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School of Industrial and Information Engineering
Master of Science in Management Engineering

# The Rise of Passive Management

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**A/Y 2018/2019**

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# Abstract

The Asset Management Industry plays a crucial role in driving the global economy, serving as an intermediary in the process of channeling resources from surplus entities (savers) to deficit ones (borrowers) by determining the value of real and financial assets, which is in essence an incentive-compatible scheme to allocate assets most efficiently.

Along the past decades, profound transformations have been observed in this sector, of which at least two of them deserve an especial attention: (1) **A change in the investment paradigm**, i.e. a structural movement from well-established active-only management funds towards an increasing allocation to passive funds, having a special influence of the disruption ignited by "factor investing/smart beta"; and (2) **Technology advancements**, enabling to offer cheaper, versatile and more sophisticated products/services such as smart beta quantitative funds, high-frequency trading, hybrid active management, and robo-advisors.

We apply in this work an analytical framework to evaluate the industry from the perspective of both portfolio management and efficient market theories, seeking to explain the rationale of the foregoing transformations, and their implications to the sector's landscape. Furthermore, state-of-art academic papers, consulting firms' reports, as well as public information extracted from asset management companies were employed to back-up our analyses and conclusions.

We finally concluded that the industry is, in fact, moving towards the direction of an equilibrium point between passive and active, because, despite the rise of passive management, we still observe significant competitive advantages in alpha-generation by some active managed funds (we focus more on the analysis of hedge funds), what suggests their sustainability over the long-run. Moreover, we observe an increase in the [already high] industry concentration levels, which might have strong implications to antitrust regulations in the foreseeable future.

**Keywords:** Finance; Asset Management; Portfolio Management; Investment; Passive Management; Active Management; Technology; Algorithmic Trading; Innovation; Smart Beta; Factor Investing; Quantitative Finance; Market Efficiency;

# Part I - Introduction

## 1.1 Inspiration

Deloitte (2019) [31] defines the outlook for investment management industry over the next years as a "mix of opportunity and challenge". This industry essentially refers to the business of professional agents managing portfolios of investments on behalf of clients, having the primary role to properly diversify and allocate risk within the available asset classes, geographies and maturities, in order to fulfill clients' needs in terms of investment timeframe, liquidity, and risk tolerance. Driven by changes in customer preferences (mostly millennials) towards digital channels, new regulatory environment, and dominance of tech-savvy firms, managers are struggling to survive and adapt to this new trends, looking for growth opportunities and a broader product mix to compensate the margins and fee pressures (Fig. 1.1).


Figure 1.1 - Ansoff matrix for Asset Management Industry [31].

Aberdeen Standard Investments (2018) [1] identifies five catalyst of significant changes within this industry related to the principal topic of this study - the increasing demand for passive investments, in special factor investing, in order to fulfill investors preferences.

1. In efficient markets, a low return potential exists for active management, which by turn **pressures the costs side of asset managers**. Hence, smart beta offers a different value-for-money scheme that might fit customers' needs;
2. Thus, a new paradigm is becoming increasingly stronger as investors demand is shifting towards a new "return per cost" utility function, together with an **increasing supply and sophistication** for **smart beta** solutions, that offers a wide array of factors to invest (such as value, momentum, etc.), as well as it can fulfill investor's emerging preferences not strictly related to achieve directly highest return but rather to satisfy, for instance, thematic areas such as ESG or activist investment.
3. **"Data Revolution"** has and still is promoting profound shaking in the status quo, making traditional incumbents fear disruption from new technology-based entrants across various industries. Hence, technological innovations such as big data, internet of things (IoT), artificial intelligence and machine learning are enabling smart beta to deliver increasingly **scalable and cost-efficient solutions**.
4. A movement from pure passive to smart beta products is being catalyzed by the fact that investors are realizing the **inherent flaws of traditional market cap-weighted** indexes of overweighting stocks that are often likely to be overpriced, while underweighting stocks that may be underpriced, hence demand of alternative weighting and rebalancing schemes are increasing as a suitable substitute.
5. A new post-crisis regulatory framework, pressuring asset managers to implement more transparent, fee-scrutinized and simpler solutions.

## 1.2 Thesis objectives

We propose a review of the scientific literature's state-of-the-art on the investment management industry, through both a theoretical and practical perspective. Indeed, we review both market efficiency and portfolio management theories to give the foundation for the elements underlying the competition between passive versus active management. Then, we analyze material data provided by public data about recent market trends, having as our ultimate goal to address the following hypothesis, in accordance to Rajamony and Woodgate (2016) [70]:

"Smart beta strategies are very likely to achieve inferior risk adjusted returns than active alpha, because passive rule-based management lacks a depth analysis of data, alpha construction, modeling, and other value adding aspects of discretionary management (Fig. 1.2). Thus, our hypothesis is that features such as (1) Lower expense ratio; (2) High degree of market efficiency; and (3) Technology advancements supporting quantitative strategies sophistication contributes to position smart beta as a strong substitute, resulting in a structural change in the investment management industry, leading to a landscape with smaller potential market share for active managers and fees compression."


Figure 1.2 - Gap between Active Alpha and Smart Beta [70].

# Part II - Literature Review

## 2.1. Portfolio Management Theory

### 2.1.1. Introduction

Although the terms *trading* and *investing* are oftentimes misinterpreted as interchangeable, in fact these two activities are so different that require distinct skills, in order to follow completely different analytical frameworks, to ultimately buy/sell securities in a distinct timeframe.

Indeed, a *trader* is a player seeking to profit with short-term transactions, to which is way more relevant to evaluate metrics related to the market sentiment, price charts and volume data, and especially to perform a timely and effectively execution. On the other hand, an investor is rather a strategist, who seeks to forecast trends that might affect the macro scenario, the industry as a whole, or even a firm-related trend, in order to quantify how these trends could impact the different business models through valuation techniques. Hence, investors build wealth gradually over time, buying, holding and rebalancing a portfolio of stocks usually for longer periods.

In fact, *investing* is not just about selecting the best individual securities, but rather having a solid strategy for managing a portfolio under a specific mandate. This chapter will outline the aspects of the art and the science of making decisions about investment such as whether to take on equity vs. debt, domestic vs. international, growth vs. value, in which proportion, and how to properly craft a strong portfolio strategy.

### 2.1.2 Portfolio of two risky assets

Let two distinct assets (A and B) be bundled together in a portfolio, in which $\boldsymbol{(R_a;\sigma_a)}$ denote the pair of monthly simple return on security A and volatility of these returns such as $\sigma^2_a = var(R_a)$, analogously, $(R_b;\sigma_b)$ denote the pair of monthly returns on security B and its related volatility such as $\sigma^2_b = var(R_b)$ and the joint parameters are $\sigma_{AB} = cov(R_a;R_b)$ and $\rho_{AB} = \frac{\sigma_{AB}}{\sigma_a\sigma_b}$

Moreover, for a rational investor it is assumed that a trade-off relationship holds between risk and return, such that it is possible to define a utility function $U = f(Return, Risk)$ that is upward sloping in respect to return and downward sloping with respect to the risk, both of which must still be properly defined. A simplified example of an utility function that satisfies the definition above is equation 2.1, in which for that specific case return is measured by the *expected return*, while risk is explicitly measured by the variance of those returns.

$$U = E(R) - \frac{1}{2}A\sigma^2 \tag{2.1}$$

The benefit of defining utility is to allow an explicit and technical explanation about the opposing relationship between risk and return, as well to classify and model the different types of investors inclination towards risk depending on factor's A magnitude (the higher it is, the more averse to risk, according to the model). The overall idea is summarized by the **mean-variance dominance theorem:** For two assets A and B, A dominates B under two possible conditions, either:

(1) if $\mu A \geq \mu B$ and $\sigma A < \sigma B$, or

(2) If $\mu A > \mu B$ while $\sigma A \leq \sigma B$.

Thus, let a manager with limited wealth ($W_0$) decide to allocate between securities A and B, therefore having to choose a pair fraction $(X_a; X_b)$ that represents the weights of the portfolio (so that the sum of weights is strictly 100% allowing also for short positions, i.e. negative weights might be addressed as long as the sum is 100%). Hence, the overall portfolio return is given by the random variable $R_p$ given by the linear combination of the returns of each individual security properly weighted (equation 2.2).

$$R_p = X_a R_a + X_b R_b = X_a R_a + (1 - X_a) R_b \tag{2.2}$$

Assuming individual returns to be normally distributed, then the portfolio return is therefore normally distributed as well, therefore by adding the standard deviation (volatility) is sufficient to model the return function, because the higher degree moments (i.e. kurtosis and skewness) are assumed to follow the ones of a gaussian distribution (no skewness and excess kurtosis). Thus, resulting volatility of the portfolio is obtained by equation 2.3.

$$\sigma^2{}_p = X^2{}_a\sigma^2{}_a + X^2{}_b\sigma^2{}_b + 2\rho_{AB}X_aX_b\sigma_a\sigma_b \tag{2.3}$$

In fact, risk managers are keen antagonists of the suitability of normal distribution (normality assumption) to discuss mean-variance themes, according to Stoyanov et. al., (2011) [86]. The rationale behind it is that normality introduces an oversimplification, unabling to capture the occurrence of extreme events such as big crisis (also known as *black swans*) due to mainly two factors, which worth being evaluated.

1. Autoregressive behavior: Volatility tends to be clustered, which is better modeled as an autoregressive function using widely known models such as ARCH, GARCH and their variations.

2. Fat Tails: Reinforcing the clustered volatility threat for risk management purposes, fat tails are an additional point of attention. Basically, fat tails stem from the higher probability of extreme events (outliers) to happen than what is predicted by the normal curve, as depicted in Figure 2.1.

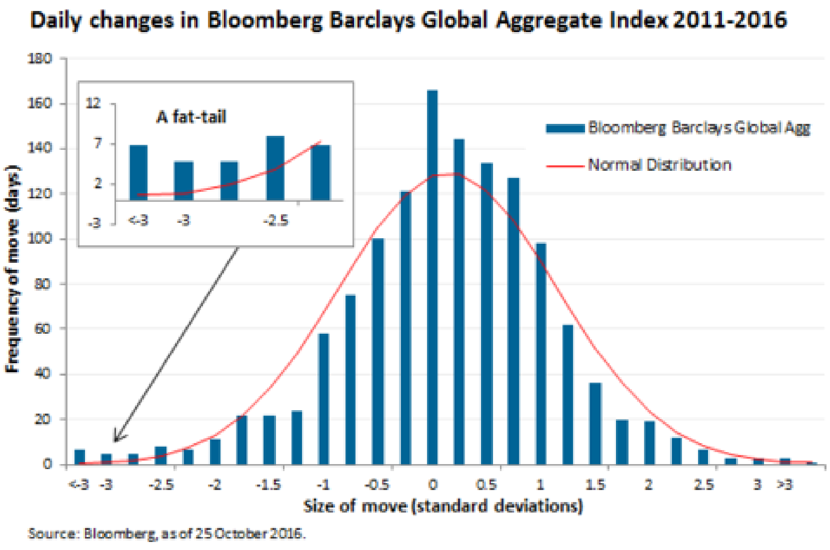


Figure 2.1 - "Fat Tails" phenomenon [22].

Despite the problems associated with normality assumption, all simplifications proposed by Markowitz (1952) [59] under Modern Portfolio Theory (MPT) works well to portfolio management in general. Indeed, MPT has a profound historical relevance because poses as the first theory to explain and guide in a systematic way the decision-making process under an asset management perspective.

Although the definition of risk and return may be intuitive to people in general, it is important to properly address precise definitions and metrics to them in order avoid misconception and to be able to sustain more complex models.

### 2.1.3 Portfolio Return

According to Reilly and Brown (2011) [72], on the return side, it is straightforward that financial assets compensate investors through either (1) **Capital appreciation**, i.e. when price $P_{t-1}$ moves to $P_t$, or (2) **Period income**, i.e. interest, dividend, or any analogous remuneration. Hence, a simple definition of return computed for single period is the Holding Period Return (HPR), which is computed as shown in equation 2.4 if the security is assumed to be a stock that pays-out just dividends.

$$HPR = \frac{P_t - P_{t-1}}{P_{t-1}} + \frac{D_t}{P_{t-1}} \tag{2.4}$$

For multiple periods returns, the sole computation of each HPR is not suitable, because it just considers two periods "beginning" and "end" but does not tell what happens "in-between". Despite the fact that the arithmetic mean is useful for purposes of computing descriptive statistics and even for building forecasting models about future returns, the most accurate measure of past returns is given by the geometric average (equation 2.5), also known as time-weighted return, because it results in the overall growth of portfolio value over the multi-period time-frame.

$$\overline{R_{Gi}} = \sqrt[T]{\prod_{j=1}^{T}(1 + Rij)} - 1 \tag{2.5}$$

An even more complete definition of return is achieved by considering that an investor facing a multi-period investment may inject or extract money in-between. In this situation a "money-weighted return" is the proper measure of return, obtained by the computation of the internal rate of return (IRR) of the investments, as shown by equation 2.6.

$$\sum_{t=0}^{T} \frac{CF_t}{(1+IRR)^t} = 0 \qquad (2.6)$$

Finally, to complete the discussion about returns, it is important to have comparability between the returns, so that three factors are relevant:

- Single vs. Composite - Returns may either be referring to a specific asset, or to a class of assets (i.e. a portfolio). For instance, equation 2.7 describes a return referring to a portfolio rather than a single security.

$$R_p = \sum_{i=1}^{N} w_i R_i \qquad (2.7)$$

- Return time basis - In order to preserve comparability, it is important that results are displayed in a comparable time period, otherwise a conversion is required. For instance, to convert from any HPR to an annual basis, one must find the time period "n" in years of HPR in order to compute equation 2.8.

$$Annual\ HPR = \sqrt[n]{HPR} \qquad (2.8)$$

- Real vs. Nominal - Nominal returns can be broken down into a compound of real risk-free return component, an inflation component and a risk premium, as shown in equation 2.9. Although nominal returns are the ones more straightforwardly computed by investors, this kind of breakdown reveals the most interesting elements underlying the performance of an asset.

$$(1+r) = \left(1+r_f\right) * (1+\pi) * (1+Risk\ premium) \qquad (2.9)$$

### 2.1.4. Portfolio Risk

Risks are originated from distinct sources of exposure, Reilly and Brown (2011) [72] identify at least five relevant categories. The rationale of understanding risk sources is to properly address specific hedging and diversification levels.

1. Business risk - Uncertainty with respect to cash flows caused by the dynamics of the business sector, which can be broken down into sales risk and operational risk. According to Kenton (2019) [50] this is influenced by several factors such as: (1) **Consumer preferences, demand, and sales volume**, i.e. customer sentiment towards the product offering with respect to direct competitors' and substitutes; (2) **Price per unit and input costs**, ultimately explained by economic concepts such as elasticity of demand and operational leverage (i.e. with respect to the proportion between fixed and variable costs); and (3) **Competition**, an idiosyncratic factor affecting business within a sector, on one hand pressuring margins, but on the other encouraging differentiation, efficiency and innovation as ways to survive. This risk source, according to an article posted by Societè Generale (2019) [84], is very sensitive to business cycle swings, such that those firms that move in accordance are classified as **cyclical**, whereas **defensive** are those less affected by those swings, i.e. that has low correlation to economic activity.

2. Financial risk - Debt funding introduces an additional risk depth to firms' risk management. Although debt may be used to fund expansions, acquisitions or other actions to enhance competitive positioning, the operational profits earned must then be sufficient to repay the debt schedule, not to mention that fluctuations in demand end up affecting the bottom line in a magnified proportion.

3. Liquidity risk: Uncertainty with respect to the availability of a secondary market liquidate securities at a fair price. It is relevant either for exiting strategies and for solvency purposes, when the need of converting securities into cash becomes latent. For instance, a piece of art may be valuable, but it may take time until one finds a counterparty willing to pay its fair value.

4. Exchange rate risk: Even though foreign exchange markets are very liquid and efficient, there is a risk associated to returns quoted in foreign currencies. For example, an american investor willing to buy japanese stocks may have a weaker return than expected if US dollar appreciates in relation to Japanese Yen. This effect becomes more impactful if the american investor holds expenses binded to US dollars.

5. Political risk or country risk: Uncertainty around government actions are probably the most unpredictable and most impactful sources of risks for the short run. Enforcement in favor of antitrust laws, tax benefits, monetary policy, trade wars, and so many actions may affect the results of specific business, whole industries, and even whole economy.

When measuring risk, though, it is impossible to attribute quantitative measures for each source. Indeed, the most straightforward measure of risk is the variance of returns (equation 2.10), which is an aggregate parameter reflecting the volatility of returns.

$$\sigma^2 = \frac{\sum_{t=1}^{T}(R_t - \mu)^2}{T} \tag{2.10}$$

A more practical measure for volatility is the sample variance (equation 2.11), which is closer to a real world in which metrics for whole population are likely to be either impossible or too much time consuming to obtain, so that $s^2$ is the best estimator in terms of efficiency, biasness, and consistency.

$$s^2 = \frac{\sum_{t=1}^{T}(R_t - \bar{R})^2}{T-1} \tag{2.11}$$

In contrast to return function, portfolio variance is not simply the weight average of single variances, but rather described by equation 2.12, which has two noteworthy parts (1) on the left side after the equality, the **quadratic terms** reflect each individual risk composition, while (2) on the right side after the equality, the **cross terms** reflect the interaction among those securities.

$${\sigma_p}^2 = (\sum_{i=1}^{N}(w_i\sigma_i)^2 + \sum_{i,j\ not\ i=j}^{N} w_i w_j \rho_{ij}\sigma_i\sigma_j) \tag{2.12}$$

These cross terms are essential from a **diversification** standpoint, because the overall volatility tends to be more sensitive to cross relationships ("$n^2$-n" terms) than to quadratic ones ("n" terms). Then, a lower correlation between individual assets, ultimately smoothes the covariances (or even turn them negative), having a stabilizer effect in portfolio returns. This is achieved by bundling into the portfolio securities with uncorrelated risks exposures, such as the five sources previously explained.

### 2.1.5. Efficiency Frontier

Let a couple of low correlated indexes be part of a portfolio: S&P 500 and Emerging market indexes, such as depicted in Figure 2.2 by CFA Institute (2018) [25], whose correlation according to the author is 0.093. Analyzing qualitatively, this low correlation likely reflects the fact that all five categories of risk sources listed previously are likely to be divergent between US and emerging markets, such as business risk (i.e. due to different mix of industries in developed and emerging countries), political risk (i.e. due to diverse political stability), and so on.

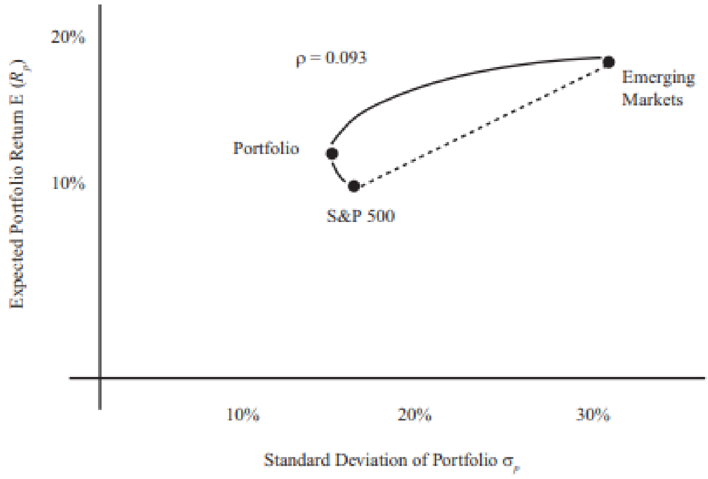


Figure 2.2 - Efficient frontier for a combination of two indexes [25].

This result is noteworthy due to formation of the **global minimum-variance portfolio** (Figure 2.3) whose standard deviation is minimal with respect to any combination of risky assets considered in the analysis. Furthermore, the loci of non-dominated portfolios in the mean-standard deviation space called **efficiency frontier** (e.g. points A and D are part of the efficiency frontier, while C is not, and X is unattainable, because lies outside the efficiency frontier.)

