order to illustrate the basic properties of the four Smart Beta indexes described above, we examined the performance and the risk profiles of these indexes over the past 20 years. More precisely, we examined returns, volatility, tail risk, performance ratios and correlation metrics. In addition, we compared their performances under different economic environments and during shorter periods of time such as ten, five and three years. This study is conducted in order to see whether these strategies actually outperform the benchmarks, under which circumstances this might happen and for how long this could last.

We tested the four Smart Beta Strategies (SRI, LVI, HDYI and SFCFI) over a testing period that spanned December 1999 through May 2020. The main performance characteristics and risk properties, calculated since inception date, are shown in Table 1 and 2 below (more details are then showed in the Appendix). Moreover, to ensure fair comparisons, as already mentioned, the starting index values are normalized to 1000 as at December 31, 1999.

Overall, considering the testing period as a whole, all of the four indexes delivered excess returns relative to the market-cap-weighted indexes (SN500 and SN1000). So, if an investor had kept his position in these indexes for the entire twenty years, he would have gained more than the overall market. It is important to note, though, that each of the strategies we examined generated different levels of outperformance, and at different times. This has important implications for portfolio diversification.

Before going into the numerical details, it can be useful to visualize the pattern of the different time series over time, to have an overall understanding of how these indexes behaved over time, before analyzing them more quantitatively.

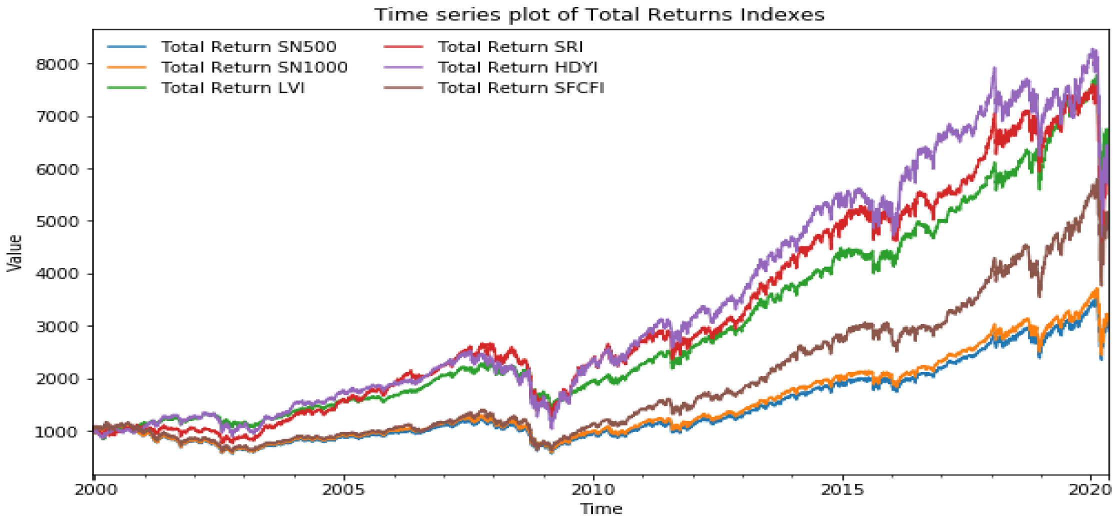


Figure 11. Source: author's elaboration. "Time series plot of Total Return Indexes".

From Figure 11 it is quite evident that, over their entire lifetime, the value of our four Smart Beta Strategies grew faster than the one of two benchmarks, which remained pretty close to each other during the whole testing period. The plot of the Total Return Indexes clearly shows that, starting from the same value at inception (1000), all four Smart Beta indexes delivered higher end values.

Moreover, it is important to note that, as we would expect, SN1000 is constantly slightly above SN500. The presence of smaller-cap stocks, indeed, allows to achieve higher returns, as the theory suggests. A more analytic view will be given in the next session, in which what we are now seeing graphically will be explained also numerically.

To develop a better understanding of our four strategies, we further studied their properties under different market regimes. In particular, we looked more in detail at their performances during the three main crisis of the last 20 years, namely the Dot Com Bubble (2000-2002), the Global Financial Crisis (2007-2008) and the outbreak of the Covid-19 pandemic. By looking at what happened during times of crisis and market uncertainty, we find an interesting result. We can observe a repetitive pattern, which is common to all these periods.

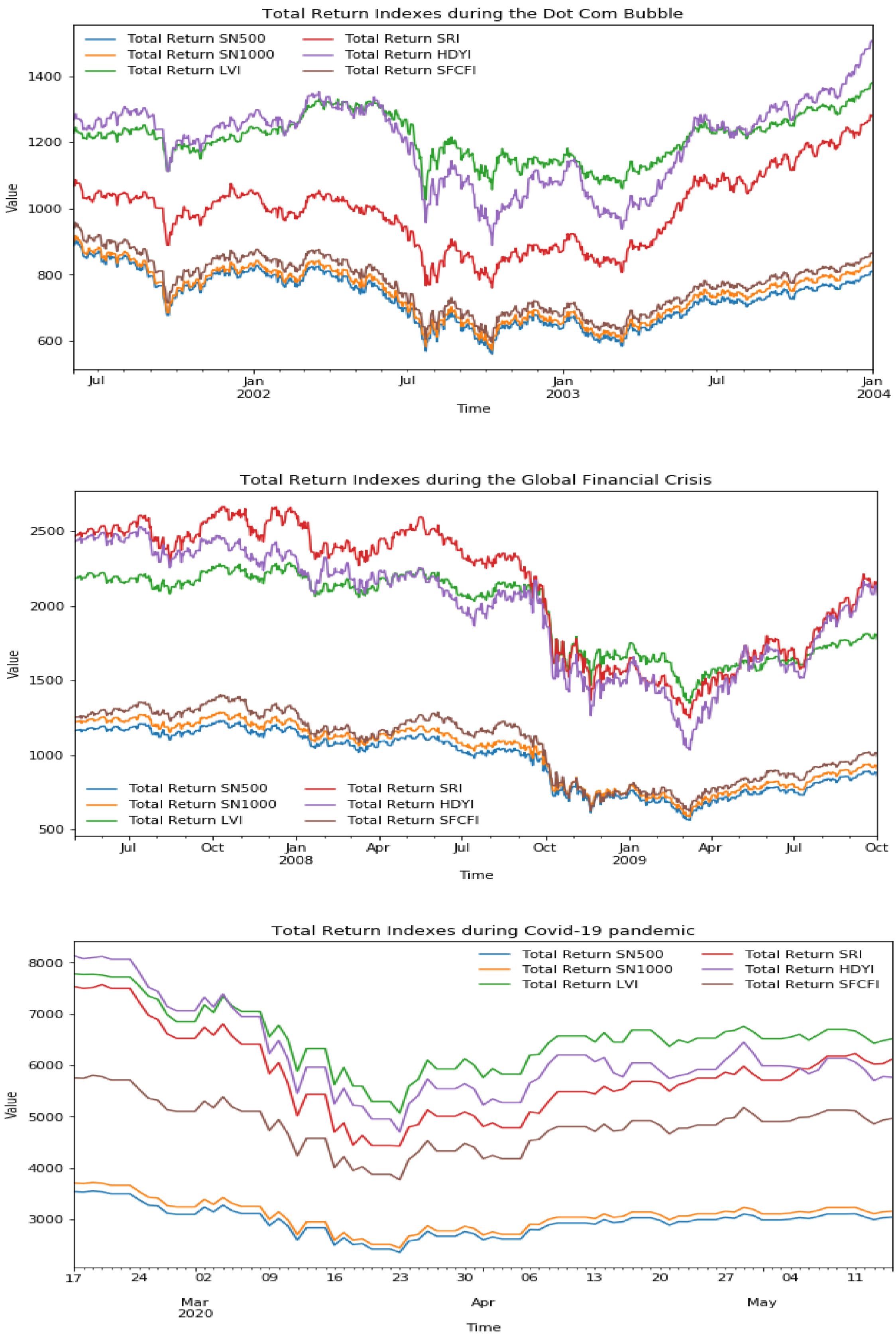


Figure 12. Source: author’s elaboration. “Total Return Indexes during times of crisis”.

Whilst during expansionary and periods of relatively calm of the market, Sharpe Ratio Index and High Dividend Yield Index (purple and red lines) tent to outperform the other indexes, during periods of market turmoil, they are overtaken by Low Volatility Index (green line).

From Figure 12, we can see that in the heart of all the above mention crisis, the Low Volatility Index (LVI) was well above the other indexes and, when the crisis in question ended, they came back to their normal path and the Low Volatility Index (LVI) was again surpassed by the Sharpe Ratio Index and High Dividend Yield Index.

During periods of growth, instead, as we can see from the graphs in the Appendix, Sharpe Ratio Index and High Dividend Yield Index showed a steeper increase and they have constantly been above the other indexes.

Since the analysis is conducted with the data only up to 15/05/2020, the Covid-19 crisis was not yet entirely overcome, and therefore, the LVI was still in his "up" phase at the time in which these graphs have been constructed. However, looking at what happened during the previous two crises, it is likely that it will present the same behavior.

Low volatility strategies outperformed in high volatility market environments most likely because during harsh periods investors prefer to invest in less risky, and therefore, less volatile stocks. During these periods, indeed, there is a persistent demand for safe haven instruments.

"High dividends" factors, instead, can be more vulnerable to market cycles, e.g. a classic episode of their failure was during the Covid-19 pandemic. These strategies, indeed, worked poorly during market distress and/or liquidity crunches.

During the most critical times, indeed, High Dividend Yield Index has been overcome both from Sharpe Ratio Index and Low Volatility Index. Most probably this was due to the fact that many companies started cutting down dividends in order to deal with the losses they were facing and to prevent potential liquidity risks.

Thus, we can say that, from our analysis, low volatility strategies are preferred during periods of stress while other strategies are preferred during times of growth. This finding clearly shows what has been already discussed in the previous chapters, that is that different strategies perform better in different market environments and that certain patterns tend to repeat themselves over time.

Thus, to summarize, we can say that when we consider the entire testing period, these factor strategies generated a clear pattern of outperformance relative to the benchmark indexes. However, there were periods when market-cap-weighted exposure generated higher returns than factor approaches. Different factors may outperform in different market environments. Therefore, investors can tilt their factor exposures in order to obtain excess returns and they can strategically combine different strategies to provide diversification potential.

