Asset Management Area

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Summary:

I. Asset Management Area – Objectives and Detailed Program

The main objective of the Asset Management Division is to create a Virtual Portfolio of financial assets and upgrade the assets selection step-by-step. To this end, we are going to implement many different asset allocation strategies and theories, from the classical Mean Variance approach and Factor Investing, to the most recent ones. The aim is that of analyzing the effects that different developments in the Asset Management field have had and still have on investors choices. Moreover, we plan to include in the passive portfolio component alternative investment assets, to analyze the potential effect that different returns and covariances structures may have on the overall portfolio.

To give you a more precise idea of our project

Steps:

- Portfolio Creation: Mean Variance Approach (Passive Component) + Sector Neutral Factor Investing (Active Component)
- Passive Portfolio Upgrade: Introduction of Portfolio Resampling
- Passive Portfolio Upgrade: Introduction of Black and Litterman Approach
- Passive Portfolio Upgrade: Introduction of Risk-Parity Approach

As a division of the Asset Management Area, the Investment Risk division will analyze the effect that different asset allocations have on the overall portfolio, in terms of Value-At-Risk, exploiting many approaches such as: Parametric Approach, Historical Approach and Simulation Approach. Studying the VAR, we will be able to judge and choose the strategy that best fit our risk expectations and aversion.

The Asset Management Area will also work closely with the Research Area. In fact, the Macro Research Division will provide us with overall economy and markets forecasts, used to incorporate views applying the B-L Approach. The Equity Research Division will analyze some of the Stocks that compose the active portion of our portfolio, to choose updated weights during future rebalancing. The Alternative Division will provide us with suggestions on potential products to include in our portfolio.

II. Portfolio Overview

Our Portfolio is split in two parts:

a) Active Component: This portion of the portfolio is based on a long-short factor investing strategy and has zero exposure (Sum of weights equal to zero). We selected the US Stock Market and the

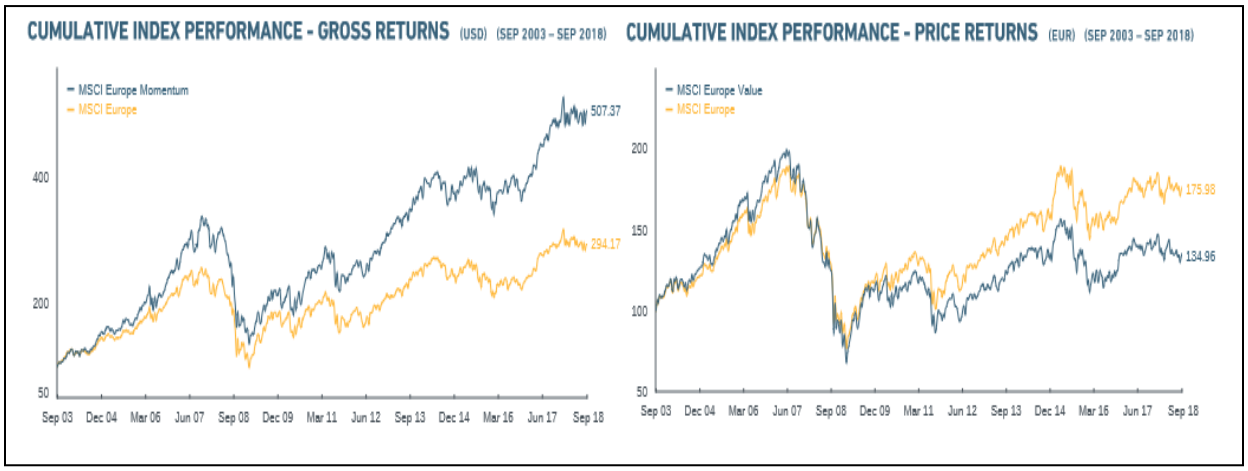
European Stock market, picking a total of 40 stocks. We are long on 10 stocks and short on 10 stocks of both the S&P 500 and EUROSTOXX 600. The factors and the steps to build this component will be exhaustively explained later. Because of the nature of factor investing, we cannot use an optimization based on mean variance or other approaches, because otherwise we would destroy the factors and the result would be a truly unbalanced and inconsistent portfolio. For this reason, we must adopt an equal weight strategy, that as we mentioned before, will be upgraded following the suggestions of the equity research team. This means that we will switch from a 1/n weight to a 2/n, 3/n, 0.5/n weight, say. Active means that, apart from changing the weights according to companies' analysis, factors updating will probably cause some of the previously held stocks lo leave the portfolio, leaving the space to new ones fitting our parameters.

