Group Homework 1

Linear Regression and the CAPM - Technology Sector

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Introduction

The objective of this paper is to conduct a comprehensive analysis of the technology market sector index, with a focus on selecting a subset of equities and applying regression modeling techniques, specifically the Capital Asset Pricing Model (CAPM) discussed in our class. The objective of this paper is to conduct an analysis on whether the empirical data coming from the returns of technology stocks in the European market is coherent with the Capital Asset Pricing Model (CAPM). By using linear regression models, we proceed to the estimation of the β's and the α's for each stock and check whether their values and their significance is coherent with the postulates of the CAPM). The reference market index for this analysis is the Euro Stoxx 600 Europe since it serves as an ideal benchmark for our analysis. As it represents a diverse range of European companies. By applying the CAPM model to our data, we aim to provide a comprehensive evaluation of risk and return dynamics in the European technology market sector, which can be of valuable insight to investors and decision-makers in the financial industry. To achieve this objective, we also provide a series of diagnostic checks to assess whether the data is coherent with the hypotheses of the CAPM. Furthermore, we use the Fama-French factors as a means to try to improve the evaluation of risk and return dynamics of our sample of stocks by including additional risk factors).

Roles

We tried to balance tasks based on our bachelor and sharing tips and techniques to improve in the respective sectors. We decided to divide tasks among members in that way:

- Riccardo Forni (Data Science): took care of the programming part, the documentation of the code and the shape of the report.

- Francesco Mazzolin (Economics): was responsible for the statistical analysis and control of the correct execution of the tests.
- Alessandro Lavarello (Engineer): took care of the report, formatting it, interpreting the output obtained from the code.
- Kaouthar Dian (Engineer): focused in drafting the report, adding details and graphs, and keeping review of the paper.

1. Data Collection and Preparation

1.1. Data Collection

In the initial phase of our analysis, we selected 26 equities belonging to the EURO STOXX Technology index, each demonstrating a consistent ten-year track record of data availability from 30/09/2013 and 30/09/2023. This selection was driven by the objective of forming a well-balanced subset of technology sector companies with relevance to the Euro Stoxx 600 Europe:

This group of equities serves as the foundation for our analysis, and it is within the framework of the Capital Asset Pricing Model (CAPM) that we will first analyze their risk and return characteristics. To enhance our analytical approach and facilitate insightful comparisons of the CAPM model empirical results, we used as short-term interest rate the **3-month Euribor rate**. **Euribor** stands for the Euro Interbank Offered Rate. It is the rate at which banks lend to each other for a period of three months. Additionally, it serves as a reference rate for a wide range of financial products, including adjustable-rate mortgages and business loans. It is a key indicator of short-term interest rate conditions in the Eurozone. This is considered safe-haven assets, and its yields are influenced by market demand and supply dynamics as well as expectations for monetary policy. Therefore, it is closely watched by investors as an indicator of risk sentiment.

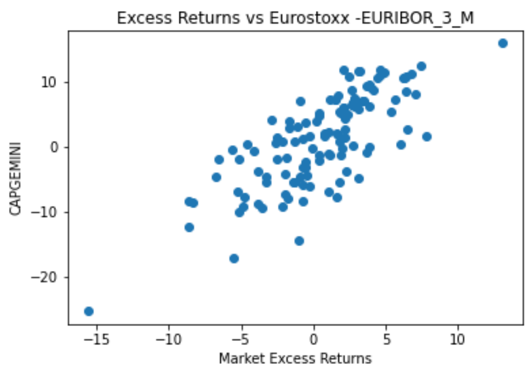
It's worth noting that we generated our data through Refinitiv to ensure data accuracy and reliability for this comprehensive analysis.

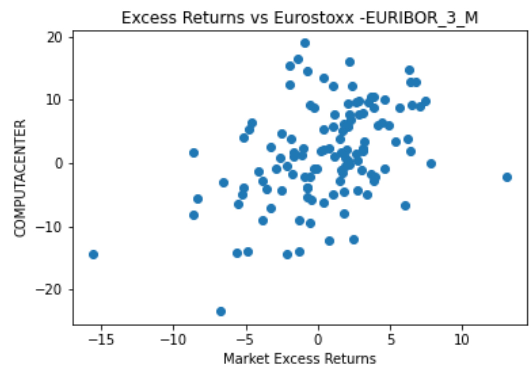
1.2. Data Preparation

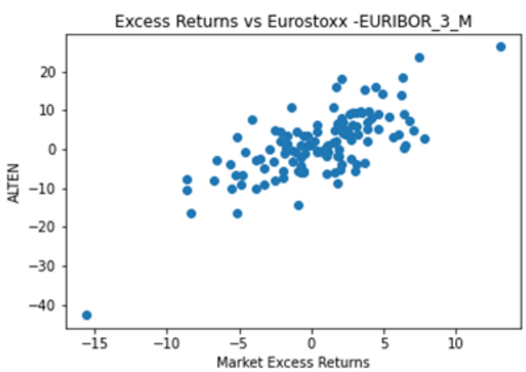
In Python, we initiated the data preparation process for financial analysis by creating a time-series of our data from 30-09-2013 to 29-09-2023 with a monthly frequency. We derived monthly rates from the time-series of annualized interest rates. Moving forward, we computed the logarithmic returns and excess returns of the EuroStoxx600 Total Return Index and of the sample of individual stocks. This step laid the foundation for our subsequent analysis as we employed scatter plots to facilitate a comparative examination of these equities in relation to the Euro Stoxx 600 Europe.