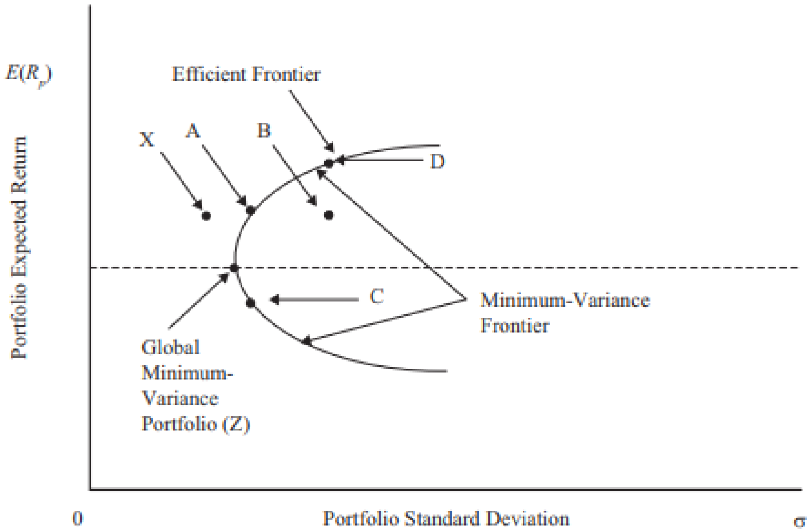


Figure 2.3 - Efficiency frontier [25].

The effect of adding further assets into portfolio expands the so called investment opportunity set, as shown in figure 2.4, that results in even more combinations of asset weights for each component of the portfolio (note that a "zero allocation weight" is allowed, i.e. $w_i = 0\%$, so the addition of an asset either expands to a more dominant efficient frontier or, at least, maintains the current configuration).

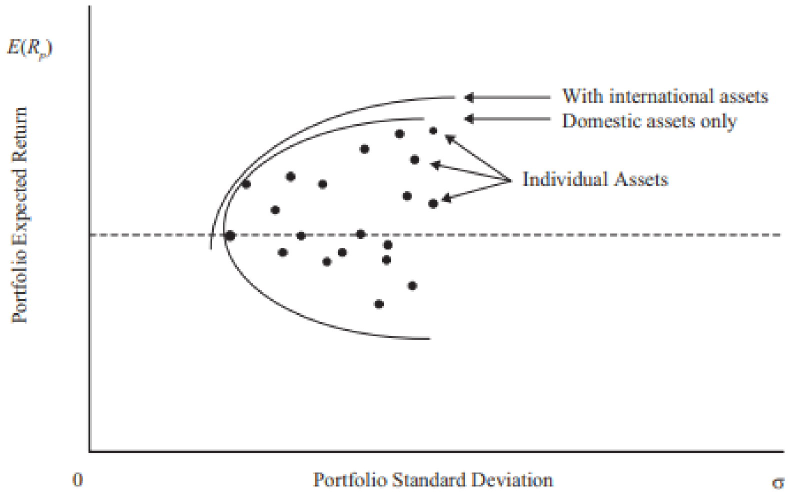


Figure 2.4 - Investment Opportunity set [25].

## 2.1.6. Capital Allocation Line

The expansion of the investment set by adding a "risk free asset" brings an extra degree of complexity to the whole analysis. Indeed, because risk free securities are those whose variance of returns are null by definition, the minimum variance portfolio can be reduced until zero variance, when the allocation is 100% composed by risk-free assets, which in practice are properly proxied by a developed country government bond (especially US treasury bonds). Those sovereign backed securities are virtually riskless, because of the good credit rating of these countries, reinforced by their control over the monetary policy, which virtually eliminates the risk of default. Nonetheless, in order to be more precise, the residual default risk can be further mitigated by the combination of a developed country sovereign debt security plus its associated credit default swap (CDS), which is likely to be as low as 20~40 bps.

Illustrated in figure 2.5, a risk-free asset lies on y-axis because of null variance, and assuming an arbitrage[1] free relationship for this security, it is modelled as a single dot, representing an unique return for investing in risk-free basis.

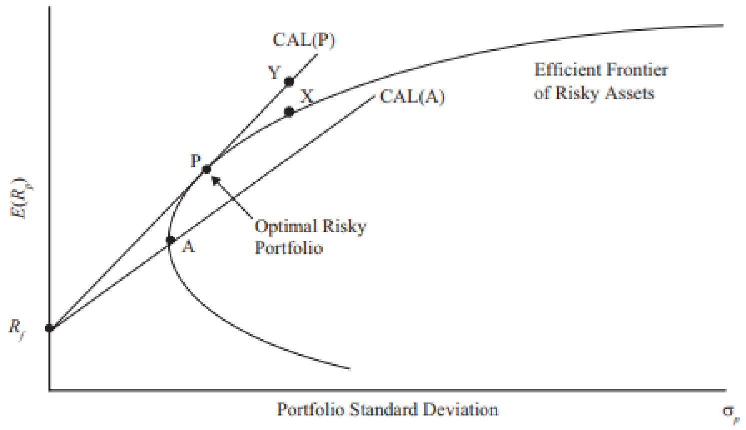


Figure 2.5 - Optimal Risky Portfolio [25].

[1]Arbitrage is defined a set of transactions whose payoff are non-negative cash flows at any probabilistic temporal state, and positive in at least one state. For instance, let a risk-free bond be trading in two different markets so that the risk-free yield is higher in market A, than it is in market B. Hence, a well-informed market agent could borrow money in market A and lend the amount obtained at market B rates, achieving a profit without bearing any risk during the process.

By constructing a basket of complementary weightings of (1) risk free asset and (2) a portfolio of risky assets, the mean-variance *loci* generated is known as Capital Allocation Line (CAL). The higher is the slope of this line, the better is the remuneration per risk exposure. Moreover, the highest slope is achieved by the line passing through points $R_f$ and P (tangent to efficient frontier, as shown in figure 2.6), being named **optimal capital allocation line.** This is a noteworthy result, because allows investors to achieve mean-variance dominant portfolios to those lying on efficient frontier (e.g. Y is dominant with respect to X), raising the overall utility (as shown by figure 2.6), i.e. reaching a superior indifference curve, not achievable only with risky assets on the portfolio.

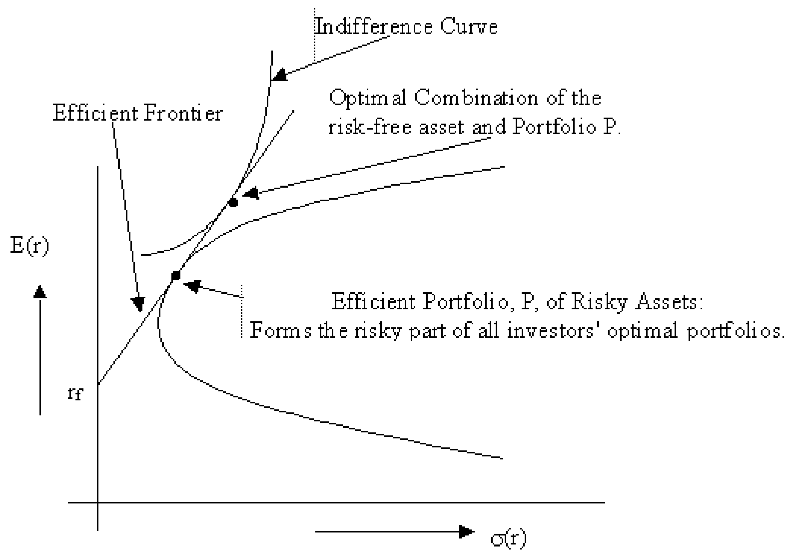


Figure 2.6 - Utility enhancement through combination of risk free and market portfolio [91].

### 2.1.7. Sharpe Ratio

The Sharpe ratio, developed by William F. Sharpe, is the first risk measure presented in this section and the most basic measure of risk adjusted return, obtained through the computation of the excess return over risk free rate, normalized by portfolio returns volatility, as presented in equation 2.13.

$$Sharpe = \frac{(R_p - R_f)}{\sigma_p} \tag{2.13}$$

## 2.1.8. Capital Asset Pricing Model (CAPM)

Interestingly enough, the Sharpe ratio is the actual slope of the capital allocation line, and for the optimal allocation line case, i.e. whose mean-variance efficiency is optimal, the Sharpe Ratio is maximized. Thus, according to Ang (2014) [4], under this theory any rational individual could simplify an investment decision-making framework into two parts: (1) **An assessment** of risk aversion in terms of volatility tolerance; then (2) **An allocation** of capital between risk-free asset and mean-variance efficient (MVE) portfolio, in a proportion consistent to risk tolerance.

Hence, ultimately assuming that investors have the same set of means, volatilities and correlations on their scenario expectations, then under equilibrium condition all investors would rationally hold the same MVE portfolio, named the market portfolio (M), as presented in Figure 2.7. The CAL passing through M is called Capital Market Line (CML).

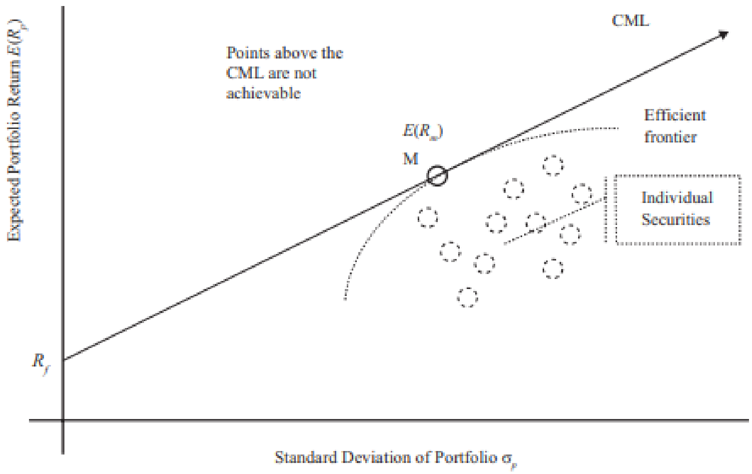


Figure 2.7 - Capital Market Line [25]

Thus, let P be a portfolio derived from the combination of $w_1\%$ risk free asset and the remaining in market portfolio, whose risk and return is modelled in terms of the weightings, so that the analytical expressions are described by equations 2.14 and 2.15.

$$E(R_p) = w_1 R_f + (1 - w_1) E(R_m) \tag{2.14}$$

$$\sigma_p = (1 - w_1)\sigma_m \tag{2.15}$$

It is noteworthy the fact that the overall portfolio weights can be eliminated, in order to derive a broad risk-return model associated to CAPM theory (equation 2.16), that has the market portfolio's sharpe ratio as slope, meaning that a portfolio of securities remunerates investors according to (1) the rate of return on riskless assets, (2) the risk exposure of the portfolio, (3) the sharpe ratio of the overall market (in practice, proxied by a broad index such as S&P 500).

$$E(R_p) = R_f + \left(\frac{E(R_m) - R_f}{\sigma_m}\right) x\sigma_p \qquad (2.16)$$

Although there is extensive evidence on CAPM's incapacity to really explain all sources of expected return of a portfolio (Ang, 2014) [4], CAPM applies the concept of market risk to parsimoniously model returns, being widely used by practitioners around the world (KPMG, 2018) [51]. Finally, it worth to stress that in fact CAPM assumptions are actually broader than exposed in this section, and even though we tried to capture the essence of them (e.g. with respect to rational investors having homogeneous expectations) properly along the argumentation, we present a broader set assumptions underlying CAPM theory according to CFA Institute (2019) [25] in appendix A.

### 2.1.9. Diversification of risk

It is intuitive that businesses within a common market are exposed to many similar risk factors, i.e. systematic risks, inherent to the market as whole, hence not diversifiable, since variables such as interest rate, inflation, economic cycles, political friction, natural disasters, etc. should affect all market's securities returns, albeit not in equal proportion.

Idiosyncratic risk factors, on the other hand, are those specific to a particular asset or industry, therefore should have an isolated impact, such as an effect of a fail on a drug test for a pharmaceutical company, or the increase in the international demand for iron ore. Those non-systematic risk factors become diluted when pooled into a well-diversified portfolio, because, in theory, the correlation of non-systematic risk among different individual assets are assumed to be negligible in aggregate, which ultimately implies that **diversification contributes to decrease the overall amount of nonsystematic (idiosyncratic) risk of a portfolio.**

In practical terms, a portfolio composed by over 30 different assets is diversified enough to cover a safe level of non-systematic variance as shown in Figure 2.8.

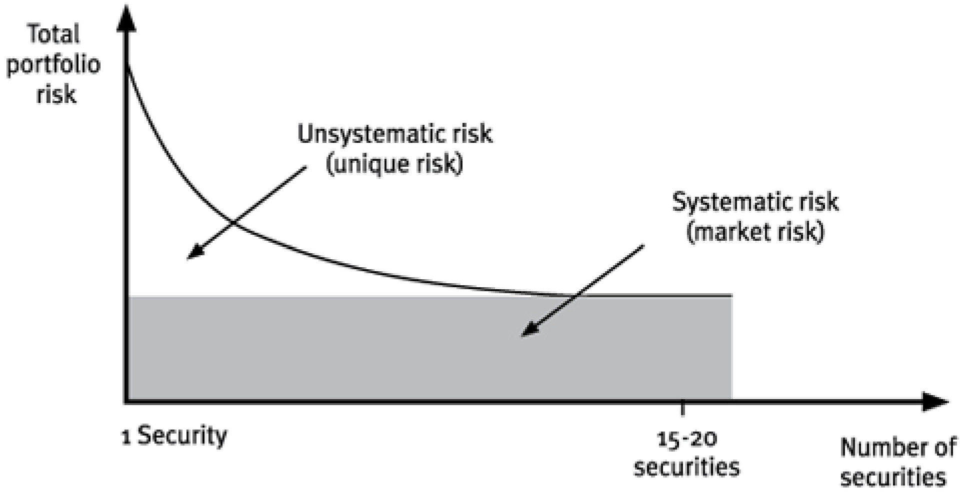


Figure 2.8 - Effect of diversification on portfolio total risk [49].

By segmenting sources of risk into systematic and non-systematic, security pricing problem can be better addressed. Given that one can mitigate idiosyncratic risk by pooling risky assets, nonsystematic risk should not be rewarded under arbitrage-free markets, i.e. if non-systematic risk was rewarded, arbitrageurs would have incentive engage into riskless profit actions that would ultimately lead to zero remuneration for non-systematic risk bearing.

### 2.1.10. Return Generating Models

The return generating model derived by CAPM complies with the rationale that return should be compensated by only systematic risk exposure. Rearranging terms of equation 2.17, its evident that the expected return over risk-free rate for a particular portfolio $(E(R_p) - R_f)_i$ is proportional to the market's portfolio excess return over risk free rate, adjusted by the ratio of volatilities $(\frac{\sigma_{pi}}{\sigma_m})$, which is the so called **beta**, a measure of sensitiveness of an asset returns performance with respect to **market risk**.

$$E(R_i) - R_f = \left(\frac{\sigma_i}{\sigma_m}\right) x\left[E(R_m) - R_f\right] = \left(\beta_i \frac{\sigma_m}{\sigma_m}\right) x\left[E(R_m) - R_f\right] \qquad (2.17)$$

Financial practitioners measure beta by regressing a particular security's historical returns against a market index such as S&P 500. Although a straightforward procedure at a first glance, this process requires a great dose of diligence on sampling and interpreting outcomes, because (1) beta is not a static measure across time, therefore the analysis may be misleading by a oversized time-frame; but also (2) a undersized time-frame misleads interpretation due to "noise" and outliers effects.

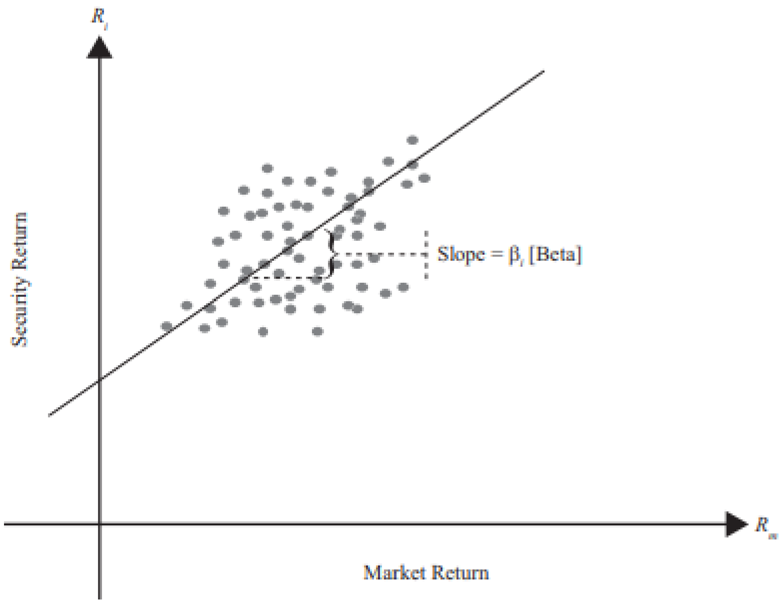


Figure 2.9 - Measuring beta through linear regression [25]

## 2.1.11. Treynor Ratio

Jack Treynor, one of the contributors to CAPM development, adapted sharpe ratio to reflect better the dependence of return expectations on systematic risk only as shown in equation 2.18, not captured by sharpe ratio.

$$Treynor = \frac{(r_p - r_f)}{\beta_p} \tag{2.18}$$

Treynor ratio is obtained by the ratio between the portfolio's excess return over risk free ratio, divided by the beta of the whole portfolio, which is simply obtained by the weighted average of individual assets beta, as proven below in the set of equations 2.19 and 2.20.

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f] \tag{2.19}$$

$$E(R_p) = \sum_{i=1}^{n} w_i E(R_i) = R_f + \left(\sum_{i=1}^{n} w_i \beta_i\right) x[E(R_m) - R_f] \qquad (2.20)$$

### 2.1.12. Jensen's Alpha

The last measure of risk, named Jensen's Alpha, computes the abnormal return measured in a risk-adjusted basis (equation 2.21), interpreted as the absolute excess return over the beta exposure.

$$\alpha = R_p - R_f - \beta_p . (R_m - R_f) \qquad (2.21)$$

This is an outstanding KPI to evaluate portfolio management performance, because it clearly segregates the component of return attributed to active management. By passive management, for instance, one expects to be compensated only by ***beta*** factor, while under active management, through discretionary stock picking and timing, surplus returns in risk adjusted basis are expected to occur, also known as ***alpha***.

### 2.1.13. Arbitrage Pricing Theory

According to Ross (1980) [75], CAPM proposes a single factor and single period model that aggregates all the risk factors into a market risk factor, under the assumption that investors have homogeneous expectations, and market equilibrium ultimately leads to a MVE market portfolio. Despite CAPM satisfactory results, Arbitrage Pricing Theory (APT), introduced by Stephen Ross (1976) [76], idealized a model under less binding assumptions, requiring only that every market equilibrium is consistent with the absence of arbitrage profit opportunities, in line with competitive and frictionless markets. The result is stated in equation 2.22, i.e. the expected returns are a linear combination of return factors, whose nature are not defined by this theory - for instance in equation 2.23, the first factor is attributed to market risk, so that CAPM turns out to be a special case of APT.

$$E(R_i) - R_i = \sum_{j=1}^{k} \beta_{ij} E(F_j) \qquad (2.22)$$

$$\sum_{j=1}^{k} \beta_{ij} E(F_j) = \beta_{i1} \left[E(R_m) - R_f\right] + \sum_{i=2}^{k} \beta_{ij} E(F_j) \qquad (2.23)$$

According to Berry et. al. (1988) [9], though, every legitimate factor must possess at least the following three properties: <<*(1) At the beginning of every period, the factor must be completely unpredictable to the market; (2) Each APT factor must have a pervasive influence on stock returns; (3) Relevant factors must influence expected return; i.e., they must have non-zero prices*>>.

Essentially the properties above determines that risk factors remunerate investors because they (1) are non-trivial, i.e. not be predictable from past information, (2) reflect systematic risk, and (3) have an empirically tested influence on expected return, assessed by econometric models. Empirical test for risk factors involves analyzing through statistical regression each factor ($F_j$) and its related sensitivity related ($\beta_{ij}$), similarly to the CAPM's beta factor. One major caveat, though, is that the selection of factors must have meaningful grounds, otherwise the results of regression analysis may assess factors statistical significance due to mere spurious regression. In a nutshell, this process matches significant sensitivities (in statistical terms) for significant risk factors (in economic terms).

Even though a number of factors may be identified, Berry et. al. (1988) [9] claims that five systematic risk factors have been shown to have significant influence over expected returns: (1) risk over default premiums; (2) risk over the term structure of interest rates; (3) risk of unanticipated inflation or deflation; (4) risk that long term expected growth rate of profits for the economy will change; and (5) residual market risk, or anything else needed to explain market risk. According to their studies rigorous statistical testing confirmed that <<*there is virtually zero probability that the five risk factors identified above add no new information over and above that already embodied in the S&P 500*>>.