Statistical profiles and analysis

If we look at the values over the entire life of these strategies (e.i. since inception) we can see that Low Volatility Index had the highest Total Return Appreciation (551,28%), followed by Sharpe Ratio Index (511,95%) and High Dividend Yield Index (476,37%). However, if we consider shorter periods of time[10] (such as the last one, three, five and ten years), we can easily note that this ranking is very much different.

If we consider the long term, indeed, all of the Smart Beta strategies have outperformed the benchmarks. However, looking at the last five years, as well as the last three years, the situation is reversed. Except for Strong Free Cash Flow Index, all the other indexes had smaller Total Returns appreciation than the benchmarks.

During the last one year, these three strategies registered even negative Total Return Appreciations, on the contrary of the two benchmarks which showed positive values. The same also applies to the Compound Annual Growth Rate (CAGR). The Strong Free Cash Flow Index is the only one that, considering all the different periods in question, performed better than the benchmarks.

However, if we look at the entire testing period, the CAGR of the Strong Free Cash Flow Index is not much higher than the other indexes (11,54% compared to an average of 9,28%). This means that it boomed during the last years, while it was quite stable for a long period of time at the beginning of our testing period. This may be linked to the fact that after the Global Financial Crisis, investors increased their interest in Value stock and stocks with good fundamentals in general.

[10] See the Appendix.

(Since inception)	SN500	SN1000	SRI	LVI	HDYI	SFCFI
Total Return Appreciation	192,27%	203,11%	511,95%	551,28%	476,37%	396,23%
Compound Annual Growth Rate (CAGR)	5,39%	5,58%	9,28%	9,61%	8,96%	11,54%
Annualized Standard Deviation	18,86%	18,93%	18,60%	14,54%	18,87%	19,61%
Sharpe Ratio	0,3160	0,3281	0,5439	0,6497	0,5621	0,6401
Skweness	-0,2453	-0,2922	-0,1865	-0,8126	-0,3514	-0,3368
Kurtosis	21,2747	20,7069	29,9052	20,0289	19,4994	16,2024

Table 1. Statistical Analysis – part 1.

Moreover, it is important to notice that there is little overlap between the constituents of SRI and HDYI. The Total Return Performance of SRI is comparable to that of HDYI, but SRI derives substantially more of its performance from ETF-Friendly Capital Gains rather than dividends.

What is worth dwelling on, is the Sharpe Ratio. The Sharpe Ratios (since inception) of the Smart Beta Indexes, indeed, are all higher than those of the benchmarks, which is positive, given that it is actually what we would like to have. However, if we look more in details at the last ten, five and three years, we see that this pattern is not constant over time and, in particular, the strategy that showed the lowest values of Sharpe Ratio is precisely the Sharpe Ratio Index, which is constructed by taking the stocks with the highest Sharpe Ratios.

During the three crises that we took into consideration, all portfolios (indexes and benchmarks) showed negative Sharpe ratios due to negative returns on average. However, during the Dot Com Bubble and the Global Financial Crisis, all four Smart Beta strategies showed better Sharpe ratio values than the benchmarks while during the Covid-19 crisis, the benchmarks had higher Sharpe ratios. Most likely, this happened because, on the contrary of the previous two crises, in the latter case the two benchmarks portfolio faced lower decline in returns and smaller increase in standard deviation than our strategies, which made it possible to achieve higher Sharpe Ratio values.

Skewness & Kurtosis

During the sample period, the distributions of returns are not normal, but, as we would expect, they are skewed (asymmetric), and have positive excess kurtosis (distributions' bar charts can be found in the Appendix). In the real world, indeed, it is very unlikely to find normal distributions, especially in financial markets.

All beta factors exhibited “fat tails” (kurtosis > 3). This means that they have a higher than normal probability of experiencing negative (or positive) returns. Periodic financial, geopolitical, and macroeconomic crises may lead to sharp losses for long-only positions in traditional assets (especially equity) and as we know, our four strategies are all constructed by taking long positions in US stocks.

Some studies conducted by JP Morgan, indeed, shows that the co-kurtosis between treasuries and equities is usually negative which suggests the use of Treasury bonds as a safe haven from equity market risks. Therefore, in our case, having four equity portfolios, we are highly exposed to several risks and to potential shocks, and the level of diversification is not optimal, even though the indexes are composed by a quite big baskets of securities.

Moreover, they are all negatively skewed, which means that the left tail of the distribution is longer than the right tail and this is generally not positive, because it highlights the risk of left tail events also known as “black swan” events. Therefore, the investor can achieve small (but more frequent) capital gains and the chances of losing money is generally lower (infrequent), however, the losses can be big if they happen.

(Since inception)	**SRI vs. SN500**	**LVI vs. SN500**	**HDYI vs. SN500**	**SFCFI vs. SN500**
Sortino Ratio	0,0250	0,0186	0,0086	0,2262
Treynor Ratio	0,0058	0,0071	-0,1042	-0,0865
Information Ratio	0,1365	0,1200	0,1300	0,1400
Downside Risk	8,17%	9,82%	28,12%	28,39%
Outperformance	308,84%	359,01%	284,10%	170,14%
Upside Capture Ratio	100,380	76,097	104,582	112,473
Downside Capture Ratio	81,676	46,818	80,904	83,505
Beta	0,9188	0,6301	0,9840	1,0722
Jensen’s Alpha (Annualized)	0,14%	0,22%	0,36%	0,44%

Table 2. Statistical Analysis – part 2.

Then, we analyzed the downside and upside capture ratio to gauge how these strategies performed during periods of weakness/strength of the benchmark indexes. In other words, how much of the market’s loss did each strategy realize? How much of the market’s gains did each strategy realize?

As already explained in Chapter 1, if a strategy shows a downside lower than 100 it has lost less than its benchmark in periods when the benchmark has been down (returns < 0). As we can see from the table above, all of the indexes have values less than 100, in particular the Low Volatility Index has a very low downside capture ratio with a value of 46,818. This is in line with the idea behind this index, that is to be less exposed to market fluctuations and to seek "safer" stocks, especially during times in which the market is "down". We can see how, even during the three crises that we considered, the Low Volatility Index realized the lowest losses relatively to the market.

On the other hand, an upside capture ratio over 100 indicates that a fund has generally outperformed the benchmark during periods of "up" of the benchmark (returns > 0). In this case, we can observe that, overall, Strong Free Cash Flow Index was the best while Low Volatility Index showed a pretty low upside capture ratio. It means that during periods of positive returns for the benchmark, it performed relatively poorly.[11]

However, given that this latter index is preferred during times of crisis and not during times of growth, this is not surprising. During expansionary times, indeed, investors prefer to invest in different strategies such as Dividend stocks or Value stocks. The more they invest in these strategies, the more their value grows, the higher the Upside Capture ratio.

Analyzing the annual returns of the above-mentioned methodologies, we can observe that they outperformed the benchmarks over multiple market cycles and in different economic climates, but they also underperformed them during others. For this reason, an investor should never stick with a strategy, but he should be able to mix and to alternate them depending on the historical period.

Our results, however, showed that they generally outperformed market-cap-weighted indexes also when adjusted for risk, which is what matters the most. Therefore, we are now going to analyze some risk-adjusted measures to see if, when the risk is taken into consideration, what we have seen until now remains still in place.

[11] These results are related to the entire life of the strategies. To see how they performed in the last 10, 5 and 3 years see the Appendix.

Ratios

In our sample, Low Volatility Index has the highest outperformance, followed by the Sharpe Ratio Index. Moreover, these strategies outperformed on other risk-adjusted measures as well, such as Sortino ratio, Treynor ratio, Information ratio.

Sortino ratio, as well as Sharpe ratio, is a risk-adjusted measures but, unlike Sharpe ratio, it penalizes only returns that fall below a certain "target return". Sortino ratio, indeed, uses the downside deviation instead of the standard deviation (which is influenced also by highly positive returns). The target return here has been set to 0, as we want to avoid negative returns. As for the Sharpe ratio, the higher the better.

Therefore, in our sample, Strong Free Cash Flow Index is the one that had the best performance. It is the only one, indeed, that has kept a positive Sortino ratios throughout its entire lifetime, while the other strategies faced one or more periods with negative values of Sortino ratios.

Unlike Sortino and Sharpe ratios, Treynor ratios, instead, is adjusted for systematic risk. The problem with Treynor ratio is that it only takes into account the systematic part of risk, which could lead to understate the real risk exposure and a non-well diversified portfolio could still show a good performance. This could actually be a problem in our case, given that, as we will also see in the next session when we will talk about the correlation matrix, our portfolios are not highly diversified. Among our strategies, however, the results of all four strategies are pretty much aligned with each other, with the Treynor ratio of the Low Volatility Index being slightly higher.

The fact that when we adjust the performance only for systematic risk, we obtain similar results for all the strategies, most likely means that they have similar exposures to systematic risk. Given that they are all US equity, precisely, makes them vulnerable to similar market shocks. Therefore, what makes the difference between these factors, is the specific risk. Indeed, for example, more mature companies (which have the highest percentage in High Dividend Yield Index) and more growing companies (which have the highest percentage in Strong Free Cash Flow Index) are exposed to different specific risks.

Lastly, Information ratio is one of the most important ratios in active management. Even though Smart Beta strategies cannot be defined as active strategies, we have seen that they are not purely passive either. Therefore, Information ratio is often used also for this kind of strategies as it helps measuring the outperformance of an active strategy over a benchmark.

As for the other ratios, a high and positive Information ratio is better because it means that an investor succeeded in outperforming the benchmark. Overall, our four indexes showed positive Information ratios, however, especially Sharpe Ratio Index and High Dividend Yield Index, had negative values more than one time during different periods. This means that more than one time, these strategies failed in beating the market.

If we look at how these strategies performed during times of stress, we see that during the Dot Com Bubble all four outperformed the benchmarks and during the Global Financial Crisis three out of four (all except for Sharpe Ratio Index) showed positive Information ratios. During the last crisis, however, these strategies failed in beating the market. As we already said when talking about the Sharpe Ratio, indeed, during the first months of this year, the two benchmarks presented higher returns than our strategies.

