# FINANCIAL MARKET ANALYTICS

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# 1 INTRODUCTION

In this group work, we want to better understand the structural characteristics that risk brings to real investment portfolios. In order to understand this empirically, we need to build real portfolios that are concentrated/tilted with respect to a specific level and kind of risk.
Our reference will be the definition of "Total," "Systematic," and "Specific" risk as defined and introduced through the CAPM we studied.
We will then rely on the SML to investigate the risk level of individual securities and then proceed to the subsequent groupings.

$$E(r_i) = r_i + \beta_i(E(R_M) - r_f) \text{ [1]}$$

In pursuit of the analysis the above SML equation, must be reconsidered in the form of a regression equation as in the Market Model, also known as single index model.
We can interpret such equation as the “ex-post” version of the SML.

$$r_i = \alpha + \beta_i(R_M) + e_i \rightarrow \text{we excluded the expectations}$$
$$\text{it is usually applied, for equivalence, in excess returns form:}$$
$$r_i - r_f = \alpha_i + \beta_i(R_M - r_f) + e_i \text{ [2]}$$

In this ex-post framework, we see two new parameters $\alpha$ and $e_i$
Given that even in the "ex-ante" version of the SML, the Beta is derived from time series, then the $\beta_{SML(i)} = \frac{COV(R_M,R_i)}{\sigma^2_M}$ and the $\beta_{MM}$ as the regression slope will match, but only if the time series are of same length.
In the setting of the Market Model we get two other coefficients, the $\alpha_i$ that should be zero if the CAPM hold and $e_i$ proxying the specific risk.
In addition, the equation [2], since it is a regression, yields an $R^2$ informing on the goodness of fit.
This way there are many possible profiles on which to do stock groupings. Firstly, the profile of fitting based on $R^2$. Then going in more detail the relations between total risk decomposed in specific risk and systematic risk:

$$Totalrisk = SystematicRisk + SpecificRisk$$
$$\sigma^2_i = \beta^2_i \sigma^2_M + \sigma^2_{ei} \text{ [3]}$$

The ratio of (Systematic Risk)/(Specific Risk) is the $R^2$, but such a separation could lead to different characteristics in case of stocks with high or low level of total risk.
The last profile interesting to investigate it is the one of excess returns

represented by the $\alpha_i$. Such a return could be positive, null, or negative, but also significant or not as expressed by the specific t-test. Also, the ratio between this potential excess return and the total stock return could be of interest.
Finally, the return/risk profile, varying the adopted measure of return and risk should be of interest.

# 2 THEORY

A portfolio is a collection of financial investments, in an efficient portfolio, investable assets are combined in a way that produces the best possible expected level of return for their level of risk — or the lowest risk for a target return.
A diversified portfolio contains a mix of distinct asset types and investment vehicles in an attempt at limiting exposure to any single asset or risk.
The Market Model, also known as single index model and developed by William Sharpe in 1963, is a simple asset pricing model to measure both the risk and the return of a stock.
To simplify analysis, the single-index model assumes that there is only one macroeconomic factor that causes the systematic risk affecting all stock returns and this factor can be represented by the rate of return on a market index, such as the S&P 500, or the Euro Stoxx 50, used in this project.
According to this model, the return of any stock can be decomposed into the expected excess return of the individual stock due to firm-specific factors, commonly denoted by its alpha coefficient ($\alpha$), the return due to macroeconomic events that affect the market, and the unexpected microeconomic events that affect only the firm.
Below, the equation of the Market Model:

$$r_i = \alpha_i + \beta_i(R_M) + \epsilon_i$$

where:

- $r_i$ : expected return on security i
- $\alpha$ : alpha coefficient, excess return
- $\beta_i$ : beta coefficient, measure of volatility
- $R_M$ : return of the market
- $\epsilon_i$ : error term

As we saw above, the relations between total risk can be decomposed in specific risk and systematic risk:

$$Totalrisk = SystematicRisk + SpecificRisk$$
$$\sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma_{ei}^2 \ [3]$$

Unsystematic risk (or diversifiable, specific risk) can be mitigated through diversification while systematic or market risk is generally unavoidable. The unsystematic risk is specific to a company, industry, market, economy, or country. The most common sources of unsystematic risk are business risk and financial risk. Because it is diversifiable, investors can reduce their exposure through diversification.