### 2.1.14. Fama & French three factor model

According to Kula et al (2017) [52] the big caveat of APT model for practitioners is the lack disclosure of a proper set of factors to reflect systematic risk. Not surprisingly, some years after the discovery of APT, Fama and French (1993) [34] proposed a three-factor return generating model for stocks based on (1) MKT: Market risk factor; (2) SMB, which stands for "*__S__mall* *[market cap]* ***M****inus* ***B****ig",* a size factor, measured by market capitalization, which has an influence on returns in the sense that small caps tend to outperform large caps; and finally (3) HML, standing for *"****H****igh [market to book ratio]* ***M****inus* ***L****ow",* which refers to the observed fact that portfolio of growth stocks tends to underperform one of value stocks, i.e. stocks characterized by a lower than average valuation multiple such as price-to-book value, price-per-earnings, Enterprise Value per EBITDA. The model is mathematically described in equation 24.

$$E(R_{it}) = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t \qquad (2.24)$$

M. Carhart (1997) [21] added momentum as a fourth factor (UMD in equation 2.25 is an acronym that stands for "*Up Minus Down*"), measured by the trailing eleven months returns (with a lag of one month). In this sense, "winners" were stocks whose recent historical return were above average - indeed, Carhart's methodology attributed an equal weight to a portfolio composed by the top 30% performers during the period analyzed.

$$E(R_{it}) = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,UMD}UMD_t \qquad (2.25)$$

The author observed the net operational performance of a total of 1892 mutual funds from years 1962 to 1993 corrected by survivor bias, in which 30% thereof were eliminated by the end of the period. Interestingly enough, the study concludes that CAPM does not capture properly the relative difference between the bests and worsts mutual funds, whose betas were in fact very similar. Thus, the CAPM alpha reproduced as much dispersion as the simple returns, i.e. abnormal returns ranged from about -5.4% to 2.2% per annum, which represents a very large dispersion. Moreover, another strong empirical evidence in favor of factor generating models is that the top 10 decile portfolios appeared to hold significantly “small caps” and momentum stocks than the bottom decile.

## 2.2. Efficient Markets Theory

### 2.2.1. Introduction

CFA Institute (2019) [25] defines an efficient market as the one in which asset prices reflect all past and present information both (1) **Rationally**, i.e. consistent to a maximization of one's utility function; and (2) **Quickly**, i.e. within a time-frame of similar magnitude of the time needed to execute the trades to exploit the price inefficiencies. Thus, under efficient markets, both borrowers and lenders are better-off, because prices are informative and transparent, which ultimately means that market prices are allocative efficient, in the sense that they reflect the intrinsic value of the underlying.

In essence, Fama (1970) [58], who initially developed this efficiency concept, argues that one cannot consistently outperform the market portfolio in an efficient market (i.e. achieve abnormal returns), because prices only react to unexpected or "surprise" elements (as it is embedded under APT model assumptions). Furthermore, the author identifies three degrees of efficiency, according to the market's response to distinct levels of data, as described in Table 1.

| | Market Prices Reflect: | | |
|---|---|---|---|
| Forms of Market Efficiency | Past Market Data | Public Information | Private Information |
| Weak form of market efficiency | ✓ | | |
| Semi-strong form of market efficiency | ✓ | ✓ | |
| Strong form of market efficiency | ✓ | ✓ | ✓ |

Table 1 - Forms of Market Efficiency [25]

A. **Weak form of market efficiency**: securities prices reflect all past market data, which refers to all historical price and trading volume information. Therefore, investors cannot profit by analyzing past prices or patterns thereof.

B. **Semi-weak form of market efficiency**: Securities prices reflect all publicly known and available information. Semi-weak markets are supposed to react (*"price-in"*) once any financial statement data (such as earnings releases, dividend payouts, changes in management) or financial market data (such as closing price or volume traded) are released, so that an investor cannot achieve abnormal returns by relying on an informative basis (except if it is private, which is forbidden due to regulations against insider trading).

C. **Strong of market efficiency:** On top of weak and semi-weak forms, the stronger degree further considers the impossibility of profiting by private information (also known as insider trading). Clearly, this kind of efficiency is not likely to be observable in real world since regulations strongly prohibits activities such as insider trading and front-running, so unless market agents are succeeding to break rules, there strong market efficiency form cannot be observable in any market.

### 2.2.2. Determinants of efficiency

In order to reach higher efficiency levels, markets must develop at least three basic elements: (1) **Number of market participants**, i.e. the more agents monitoring prices and news releases contributes to grow a network of well-informed players. It may be noted that the definition of market participants comprises algorithmic trading robots. (2) **Information availability and financial disclosure**, i.e. in order to information be present into analyst's models, it has to reach the market by effective and reliable channels. Due to strong disclosure regulations for public companies, pressure towards convergence of accounting standards, and well developed real and internet-based media channels, market agents are able receive information in a readily and efficient manner. (3) **Less limits to trading**, in order to let the process of arbitrage to work frictionless. Indeed, arbitrageurs are incentivized to profit on market inefficiencies, leading ultimately to the elimination of price discrepancies towards a market equilibrium. Therefore, elements such as high transaction costs, regulation against arbitrage profit, or even limits on short selling end up undermining market efficiency mechanisms.

## 2.2.3. Test for Efficient Markets Hypothesis (EMH)

In order to test efficiency based on empirical data, the process to be adopted is named "event study", described in Figure 2.10. For instance, in a event of a quarterly result release, this method proposes to gather data within a time frame that encompasses a time span before and after that information release, in order to analyze the degree and velocity of price incorporation due to the event. This is assessed by the comparison between the actual results and those predicted by a statistical model whose inputs are ex-ante the release. Finally, the results are tested under the null hypothesis of no abnormal returns, so that if there is significant discrepancy, market efficiency may be rejected.

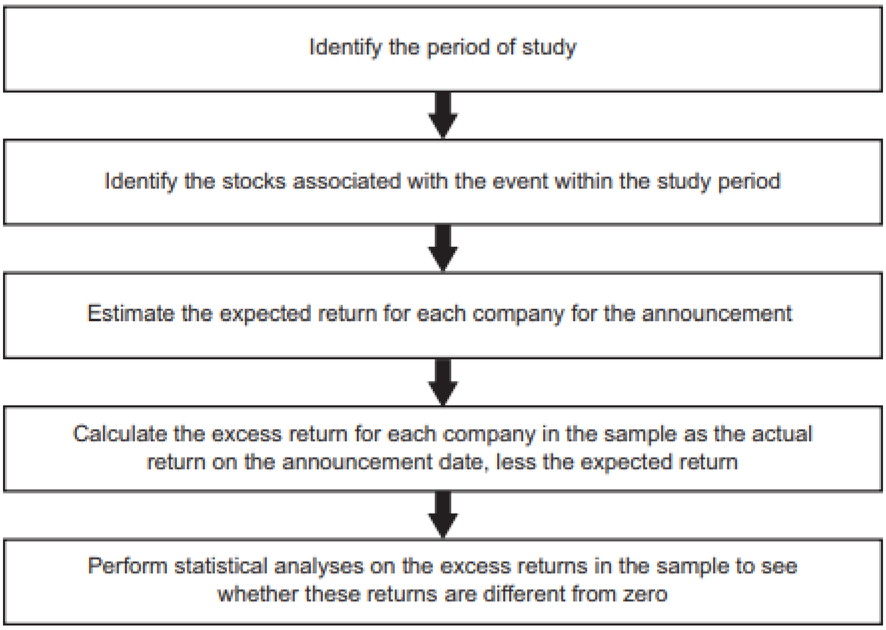


Figure 2.10 - Event Study Process [25].

Efficient Market Hypothesis is one of the most controversial topics in finance, especially because this process of finding evidences to support or reject it is susceptible to biases such as data mining, data snooping, sample selection, survivorship bias, look ahead bias and time period bias. It is out of the scope of this work explain all the details related to them, but in essence, biases are result of one's subjective judgement, that influences the search and conclusions of a given research. Moreover, as explained by Titan (2015) [88], <<*testing for market efficiency is difficult and there is a high possibility that, because of changes in market conditions, new theoretical model should be developed to take into consideration all changes*>>. No wonder the bottom line of this fact is that the number of articles corroborating the hypothesis is comparable to the number of articles rejecting it.

Notwithstanding the foregoing, according to CFA Institute (2018) [25] most researchers support the suitability of either weak or semi-strong form efficiency on developed markets, while for emerging markets the tendency is be classified either as weak-form efficient or just inefficient. For instance, evidence supports that in countries such as Hungary, Bangladesh, Turkey, for instance, still offer good opportunities to profit on technical analysis (appendix B), what violates weak form efficiency.

As a counterpoint to the traditional idea of efficiency, Grossman and Stiglitz (1980) [40] developed the concept of near-efficiency market, arguing that it is impossible for markets to achieve full efficiency, because information research has a cost, hence it would be paradoxical if market agents bear expenses in obtaining information if all information was already embedded on prices. Thus, the authors claim that market agents seek to profit on inefficiencies, leading ultimately to increased levels of efficiency, which seems to be closer to what is observed in reality. This theory has profound implications, introducing an initial counterargument against fully efficient markets, in favor of what active management advocates to be considered a value-adding activity.

Endorsing the views of Grossman and Stiglitz (1980) [40], several event studies found evidence of market anomalies on which an investor could obtain above market profits systematically, those will be studied in the next topic.

### 2.2.4 Market Pricing Anomalies

Although evidence supports market efficiency for the majority of markets around the world, researchers have found several market anomalies on which a well-informed rational player could exploit. There are also controversial opinions on whether one can indeed consistently earn abnormal returns, since once an anomaly is publicly known, players are incentivized to profit over, ultimately undermining its effectiveness in terms of excess profit adjusted by risk. The CFA Institute (2018) [25] recognizes three different categories of market anomalies, segmented into time-series anomalies, cross-sectional anomalies and others (appendix C).

### A) Cross-sectional anomalies

This section refers to observed anomalies across companies differing in some key characteristics, in special this section will focus on two anomalies already observed in Fama & French three factor model, they are (1) **Size**, in terms of market capitalization and (2) **Value,** in terms of valuation measures.

Value-effect: Through observation of stock's valuation multiples, it is possible to classify them between (1) **Value stocks**, i.e. those whose valuation multiples such as P/E (price per earnings) or M/B (Market value per book value) ratios are below average; and (2) **Growth stocks**, i.e. the exact opposite definition. The market anomaly associated to them was already described in Fama & French three factor model section, but as a refresh, the authors argue that value stocks are observed to systematically outperform growth stocks in a risk adjusted basis.

Size-effect: As also observed by Fama & French model, small cap equities tend to outperform large cap ones in a risk-adjusted basis. However, as observed by Ang (2014) [4], since 1980, apparently size effect has lost its effectiveness, what may be either because this anomaly became so widespread that has lost its power, or that initially this factor was originally a chance outcome. Despite of that, SMB is still a factor sought by investors in general.

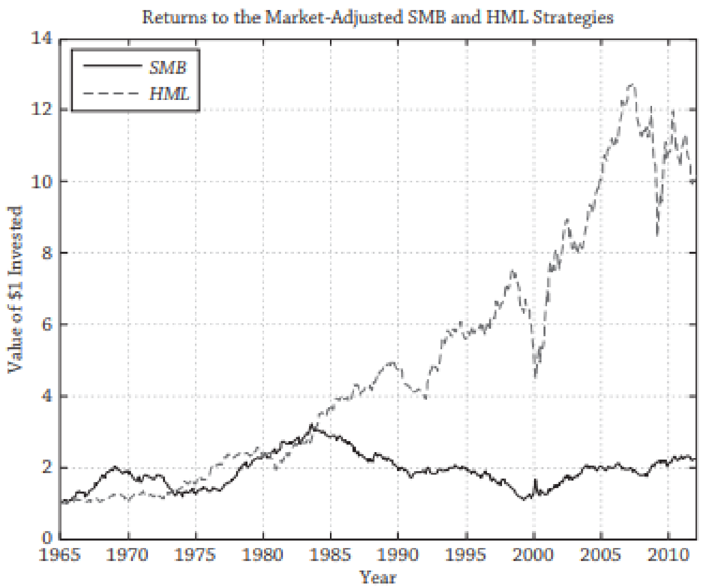


Figure 2.11 - Returns to Market-Adjusted SMB and HML Strategies [4]

### B) Time series anomalies

Those anomalies are manifested across time (not across companies), therefore can be detected by time-series data analysis. According to CFA Institute (2018) [25] there are two categories of time series anomalies (1) **Calendar**, i.e. referring to periodic effects observed monthly, weekly or even related to holidays and (2) **Momentum**, i.e. effects mostly related to behavioral biases, that can be captured by time series analysis. Under calendar anomalies, we will restrict our analysis to the “January effect”, because in general calendar anomalies lack economic rationale, thus are out of the scope of this work.

For instance, Brockman and Michayluk (1998)[19] explain the "January effect", one of the most famous calendar anomaly, associated with the observation that stock prices are likely to over appreciate in January.

One likely explanation for this observed phenomenon involves the concept of "tax-loss selling", in which investors are likely to sell worst performer securities on end december for the purpose of reducing tax base by offsetting capital gains. This ultimately decreases even more these share prices due to increased supply and low demand, so that in January those "loser" stocks are found quite undervalued. Tax loss selling is just one of the reasons researchers attributes to january anomaly effect, whose occurrence is not proven to be persistent.

Calendar anomalies are very unlikely to be reflected on formal return generating models such as Fama and French’s, due to a weak economic rationale behind them. However, this is not the case of Momentum, present in Carhart’s four factor model, whose fourth factor reflects the phenomenon observed by Jegadeesh and Titman (1993) [47] that stocks with recent positive returns (3 to 12 months holding periods) tend to overperform the average (Figure 2.12). So that a long-short neutral portfolio composed by long positions on stocks with high momentum, while short in low momentum, tends to generate alpha sustainably.

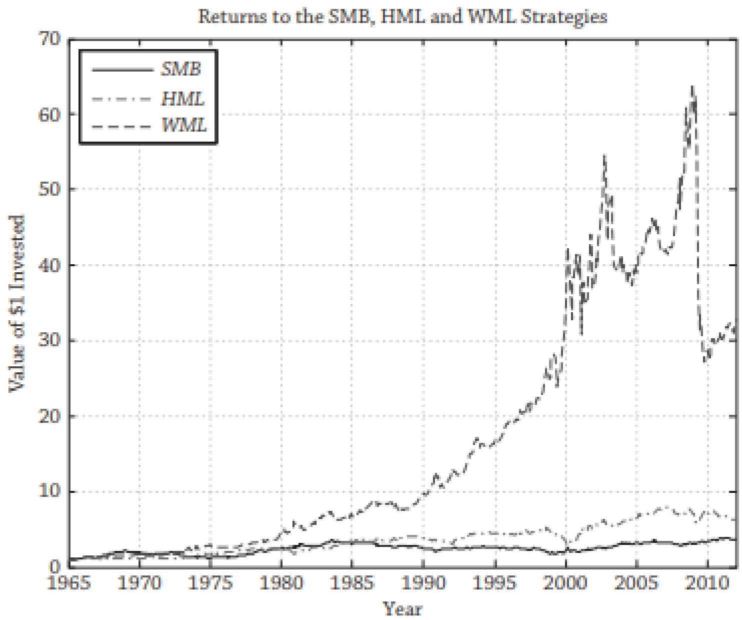


Figure 2.12 - Superior Returns of Momentum with respect to value and size [4]

### 2.2.5. Behavioral Biases

Many of the foregoing anomalies are result of behavioral biases influencing human decision making process, either individually or collectively, hence the role of behavioral finance is to examine the effects of psychological biases on investment decisions, to understand its causes and ultimately how to mitigate and to create mechanisms to prevent it from happening. It may be stressed that a rational action is not strictly the one whose outcome is superior "*ex-post*", rationality in this theory is about backing-up a decision based on one's utility maximization under budget constraint (and potentially other constraints), applying a fair analysis of available information.

According to CFA Institute (2019) [24] behavioral biases can be categorized as either (1) cognitive errors, or (2) emotional biases. While the first refers to **faulty reasoning**, i.e. result of a poor process of analyzing information; the other stems from **impulse or intuition**, which has associated three behavioral biases (Loss Aversion, Herding, and Overconfidence) that worth to be analyzing more in depth. Further biases are also relevant (e.g. information cascade, conservatism, representativeness) but not comprised in the scope of this thesis.

1. <u>Loss Aversion</u>: When dissatisfaction with losses is greater than a satisfaction with comparable gains, traditional finance theory fails to model investor's utility logic,

because this orthodox theory assumes that rational investors seek the highest return achievable up to a given risk tolerance threshold, which is often not observable in practice. Indeed, Shefrin and Statman (1984) [80] observed behavior patterns of both gain and loss realization consistent to the idea of a "disposition effect", i.e. the authors advocate that investors have an irrational (psychological) tendency to sell winners too early, while are persistent to hold losers for longer periods. This phenomenon has strong links to the momentum effect empirically observed in markets worldwide.

2. Herding: Baddeley et. al (2007) [8] explains herding as type of bias occurring when individuals mimic actions of a herd or a larger group, regardless of the substantive own private information. The psychological motives for this behavior are usually attributed to both (1) **Social pressure** for conformity, i.e. a natural desire to be accepted by a group, and to dilute the responsibility if proven wrong; and (2) **Heuristic bias** to believe that the more people backing up a decision, the more likely it is to be right, which is especially likely to occur for individuals with limited knowledge or expertise to take a decision.

3. Overconfidence: Is the effect stemmed from a miscalibration (skewed upwards) between a subjective judgement about an event probability and the actual likelihood of occurrence. According to Barber and Odean (2000) [66], overconfidence is a behavior bias strongly linked to Loss Aversion, i.e. the author claims that the human desire to avoid regrets, leads to a tendency to overweight information that proves own points right, what ultimately results in a bias to hold loser portfolios, while selling upfront winners. Moreover, overconfidence bias causes excessive trading, what tends to reduce realized alpha, even if the trading is realized in good timing. This is an effect of both (1) **Excessive costs** related to trading; (2) **Less information** gathered, processed and analyzed per trading.

### 2.2.6. Adaptive Markets Hypothesis

The previously mentioned concept of near-efficient market (Grossman and Stiglitz, 1980) [40] introduced a first argument against fully efficient markets through the inclusion of costly information research. On top of that, Lo (2004) [54] further enhances the views on efficiency through the *adaptive markets hypothesis (AMH)*, a theory based on an evolutionary approach, in which Professor Lo claims that market players are analogous to species (for instance, in his view, pension funds would be one kind of species, while retail investors would be another one, and so on) competing for scarce resources (e.g. one kind could be 10-year U.S. treasury notes, or any other security).

In markets whereby multiple species are competing for scarce resources, the pressure for survival leads to efficiency, which is achieved through multiple iterations of trial-and-error, mimicking “natural selection”. And vice-versa, with fewer species competing for abundant supply of resources, less evolutionary pressure exists, so that markets are expected to be less efficient. In this scenario, behavioral biases (heuristics) are result of that trial-and-error process driven by individuals’ efforts to adapt to a changing environment. As explained by the author (Lo, 2004) [54], <<*individuals develop heuristics to solve various economic challenges, and as long as those challenges remain stable, the heuristics will eventually adapt to yield approximately optimal solutions to them*>>. This Darwinian argument sheds a light on interesting markets’ phenomena, for instance, behavioral finance is better addressed by this theory, which rather than labelling those as “irrational” decisions, Lo interprets behavioral biases expressed by individuals in periods of intense “environmental” transformations as natural suboptimal responses, consistent to the scenario of individuals trying to adapt to new information flow.

Interestingly enough, this evolutionary trial-and-error approach (meta-heuristics) underlying thinking process is consistent to the computer science theory of partial search optimization by genetic algorithms, developed by Holland (1988) [37], to which optimization is achieved through computer simulation of multiple populations, whose fitness to environment is evaluated according to an objective function. Indeed, the explanation for Holland’s theory is out of this report’s scope, however, under a circumstance in which a change of the objective function is introduced, previously optimal results are sub-optimal, but definitely not irrational. Overall, Lo’s views on the market are much more consistent to a human perspective of taking decisions, through learning and adapting, rather than considering analytical responses in order to optimize outcomes.

Overall, AMH has five great implications on markets, as explained by (Lo, 2005) [53]: (1) **Equity risk premium**, instead of being a static measure, varies according to the recent path of the stock market and the demographics of investors; (2) **Asset allocation** can add value by exploiting the market's path dependence as well as systematic changes in behavior; (3) **Investment products** tend to experience cycles of superior and inferior performance; (4) **Market efficiency** is not a binary (i.e, efficient or not) property, but rather varies continuously over time and across markets; and (5) **Individual and institutional risk profile,** alike equity risk premium, is not likely to be static over time.