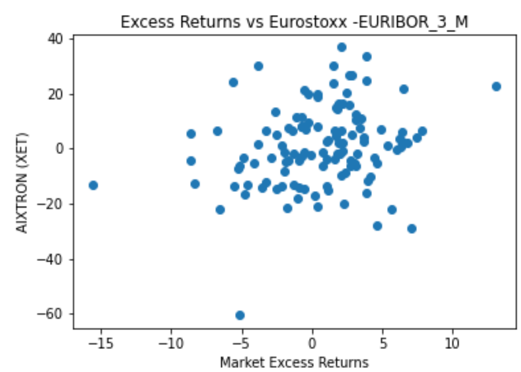
2. Returns and Excess Returns

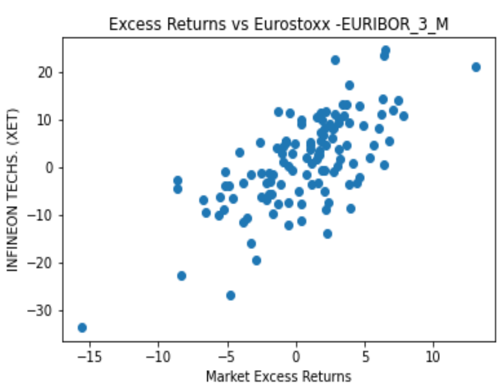
What became immediately evident was the presence of visible linear relationships among the excess returns of certain equities with respect to the excess returns of the market index. To provide a more comprehensive perspective on our findings, we present six illustrative examples below. On the left side, you will find plots that show evidence of a positive linear relationship, while the ones on the right do not noticeably manifest such a strong relationship.

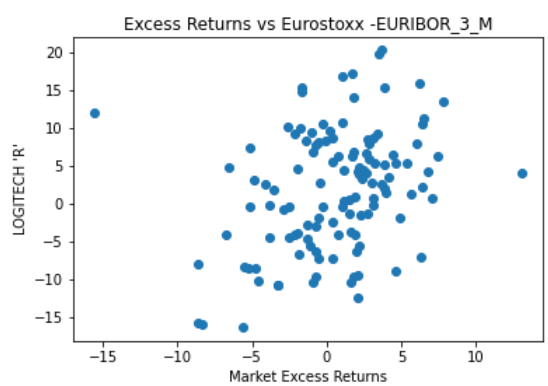












For example, in the case of CAPGEMINI, ALTEN, and INFINEON TECHS with respect to the Euro Stoxx 600 Europe total return index, the plots visually demonstrate that as the market index increases, the returns of equities also tend to increase. This positive correlation suggests a potential alignment between the stocks' performance and overall market trends. This observation is particularly relevant in the context of financial analysis, as it implies that changes in the market return can be associated with predictable changes in the stocks returns which is an important consideration for investors assessing the potential risk and return profile of the stocks in relation to broader market movements. For the scatter plots in the right side, they are revealing a non-clear positive linear correlation. This lack of clarity suggests that the association between these equities with respect to the market index may not adhere to a simple linear pattern. Several factors could contribute to this ambiguity, including outliers, the complexity of market dynamics or the presence of additional risk factors that may explain the stocks' returns. To uncover the underlying dynamics governing the relationship between our variables, we used the CAPM model.

3. CAPM Estimation and Analysis

3.1. Linear Regression Results for equities

In this analysis, the Capital Asset Pricing Model (CAPM) serves as a cornerstone for understanding the risk and return dynamics of the equities under consideration in relation to the Euro Stoxx 600 Europe Total Return INDEX. To assess the validity of the CAPM model we employ a linear regression model for the estimation of key parameters such as alpha and beta, providing insights into the expected returns and market sensitivities of individual stocks.

