ICADE BUSINESS SCHOOL

"Robo-Advisory: a theoretical and practical approach"

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ABSTRACT:

This project proves how robo-advisory aims to lead the portfolio management panorama by developing a practical tool that finds its pillars on both traditional and actual investment theories, combining computer science and financial knowledge.

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0. INTRODUCTION:

The goal of this project is to develop an automated database to optimize investing following a determined strategy by using programming languages in order to have a practical tool that helps investors maximize their returns. This program is broadly known as Robo-advisory, and mainly aims to recommend or pursue the full investment process for investors. For this purpose –and since we're talking about a mainly practical tool-, a strict methodology has to be followed to fulfill the theoretical component of the tool:

"Robo-advisors provide algorithm-based portfolio management services online at a fraction of the costs associated with traditional portfolio managers and traditional investment advisors". Such statement, made by Vítor Constâncio, Vice-President of the ECB at the Conference on "European Banking Industry: what's next?" defines and provides the key points of robo-advisory and its future, since the technology itself sets a departure point where competitive advantage can be found against traditional investment advisory.

This new way of investment management service was born from the convergence of investment theory and computer science. Harry Markowitz introduced in 1952 the so-called modern portfolio theory through mean-variance optimization, mathematically formulating risk and diversification indirect relationship, thus recognizing the efficient frontier. His techniques marked a starting point for the use of sophisticated and, ultimately, state-of-the-art computational systems in the form of algorithms that were optimized at the same time as technology development achievements.

Nonetheless, it was not only Markowitz's contribution that sowed robo-advisory's seed. In 1958, James Tobin included in the analysis an asset that pays a risk-free rate, identifying the unique efficient portfolio by weighting risky securities and the risk-free investment. The Capital Asset Pricing Model (CAPM), developed by William Sharpe in 1964 exhibiting assumptions, states that the efficient portfolio has to be the market portfolio. Consequently, Eugene Fama (1970) formulated the Efficient Market Hypothesis (EMH), which statements argue that stocks always trade at their fair value due to the reflection of the available information, implying that consistently beating the market is improbable when working on a risk-adjusted basis. Ultimately, in 1973 Princeton economist Burton Malkiel, author of "A Random Walk Down Wall Street", defended mutual funds attempting to replicate the performance of market indices since asset prices are subject to external factors that impede past movements to be used to predict future movements, although prices are proven to maintain an upward trend over the time.

Exchange traded funds (ETFs) were introduced in the late 1980s as a replication instrument in the evolution of passive investment, operating as index funds but trading on an exchange and acting on a more liquid and transparent basis. ETFs have provided the public access to diversified portfolios according to different investment needs.

Starting at the beginning of the 1990s, and driven by the technological development, digital investment tools were developed. This evolution continued up to 2008, when the land for improvement expanded due to the after-crisis regulation intensification that financial institutions faced (and still face). As a result, robo-advisory developers are currently able to offer cheaper investment advice, hence better performance on an equally weighted portfolio.

The same inflexion year set factor investment decisive moment thanks to a studio that analyzed the Norwegian Government Pension Fund behavior and its returns, proving that earlier theories did not avoid excessive losses when correlations between different asset classes peaked due to the financial crisis. As to solve this obstacle, different factors were included as possible risk-related drivers, giving birth to factor investing.

This studio develops a theoretical and practical approach of robo-advisory given the above-mentioned theories. Departing from the academic approach angle, the best strategy is chosen by the author, applied and, ultimately, tested. Hence, once the different theories explained and the importance of each approach to data understanding surrounding financial markets, and the main variables of the model have been defined, The project will proceed with the following steps:

I. Data collection via different services, such as Morningstar, that can be integrated and auto-updated using different modules included in a model
II. Search, find and arrange the data so it's prepared to be analyzed
III. Apply a consistent model
IV. Obtain an understandable output from the process that will take us to the investment process.
V. Decide and form a portfolio
VI. Contrast the results

Following with the example used in point "V", a full example of the appliance of this thesis would be: technical analysis and statistical inference have been exposed and understood, and can be applied to this "X" stock, which historical prices are downloaded in the database, arranged by columns, understood through a statistical model, and reinforced by related economic variables understanding. If these conditions happen at the same time the manager be able to estimate an efficient portfolio, so the investor could possibly trust the output of the model, which would come in the form of: "Buy 'Y%' of the Action which symbol is 'Z'", if that'd be the case.

Thus, by reading this paper the reader is able to understand the origins, the development, the present and the short-term future of portfolio management through the combination of the literature review, a theoretical approach, and a practical approach.

1. LITERATURE REVIEW

1.1. MARKET EFFICIENCY

Investment advisors and managers significantly base their entire strategy on the degree of reliance they set on market efficiency. This concept was introduced by Eugene Fama in 1970, and as mentioned above, it has changed the understanding of markets and, specially, financial markets. It is based on the assumption of rationalism and profit maximizing among market participants, which derives on pricing adjustment according to information flows. Three cumulative levels of the hypothesis were exposed: (1) The weak form argues that securities prices reflect past information, (2) the semi-strong form claims that future, present or past publicly available information is reflected in the price, (3) the strong form states that prices reflect every kind of information, even insider or hidden information. When markets reach their fully efficient form, securities are traded at their fair value.

Paradoxically, anomalies can be effectively exploited by those market participants that scout them, consequently eliminating mispricing while profiting from an advantageous market position that will be mimicked by those late-movers following the pioneer.

Fama also states that this excess of return must compensate the cost of obtaining new information. Investors might as well misunderstand this new information since it can happen to be irrelevant for the market. This phenomena was pointed out by Black in 1986, whose theory labels two types of investors: informed traders, defined those who seek out the mispricing and profit from it; and noise traders, those who misinterpret information or are driven by other motives ending up paying a premium for it.

Later on, Kenneth French (2012) empirically demonstrated the similar performance of US mutual funds and the returns that a supposed unskilled fund manager would obtain. This similitude endorses the efficient market hypothesis.

1.2. INVESTMENT MANAGEMENT

An investment is defined as the current commitment of dollars (or any currency) for a period of time in order to derive future payments that will compensate the investor for the time the funds are committed, the expected rate of inflation, and the uncertainty of the future payments (FK Reilly, KC Brown, 2002). The given definition includes all kinds of investments, from fixed assets by a company to boost their production, to bonds, equities, real estate or commodities carried out by individuals.

The financial system, through its different markets -and consequent platforms-, allows supply and demand to meet in order to carry out different operations, such as the exchange of assets, hedging risks, and moving money through time (Michael G. McMillan et al., 2011). It is within this financial system where investment management relates to the origination, structuring, and management of financial assets (Sironi, 2016).

Having settled this framework, it can be stated that investment management industry acts as a financial intermediary, connecting private and institutional investors with issuers of financial products. Three main parties stem from these mechanisms: companies, governments or financial institutions looking for the cheapest available funds; intermediaries willing to maximize their profits via margins; and, investors looking for the best risk-return balance possible.

From a historical point of view, we find a progressive advance, shifting the industry's traditional investment management into investment management shaped as robo-advisors. Starting on the 1950s, the conventional advisors were based on human dialogue and high advisory price, aiming for high-wealth profile clients. In the 1970s, discount brokers made it possible for middle class individuals to access to financial advice, counting as well with human dialogue but lowering the previously established fees. Online trading appeared on the 1990s, opening the gates of financial advice to more individuals, incurring in limited human dialogue, a transaction based cost and almost no advice. Ultimately, robo-advisors appeared during the last decade, recovering advisory at a low price, eliminating human dialogue and simplifying the processes. (Sironi, 2016)

Carrying on with the interest of the studio, among the intermediaries as advisors searching for the best risk-adjusted strategies according to a specific investor, we can mainly differentiate two types of management:

1.2.1. Active Portfolio Management

Also referred to as traditional investment management, it is commonly driven by the use of the analytical skills of the human element given a time horizon, a risk profile derived from the client's preferences, and the available financial products in the market. It is typically divided into to methodologies: technical and fundamental analysis. Fundamental analysis proposes that misprices on securities prices may take place on the short run. Its proponents believe in the use of information (key performance indicators or KPIs) to valuate companies and profit from mispricing. Technical analysis maintains that trends and past market data allow us to forecast future prices (Murphy, 1999).

Two components form the main excess return that can be achieved by active management: security selection and market timing. Market timing refers to active asset allocation, a strategy through which the manager balances the different weights of a portfolio according to market expectations. Security selection is the act of choosing those specific assets within a class that will ensure higher returns than the others.

The main goal of these funds is to perform better than the chosen reference index or benchmark (such as S&P 500), through which clients can clump the large number of investment advisers into recognizable categories (Grinold and Kahn, 1999). It's worth to mention that benchmarks used to be set by cash in before the 1980s.

Financial institutions classically employ these managers, allowing possible conflict of interests (Sironi, 2016).

1.2.2. Passive Portfolio Management

Passive investment management defenders trust indexing as a sensible strategy since it alleges the efficiency of the markets. The market commonly absorbs information quasi-immediately, and these phenomena tend to happen at higher paces due to technology development. Therefore, as stated by Burton G. Malkiel, transaction and advice costs are higher than the negative output of market anomalies that may take place.

A second pillar of passive investment management is the zero-sum game theory, through which it is exhibited that any high-cost strategy makes an individual underperform the market. Lets imagine a world with only four individuals: two investors respectively trusting their funds to two investment managers. If the managers chose to follow opposite strategies, one will outperform and the other one will underperform, nonetheless, both would be charged with higher fees under active management, thus value would be loss in the form of fees. On the other hand, passive management fees are lower and have a lower negative impact on the investment performance. As a result, passive management should always be preferred due to value creation optimization (Malkiel, 2003).

Anyhow, since this studio focuses on fee optimization as the essence of a strategy, we will pick up the thread in the following chapters.

Consequently, and relating passive and active strategies to market efficiency theories, if every market operator followed a passive investment strategy, markets would turn inefficient due to the lack of mispricing corrections. A (bigger) gap would be opened between the company's real value and the share price. This relationship highlights the importance of active management, even as a zero-sum game.

1.2.3. The Importance of Asset Allocation

Asset allocation, defined the fund's capital portion investment on the different asset classes (typically bonds, stocks, and money market instruments), was largely uninvestigated until 1986, when Gary P.Brinson, Randolph Hood, and Gilbert L.Beebower (BHB) published “Determinants of Portfolio Performance”, priming asset allocation versus security selection[1] and market timing[2] as determinant of a portfolio’s return variability. As a result, asset allocation concluded to justify 93.6% of this variability. 91 U.S. pension funds returns between 1974 and 1983 were analyzed and compared to the returns obtained by indexed investments.

The investing community broadly embraced this theory. William Jahnke (1997) criticized the BHB study by pointing out that investors should be more concerned with the outcome of their investments than with the volatility returns. The author did also stand out for the rebalancing of asset allocation as market opportunities vary.

As a response to this critique, Paul D. Kaplan and Ibbotson published in 2000 “Does Asset Allocation Policy Explain 40, 90 or 100 Percent of Performance?”. Kaplan and Ibbotson empirically proved how asset allocation explain 90% of the returns of a portfolio by contrasting the returns of 10 years of 94 mutual funds versus those happened 58 pensions funds.