# 3 INDEX

The EURO STOXX 50 [2] is a stock index of Eurozone stocks designed by STOXX, an index provider owned by Deutsche Börse Group. The eurozone (EZ), officially called the euro area, is a monetary union of 19 member states of the European Union (EU) that have adopted the euro (€) as their primary currency and sole legal tender.
The index is composed of 50 stocks from 11 countries in the Eurozone. EURO STOXX 50 represents Eurozone blue-chip companies considered as leaders in their respective sectors. A blue chip is a stock in a stock corporation with a national reputation for quality, reliability, and the ability to operate profitably in good and bad times.
It is made up of fifty of the largest and most liquid stocks. The index futures and options on the EURO STOXX 50, traded on Eurex, are among the most liquid products in Europe and the world.
The EURO STOXX 50 was introduced in 1998. The composition of EURO STOXX 50 is reviewed annually in September. As of April 2021, the most countries with most companies represented are France (representing 36.6% of all total assets) and Germany (33.2%).

# 4 DATA

- 1. You must download the daily time series of prices of a set of stocks. Expected timespan must be at least 5 years. You also need the related market index.
- 2. The reference market, could be a specific country (ex. Italy) or a subpart of it (ex. FTSE MIB, only Italian Big stocks)

The first step to download the data was to extract/scrape the tickers of the stocks that compose the index from Wikipedia. With a simple

script I scraped the tickers and added them to a list, plus the ticker of the index (STOXX50E). Then I defined the relevant period to download the data, in this case from 01/01/2016 to 01/06/2022. Finally, with the help python and Yahoo I downloaded the data for all the stocks and the index, based on the selected time period.
Below, the first five rows of the dataset:

| | Date | EuroStoxx50 | ADS.DE | ADYEN.AS | AD.AS | AI.PA | AIR.PA | ALV.DE | ABI.BR | ASML.AS | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2016-01-04 | 3164.760010 | 78.004707 | NaN | 15.247333 | 63.063118 | 53.968327 | 111.405846 | 90.266624 | 74.629242 | ... |
| 2 | 2016-01-05 | 3178.010010 | 77.737396 | NaN | 15.321729 | 62.687923 | 55.059048 | 111.762909 | 91.510849 | 75.216354 | ... |
| 3 | 2016-01-06 | 3139.320068 | 76.837410 | NaN | 15.223837 | 61.812473 | 54.331902 | 112.119972 | 90.306778 | 73.464317 | ... |
| 4 | 2016-01-07 | 3084.679932 | 75.643364 | NaN | 15.145526 | 60.386761 | 53.241184 | 109.799019 | 88.781578 | 71.749557 | ... |
| 5 | 2016-01-08 | 3033.469971 | 74.360207 | NaN | 15.176851 | 59.467541 | 52.106125 | 108.406448 | 86.333267 | 68.720772 | ... |

5 rows × 52 columns

**Figura 1:** ES50 Dataset

We can observe the date column at the beginning of the dataset, followed by the index and all the stocks. The data in the cells refers to the closing price for the date indicated in the corresponding row.
After some initial data exploration, I isolated the index column to plot a graph to visualize the trend during the selected time period. In the figure below, we can observe it:

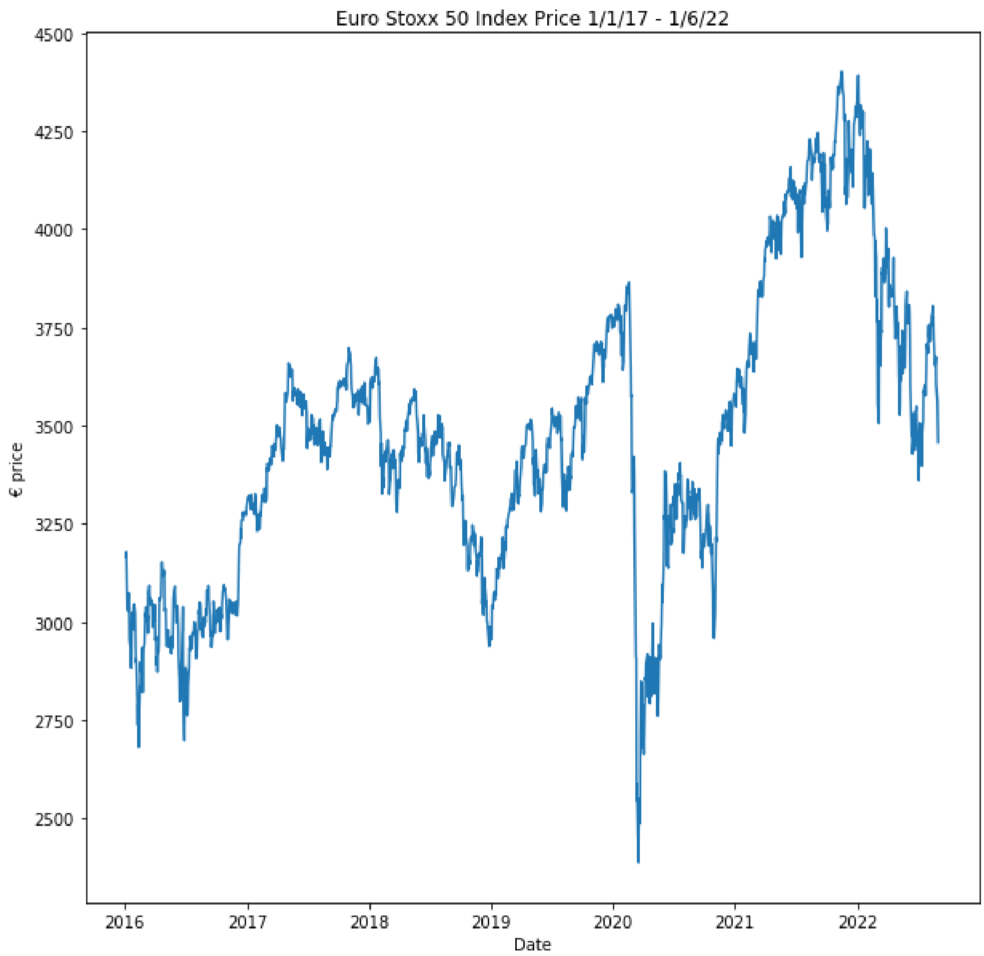


**Figura 2**: ES50 - Trend

# 5 DATA PRE-PROCESSING

- 3. For each stock in the dataset you should execute a rolling regression of log-returns as prescribed by the Market Model.
- 4. The sample for the rolling regression must be 180 days. You will lose the first 180 days of the sample.

As requested by the introduction of the project, I calculated the logarithmic returns of the closing prices for each of the downloaded stocks, plus the index.
Logarithmic returns are simply calculated by taking a natural logarithm of each closing price and then subtract to it the logarithm of the closing price from the previous day.
This is done in python with the 'shift' parameter.

| | Date | EuroStoxx50 | ADS.DE | ADYEN.AS | AD.AS | AI.PA | AIR.PA | ALV.DE | ABI.BR | ASML.AS | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 2016-01-05 | 0.004178 | -0.003433 | NaN | 0.004867 | -0.005967 | 0.020009 | 0.003200 | 0.013690 | 0.007836 | ... |
| 3 | 2016-01-06 | -0.012249 | -0.011645 | NaN | -0.006410 | -0.014064 | -0.013295 | 0.003190 | -0.013245 | -0.023569 | ... |
| 4 | 2016-01-07 | -0.017558 | -0.015662 | NaN | -0.005157 | -0.023335 | -0.020279 | -0.020918 | -0.017033 | -0.023618 | ... |
| 5 | 2016-01-08 | -0.016741 | -0.017109 | NaN | 0.002066 | -0.015339 | -0.021550 | -0.012764 | -0.027964 | -0.043130 | ... |
| 6 | 2016-01-11 | -0.001973 | 0.021458 | NaN | 0.008222 | -0.012060 | -0.011123 | 0.003945 | 0.019794 | 0.026101 | ... |

5 rows × 52 columns

**Figura 3:** ES50 - Log-Returns

At this point, I created the variable 'sample_size', corresponding to the value of the sample for the rolling regression (180).
This window will be used as a sample for the rolling regression, so it won't be included in the following part of the portfolios.
This window contains only the data that don't have null values in the selected period. In my case, 43 stocks from the initial 51 are included in the window. So, 8 stocks contained NaN values in the first 180 days, and for this reason they weren't considered.

## 5.1 Rolling Regression

In this section, the aim was to execute a rolling regression between each stock in the dataframe against the index.
This model is calculated from the selected window, so it's based on the first 180 rows of the dataframe.
From the resulting model, it's possible to extract some useful and interesting parameters, parameters that will be used to build the portfolios later.
Below, the list of the parameters extracted and calculated thanks to the model:

- 'tickers' : the name of the stock considered
- 'r2' : the r-squared value from the model
- 'beta' : the beta value
- 'alpha' : the alpha value
- 'alpha_significance' : the p-value related to the alpha column
- 'absolute_returns' : the sum of the ticker returns
- 'specific_risk' : unsystematic or specific risk
- 'systematic_risk' : calculated as $\beta^2 \times \mathtt{ndx\_returns.std()}^2$

- 'total_risk' : calculated as the sum between systematic risk and specific risk

| | tickers | r2 | beta | alpha | alpha_significance | absolute_returns | specific_risk | systematic_risk | total_risk |
|---|---|---|---|---|---|---|---|---|---|
| 0 | ADS.DE | 0.177656 | 0.41288 | 0.003112 | 0.002831 | 0.559717 | 0.013751 | 0.042638 | 0.056389 |
| 1 | AD.AS | 0.319903 | 0.473584 | 0.000715 | 0.371868 | 0.128262 | 0.010689 | 0.056098 | 0.066787 |
| 2 | AI.PA | 0.536992 | 0.719739 | 0.000329 | 0.671121 | 0.058461 | 0.010346 | 0.129569 | 0.139915 |
| 3 | AIR.PA | 0.587508 | 0.947977 | -0.000391 | 0.671284 | -0.0713 | 0.012296 | 0.224775 | 0.237071 |
| 4 | ALV.DE | 0.81318 | 1.058462 | -0.000226 | 0.700797 | -0.041755 | 0.007854 | 0.280222 | 0.288076 |