After estimating the CAPM model for each stock, we obtained the following results summarizing the parameters of assessing the significance and effectiveness of the CAPM model in explaining the relationship between asset returns and market returns:

	Alpha	p-value_alpha	beta: Market	p-value_beta: Market	R-Squared
FORTNOX AB	2,721492	0,005144186	1,347847803	7,34986E-08	0,21849326
ASM INTERNATIONAL	1,665207	0,028276045	1,415921989	5,10013E-12	0,33332591
LOGITECH 'R'	1,519524	0,030964323	0,63629964	0,000306966	0,10494143
BE SEMICONDUCTOR INDUSTRIES	2,054731	0,033900063	1,50495781	3,3624E-09	0,2573371
ASML HOLDING	1,115916	0,039694858	1,153329529	1,82912E-14	0,39319534
NEMETSCHEK (XET)	1,596703	0,041924843	1,328978115	2,01667E-10	0,29122277
LAGERCRANTZ GROUP B	1,259763	0,076822066	1,262187286	4,14386E-11	0,30963936
BECHTLE (XET)	1,170001	0,083968342	0,980789246	2,90932E-08	0,2303511
REPLY	1,110216	0,095012944	1,25035572	4,38195E-12	0,33501156
COMPUTACENTER	1,02363	0,117397483	0,795681165	2,12782E-06	0,17409103
SAGE GROUP	0,753494	0,138409893	0,632195456	1,36012E-06	0,18011455
AMS-OSRAM AG	-2,04762	0,142666388	2,202871246	2,46485E-09	0,26114885
DASSAULT SYSTEMES	0,638453	0,217759124	0,814346872	2,84161E-09	0,25940505

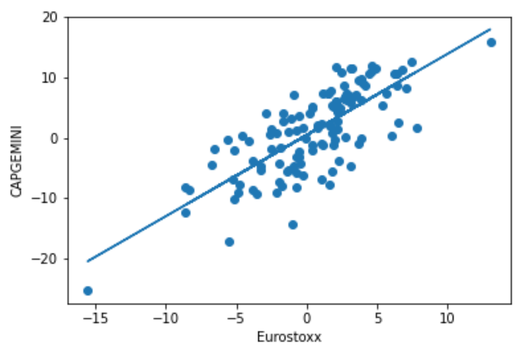
CAPGEMINI	0,468524	0,27574468	1,348783519	4,15505E-24	0,5821764
STMICROELECTRONICS (MIL)	0,804773	0,295847148	1,474301081	2,411E-12	0,34160764
Mean	0,731807	0,357077669	1,255366289	0,000367585	0,31062774
HEXAGON B	0,439513	0,413584175	1,158355369	1,38316E-14	0,39602751
ALTEN	0,375721	0,494372515	1,53307713	1,06601E-20	0,52313686
INFINEON TECHS. (XET)	0,385231	0,55308097	1,611017916	1,04693E-17	0,46459107
NORDIC SEMICONDUCTOR	0,565439	0,55627516	1,282619325	2,87019E-07	0,20077198
TEMENOS N	0,287453	0,71492442	1,164298365	1,90877E-08	0,23569038
SAP (XET)	0,161013	0,73684343	1,134870935	1,30424E-16	0,44143867
AIXTRON (XET)	0,382792	0,772869683	0,860869654	0,009246344	0,05602406
SOPRA STERIA GROUP	0,195139	0,783285239	1,491610226	4,62508E-14	0,38370161
TIETOEVRY	0,111708	0,814081051	0,984470791	8,88351E-14	0,37693588
SOITEC	0,263683	0,827901059	1,985952726	8,49499E-10	0,27408831
AMADEUS IT GROUP	0,004475	0,993269303	1,283534595	4,24803E-17	0,45185367

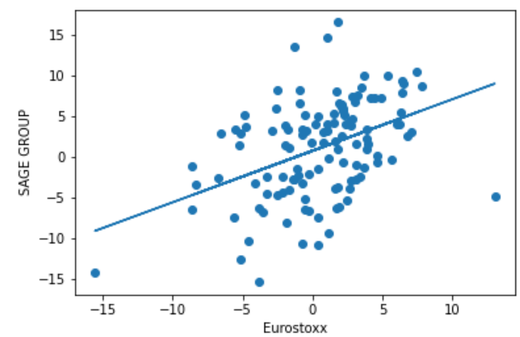
We notice at this stage that this table includes estimation that used HAC standard errors if the White test showed a p-value lower than 0.05 and/or the Breusch-Godfrey test using one lag showed a p-value lower than 0.05. The test will be explained below as a comparison of the standard errors between the case in which non-robust standard errors were used in estimation models that exhibited heteroskedasticity and/or serial correlation among the residuals.