b) Passive Component: This portion of the portfolio is a well-diversified component across different asset classes and markets. We picked many indexes able to represent a good portion of the investable universe. Since nowadays most indexes are well replicated by Exchange-Traded-Funds (ETF), we chose an ETF for each index, paying attention to the costs of this replication and trying to choose the ETF wit lower Total Expense Ratio (TER). However, it is worth to mention that, although a high TER is not in any way a signal of a good asset manager, and it is by the way the main cause of bad total performances for expensive funds, it seems that in some cases we must accept a higher TER to have a longer history of performances. In fact, many cheap ETF are relatively young and do not provide us with enough data to perform an historical analysis on expected returns and standard deviations, that are fundamental in a Mean-Variance context.

III. Active Component

Factor Choices:

We decided to pick factors of different types to avoid too high exposure to one single family of indicators, in fact recently Momentum portfolios have performed better than Value Strategies but considering the yet very high stock market values (especially for the US) we do not feel safe getting 100% exposed to this index. These factors' behavior represents a well-known phenomenon commonly referred by literature as "Factor Cyclicality". This argument supports the idea and the empirical confirmation that in the long-run factor indexes' risk adjusted returns outperform their capitalization-weighted benchmark's returns but showing significant cyclicality and periods of underperformance in the short-run. There are three main strategies to overcome this problem: set appropriately long-time horizons, establish an explicit timing mechanism for the initial investment, adopt a multiple factor approach and employ factors that diversify each other. The latter is the most straightforward and widespread option and it seems to be effective since periods of underperformance for different factors have not coincided historically. We provide you with a proof of this last statement looking at the MSCI Factor Indexes, in particular at the MSCI Europe Value Index and MSCI Europe Momentum Index from 2008.



We expect to monthly rebalance the portfolio according to current factors, but also to review the factors choices and or weights at least each 3 months to listen to market trends and expectations.

Value Factors (Buy cheap, Sell expensive)

-P/BV: A higher P/BV, …, represents a selling signal because it means the company equity is very expensive compared to the underlying book-value

-EV/EBITDA: A higher EV/EBITDA, …, represents a selling signal because it means that the company assets are very expensive compared to operating results before depreciation. We picked this factor instead of the P/E mainly because of data availability. In fact, since it is more likely to have a positive EBITDA rather than a positive Net Income, there were available much more data on EV/EBITDA compared to P/E

Momentum Factors (Buy recently best performing stocks, Sell worst performing stocks)

+MOM: A higher MOM (computed as the compounded monthly return over the previous 13 months excluding the last one), …, represents a buy signal since we are assuming the market will not invert its trend soon.

Quality Factors: (Buy high quality stocks, Sell low quality stocks)

+(FW 12m EPS – Trailing EPS): A higher factor, …, represents a buy signal. We introduced this factor that is not a widespread one to capture analysts' views (Analysts' Revisions). It is in fact built as the difference between the 12 months forecast of EPS made by analysts and the trailing EPS recorded (Last 12 months EPS). This means that for companies with an EPS forecasts that highly positively differ from the last recorded, we assume an increase in the stock price in the future that would mirror earnings behavior.

+ ROE: A higher ROE, normalized for Industry influence, w.r.t other constituents of the Index, represents a buy signal. Thus, we are assuming that investors' profitability will maintain its trend in the future and that it is a reliable driver of future increases of stock prices

To summarize, we are picking stocks that, according to our assumptions, we expect to perform well in the future because of Momentum and Quality characteristics, but among these, in our selection process, we attribute 2 negative scores to those that look very expensive relative to fundamentals. In the following months we expect also to compare the performance of this portfolio component to the relative benchmark, that should be a non-equally weighted portfolio composed by some of the MSCI Factor Indexes.