As compiled above, the different theories on asset allocation make it determinant for the return-achievement process.

[1] Security selection: the activity of picking the securities that better fit a fund’s goal (for example, top-performance stocks)

[2] Market timing: position opening according to the fund’s goal

1.3. MODERN PORTFOLIO THEORY

Introduced by Markowitz in 1952, mean-variance analysis represents the main pillar of modern portfolio theory. James Tobin (1958) extended the analysis by optimizing the previous framework, constituting the commonly known mean-variance optimization. Sharpe (1964) later converged asset pricing and mean-variance optimization models. Still nowadays, modern portfolio theory is based on an unchangeable basic structure, adding different elements that may also be described as follows.

1.3.1. Diversification

The process through which risks is mitigated by allocating resources in imperfectly correlated assets is called diversification. Although it has existed for centuries, it was not formulated until the XX century, proving that returns are not constrained by diversification but risks are reduced thanks to the different reactions to market events among asset classes.

Even though the power of diversification helps to reduce risks, Markowitz found that the total risk could not be vanished by the use of it. Two other different types of risks are found in any portfolio: firm-specific risk, which refers to fluctuations in a single asset and can be mitigated by portfolio enlargement (Berk & De Marzo 2014); and systematic risk, such as economic cycles, that affects every asset and will be present in any portfolio.

As stated by Berk & De Marzo, the expected return of a given portfolio equals the weighted average of the single assets expected returns. Meanwhile, the risk of the same portfolio will be lower that the weighted average of the single volatilities (risks) of the single assets.

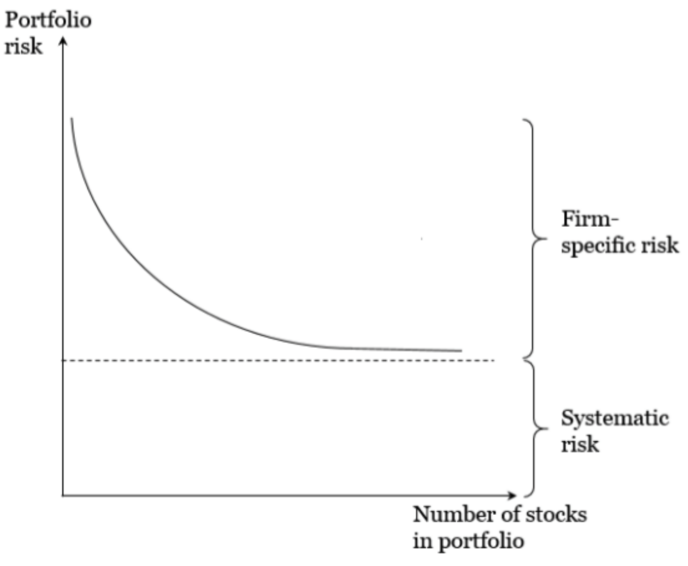


Figure 1: 'Risk' - 'Number of Stocks' Relationship

Also on diversification, increased correlation due to markets globalization implicates a challenge to diversification. Fund managers are looking for a risk mitigation resource across oceans, internationalizing equity funds and finding risk-hedgers in different asset classes than bonds (BlackRock, 2018).

1.3.2. Time Horizon

The time horizon of an investment refers to the period of time that such investment will be held until the investor liquidates it to obtain consequent returns. According to Paul Samuelson's theory (1963), investor's risk profile should be constant despite time horizon changes if: (1) the risk aversion of any investor is constant, (2) returns are independently and identically distributed, (3) future wealth only relies on investment returns.

Contrarily, other authors proved how risk is directly related with time horizon, it was the case of Merril and Thorley (1996) based their theory on financial option pricing. Kritzman and Rich (1998) later described how an investor's utility function might ignore time frame and, therefore, have a perception of risk that is independent from time horizon. However, they argued that if variance is expected to grow on a linear basis over time, so is volatility, or in other words, risk.

1.3.3. Mean-Variance Optimization

As mentioned earlier on this studio, Markowitz introduced mean-variance optimization framework in 1952. Its goal is to form optimal portfolios by combining expected returns and volatility of the asset classes that may conform the total investment. This way, and as explained earlier in this studio, higher returns are achieved through diversification while choosing assets with imperfect correlation coefficients that reduce the volatility of the portfolio. Maximizing expected returns and lowering variance leads us to the efficient frontier, the set of portfolios that optimize the proposed equation.

It was Tobin (1958), the author who extended Markowitz's theorem by adding the risk-free investment, the zero-risk asset that sets the minimum unique rate at which borrowers may borrow funds. Through this combination, the author described a tangent portfolio between the risk-free asset and the efficient frontier, forming as well the so-called capital asset line (CAL).

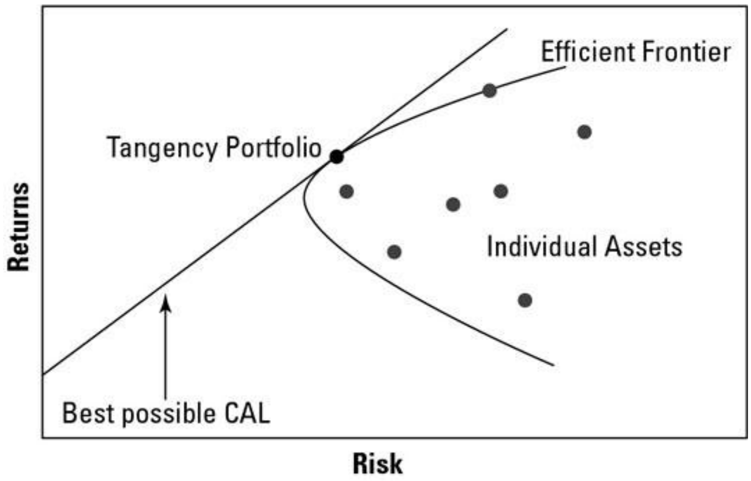


Figure 2: Efficient Frontier and Tangency Portfolio

1.3.4. Capital Asset Pricing Model (CAPM)

Following Tobin's theory, William Sharpe (1964) improved portfolio theory. As shown above, specific risk can be removed by diversification. Nevertheless, systematic risk is still dormant, regardless the level of diversification.

Following a set of assumptions, the author developed his theory. Firstly, Sharpe found that the return of a portfolio of stocks has to equal its cost of capital. Secondly, CAPM reformulated investment yields as a measure of extra compensation demanded and awarded to and by the investor due to the added absorbed risk. This concept is called risk premium and is calculated by the difference between the expected market return and the risk free rate.

By summing the risk free rate to the market premium multiplied by the factor Beta[3], the cost of capital (and return, according to Sharpe's theory) is obtained. The line formed by this equation is referred to as Security Market Line (SML).

Different authors would later prove that CAPM explains an average of 70% of a diversified portfolio returns.

1.3.5. The Three Factor Model

Fama and French (1992) expanded the CAPM by adding two risk-drivers or factors that describe stock returns. Besides the firstly-established market risk, the outperformance of small companies versus big companies and the outperformance of high book/market value versus small book/market value companies were recognized and added to the formula.

[3] Beta is a mesure of relative volatility that compares the stock or portfolio movements on price to the ones that happen in the market. That is, if a stock has a beta equal to 1, its price will move along with the market. It is calculated as the covariance between the asset and the market, divided by the variance of the market.

The proposed model was found to explain over 90% of a diversified portfolio returns, bettering CAPM results.

1.3.6. Factor Investing

As a consequence of the existing confrontation between active and passive management, factor investment flourished like an alternative management trend.

The term factor was firstly popularized by Ross (1976) in "The Arbitrage Theory of Capital Asset Pricing" (APT), extending multi-factor models without concreting on the factors that influence securities prices. As showed, various authors introduced this technique since the late XX century, although it found its critical moment in 2008, thanks to a studio that analyzed the Norwegian Government Pension Fund behavior and its returns (Ang, Goetzmann and Schaefer, 2009), proving that earlier theories did not avoid excessive losses when correlations between different asset classes peaked.

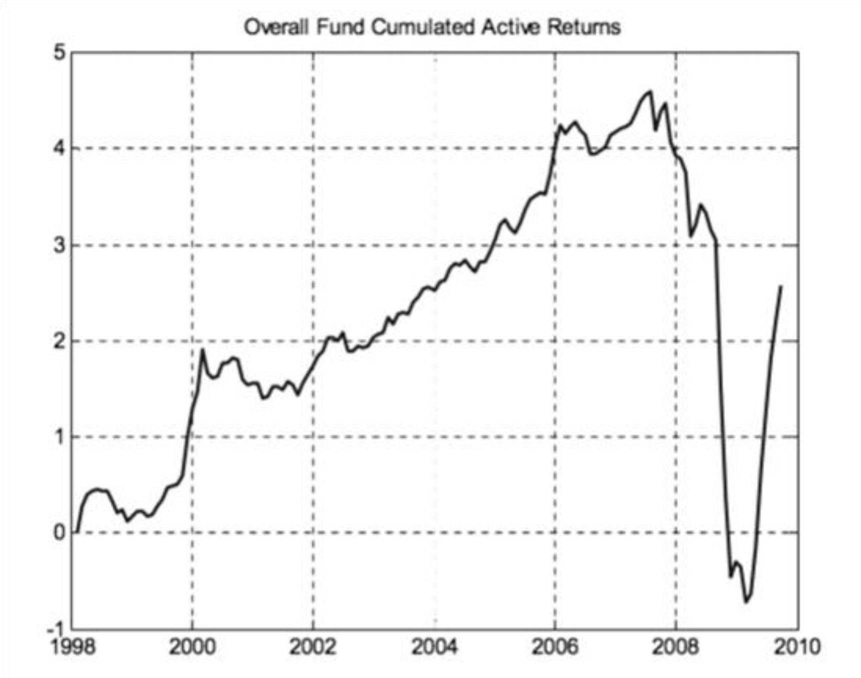


Figure 3: Cumulated Active Returns on the Overall Norwegian Government Pension Fund

The figure above shows the precipitous losses happened in the year 2008 due to the global financial crisis, which damaged the fund's returns consistency and drove it to negative cumulated results in 2009. As Ang, Goetzmann and Schaefer, enunciate: "Active management contributions to the overall return were extremely small. […] In fact, approximately 70% of all active returns on the overall Fund can be explained by exposures to systematic factors over the sample (portfolio)". Liquidity, volatility and other factors were logical risk-drivers as a result of the fund return appetite. The lack of dispersion among factors exposure drove the fund to surprisingly unexpected losses, summed to the unexpected character of the crisis were the main drivers of such a fund crisis.

As a proposal to solve this obstacle, different factors were included as possible risk-related drivers, giving birth to factor investing. The main factors are summarized in the following table.