**Figura 4:** ES50 - Ranking Dataframe

# 6 DATA PROCESSING

- 5. You must build tilted portfolios based on the $R^2$, $\sigma_i^2$, $\beta_i^2\sigma_M^2$, $\sigma_{ei}^2$, $\alpha_i$, $r_i$
- 6. To get a tilted portfolio you should sort all the stocks in ascending or descending order depending on the feature or combination/ration of them.
- 7. If you have 100 stocks, when sorted you must select the upper and lower quantile, for example 10% or 20%.
- 8. To build a portfolio with the selected stocks you can simply set an equally weighted portfolio. For example, in case of 10 stocks, 10% is invested in each asset.

From the ranking dataframe, it's possible to extract the various parameters to construct the desired portfolios. The procedure start with sorting the column (the parameter) of interest and extract the first n tickers based on the ranking.
In the case of this project, the first 10 stocks (the first ten rows) are extracted and used to build the portfolios.

## 6.1 Portfolios Building

I chose to build seven different portfolios:

**MAX $R^2$** This portfolio take into consideration the first ten stocks with the highest level of r-squared derived from the model. $R^2$ is the coefficient of determination, it ranges between 0 and 1 and it measures how a change in the price is correlated with respect to the index. These are the selected stocks: ['ALV.DE', 'CS.PA', 'BNP.PA', 'INGA.AS', 'SAN.MC', 'BAS.DE', 'BBVA.MC', 'BMW.DE', 'SIE.DE', 'MUV2.DE']

| | tickers | r2 | beta | alpha | alpha_significance | absolute_returns | specific_risk | systematic_risk | total_risk |
|---|---|---|---|---|---|---|---|---|---|
| 4 | ALV.DE | 0.813180 | 1.058462 | -0.000226 | 0.700797 | -0.041755 | 0.007854 | 0.280222 | 0.288076 |
| 7 | CS.PA | 0.788997 | 1.495205 | -0.000472 | 0.598192 | -0.086560 | 0.011970 | 0.559182 | 0.571152 |
| 13 | BNP.PA | 0.782196 | 1.523465 | 0.000256 | 0.783756 | 0.044451 | 0.012445 | 0.580520 | 0.592965 |
| 23 | INGA.AS | 0.764207 | 1.501316 | 0.000353 | 0.714772 | 0.062031 | 0.012910 | 0.563762 | 0.576672 |
| 11 | SAN.MC | 0.755679 | 1.786274 | 0.000213 | 0.856557 | 0.036456 | 0.015723 | 0.798083 | 0.813806 |
| 8 | BAS.DE | 0.736871 | 0.870956 | 0.000719 | 0.234398 | 0.128438 | 0.008057 | 0.189734 | 0.197791 |
| 10 | BBVA.MC | 0.735194 | 1.559311 | -0.000344 | 0.750962 | -0.063557 | 0.014487 | 0.608159 | 0.622646 |
| 12 | BMW.DE | 0.717737 | 1.143192 | -0.000466 | 0.575273 | -0.084990 | 0.011098 | 0.326881 | 0.337979 |
| 36 | SIE.DE | 0.713783 | 0.919542 | 0.001441 | 0.033833 | 0.258409 | 0.009014 | 0.211493 | 0.220507 |
| 29 | MUV2.DE | 0.698328 | 0.849834 | 0.000036 | 0.955419 | 0.005638 | 0.008647 | 0.180642 | 0.189289 |

**Figura 5:** Max $R^2$

**MAX ABSOLUTE RETURNS** This portfolio is sorted according to the maximum value of absolute returns. Absolute returns are calculated as the sum of the ticker returns in the selected period.
These are the selected stocks: ['ADS.DE', 'SIE.DE', 'IFX.DE', 'VNA.DE', 'KER.PA', 'SU.PA', 'DG.PA', 'ASML.AS', 'RMS.PA', 'SAP.DE']