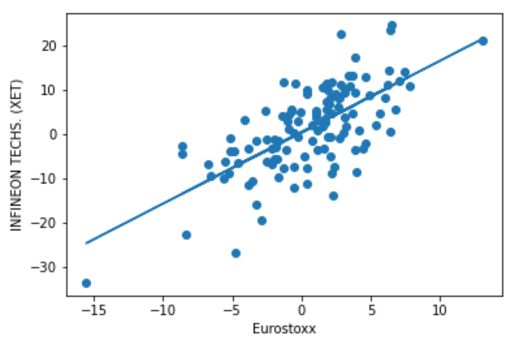
It is worth mentioning that FORTNOX AB, ASM INTERNATIONAL, and BE SEMICONDUCTOR INDUSTRIES exhibit positive alphas with low p-values, which reinforces the statistical significance of their potential to outperform the market. These low p-values add confidence to the notion that other factors exist to contribute to excess returns beyond what is explained by general market movements. Therefore, investors may find these stocks attractive for potential above-average returns. However, this could also represent evidence that the hypothesis of the CAPM that the excess returns of a stock are driven solely by their correlation with the overall market is not correct. On the other hand, ASML HOLDING, HEXAGON B, and ALTEN exhibit high betas with very low p-values, supporting the statistical significance of their responsiveness to changes in market conditions, particularly with respect to conditional expected returns. Additionally, AMS-OSRAM AG and ALTEN stand out with high R-squared values, indicating that a substantial proportion of their returns can be explained by the Euro Stoxx 600 Europe index. This suggests that the CAPM model effectively captures the risk and return dynamics for these stocks within the technology sector.

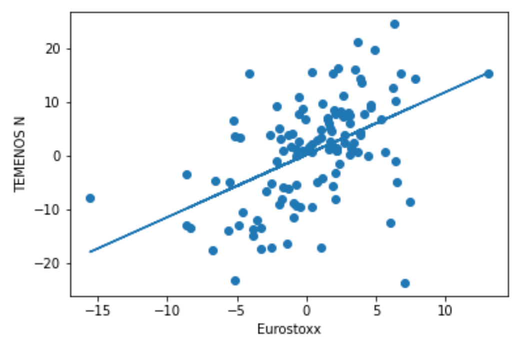
Looking at the combination of low p-values for alpha, beta, and high R-squared values, we can notice a significant relationship with the market and a good fit of the CAPM model. For instance, ALTEN, CAPGEMINI, and INFINEON TECHS. (XET) have positive alpha with a low p-value indicating potential for outperformance. The Beta is close to 1 which suggests alignment with the market and the R-squared value indicates a relatively good fit of the CAPM model. However, SAGE GROUP, AIXTRON (XET), and TEMENOS N have a relatively low alpha with a higher p-value suggesting a weaker potential for outperformance with a low R-squared value indicating a weaker fit with the CAPM model.

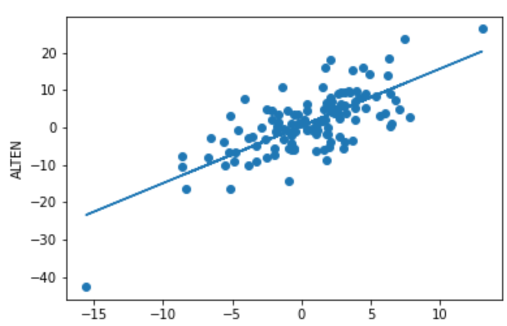
For a visual illustration of the goodness of the fit of the model for our data, below are the scatter plots with the OLS fitted line. On the left are the best linear approximations while on the right, the least desirable linear approximations as per the CAPM analysis and as described above.