Beta & Alpha

In order to measure the performance of a strategy it is not sufficient to look only at its returns. Even though a strategy had higher returns the others, indeed, it may be that, when adjusted for risk, the scenario is not as good as it looked. Those higher returns could be justified by a higher risk exposure. In addition, a strategy could even show negative returns and still be a good investment. Indeed, negative returns do not imply necessarily a bad performance, if the market performed even worse during that period of time.

To analyze how our strategies performed relatively to the overall market (which is assumed to be represented by the 500 largest companies by market-cap), we can look at Jensen's Alpha. What we have already seen with the other risk-adjusted measures, is confirmed one again here. Our results, indeed, show that all four strategies outperformed the market during the last 20 years.

Moreover, three out of four strategies (namely LVI, HDYI and SFCFI) presented positive values also during shorter periods of time (see Appendix), with the only exception being Sharpe Ratio Index which had negative Jensens's Alpha for the last ten, five and three years. Even during periods of market instability, these smart indexes showed, on average, good performances relatively to the market, with the exception, once again, of the first months of 2020.

With regard to the Beta, we see that the Low volatility Index is the one with the lowest value over the entire testing period. This means that it is less volatile than the overall market and these findings are in line with the way this index is constructed. On the other hand, all other indexes have values very close to one and, most of the time, even higher than one. In other words, they are very sensitive to the market movements (they swing even more than the market). This, in general, may lead to higher returns but also to higher risk levels.

As well as during other time frames, also during the Dot Com Bubble, the Global Financial Crisis and the Covid-19 Pandemic the Low volatility Index has been less volatile than the other indexes and the market in general. High Dividend Yield Index and Strong Free Cash Flow Index, instead, are the ones with the highest betas (> 1) throughout all the different testing environments. These two indexes present high values of Alpha, which is a good feature, but at the same time, they also have high Betas. Thus, it is a matter of trade-off between risk and return and the investor's preferences once again.

However, when considering long-term risk, beta is not always reliable. Given that stocks tend to flip around over time, beta could be a fairly good measure when analyzing short-term risk but it is not as good for long-term horizons (Kenton, 2020).

Moreover, stocks with a low beta may have smaller price swings, yet they could be in a long-term downtrend. Similarly, stocks with high betas will increase portfolio volatility, but they may add gains as well if they are volatile in a mostly upward direction. It does not distinguish between upside and downside price movements. For this reason, investors should also evaluate them from other perspectives.

Some "margin of safety" needs to be considered in order to withstand unpleasant surprises. In this case the balance sheets may help in identifying some key elements such as low ratio of debt-to-total capital, consistency in earnings or dividends growth.

Correlations

Over the past several years the correlation between traditional asset classes, and especially in the stock market, rose to historical highs and often showed significant instability. High market volatility and unstable correlations damaged portfolios diversification. As it has been said in Chapter 2, two main benefits of "factor investing" approach are: providing access to new sources of premia and reducing portfolio correlation, enhancing diversification benefits.

Other than analyzing asset correlation levels, investors should also pay attention to correlation during periods of high market volatility. It is especially during volatile markets, indeed, that hidden correlations between assets may show up and give rise to portfolio downside tail risk.

Factors' correlation structure should be one of the key inputs in factor selection, and in the risk management of multi-factor portfolios. We could analyze separately the ability of different factors to generate a risk premium and then compare them and pick the ones with the characteristics that are closest to our preferences.

However, in order to understand the diversification value of a factor, or, in other words, the diversification benefits that it brings to the overall portfolio, we need to analyze the factor's relationship to other factors in that portfolio. Moreover, the correlation of a factor to other assets not only changes if considered together with other assets, but it may also change under different market regimes such as growth, volatility or inflation.

In an idealized world, risk factors are designed to be independent of each other. In the real world, factors will have non- zero correlations and in some cases may have significant overlap with others, as in our case. We will first study correlation properties of our smart beta strategies: Sharpe Ratio Index, Low Volatility Index, High Dividend Yield Index, Strong Free Cah Flow Index. We will then see how these values behaved during times of market stress with respect to normal market conditions.

(since inception)	*Total Return SN500*	*Total Return SN1000*	*Total Return LVI*	*Total Return SRI*	*Total Return HDYI*	*Total Return SFCFI*
Total Return SN500	1,000000	0,999258	0,954218	0,955396	0,944280	0,949732
Total Return SN1000	0,999258	1,000000	0,952840	0,958744	0,947176	0,955059
Total Return LVI	0,954218	0,952840	1,000000	0,925885	0,921186	0,897424
Total Return SRI	0,955396	0,958744	0,925885	1,000000	0,926534	0,922460
Total Return HDYI	0,944280	0,947176	0,921186	0,926534	1,000000	0,893755
Total Return SFCFI	0,949732	0,955059	0,897424	0,922460	0,893755	1,000000

Table 3. Correlation Matrix.

Table 3 shows a correlation matrix for the four Smart Beta strategies and the benchmarks indexes analyzed earlier in this section. The correlations showed here are calculated for the full sample period (December 1999- May 2020).

Given that these four portfolios have been constructed to be all long-only and made up with only one asset class (equity), they are among the most basic strategies. Indeed, as we can see from the correlation matrix, they are highly correlated with each other. Even the less correlated, which are Low Volatility Index-Strong Free Cash Flow Index and High Dividend Yield Index-Strong Free Cash Flow Index, show a very strong correlation.

Even though, in general, investing in indexes should lead to high degrees of diversification given the consistent number of constituents, in reality, they are all exposed to similar risks and therefore, they are highly correlated. Especially the four portfolios in question, which seek to capture different source of risk premia, but they are fully composed by US listed companies.

Although we have already a very high level of correlation among the four strategies throughout the entire testing period, we also note a trend of increasing correlation between the various strategies during periods of crisis. Correlation properties were slightly different for different alternative risk factors, however, all correlations increased during times of market stress (See Appendix). Under normal market condition the lowest and the highest correlation values have been, respectively, 0,8937 and 0,9553. During times of stress, instead, they have been 0,9288 and 0,9868.

Even though the jump has not been dramatic (since they had already high correlation values), we can still see a clear increasing trend. This should come as no surprise if we recall the concept of correlation breakdown that we discussed in Chapter 2. Given that all the constituents of our indexes belong to the same assets class and they are also listed in the same stock market, they are subject to similar shocks.

In order to achieve a diversification benefit, investors would need to combine different strategies, to add other types of securities such as bonds or commodities, and/or to take long-short positions depending on the different market cycle in which the economy is. Also the addition of assets from different geographic areas may help increasing the diversification since different markets and different economies could exposed to different shocks or, at least, not in the exact same way.

Risk-Return Profiles

One of the first steps in the factor selection process is to analyze the historical performance of factors. For instance, an investor can rank a universe of factors based on annualized returns or historical risk measures. Alternatively, investors can rank factors based on their diversification ability that is looking at the average correlation to other risk factors.

To construct a well diversified portfolio, investors can rank each of the factors by weighting measures such as performance (Sharpe ratio, Sortino ratio, etc.), diversification and tail risk at their discretion.

The metric used to evaluate factors and assign a ranking will differ based on investors' risk preference and risk aversion. For instance, unlevered investors probably will prefer to use absolute returns instead of Sharpe ratios, and risk-averse investors may emphasize tail risk ranking and include additional risk rankings such as duration of draw-down, downside risk or co-kurtosis.

One of the main questions for an investor, most of the times, is if the historical performance and risk properties of a certain factor will persist or they will mean revert. Past performances, indeed, may be a good starting point, but they are not a guarantee for the future performances.

In terms of risk and returns, as already said, each investor may have different views and there is not a unique solution about the best strategy to pick. If we look at our strategies' profiles, we clearly see that they are very different from each other. While some of them are clearly suboptimal, the others could all be potentially chosen by the investor, depending on his preferences.

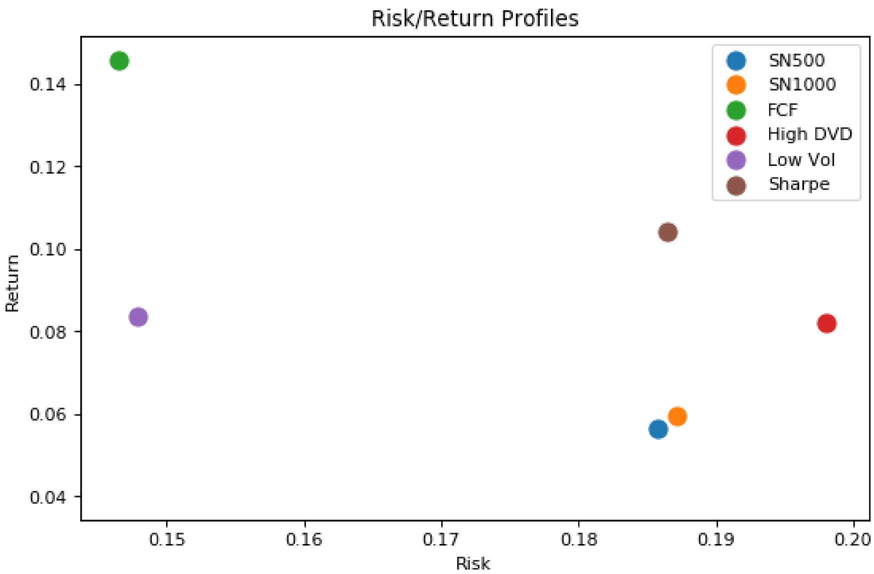


Figure 13. Source: author's elaboration. "Risk/Return Profiles".

In Figure 13, we find the returns on the vertical axis and the risk, intended as the annualized standard deviation of returns, on the horizontal axis. As we can see, SN500 and SN1000 are close to each other both in terms of risk and returns. SN1000 has slightly higher risk as well as slightly higher returns. This is justified by the presence of mid- and small-cap stocks in its basket, which, as we know, are usually subject to higher risks but also higher rewards.

Regarding our four Smart Beta strategies, from this point of view, Low Volatility Index clearly outperforms the High Dividend Yield Index. While they have a very similar value for returns, the High Dividend Yield Index has a much higher level of risk, which makes it unpreferable to a rational investor. The same applies to the Sharpe Ratio Index, which has higher returns and lower risk than the High Dividend Yield Index.

Looking at this graph, it seems that the Strong Free Cash Flow Index is superior to every other index, given that it has very low risk and high returns. However, we have to keep in mind what we have seen in the previous sessions, namely that these results are based on a long-time horizon which considers the whole life-time of these strategies up to now and therefore, single periods of time taken alone could present different scenarios.