| | tickers | r2 | beta | alpha | alpha_significance | absolute_returns | specific_risk | systematic_risk | total_risk |
|---|---|---|---|---|---|---|---|---|---|
| 0 | ADS.DE | 0.177656 | 0.412880 | 0.003112 | 0.002831 | 0.559717 | 0.013751 | 0.042638 | 0.056389 |
| 36 | SIE.DE | 0.713783 | 0.919542 | 0.001441 | 0.033833 | 0.258409 | 0.009014 | 0.211493 | 0.220507 |
| 22 | IFX.DE | 0.526103 | 0.948102 | 0.001393 | 0.182492 | 0.249844 | 0.013930 | 0.224834 | 0.238764 |
| 40 | VNA.DE | 0.272437 | 0.524583 | 0.001345 | 0.176865 | 0.241541 | 0.013271 | 0.068830 | 0.082101 |
| 24 | KER.PA | 0.613133 | 0.937726 | 0.001303 | 0.132314 | 0.233597 | 0.011531 | 0.219940 | 0.231471 |
| 35 | SU.PA | 0.689637 | 1.117097 | 0.001293 | 0.137828 | 0.231509 | 0.011601 | 0.312129 | 0.323730 |
| 38 | DG.PA | 0.569220 | 0.672309 | 0.001189 | 0.080657 | 0.213317 | 0.009054 | 0.113055 | 0.122109 |
| 6 | ASML.AS | 0.403689 | 0.685672 | 0.001162 | 0.229851 | 0.208418 | 0.012901 | 0.117594 | 0.130495 |
| 19 | RMS.PA | 0.380122 | 0.621735 | 0.001071 | 0.245272 | 0.192130 | 0.012291 | 0.096686 | 0.108976 |
| 34 | SAP.DE | 0.641768 | 0.734148 | 0.001069 | 0.093815 | 0.191691 | 0.008491 | 0.134809 | 0.143300 |

**Figura 6:** Max *Absolute Returns*

**MIN TOTAL RISK** Inside this portfolio there are the first ten stocks with the lowest value of total risk. Total risk is computed as the sum between specific and systematic risk.
These are the selected stocks: ['LIN.DE', 'ADS.DE', 'AD.AS', 'VNA.DE', 'BN.PA', 'RI.PA', 'RMS.PA', 'OR.PA', 'IBE.MC', 'ABI.BR']

| | tickers | r2 | beta | alpha | alpha_significance | absolute_returns | specific_risk | systematic_risk | total_risk |
|---|---|---|---|---|---|---|---|---|---|
| 26 | LIN.DE | 0.002430 | -0.004056 | 0.000165 | 0.083798 | 0.029768 | 0.001272 | 0.000004 | 0.001276 |
| 0 | ADS.DE | 0.177656 | 0.412880 | 0.003112 | 0.002831 | 0.559717 | 0.013751 | 0.042638 | 0.056389 |
| 1 | AD.AS | 0.319903 | 0.473584 | 0.000715 | 0.371868 | 0.128262 | 0.010689 | 0.056098 | 0.066787 |
| 40 | VNA.DE | 0.272437 | 0.524583 | 0.001345 | 0.176865 | 0.241541 | 0.013271 | 0.068830 | 0.082101 |
| 14 | BN.PA | 0.480596 | 0.596594 | 0.000724 | 0.314301 | 0.129734 | 0.009601 | 0.089024 | 0.098625 |
| 30 | RI.PA | 0.441740 | 0.608812 | 0.000304 | 0.701500 | 0.054099 | 0.010595 | 0.092708 | 0.103303 |
| 19 | RMS.PA | 0.380122 | 0.621735 | 0.001071 | 0.245272 | 0.192130 | 0.012291 | 0.096686 | 0.108976 |
| 25 | OR.PA | 0.556763 | 0.636113 | 0.000801 | 0.224252 | 0.143506 | 0.008786 | 0.101209 | 0.109995 |
| 20 | IBE.MC | 0.505841 | 0.648368 | 0.000100 | 0.892696 | 0.017363 | 0.009920 | 0.105147 | 0.115067 |
| 5 | ABI.BR | 0.490413 | 0.657434 | 0.000438 | 0.572944 | 0.078152 | 0.010374 | 0.108108 | 0.118482 |

**Figura 7:** Min *Total Risk*

**MIN SYSTEMATIC RISK** This portfolio includes the ten stocks with the minimum level of systematic risk. Systematic risk refers to the risk inherent to the entire market or market segment. Systematic risk is also known as 'undiversifiable' risk.
We can observe that the selected stocks are the same of the above portfolio.
These are the selected stocks: ['LIN.DE', 'ADS.DE', 'AD.AS', 'VNA.DE', 'BN.PA', 'RI.PA', 'RMS.PA', 'OR.PA', 'IBE.MC', 'ABI.BR']