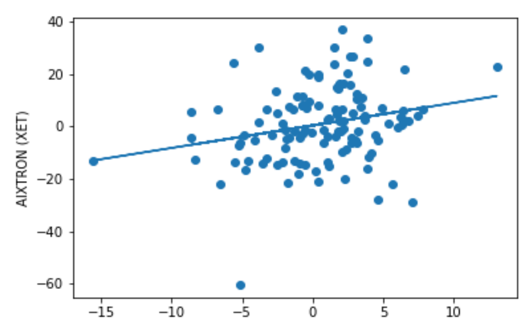








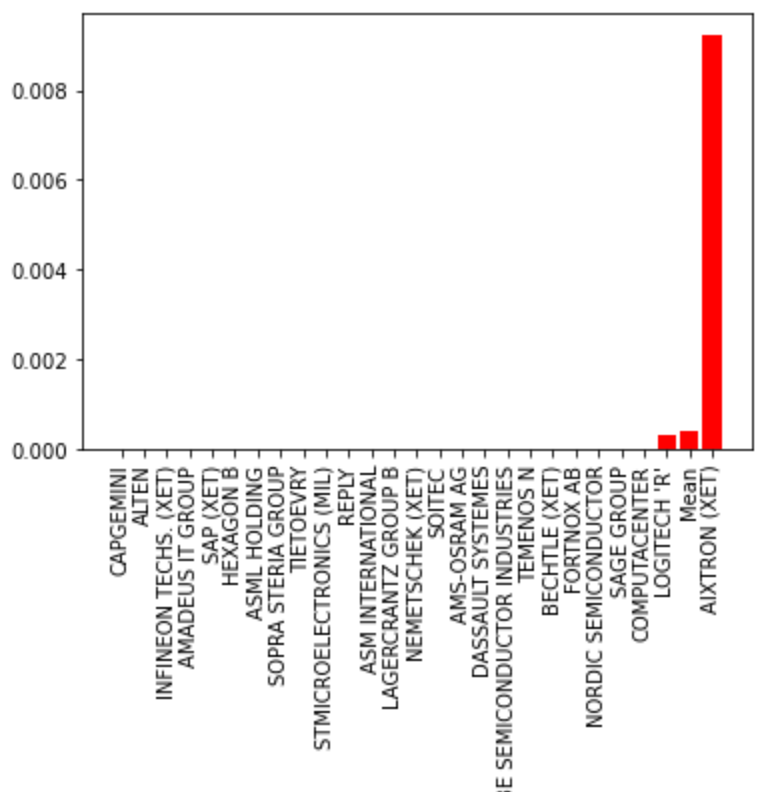




3.2. P-values analysis

When conducting hypothesis testing on the beta coefficient, the null hypothesis (H0) is that there is no relationship or influence from the market on the asset's returns (beta = 0). A low p-value, close to 0, signifies the ability to reject the null hypothesis as it indicates a strong statistical significance for the beta coefficients. In our analysis, all beta coefficients exhibit extremely low p-values. To illustrate, the bar chart below demonstrates the p-values for each beta, revealing values so minuscule that they are not visually represented on the chart. Even the highest p-value, attributed to AIXTRON at 0.009, is notably low which emphasizes the strong statistical significance across our sample. For those not visually represented, their p-values fall within an impressive range spanning from 10^(-6) to 10^(-24).

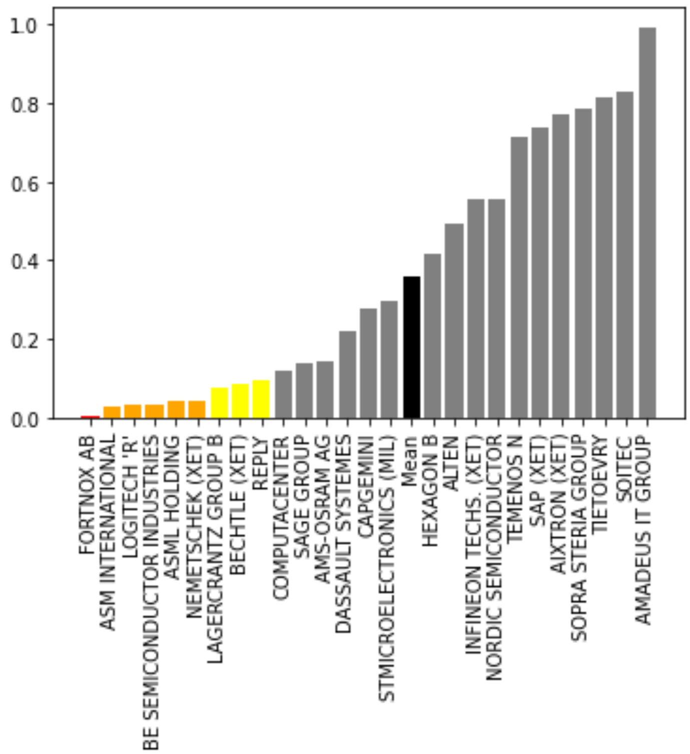
p-values for every beta



In contrast to the beta coefficients, where rejection of the null hypothesis ($\beta = 0$) signifies a significant relationship with market returns, the null hypothesis for alpha is typically postulated as being equal to zero. This aligns with the CAPM's assumption that, in an efficient market, assets should not consistently outperform or underperform beyond what is predicted by the model. The p-values associated with the alpha coefficients exhibit a diverse range of values. Given this variability, we calculated the mean p-value, which stands at 0.357. The decision to accept or reject the null hypothesis for alphas would depend on the chosen significance level. In the bar chart presented below, we illustrate the distribution of p-values for alpha coefficients, with the mean value highlighted in black. This representation provides a visual overview of the statistical significance of the alpha coefficients in our sample and would inform the decision-making process based on the chosen significance level.

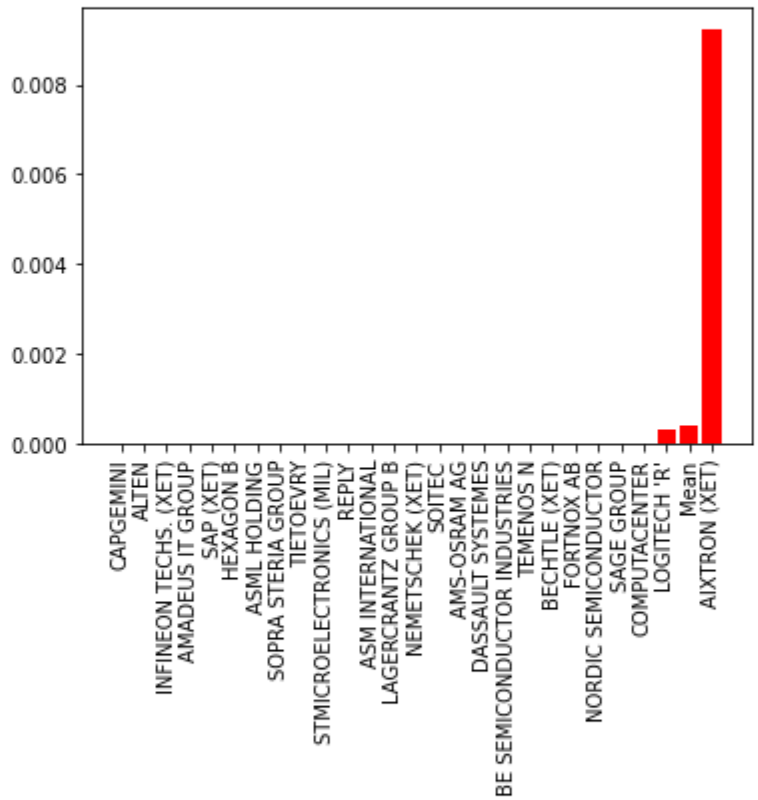
In the plot below we reject the null hypothesis for some stocks at different levels, with yellow representing the rejection of the null hypothesis at a confidence level of 10%, the orange at 5 % and the red at 1%.