Normalization by sector (Sector Neutrality):

In order to avoid a too high concentration towards certain industries and to depurate our data from industry characteristics and outliers, we adopted a Winsorization technique and a data normalization procedure to create a sector neutral portfolio. We followed the following steps for both the S&P 500 and the EUROSTOXX 600. For the sake of simplicity, we only refer here to the S&P 500 procedure.

1) We used the ICB Industry Name indicator provided by DataStream to classify S&P 500 components into 10 different industries.
2) For each index used (ROE, -EV/EBITDA, (FW 1y EPS-TRAILING EPS), -P/BV, MOM) we computed the mean and the St.Dev of each industry.
3) For each index of each industry we computed a Max and a Min, respectively given by: Mean+(3xSt.dev) and Mean-(3+St.Dev)
4) We adjusted stocks' indexes to remove outliers limiting them between the Max and the Min previously computed

Steps from 1 to 4 (The so called Winsorization process) have been repeated 3 times, the most common practice in investment funds. The reason behind repeating this procedure lies behind some truly extreme outliers that are only partially constraint applying step number 3 and 4 one single time.

5) For each Index we computed a score of the stock given by: $\frac{\text{Index}-\mu}{\sigma}$, where μ is the mean of that particular index for the industry in which the related stock operates and σ is the related St.dev.
6) Each stock is then assigned a final score given by $\frac{1}{5} \times (\text{Score1} + \text{Score2} + \text{Score3} + \text{Score4} + \text{Score 5})$
7) Stocks are then ranked according to their score from the highest to the lowest. Highest score stocks compose the long portion of our active portfolio, lowest score stocks compose instead the short portion.

The main issue now is to well diversify the portfolio across sectors and limit the exposure to such sectors. This aim would not be achieved simply taking the first 10 stocks and the last 10 stocks in the list. If we strictly follow the sort, we would be truly exposed to the Industrial/Oil&Gas sectors on the long side, not

having a short positions counterbalance. For this reason, we decided to choose for both the S&P and the EUROSTOXX 600, one long stock and one short stock for each sector, still following the score's sort. In this way, we are basically investing on a spread strategy aimed at capturing the differential in performances of companies of the same sector due to individual characteristics, limiting the exposure to changes in the industry itself.

Output:

EUROSTOXX 600	ICB Industry Name	Weight (n=20)	S&P 500	ICB Industry Name	Weight (n=20)
ASHTEAD GROUP	Industrials	1/n	LOCKHEED MARTIN	Industrials	1/n
JARDINE LLOYD THOMPSON	Financials	1/n	SVB FINANCIAL GROUP	Financials	1/n
LUNDIN PETROLEUM	Oil & Gas	1/n	HOLLYFRONTIER	Oil & Gas	1/n
NEXT	Consumer Services	1/n	MCDONALDS	Consumer Services	1/n
GLAXOSMITHKLINE	Health Care	1/n	WELLCARE HEALTH PLANS	Health Care	1/n
SILTRONIC (XET)	Technology	1/n	SEAGATE TECH.	Technology	1/n
BRITISH AMERICAN TOBACCO	Consumer Goods	1/n	MICHAEL KORS HOLDINGS	Consumer Goods	1/n
EDF	Utilities	1/n	NEXTERA ENERGY	Utilities	1/n
EVRAZ	Basic Materials	1/n	CF INDUSTRIES HDG.	Basic Materials	1/n
TELIA COMPANY	Telecommunications	1/n	VERIZON COMMUNICATIC	Telecommunication	1/n
LAFARGEHOLCIM	Industrials	-1/n	GENERAL ELECTRIC	Industrials	-1/n
BANKIA	Financials	-1/n	SL GREEN REALTY	Financials	-1/n
WOOD GROUP (JOHN)	Oil & Gas	-1/n	BAKER HUGHES A	Oil & Gas	-1/n
ZALANDO (XET)	Consumer Services	-1/n	NEWS 'A'	Consumer Services	-1/n
GETINGE B	Health Care	-1/n	NEKTAR THERAPEUTICS	Health Care	-1/n
MICRO FOCUS INTL.	Technology	-1/n	WESTERN DIGITAL	Technology	-1/n
REMY COINTREAU	Consumer Goods	-1/n	CAMPBELL SOUP	Consumer Goods	-1/n
SSE	Utilities	-1/n	SCANA	Utilities	-1/n
EMS-CHEMIE 'N'	Basic Materials	-1/n	INTL.FLAVORS & FRAG.	Basic Materials	-1/n
INMARSAT	Telecommunications	-1/n	AT&T	Telecommunication	-1/n