Factor	What is it?	Main Indicator/s
Size	Smaller quoted companies are proven to provide the best long-term returns.	Market capitalization
Value	According to fundamental analysis basis, undervalued stocks provide future returns	B/P ratio, EPS, sales, cash flow, dividends, net profit…
Momentum	Price variations provide investment opportunities	Relative returns and historical alpha
Yield	Higher dividend yield stocks provide excess returns	Dividend yield
Quality	According to established metrics, it captures those stocks that may have, for example, low debt.	Cash flows, financial leverage, Return On Equity (ROE), earnings stability
Low Volatility	Lower than average volatility, beta and idiosyncratic risk stocks provide higher returns	Standard deviation, beta

The most extended factor use among investment managers is the value one. It agrees with fundamental analysis basics, incurring in high costs due to the necessary analysis that requires more human intervention. Thus, it commonly mismatches Malkiel's (2003) analysis of fee importance. On the other hand, those factors that match low fee importance are low volatility, quality, yield, and alpha. They can be easily programmed thanks to their independence on specific and possibly private information.

As stated by Ross (1976), factors may vary depending on the region. The consistency of these strategies can fluctuate and eventually debilitate depending on, for example, the economic and political development of the region or country the security is from. These fluctuations can probably make a fund underperform.

In addition, these strategies find their limits on the imagination of the portfolio manager. They basically rely on a consistent method to determine the weights of each investment in their portfolio.

It is worth mentioning that all the strategies mentioned above could be performed by robo-advisors, since they all focus on measurable determinants which releases are automated and frequently publicly accessible.

1.3.6. Robo-Advisory

As defined above, robo-advisors provide algorithm-based portfolio management services online at a fraction of the costs associated with traditional portfolio managers and traditional investment advisors. According to EnFintech (2017), "Robo-advisors are computer programs that automate investments by applying modern portfolio management theories, which play with variables related to volatility and expected returns, among many other variables. Robo-advisors profile the client based on questionnaires about their knowledge, experience and investment objectives, then offer a portfolio of assets adapted to the saver. The human factor is no longer relevant when making investment decisions in the short term, but always a human adviser is a vital aid to the investor, both to receive global financial advice (taxes, assets, insurance, inheritance, etc.), As well as to receive a long-term vision that will help the investor to take short decisions, such as using one type of theft advisor or another".

Regardless the definition –to which many different companies and authors have collaborated-, either as a whole package of investment assessment that reaches trading or without reaching the direct contact with the market and limiting their activity to advisory, for the purpose of this project, robo-advisory is defined as a computer-based program in which calculi is performed in order to assess investors through an internet-based platform. Additionally -and given the definition-, the project will not take into consideration risk-profiles as the starting point in order to form strategies, but will develop them and then these could be fit to the risk-profile of a given investor.

It is also worth mentioning that robo-advisory' industry is growing towards process automation. In these terms, the United States lead the field with over 200 programs, followed by Germany (31). The Spanish market has not been yet fully developed, finding 4 robo-advisors in the territory (Techfluence, 2017).

According to Statista (2018), assets under the management of robo-advisors have been increasing during the past years. Additionaly, it estimates these funds will reach 2.2 million dollars by 2020. Even if the numbers are still small, this industry has been exponentially growing and it deserves respect due to (1) the simplification and optimization of investment through automation and lower fees, and (2) the risks derived (mostly shown as Flash Crashes[4], and Dark Pools[5]) by the non-focused legislation that allow programs access to unreachable advantages for human beings. The second point is especially important due to the current reforms of the financial markets, which do not form a core part of this paper but show inefficiencies since they are mainly driven by and for humans. Therefore, the market is decompensated, causing some phenomena that drive to systemic risk, which must be mitigated by the authorities.

All in all, this paper aims to develop a computer-based automated investment program, in other words, a robo-advisor. For this development, a theoretical and practical

[4] A flash crash is defined by the Financial Times as follows: "On May 6 2010 investors were stunned when the Dow Jones plunged 1,000 points (almost 6 per cent) before recovering – all in 20 minutes. Dubbed the "flash crash" market participants and regulators were immediately trying to identify the culprits. During the flash crash a large sell order triggered a high-speed selling frenzy among the high frequency traders that dominate the futures and equities markets. It took about five minutes for markets to hit bottom, erasing almost $1tn in market value. Markets then recovered just as quickly and just as mysteriously".

[5] A Dark Pool is defined by the Financial Times as follows: "A dark pool is the romantic – or sinister, depending on your viewpoint – name given to a network that allows traders to buy or sell large orders without running the risk that other traders will work out what is going on and put the price up, or down, to take advantage of the order. They have been criticised for their lack of transparency and because the inevitable fragmentation of trading could lead to less efficient pricing in traditional open stock exchanges."

approach is needed. The theoretical approach aims to seek for a consistent strategy, while the practical will deliver strategies to then test them to proof their efficiency.

2. STRATEGY ON ETFs

The following strategy consists of the use of the previously mentioned theories and the internationalization of a portfolio through Exchange-Traded Funds. This second part will be divided into three parts: (1) Theoretical Approach, where the reasons of this investment procedure will be explained; (2) the Practical Approach, in which the investing criteria will be explained; (3) the Results, where the outcome of the different strategies will be analyzed and commented.

2.1. THEORETICAL APPROACH

It was earlier mentioned that factors might be inconsistent because of macroeconomic causes. This paper aims to combine an empirical review of a self-made strategy with the usage of a broad range of international Exchange-Traded Funds, as to achieve a multi-asset portfolio. Ergo, the target is set to deepen in the possibility of obtaining extra returns on the long-term.

Economic development is allegedly predicted in stock prices (Levine and Zervos, 1998). In addition, markets have reached a level of globalization in which it is not products that are shared but knowledge (Baldwin, 2016). This knowledge is quasi-automatically transferable and find to borders due to the technology development, even though some countries may try to constraint international trade. Thus, economic development is a common interest between the different nations, which may suffer recessions and instabilities, but that may as well grow in the long-term. This implies that stocks (the most volatile asset category) will grow in the long run.

Pim Van Vliet and Jan de Koning (2017) checked the effectiveness of low-volatility versus high-volatility strategy through a studio in which they examined stock returns from 1929 until 2016.

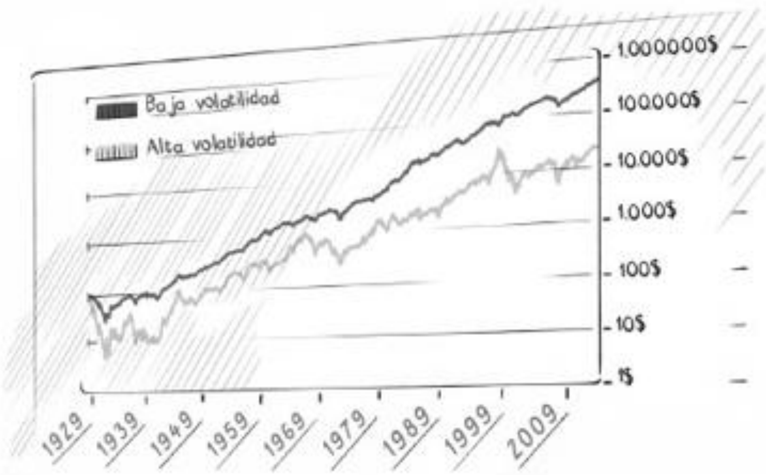


Figure 4: Low-Volatility vs. High-Volatility Returns

Low-volatility can be achieved through the internationalization of the asset allocation of a portfolio. Volatility is reduced by the application of imperfect coefficients of correlation between the different assets. Nonetheless, increasing correlations between the different asset' classes, and specially, in equities (Charles Schwab & Co., Inc., 2018), make it harder to diversify a portfolio.

Exchange-traded funds (ETFs) are worth mentioning in this context. An ETF is a marketable security that tracks bonds, commodities, indexes, or a basket of stocks that share a common characteristic or factor. Thanks to their marketable characterization, they are usually liquid assets that enable automatic opening and closing position that fully represents the ongoing value of the fund. This way, mutual fund's time losses are avoided, considering they require a time interval to represent the net asset value, and to buy or to sell participations. ETFs can only be created by authorized participants, which are large financial institutions (mainly banks and investment companies). These funds commonly offer lower expense ratios than those of mutual funds, and enable derivatives on themselves (since they trade as common stocks).

Thanks to the accessibility of this kind of funds, finding different assets in each of them, the robo-advisor's strategy is simplified and the higher correlation issue can be mitigated.

The reported strategies will use ETFs to reach a high level of internationalization and miscorrelation between asset classes in order to optimize results, either by lowering the risk or by maximizing the return. Thus, the changes of macroeconomic environment have to be understood as to interpret the correct weights of each asset class, which is determined by the minimization of the standard deviation. This analysis will not focus on the causes of those "bad years", however it is important to understand how the different asset classes yield in different periods of time. The table below shows the returns obtained by investments in the different asset classes between the years 2003 and 2017.

2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
EM 56.3%	REIT 31.6%	EM 34.5%	REIT 35.1%	EM 39.8%	HG Bnd 5.2%	EM 79.0%	REIT 28.0%	REIT 8.3%	REIT 19.7%	Sm Cap 38.8%	REIT 28.0%	REIT 2.8%	Sm Cap 21.3%	EM 37.8%
Sm Cap 47.3%	EM 26.0%	Int'l Stk 14.0%	EM 32.6%	Int'l Stk 11.6%	Cash 1.4%	HY Bnd 57.5%	Sm Cap 26.9%	HG Bnd 7.8%	EM 18.6%	Lg Cap 32.4%	Lg Cap 13.7%	Lg Cap 1.4%	HY Bnd 17.5%	Int'l 25.6%
Int'l Stk 39.2%	Int'l Stk 20.7%	REIT 12.2%	Int'l Stk 26.9%	AA 7.6%	AA -22.4%	Int'l Stk 32.5%	EM 19.2%	HY Bnd 4.4%	Int'l Stk 17.9%	Int'l Stk 23.3%	AA 6.9%	HG Bnd 0.6%	Lg Cap 12.0%	Lg Cap 21.8%
REIT 37.1%	Sm Cap 18.3%	AA 8.9%	Sm Cap 18.4%	HG Bnd 7.0%	HY Bnd -26.4%	REIT 28.0%	HY Bnd 15.2%	Lg Cap 2.1%	Sm Cap 16.4%	AA 11.5%	HG Bnd 6.0%	Cash 0.1%	EM 11.6%	Sm Cap 14.7%
Lg Cap 28.7%	AA 14.1%	Lg Cap 4.9%	AA 16.7%	Lg Cap 5.5%	Sm Cap -33.8%	Sm Cap 27.2%	Lg Cap 15.1%	AA 0.3%	Lg Cap 16.0%	HY Bnd 7.4%	Sm Cap 4.9%	Int'l Stk -0.4%	REIT 8.6%	AA 14.6%
HY Bnd 28.2%	Lg Cap 10.9%	Sm Cap 4.6%	Lg Cap 15.8%	Cash 4.4%	Lg Cap -37.0%	Lg Cap 26.5%	AA 13.5%	Cash 0.1%	HY Bnd 15.6%	REIT 2.9%	HY Bnd 2.5%	AA -1.3%	AA 7.2%	REIT 8.7%
AA 25.9%	HY Bnd 10.9%	Cash 3.2%	HY Bnd 11.8%	HY Bnd 2.2%	REIT -37.7%	AA 24.6%	Int'l Stk 8.2%	Sm Cap -4.2%	AA 12.2%	Cash 0.1%	Cash 0.0%	Sm Cap -4.4%	HG Bnd 2.7%	HY Bnd 7.5%
HG Bnd 4.1%	HG Bnd 4.3%	HY Bnd 2.7%	Cash 4.7%	Sm Cap -1.6%	Int'l Stk -43.1%	HG Bnd 5.9%	HG Bnd 6.5%	Int'l Stk -11.7%	HG Bnd 4.2%	HG Bnd -2.0%	EM -1.8%	HY Bnd -4.6%	Int'l Stk 1.5%	HG Bnd 3.5%
Cash 1.0%	Cash 1.4%	HG Bnd 2.4%	HG Bnd 4.3%	REIT -15.7%	EM -53.2%	Cash 0.2%	Cash 0.2%	EM -18.2%	Cash 0.1%	EM -2.3%	Int'l Stk -4.5%	EM -14.6%	Cash 0.3%	Cash 1.0%