p-values for every alpha



A similar result to the p-value analysis of the T-test for the beta coefficients was reached by the F-test, reminding that if p-value < α: we Reject $H0$ (That is what we want). We conclude again that the model is significant for all the equities if $\alpha=1\%$. On the plot below are shown the p-values for the F-test.

p-values for the F-test



3.3. ***Excess returns of an equally weighted portfolio***

To assess the CAPM model for an equally weighted portfolio of our stock we computed for each month the average return across the equities' excess returns and estimated the CAPM regression using the monthly excess returns of the equally weighted portfolio as the dependent variable and the market excess returns as the independent variable. Once we obtained the results, we conducted a comparative analysis between the average value of the parameters obtained for the single stocks and the value of the parameters obtained using the equally weighted portfolio. The table below demonstrates the mentioned comparison:

	F-Value	p-value
AMADEUS IT GROUP	29,95286	3,13E-11
ALTEN	14,49116	2,38E-06
LOGITECH 'R'	9,530977	0,000146
AMS-OSRAM AG	9,413766	0,000162
SOPRA STERIA GROUP	8,306562	0,000423
TIETOEVRY	4,842598	0,009537
ASML HOLDING	4,264148	0,016311
TEMENOS N	1,686253	0,189682
SAP (XET)	1,447605	0,239313
STMICROELECTRONICS (MIL)	1,239991	0,293161
REPLY	1,052468	0,352356
Mean	3,322054	0,526143
BECHTLE (XET)	0,627824	0,535541
BE SEMICONDUCTOR INDUSTRIES	0,611134	0,544459
DASSAULT SYSTEMES	0,379151	0,68528
SAGE GROUP	0,354077	0,70257
COMPUTACENTER	0,282556	0,754367

Portfolio - EW	0,243899	0,783964
CAPGEMINI	0,208903	0,811776
SOITEC	0,177614	0,837491
FORTNOX AB	0,150091	0,860795
HEXAGON B	0,14143	0,868265
INFINEON TECHS. (XET)	0,124079	0,883426
LAGERCRANTZ GROUP B	0,049516	0,95171
AIXTRON (XET)	0,03865	0,962099
NEMETSCHEK (XET)	0,038085	0,962643
ASM INTERNATIONAL	0,027552	0,97283
NORDIC SEMICONDUCTOR	0,01252	0,987559

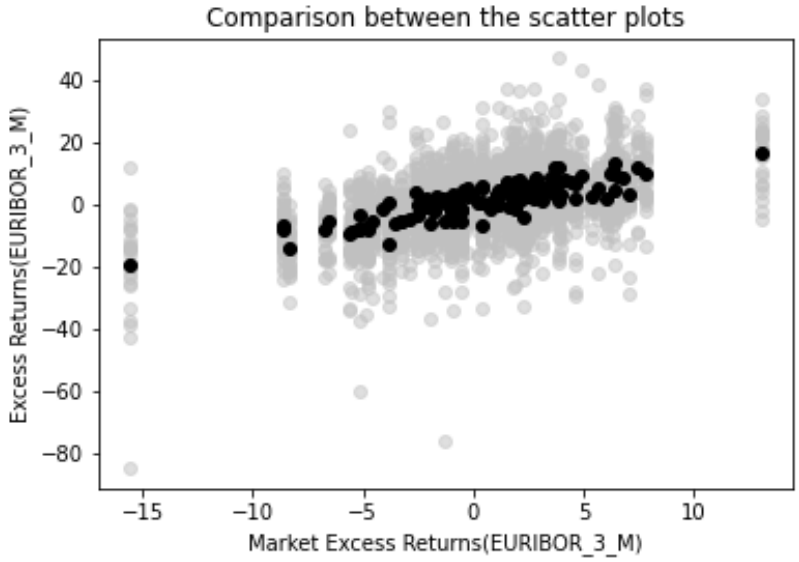
We can see from the table above that the average of the parameters estimated for the single stocks is equal to the parameters of the equally weighted portfolio. This is a result that is expected, since the value of the parameters of a portfolio is a linear combination of the parameters for each stock weighted for their weights, the value of the parameters is equal to the average value of the stocks' parameters. Regarding the significance of the parameters and the value of the R-Squared, instead, we see some differences emerging.