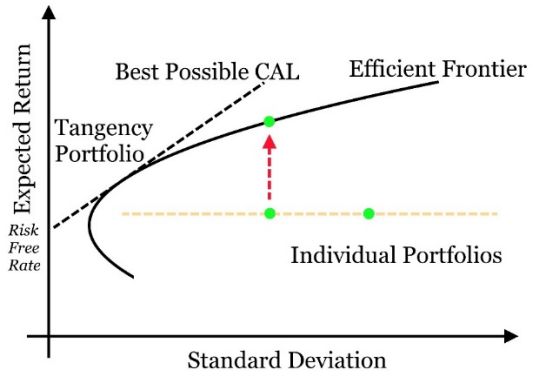
IV. Passive Component

We initially report the chosen markets, Indexes (Benchmarks) and related ETF:

Mkt	ETF	Benchmark	TER
US Stock Market	iShares Core S&P 500 ETF	S&P 500	0.04%
US 1-3y Treasury mkt	iShares 1-3 Year Treasury Bond ETF	ICE U.S. Treasury 1-3 Years Bond Index	0.15%
US 7-10y Gov Bond mkt	iShares 7-10 Year Treasury Bond ETF	ICE U.S Treasury 3-7 Years Bond Index	0.15%
US Corporate Bond mkt	iShares Broad USD Investment Grade Corporate Bond ETF	ICE BofAML US IG Corporate Index	0.06%
Europe Stock Market	iShares MSCI Europe UCITS ETF EUR (Acc)	MSCI Europe	0.12%
Europe 1-3y Gov Bond mkt	iShares € Govt Bond 1-3yr UCITS ETF EUR (Acc)	Bloomberg Barclays Euro Government Bond 1-3 Year Term Index	0.20%
Europe 7-10y Gov Bond mkt	iShares € Govt Bond 7-10yr UCITS ETF	Bloomberg Barclays Euro Government Bond 10 Year Term Index	0.20%
Europe Corporate Bond mkt	iShares € High Yield Corp Bond UCITS ETF	Markit iBoxx Euro Liquid High Yield Index	0.50%
EM Stock mkt	iShares MSCI EM UCITS ETF USD (Acc)	MSCI Emerging Markets Index (SM)	0.68%
EM Gov Bond mkt	iShares J.P. Morgan EM Local Govt Bond UCITS ETF USD (Dist)	J.P. Morgan GBI-EM Global Diversified 10% Cap 1% Floor	0.50%
EM Corporate Bond mkt	iShares J.P. Morgan $ EM Corp Bond UCITS ETF USD (Dist)	J.P. Morgan CEMBI Broad Diversified Core Index	0.50%

(TER is computed on annual basis, we used Monthly Prices from 2012)

It is easy to notice that the fees required by ETF Funds managers for Emerging Countries' Bonds' markets are extremely high, and they look even more expensive if we consider their poor performances. As we mentioned above, there are some "cheaper" ETFs available on the market also per Emerging Markets (EM), however they were born in 2017-2016, and since we use monthly data for our analysis, we are not able to select them.