Indeed, to give an example, if we look at annual returns (see Appendix), the Strong Free Cash Flow Index in 2008, with a -40,63%, had the worst performance among all the other indexes, included the benchmarks.

During different market regimes and different time periods, indeed, the performance of these strategies has been very much different. For this reason, an investor should always be careful when choosing a risk factor and fully understand the market cycle in which he currently is when investing.

However, assuming that an investor would have kept these strategies in his portfolio for the entire period, three out of four Smart Beta Strategies (Low Volatility Index, Sharpe Ratio Index, Strong Free Cash Flow Index) were to be preferred over the benchmarks since they had higher returns and lower risk. The only exception is the High Dividend Yield Index that had higher returns but it also also higher risk and therefore, in this specific case, the choice depends on the risk aversion of the investor.

All that being said, historical information is not indicative of future results and current data may differ from data quoted. Moreover, investors cannot invest directly in indexes, but they need to use some specific tools such as ETFs. Therefore, the index returns analyzed in this study, do not reflect any management fees or brokerage expenses which may slightly affect the overall returns for the investor.

Conclusions

The present work aimed at studying four different Smart Beta Strategies (namely Low Volatility Index, Sharpe Ratio Index, High Dividend Yield Index and Strong Free cash Flow Index) and at analyzing their behaviors, performances and characteristics over time. The main question to which this work tries to answer is if these kinds of strategies are really able to outperform the market or if their reputation is not confirmed by the actual data. Moreover, this study shows the positive and negative sides of each one, highlighting the differences between them.

After analyzing these strategies under different aspects, we can say that they may be a valid alternative to many active funds. Their ability to generate extra returns, also when the market is in conditions of crisis, like seen for the Low Volatility Index, makes them highly competitive products in the financial world.

Smart Beta ETFs and, in general, multi-factorial models strategies are aimed at a wide and diversified audience. The choice of a smart beta, a combination of these, or a multifactorial model, always depends on the characteristics of the investor, as well as his utility function and performance objectives, his risk aversion and the holding period. Especially the latter is a crucial element in investment decisions since the indexes' performances over different time horizons are highly fluctuating. Indeed, they all outperformed the benchmarks over the long-term, however, there have been many occasions in which the situation was completely opposite.

Under "normal" market conditions, e.i. under period of relatively calm of the market, all the analyzed portfolios offered higher returns with respect to the benchmarks. However, as we have seen, the trade-off between risk and return of these products may vary according to market trends. Consequently a High Dividend Yield Index is not convenient anymore in a moment of recession, so like a Sharpe Ratio Index is not adapted in a situation of elevated volatility in the markets.

Thus, the possibility of generating an extra-return compared to the market should not lead investors to think about using Smart Beta ETFs as a way to replace traditional Exchange Traded Funds. Their implementations in a portfolio, indeed, have different functions. In particular, traditional market-cap ETFs are the only ones that allow to pursue a purely passive strategy over the long-term, with low turnover. On the other hand, Smart Beta ETFs offer a partial exposure to the market so that the investor can express his vision and he can benefit from an excess return that was previously accessible only through mutual funds but at a higher cost.

In addition, when approaching these new products, investors should take into account certain elements such as transaction costs when assessing alternatives, costs associated with rebalancing and reconstitution activities and the intrinsic cyclicity of the factors used. Moreover, the potential yield created by these products may be adversely affected by exchange rates, interest rates, or other economic and political factors. Therefore, we can confirm the overall superiority of these strategies only if used properly. This means that investors should be able to select the right strategy for the right moment, that is depending on which phase of the market cycle they are investing.

However, that being said, the four portfolios analyzed in this paper are among the most basic Smart Beta strategies and they are obviously not enough to have a full awareness of this huge world regarding alternative risk premia. They could be improved by adding different asset classes in order to increase diversification (not only equity), including assets from various geographic regions (not only USA) and also going short on some of them (not only long).

Appendix

Python Code for the MVO Portfolio

```
import pandas as pd
import numpy as np
from pandas_datareader import data, wb
import datetime
import scipy.optimize as sco
from scipy import stats
import matplotlib.pyplot as plt
%matplotlib inline

In [185]:
#take adjusted closed prices of Apple, Facebook, Netflix and Amazon
stocks from 15th May 2010 to 15th of May 2020.

Tickers = ['AAPL','FB', 'NFLX', 'AMZN']
start = datetime.datetime(2010, 5, 15)
end = datetime.datetime(2020, 5, 15)
df = pd.DataFrame([data.DataReader(ticker, 'yahoo', start, end)['Adj
Close'] for ticker in tickers]).T
df.columns = tickers

In [186]:
#simulate random portfolios and calculate returns, standard deviation and
Sharpe Ratio

def calc_portfolio_perf(weights, mean_returns, cov, rf):
    portfolio_return = np.sum(mean_returns * weights) * 252
    portfolio_std = np.sqrt(np.dot(weights.T, np.dot(cov, weights))) *
np.sqrt(252)
    sharpe_ratio = (portfolio_return - rf) / portfolio_std
    return portfolio_return, portfolio_std, sharpe_ratio
def simulate_random_portfolios(num_portfolios, mean_returns, cov, rf):
    results_matrix = np.zeros((len(mean_returns)+3, num_portfolios))
    for I in range(num_portfolios):
        weights = np.random.random(len(mean_ret      urns))
        weights /= np.sum(weights)
        portfolio_return, portfolio_std, sharpe_ratio =
calc_portfolio_perf(weights, mean_returns, cov, rf)
        results_matrix[0,i] = portfolio_return
        results_matrix[1,i] = portfolio_std
        results_matrix[2,i] = sharpe_ratio
        #iterate through the weight vector and add data to results array
        for j in range(len(weights)):
            results_matrix[j+3,i] = weights[j]
```

```
    results_df =
pd.DataFrame(results_matrix.T,columns=['ret','stdev','sharpe'] + [ticker
for ticker in tickers])

    return results_df
In [187]:
mean_returns = df.pct_change().mean()
cov = df.pct_change().cov()
num_portfolios = 10000
rf = 0.0 #risk-free rate
results_frame = simulate_random_portfolios(num_portfolios, mean_returns,
cov, rf)

In [188]:
#locate position of portfolio with highest Sharpe Ratio and portfolio with
minimum standard deviation

max_sharpe_port = results_frame.iloc[results_frame['sharpe'].idxmax()]
min_vol_port = results_frame.iloc[results_frame['stdev'].idxmin()]
#create scatter plot coloured by Sharpe Ratio
plt.subplots(figsize=(15,10))
plt.scatter(results_frame.stdev,results_frame.ret,c=results_frame.sharpe,cm
ap='RdYlBu')
plt.xlabel('Standard Deviation')
plt.ylabel('Returns')
plt.title('Simulated portfolios illustrating efficient frontier')
plt.colorbar()
#plot red star to highlight position of portfolio with highest Sharpe Ratio
plt.scatter(max_sharpe_port[1],max_sharpe_port[0],marker=(5,1,0),color='r',
s=500,label='Max Sharpe ratio')
#plot green star to highlight position of minimum volatility
plt.scatter(min_vol_port[1],min_vol_port[0],marker=(5,1,0),color='g',s=500,
label='Min Volatility')
plt.legend(fancybox=True, framealpha=1, shadow=True, borderpad=2,loc='lower
right',labelspacing=1.5)
plt.show()
```

Full list of Indexes' Components as at 31.03.2020

Sharpe Ratio Index Components as of 31.03.2020			
Ticker	Company Name	Country	Sector
MNST US	Monster Beverage Corp	United States	Consumer Staples
MSCI US	Msci Inc	United States	Financials
NFLX US	Netflix Inc	United States	Communication Services
REGN US	Regeneron Pharmaceuticals Inc	United States	Health Care
WMB US	The Williams Companies Inc	United States	Energy
AWI US	Armstrong World Industries	United States	Industrials
BLL US	Ball Corp	United States	Materials
KMI US	Kinder Morgan Inc	United States	Energy
LBRDK US	Liberty Broadband Corp C	United States	Communication Services
BRO US	Brown & Brown Inc	United States	Financials
OKE US	Oneok Inc	United States	Energy
VRSK US	Verisk Analytics Inc	United States	Industrials
DAR US	Darling Ingredients Inc	United States	Consumer Staples
DPZ US	Domino'S Pizza Inc	United States	Consumer Discretionary
LW US	Lamb Weston Holdings Inc	United States	Consumer Staples
KR US	Kroger Co	United States	Consumer Staples
CLX US	Clorox Co	United States	Consumer Staples
NEE US	Nextera Energy Inc	United States	Utilities
ETSY US	Etsy Inc.	United States	Consumer Discretionary
DOCU US	DOCUSIGN INC	United States	Information Technology
ALB US	Albemarle Corp	United States	Materials
SITE US	Siteone Landscape Supply Inc	United States	Industrials
ZTS US	Zoetis Inc	United States	Health Care
NEM US	Newmont Corp	United States	Materials
TDOC US	Teladoc Health Inc	United States	Health Care
NYT US	New York Times Co A	United States	Communication Services
THO US	Thor Industries Inc	United States	Consumer Discretionary
AEE US	Ameren Corp	United States	Utilities
TMUS US	T-Mobile Us Inc	United States	Communication Services
RNG US	Ringcentral Inc A	United States	Information Technology
Z US	Zillow Group Inc C	United States	Communication Services
ZM US	Zoom Video Communications Inc – A	United States	Information Technology
TW US	Tradeweb Markets Inc – A	United States	Financials
APA US	Apache Corp	United States	Energy
SMG US	Scotts Miracle-Gro Compnay	United States	Materials
PCG US	Pg&E Corporation	United States	Utilities
SYNH US	Syneos Health Inc	United States	Health Care

SLM US	Slm Corp	United States	Financials
DXCM US	Dexcom Inc	United States	Health Care
NUAN US	Nuance Communications Inc	United States	Information Technology
AJRD US	Aerojet Rocketdyne Holdings Inc	United States	Industrials
CTVA US	CORTEVA INC	United States	Materials
TERP US	Terraform Power Inc A	United States	Utilities
CVX US	Chevron Corp	United States	Energy
SEDG US	Solaredge Technologies Inc	United States	Information Technology
CWEN US	Clearway Energy Inc Cl C	United States	Utilities
CHWY US	Chewy Inc Class A	United States	Consumer Discretionary
VIRT US	Virtu Financial Inc. A	United States	Financials
SCI US	Service Corp Intl	United States	Consumer Discretionary
TREX US	Trex Co	United States	Industrials