The table, indeed, reveals notable differences in the p-values for both alpha and beta parameters. Specifically, the p-value for alpha is lower for the equally weighted portfolio (0.0134) compared to single stocks (0.3571), indicating a higher level of statistical significance. Similarly, the p-value for beta related to the market is substantially lower for the equally weighted portfolio (1.29105E-34) compared to single stocks (0.000367585), further supporting the enhanced statistical significance of the CAPM model parameters when applied to the equally weighted portfolio.

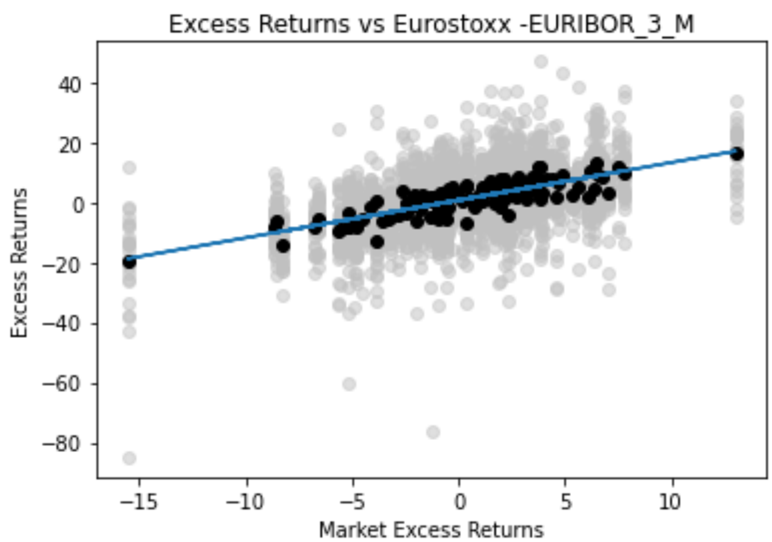
The mean R-squared for Single Stocks is 0.3106, and for the Equally Weighted Portfolio, it is higher at 0.7222. This indicates that the CAPM model explains a larger proportion of the variability in excess returns for the Equally Weighted Portfolio compared to individual stocks.

This difference between the R-squared values is likely attributed to the phenomenon known as the "law of large numbers." The law of large numbers suggests that as the number of observations or data points increases, the impact of random fluctuations or variations in the data tends to diminish. In the case of an equally weighted portfolio, which aggregates returns from multiple stocks, the law of large numbers comes into play. The rationale behind this is that random fluctuations in individual stock returns, which may be purely due to chance and not reflective of systematic trends, tend to cancel each other out when aggregated across a larger number of observations. In other words, the increased number of data points contributes to a more stable and accurate estimate of the true relationship between the portfolio's returns and market returns. Therefore, the higher R-squared value for the equally weighted portfolio suggests that the model's explanatory power is enhanced when considering a diversified portfolio. The portfolio's performance becomes less susceptible to the influence of random fluctuations, leading to a more reliable representation of the systematic relationship between the portfolio and the market. This is well represented by the following scatterplots, where the grey points represent all the equities log-returns, while the black points represent the log-returns of the equally weighted portfolio:

Comparison between scatter plots of all equities and the equally weighted portfolio



Comparison between scatter plots of all equities and the equally weighted portfolio



As observed, the data points of the equally weighted portfolio (in black) are closer to the fitted line compared to the individual equities, which generally suggests that the CAPM model fits the portfolio's returns more closely than it does for individual stocks and thus confirms our analysis above.

This line of reasoning is related to the financial concept of diversification, which states that thanks to the investment in a wide range of assets we limit our exposure to risks that affect assets singularly. From this we can explain the steep drop in the significance of the alpha parameter in the portfolio case, as risk factors that may have affected the performance of single stocks have a much smaller impact on the performance of the portfolio. As a result, it could be that the increase in significance of the beta parameter could be attributed to this lessened impact of idiosyncratic risks.

4. Diagnostic Tests

In this section, we performed diagnostic tests to assess the validity of the assumptions underpinning the CAPM model and the presence of specification errors.

4.1. Reset Test Results

The Reset test assesses whether there are misspecifications or omitted variables in the regression model. In the context of our analysis, the RESET test is used to challenge the hypothesis that the relationship between the log returns of the stocks and the overall market returns is linear. The test involves two hypotheses: **(H0)** and **(H1)** such that the null hypothesis for the Reset test is that the model is correctly specified, meaning there are no omitted variables or misspecifications. In other words, the linear functional form of the model is accurate. However, the alternative hypothesis posits that the model is mis-specified and/or there are omitted variables. If the p-value associated with the Reset test is low (below our significance level, 0.05), we reject the null hypothesis in favor of the alternative. This suggests that there is evidence of misspecification in the model.