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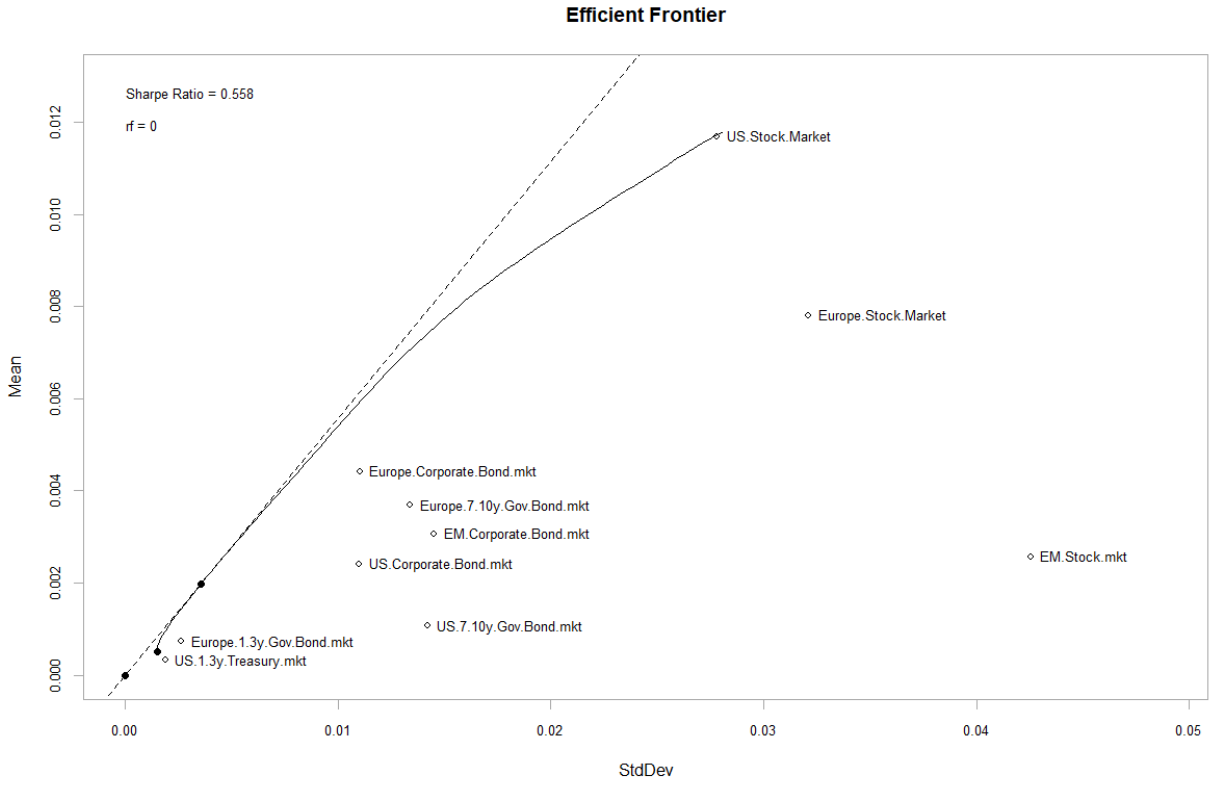
- Here is a small plot as a reminder of the mean variance approach output.
- In our model we reduce the investable universe to our chosen ETFs
- According to the MV approach, we only focus on Expected Return, Standard Deviations and Covariances (estimated using historical returns) to perform our ETFs and weights selection

We proceeded to mean-variance optimization using R and the Portfolio Analytics tool that allows us to define a portfolio, add portfolio objectives and constraints, such as the full investment constraint (Sum of weights equal to 1) and the Long-Only constraint (All weights greater than or equal to zero).