Abbr.	Asset Class – Index	Annual	Best	Worst
Lg Cap	Large Caps Stocks – S&P 500 Index	10.15%	32.4%	-37.0%
Sm Cap	Small Cap Stocks – Russell 2000 Index	11.17%	47.3%	-33.8%
Int'l Stk	International Developed Stocks – MSCI EAFE Index	8.60%	39.2%	-43.1%
EM	Emerging Market Stocks – MSCI Emerging Markets Index	12.68%	79.0%	-53.2%
REIT	REITs – FTSE NAREIT All Equity Index	11.13%	37.1%	-37.7%
HG Bnd	High Grade Bonds – Barclay's U.S. Aggregate Bond Index	4.14%	7.84%	-2.0%
HY Bnd	High Yield Bonds – BofAML US High Yield Master II Index	9.08%	57.5%	-26.4%
Cash	Cash – 3 Month Treasury Bill Rate	1.18%	4.7%	0.0%
AA	Asset Allocation Portfolio*	8.74%	25.9%	-22.4%

Past performance does not guarantee future returns. The historical performance shows changes in market trends across several asset classes over the past fifteen years. Returns represent total annual returns (reinvestment of all distributions) and does not include fees and expenses. The investments you choose should reflect your financial goals and risk tolerance. For assistance, talk to a financial professional. All data are as of 12/31/17.

*Asset Allocation Portfolio is made up of 15% large cap stocks, 15% international stocks, 10% small cap stocks, 10% emerging market stocks, 10% REITs, 40% high-grade bonds, and annual rebalancing.

Figure 5: Asset Classes Returns

According to what the table above indicates, the different asset classes' returns vary over the years, and there are no classes that remain on the top tier. They show the risk-return relationship results. Taking as an example EM (Emerging Markets' equities), it is proven how their yield can peak intensely and sinks dramatically, like it happened in 2008 (-53.2%) and in 2009 (+79.0%). This instability causes losses, even though it appears to be profitable due to the higher returns in 2009.

	2007	2008	2009
Returns	-	-53,20%	79,00%
Value	100,00	46,80	83,77

Setting 2007 as base 100 for a calculation, the value of an investment would have had a negative yield due to the changes of the base in the calculus. During these two years, it would have ended up on an overall -16.23% loss. Thus, choosing the best years in the most risky asset classes is core in active management strategies.

On the other hand, High Grade Bonds (HG) and Cash (Cash) categories remain stable due to their low-risk profile accordance.

It is also core to point out how "bad years" are unavoidable if a portfolio is invested in all the asset classes. The difficultness of predicting the future results of each asset class makes it a struggle to obtain positive results every year. For example, in the year 2008 almost every asset class obtained negative results. In contrast, those that ensure low-risk, and therefore yield less –HG and Cash-, attracted money flows during this volatile year. The strategy to follow seeks to lower this kind of losses by the application of the miscorrelation through internationalization.

By setting 2002 as the base year (100) for our calculus, the interpretation of the returns of each asset class becomes easier:

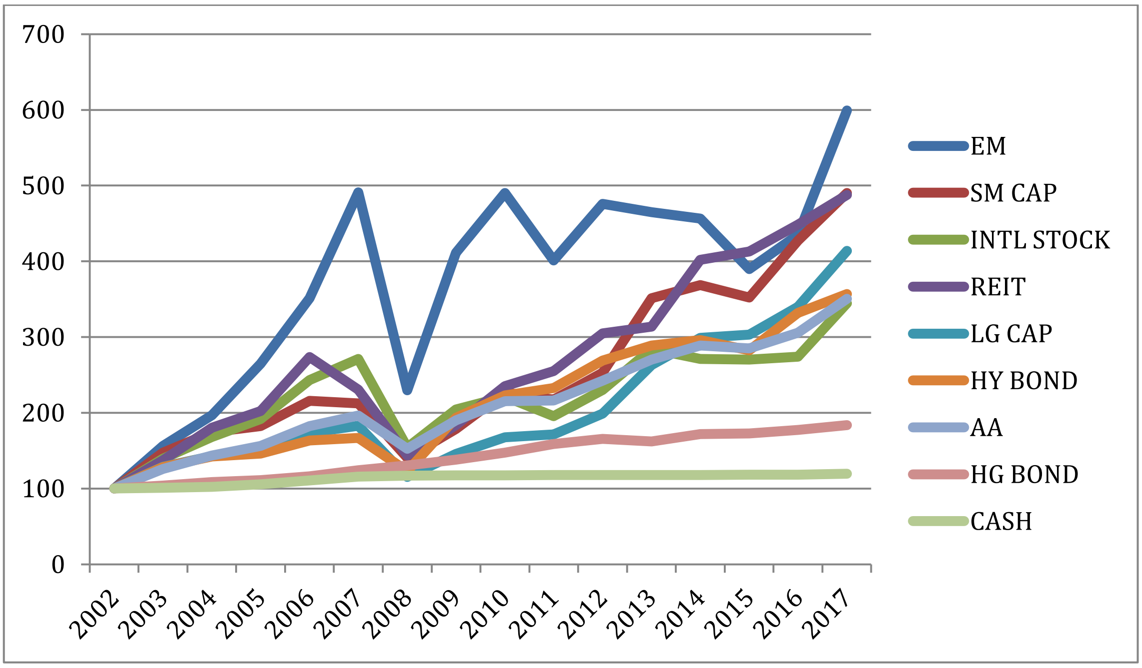


Figure 6: Asset Classes Returns. 2002 as Base Year (100)

It is simple to become aware that all asset classes have accumulated positive returns. Thus, a profitable strategy seems achievable. However, there is a strong need of determining which assets will form the portfolio and how will they be weighted.

2.1.1. Asset Allocation

The asset allocation of a portfolio determines the amount of the funds that will be invested in each of the assets that form it. In this case, and since the goal is to internationalize the portfolio, the funds will only be allocated in ETFs to enforce the liquidity and simplify the investment procedure.

Starting from the asset class review, the eligible ETFs are those that replicate the indexes that represent the previously mentioned classes. However, the following criteria is required to choose the exchange tradable funds:

a) Similarity to the previously mentioned asset classes: the funds must be as similar as possible to those asset classes' indexes that the portfolio aims to allocate.
b) Volume: the funds must be as liquid as possible, thus they must have a big volume to avoid liquidity risk.
c) Inception date: the funds must have been originated more than ten years ago due to the purpose of this project, which –remember- aims to pursue a long-term investment strategy.
d) Available in Morningstar: due to the source of the used data, the funds must be available in Morningstar's database.

To simplify the procedure, no transaction costs or expense ratios will be considered when choosing the investable securities. In addition, the dividend distribution of the funds has been ignored due to the high level of diversification that each of the ETFs provides. Anyhow, the dividend distribution makes a stock yield less in uptrends but allows stopping losses if these occur during a downtrend.

Therefore, the chosen list of ETFs is the following:

1. SPDR S&P ETF Trust (SPY): SPY is the most traded ETF, which indicates a high grade of liquidity. It tracks the S&P 500 US index, which represents the US large-cap companies. It fully replicates the index and does not reinvest dividends, thus follows the stocks' performance more accurately. It will be used to replicate the large cap companies.
2. iShares Russel 2000 ETF (IWM): IWM offers exposure to the Russell 2000 Index, a measure of small cap U.S. stocks. Every sector of the countries' economy is well represented due to the nature of the underlying portfolio, which is widely diversified in terms of sectors. It will be used to replicate de small cap companies.
3. iShares MSCI EAFE ETF (EFA): EFA is an international cornerstone of geographical diversification among international ETFs. It provides access to developed markets' equities through a single marketable security. In addition, it is the most liquid ETF among the ones in its class. It will be used to replicate de international equities.
4. iShares MSCI Emerging Markets ETF (EEM): as well as EFA, EEM is a highly liquid ETF that provides geographical diversification among international ETFs. It focuses its portfolio on emerging markets' securities and is reportedly well balanced between the broad markets that it represents. It will be used to replicate the emerging market equities.
5. Vanguard Real Estate Index Fund (VNQ): it offers exposure to two-thirds of the value of the whole REITS U.S. funds, thus it enables the replication of the Real Estate asset class.
6. iShares U.S. Aggregate Bond ETF (AGG): AGG enables the replication of the High Grade bonds market through a portfolio composed by U.S. bonds. AGG is unmatched in terms of liquidity.
7. iShares iBoxx $ High Yield Master II (HYG): HYG represents the dollar denominated high yield liquid corporate bond market. It keeps most of its assets inside the U.S. borders. However, it offers a slight range of internationalization. It will be used to replicate the high yield bonds asset class.

Ultimately, cash will no longer be considered an asset class due to the lack of return during the last years when dealing with developed economies. Thus, it would be underweighted and has not represented a feasible investment for over 3 years due to the low interest rate environment in both the U.S. and the European Union.

This asset allocation will follow solid criteria to calculate the respective weights for each asset class. Once the assets have been chosen, the database can be created.

2.2. PRACTICAL APPROACH

To commence with a practical approach of the analysis, there is a first need to fulfill: the database completion. This database is needed to activate the possibility of creating a dynamic analysis, since the usage of certain programs allows the investor to recreate different scenarios where the criteria can be switched and compared. The tools used for this purpose are Excel and Python. Secondly, the different strategies will be commented and explained. Ultimately, the strategies will be back-tested through a static allocation policy and a dynamic one, in which weights vary on a yearly basis.

2.2.1. Database Building and Ordering

The database of the project has been built in a Python environment, allowing the analysis to access to the latest data. For the purpose, and as it was previously mentioned, the chosen source is Morningstar. It allows access to the historical data of the chosen ETFs.

The historical data reaches back to April 2007, because the program was activated on June 2018. The start of this analysis is found there. The selection of the date is due to the origin of the Vanguard Real Estate Index Fund, which was created a month before but did not reach reliable levels of liquidity (traded volume) until a month after. Thus, the data bulk download calls the latest date time (the one of the current day) and goes back 4069 days. This limited retrospective download enables the dynamic part of the database, which consists on analyzing the different securities on slightly different time-periods. At a first glance, this will not change the analysis. Anyhow, it combines with the long-term perspective objective of the portfolio.