| | tickers | r2 | beta | alpha | alpha_significance | absolute_returns | specific_risk | systematic_risk | total_risk |
|---|---|---|---|---|---|---|---|---|---|
| 26 | LIN.DE | 0.002430 | -0.004056 | 0.000165 | 0.083798 | 0.029768 | 0.001272 | 0.000004 | 0.001276 |
| 0 | ADS.DE | 0.177656 | 0.412880 | 0.003112 | 0.002831 | 0.559717 | 0.013751 | 0.042638 | 0.056389 |
| 1 | AD.AS | 0.319903 | 0.473584 | 0.000715 | 0.371868 | 0.128262 | 0.010689 | 0.056098 | 0.066787 |
| 40 | VNA.DE | 0.272437 | 0.524583 | 0.001345 | 0.176865 | 0.241541 | 0.013271 | 0.068830 | 0.082101 |
| 14 | BN.PA | 0.480596 | 0.596594 | 0.000724 | 0.314301 | 0.129734 | 0.009601 | 0.089024 | 0.098625 |
| 30 | RI.PA | 0.441740 | 0.608812 | 0.000304 | 0.701500 | 0.054099 | 0.010595 | 0.092708 | 0.103303 |
| 19 | RMS.PA | 0.380122 | 0.621735 | 0.001071 | 0.245272 | 0.192130 | 0.012291 | 0.096686 | 0.108976 |
| 25 | OR.PA | 0.556763 | 0.636113 | 0.000801 | 0.224252 | 0.143506 | 0.008786 | 0.101209 | 0.109995 |
| 20 | IBE.MC | 0.505841 | 0.648368 | 0.000100 | 0.892696 | 0.017363 | 0.009920 | 0.105147 | 0.115067 |
| 5 | ABI.BR | 0.490413 | 0.657434 | 0.000438 | 0.572944 | 0.078152 | 0.010374 | 0.108108 | 0.118482 |

Figura 8: Min *Systematic Risk*

**MAX SPECIFIC RISK** This portfolio comprises the ten stocks with the highest level of specific risk. To an investor, specific risk is a hazard that applies only to a particular company, industry, or sector. It is the opposite of overall market risk or systematic risk. Specific risk is also referred to as unsystematic risk or diversifiable risk.
These are the selected stocks: ['VOW.DE', 'SAN.MC', 'BBVA.MC', 'IFX.DE', 'ADS.DE', 'SAF.PA', 'VNA.DE', 'INGA.AS', 'ASML.AS', 'DB1.DE']

| | tickers | r2 | beta | alpha | alpha_significance | absolute_returns | specific_risk | systematic_risk | total_risk |
|---|---|---|---|---|---|---|---|---|---|
| 39 | VOW.DE | 0.535020 | 1.147920 | 0.000076 | 0.951017 | 0.012530 | 0.016566 | 0.329591 | 0.346157 |
| 11 | SAN.MC | 0.755679 | 1.786274 | 0.000213 | 0.856557 | 0.036456 | 0.015723 | 0.798083 | 0.813806 |
| 10 | BBVA.MC | 0.735194 | 1.559311 | -0.000344 | 0.750962 | -0.063557 | 0.014487 | 0.608159 | 0.622646 |
| 22 | IFX.DE | 0.526103 | 0.948102 | 0.001393 | 0.182492 | 0.249844 | 0.013930 | 0.224834 | 0.238764 |
| 0 | ADS.DE | 0.177656 | 0.412880 | 0.003112 | 0.002831 | 0.559717 | 0.013751 | 0.042638 | 0.056389 |
| 32 | SAF.PA | 0.540593 | 0.935185 | 0.000361 | 0.717683 | 0.064060 | 0.013346 | 0.218750 | 0.232095 |
| 40 | VNA.DE | 0.272437 | 0.524583 | 0.001345 | 0.176865 | 0.241541 | 0.013271 | 0.068830 | 0.082101 |
| 23 | INGA.AS | 0.764207 | 1.501316 | 0.000353 | 0.714772 | 0.062031 | 0.012910 | 0.563762 | 0.576672 |
| 6 | ASML.AS | 0.403689 | 0.685672 | 0.001162 | 0.229851 | 0.208418 | 0.012901 | 0.117594 | 0.130495 |
| 15 | DB1.DE | 0.500153 | 0.824973 | -0.000065 | 0.945614 | -0.012582 | 0.012767 | 0.170228 | 0.182995 |

Figura 9: Max *Specific Risk*

**MAX $\beta$** In this portfolio we can find the ten stocks with the highest value of beta. Beta is a measure of the volatility of a security or portfolio compared to the market as a whole (in this case the index Euro Stoxx 50). Stocks with betas higher than 1.0 can be interpreted as more volatile than the index.