Low Volatility Index Components as of 31.03.2020			
Ticker	Company Name	Country	Sector
MNST US	Monster Beverage Corp	United States	Consumer Staples
MSCI US	Msci Inc	United States	Financials
NFLX US	Netflix Inc	United States	Communication Services
REGN US	Regeneron Pharmaceuticals Inc	United States	Health Care
WMB US	The Williams Companies Inc	United States	Energy
AWI US	Armstrong World Industries	United States	Industrials
BLL US	Ball Corp	United States	Materials
KMI US	Kinder Morgan Inc	United States	Energy
LBRDK US	Liberty Broadband Corp C	United States	Communication Services
BRO US	Brown & Brown Inc	United States	Financials
OKE US	Oneok Inc	United States	Energy
VRSK US	Verisk Analytics Inc	United States	Industrials
DAR US	Darling Ingredients Inc	United States	Consumer Staples
DPZ US	Domino'S Pizza Inc	United States	Consumer Discretionary
LW US	Lamb Weston Holdings Inc	United States	Consumer Staples
KR US	Kroger Co	United States	Consumer Staples
CLX US	Clorox Co	United States	Consumer Staples
NEE US	Nextera Energy Inc	United States	Utilities
ETSY US	Etsy Inc.	United States	Consumer Discretionary
DOCU US	DOCUSIGN INC	United States	Information Technology
ALB US	Albemarle Corp	United States	Materials
SITE US	Siteone Landscape Supply Inc	United States	Industrials
ZTS US	Zoetis Inc	United States	Health Care

NEM US	Newmont Corp	United States	Materials
TDOC US	Teladoc Health Inc	United States	Health Care
NYT US	New York Times Co A	United States	Communication Services
THO US	Thor Industries Inc	United States	Consumer Discretionary
AEE US	Ameren Corp	United States	Utilities
TMUS US	T-Mobile Us Inc	United States	Communication Services
RNG US	Ringcentral Inc A	United States	Information Technology
Z US	Zillow Group Inc C	United States	Communication Services
ZM US	Zoom Video Communications Inc – A	United States	Information Technology
TW US	Tradeweb Markets Inc – A	United States	Financials
APA US	Apache Corp	United States	Energy
SMG US	Scotts Miracle-Gro Compnay	United States	Materials
PCG US	Pg&E Corporation	United States	Utilities
SYNH US	Syneos Health Inc	United States	Health Care
SLM US	Slm Corp	United States	Financials
DXCM US	Dexcom Inc	United States	Health Care
NUAN US	Nuance Communications Inc	United States	Information Technology
AJRD US	Aerojet Rocketdyne Holdings Inc	United States	Industrials
CTVA US	CORTEVA INC	United States	Materials
TERP US	Terraform Power Inc A	United States	Utilities
CVX US	Chevron Corp	United States	Energy
SEDG US	Solaredge Technologies Inc	United States	Information Technology
CWEN US	Clearway Energy Inc Cl C	United States	Utilities
CHWY US	Chewy Inc Class A	United States	Consumer Discretionary
VIRT US	Virtu Financial Inc. A	United States	Financials
SCI US	Service Corp Intl	United States	Consumer Discretionary
TREX US	Trex Co	United States	Industrials

Strong Free Cash Flow Index Components as of 31.03.2020			
Ticker	Company Name	Country	Sector
MTCH US	Match Group Inc.	United States	Communication Services
CMCSA US	Comcast Corp A	United States	Communication Services
WSM US	Williams-Sonoma Inc	United States	Consumer Discretionary
NVR US	Nvr Inc	United States	Consumer Discretionary
DHI US	Horton D.R. Inc	United States	Consumer Discretionary
ULTA US	Ulta Beauty Inc	United States	Consumer Discretionary
LKQ US	Lkq Corp	United States	Consumer Discretionary
DPZ US	Domino’S Pizza Inc	United States	Consumer Discretionary

POOL US	Pool Corp	United States	Consumer Discretionary
BURL US	Burlington Stores Inc	United States	Consumer Discretionary
KMX US	Carmax Inc	United States	Consumer Discretionary
IPG US	Interpublic Group Cos	United States	Communication Services
TSCO US	Tractor Supply Co	United States	Consumer Discretionary
EL US	Estee Lauder Cos. A	United States	Consumer Staples
SYY US	Sysco Corp	United States	Consumer Staples
PRAH US	Pra Health Sciences Inc	United States	Health Care
MTD US	Mettler-Toledo Intl	United States	Health Care
TMO US	Thermo Fisher Scientific	United States	Health Care
WST US	West Pharmaceutical Services Inc	United States	Health Care
ZTS US	Zoetis Inc	United States	Health Care
LMT US	Lockheed Martin	United States	Industrials
ROP US	Roper Technologies Inc	United States	Industrials
JBT US	John Bean Technologies Corp	United States	Industrials
TNET US	Trinet Group Inc	United States	Industrials
UTX US	United Technologies Corp	United States	Industrials
EME US	Emcor Group Inc	United States	Industrials
MIDD US	Middleby Corp The	United States	Industrials
ROLL US	Rbc Bearings	United States	Industrials
TRU US	Transunion	United States	Industrials
HUBB US	Hubbell Inc	United States	Industrials
HEI US	Heico Corp	United States	Industrials
CTAS US	Cintas Corp	United States	Industrials
ASGN US	ASGN Incorporated	United States	Industrials
MSA US	Msa Safety Inc	United States	Industrials
GDDY US	Godaddy Inc A	United States	Information Technology
ANSS US	Ansys Inc	United States	Information Technology
FLT US	Fleetcor Technologies Inc	United States	Information Technology
MSFT US	Microsoft Corp	United States	Information Technology
JKHY US	Jack Henry & Associates Inc	United States	Information Technology
FISV US	Fiserv Inc	United States	Information Technology
INTU US	Intuit Inc	United States	Information Technology
TRMB US	Trimble Navigation Ltd	United States	Information Technology
KLAC US	KLA Corporation	United States	Information Technology
EEFT US	Euronet Services Inc	United States	Information Technology
CACI US	Caci Intl Inc A	United States	Information Technology
MA US	Mastercard Inc A	United States	Information Technology
V US	Visa Inc A	United States	Information Technology
ENTG US	Entegris Inc	United States	Information Technology
SNX US	Synnex Corp	United States	Information Technology

SHW US	Sherwin-Williams Co	United States	Materials
MLM US	Martin Marietta Materials	United States	Materials
CBRE US	Cbre Group Inc.	United States	Real Estate
TKR US	Timken Co	United States	Industrials
CHD US	Church & Dwight Co	United States	Consumer Staples
GWW US	Grainger W.W. Inc	United States	Industrials
CW US	Curtiss-Wright Corp	United States	Industrials
ODFL US	Old Dominion Freight Line Inc	United States	Industrials
WWD US	Woodward Inc.	United States	Industrials
BSX US	Boston Scientific Corp	United States	Health Care
COO US	Cooper Companies Inc	United States	Health Care
TECH US	Bio-Techne Corp	United States	Health Care
CSL US	Carlisle Cos	United States	Industrials
AME US	Ametek Inc	United States	Industrials
CLH US	Clean Harbors Inc	United States	Industrials
TJX US	Tjx Cos Inc	United States	Consumer Discretionary
IEX US	Idex Corp	United States	Industrials
INTC US	Intel Corp	United States	Information Technology
ZBRA US	Zebra Technologies Corp A	United States	Information Technology
AMED US	Amedisys Inc	United States	Health Care
VRSN US	Verisign Inc	United States	Information Technology
ITT US	Itt Corporation	United States	Industrials
PWR US	Quanta Services Inc	United States	Industrials
BKNG US	Booking Holdings Inc	United States	Consumer Discretionary
TDY US	Teledyne Technologies Inc	United States	Industrials
VZ US	Verizon Communications Inc	United States	Communication Services
GPN US	Global Payments Inc	United States	Information Technology
ROK US	Rockwell Automation Inc	United States	Industrials
CCK US	Crown Holdings Inc	United States	Materials
JAZZ US	Jazz Pharmaceuticals Plc	United States	Health Care
SSNC US	Ss&C Technologies Holdings Inc	United States	Information Technology
LULU US	Lululemon Athletica Inc	United States	Consumer Discretionary
GNRC US	Generac Holdings Inc	United States	Industrials
SABR US	Sabre Corporation	United States	Information Technology
BFAM US	Bright Horizons Family Solutions Inc	United States	Consumer Discretionary
GRMN US	Garmin Ltd	United States	Consumer Discretionary
SAIC US	Science Applications International Corp	United States	Information Technology
NGVT US	Ingevity Corp	United States	Materials
STE US	Steris Plc	United States	Health Care
ECL US	Ecolab Inc	United States	Materials