As to finish with the database construction, Python exports the data to a .csv file, which includes the latest 4069 days. Python does also offer the possibility of looping the action every twenty-four hours. This way, the database could be refreshed everyday, therefore automated. The used code is explained in the following lines:

```
import datetime
import pandas as pd
import pandas_datareader.data as web
N = 4069
end = datetime.datetime.now()
start = datetime.datetime.now() - datetime.timedelta(N)
accion = ['SPY', 'IWM', 'EFA', 'EEM', 'VNQ', 'AGG', 'HYG']
fuente = 'morningstar'
df = web.DataReader(accion, fuente, start, end)
print(df)
df.reset_index(inplace=True)
df.set_index("Date", inplace=True)
df.to_csv('etfs.csv')
data = pd.read_csv('etfs.csv',index_col='Date', parse_dates=True)
```

When this database is already built, Excel[6] is enabled to process the data. It first imports the previously created .csv file[7]. Secondly, it eliminates those rows, which appear with

[6] It is highly recommendable to read the following lines while following the attached Excel file.

[7] Datos (2) Sheet

total traded volume equal to zero. This is done in order to avoid analyzing non-tradable days such as weekends. It later reorders and cleans the numbers exported by Python, since some of them come with more decimals and break up the import parameters. To follow with the process, Excel creates a pivot table[8] that sets the chosen ETFs as column indexes, the dates as row indexes, and the daily closing quotes as the table values. Consequently, the program calculates the daily returns for each security. These returns are later separated into years, assigning a table to each year[9].

Once the process is completed, the different ETFs can be compared according to different parameters.

2.2.2. Parametrical Analysis – Factors and Procedures

To complete a successful analysis, this paper has briefly described the different investment perspectives that an investor can take during the asset allocation process. An investment can follow a passive strategy or an active one. One can rely on optimization models or in a single factor, pursuing a single motivation. As mentioned before, the factors used when investing allow portfolio a broad range to use the imagination. Anyhow, these factors must rely on return and/or risk premises to comply with the investors' needs.

The chosen factors find their origins on the way children are raised. Many experts point out the importance of giving a reward every time a kid does something well and giving them nothing whenever he or she does something wrong. On the other hands, others prefer a more "rigid" education, in which the kid is punished if he or she does something wrong, but is not rewarded when doing something right. These dichotomous relationship (good – bad) sets the bases for the upcoming analysis.

This project uses two different criteria that later branch into four models that allow comparison-based conclusions.

The main chosen indicator as to compare the results of the different strategies is the Sharpe ratio. This ratio establishes a relationship between the portfolios' return, the risk-free assets' return, and the volatility of the portfolio.

$$Si = \frac{Ri - Rf}{\sigma i}$$

Thus, the results of the Sharpe ratio (Si) will be higher as the difference between the return of the portfolio (Ri) and the risk-free asset (Rf) increases, and/or if the volatility of the portfolio (σi) decreases.

The return of the portfolio is based on the historical performance over the 4069 available. This return is accumulated and then weighted according to the respective

[8] Pivot

[9] Note that the possiblity of analyzing 2019 has already been included due to the dynamic perspective of this work.

allocation that is derived from the calculus occurred in the strategy. Thus, the return of the portfolio is the sum of the multiplications of each asset and their respective weights.

The volatility of the portfolio is calculated as the standard deviation of the historical series, which results from the square root of the variance. In order to obtain the variance, a covariance matrix is needed. This matrix is obtained by multiplying the correlation matrix and an intermediate matrix formed by the historical standard deviation of each asset times the same variable of the different assets.

The chosen risk-free asset is the 10-year U.S. bond. This asset has been taken as a reference due to the importance of American stocks in the used asset classes' ETFs, which partially or totally on this countries stocks as a reference for Real Estate, High Yield Bonds, High Grade Bonds, Small Cap Stocks, and Big Cap Stocks. The United States also represent a major reference of the global economy and the strategic power of the country sets it as the most important global economic and geopolitical reference. In June 2018 the 10-year U.S. bond yielded 2.92%. However, this variable can also be automated by setting a loop on its search.

In addition, the cumulated days are calculated for each year (these are later summed to acknowledge the total number of days that are to be analyzed), forming the n factor. The importance of the dates has also been taken into account. This importance depends on a factor "k" that varies according to the following function:

$$k = n^3$$

This way, and placing the date as of June 1st 2018, the percentage of the total of the decision making process is assigned as follows:

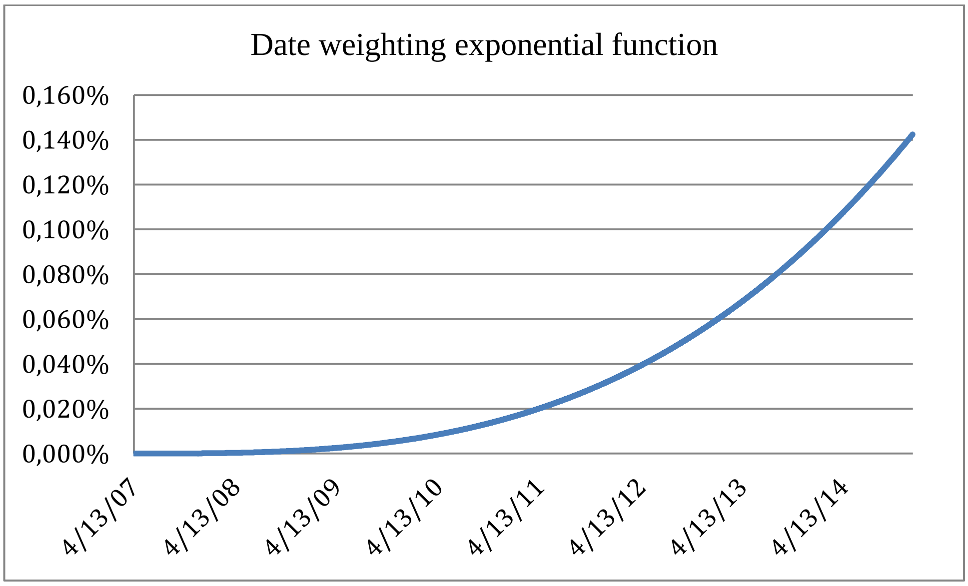


Figure 7: Date Weighting Exponential Function

Notice that the assigned contribution of each day increases when the days are more recent. The more recent the data is, the more important it is. This way, the latest day counts for 0.1422% of the total weight of an ETF, while the oldest data amounts for less than 0.0001% of the total weight of an ETF in the formed portfolio. The third day cumulated and risen to the third equals to 27, while the last one is higher than 2,22E+10. The sum of the cumulated risen numbers constitutes the denominator of the fraction that leads to the date weighting key (wd), while the cumulated risen number (k) of each day is the numerator of the fraction:

$$wd = \frac{k}{\sum k}$$

The result of the multiplication of the obtained scored, which depend on the applied factor, times the date weighting key (wd), makes the model take into account the importance of the recent events over the past events.

2.2.3. Reward Factor

Nowadays, the most common educational system in the developed countries (either academically, either personally speaking) appears to be the one that reinforces positive attitudes through the delivery of prizes, which do not necessarily relate to materialistic goods. It is also known as the reward system.

For the purpose of this project, the reward system will be called the Reward Factor. This factor prizes those securities which daily returns are positive. It does not take into consideration what has occurred in the previous sessions, but what has occurred between the closing price of the previous day and the one of the analyzed day. It also compares the daily returns to those of the peers, which are the other securities that are included in the portfolio. Following this method, a hundred percent prize is distributed between those that obtain the highest daily results and the ones with the lowest daily results. However, if none of the chosen ETFs obtain positive returns on a day, none of them will obtain a reward (will not be overweighed).

In addition, as happens with kids, the recent past prevails in the chosen ETFs' minds. This means that the factor is overweighed in comparison with the previous days as was explained earlier.

The Reward Factors requires of an ultimate adjustment due to the existence of days when all the portfolios' securities present negative returns. Thus, these days do not find any weights, but the total score is adjusted by a multiplier, which is formed by the maximum weights that the whole portfolio could have achieved divided by the sum of the total weights that correspond to each ETF. For example, when taking into account the whole dataset, in 2018 (only the days that have already occurred account for the calculus), the sum of the obtained weights amounts for 12.23%, while the total maximum weights, as for June 1st, 2018, equals 14.00%. The multiplier (l) equals 14.00% divided by 12.23%, and applies to the resulting weight of each security. In the case of a yearly analysis, the applicable weight is 100%, but, as of June 1st, 2018, the weights account for 89.82% of the total amount. As it is expected, the ratio between resulting weights and maximum weights is similar in both cases (around 87% and 89%), and the only difference is due to the exponential increment caused by the amount of days. In other words, when taking into account other years the program only takes into account a part of the curve (in this case, the most steepened one), while if the analysis happens to occur yearly the whole shape of the curve affects the result.

Therefore, the daily positive returns (p) of each ETF are summed to form the denominator ($\sum p$), forming the return-weighting key (wr):

$$wr = \frac{p}{\sum p}$$

This weighting key is later multiplied by the date-weighting key (wd) of each day. The results are summed and, ultimately, the return-weighting key is adjusted, forming the return-weighting adjusted key (wra):

$$l = \frac{\sum wd}{\sum wr}$$

$$wra = l * wr$$

The sum of the yearly return-weighting adjusted keys constitutes the weight of each asset according to the Reward Factor.

2.2.4. Punishment Factor

Following the commonly named as traditional education lines, the Punishment Factor does not prize good behavior but punishes bad one. In the case of the chosen ETFs, it ignores positive daily returns while underweighting the securities that obtain negative results. The aim is to minimize the negative conducts without prizing the positive attitudes.

Unlike the Reward Factor, the Punishment Factor does not allocate penalizations by proportionally dividing a hundred percent between all those that did right and wrong, but accounts for each one individually in terms of those that also underperformed. It penalizes those securities that obtain negative daily returns (numerator) in comparison to the total percentage loss of the whole set of ETFs (denominator). As well as in the case of the Reward Factor, it takes into consideration the moment of the negative event, overweighing those that have recently occurred and underweighting the ones that occurred in the early dates of the analyzed database by following the exponential date function, which again depends on the analyzed period (single year or whole dataset).

Thus, as opposed to the Reward Factor, the daily negative returns (n) of each ETF are summed to form the denominator ($\sum n$), forming the return-weighting key (wr):

$$wr = \frac{n}{\sum n}$$

This weighting key is later multiplied by the date-weighting key (wd) of each day. The results are then summed. The sum represents a grading system for each ETF, where the lowest score represents the best scenario and, consequently, the highest score represents the worst scenario. For this reason, the results are inversed as described below:

$$a = \frac{1}{\sum wd * wr}; \quad b = \sum a; \quad c = \frac{a}{b}$$

Ultimately, "c" represents the assigned different weights that agree with what its established by the Punishment Factor.