# Part III - Overview on Investment Management Industry

## 3.1. Introduction

Investment management professionals succeed to add value to their clients as long as they provide management services with respect to a *suitable*[1] and well diversified portfolio that yields reasonable risk-adjusted returns. With the ultimate purpose to evaluate whether this value proposition is being successfully delivered, the purpose of this chapter is to analyze the current industry arrangement, segmenting the analysis into three broad areas: (a) **Asset Managers**, in order to evaluate their needs and fitness to smart beta value proposition; (b) **Investment Products**, in order to assess the benefits and weak spots of both passive and active management styles, making especial considerations about smart beta; and finally (c) **Recent trends promoting structural changes** in asset management, specially focusing on how technology is transforming markets towards increasing informational efficiency, and lighter fee margins structure.

## 3.2. Asset Managers

From a demand standpoint, financial markets can be segmented into two broad categories (1) **Retail Investors**, i.e. individuals managing investments through a direct channel between own investment and investment markets, that even might be assisted by broker-dealers, financial advisors and other professionals. Those investors have the overall goal of obtaining extra income to fulfill personal goals; and (2) **Institutional Investors**, who are legal entities taking investment decision on behalf of clients, playing a very impactful role in taking decisions about worldwide asset allocation of about US$ 90 trillion of AuM, according to (McKinsey & Company, 2018) [63] in Fig. 3.1. In addition, according to EY Global survey (2017) [32], institutional investors are the dominant source of assets inflow to ETFs (appendix D), which is the principal mean of investing in passively managed funds.

[1]Suitability is a requirement for portfolio managers to adequate any investment actions to the fund's mandate or to financial advisors to make reasonable inquiry on clients' profile (financial situation, investment experience, risk and return objectives, etc.), to properly judge whether investments are suitable to clients' profile.

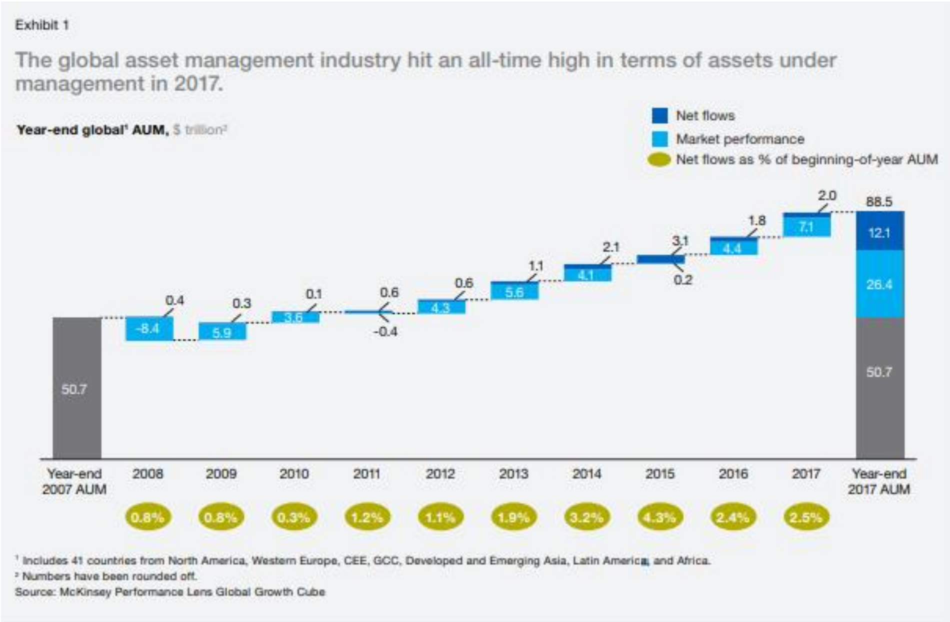


Figure 3.1 - Global AuM growth from 2007 to 2017 [63]

Hence, we will narrow our analysis to the most relevant institutional investor classes in terms of AuM share of global equity (OCDE, 2014) [23] as presented in Figure 3.2. The rationale of this decision is to prioritize the big flows of AuM by focusing on the following players: (1) Investment Companies (our definition comprises ETFs and Hedge Funds), (2) Insurance Firms, (3) Pension Funds.

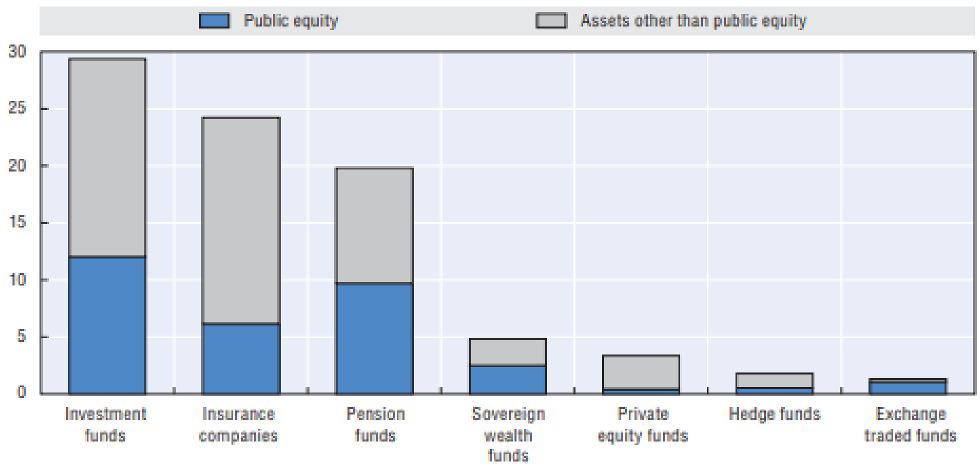


Figure 3.2 – Total AuM in public equity by different institutional investors (US$ trillion, 2011) [23]

We would like to stress two further points, in order to stay in line to the analytical structure we are proposing to this report: (1) Because of the Institutional Investors' fiduciary duty of defending best interest of clients with respect to investment decisions, they are typically bound to follow an *ex-ante* defined investment mandate, which specifies the objectives, the risk tolerance, and time horizon of investments. Moreover, (2) Due to the relevant role on systemic stability exercised by major asset managers such pension funds and insurance companies on systemic stability, some institutional investors end up bearing more protective regulations, despite their classification as accredited investors[1].

Therefore, we will focus our research on probing both (1) **Insights** how passive strategies (especial focus on smart beta) may raise clients' utility in terms of meeting mandate criteria with increased efficiency; and (2) **Potential concerns** deterring the switch to passive investing, especially with regards to regulation restrictions.

### A) Investment Companies

Investment firms may be segmented according to (1) **Vehicle structure**, i.e. divided in four categories: Mutual funds, Closed-ended funds, Exchange-Traded Funds (ETFs) and Hedge Funds, all of them properly addressed in appendix D; or concerning the (2) **Investment mandate**, i.e. a particular set of investment objectives, strategies adopted, risk profile and investment time horizon.

Mandates vary a lot across firms, having a spectrum ranging from a conservative money market fund to a very aggressive hedge fund. The former, for instance, is qualified to invest only in short-term and highly liquid securities such as government bonds, treasury bills and certificates of deposits, with the primary objective of being highly liquid, preserving capital investing, while generating returns near to risk free rate. The latter, on the other hand, is eligible to use leverage and short-selling as mechanisms to achieve respectively higher risk and return, and to neutralize market risk, while having the benefit of a better control of liquidity of the AuM.

[1]An individual or entity who has broad expertise and manages a sufficient amount capital, that makes them eligible to some benefits, for instance the ability to invest in highly leveraged or illiquid funds.

It might be added that although hedge funds are perceived as very risky investments (and some of them indeed are), mandates are very diverse, and should not be classified as a single class. De facto, some examples of strategies are macro hedge funds, arbitrage driven (e.g. convertible arbitrage strategies, offering exposition to liquidity risk premium by entering in long/short positions in equities and convertible bonds), long-short equities (either quantitative driven or not), event driven (in which trading ideas are triggered from corporate events), activist hedge fund, long/short sector specific (e.g. ones that operates only healthcare or technology securities), and so many others.

Furthermore, a more comprehensive and diversified strategy is achieved by hedge fund of funds (HFOF), which have a mandate to select a defined number of hedge funds (usually from 5 to 20, but can be even more) to compose a new vehicle, bearing the trade-off between diversification and a double layered fee structure. Some HFOF indeed are very well diversified that can display returns and volatilities comparable to their benchmark (e.g. 10Y US treasury bond). Hence, due to this close positioning – a sort of substitute relationship - between HFOFs and their benchmark, managers can expand the investment opportunity set by adding Hedge Fund of Funds having sufficiently uncorrelated strategies under their umbrella.

Depending upon each fund's business model, smart beta may be a value-adding product in distinct instances, i.e. while for an Index Fund, smart-beta passive products may be employed in a model based on high scale, high automation and efficiency, contributing to achieve compressed fees, what requires intensive investments on computing infrastructure and development expenses. Fund of Funds, on the other hand, may use them to continue operating in the traditional business model, but use smart beta to achieve superior uncorrelated returns by employing versatile factor expositions at low costs, while maintaining liquidity. In fact, this purpose may be even sought for Hedge Funds, which already are used to apply ETFs into their strategy, especially leveraged and inverse ETFs, in order to build high conviction long or short positions (EY Global Survey, 2017) [33]. Thus, a movement towards smart beta ETFs is justifiable, if properly motivated, for instance, with the ultimate goal to achieve uncorrelated (leveraged or not) risk-return strategies, having the benefit of better liquidity management

Few public data sources allow to probe the current expositions of market players to ETFs, because especially hedge funds are incentivized to treat it as confidential information, in order to maintain hidden competitive advantage sources. However, we found out, at WhaleWisdom, (2019) [94], that Bridgewater Associates, a leading US hedge fund, has disclosed in its 13-F filing a very high concentration in ETFs, i.e. the top 16 holdings were all ETFs with a wide array of expositions, e.g. emerging markets equities, fixed income, gold.

### B) Pension funds and Insurance Firms

According to CFA Institute (2019) [28], pension funds are investment vehicles set up to provide retirement plans for either employees or to employers who assign employees a pension right as a balance sheet liability. Their mandate is generally long-term biased, bearing relatively predictable liquidity requirements, what contributes to a riskier profile. Therefore, pension funds are more leaned towards equities, especially when interest rates are low, and alternative investments, which are attractive both because the uncorrelated returns to the other asset classes (equities, bonds, etc.), and because they usually have an illiquidity premium associated.

In our view pension funds may be benefitted by smart beta strategies in three grounds: (1) **Return enhancement**, through diversification stemmed from uncorrelated strategies, combining different set of factor exposures overtime; (2) **Increased transparency and simplified governance**, in order to better satisfy requirements of regulators such as ERISA for US and EIOPA for EU; (3) **Lower expense ratio**, which contributes to increased capitalization of wealth, especially relevant in long-term investments.

In addition, as defined by CFA Institute (2018) [25], insurance companies are specialized in non-market risk management, such as life, property and casualty. The insurance business model comprises revenue streams from policyholders (also known as premium) compatible to the level of risk provisioning (associated with the whole portfolio of policies) and to the capital appreciation a company can achieve over these committed capitals until the call of proceeds. Therefore, insurance businesses bear unpredictability both on liquidity needs and investment horizon, which may vary with respect to the portfolio of policies. In general terms, though, time horizon should be tilted to long-term investments for life insurance, while short-term for the remaining ones (auto, property, etc.).

Hence, from our analysis, insurance companies may be benefitted by smart beta strategies two-fold, besides the three benefits above mentioned for pension funds: (1) **Better Liquidity**

**management**, achieved through structural features of ETFs; (2) **Access to new product offerings**, such as low-volatility products or other tailored systematic strategies.

## 3.3. Management style

The primary impact of market efficiency on portfolio management refers to the degree in which information-based strategies may achieve consistent abnormal returns. As depicted in Figure 3.3, investment strategies have historically been massively inclined toward active management, due to the belief that most of the returns were attributable to managerial skill (with some degree of noise[1] embedded on data).

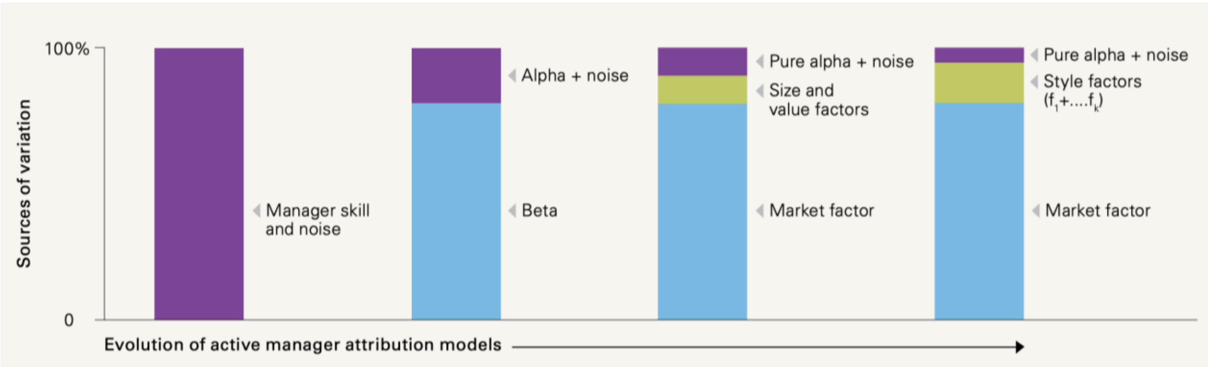


Figure 3.3 - Equity attribution models evolution overtime [4].

However, with the development of CAPM, it became evident to investors that active management had, in fact, less attribution on returns, which were explainable by only the alpha fraction. Then, with another round of enhancements to return generating models, Fama & French segmented alpha into two further components, i.e. pure alpha and size/value factors, narrowing even more the active management attribution towards alpha. Nowadays, more factors have been discovered, so that pure alpha accounts for a even narrower fraction of the overall return, which still may be pretty significant in some cases, though.

[1]The difference between actual results and the results predicted by a return generating model has two components that the model cannot separate: (1) Alpha, i.e. some sort of product of manager's skill, which the model is incapable to explain, and (2) Noise, i.e. the statistical residuals, usually distributed as a white noise (i.i.d. normal random variables with mean value zero).

In this section, we will discuss more in depth the elements in favor of each management style, introducing smart beta as a strong substitute product, with an interesting positioning in comparison to pure passive and active offerings.

## 3.3.1) Passive Management

By definition according to the CFA Institute (2019) [25], Passive Investment refers to *"any rules-based, transparent and investable strategy, that does not involve identifying mispriced individual securities"*. Albeit the tendency to treat passive investing and indexing as synonyms, the former is a broader definition that encompasses indexing, which by itself refers to *"a strategy intended to replicate the performance of a benchmark index"*. However, since the most common type of passive investment is indexing, throughout this work we will be flexible with respect to that distinction, sometimes treating them as synonyms throughout the argumentation.

Indexing is a strategy that seeks to track specific portfolios representative of a whole asset class, or a whole market, a sector, etc. In the case of equities (the most popular asset class when it comes to indexing), these indexes track either (a) **Market indexes**, i.e. pure passive investing, looking for beta exposure (or multiples thereof through leveraged or inverse funds); or (b) **Factor indexes**, i.e. seeking exposure to a long-term driver of return, other than a market portfolio. Intuitively, as consequence of the mandate to track an index, a proper measure of performance of these funds is generally the tracking error with respect to the index, whose sources are generally explained by either (1) Trading costs; (2) Fees; or (3) Cash drag, i.e. dilution of return on assets due to cash held.

### A) Market Indices

The rationale behind pure passive indexing is to achieve reasonable returns that compensate the exposure to market risk, which would, in fact, be an optimal outcome under the assumption of a MVE market portfolio as idealized by the CAPM theory. According to CFA Institute (2018) [25], in order to have exposure to market factor, a portfolio indexed to the S&P 500 would be a good market proxy, since its composition is parsimonious but still representative enough. Indeed, the S&P500 index is made of the 500 most valuable companies weighted by market capitalization comprises roughly 80% of the total US equity market capitalization. Besides the S&P500, there are several other relevant indexes such as Russell 3000, which satisfies the same purpose of tracking US equities market (covering 98% thereof), as well as indexes of other geographies like FTSE 100, which tracks the 100 highest market cap stocks of london stock exchange, analogously the FTSE MIB for Milan stock exchange, and Ibovespa for Brazil.

Even though the concept of a pure passive investing is relatively simple, its availability as a market product was introduced quite recently by Jack Bogle, founder of Vanguard Asset Management, by the 70s. The movement to introduce passive investment was profoundly influenced by Professor Malkiel, whose investment philosophy is described in the book *"A Random Walk Down Wall Street"* (1999) [56]. Malkiel not only became one of Vanguard's directors, but reiterated among academics the advantages of a passive index fund, capable to offer investors benefits such as diversification, low expense ratio services and tax efficiency in order to obtain long-term returns, without having to rely on forecasts and short-termism of active managers, who were trying to predict the outcomes of a "random walk" (an econometric jargon, which refers to a time series whose value one step ahead is unpredictable based on past data, i.e. a brownian process, or a stochastic random process).

The argumentation is two-fold, as summarized by Vanguard (2017) [90]: (1) If markets were efficient, achieving outperformance through asset selection and/or timing would be impossible, because every material public information would be already embedded on price, thus outperformance would be unlikely; However, Malkiel adds (2) Even for a non-efficient market, passive investment is a statistically the best choice because of the "zero-sum game" (figure 3.4).

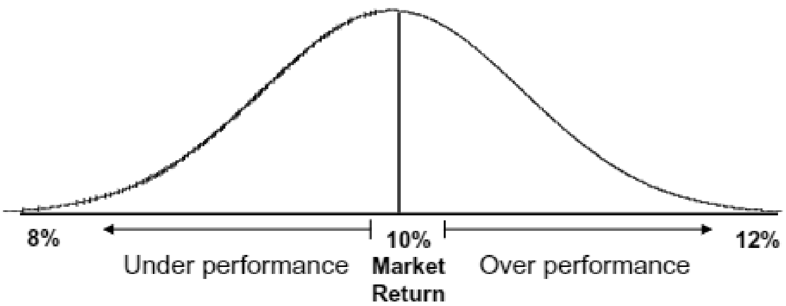


Figure 3.4 - Distribution of returns (zero-sum game) [57]

This theory argues that a zero-sum game dictates the dynamics of active managed funds, so that for a manager to outperform the market, another one must be underperforming, in order to logically maintain average of fund's return at the actual market return.

When accounted for the management costs involved in the process, overperform the passive performance threshold becomes even more challenging, characterized by a negative sum game, as shows the figure 3.5.

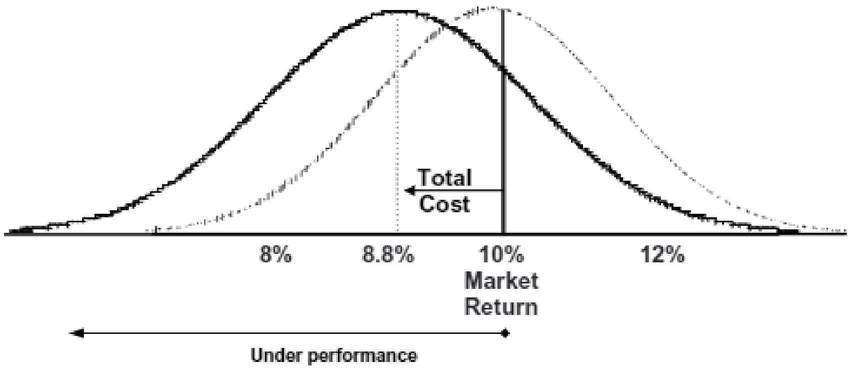


Figure 3.5 - The negative sum game after expenses [57]

Hence investors might be better off by just choosing the cheapest and most tax efficient investment product instead of trying to bet on the *"best horse"*. As shown in Fig. 3.6, equity fund performance between 1970 to 2000 had a negative skew towards losers rather than winners, being most of them on the zero-sum zone.