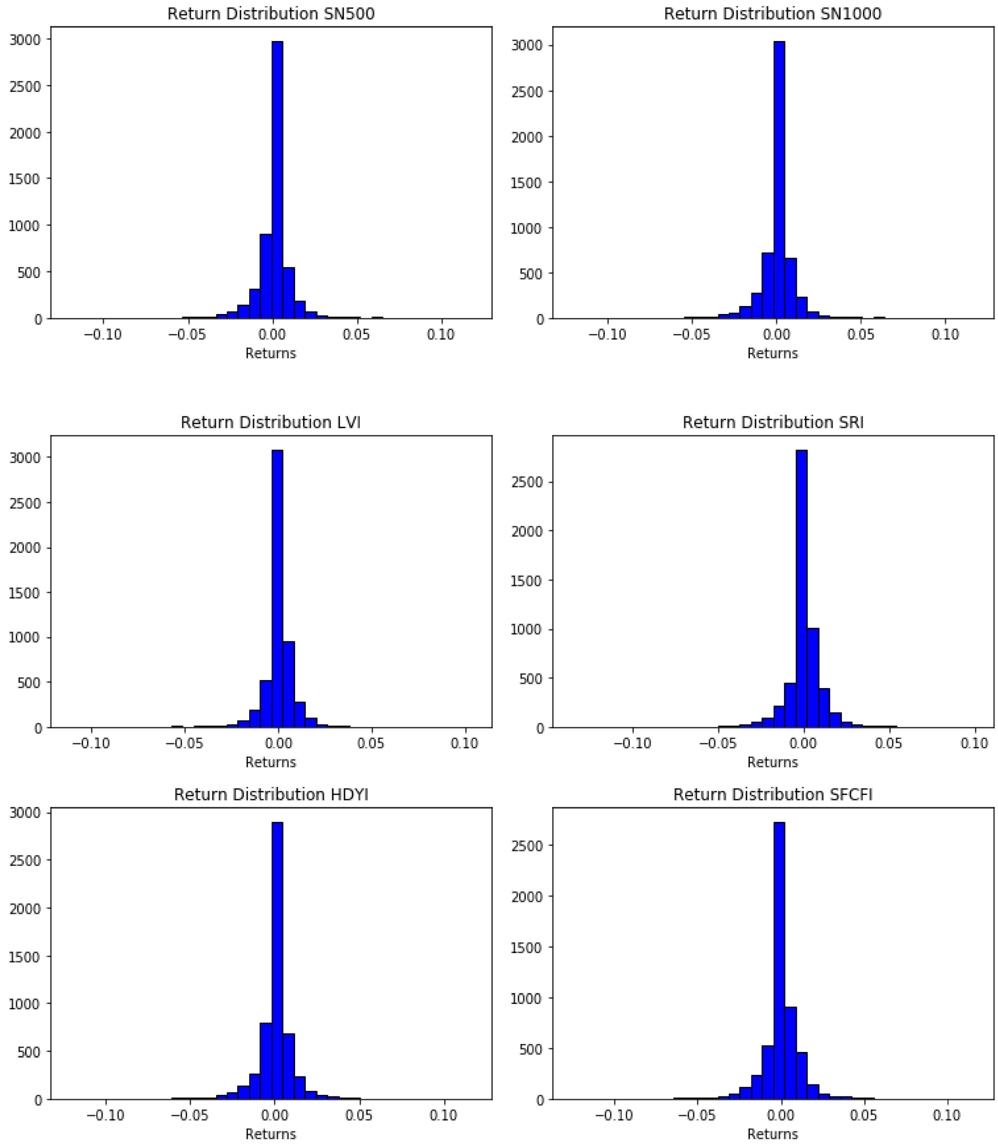
UNF US	Unifirst Corp	United States	Industrials
RTN US	Raytheon Co	United States	Industrials
LEN US	Lennar Corp A	United States	Consumer Discretionary
CHE US	Chemed Corp	United States	Health Care
TSN US	Tyson Foods Inc A	United States	Consumer Staples
LIN US	Linde plc	United States	Materials
IT US	Gartner Inc	United States	Information Technology
DECK US	Deckers Outdoor	United States	Consumer Discretionary
AMZN US	Amazon.Com Inc	United States	Consumer Discretionary
LUV US	Southwest Airlines Co	United States	Industrials
BIIB US	Biogen Inc	United States	Health Care
ALGN US	Align Technology Inc	United States	Health Care
OMCL US	Omnicell Inc	United States	Health Care
GPK US	Graphic Packaging Holding Co	United States	Materials
CAN US	Accenture Plc A	United States	Information Technology
RP US	Realpage Inc	United States	Information Technology
HBI US	Hanesbrands Inc	United States	Consumer Discretionary
AZO US	Autozone Inc	United States	Consumer Discretionary
BYD US	Boyd Gaming Corp	United States	Consumer Discretionary
HXL US	Hexcel Corp	United States	Industrials
ABMD US	Abiomed Inc	United States	Health Care
COLM US	Columbia Sportswear Co	United States	Consumer Discretionary
ABT US	Abbott Laboratories	United States	Health Care
URI US	United Rentals Inc	United States	Industrials
LW US	Lamb Weston Holdings Inc	United States	Consumer Staples
NYT US	New York Times Co A	United States	Communication Services
DIS US	Walt Disney Co	United States	Communication Services
CDNS US	Cadence Design Systems Inc	United States	Information Technology
TWTR US	Twitter Inc	United States	Communication Services
VMC US	Vulcan Materials Co	United States	Materials
PAG US	Penske Auto Group	United States	Consumer Discretionary
BLD US	Topbuild Corp	United States	Consumer Discretionary
MRCY US	Mercury Systems Inc	United States	Industrials
FCN US	Fti Consulting	United States	Industrials
MRK US	Merck & Co Inc	United States	Health Care
EMR US	Emerson Electric Co	United States	Industrials
BKI US	Black Knight Inc.	United States	Information Technology
VST US	Vistra Energy Corp	United States	Utilities
NKE US	Nike Inc B	United States	Consumer Discretionary
AJRD US	Aerojet Rocketdyne Holdings Inc	United States	Industrials
UAL US	United Airlines Holdings Inc	United States	Industrials

DG US	Dollar General Corp	United States	Consumer Discretionary
QLYS US	Qualys Inc.	United States	Information Technology
DISCA US	Discovery Inc A	United States	Communication Services
LDOS US	Leidos Holdings Inc	United States	Information Technology
AWI US	Armstrong World Industries	United States	Industrials
SITE US	Siteone Landscape Supply Inc	United States	Industrials
AKAM US	Akamai Technologies Inc	United States	Information Technology
CNC US	Centene Corp	United States	Health Care
CF US	Cf Industries Holdings	United States	Materials
PAYX US	Paychex Inc	United States	Information Technology
JJSF US	J&J Snack Foods	United States	Consumer Staples

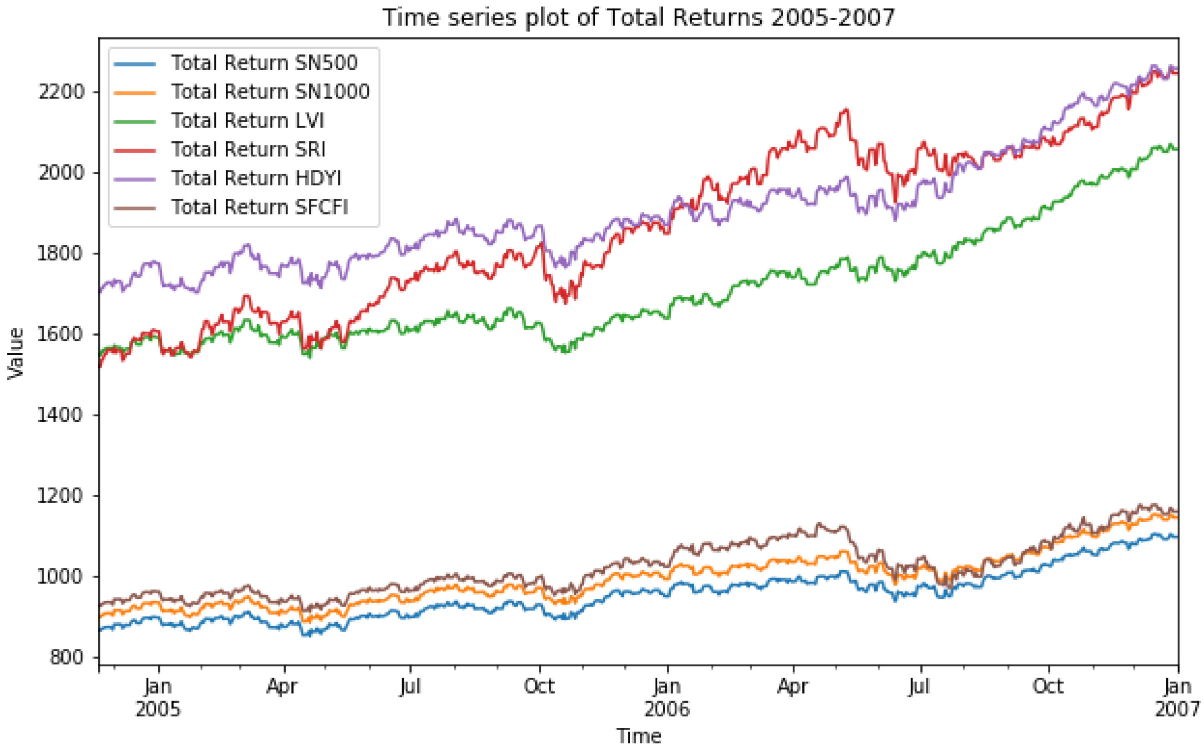
High Dividend Yield Index Components as of 31.03.2020			
Ticker	Company Name	Country	Sector
MMM UN	3M Co	United States	Industrials
T UN	AT&T Inc	United States	Communication Services
ABBV UN	AbbVie Inc.	United States	Health Care
MO UN	Altria Group Inc	United States	Consumer Staples
BMY UN	Bristol-Myers Squibb	United States	Health Care
AVGO UQ	Broadcom Inc	United States	Information Technology
CAH UN	Cardinal Health Inc	United States	Health Care
CNP UN	Centerpoint Energy Inc	United States	Utilities
CTL UN	CenturyLink Inc	United States	Communication Services
COTY UN	Coty Inc.	United States	Consumer Staples
CMI UN	Cummins Inc	United States	Industrials
D UN	Dominion Energy Inc	United States	Utilities
DUK UN	Duke Energy Corp	United States	Utilities
EMN UN	Eastman Chemical Co	United States	Materials
ETN UN	Eaton Corp plc	United States	Industrials
EMR UN	Emerson Electric Co	United States	Industrials
XOM UN	Exxon Mobil Corp	United States	Energy
F UN	Ford Motor Co	United States	Consumer Discretionary
GPS UN	Gap Inc	United States	Consumer Discretionary
GILD UQ	Gilead Sciences Inc	United States	Health Care
HP UN	Helmerich & Payne Inc	United States	Energy
HBAN UQ	Huntington Bancshares (OH)	United States	Financials
IPG UN	Interpublic Group Cos	United States	Communication Services
IBM UN	Intl Business Machines Corp	United States	Information Technology
IP UN	Intl Paper Co	United States	Materials