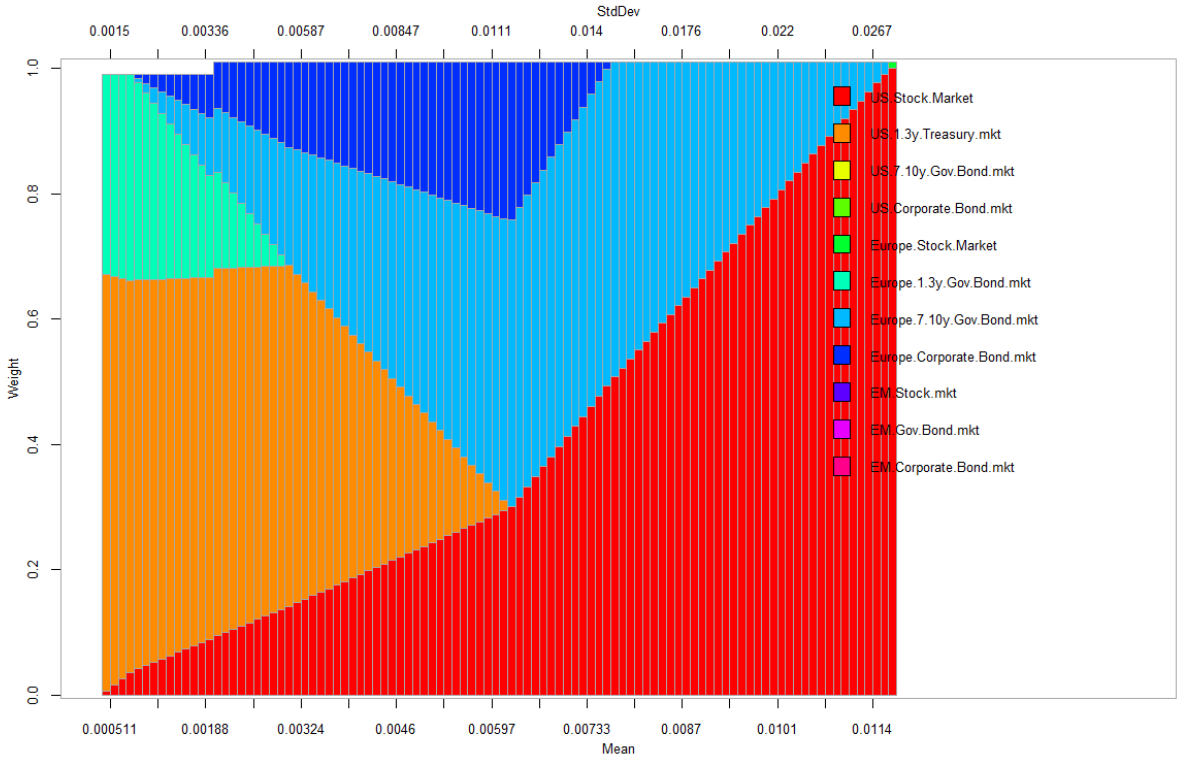
Efficient Frontier:

We created and plotted an Efficient Frontier composed by 100 portfolios, assuming a risk free of 0%. Even though we should recall that we are using monthly returns and so we are referring to a Monthly Mean return, we notice that our investment universe returns are mostly driven by US Stocks. European stocks seem to be less profitable but riskier, worst is the case of EM Stocks that we do not expect to be selected by our optimization.

Recall that applying the MV approach, we are neglecting all the possible views about market trends in terms of forecasted interest rates, say, and our selection in only based on historical data. In future reports we will incorporate our views about future markets' development in the model to see how results may change.



Weights distribution:



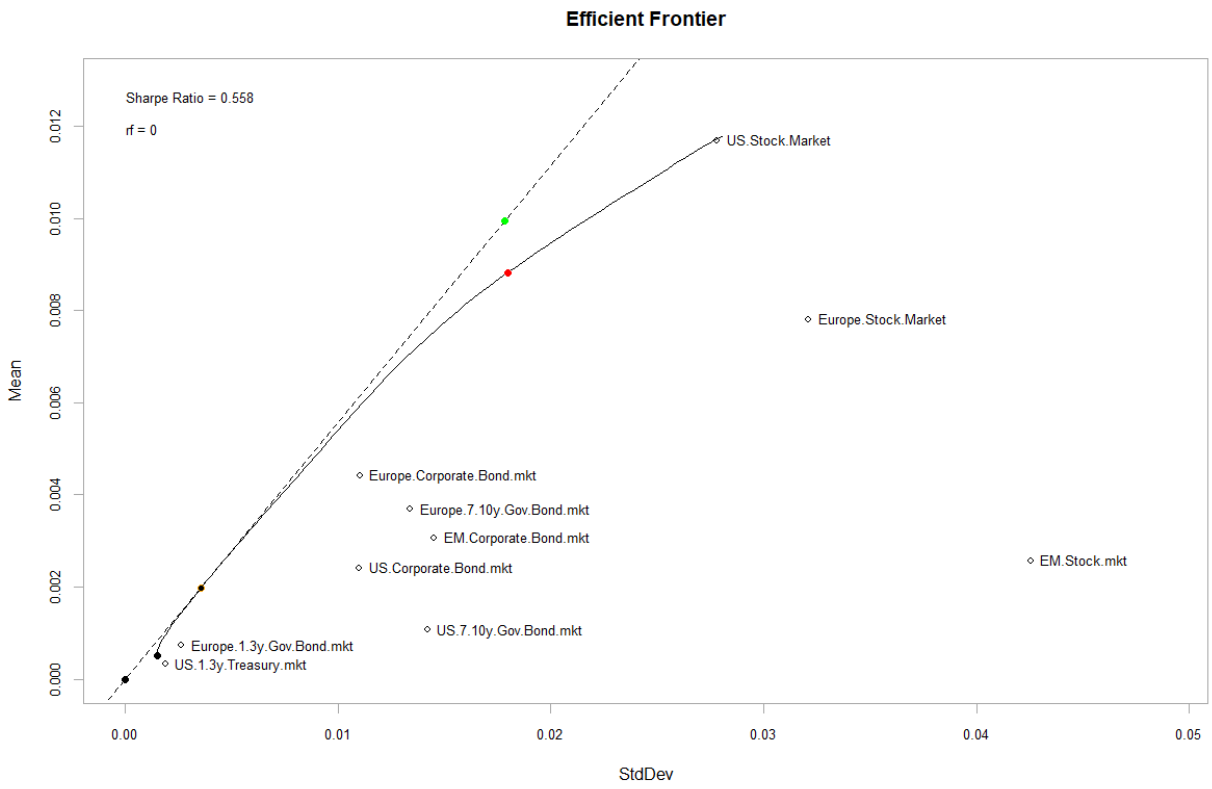
This plot describes the evolution of optimal weights for each level of Expected Return and Standard deviation. We notice that our optimization selected only a few of our Investable Universe assets because we did not include groups constraints for some of the assets and we did let the optimization choose basing the selection only on real data. Below we provide you with a plot of weights produced after introducing constraints, traying to include also the other asset classes. The results are truly unrealistic and inconsistent because we basically forced the model to produce a certain output and apart from strange weights' behaviors, it causes a drastic reduction of the Sharp ratio. Back to our real case, we notice as for very low Expected returns targets, the optimization includes the European Short-Term Government Bond ETF along with the US Treasuries ETF. Moving on the right and so switching to higher expected returns and so higher standard deviations, the model gradually include the US Stocks ETF along with the European 7-10y Government Bond ETF and European Corporate Bond ETF, with the letter also gradually decreasing after reaching a pick for a specific Expected return and St.dev target.

As we mentioned, ETFs have different costs and length of available data, however, even though they are supposed to replicate the same kind of index, they may also have very different historical performances. In our code we tried to change the European Corporate Bond ETF with a cheaper and broader one, in this case

optimization results do not pick this ETF for any target expected returns. We get a pretty similar weights distribution except for the above-mentioned ETF.

Now that we have our efficient frontier, we are left with selecting our portfolio, that should lie on tangent line or on the efficient frontier, according to our choice of leveraging our investment using risk free debt. In the next page we present you a plot showing two different portfolios with the same standard deviation but different expected returns, respectively obtained using the aforementioned options. The green point in the plot represents a portfolio composed by a short position of 4x at the risk-free rate and a 5x investment on the tangent portfolio. The red point instead, represents a portfolio only composed by the ETF we used, without leveraging using the risk free, that has a different composition in terms of ETFs with respect to the other. This portfolio has been found using a quadratic utility function and a determined risk aversion coefficient.

(Weights distribution introducing groups constraints)



We notice how the red portfolio has an Expected return similar to that of the European Stock Market ETF but having a pretty lower St.dev. The green portfolio theoretically dominates the red one, so we should choose it. However, we do not consider the hypothesis of getting a so high leverage at the risk-free rate feasible, moreover we are not sure about our risk aversion coefficient. For these reasons, along with the choice to maintain, at least for the passive component, a low risk profile, we decided to invest in the tangency portfolio, represented by the orange point in the plot. This portfolio is composed by the same ETFs as the Green portfolio but does not require leverage and is characterized by lower St.dev and lower expected returns.