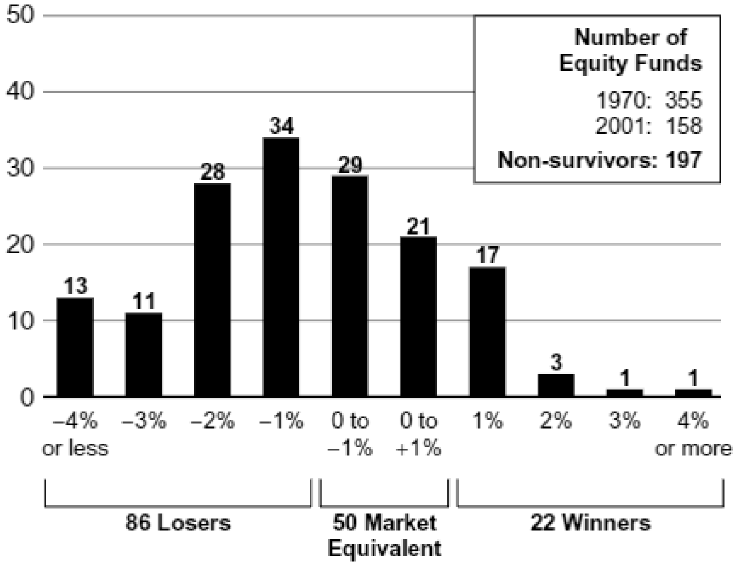


Figure 3.6 - The odds of success: returns of surviving mutual funds 1970-2001 [57]

Although this zero-sum game provides straightforwardly an argument against active management, one may criticize the effectiveness of such assumption. Indeed, since AuM inflows and outflows occur across investment funds of different mandates a temporary unbalance may happen such that it results in either a positive sum or a negative sum.

### B) Factor Indices

As an alternative to a pure beta factor exposition, exposure to factor investing yields certain elements of active returns, while still having most of the benefits outlined by Malkiel about passive managed funds. Andrew Ang (2014) [4] outlines a dozen of factors (Figure 3.7) usually sought by investors, segmented into macro, i.e. factors linked to fundamental macro systematic risk sources such as inflation risk, liquidity risk , credit risk, and so on; and style drivers, i.e. investment strategies based on specific rationales explained by either (1) **above rewarded risk**, i.e. an above average return for bearing higher risks; (2) **structural impediment**, i.e. market rules/constraints on certain investors (e.g. regulations on pension funds against leverage or even restrictions on short selling for mutual funds) that may generate interesting opportunities to other players; (3) **investor's biases**, i.e. behavioral biases affecting investors' rational decision making. A thorough analysis of these style factors is presented on chapter IV.

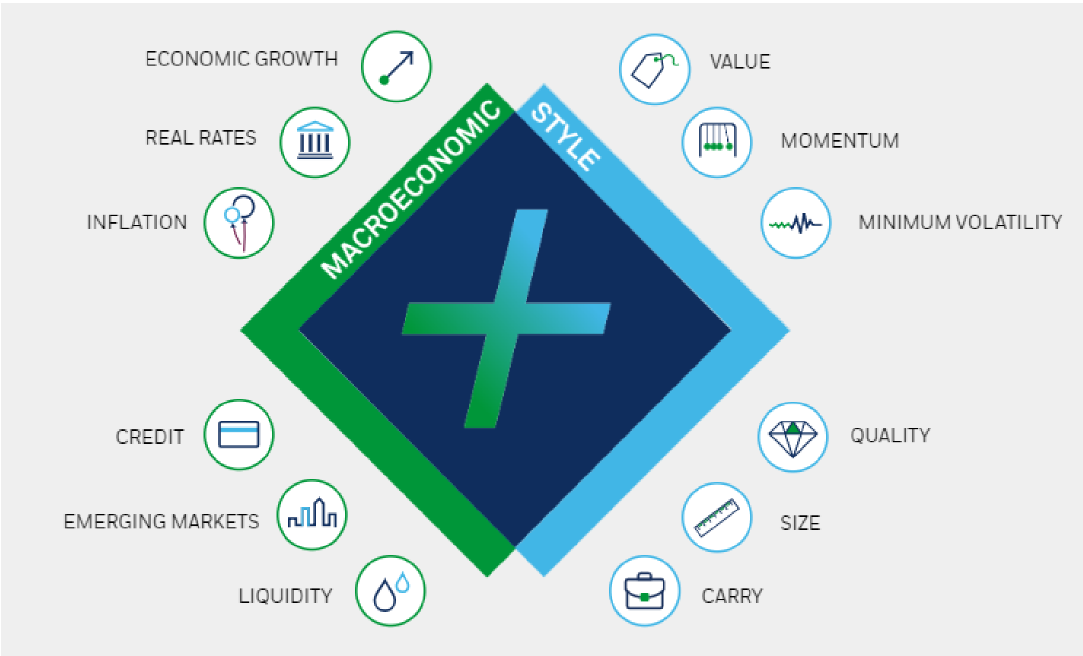


Figure 3.7 - Factor Investing [14]

## C) Passive Investment products

Investors get access to index investing most likely through ETFs, even though some passive managed mutual funds exist. Since its inception, ETFs have been triggering interest from investors, and, as a matter of fact, EY Global Survey (2017) [33] estimated that as of September 2017 the amount invested in ETFs globally was around US$ 4.4 trillion of assets under management (AUM), with potential to reach US$ 7.6 trillion by the end of 2020, i.e. an increase of roughly 20% CAGR over the near future. It must be stressed that despite the existence of active managed ETFs, they are still a nearly negligible minority.

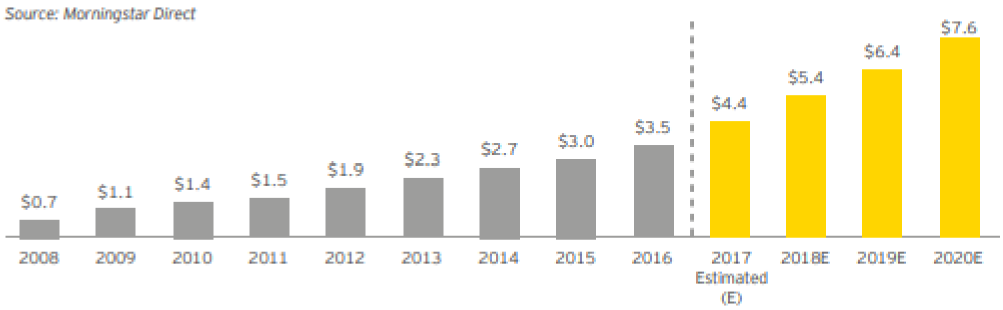


Figure 3.8 - ETFs global market survey [33]

Among those US$ 7.6 trillion dollars estimated for AuM in 2020, US$ 1.2 trillion (~15%) are expected to be allocated on global smart beta ETFs, against US$ 0.6 trillion in 2016. It is noteworthy the increasing on smart-beta popularity. On “single factor” funds, demand has increased particularly driven by dividend yield and low-volatility factors, due to its easy implementation and broad institutional appeal, but still the major trend is regarding multifactor funds side, due to its robustness derived from a wide diversification together with an embedded risk management scheme.

For instance, according to Blackrock (2018) [46] the iShares Edge MSCI Multifactor USA ETF already offer investors four investment styles (value, quality, momentum, low-size) by selecting equities from MSCI USA index. For that, BlackRock charges an expense ratio of 20 basis points, lying on the lower end of expense ratio (i.e. $\frac{Management\ fees}{AuM}$) spectrum according to Figure 3.9

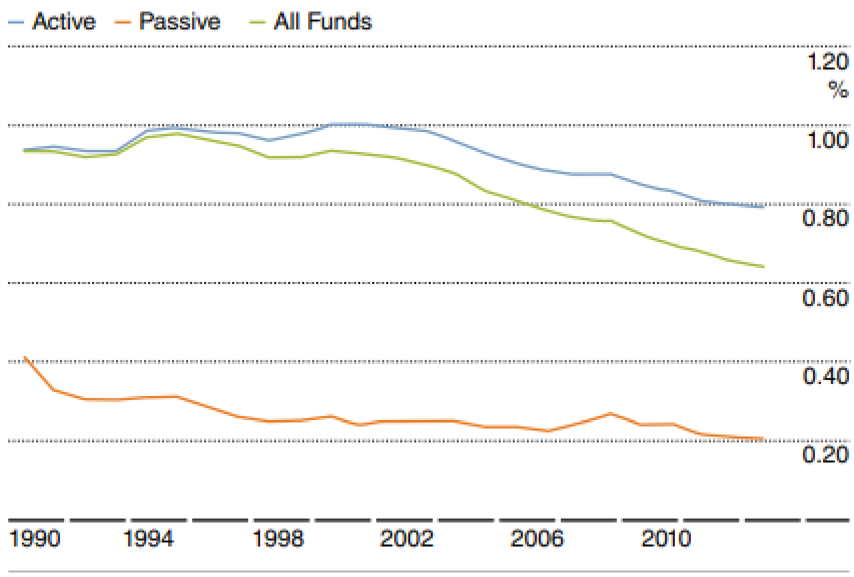


Figure 3.9 - Expense Ratio for Active and Passive Investment funds [52]

Up to this point, we just presented data regarding equities, because it is the main asset class currently driving the demand for smart beta. Indeed, according to Invesco (2018) [44], smart beta strategies are still in early stage with respect to fixed income securities, especially because of lack of data available due to significant share of transaction being done through OTC markets, so that data ends up being restricted to some US corporate bonds and US treasury bonds. However, since the usual market capitalization indexing may cause distortion on a fixed income index, due to the tendency to overweight mostly highly indebted countries and companies, factor weighting may be a good alternative to achieve higher risk adjusted returns. Some promising approaches that may be applied are detailed in Figure 3.10.

| Systematic factors | Seeks to capture | Commonly captured by |
|---|---|---|
| Value | Excess returns to bonds that have low prices relative to peers with higher prices in the long run | Relative value measures: Yield-to-maturity, yield-to-worst, option-adjusted spread (OAS) |
| Size | Excess return of smaller firms relative to their larger counterparts within the universe considered | Total issuer debt outstanding, individual bond size |
| Momentum | Excess returns to bonds with stronger past performance | Price change (i.e. 3-month, 6-month) |
| Low volatility | Excess returns to bonds with lower than average volatility | OAS volatility, yield volatility, duration times spread |
| Quality | Excess returns to bonds that are characterised by low debt, stable earnings growth, profitability, and other "quality" metrics | Financial leverage, debt servicing capacity, free cash flow, earnings capacity, capitalization, credit ratings |

Fig. 3.10. Systematic Factors for Bond ETFs [44]

### 3.3.2) Active Management

According to Shukla (2004) [81], active management provides investors discretionary selection of assets, aiming at value creation two-fold: (1) **Selection of securities** whose intrinsic value is significantly mismatched with its market value (i.e. stock picking), as well as timing the entry/exit of positions; and (2) **Monitoring and revising portfolio,** continuously, in response to new material information. For advocates of active management strategies, the underlying belief is that markets are inefficient to a certain degree that justifies the costly process involved in research for trading information, in order to generate alpha. De facto, some of the foregoing theories already addressed the compatibility between market efficiency and alpha stemmed from active management, e.g. adaptive markets theory.

Although we classified smart beta products under the passive umbrella, they essentially gather features of both passive and active strategies, due to the fact that despite the systematic scheme of passively select securities, factor investing sort of mimics active management, but through quantitative analysis of data. In fact, smart beta funds offers three of the four building blocks of active portfolio construction described by (CFA Institute, 2019) [26] (1) R**ewarding factors**, i.e. capital allocation (over or underweighting) to factors instead of a broad market portfolio; (2) **Alpha skills**, with respect to multi-factor balancing and timing, although not present in all smart beta products, it is a implementable feature; (3) **Sizing positions**, i.e. proper allocation to distinct sites, and risk management according to fund mandate. In summary, Smart beta offers a tradeoff between the alpha generation stemmed from active discretionary monitoring and the substantially lower management costs of a passive strategy.

Authors such as Chen et. al. (2000) [29], Shukla (2004) [81] and Comer et. al. (2008) [30] carried on empirical studies rejecting the hypothesis that active managed mutual funds can generate consistent abnormal returns after management fee and risk-adjustment. These are noteworthy results, because suggest a strong evidence against traditional (long-only) active management superiority, which implies, ultimately, a legitimate change of paradigm from active to passive management, even though some mutual funds yet achieve very attractive returns, what would satisfy the needs of risk-seeking investors.

Indeed, Shukla (2004) [81] found a positive relationship between excess returns and expense ratios, which suggests that excellent firms will likely keep to charge very high management fees in the foreseeable future, because of a genuine superior capacity of generating alpha.

We propose a brief investigation about the foregoing, taking as case study two leading US hedge funds, *Bridgewater Associates* and *Renaissance Technologies.* Our goal is to assess whether the competitive advantage arisen from their hybrid business model (i.e. employing technology to enhance discretionary decision making) build a strong alpha-generating capacity, ultimately making them eligible to sustain this higher degree of pricing power. As an example of that, even though hedge fund's management fees are subject to negotiation and individual arrangements, being poorly disclosed to the public, Renaissance explicitly discloses that the total fee is a combination of a management fee in the range of 0 to 5%, plus a 0 to 44% performance fee, which is definitely above average (Bloomberg, 2017) [17].

### A) Renaissance Technologies

In a session of the Hearing of the Senate Permanent Subcommittee on Investigations (2014) [73], the excerpt explains a public disclosure of Medallion's business model made by its own managers:

*"We collect all the publicly available data we can find that we believe might bear on the movement of the prices of tradable instruments— news stories, analysts' reports, energy reports, crop reports, weather reports, regulatory filings, accounting data, and, of course, quotes and trades from markets around the world. Our models use this data to make predictions about future price changes. Although we use different strategies in managing our different funds, all of our strategies depend on the output of our data driven models. Of particular note for today's discussion is the fact that our models do not factor in tax rates when making trading recommendations."*

De facto, in a talk session (MIT Sloan Finance Group, 2019) [83] held at MIT Sloan School Renaissance's founder Jim Simons explained the main principles underlying the fund's sustained superior performance: *"At the core of the company, which employs about 300 people, is a great computing system, good scientists and low turnover"*. Jim Simons acknowledges that the core strategy strongly relies on this synergy between technology and human capital, in the sense that their competitive advantage stems from cutting-edge pricing and risk management models developed by the most brilliant mathematicians and statisticians (mostly successful PhDs). On top of that, Jim recognizes another crucial ingredient to Renaissance's success, which is a culture where people are truthy incentivized to collaborate, an aspect oftentimes either neglected by most asset management firms, or even encouraged against (i.e. nurturing competition among employees). The fact is, a collaboration culture is a great challenge to run in practice, especially within the asset management world, where a big chunk of compensation is oftentimes variable and attached to one's performance.

Finally, Mr. Simons claims the last aspect idenfied by us (but maybe most import one, technically) explaining Reinassance's leading position: *"There's room for new inefficiencies to materialize [on the market]. We keep finding new things and throwing out old things."*, i.e. following AMH principles, a market eventually adapts to winning strategies, ultimately *"wearing them down"*. Thus, for a fund to consistently generate alpha, an effective renewal governance is essential to enable a fast and systematic adaption, and discovery of new inefficiencies.

### B) Bridgewater Associates

Another very successful active management case is the company Bridgewater Associates, a hedge fund that managed to consistently generate alpha through an innovative business model, combining intellectual capacity with technology, in order to take better and less biased decisions. These factors, together with a very strong corporate culture of extreme honesty and accountability, created a strong competitive edge to the firm.

As it was presented in "How to build a company where the best ideas win" [82], a TED Talks session presented by the founder and current Co-CIO Raymond Dalio, rather than a culture based on seniority hierarchy, in which decisions are centered in people considered to be more experienced than others, the firm advocates the principle of "ideas meritocracy", whereby employees are encouraged to confront each other's ideas, in order to ultimately dissect the root cause of each decision making, with the goal to exhaustively stress test ideas before working them in practice.

Despite the notable success, an "ideas meritocracy" culture is very difficult to be executed in practice, because not everyone is willing to accept such an extreme criticism environment. As a result of that, Bridgewater’s employee turnover rate (i.e. the ratio between number of layoffs and voluntary exits divided by the total entrants) is estimated to be as high as ⅓ during the first and second years of adaptation (NY Times, 2017) [85], which demonstrates the main resistance to Renaissance’s model.

Besides that, technology is intensely employed to assist decision making, working in a hybrid scheme between traditional discretionary management, whose mandate leans more towards to a macro hedge fund, distinct to the quant approach of Renaissance Technologies strategy, designed in a more scientific/algorithmic intensive approach.

For instance, Bridgewater adopts an AI algorithm internally developed, named “The Dot Collector”, which is basically a rating system tailored to the principles constituting the pillars of Ray Dalio's thinking process, to assist the collective decision-making process. Therefore, when an internal meeting is being held, every participant is invited to share their perspective about the subject, while using the “Dot Collector” to rate in a critical way the views of the other participants. The idea is to both provoke self-reflection, because one ends up being promptly criticized by its peers, but mainly used to systematically compute a sort of weighted average of the group’s perspective, seeking to an AI optimized unbiased decision.

We cannot attribute a firm link between Bridgewater’s performance, and the competitive advantage stemmed from the decision making process and the extreme transparency culture, because it can be the case that the performance is not the result of the process *per se*, but rather of the talent of people involved, or even it could be the outcome of pure luck. However, it is out of the scope of this report to investigate further data to prove or reject this hypothesis, we just conclude that there is a legitimate rationale underlying the superior performance of both hedge funds aforementioned, and this superior alpha generation capacity is somehow related to a hybrid business model in which technology and human capital (or rather, an organizational governance) work synergistically.

## 3.4. Structural factors

Amidst transformations occurring in the industry with respect to a shift from active towards passive management, few technological trends deserve an especial attention due to their influential power on market efficiency by promoting structural transformations. Besides that, we acknowledge that recent changes to the industry regulatory framework - e.g. with the introduction of MiFID II regulation in EU - is another topic that deserved to be added to complement the analysis, but we considered that would be more prudent to just narrow the analysis to technological transformation, to elaborate a more in-depth analysis, without compromising the length of this report.

### 3.4.1. Fintechs

Despite the highly regulated environment permeating banking business, in which reputation, trust and expertise have traditionally played a relevant role in terms of consolidating high barriers to entry. Small entrants leveraging on intense technology innovation, namely fintechs, are being able to capture an expressive share of the market, disrupting the business model of traditional banking products and services.

According to a study carried on by McKinsey (2016) [62], the demand for fintechs is being driven especially by millenials (i.e. individuals born between early 80s and late 90s), small business (SME) and underbanked customers, i.e. segments particularly sensitive to both cost and digital experience. The article further acknowledges that most of the disruption is still more intense with respect to retail banking business, despite some interesting innovations are being introduced in the traditional corporate and investment banking (e.g. in asset and cash management). Indeed, fintechs cover areas ranging from lending & finance (with the increased popularity of crowdfunding and P2P lending) to the insurance business, payment, cybersecurity, asset management and so on.

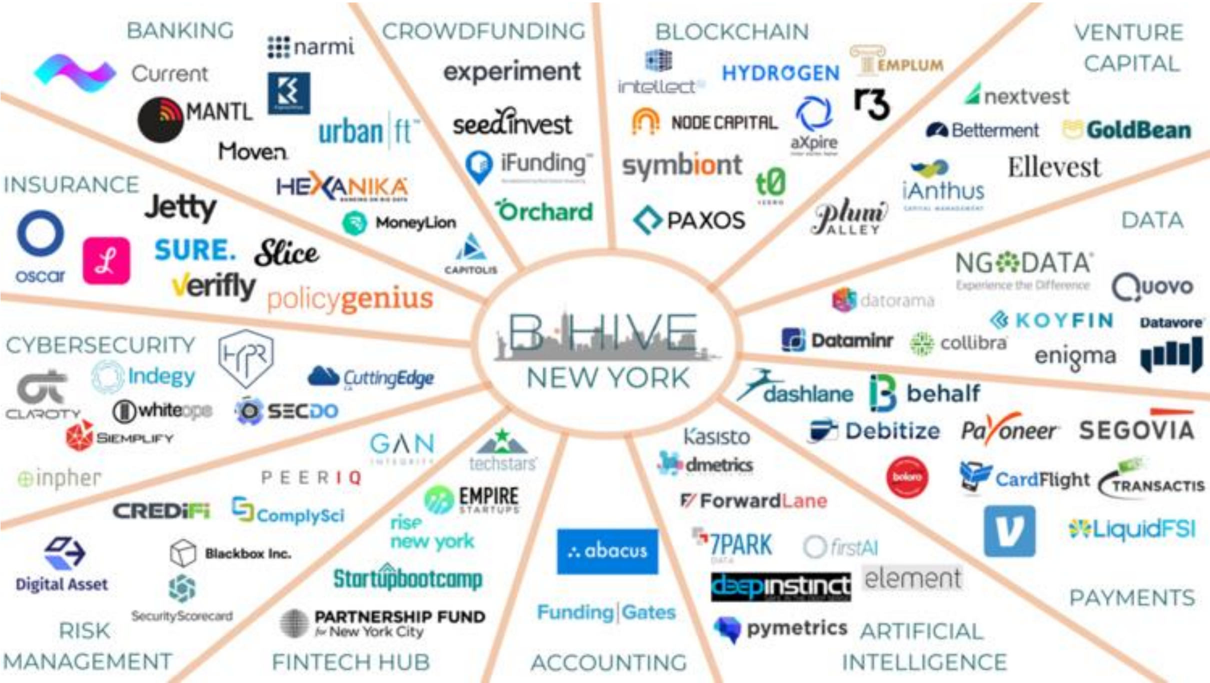


Figure 3.11 - Fintechs areas of influence [7]

Besides that, instead of a fierce competition between incumbents and fintechs, what has been observed is a sort of "coopetition" as defined by McKinsey (2016) [62], whose concept refers to the movement of fintechs and incumbents seeking to partnership, in order to take advantage of the synergy between an innovative culture on fintech's side, and a solid balance-sheet and expertise on current business practices on traditional bank's side.