These are the selected stocks: ['SAN.MC', 'BBVA.MC', 'BNP.PA', 'INGA.AS', 'CS.PA', 'VOW.DE', 'BMW.DE', 'SU.PA', 'ALV.DE', 'MBG.DE']

| | tickers | r2 | beta | alpha | alpha_significance | absolute_returns | specific_risk | systematic_risk | total_risk |
|---|---|---|---|---|---|---|---|---|---|
| 11 | SAN.MC | 0.755679 | 1.786274 | 0.000213 | 0.856557 | 0.036456 | 0.015723 | 0.798083 | 0.813806 |
| 10 | BBVA.MC | 0.735194 | 1.559311 | -0.000344 | 0.750962 | -0.063557 | 0.014487 | 0.608159 | 0.622646 |
| 13 | BNP.PA | 0.782196 | 1.523465 | 0.000256 | 0.783756 | 0.044451 | 0.012445 | 0.580520 | 0.592965 |
| 23 | INGA.AS | 0.764207 | 1.501316 | 0.000353 | 0.714772 | 0.062031 | 0.012910 | 0.563762 | 0.576672 |
| 7 | CS.PA | 0.788997 | 1.495205 | -0.000472 | 0.598192 | -0.086560 | 0.011970 | 0.559182 | 0.571152 |
| 39 | VOW.DE | 0.535020 | 1.147920 | 0.000076 | 0.951017 | 0.012530 | 0.016566 | 0.329591 | 0.346157 |
| 12 | BMW.DE | 0.717737 | 1.143192 | -0.000466 | 0.575273 | -0.084990 | 0.011098 | 0.326881 | 0.337979 |
| 35 | SU.PA | 0.689637 | 1.117097 | 0.001293 | 0.137828 | 0.231509 | 0.011601 | 0.312129 | 0.323730 |
| 4 | ALV.DE | 0.813180 | 1.058462 | -0.000226 | 0.700797 | -0.041755 | 0.007854 | 0.280222 | 0.288076 |
| 28 | MBG.DE | 0.687264 | 1.029591 | -0.000315 | 0.695503 | -0.057767 | 0.010752 | 0.265144 | 0.275895 |

**Figura 10:** Max $\beta$

**MAX AND SIGNIFICANT** $\alpha$ This portfolio includes the stocks with the highest level of alpha, but with one condition. The significance of alpha, the p-value in the column to the right, must be valid, lower than the 0.05 threshold.
As we can point out from the image below, only two stocks satisfied this condition. For this reason, this portfolio won't be included in the following sections of the project.
These are the selected stocks: ['ADS.DE', 'SIE.DE']

| | tickers | r2 | beta | alpha | alpha_significance | absolute_returns | specific_risk | systematic_risk | total_risk |
|---|---|---|---|---|---|---|---|---|---|
| 0 | ADS.DE | 0.177656 | 0.412880 | 0.003112 | 0.002831 | 0.559717 | 0.013751 | 0.042638 | 0.056389 |
| 36 | SIE.DE | 0.713783 | 0.919542 | 0.001441 | 0.033833 | 0.258409 | 0.009014 | 0.211493 | 0.220507 |

**Figura 11:** Max and Significant $\alpha$

# 7 PORTFOLIOS ANALYSIS

- 9. To get the returns of the portfolio, simply calculate the weighted average of stock returns involved.
- 10. The portfolios must be rebalanced weekly until the end of the sample.
- 11. Calculate final statistics to compare the different tilted portfolios together with the index. The typical output should be a price chart (price must be restored starting from 100) of the portfolio and the index, or all the portfolios with the index, and tables reporting average return of each portfolio, volatility, the ratio of the two.

Once at this stage, the next step was to compute the weekly logarithmic returns of each portfolio, plus the index as always.

The weights are calculated as $\frac{1}{N}$. Basically, each stock has the same weight inside the portfolio. So, since there are ten stocks in each portfolio, the weights are computed as $\frac{1}{10}$.
The returns of each portfolio are calculated as the sum of the returns for each stock, divided/multiplied by their weight.

## 7.1 Returns and Volatility

To analyze and compare the various portfolios, it's necessary to compute the annualized returns and the annualized volatility.
Annualized returns are computed as the average return multiplied by 52 (number of weeks in a year).
Annualized volatility is computed as the average standard deviation of returns multiplied by the square root of 52.

## 7.2 Final Statistics

At this stage, I built a dataframe with each portfolio and the relative annualized returns and annualized volatility value.
This table lets us observe and compare the resulting statistics of the portfolios.
From the table, we can observe that the index obtained a 4.7% annualized returns, with a volatility of 24.43%.
All the portfolios obtained a higher level of returns, but with a higher level of volatility too.
The highest level of returns was achieved by the *Max Absolute Returns* portfolio (17.44%), while the lowest level of volatility was achieved by the *Min Total Risk* portfolio (29.23%).
As we already pointed out in the phase of portfolio building, the *Min Total Risk* and the *Min Systematic Risk* were composed by the same set of stocks. We can in fact observe that they reached the same value of returns and volatility.
The *Max Specific Risk* portfolio reached the highest level of volatility (38.68%).