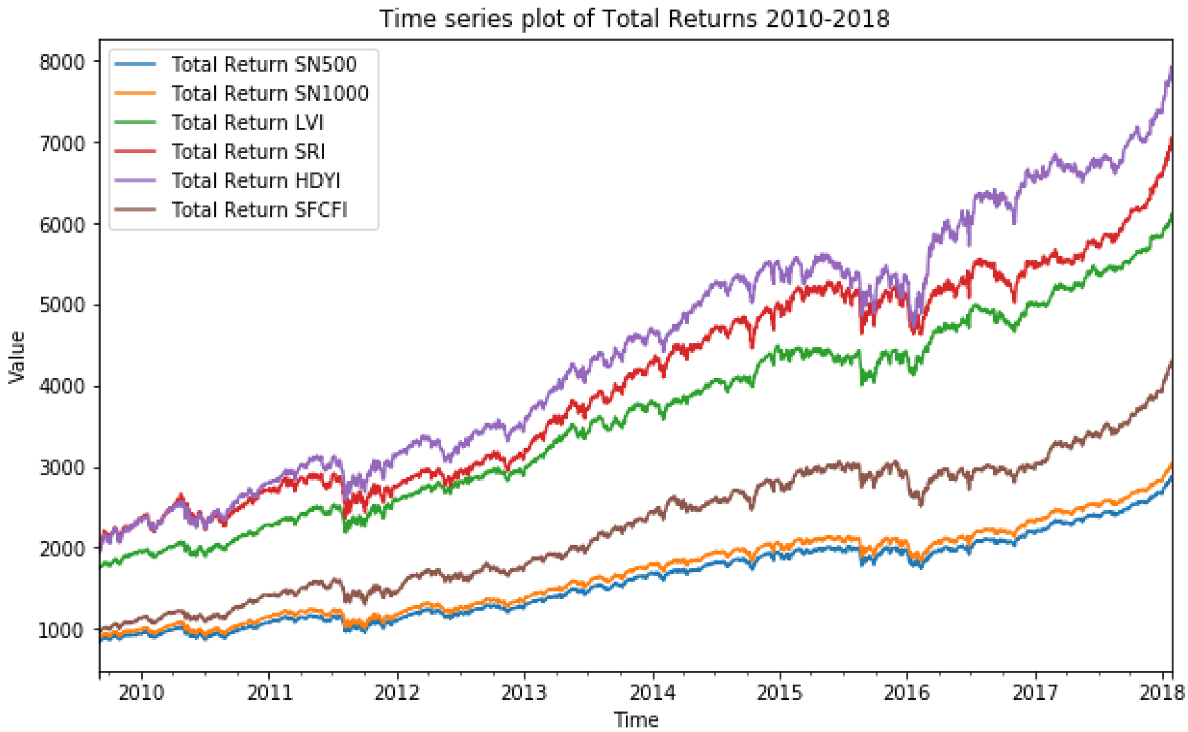
IVZ UN	Invesco Ltd	United States	Financials
KSS UN	Kohl’s Corp	United States	Consumer Discretionary
LB UN	L Brands Inc	United States	Consumer Discretionary
LYB UN	LyondellBasell Industries N.V.	United States	Materials
MXIM UQ	MAXIM INTEGRATED	United States	Information Technology
M UN	Macy’s Inc	United States	Consumer Discretionary
TAP UN	Molson Coors Beverage Co B	United States	Consumer Staples
NUE UN	Nucor Corp	United States	Materials
OXY UN	Occidental Petroleum	United States	Energy
OMC UN	Omnicom Group	United States	Communication Services
PPL UN	PPL Corp	United States	Utilities
PBCT UQ	People’s United Financial Inc	United States	Financials
PFE UN	Pfizer Inc	United States	Health Care
PM UN	Philip Morris International	United States	Consumer Staples
PFG UQ	Principal Financial Group	United States	Financials
PRU UN	Prudential Financial Inc	United States	Financials
SLB UN	Schlumberger Ltd	United States	Energy
STX UQ	Seagate Technology	United States	Information Technology
SO UN	Southern Co	United States	Utilities
KHC UQ	The Kraft Heinz Company	United States	Consumer Staples
WMB UN	The Williams Companies Inc	United States	Energy
UPS UN	United Parcel Service Inc B	United States	Industrials
VZ UN	Verizon Communications Inc	United States	Communication Services
WRK UN	WestRock Co	United States	Materials
WDC UQ	Western Digital Corp	United States	Information Technology

Return Distributions from 1999 to 2020



Time Series Plot During Growth Periods





Statistics

Total Return Appreciation	Date Range	SN500	SN1000	SRI	LVI	HDYI	SFCFI
Since Inception	**12/31/1999–05/15/2020**	192,27%	203,11%	511,95%	551,28%	476,37%	396,23%
10 Year	**05/15/2010–05/15/2020**	218,76%	212,45%	148,26%	227,41%	137,54%	328,54%
5 Year	**05/15/2015–05/15/2020**	52,31%	48,63%	16,91%	46,90%	2,65%	66,02%
3 Year	**05/15/2017–05/15/2020**	29,07%	26,71%	8,89%	23,82%	-12,99%	49,19%
1 Year	**05/15/2019–05/15/2020**	4,03%	2,52%	-11,23%	-4,17%	-21,06%	9,77%

Compound Annual Growth Rate (CAGR)	Date Range	SN500	SN1000	SRI	LVI	HDYI	SFCFI
Since Inception	**12/31/1999–05/15/2020**	5,39%	5,58%	9,28%	9,61%	8,96%	11,54%
10 Year	**05/15/2010–05/15/2020**	12,29%	12,07%	9,52%	12,59%	9,04%	15,66%
5 Year	**05/15/2015–05/15/2020**	8,78%	8,25%	3,17%	7,99%	0,53%	10,67%
3 Year	**05/15/2017–05/15/2020**	8,88%	8,21%	2,88%	7,38%	-4,53%	14,26%
1 Year	**05/15/2019–05/15/2020**	4,03%	2,52%	-11,23%	-4,17%	-21,06%	9,77%

Annualized Standard Deviation	Date Range	SN500	SN1000	SRI	LVI	HDYI	SFCFI
Since Inception	**12/31/1999–05/15/2020**	18,86%	18,93%	18,60%	14,54%	18,87%	19,61%
10 Year	**05/15/2010–05/15/2020**	14,70%	14,87%	14,60%	11,62%	14,47%	16,42%
5 Year	**05/15/2015–05/15/2020**	13,70%	13,73%	13,08%	10,89%	14,29%	15,75%
3 Year	**05/15/2017–05/15/2020**	13,71%	13,73%	12,37%	10,43%	13,17%	15,82%
1 Year	**05/15/2019–05/15/2020**	12,59%	12,70%	11,55%	9,99%	14,06%	14,97%

Sharpe Ratio	Date Range	SN500	SN1000	SRI	LVI	HDYI	SFCFI
Since Inception	**12/31/1999–05/15/2020**	0,3160	0,3281	0,5439	0,6497	0,5621	0,6401
10 Year	**05/15/2010–05/15/2020**	0,9218	0,9070	0,8223	1,1914	0,9026	1,0265
5 Year	**05/15/2015–05/15/2020**	0,8033	0,7805	0,5671	0,9885	0,5573	0,8317
3 Year	**05/15/2017–05/15/2020**	0,9201	0,8982	0,7971	1,1694	0,5420	1,1573
1 Year	**05/15/2019–05/15/2020**	1,6638	1,6062	1,0278	1,4161	1,1934	1,8613
Dot Com Bubble	**2000-2002**	-0,3970	-0,3791	-0,2803	-0,0977	-0,0891	-0,3880
Global Financial Crisis	**2007-2008**	-0,1439	-0,1356	-0,0622	-0,1513	-0,0107	-0,0645
Covid-19 Pandemic	**01/02/2020-15/05/2020**	-0,1645	-0,1866	-0,3323	-0,2504	-0,4098	-0,1272

Sortino Ratio	Date Range	SRI vs. SN500	LVI vs. SN500	HDYI vs. SN500	SFCFI vs. SN500
Since Inception	**12/31/1999–05/15/2020**	0,0250	0,0186	0,0086	0,2262
10 Year	**05/15/2010–05/15/2020**	-0,0143	0,0025	-0,0012	0,4896
5 Year	**05/15/2015–05/15/2020**	-0,0301	-0,0020	-0,0084	0,3182
3 Year	**05/15/2017–05/15/2020**	-0,0231	-0,0035	-0,0166	0,3633
1 Year	**05/15/2019–05/15/2020**	-0,0824	-0,0701	-0,0162	0,2263
Dot Com Bubble	**2000-2002**	-0,3216	-0,0921	-0,0892	-0,4081
Global Financial Crisis	**2007-2008**	-0,4133	-0,3484	-0,2347	-0,2341
Covid-19 Pandemic	**01/02/2020-15/05/2020**	-0,4086	-0,3289	-0,4771	-0,1916

Treynor Ratio	Date Range	SRI vs. SN500	LVI vs. SN500	HDYI vs. SN500	SFCFI vs. SN500
Since Inception	**12/31/1999–05/15/2020**	0,0088	0,0130	0,0087	0,0068
10 Year	**05/15/2010–05/15/2020**	0,0082	0,0143	0,0084	0,0120
5 Year	**05/15/2015–05/15/2020**	0,0029	0,0094	0,0033	0,0089
3 Year	**05/15/2017–05/15/2020**	0,0026	0,0092	-0,0002	0,0115
1 Year	**05/15/2019–05/15/2020**	-0,0075	0,0010	-0,0060	0,0096
Dot Com Bubble	**2000-2002**	-0,0112	-0,0018	0,0018	-0,0141
Global Financial Crisis	**2007-2008**	-0,0292	-0,0223	-0,0340	-0,0237
Covid-19 Pandemic	**01/02/2020-15/05/2020**	-0,0371	-0,0274	-0,0462	-0,0137

Information Ratio	Date Range	SRI vs. SN500	LVI vs. SN500	HDYI vs. SN500	SFCFI vs. SN500
Since Inception	**12/31/1999–05/15/2020**	0,1365	0,1200	0,1300	0,1400
10 Year	**05/15/2010–05/15/2020**	-0,1384	0,0100	-0,0822	0,1700
5 Year	**05/15/2015–05/15/2020**	-0,2661	-0,0540	-0,2119	0,1205
3 Year	**05/15/2017–05/15/2020**	-0,2584	-0,0752	-0,4210	0,3196
1 Year	**05/15/2019–05/15/2020**	-0,4623	-0,2523	-0,4548	0,2758
Dot Com Bubble	**2000-2002**	0,1386	0,3267	0,7092	0,4092
Global Financial Crisis	**2007-2008**	-0,1584	0,2199	0,1420	0,2425
Covid-19 Pandemic	**01/02/2020-15/05/2020**	-0,7081	-0,6465	-1,0292	0,1781