Thus, the bottom-line of these transformation on banking business is two-fold: (1) **Margin compression**, through competition endurance due to weaker barriers to entry, together with an increased scalability, disintermediation and operational efficiency on fintech's side; (2) **Product & business model sophistication**, due to the increased supply of new technologies such as blockchain and machine learning (ML), revolutionizing product offering, as well as a trend towards digital platforms, disrupting incumbent's distribution model.

### 3.4.2. Technology & Asset Management

De facto, in regarding the investment management business, fundamental transformations are being promoted by advancements such as big data, artificial intelligence, machine learning and blockchain. According to CFA Institute (2019) [27], these developments are affecting not only "quant" asset managers (i.e. those applied strategies based on quantitative finance, such as Renaissance hedge fund), but also fundamental asset managers who are increasingly adopting hybrid forms of decision making, such as presented on Bridgwater's case.

Firms can use these technologies to improve their investment evaluation methodologies, optimize portfolio diversification, mitigate risks, and offer customized solutions to clients. For the scope of this report, we are going to address two technologies related to the development of Machine Learning (ML), as well as we will address their implications on markets, they are: (1) **Algorithm trading**, i.e. use of process and rule based algorithms to employ trading strategies; and (2) **Robo-advisors**, i.e. automated advisory services to themes such as portfolio optimization, trade execution, rebalancing and tax planning.

### 3.4.3. Algorithmic Trading

Yadav (2015) [95] reported an abnormal increase (almost 460 times) in US trading submissions volume, observed from the height of the internet boom (in 2000) to a normal trading session in 2012. Investors' trading appetite may have changed during this period, but it is definitely not the explanation for this gigantic rise. Rather, the author attributes this phenomenon to the dissemination of pre-programmed algorithms, many of them set to execute a high frequency buy/sell orders, based on complex quantitative models. In this report, we will focus on two effects stemmed from the application of Machine learning in the context of quantitative finance: (1) **Product offering,** i.e. analyzing the major advantages and flaws stemmed from quantitative funds, both active and passive; (2) **Market Efficiency**, discussing the impacts on efficiency *vis-à-vis* the increase in supply of systematic trading strategies influencing securities price.

Although algorithmic trading is not a novelty *per se*, it is transforming the asset management business through a continuous improvement, following the development of machine learning techniques. However, despite the availability of dozens of machine learning algorithms, a major challenge to implement an effective **"regime switch"** to an algorithm yet persists (Mathworks, 2019) [60], for instance despite the good functioning of algorithms under stable conditions, the so called *"black swans"* still pose a real systematic threat to systematic trading models, having potential catastrophic consequences as occurred with *Long Term Capital Management (LTCM)*, a former leading hedge fund operating mostly on quantitative fixed income arbitrage strategies, with a significant degree of leverage. LTCM failed in 1998, triggered by a rapid increase in liquidity premium due to the event of Russian sovereign debt default, leading to a harmful bailout as described in the book *When Genius Failed (2000)* [55]. Notwithstanding, nowadays, algorithms are advanced enough to capture market sentiment through Natural Language Processing, which is a recent development that can be a potential *"game changer"* vis-à-vis this **"regime switch"** challenge.

Houlihan and Creamer (2015) [42] argue that with the recent technological advances measuring the sentiment of millions became a reality, which can be used to enhance pricing models, especially to timing reversals on ongoing trends. The authors employed natural language Processing techniques to extract market sentiment from social media messages, using statistics such as daily average and standard deviation of the volume of messages in which a stock was mentioned. To do this, the authors tokenized[1] words to determine if the sentiment was positive or negative, by comparing to a set of pre-defined lexicons. This way, a regime switch between a *"bull"* vs *"bear"* market could be implemented by a news flow.

De facto, another approach to address this **regime switch** problem is through smart beta funds operating in an active factor rotation scheme, in which a portfolio manager actively analyzes long term trends in order to allocate properly the resources among each factor. Under this method, instead of having an automated system concentrating efforts on regime switch, ML algorithms would have the role of enhancing the automation, screening & selection and rebalancing of smart beta funds, aiming at provide a more robust and comprehensive framework to track traditional factors such as value, size, momentum, low beta, as well as other tailored strategies, so that they reflect the factor exposure efficiently (therefore, with low expense ratios).

[1]Tokenization is a technique of lexical analysis, employing the process of separating strings from a text to produce arrays of tokens, that can be better managed to extract information

Overall, the development of ML algorithms is beneficial to the market, by offering of more robust, sophisticated and cheaper investment products. Furthermore, it must be acknowledged that this revolution was only possible due to the contribution offered by the development of complementary businesses such as (1) **Data provider firms,** i.e. Bloomberg, Thomson Reuters Eikon, S&P500 Capital IQ and FactSet, by enhancing the supply and the quality of information obtained; and (2) **Software companies and open source APIs,** such as the example of MATLAB (2019) [61], which is facilitating the development of smart beta strategies by providing back testing and pre-programmed functions to developers and students.

### 3.4.4. Implications of Algorithmic Trading on Market Efficiency

Due to advancements in ML applied to finance, algorithms are currently capable to take rational decisions, even processing a superior amount of data than a human being. Hence, because one of the fundamental elements contributing to market efficiency is a high number of individuals actively monitoring the market, and due to the fact that algorithms are capable of taking decisions fastly, rationally and systematically (without biases, except from any residual bias stemmed from programming process), one may believe that market efficiency is utterly advantaged by the development of quantitative finance.

Yadav (2015) [95] challenges this belief arguing about the existence of a trade-off between informational and allocative efficiency by the dissemination of algotrading, i.e., with a higher sophistication of algorithms and a higher processing power stemming from cutting-edge computing infrastructure, the process of analyzing market data becomes faster, stronger and even less susceptible to behavioral biases, contributing to an increased informational efficiency. However, the author defines two grounds for skepticism with respect to allocative efficiency, i.e. the fair allocation of resources to the most valuable instances: (1) **Information loss**, i.e. a dependence on pre-programmed algorithms fail to capture relevant aspects of the messy finance world. Indeed, the majority of quantitative models have a tendency to either be oversimplified (e.g. linear) or overfitted (e.g. to optimize outcomes on backtesting) as claimed by Bailey et. al. (2013). This is a reflect of the difficulty to implement the complex reasoning a portfolio manager employs to take a decision in a systematic way. (2) **Irreparable model risks and informational deficits**, i.e., enforcing the last point, model's lack of robustness introduces a serious degree of systematic model risk into the whole financial system, which already has shown its fragility for example on the case of United Airlines' fake bankruptcy, explained on the documentary “Quants - The Alchemists of Wall Street” [93]. The case happened when fake rumors of a bankruptcy of United Airlines triggered negative sentiment on trading systems, ultimately leading to a strong selling momentum, and the stock plummeted roughly 11% according to this article from the NY times (2008) [87]. This event corroborates the point of an increased informative efficiency in detriment to an allocative efficiency, i.e. this episode meant a temporary huge mispricing of United’s shares, without having any real effect/concern about the underlying business. In addition to that, the author acknowledges another point of conflict arisen by the competition between algorithmic trading systems and market agents, claiming that the former ultimately discourages market agent’s investment on thorough research and analysis, because the shared profits (i.e. between information trading agents and algorithms) result in a decrease on the potential return over investment on good quality information (on market agents' side).

### 3.4.5. Digitalized Wealth Advisory

Robo-advisors are introducing an extra layer of innovation to the investment industry, by ultimately disrupting the distribution model of firms, i.e. democratizing the access to a good-quality financial and tax planning to a broader public. Although still very concentrated to high net worth individuals, wealth management is becoming increasingly available to retail investors of all kinds, with less restrictions on minimum wealth, as well as lower advisory expenses, what ultimately reduces frictions deterring individuals to invest properly. According to McKinsey (2018) [64], these robo-advisory platforms work with machine learning algorithms, that essentially gather clients’ data to understand their suitability needs, especially related to both investment objectives and risk tolerance, in order to build tailored asset allocation and rebalancing advisory.

As an example, Betterment (a leading independent robo advisor firm) successfully implemented a digital advisory scheme, whose portfolio construction relies on a selected group of equity and bond ETFs, offering not only an easy to understand investment process, but also a compelling and user-friendly digital platform. Both features are essential to gain customers’ trust and loyalty, which for long worked to raise barriers to entry, in favor of investment banks, but now are being disrupted by fintechs like Betterment. In addition to that, the service offering through ETFs enhances the firm performance, minimizing issues related to tax-efficiency, lack of diversification, liquidity and abnormally higher management costs.

Blenman, 2019 [15] attributes four major benefits to the overall wealth management industry : (1) **Compressed fees**, i.e. every sort of fee income within financial industry is being (or in threat of being) pressured by disruptive technologies, on wealth management the scenario is no different, through scalability achieved by these technological advancements, fees can be drastically reduced. For instance, Betterment (2019) [10] charges an average 10 bps in expense ratio (Figure 3.12), versus an average 50 bps of the industry;


Figure 3.12 - Betterment average expense ratio versus industry average [10].

(2) **Minimized conflicts of interest**, i.e. through a systematic (and maybe even audited) process, the likelihood of having underlying conflict of interest in the final recommendations is mitigated; (3) **Low Minimum Requirements**, i.e. as already disclosed, Betterment (2019) [10] offers advisory services without requiring any minimum balance for its basic version; (4) **Availability**, i.e., a continuous assistance can be provided by a digital platform, even with additional content to better inform clients about the allocations and potential risks.

## 3.5. The future of Asset Management

A market survey conducted by FTSE Russell (2016) [36] evaluated three case studies about current use of smart beta strategies by their clients, whose main drivers leading to smart beta in each case were respectively: (1) Reduced expenses on Portfolio management; (2) Lower beta, while still obtaining improved returns; and (3) Increased transparency and long term results, maintaining sufficient liquidity and risk metrics in line with policy requirements.

1. The first case was ignited by a US public sector pension fund expressing the need of reducing investment management costs, as well as managing to better exploit their investment strategies in terms of long term returns, arguing that consistent active alpha returns can be replicated via indexes regardless of the use of active managers, thus reducing costs.

2. The second case, though, had a UK insurance client, which requested to have additional return levels, while maintaining low variance, in order to maintain a prudent management of its financial affairs on behalf of current and potential beneficiaries. Thus, it was considered a suitable match to FTSE Global Minimum Variance index proposition.

3. Finally, the third case study approached also an US public sector pension fund, in this occasion, aiming to increase transparency, while maximizing the level of long-term return, avoiding conflict with policies of liquidity, diversification and investment risk.

Finally, after all research done on the topic, we would like to dedicate this section to a synthesis of the main drivers, in order to draw some forecasts and opinions about the path we observe the industry is taking.

Overall, we observe a tendency to an equilibrium point between active and passive management, instead of a dominance in favor of one side. In summary, we covered the following topics to support this statement (1) **low alphas achieved by traditional active managers,** i.e., apart from the alternative investment classes (e.g. Hedge Funds, Private Equity, etc.), traditional long-only asset management firms bear several restrictions, resulting in a sort of "expensive beta" offering by those mutual funds; plus (2) **Institutional investors appeal** to operate investments in passively managed ETFs, which contributes to the increasing inflows to both pure passive and smart beta funds. As stated by Bloomberg (2017) [16], while in 2009 only 19% of the U.S. domiciled equity funds were passively managed, seven years later this grew to about 37%; (3) Passive fund's **high transparency and governance simplicity** also plays a relevant role as catalyst to this transformation, especially due to all the existent and new regulation (e.g. MiFID II). However, (4) **Technology effect** may work in synergy with active management, so that successful hybrid asset managers end up yet having a sustainable competitive advantage with respect to alpha generation, even exerting pricing power on management fees to sustain their business model.

Moreover, a major concern shall be acknowledged when it comes to the global dominance of disruptive tech companies, pressuring the exit of all other competitors, such as what Amazon is promoting in the e-commerce retail business, or as Google has done to search engine business. A very high concentration level is already held by BlackRock, an investment company managing over than US$ 6.5 trillion assets (BlackRock, 2019) [12], and Vanguard group, managing over than US$ 5.2 trillion AuM (Vanguard, 2019) [89], which together already account over than 10% of the global AuM. According to an article published by Bloomberg (2017) [16], the authors acknowledge that current levels of concentration are already high, and may get even higher, reaching a combined US$20 trillion over the next decade with the global trend of shifts towards ETFs, massively supplied by those two gigantic companies. The first motive of concern is **power,** as the authors explain *"Imagine a world in which two asset managers call the shots, in which their wealth exceeds current U.S. GDP and where almost every hedge fund, government and retiree is a customer.* Besides that, these high levels of concentration may lead to these firms taking monopolistic decision with respect to management fees and innovation management, which will definitely be a concern for antitrust regulators.

# Part IV - Factors of investments

## 4.1. Introduction

As previously introduced, equity passive strategies are segmented into pure passive (i.e. weighted by market capitalization, in order to have exposure to market risk) and style factor investment (i.e. weighted by a fundamental and/or technical factor to have exposure to other systematic risk factors). Indeed, as observed by Kahn and Lemmon (2015) [48] in figure 4.1, although smart beta funds are passively managed, they still offer an active return component over time, in order to combine both (1) the benefits of active investment enhanced returns with the (2) efficient, systematic and transparent implementation of passively managed funds.

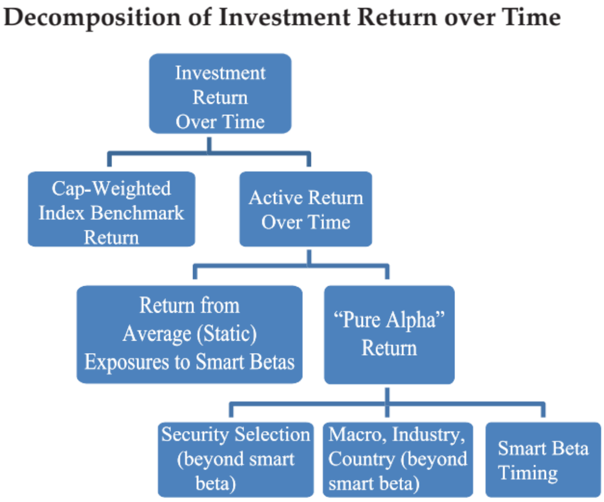


Figure 4.1 - Decomposition of Investment Return overtime [48]

The authors also recognize what Rabener (2019) [69] stresses in his article about the existence of a subtle but essential distinction between smart beta and factor investing, as expressed in the following excerpt *"[...] constructing factor portfolios in academic research is very different from building investable smart beta ETFs. At a high level, factor portfolios represent long–short baskets of stocks ranked by a particular factor, while smart beta ETFs are simply index products with factor tilts.[...]"*.

Indeed, what both authors mean is that smart beta are subject to a *"reality distortion"*, which ends up restricting them to have only **factor tilts** instead of a **pure factor exposure** - what

Kahn and Lemmon (2015) [48] identify into the framework as "beyond smart beta" components, that might impact significantly the tracking error between factor investing and smart beta ETFs, as shown in figure 4.2.

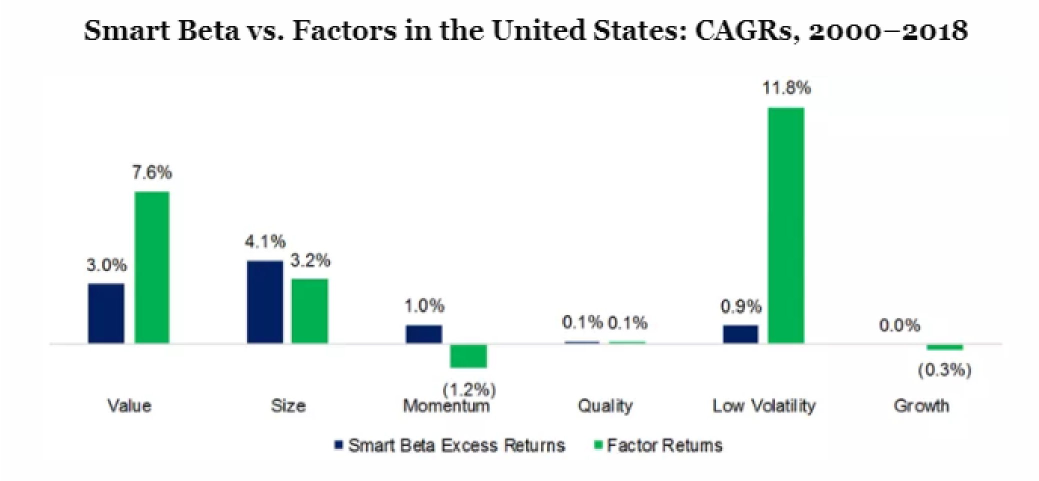


Figure 4.2 - Smart Beta vs. Factors in US since 2000 [69]

Notwithstanding this notable difference between factor investing and smart beta products, along this section we will focus on returns stemmed from factor investing, making special considerations with respect to (1) features of four of the most widely accepted investment factors (value, momentum, quality, low-volatility), as well as about (2) smart beta factor timing along economic cycle as shown in figure 4.3.

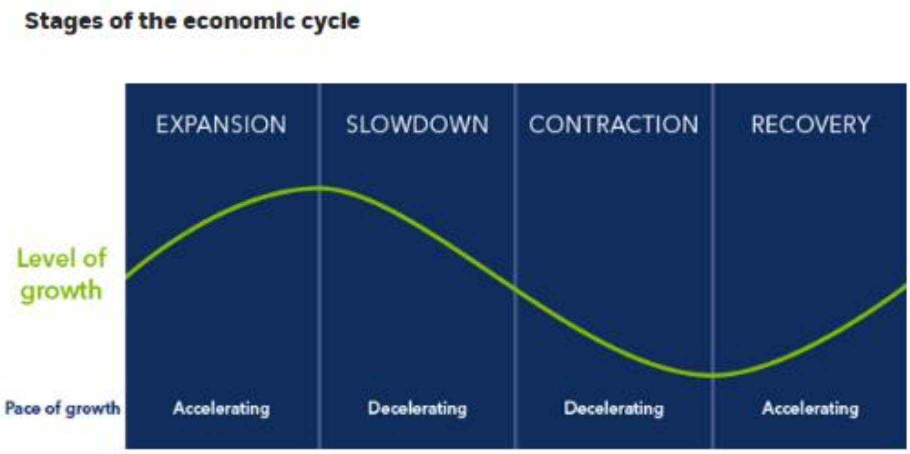


Figure 4.3 - Stages of the economic cycle [48]

## 4.2. Factors

Ang (2014) [4] argues that a factor is a systematic driver of long-term returns, due to an underlying rationale that might be identified as either a **rewarded risk,** a **structural impediment,** and/or **behavioral bias.** For each of the four investment factors (value, momentum, quality and low-beta), we will (1) analyze the economic rationale for it existence, (2) if possible providing also a historical background about the factor, as well as (3) we are going to give thoughts about weighting schemes and (4) about factor timing along the business cycle.

### A) Value

Value Investing was attributed to Benjamin Graham and David L. Dodd following the publication of the book Security Analysis (1934) [39], nowadays, this investment style is probably the most widespread across managers. Due to its solid economic rationale, Graham was able to obtain 20% CAGR returns between 1936 and 1956, versus 12.2% average market return.

To introduce Graham's theory, first off it is necessary to describe properly the concept of value, which is frequently misunderstood by investors. In order to clarify terms, an important distinction between market and intrinsic values shall be introduced. Whilst the former refers to the price formed by convergence of demand and supply forces at a market, intrinsic value is the theoretical result of the sum of future cash flows discounted at present value, therefore, its actual value is by definition unknown, because depend on expectations of market players with respect to the projected values and to the discount rate, which may not be homogeneous across agents' expects. Hence, whenever a security's intrinsic value exceeds its market value, an long term abnormal return opportunity exists, what justifies the existence of such factor.