2.2.5. Reward & Punishment Factor (R&P)

Both explained factors are easily mixable. The combination of the two forms a model in which stocks weights in the portfolio are weakened when negative returns occur, and they are strengthened when the event is positive. Therefore, merging both allows the investor to analyze the possibilities from a third point of view, which results from the weighting (50%/50%) of the obtained results from both the Reward Factor and the Punishment Factor.

$$\text{Weights } (R \,\&\, P) = 50\% * wra + 50\% * c$$

2.2.6. The Equally Weighted Portfolio

The equally weighted portfolio (EWP) is included to check if any or all of the three created strategies allocate the funds efficiently or if they actually do not report any extra profit to the investor. It answers to the following question: what would happen if by allocating the funds through the division the total amount between the total number of the different available securities the chosen factors would be beaten? The answer will be later revealed, but the question is the main reason why this fourth way of portfolio building has been added. If the Equally Weighted Portfolio beats the three factors, these would result useless.

It consists of a simple division: the funds divided by the number of ETFs. It does not adapt in terms of the date or the results. It is a completely static portfolio.

$$\text{Weights } (EWP) = \frac{100\%}{7}$$

2.3. RESULTS

In order to compare the results of the chosen strategies two different methods have been used: the dynamic back testing and the static back testing. Before checking and commenting the results, and since both methodologies share a considerable part of their techniques, the common points must be commented.

The results of the strategies depend on the return and the volatility that outcome from the different allocations. A third variable is later derived from both: the Sharpe Ratio, which has already been explained above. These variables are calculated as follows:

- Return: the return of the portfolio measures profitability. It is the result of the weight matrix times the result. This can be yearly or cumulated, as will be explained further.

$$Return\ of\ the\ Portfolio = \begin{pmatrix} W_a \\ W_b \\ \dots \\ W_n \end{pmatrix} * \begin{pmatrix} R_a \\ R_b \\ \dots \\ R_n \end{pmatrix}$$

- Volatility: the volatility of the portfolio measures risk. As happens with the return, this variable can be yearly or cumulated, as will be explained further. It is calculated as the square root of the variance. The variance is the result of the successive multiplication of the weights matrix times the covariance matrix. This matrix is obtained by the multiplication of the correlation matrix times an intermediate matrix, which is the result of the serial multiplication of the standard deviations of each asset in the period.

  This procedure can be mathematically explained:

$$Covariance\ Matrix = \begin{pmatrix} \sigma_1^2 & \sigma_1 * \sigma_2 & \dots & \dots \\ \sigma_2 * \sigma_1 & \sigma_2^2 & \dots & \dots \\ \dots & \dots & \sigma_3^2 & \dots \\ \dots & \dots & \dots & \sigma_n^2 \end{pmatrix} * \begin{pmatrix} 1 & \rho_{12} & \dots & \dots \\ \rho_{21} & 1 & \dots & \dots \\ \dots & \dots & 1 & \rho_{3n} \\ \dots & \dots & \rho_{n3} & 1 \end{pmatrix}$$

$$\sigma^2 = * \ (W_a \quad W_b \quad \dots \quad W_n) * Covariance\ Matrix * \begin{pmatrix} W_a \\ W_b \\ \dots \\ W_n \end{pmatrix}$$

$$\sigma = \sqrt[2]{\sigma^2}$$

- Sharpe ratio: the functionality of this ratio has already been explained above. However, it is important to point out that it has been calculated on a yearly basis, according to what the 10-year U.S. bond yielded on the latest available data for each year.

According to these parameters, both testing methodologies have been applied. The results will be now analyzed:

2.3.1. Static Back Testing

Borrowed from the Value-at-Risk (VaR) methodology, the static back testing checks the performance of the chosen strategy in the past. As a difference with the most traditional VaR models, the used procedure takes into account the importance of time thanks to the usage of the exponential time function that is implied in the strategy building process. This premise does not take place in the case of the equally built portfolio. This strategy remains still on allocation terms. Anyhow, the weights that form the different portfolios, which are chosen according to the latest available data, do not vary but are carried from the present to the past. For the purpose of the project, the back testing has been carried back to the year 2008.

As of June 1st, 2018, the static back testing reported the following results:

Strategy/Securities	AGG	EEM	EFA	HYG	IWM	SPY	VNQ
Reward	16.75%	18.10%	12.18%	7.19%	16.74%	10.56%	18.49%
Punishment	92.03%	1.92%	0.60%	1.77%	1.52%	0.80%	1.36%
Reward & Punishment	54.39%	10.01%	6.39%	4.48%	9.13%	5.68%	9.93%
Equally Weighted	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%

Table 1: Static Back Testing. Weights as of June 1st, 2018

Strategy/Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Reward											
Return	-39.30%	17.87%	10.81%	-7.78%	10.54%	6.59%	3.34%	-8.56%	7.72%	13.05%	-1.42%
Volatility	26.89%	19.47%	11.33%	14.25%	7.35%	6.68%	5.51%	7.72%	7.95%	4.02%	7.61%
Sharpe Ratio	-1.5438	0.7203	0.6638	-0.6778	1.1946	0.5328	0.2123	-1.4032	0.6631	2.6452	-0.5699
Punishment											
Return	-2.09%	1.50%	2.89%	3.01%	1.65%	-3.29%	3.31%	-2.98%	0.92%	1.95%	-2.73%
Volatility	7.53%	3.82%	2.32%	2.12%	1.49%	2.43%	1.65%	2.27%	2.06%	1.71%	1.93%
Sharpe Ratio	-0.5717	-0.6126	-0.1714	0.5304	-0.0744	-2.6072	0.6904	-2.3192	-0.7451	-0.2715	-2.9324
Reward & Punishment											
Return	-20.69%	9.68%	6.85%	-2.39%	6.09%	1.65%	3.33%	-5.77%	4.32%	7.50%	-2.07%
Volatility	14.93%	10.64%	5.94%	7.42%	3.78%	4.14%	3.02%	4.23%	4.47%	2.35%	4.27%
Sharpe Ratio	-1.5344	0.5491	0.6000	-0.5755	1.1454	-0.3334	0.3829	-1.9027	0.4182	2.1630	-1.1691
Equally Weighted											
Return	-37.93%	17.50%	9.49%	-7.28%	10.20%	7.61%	2.44%	-8.26%	7.61%	12.62%	-1.30%
Volatility	25.05%	18.11%	10.77%	13.73%	7.14%	6.32%	5.34%	7.44%	7.69%	3.78%	7.35%
Sharpe Ratio	-1.6030	0.7544	0.5754	-0.6672	1.1834	0.7242	0.0497	-1.4149	0.6710	2.6988	-0.5735
10y U.S. Bond yield	2.22%	3.84%	3.29%	1.88%	1.76%	3.03%	2.17%	2.27%	2.45%	2.41%	2.92%

Table 2: Static Back Testing Results

As shown in “Table 1”, the Static Back Testing reports fixed weights for all the years that are analyzed. The cumulated returns of each strategy are shown in the table below:

Cumulated Returns	
Reward	60.99%
Punishment	6.07%
Reward & Punishment	31.91%
Equally Weighted	59.01%

Table 3: Static Back Testing Results. Cumulated Returns (2008 - 2018)

The different outputs will be now analyzed.

2.3.1.1. Reward Factor

The Reward Factor allocation comprehends a mixed portfolio in which weights shift from 7.19% until 18.49%, which correspond to iShares iBoxx $ High Yield Master II (HYG, the High Yield Bond chosen ETF) and to the Vanguard Real Estate Index Fund (VNQ, the Real Estate chosen ETF). This means that –no matter how great its losses were-, VNQ had the most positive days in terms of its movement in the price, and/or that it moved in a positive trend when the rest of securities did not. On the other hand, HYG moved downwards more days than the rest, thus its score or reward is significantly lower than the rest.

In addition, the Reward Factor portfolio presents the highest annual volatilities (10.80%). It is a risky strategy that may result in higher returns, but as seen in 2008, 2011, and 2015 (“Table 2”), the results can drop more than in the rest of the strategies. This phenomenon, as commented above, may bring lesser cumulative returns due to the difficultness of reversing negative effects when cumulated. However, the cumulated returns of the portfolio are the highest shown in “Table 3” (+60.99%).

Ultimately, the strategy shows the highest average Sharpe Ratio (+0.2216), which shows that it beats the benchmark and reports positive returns.

All in all, according to the static back testing methodology, the Reward Factor is an investable strategy recommendable for high-risk investor profiles.

2.3.1.2. Punishment Factor

The Punishment Factor portfolio tends to show low volatilities over the years (2.67% average, the lowest). This is due to the importance of reducing negative effects in the strategy, which summed to the omission of the positive ones, lead to the reduction of volatility, and the consequent contraction of risk. This strategy shows a low variation of the annual returns. Furthermore, the cumulated returns of the Punishment Factor strategy are clearly the lowest shown (+6.07%).

The asset allocation of the strategy is merely diversified. Its main asset is AGG (iShares Core U.S. Aggregate Bond ETF, the High Grade Bond ETF). This can be due to the low volatility that high-grade bonds present in the market.

Ultimately, the Punishment Factor portfolio averages a negative annual Sharpe Ratio (-0.8259). The causes of the negative Sharpe Ratio are found in the years 2013 and 2015 (2018 is not taken into account since it has not finished). These years coincide with the moments of low yields that the bond market offered, as happens nowadays in Europe. Anyhow, this fact makes the strategy non-investable, since it means it does not beat the benchmark. Consequently, aiming to recommend a low-risk profile investor and according to the static back testing, it would be better to invest in 10-year U.S. bonds than in the Punishment Factor strategy.

2.3.1.3. Reward & Punishment (R&P)

The combination of the previously explained strategies shows a slightly negative average annual Sharpe Ratio (-0.0233). As recently explained, this implies that it would not be a recommendable strategy to follow. However, it shows positive cumulative returns (+31.91%) and a low annual average volatility (5.93%).

As happens with the Punishment Factor strategy, the R&P strategy is negatively affected by the importance of the bond yields. This is caused by the high allocation in AGG (54.39%) –as a reminder: it is the High Grade Bond ETF-.

The strategy profits from the low volatility of the Punishment Factor and the high returns of the Reward Factor. It would be recommendable for a medium-to-high-risk profile investor if the Sharpe Ratio exceeded 0.

2.3.1.4. Equally Weighted Portfolio

The equally weighted portfolio presents a perfectly diversified asset allocation. In cumulative terms, it yielded +59.01%. This yield is placed very close to the one presented by the Reward Factor strategy (+60.99%). The presented volatility is as well similar to the firstly commented factor (10.25%). These similarities are due to the diversification that characterizes both portfolios.

The strategy presents an annual average Sharpe Ratio of 21.80. It is slightly lower than the one found in the Reward Factor strategy. This fact would lead to the situation in which, according to the static back testing methodology, the equally weighted portfolio would not be preferable, since it aims to attract funds from high-risk profile investors as the Reward Factor strategy.

2.3.2. Dynamic Back Testing

The dynamic back testing follows the premise under which the allocation is readjusted based on the last available years' results. Thus, the weights vary every year. For example, the weights in 2008 depend on the results of 2007. To follow this methodology, the date weighting factor has been calculated separately for each of the years, so the exponential function reboots in each first day of the year. Thanks to this readjustment, each year weights the last day as the most important day, while the first one accounts the lesser in terms of weights.