Annualized Information Ratio	**Date Range**	**SRI vs. SN500**	**LVI vs. SN500**	**HDYI vs. SN500**	**SFCFI vs. SN500**
Since Inception	**12/31/1999–05/15/2020**	0,4729	0,4100	0,4500	0,4800
10 Year	**05/15/2010–05/15/2020**	-0,4793	0,0500	-0,2849	0,5800
5 Year	**05/15/2015–05/15/2020**	-0,9219	-0,1869	-0,7300	0,4173
3 Year	**05/15/2017–05/15/2020**	-0,8953	-0,2605	-1,4584	1,1073
1 Year	**05/15/2019–05/15/2020**	-1,6013	-0,8742	-1,5754	0,9555

Downside Risk	**Date Range**	**SRI vs. SN500**	**LVI vs. SN500**	**HDYI vs. SN500**	**SFCFI vs. SN500**
Since Inception	**12/31/1999–05/15/2020**	8,17%	9,82%	28,12%	28,39%
10 Year	**05/15/2010–05/15/2020**	5,43%	6,15%	20,88%	22,53%
5 Year	**05/15/2015–05/15/2020**	5,74%	6,33%	19,05%	20,63%
3 Year	**05/15/2017–05/15/2020**	5,62%	6,08%	17,23%	19,12%
1 Year	**05/15/2019–05/15/2020**	5,42%	5,08%	13,44%	13,50%

Upside Capture Ratio	**Date Range**	**SRI vs. SN500**	**LVI vs. SN500**	**HDYI vs. SN500**	**SFCFI vs. SN500**
Since Inception	**12/31/1999–05/15/2020**	100,380	76,097	104,582	112,473
10 Year	**05/15/2010–05/15/2020**	83,310	80,926	91,759	108,676
5 Year	**05/15/2015–05/15/2020**	75,591	77,636	85,381	111,847
3 Year	**05/15/2017–05/15/2020**	79,812	78,395	80,587	119,244
1 Year	**05/15/2019–05/15/2020**	63,826	63,543	92,043	112,471
Dot Com Bubble	**2000-2002**	92,8199	56,0272	115,3619	102,0662
Global Financial Crisis	**2007-2008**	108,6293	59,6199	145,1127	142,1018
Covid-19 Pandemic	**01/02/2020-15/05/2020**	96,0499	86,0561	60,0456	103,4265

Downside Capture Ratio	**Date Range**	**SRI vs. SN500**	**LVI vs. SN500**	**HDYI vs. SN500**	**SFCFI vs. SN500**
Since Inception	**12/31/1999–05/15/2020**	81,676	46,818	80,904	83,505
10 Year	**05/15/2010–05/15/2020**	90,748	60,637	100,543	92,808
5 Year	**05/15/2015–05/15/2020**	106,808	70,392	117,912	107,271
3 Year	**05/15/2017–05/15/2020**	113,092	74,970	136,138	101,928
1 Year	**05/15/2019–05/15/2020**	130,267	79,476	156,866	98,709
Dot Com Bubble	**2000-2002**	70,4288	27,1859	54,4289	99,7470
Global Financial Crisis	**2007-2008**	96,7207	67,6764	107,1644	117,8341
Covid-19 Pandemic	**01/02/2020-15/05/2020**	164,6235	105,5423	155,7921	97,3613

Outperformance	Date Range	SRI vs. SN500	LVI vs. SN500	HDYI vs. SN500	SFCFI vs. SN500
Since Inception	**12/31/1999–05/15/2020**	308,84%	359,01%	284,10%	170,14%
10 Year	**05/15/2010–05/15/2020**	-64,19%	8,66%	-81,22%	109,78%
5 Year	**05/15/2015–05/15/2020**	-31,72%	-5,41%	-49,66%	13,71%
3 Year	**05/15/2017–05/15/2020**	-17,82%	-5,25%	-42,05%	20,12%
1 Year	**05/15/2019–05/15/2020**	-13,74%	-8,19%	-25,09%	5,75%

Beta	Date Range	SRI vs. SN500	LVI vs. SN500	HDYI vs. SN500	SFCFI vs. SN500
Since Inception	**12/31/1999–05/15/2020**	0,9188	0,6301	0,9840	1,0722
10 Year	**05/15/2010–05/15/2020**	0,9460	0,7238	1,0156	1,0718
5 Year	**05/15/2015–05/15/2020**	1,0325	0,7757	1,1333	1,1270
3 Year	**05/15/2017–05/15/2020**	1,0981	0,7995	1,1837	1,1372
1 Year	**05/15/2019–05/15/2020**	1,2204	0,8286	1,3001	1,0977
Dot Com Bubble	**2000-2002**	0,7218	0,3536	0,7468	1,0025
Global Financial Crisis	**2007-2008**	0,9852	0,8369	1,0483	1,2739
Covid-19 Pandemic	**01/02/2020-15/05/2020**	1,3694	0,9303	1,2462	1,0610

Annualized Alpha	Date Range	SRI vs. SN500	LVI vs. SN500	HDYI vs. SN500	SFCFI vs. SN500
Since Inception	**12/31/1999–05/15/2020**	0,1491%	0,1912%	0,4180%	0,4816%
10 Year	**05/15/2010–05/15/2020**	-0,0188%	0,1317%	0,4696%	0,5968%
5 Year	**05/15/2015–05/15/2020**	-0,0648%	0,1056%	0,3002%	0,4928%
3 Year	**05/15/2017–05/15/2020**	-0,0045%	0,1389%	0,2967%	0,6981%
1 Year	**05/15/2019–05/15/2020**	-0,1167%	0,0201%	0,6422%	1,0657%

Jensen's Alpha (Annualized)	Date Range	SRI vs. SN500	LVI vs. SN500	HDYI vs. SN500	SFCFI vs. SN500
Since Inception	**12/31/1999–05/15/2020**	0,14%	0,22%	0,36%	0,44%
10 Year	**05/15/2010–05/15/2020**	-0,02%	0,18%	0,45%	0,58%
5 Year	**05/15/2015–05/15/2020**	-0,07%	0,14%	0,26%	0,45%
3 Year	**05/15/2017–05/15/2020**	-0,01%	0,16%	0,24%	0,63%
1 Year	**05/15/2019–05/15/2020**	-0,13%	0,04%	0,58%	0,99%
Dot Com Bubble	**2000-2002**	0,0044	0,0058	0,0141	0,0004
Global Financial Crisis	**2007-2008**	-0,0001	0,0062	0,0092	0,0061
Covid-19 Pandemic	**01/02/2020-15/05/2020**	-0,0263	-0,0091	-0,0353	0,0043

Annual Returns

Annual Returns	*Total Return SN500*	*Total Return SN1000*	*Total Return LVI*	*Total Return SRI*	*Total Return HDYI*	*Total Return SFCFI*
31/12/2000	-9,84%	-9,20%	16,76%	9,26%	8,11%	-9,52%
31/12/2001	-13,51%	-12,73%	6,33%	-4,12%	18,20%	-13,12%
31/12/2002	-21,34%	-20,90%	-8,18%	-16,70%	-15,13%	-21,12%
31/12/2003	27,03%	28,40%	21,10%	46,47%	39,08%	27,72%
31/12/2004	10,43%	11,15%	15,15%	25,53%	17,52%	10,79%
31/12/2005	5,89%	6,27%	2,98%	15,11%	5,45%	6,43%
31/12/2006	15,55%	15,44%	25,60%	21,53%	20,73%	13,42%
31/12/2007	6,86%	6,82%	9,54%	16,55%	3,34%	12,14%
31/12/2008	-36,87%	-36,92%	-23,91%	-38,39%	-33,01%	-40,63%
31/12/2009	26,24%	27,61%	13,29%	44,54%	48,37%	45,62%
31/12/2010	15,01%	16,02%	17,37%	16,10%	20,33%	24,93%
31/12/2011	1,69%	1,52%	13,54%	1,35%	12,34%	2,54%
31/12/2012	16,13%	16,21%	12,87%	14,52%	11,24%	21,39%
31/12/2013	33,47%	34,20%	30,49%	37,00%	34,99%	40,20%
31/12/2014	13,43%	12,70%	15,90%	14,92%	15,60%	14,12%
31/12/2015	1,45%	1,00%	-1,43%	2,49%	-2,83%	3,69%
31/12/2016	11,65%	12,04%	14,39%	7,48%	23,05%	2,40%
31/12/2017	22,56%	22,27%	17,09%	20,80%	13,18%	32,05%
31/12/2018	-4,33%	-4,86%	1,30%	-4,98%	-10,93%	-2,96%
31/12/2019	31,88%	31,70%	26,88%	19,81%	24,72%	43,79%

Correlation Matrixes

Correlation During Global Financial Crisis						
	Total Return SN500	**Total Return SN1000**	**Total Return LVI**	**Total Return SRI**	**Total Return HDYI**	**Total Return SFCFI**
Total Return SN500	1,00000	0,99973	0,97405	0,97528	0,96912	0,96628
Total Return SN1000	0,99973	1,00000	0,97292	0,97653	0,97100	0,96995
Total Return LVI	0,97405	0,97292	1,00000	0,95999	0,94298	0,93578
Total Return SRI	0,97528	0,97653	0,95999	1,00000	0,95053	0,95881
Total Return HDYI	0,96912	0,97100	0,94298	0,95053	1,00000	0,93961
Total Return SFCFI	0,96628	0,96995	0,93578	0,95881	0,93961	1,00000

Correlation During Covid-19 Pandemic						
	Total Return SN500	Total Return SN1000	Total Return LVI	Total Return SRI	Total Return HDYI	Total Return SFCFI
Total Return SN500	1,00000	0,99974	0,98078	0,95941	0,96001	0,98394
Total Return SN1000	0,99974	1,00000	0,98158	0,96341	0,96358	0,98679
Total Return LVI	0,98078	0,98158	1,00000	0,93992	0,96882	0,97195
Total Return SRI	0,95941	0,96341	0,93992	1,00000	0,92879	0,95805
Total Return HDYI	0,96001	0,96358	0,96882	0,92879	1,00000	0,96675
Total Return SFCFI	0,98394	0,98679	0,97195	0,95805	0,96675	1,00000

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