Thus, BlackRock (2019) [13] identifies both a (1) **behavioral bias** effect associated to the hypothesis that value stocks tend to be overlooked by investors dazzled by potential high returns of growth stocks and a (2) **rewarded risk** with respect to the rationale that lower multiples already embeds low expectations of growth, so positive surprises are unlikely to be found - but when they are, the reward is expressive.

Since the process of identifying intrinsic value is difficult to be managed in a quick and systematic basis, because relies in the analysis of a large set of data and subjective (but reasonable) assumptions about company future prospects, management capacity of execution and other intangible components, relative valuation became largely employed as an alternative, relying on the assumption that comparable firms should have similar valuation multiples. Therefore, value factor overweights securities whose valuation multiples are below to its peers', while does the opposite to higher multiple valued securities. A major caveat to systematically implement a weighting scheme is that for different sectors, distinct multiples are more relevant, for instance, price per book value (P/BV) might be more consistent to retail banks valuation, while enterprise value per EBITDA (EV/EBITDA) might fit better to an industrial conglomerate.

Along the economic cycle value stocks intuitively tend to perform better after recessions, because it is the period when market corrects itself, market value of stocks are generally depressed (sometimes overly depressed due to loss aversion) and ready for a rebound.

### (B) Quality

Quality factor works under the premise that higher quality firms outperform lower quality ones systematically. Higher quality companies are those able to generate strong future cash flows and show good levels of profitability and efficiency. Cash flow fundamentals, according to Campbell et. al. (2010) [20], influence stock prices more than macroeconomic variables, minimizing over-capitalization or over-leveraging levels, which avoids prices to go up. This flight-to-quality or flight-to-safety introduced by (Asness et al., 2014) [6] arguments that bad economic times are a good moment to exploit quality stocks, because of deteriorating macroeconomic conditions, there will be more risk averse investors which will invest more on safer, quality stocks and selling what they recognize as higher-risk investments.

While developing value investing theory, Graham (1965) [38] proposed that quality and value were frequently found together. His strategy, thus, consisted in identifying stocks that at the same time met quality criteria and were undervalued. Graham's mentee, Warren Buffett, also followed the same strategy achieving outstanding results, as shown in Figure 4.4 - Patel (2018) [67] describes <<*Buffett picks stocks that are safe, cheap, and high quality. These factors almost completely explain the performance of Buffett's public portfolio, as well as a large part* *of Berkshire's overall stock return and the performance of its private portfolio. The authors note that Buffett has timed entry and exit exposure to the various positive factors>>*

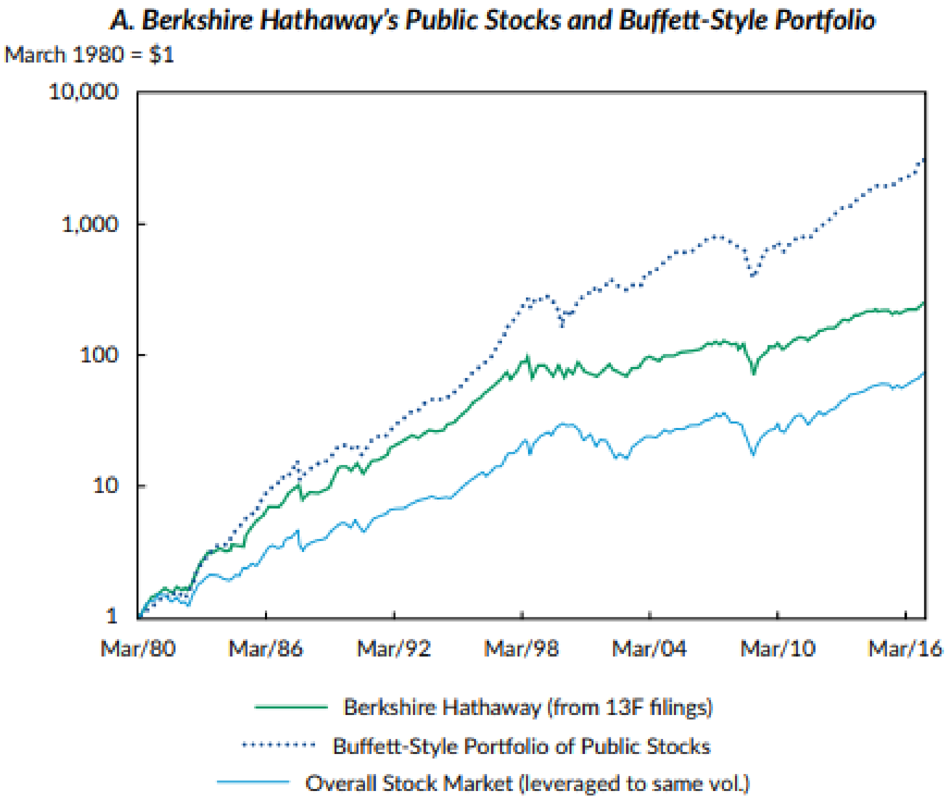


Figure 4.4 - Berkshire Hathaway's Public Stocks and Buffett-Style Portfolio [67]

Quality investing consists in monitoring metrics such as debt ratios, past earnings and dividend growth, as well as price-to-earnings and price-to-book ratios for selecting stocks. A report by (Norges Bank, 2015) [65] also identified net profit-based measures as quality ratios, such as return on equity (ROE), return on assets (ROA), Net and EBITDA margins (%).

The quality factor has worked due to the strong influence of **investor biases**. High titles earnings attract superficial investors while more skeptical investors try to study the causes of those earnings. In this sense, the periods that this kind of factor should be used are slowdown and contraction phases, that is, a period of slowdown and safety seek where firms which are stable and financially healthy prevail.

### (C) Low Volatility

The observation that lower volatility companies display systematically a higher alpha in comparison with the ones that have higher volatility is the basis for this anomaly. Low volatility, measured by the standard deviation of returns over time, can be exploited in order to dramatically reduce the risk of overpaying for stocks.

Blackrock (2017) [11] explains the satisfactory results stemmed from low beta strategy by basically two reasons. (1) **Structural impediment**, i.e. some pensions and endowments may face strong regulation against leverage, which compels them into stocks that have higher risks associated, in order to meet high return targets; and (2) **Investor bias**, i.e. alike to what happens to quality and value stocks, investors may be dazzled by high returns in short periods of growth and momentum stocks, and end up overlooking low-volatility opportunities.

There is one characteristic that sets the low volatility index apart from the other factors. Unlike the previous ones, that have been used by investors in order to enhance their returns on portfolios, the low volatility factor has the task of reducing portfolio risk. As Hsu and Chen (2017) [43] argue, what happens is that securities whose prices float less end up delivering returns that are similar to the market but with less risk. Other interesting point is the investor bias that takes place at the moment that low-risk stocks attract the attention of many investors. Moreover, this phenomenon can further capture the proneness for investors to speculate.

The methodology of using this factor is relatively simple because volatility is already a given statistical measure using standard deviation between returns from that same security or market index, value that is available in the stocks database. The implementation consists in identifying a subset of stocks with reduced volatility characteristics and rebalance the portfolio given a specific time space according to the ranking from the lowest volatility to the highest volatility stocks.

The minimum volatility factor, similarly, to quality, performs better during slowdown and contraction phases since the market pursues, in times of deceleration, safer investments. Low volatility stocks bring indeed less risk associated to their portfolio. A small but still sharp point was brought up but Russo (2015) [77] when he stated that the final phase of recession is usually depicted by a strong equity market rebound in the case markets manage their way to recover earlier, that may mitigate the statistics of the factor's success, as it happened after the financial crisis of 2008.

### (D) Momentum

Momentum is the natural tendency to a trend to persist, regardless whether it is rising or falling. Empirical results about momentum anomaly has led Carhart (1997) [21] come up with the fourth factor return generating model, introducing UMD factor (Up Minus Down).

Momentum analysis leads to the selection of stocks showing a strong recent performance, believing on the prospect that it will remain delivering satisfactory results in the short-term. Notwithstanding, in the event of any reversal trend, positive returns can be instantly swept out, what would, instead, explain the rationale of the contrarian investment strategy. Thus, the economic rationale of this factor is two-fold: (1) **Reward** by bearing the risk of a reversal trend, and (2) **Behavioral bias** of investors to under or overreact on existing trends (Blackrock, 2017) [11]

According to Jegadeesh and Titman (1993) [47], assets performing well over a 3 to 12 month period tend to continue to perform well into the future. In fact, a backtesting ran by the authors employing data from 1965 to 1989,  showed that excess returns of an strategy that buys past stock winners and sells losers (based on their past 6-month return) would yield impressive 12% compounded annual **excess** return over benchmark, in line with what was observed in momentum anomaly section.

Antonacci (2016) [5] reported that this financial phenomenon was observed across various industries, markets (developed and emerging), and asset classes (stocks, commodities, indices, corporate bonds, and so on). Moreover, the author defined an important distinction between (1) **relative** strength momentum, which refers to the comparison between an asset's performance relative to others, reason why it is also known as **cross-sectional** momentum, and (2) **absolute** momentum, that refers to relation between current price behavior with respect to past performance, thus the attributed name of **time-series momentum.** Finally, Antonacci concludes his argument by stating that both types of momentum are relevant for a healthy momentum portfolio, and the combination of both strategies is beneficial as it turns diversification more effective - strategy known as **dual momentum**.

Richard Driehaus, founder of Driehaus Capital Management, is considered the father and guru of momentum investing, believing in the principle of *"buy high and sell higher"*. Following his success, the American Association of Individual Investors' developed a Driehaus screening criteria (AAII, 2017) [2] in the attempt to capture momentum factor, and these are some metrics relevant to the process of screening securities to compose a momentum portfolio.

- The year-to-year growth rate in continued ops EPS increased both over each of the last three fiscal years and TTM.
- The latest quarterly earnings per share surprise (defined as the percentage difference between the actual earnings and consensus estimate) greater than or equal to 10%.
- The percentage change in stock price over the last four weeks is positive.
- The market capitalization for the latest fiscal quarter is greater than $50 million and less than $3 billion.
- The average daily volume for the last 10 days is in the top 50% of all stocks

Along the economic cycle momentum stocks perform better in moments of intense bull market, because it is the period when a general optimism wave contributes more to favor momentum in stocks

## 4.3. Portfolio of factors

Ang (2014) [4] argued that "*it is precisely because factors episodically lose money in bad times that there is a long-run reward for being exposed to factor risk. Factor premiums are rewards for investors enduring losses during bad times.*" His statement captures the necessity to both (1) **Factor rotation**, i.e. factor tilting across different stages of the macroeconomic cycle, because of the fact that factors are inherently cyclical; and (2) **Factor diversification**, i.e. as long as factors hold low correlation levels, diversification contributes to reduce the overall systematic risk of the portfolio.

The hard question is "How to manage factor rotation?". So far, BlackRock is a pioneer in this process by introducing the actively managed ETF DYNF, which still maintains low expense ratio (30bps). It is still a novelty, whose inception is dated as of March 2019, but from its iShares

(2019) [45] prospectus, it can be confirmed that the fund works rotating five fundamental factors (value, quality, momentum, low volatility and size) underlying US Equities in a discretionary basis with respect to factor rotation based on management forward-looking insights.

In our opinion, this structure has potential to be the height state of art in factor investing, since it gathers the most positive elements of passive investing - especially the low expense ratio, transparency and diversification - with the discretionary allocation of factors, which is able to capture elements difficult to implement systematically by quantitative methods (i.e. mitigated model risk)

Moreover, Rabener (2019) [68] studied diversification effects on momentum factor in U.S. stocks, which, despite the high abnormal returns achieved over the last 50 years, has delivered very disappointing returns over the last 2 decades, mainly explained by the high volatility of the internet bubble in 2000 and mainly by the market crash 2008-2009, as it can be observed by the plot on Figure 4.5, which even understates the bad performance because does not include transaction costs.

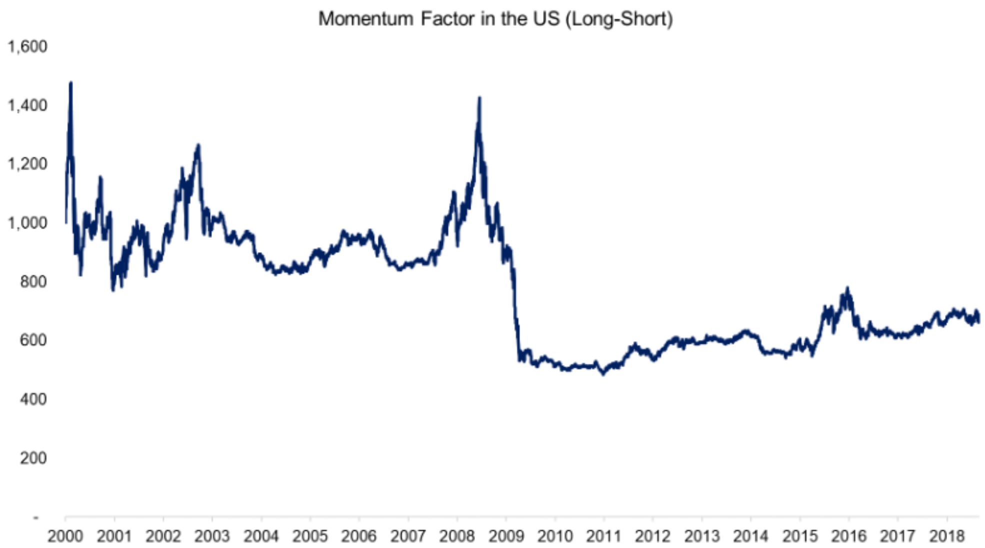


Figure 4.5 - Momentum factor excess returns over the last two decades [68].

The author employs an interesting alternative method to implement diversification through an **intersectional technique**, which proposes to rank and filter stocks by multiple metrics simultaneously, instead of attributing distinct weightings to independent portfolios of factors. The result of combining momentum and other factors using this method is described in Figure

4.6. An outstanding performance is observed by the combination of “Momentum & Low-Volatility” and “Momentum & Value”. For both cases, diversification benefits are explained by the low correlation between the factors, which ultimately aids to bypass highly speculative companies usually selected by momentum filter. Moreover, the combination with a value filter contributes to identify companies that are succeeding in corporate turnarounds, which yields very attractive returns to shareholders, besides that, the method contributes to avoid value traps.

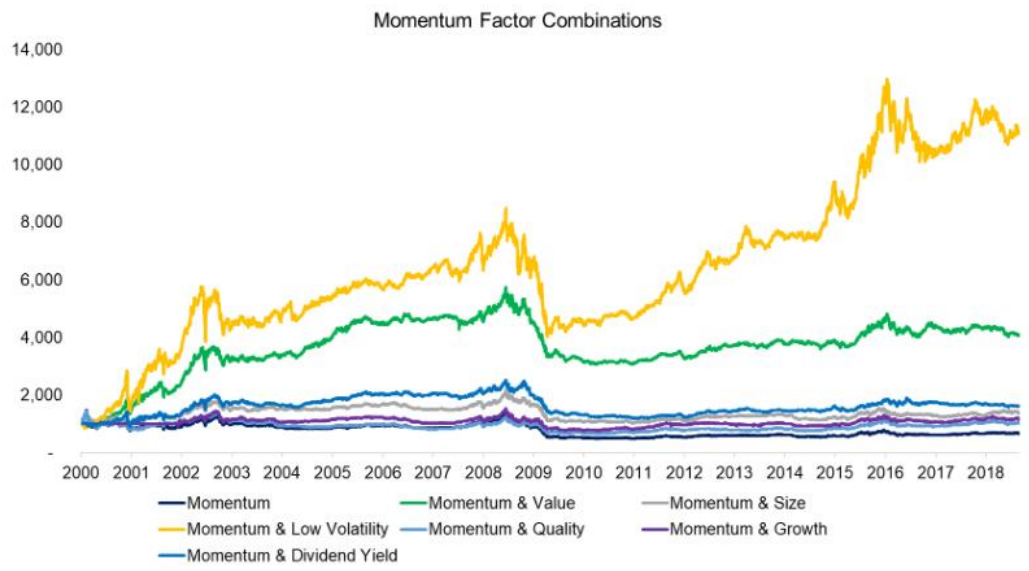


Figure 4.6 - Momentum Factor Combinations [68]

Additional filters may be incorporated to the selection to sophisticate momentum strategy. The author proposed basically two categories of filters: (1) **Valuation spread,** i.e. unabling stock selection in valuation spread top quartile, to avoid hindsight bias. However, no enhancement was observed on backtesting; and (2) **Volatility filter**, i.e. similarly to the strategy of intersecting momentum and low-volatility screening, different degrees can be added to the threshold allowed for stock volatility (e.g. top decile elimination), in this case, significant enhancements were observed by backtesting, specially damping the effect of the crash in 2008-2009, but with no clear pattern with respect to the optimal degree of volatility filter.

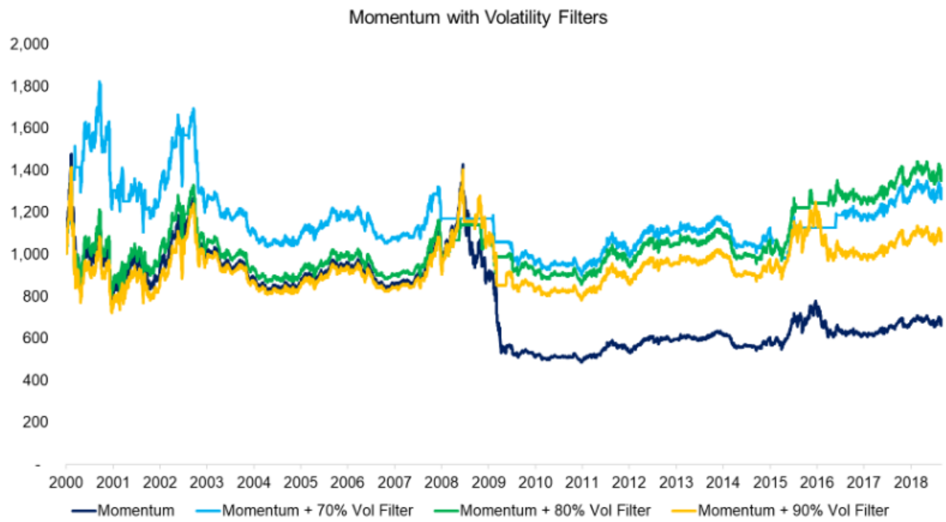


Figure 4.7 - Momentum with Volatility Filters [68]

# Part V - Innovation Perspective of Asset Management

## 5.1. Open Innovation

Traditional banking dynamics have always showed up as a conservative industry, resistant to transformations. This paradigm, though, has been changing during the last few years as technology brings new features such as speed, flexibility, reliance, and efficiency, as well as the market experiences new entrants and an increasing competition scenario arises. Continuous adaptations are essential for financial institutions to remain competitive and business model's innovation is one source for profitable growth. One crucial change that highlights this tendency is the process by which ideas are identified, required knowledge is incorporated and utilized, innovations developed and distributed. As Fasnacht (2009) [35] observes, *<<The demise of the dotcoms, the terror act on September 11, 2001, rapid growth of developing economies like Brazil, Russia, India, and China, as well as the boom in the equity markets has resulted in rapid and substantial wealth creation in the mass-affluent segment (commonly individuals with US$100,000 to 1 million of liquid financial assets).>>*

This trend impacted the way that asset management worked due to an increased demand of (1) **Professional guidance** for growth, protection and diversification and (2) **Openness and flexibility**, moving from a closed to an open innovation paradigm, forcing banks to make huge changes in their value chain and to embrace open architecture characterizing their core business.

Martovoy et al. (2012) [78] identified organizational structure, cultural inertia and costs related to the cooperation (money, time, etc.) as the most evident ones about why open innovation is still not so widely used. Shifting to an open innovation model requires, above all, a cultural change that reflects how firms treat certain points. The advent of open innovation requires companies to shift intellectual property from protection to a tradable good. The creation of patents, according to Schumpeter (2000) [79], intends to create incentives for inventors and entrepreneurs to invest in innovations. This works because this protection against imitators enables temporary monopolistic profits. On the other hand, a secondary though attractive market shows up in which new players enter. This phenomenon was observed along the 1990s hedge funds when arbitrage margins attracted players to the financial industry.