	Er monthly	St.Dev	US stock	US Treasury	Europe 1-3y Gov	Europe 7-10y Gov	Europe Corp
Green	1.00%	1.78%	10%	58%	16%	9%	7%
Red (Dominated)	0.88%	1.78%	64%	0%	0%	36%	0%
Orange (Tangent)	0.20%	0.36%	10%	58%	16%	9%	7%

We notice that our passive portfolio component is composed by a few ETFs. This fact is due to both model characteristics and absence of constraints, but it also depends on our expected returns estimation. In this first portfolio we are using Historical Returns to estimate expected returns, but it is well known that the average of historical returns is not a good estimator for expected returns. Thus, we will also show you how through the back-engineering process proposed by B-L as the first step of their approach, using market weights, we can produce more reliable estimates of expected returns and these will affect the choices of our

ETFs. In the next paper we will see how portfolio weights' instability affects the composition of our portfolio and how to solve this problem using Portfolio Resampling. We are also going to show how extending the investable universe we might obtain an improved efficient frontier.

V. Final Output – Conclusions

	EUROSTOXX 600	ICB Industry Name	Weight (n=20)	S&P 500	ICB Industry Name	Weight (n=20)
ACTIVE COMPONENT	ASHTEAD GROUP	Industrials	1/n	LOCKHEED MARTIN	Industrials	1/n
	JARDINE LLOYD THOMPSON	Financials	1/n	SVB FINANCIAL GROUP	Financials	1/n
	LUNDIN PETROLEUM	Oil & Gas	1/n	HOLLYFRONTIER	Oil & Gas	1/n
	NEXT	Consumer Services	1/n	MCDONALDS	Consumer Services	1/n
	GLAXOSMITHKLINE	Health Care	1/n	WELLCARE HEALTH PLANS	Health Care	1/n
	SILTRONIC (XET)	Technology	1/n	SEAGATE TECH.	Technology	1/n
	BRITISH AMERICAN TOBACCO	Consumer Goods	1/n	MICHAEL KORS HOLDINGS	Consumer Goods	1/n
	EDF	Utilities	1/n	NEXTERA ENERGY	Utilities	1/n
	EVRAZ	Basic Materials	1/n	CF INDUSTRIES HDG.	Basic Materials	1/n
	TELIA COMPANY	Telecommunications	1/n	VERIZON COMMUNICATIC	Telecommunication	1/n
	LAFARGEHOLCIM	Industrials	-- 1/n	GENERAL ELECTRIC	Industrials	-- 1/n
	BANKIA	Financials	-- 1/n	SL GREEN REALTY	Financials	-- 1/n
	WOOD GROUP (JOHN)	Oil & Gas	-- 1/n	BAKER HUGHES A	Oil & Gas	-- 1/n
	ZALANDO (XET)	Consumer Services	-- 1/n	NEWS 'A'	Consumer Services	-- 1/n
	GETINGE B	Health Care	-- 1/n	NEKTAR THERAPEUTICS	Health Care	-- 1/n
	MICRO FOCUS INTL.	Technology	-- 1/n	WESTERN DIGITAL	Technology	-- 1/n
	REMY COINTREAU	Consumer Goods	-- 1/n	CAMPBELL SOUP	Consumer Goods	-- 1/n
	SSE	Utilities	-- 1/n	SCANA	Utilities	-- 1/n
	EMS-CHEMIE 'N'	Basic Materials	-- 1/n	INTL.FLAVORS & FRAG.	Basic Materials	-- 1/n
	INMARSAT	Telecommunications	-- 1/n	AT&T	Telecommunication	-- 1/n
PASSIVE	ETF		Weight			
	iShares Core S&P 500 ETF		10%			
	iShares 1-3 Year Treasury Bond ETF		58%			
	iShares € Govt Bond 1-3yr UCITS ETF EUR (Acc)		16%			
	iShares € Govt Bond 7-10yr UCITS ETF		9%			
	iShares € High Yield Corp Bond UCITS ETF		7%			
Total Weight = 100%, Capital Invested = 100,000 €						

In conclusion, the sum of weights of our passive portfolio component is 100%, this means that we have invested the full capital in these 5 ETFs. On the other side instead, all the positions of our active portfolio have a $|w(i)| = 1/20$ for $i = 1, \dots, 40$. The sum of these weights is equal to 0 and this is possible since we use the proceeds obtained from selling the Short-Side component to invest in the Long-Side component. This means that in an ideal world without transactions costs and short-sale constraints, the active component of our portfolio could be obtained at zero cost.

Portfolio Inception Date: 26/10/2018