| | Portfolio | Annualized Returns | Annualized Volatility |
|---|---|---|---|
| 0 | NDX ES50 | 4.70 | 24.43 |
| 1 | Max R2 | 6.89 | 36.63 |
| 2 | Max Absolute Returns | 17.44 | 33.96 |
| 3 | Min Total Risk | 13.25 | 29.23 |
| 4 | Min Systematic Risk | 13.25 | 29.23 |
| 5 | Max Specific Risk | 11.69 | 38.68 |
| 6 | Max Beta | 9.25 | 38.40 |

**Figura 12:** Final Statistics (%)

In addition to annualized returns and volatility, I computed the measure of 'efficiency'. Efficiency is a measure that let us simply interpret the whole market of investments. It is calculated as the annualized returns divided by the annualized volatility:

$$\mathsf{Efficiency} = \frac{R_A}{\sigma_A}$$

The column to the right end contains the values of the efficiency for each portfolio.

| | Portfolio | Annualized Returns | Annualized Volatility | Efficiency |
|---|---|---|---|---|
| 0 | NDX ES50 | 4.70 | 24.43 | 0.19 |
| 1 | Max R2 | 6.89 | 36.63 | 0.19 |
| 2 | Max Absolute Returns | 17.44 | 33.96 | 0.51 |
| 3 | Min Total Risk | 13.25 | 29.23 | 0.45 |
| 4 | Min Systematic Risk | 13.25 | 29.23 | 0.45 |
| 5 | Max Specific Risk | 11.69 | 38.68 | 0.30 |
| 6 | Max Beta | 9.25 | 38.40 | 0.24 |

**Figura 13:** Final Statistics - Efficiency

## 7.3 Price Chart

To plot the price chart, the first step was to get the cumulative returns for all the portfolios.
The price chart starts with an initial investment of 100 $.

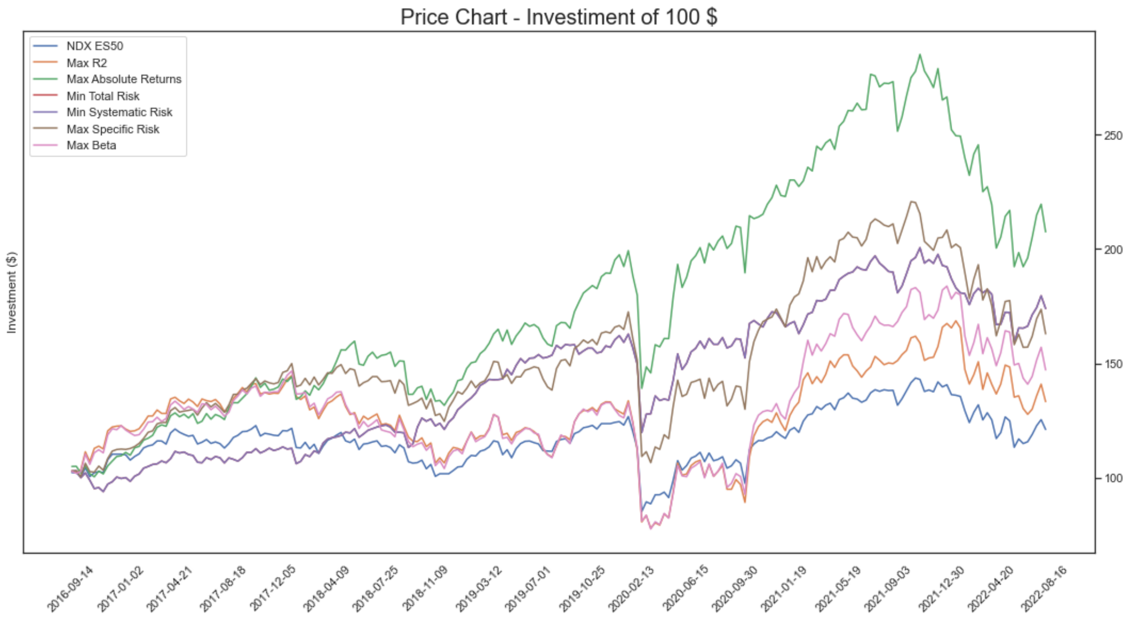


**Figura 14:** Final Statistics - Price Chart

# 8 CONCLUSION

The results showed that the portfolios created over-performed compared to the index during the period under consideration. However, the same results also showed higher volatility than that of the index.
The results were shown through a comparative table relating annualized returns and volatility, to which a column relating to efficiency was added, and a price chart.
It was found that the best portfolio in terms of annualized returns is the one called 'Max Absolute Returns', while the one with the lowest volatility, aside from the index, is the one called 'Min Total Risk'.
This project can be improved by adding the use of risk-free rate to the process, but also by considering in detail the risks introduced by survivorship bias. In addition, more portfolios can be constructed than considered, and a momentum strategy can be developed.

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