To better illustrate our point, we briefly studied Quantopian, a crowd-sourced quantitative investment firm that provides an online platform for developers, who are able to back test strategies (in the platform provided by the firm, with developers' intellectual property protection guaranteed) as well as to enhance skills and knowledge about quantitative finance by using Quantopian's open source education platform. Developers that succeed to build, test and validate a robust model - suitable enough to fit the needs of Quantopian's portfolio of strategies – are eligible to receive a proposition to sell the intellectual property and receive royalties based on the profit obtained by the algorithm.

Quantopian was a pioneer in the sense that they realized that investment industry could be a target for open innovation. By providing the right tools and education, the firm opened their sources for people to develop their own investment ideas. This is disruptive due to (1) An **open innovation** funnel as ideas in the industry have been becoming very scarce and rare because of competition, and to (2) Wiping out of **R&D costs**, i.e. knowledge is crowdsourced at no cost, combined with a different fee structure: the only compensation to the author comes in case a picked-up algorithm strategy is indeed profitable. The technological barriers have recently been overcome, letting material innovation to be finally sustainable. In this context, open innovation appears as a way of achieving cost reduction and flexibility by (1) sharing knowledge, i.e. as a way to cover the huge space between academic contributions and really applied methodologies by managers, as examined by Bose and Sugumaran (2003) [18]; (2) breaking the rebound effect brought by the patents creation, as well as (3) impacting a wider range of clients - such as the previously mentioned mass-affluent segment.

## 5.2. Disruption

Russell (2016) [36] carried a survey that determined the six major demand drivers of factor investing, segmented across different asset owners' profile in terms of AuM. Clients investing in smart beta mostly pursue enhanced uncorrelated superior risk-return, and interestingly, relatively low weight was given to cost reduction, tax benefits, and transparency, as it is depicted in Table 2. These results demonstrate a clear well positioning on smart beta offering with respect to the other solutions in asset management available (including alternative investments such as hedge funds, real estate, private equity, etc.).

**Return, risk and cost considerations are driving interest in smart beta**

| | <$1B | $1-$10B | $10B+ |
|---|---|---|---|
| Return enhancement | 56% | 51% | 63% |
| Risk reduction | 44% | 43% | 50% |
| Provide specific factor exposure | 16% | 25% | 47% |
| Cost savings | 22% | 19% | 34% |
| Improve diversification | 47% | 35% | 34% |
| Other | 0% | 7% | 6% |
| Income generation | 3% | 7% | 3% |

Table 2 - Considerations driving interest in Smart Beta [36]

Additionally, when it comes to finding a satisfying motivation to move away from active management, Voss (2016) [92] discusses some considerations arisen from the relationship between active managers and investment consultants, in which three pitfalls worth mentioning. (1) **Style drift**, i.e. when a manager is given a task to follow a specific style (e.g. Value) but ends up deviating and choosing other paths and strategies (e.g. Growth). (2) **Flawed governance** especially with respect to internal control systems to monitor and hedge against risk.

The foregoing observations corroborate the classification of smart beta products as disruptive innovations, with a great potential to shake the institutional investment paradigm. Therefore, it is interesting to analyze that disruptive innovations are rare, and they appear as a way to satisfy not exactly client's demands, but the previously mentioned clients' latent needs, which are often not grasped from interviews, focus groups or any kind of exchange of ideas with the end user, but rather these ideas permeate their unconscious desires. An illustration of that situation is the invention of computer. Indeed, no one really expressed the need of a computers before they were actually launched into the market. People could solve problems, make calculations, arrange schedules, do research about a certain object of study, pay bills and many other things without the use of a digital device such as a desktop computer.

With time, computers had been gaining increments in their capacity of computing, in their interface, and the capability of synchronizing with many services around the world, what ultimately led to a situation whereby people realized the need to save time. Thus, they did not demand such innovation but had the latent need of it. Analogously, the trend observed by Kahn and Lemmon (2016) [48] that many traditional active managers have been delivering a significant parcel of their active returns via static exposures to smart beta factors while charging active fees. In this sense, investors are refining their demands, therefore, active managers failing to either increase alpha delivered or to lower expense ratios (e.g. using automation to operate more efficiently) will eventually lose share for smart beta providers.

# Part VI - Conclusion

The report addressed the causes and effects of the paradigm shift away from the traditional long-only funds industry to a sort of *"tailing", i.e.* moving towards either to the (1) **Efficiency side**, of specialized passive funds, with very low expense ratios and very high automation, scale and systematization, or to the (2) **Effectiveness side**, of high value added active management, achieved mainly through alternative investments such as hedge funds, private equity funds and so on.

Initially, we have brainstormed three potential factors causing this phenomenon, they were: (1) **High expense ratios**, i.e. a significant unbalance between the expense ratio charged by long-only traditional funds, and their return in true alpha (delivering most exposition through traditional beta); (2) High degree of **market efficiency**; and (3) **Technology** advancements supporting quantitative strategies sophistication. Indeed, they are relevant factors explaining this paradigm shift, but we also found out that diversification, liquidity, transparency, exposition to specific risk factors, versatility and easy applicability are also additional attractive features making smart beta product offering more compelling as substitute, especially to institutional investors. Moreover, we concluded that those transformations are having positive impacts on the industry's business model (with regards to both value creation and distribution), however negative ones on the informational market efficiency in detriment to allocative market efficiency, as well as we observed already high industry concentration levels (which tends to be structurally present going forward). In the following paragraphs we briefly summarize the main aspects covered in each part of this work, and the findings thereof.

On **Part II**, we revised the literature vis-à-vis both Portfolio Management and Efficient Markets Hypothesis. On the first one, we gave a historical perspective of the models' evolution from the Capital Asset Pricing Model (CAPM), passing through the Arbitrage Pricing Theory (APT), then Fama & French three-factor model, having addressed also the augmented model done by Carhart. In general, return generating models were essential to introduce the idea of beta and alpha, by explicitly separating performance attributable to portfolio managers and those stemmed from different sources of risk factors such as market risk, value, size, momentum, market risk, etc. On the other point, we covered the classic market efficiency theory, giving also a brief explanation on some market anomalies, relating them subsequent articles proposed by Grossman and Stiglitz (about the near-efficient markets theory), as well as the darwinian approach introduced by Professor Andrew Lo about adaptive markets theory. Finally, we linked those theories to the idea of behavioral finance, since it is an important element to understand the paradigm shift from active to passive

On **Part III**, we proposed an analytical framework to study the asset management industry. We evaluated three broad areas: (1) **Market Players**, i.e. the asset managers, in this report we focused only on the three largest Institutional Investor classes, in order to address their necessity in terms of investment time horizon, of risk profile and of liquidity needs, to ultimately determine their fitness to the smart beta value proposition, and also to find the key aspects deterring them to invest on either pure passive or smart beta ETFs. Then, we studied the (2) **Product** itself, i.e. we evaluated the value proposition of both active and passive management, introducing more in depth the concept of smart beta. Along the study, we acknowledged an intense momentum on the inflow of assets towards passively managed ETFs backed up by data from a major consulting firm. However, since we also observed active managed firms showing a strong competitive advantage with respect to alpha generation, we concluded that there are reasons to support the idea of a medium to long run equilibrium between passive and active (specially with respect to alternative investments), instead of a domination of one single style. In fact, we investigated two firms (Renaissance Technologies and Bridgewater Associates), both employing a hybrid business model, in the sense that technology and innovative business model (or rather, governance) are key factors explaining the sustainable above average returns, despite the high management fees associated to the investment vehicle operation. Finally, we evaluated the (3) **Industry structure**, in which we observed the effects of technological advancements on the asset management industry. We acknowledged that the entire financial industry is under profound transformations promoted by fintechs, which are pressuring incumbents to become more digital, asset lighter on their balance-sheet, operationally efficient, and ultimately to fight for scale, because of the overall fee compression being promoted. In fact, we focused on two advancements, both related to the sophistication of machine learning (ML) - the first is about ML applied to quantitative finance, which not only is enhancing the offering of passive products, but also affecting the whole market through high-frequency trading, having interesting impacts on allocative efficiency, whereas the second is the robo-advisor, which is sort of democratizing the process of financial and tax advisory, whose implication under our scope is an increased demand for passive products (including smart beta), as they have a good match to the needs of digitalized wealth managers, due to the cheap, transparent, simple, diversified and tax-efficient offering.

On **Part IV**, we evaluated some more technical aspects of factor investing, investigating the root-cause explaining systematical returns underlying factors, to which we attributed three primary reasons: (1) A favorable **Risk-reward** relationship; (2) **Behavioral Biases**; or (3) **Structural Impediments**. Finally, we conclude the session summarizing some results obtained by researchers with respect to diversification effects on factor investing, as well as with respect to factor timing across the business cycle.

Finally, on **Part V**, we analyzed the smart beta proposition from an innovation perspective, in which we defended the argument that passive funds are disruptive products well positioned to satisfy clients' needs, as well as we investigate an interesting trend of open innovation, employed by the Quantopian hedge fund to foster disruption on the quantitative asset management sector.

## Suggested Further Research

Due to the number of topics covered in this literature review of the state-of-art, we have not managed to study in depth some topics we would like to, but we left them as suggestion to further researches. In summary, they are:

1. **Expand the research to evaluation of the demand of retail investors**, i.e. since we narrowed our research to cover only the study of the biggest institutional investors classes, and how smart beta could fit their needs, it would be appropriate to study also the suitability of this product to classes of retail investors.

2. **Case-study on smart beta value for an institutional investor such as a pension fund, or an insurance company**, i.e. although we evaluated a case study carried on by Russell FTSE on two pension funds and one insurance company, it was more commercial oriented, rather than a scientific finding. Therefore, we suggest a more complete study on the advantages for institutional investors of switching from current portfolios to increased passive/factor investing positions.

3. **Regulations as structural factors**, i.e. we end up narrowing the study of structural factors to technology, but we recognize that the regulation environment is also another important one, especially with the MiFID II implementation in Europe, which pressures a simpler and more transparent portfolio management.

4. **Assess empirically a quantitative strategy performance** involving factor timing, factor diversification (especially with the intersectional method presented in Part V).

# Appendices

## Appendix A - CAPM Assumptions

According to the CFA Institute (2019) [25], Capital Asset Pricing Method is a theory founded under five main assumptions:

1. Investors are assumed to be rational, which means that they will act on a mean-variance optimization basis, so that ultimately all of them will be holding the same optimal portfolio of risky securities, which is tangent to efficient frontier (Martin Haugh, 2016) [41].

2. Markets are assumed to be free and operationally frictionless, what neglects the influence of restrictions on trading (such as prohibitions to short-selling), and of operational features such as bid/offer spread. As well as it neglects effects derived from transaction costs and taxes.

3. Investors are supposed to plan for the same holding period, since CAPM is a single period model.

4. Investors have homogeneous expectations, i.e. their analysis apply the same probability of events occur, therefore they arrive at the same pricing outcome and ultimately same optimal risky portfolio, the market portfolio. If this assumption is broken, it might occur that two analysts diverge on the proportion of the optimal risky portfolio.

5. All investors are theoretically price takers in the sense that no investor is able to influence prices - although institutional investors may indeed influence prices of single small cap stocks, they generally are not significant enough to undermine CAPM theory. Moreover, investments are assumed to be infinitely divisible, because it is convenient to model return as a continuous function.

## Appendix B - Technical versus Fundamental Analysis

Although there is a fundamental rationale to support weak or semi-strong market efficiency, evidence on market anomalies and behavioral finance theory pose as strong disagreement points against it. Corroborating the thesis against efficiency, graphist traders claim their ability to achieve superior to risk-adjusted returns based on past price (charts) information trading such as candle patterns and momentum measures using the so called "technical analysis" principles.

To make the point clear, take Figure B.1 as example. A technical analyst trader probably would claim that the pattern formed is denominated head and shoulders, and affirm that it is a type of reversal pattern, what means that a current upward trend is now changing direction downwards, and the neckline that was serving as a support line, now is changing polarity to become a new resistance line (i.e. whenever prices reach the region close the neckline again, there will be a strong pressure from market players to sell it). The pattern must be further confirmed by volume of transactions metrics, i.e. for the left shoulder advance part, volume must be higher in comparison to head's, as well as volume might just increase again at declining part of the right shoulder.


Figure B.1 - Example of technical analysis pattern head and shoulders [71].

Although these heuristics are fiercely criticized by academics, who discredit technical analysis due to lack of proper statistical significance. The objective underlying this thesis is to analyze the industry as a whole, and indeed, there are many players acting on technical analysis basis, thus it is significant to understand why it happens as well as its implications on market patterns.

Despite the fact that what determines prices on long run are the underlying fundamentals of securities, short-term price behavior is unpredictable since the behavioral component can drive the demand-supply relationship. For instance take the case of a technology enterprise such as Apple Inc, the long term value for shareholders is driven by factors such as the growth of the smartphone, notebook (and other related products) market, by the market share Apple succeeds to capture in respect with their competitors such as Samsung, as well as by the level of cost efficiency on operations, distribution, manufacturing, sales & marketing and so on, which is obtained through economies of scale, automation, waste reduction, material selection, best practices, among other factors. However, right after (short-term) some new information becomes public to market, the processing of data and reaction of participants has an “irrational” component that can lead for example to under or overreaction, resulting in repeated graph patterns observed by graphists, oftentimes this is referred as the "market sentiment". Technicians believe that whenever sentiment is positive, there is a bias towards over-optimistic behavior and upward momentum is likely to occur, and vice-versa. For instance, an investor with a pessimistic sentiment might sell an underpriced security for mere irrational reasons, with an special attention to the fact that an irrational behavior is not exactly "wrong", but it's just not optimal under all available information.

Another point in favor technical analysis effectiveness is that big players (i.e. those who trade significant amount, therefore are able to influence prices) indeed trade on an informed basis, but they are not able to completely move prices by themselves. Thus, without knowing the underlying fundamentals, instead just relying on volume and price data, technicians are able to understand the price movement of a security sparked by a well-informed player, in order to profit on an operation whose downside is usually limited by a stop order. Besides that, the more players willing to follow the same trading rules, the more effective technical analysis become (for the ones who identify the patterns faster), due to the “bandwagon” effect.

## Appendix C - Other market anomalies

Apart from time series and company specific factors, there are several other triggers for market anomalies, such as the discounts on closed-end investment fund, and the abnormal returns on first day of IPO listing on stock exchange:

### Appendix C.1 - Closed ended mutual funds discount

Closed-end investment funds issue a predetermined number of shares at inception and does not sell any additional shares after the initial offering. Hence, fund capitalization is fixed across time except in a case of a secondary public offering. However, shares of a closed-end funds are liquid because they are traded on stock exchanges (i.e., their prices are determined by supply and demand equilibrium). The sum of total fund's holdings market value subtract by the fund's liabilities is denominated NAV (Net Asset Value), which theoretically should be equivalent to the number of quotas of this particular fund times the price of each quota, however, what is observed in reality is a permanent discount of about 4 to 10%. The real root cause for that discount is not completely understood, however it is likely to be either due to the tax liabilities associated with unrealized capital gains and losses (although this does not explain the whole discount), or (more likely) due to liquidity issues and errors in calculating NAV. Apart from tax issues and errors in calculation, under an investor perspective, having to abdicate the option to select own securities must have a premium associated, what is a good explanation for discounting NAV.

### Appendix C.2 - First day IPO return

It is a common practice of underwriters to *"leave money on the table"*, i.e. to underprice the offering in an event of an IPO, due to several reasons amongst which the most frequent are (1) To send a signal to the market that the company is a good quality (mitigating information asymmetry issues), since a bad company would not be willing to underprice their shares; (2) To assist the underwriter process of book-building by stimulating demand for shares through creation of an incentive to truthful reporting on demand instead of collusion or "bluffing". It is noteworthy that during the internet bubble (1995-2000) the average return for first IPO day peaked the impressive mark of 70%, but for normal conditions the average return is around 15% (Figure C.1).

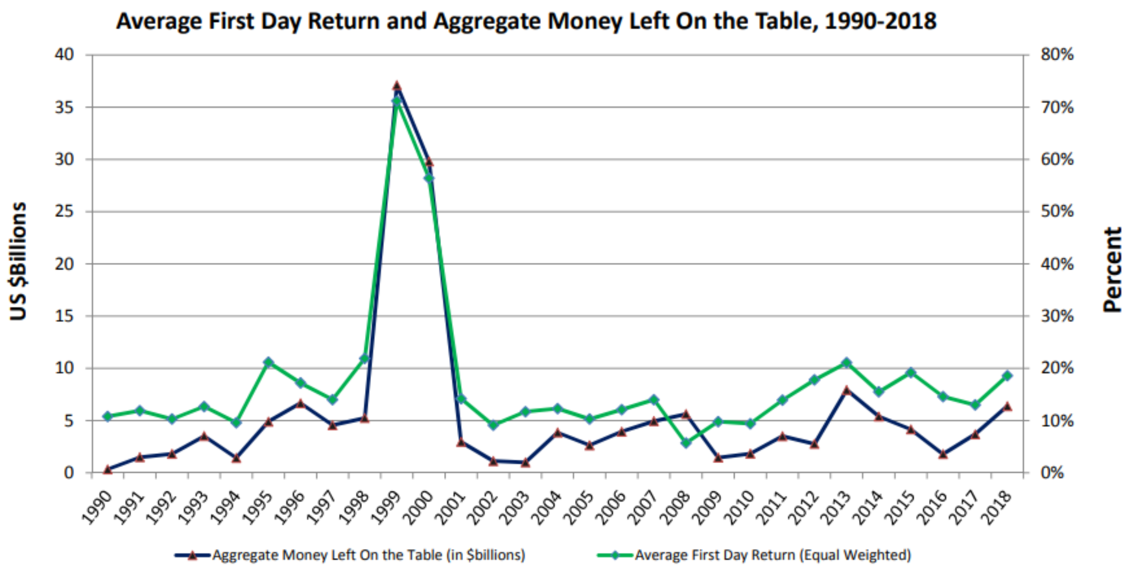


Figure C.1 - Average first day IPO return over last 40 years [74]

## Appendix D: Investment Vehicles structures

According to Anderson et. al. (2010) [3], the investment management industry is segmented into four distinct structures:

1. Open-ended funds (OEFs): Commonly referred as "*mutual funds*" these investment companies work through continuously issuance and redemption of ownership shares, which are not traded in any organized exchange nor in any secondary market, but rather, investors access these shares directly from the company, so that the overall AuM floats according to the net flux of capital entering and exiting the fund. The distribution of a mutual fund's shares may be directly between investor and fund or assisted through a licensed broker. A fund prospectus is required to be available for investor, in which the manager discloses relevant information such as the investment philosophy, track record and management fee structure.

2. *Closed-ended* funds (CEFs): In opposition, *closed-ended* funds issue shares through a public offering to manage investor's money following the mandate specified in the prospectus, with no possibility to continuously issue new shares, nor to redeem them.

Therefore, the only possibility to investors liquidate or get access to shares of a CEF is through negotiations on secondary market (either through a specific *exchanges or* through a bilateral transaction on OTC, *over the counter* market). Once close ended funds are subject to a finite supply of shares not redeemable, the market value (MV) of them may not correspond to the so called NAV (net asset value), which is the theoretical amount per share obtained if all investments were liquidated. So for CEFs, it is defined the *discount parameter*, *D*, and as already discussed, discounts are fairly present in CEFs what is even studied as a market anomaly (appendix C).

$$D = \frac{\text{NAV} - \text{MV}}{\text{NAV}},$$

3. Exchange traded funds (ETFs): An ETF is created through an issuance of large blocks of "creation units" for brokerage houses or institutional investors, who pay a "portfolio deposit", which is equal to the NAV of the ETF shares at creation. After that, ETF shares are traded in secondary markets (usually are very liquid, traded on exchanges) and they are not redeemable unless bundled in "creation units" aggregations, so that the price of ETF shares may float, but is subject to arbitrage whenever a discount threshold is trapassed. This way, ETFs are good vehicles to craft index investing funds, as it will be explored in future sections.

4. Hedge Funds: Although resembles a mutual fund, this vehicle has more flexibility to craft unusual strategies involving (or not) leverage, short selling, and arbitrage techniques to trade virtually any asset class, with the aim of obtaining aggressive short-term results. Because of that, securities agencies only allows sophisticated investors to own their shares. Historically, hedge funds have drawn investors' attention due to aggressive activities that promises leveraged returns, albeit very illiquid and incentive fees are generally high. Besides that, since hedging strategies (e.g. long-short or arbitrage) are allowed, hedge fund managers have the freedom to craft absolute return strategies, in which are empirically "uncorrelated" to standard factors obtained by long-only asset managers, what is very interesting under a portfolio management perspective.

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