As of June 1st, 2018, the dynamic back testing methodology reported the following results:

Strategy/Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Reward											
AGG	23.83%	30.65%	18.97%	18.01%	29.79%	23.94%	10.91%	16.50%	25.96%	9.45%	15.23%
EEM	19.01%	12.09%	16.34%	14.68%	12.18%	18.44%	20.99%	17.72%	14.19%	18.90%	20.69%
EFA	10.95%	9.22%	12.00%	13.30%	12.94%	14.20%	14.04%	11.35%	9.62%	10.98%	11.13%
HYG	12.62%	11.02%	14.61%	12.70%	8.85%	7.22%	7.82%	6.47%	8.90%	9.45%	5.75%
IWM	12.00%	10.51%	11.29%	15.60%	12.45%	13.11%	19.08%	19.90%	13.68%	18.42%	16.52%
SPY	6.60%	9.14%	9.58%	10.33%	9.65%	9.04%	10.91%	10.49%	9.70%	9.03%	11.46%
VNQ	15.00%	17.36%	17.20%	15.38%	14.14%	14.06%	16.25%	17.57%	17.95%	23.77%	19.23%
Punishment											
AGG	7.96%	9.82%	7.39%	7.48%	6.37%	7.62%	14.69%	12.55%	10.36%	10.89%	11.00%
EEM	13.88%	9.34%	14.10%	13.30%	11.48%	14.87%	8.58%	9.90%	9.54%	10.63%	10.66%
EFA	14.38%	17.25%	13.13%	10.42%	13.94%	15.99%	13.59%	13.58%	16.43%	14.70%	16.87%
HYG	15.99%	15.22%	15.38%	17.89%	19.31%	25.69%	19.88%	14.19%	16.48%	20.80%	21.10%
IWM	15.74%	17.61%	14.12%	13.28%	13.65%	12.36%	11.91%	13.91%	12.84%	14.32%	10.27%
SPY	23.38%	21.42%	26.92%	26.14%	20.00%	13.58%	23.98%	23.12%	20.85%	19.86%	20.95%
VNQ	8.66%	9.33%	8.95%	11.49%	15.26%	9.89%	7.35%	12.75%	13.50%	8.81%	9.15%
Reward & Punishment											
AGG	15.90%	20.24%	13.18%	12.74%	18.08%	15.78%	12.80%	14.52%	18.16%	10.17%	13.12%
EEM	16.44%	10.72%	15.22%	13.99%	11.83%	16.66%	14.79%	13.81%	11.87%	14.76%	15.68%
EFA	12.67%	13.24%	12.57%	11.86%	13.44%	15.09%	13.82%	12.46%	13.02%	12.84%	14.00%
HYG	14.30%	13.12%	15.00%	15.29%	14.08%	16.46%	13.85%	10.33%	12.69%	15.13%	13.42%
IWM	13.87%	14.06%	12.71%	14.44%	13.05%	12.73%	15.50%	16.91%	13.26%	16.37%	13.39%
SPY	14.99%	15.28%	18.25%	18.24%	14.82%	11.31%	17.45%	16.80%	15.27%	14.44%	16.20%
VNQ	11.83%	13.35%	13.08%	13.43%	14.70%	11.98%	11.80%	15.16%	15.73%	16.29%	14.19%
Equally Weighted											
AGG	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%
EEM	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%
EFA	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%
HYG	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%
IWM	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%
SPY	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%
VNQ	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%

Table 4: Dynamic Back Testing. Weights

Strategy/Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Reward											
Return	-34.90%	13.25%	9.31%	-7.08%	8.72%	5.22%	2.22%	-8.57%	6.73%	12.90%	-1.47%
Volatility	23.68%	15.87%	10.23%	13.36%	5.91%	6.19%	6.03%	7.79%	6.85%	4.35%	7.94%
Sharpe Ratio	-1.57	0.59	0.59	-0.67	1.18	0.35	0.01	-1.39	0.62	2.41	-0.55
Punishment											
Return	-39.39%	17.57%	9.43%	-6.88%	10.77%	7.30%	2.11%	-7.42%	7.65%	12.55%	-1.18%
Volatility	25.53%	17.64%	11.25%	14.18%	7.46%	6.23%	5.09%	7.53%	7.73%	3.68%	7.29%
Sharpe Ratio	-1.63	0.78	0.55	-0.62	1.21	0.69	-0.01	-1.29	0.67	2.75	-0.56
Reward & Punishment											
Return	-37.14%	15.41%	9.37%	-6.98%	9.75%	6.26%	2.16%	-8.00%	7.19%	12.73%	-1.32%
Volatility	24.58%	16.72%	10.73%	13.77%	6.68%	6.20%	5.54%	7.65%	7.27%	3.99%	7.60%
Sharpe Ratio	-1.60	0.69	0.57	-0.64	1.20	0.52	0.00	-1.34	0.65	2.59	-0.56
Equally Weighted											
Return	-37.93%	17.50%	9.49%	-7.28%	10.20%	7.61%	2.44%	-8.26%	7.61%	12.62%	-1.30%
Volatility	25.05%	18.11%	10.77%	13.73%	7.14%	6.32%	5.34%	7.44%	7.69%	3.78%	7.35%
Sharpe Ratio	-1.60	0.75	0.58	-0.67	1.18	0.72	0.05	-1.41	0.67	2.70	-0.57
10y U.S. Bond yield	2.22%	3.84%	3.29%	1.88%	1.76%	3.03%	2.17%	2.27%	2.45%	2.41%	2.92%

Table 5: Dynamic Back Testing. Results

Cumulated Returns	
Reward	46.00%
Punishment	61.19%
Reward & Punishment	53.45%
Equally Weighted	59.01%

Table 6: Dynamic Back Testing. Cumulated Returns (2008 - 2018)

2.3.2.1. Reward Factor

According to the dynamic annual back testing procedure, the Reward Factor strategy presents a cumulated return of 46.00%, which is the lowest among the results of the four analyzed strategies. It shows a diversified portfolio in which firstly SPY (SPDR S&P ETF Trust, the Large Cap ETF) and later HYG are underweighted. These phenomena – as shown in “Figure 6”- occur due to the lower profitability offered by these asset classes from to 2008 to 2012 for Large Cap investments, and from 2011 until the present for the case of the High Yield Bonds. High Grade Bonds’ category (AGG) is firstly overweighed if compared to the rest of the peers due to the lack of daily losses among these securities. The rest of the chosen ETFs shift according to their yearly profitability, but keep reasonable values in terms of diversification.

As for the rest of the outputs of the commented asset allocation, the Reward Factor strategy presents a low average annual return (+0.57%), high volatility levels (9.84%), and a positive Sharpe Ratio (0.1429). It would be a recommendable strategy, although the risk level is too high for the obtained results, thus high-risk profile investors would be recommended to look for a more profitable strategy.

2.3.2.2. Punishment Factor

The Punishment Factor, as opposed to the Reward one, underweights High Yield Bonds and consistently overweighs Large Cap stocks. It presents the highest cumulated returns among the dynamic back testing results (+61.19%).

Furthermore, the Punishment Factor strategy high volatility levels (10.33%). The average annual contrast between the results, the risk-free asset and the volatility provides the investor with a Sharpe Ratio equal to 0.2306. Thus, the strategy would result interesting for high-risk profile investors since it beats the benchmark in the long run and provides high levels of cumulated results.

2.3.2.3. Reward & Punishment (R&P)

Since the previously commented factors present almost opposite investment strategies, the R&P strategy shows a well-diversified portfolio in which weights shift from 10.17% (AGG, 2017) up to 20.24% (AGG, 2009). This advance in the High Grade bonds finds its reasons in the impact of the Reward Factor strategy.

The R&P strategy, presents a cumulated 10-year return equal to 53.45%, with an average annual standard deviation of 10.07% and a moderate Sharpe Ratio (0.1878). The strategy would be interesting for high-risk investors, although the profitability is lower than the one of the Punishment Factor strategy, while presenting a similar volatility.

2.3.2.4. EQUALLY WEIGHTED PORTFOLIO

The equally weighted portfolio presents the same outputs and results as the ones of the Static Back Testing. This is due to the fixed allocation of the strategy.

2.4. CONTRAST

In this chapter, the different results will be contrasted. This will be done (1) in terms of each strategy, and (2) in terms of an overall preferable outcome.

2.4.1. Reward Factor

The Reward Factor resulting strategy dramatically shifts from the “best” strategy in the Static Back Testing methodology to the “worst” one when applying the second method. The main alleged reason for this to happen is that the different asset classes tend to bounce. In other words, those asset classes that consistently show positive results in a year might consequently present a negative trend or losses.

When taking into account the whole dataset, the Reward Factor strategy adjusts its weights to the whole bulk of data and chooses the most profitable strategies based on daily results. Consequently, and in the long run, it hand outs a consistent strategy.

On the other hand, when presenting results based on the previous data, the asset class set as reference (for this example, lets take International Stocks) only accounts for the previous year results. This way, if the majority of the days presented negative results, as occurred in 2008 and 2009 with International Stocks, the respective ETF is underweighted and, as a consequence, the strategy does not profit from the bounce effect produced by the shift of profitability that takes place among asset classes (for this purpose, please check “Figure 5” again).

All in all, the Reward Factor provides the investor with a profitable strategy if he/she investors aims to obtain results with a long-term strategy, and this profits mainly derive from the diversification of the allocation rather than from the strategy itself. In addition, it does not fit a short-term investment strategy, since it does not profit from the asset class rebalance.

2.4.2. Punishment Factor

Contrary to what occurs in the Reward Factor, the Punishment Factor does not fit a long-term investment strategy due to the minimization of the risk caused by the stability of some asset classes, which show less negative daily returns over the years. This phenomenon takes the most secure asset classes to be overweighed, as in the case Static Back Testing method.

However, the Punishment Factor adapts to short-term investment strategies since it profits from the bounce effect. The biggest losers are frequently the biggest winners after a year. This simple shift adapts the Punishment Factor strategy to make profit if adapted in the short-term.

2.4.3. Reward & Punishment (R&P)

The mixed portfolio is in disadvantage in both methodologies due to the lack of profitability of the Punishment Factor in the Static method, and the Reward Factor in the Dynamic method. Thus, it does not represent a feasible alternative either in the long term, either in the short term.

2.4.4. Equally Weighted Portfolio

The equally weighted portfolio adds a fourth strategy that fights against the principles of investment. The differences between this strategy and the winner ones (Reward Factor in the Static method, and Punishment Factor in the Dynamic method) in terms of profit are relatively small.

According to what was previously established, this project does not take into consideration transaction costs. Anyhow, if these were to be included in the model, and since all the strategies continuously –either yearly, either daily- would rebalance their portfolios (even if it was a slight rebalance, it would lead to trade costs), the equally weighted portfolio could beat both of them and be elected as the best possible strategy when ETFs' price proportions remained still.

2.5. LOOPING AND REALLOCATING FUNDS

Looping means to encircle something, usually a procedure when dealing with investments. In this case, it refers to the continuous repetition of the analysis. This way, if the strategy looped every twenty-four hours it would reallocate funds every day. This dynamism would encourage the developed strategies to remain updated and offer the investor a more accurate investment policy.

To perform it daily, the Python-based program should contain these lines:

```
import time
def executeStrategy():
#The Strategies’ Code Would be Placed Here
time.sleep(86400)
while True:
executeStrategy()
```

This way, the strategy would be repeated on a daily basis, since the timer is set at 86,400 seconds (60 seconds, times 60 minutes, times 24 hours). If the desire was to readjust the strategies every week, then the timer should count up to 604,800 seconds (60 seconds, times 60 minutes, times 24 hours, times 7 days).

As to loop calculi in Excel, the code is very similar:

```
Sub wholeStrategy()
Call importar
Call rowdeleting
…
Call timer
End Sub
Sub timer()
Application.OnTime Now + TimeValue("24:00:00"), "wholeStrategy "
End Sub
```

This way, the procedure would be repeated every time 24 hours went by. It would happen by calling the different codes that enable the analysis. In other words, the loop would work by repeatedly importing, cleaning, organizing, calculating and showing the results the strategies.

Due to the lack of technological resources in a common household, such as the one where the project was developed, and in most of companies, the most common step to move forward a looped strategy would be picking a hosted server where the program could work by itself. The most potent and broadly used is Amazon Web Service, which charges 6.52 $/month for a twenty-four hours availability, when running Windows applications (such as Excel and Python) on an on-demand basis. The price of this service does not suppose a problem for the program, since the latter would allegedly run enough funds to dilute the cost of the web service.

Through the combination of the server availability and the loop of the strategies the output could be obtained on the desired looping periods, therefore, the strategy could be rebalanced if the program was connected to a broker. However, the continuity of the calculi allows both investor and portfolio manager access to automatic results that can help on the investment-related decisions.

It is also worth mentioning that the developed strategies are feasible for any combination of quoted stocks. Thus, the portfolio can vary according to the investor's risk-profile. As a counter, it can only work with up to seven stocks. Anyhow, adding columns and rows in the program could easily modify this limitation.

3. CONCLUSIONS

This project has first introduced and explained portfolio management theory, to then focus on a dynamic strategy development that has been back tested through two different methods. Therefore, the conclusions deserve to be clustered into the corresponding chapters to be later understood as a whole:

3.1. LITERATURE REVIEW & ROBO-ADVISORS

After briefly reviewing investment management theory and its progress, it is checked that even the most complicated theories can be implemented in robo-advisors. In fact, these outstanding theories are the ones that better fit robo-advisory, since algorithmic trading feeds its models from a wide range of variables and sources. However, the point is that "traditional theories", such as mean-variance optimization, are easily implementable and automatable.

3.2. STRATEGY DEVELOPMENT

As a first conclusion, depending on how the strategy works, and especially on how it is rebalanced, the outcome dramatically varies. This fact proves how not only asset allocation determines the returns of a portfolio, but timing does as well, since two robo-advisors might be configured to perform the same strategy but develop their calculus daily, weekly, monthly, or yearly, and show extremely different results as the ones between the dynamic and static back testing. Thus, the portfolio manager must control the timing of these calculi and attend to what is best for the investor.

Secondly, the fact of calculating a determinant or factor for a portfolio allocation does not necessarily account for much profit, or the developed factors are not the most profitable ones, as the equally weighted portfolio demonstrated. It provides a similar outcome with a fixed strategy. Daily returns may not prove if a security is profitable or not, and can be extremely affected by short-term noise.

Thirdly, the effect of the asset classes' profitability shifts makes the difference between a profitable strategy and one that is not. Thus, the bounce effect is a major factor to take into account when rebalancing a portfolio with a short-term perspective.

Moreover, an automated strategy can be further developed. Thus, these would be the steps to follow and challenges ahead: (1) provide the program with a potent server that allows daily back testing through programming; (2) connect the program to the internet and allow it to access a broker to close and open positions; (3) provide the program with an access for possible investors, as to collect funds.

3.3. FINAL CONCLUSION

Database development and analytics could provide easy access to simple strategies that fit any kind of investor. It appears to be the future of investing and the automation of procedures may as well lead to a more efficient financial panorama, where the advisor would only fit the products according to the available profiles. However, the decision making process is hardly fully automatable, since it responds to a model created by human beings. This model has to take into consideration a full stack of variables that can be hard to access. In these terms, this project does not aim to collect all of them but to simplify the procedure and show how, even from a simplistic point of view, the different investors can account for feasible strategies. This simplification allows the reader to understand the viability of robo-advisory, the reasons for its recent expansion, and to acknowledge the needs of a regulation for this kind of investors, which currently respond to the human-like laws, therefore produce risks.

In these terms, **robo-advisory development is accessible to everyone (individuals, groups of individuals or companies) that understands coding and financial markets**. It requires big amounts of data that may lead to some costs that are not representative when compared to personal advisory such as traditional wealth managers. Given its low-cost characteristic and the accessibility related to technology, the specific market will continue to grow as the strategies can outperform the market by following the terms established in the algorithms. In addition -and before the robo-advisory market is too big-, the authorities should promote legislation that focuses on algorithm-based strategies rather than generic laws that mix human-based investment procedures with the ones analyzed in this paper. This way, the evolution could be safe and the systemic risk would be reduced.

APPENDIX A. PYTHON

Definition (Python Software Foundation): "Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together".

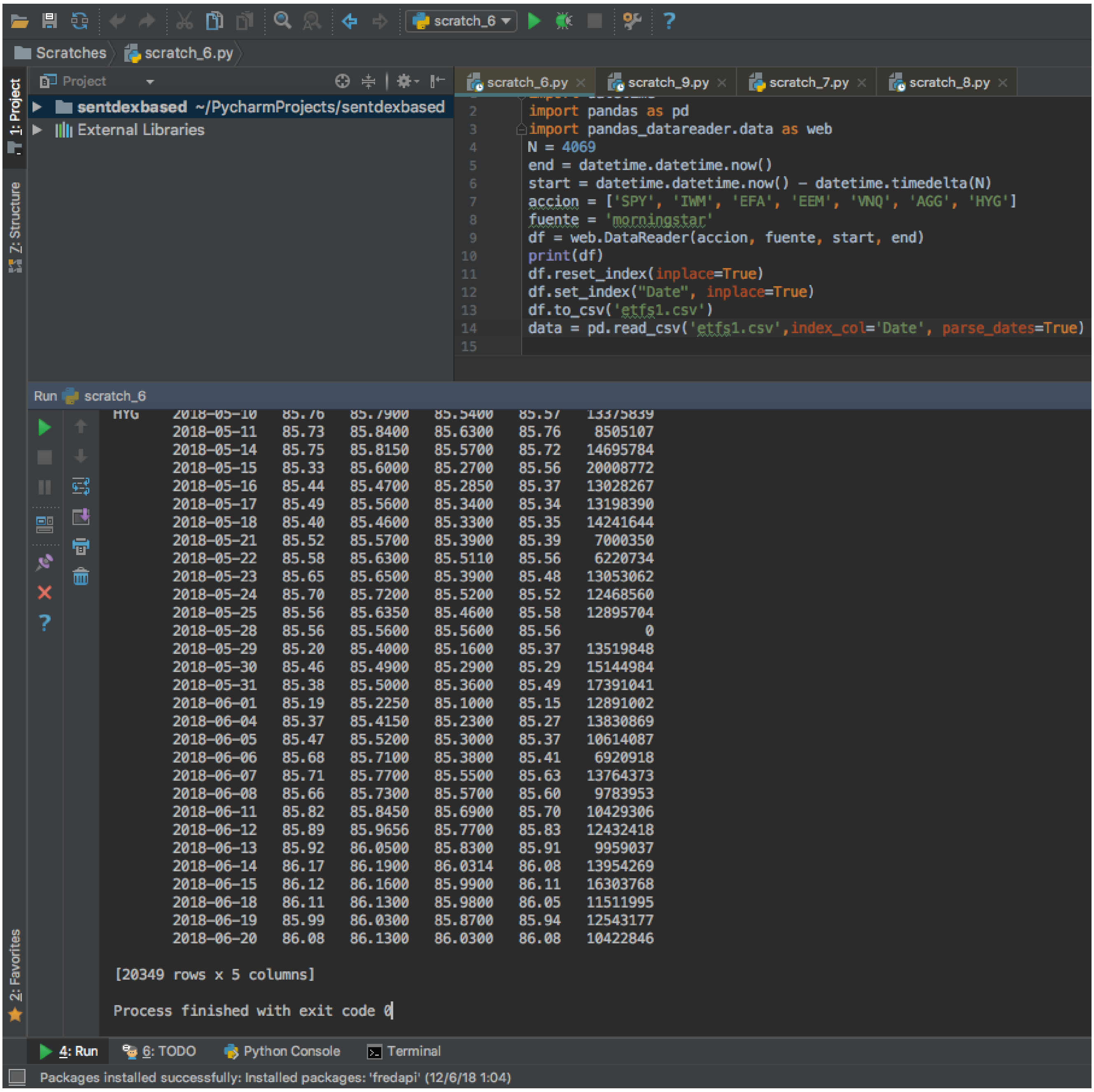
How does it work? Python works through modules and open-file repositories. Users may download the desired modules in order to activate a determined function and develop an activity. So it happens with open-file repositories, where users can upload/download and share their programs. Python can be run on its own launcher or through other platforms that simplify operations such as module installing and language corrections. The latter has been chosen for the purpose of this studio (PyCharm).

Finance application: database development, as pointed out in the official definition of the language, is one of the core functions of Python. Therefore, and since finance is lately based on the analysis of big loads of data, it presents a great environment for the development of automated processes.

Installed modules (April 17th, 2018):

- Pandas: a Python package that includes different modules. It is focused on data structures and allows flexible and quick data usage, allowing grouping, alignment, missing data detection, merging, slicing, flat files conversion (CSV format).
- Datetime: a Python module that enables the option of checking the current date. It's useful for API services calling. In other words, it enables the possibility of asking for updated data, otherwise, the program would not recognize the latest data, and thus it should be fixed.
- Pandas_datareader: a Python module that enables data reading from previously written flat files.

Process of programming:



Lines 1 to 3: as previously described, importing modules enables Python functions. Therefore, datetime, pandas, pandas_datareader are called in order to set a framework.

Line 4: the variable N sets the days the program will go back in time to download stock prices

Line 5: the end date is set at the todays date

Line 6: the start date is set at the todays date minus the variable N (4069 days)

Line 7: the stocks to download are named by their symbols

Line 8: Morningstar is chosen as a source for the stock data download

Line 9: the web data reader is enables, calling Morningstar and asking for SPY (this process can include various calls at the same time) setting the pre-established dates as time boundaries.

Line 10: the results are shown in order to check the correct download

Line 11 and 12: corrections are made to order data according to date

Line 13: data is transposed into a .csv file, under the given name

Line 14: data is read from the .csv file

For further information about the data analysis procedure applied to the case, please consult the excel file attached to this project.

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