Running the Reset test, we obtained F-Values and a p-values for each company and the equally weighted portfolio as shown in the table below:

	F-Value	p-value
STMICROELECTRONICS (MIL)	0,092446	0,911766
HEXAGON B	0,093091	0,911178
AIXTRON (XET)	0,100301	0,904644
ASM INTERNATIONAL	0,1416	0,868118
FORTNOX AB	0,196185	0,822133
CAPGEMINI	0,261414	0,770415
BE SEMICONDUCTOR INDUSTRIES	0,335705	0,715526
NORDIC SEMICONDUCTOR	0,371041	0,690832
Portfolio - EW	0,474211	0,623577
LAGERCRANTZ GROUP B	0,515766	0,598406
INFINEON TECHS. (XET)	0,58312	0,559782
NEMETSCHEK (XET)	0,897275	0,41049
SOPRA STERIA GROUP	1,41653	0,246718

SAGE GROUP	1,490591	0,229521
TEMENOS	1,578406	0,210702
SOITEC	1,606911	0,204937
DASSAULT SYSTEMES	1,646841	0,19713
BECHTLE (XET)	1,782347	0,172819
COMPUTACENTER	1,864934	0,159521
REPLY	2,012324	0,138318
SAP (XET)	3,469345	0,034405
ASML HOLDING	3,551489	0,031841
LOGITECH 'R'	3,755175	0,026289
TIETOEVRY	5,11762	0,007415
ALTEN	7,341988	0,000995
AMS-OSRAM AG	7,950432	0,000581
AMADEUS IT GROUP	12,54126	1,17E-05

Analyzing the table above, for CAPGEMINI, the Reset test yielded an F-Value of 0.261414 with a corresponding p-value of 0.770415. The high p-value suggests that there is insufficient evidence to reject the null hypothesis of correct specification for CAPGEMINI which implies that the regression model for CAPGEMINI appears to be appropriately specified, with no apparent functional misspecifications or omitted variables.

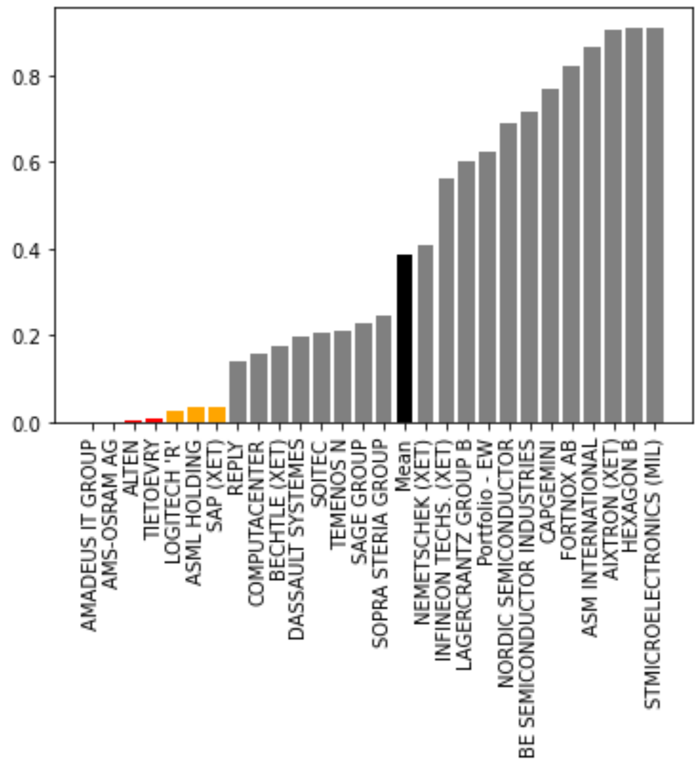
Contrastingly, for TIETOEVRY, the F-Value is 5.11762, and the p-value is 0.007415. The low p-value provides evidence to reject the null hypothesis, indicating a potential misspecification in the regression model for TIETOEVRY. It suggests that there may be omitted variables or other issues affecting the accuracy of the model. Similar conclusions are obtained for LOGITECH ‘R’, ALTEN and AMS-OSRAM AG.

Similarly, for LOGITECH 'R', the F-Value is 3.755175, and the p-value is 0.026289. The significant p-value suggests that there is evidence against the null hypothesis for LOGITECH 'R', pointing towards a potential misspecification in its regression model. Moreover, the results for ALTEN and AMS-OSRAM AG stand out with extremely low p-values of 0.000995 and 0.000581, respectively. These low p-values strongly reject the null hypothesis, indicating a high likelihood of misspecification in the regression models for ALTEN and AMS-OSRAM AG.

On the other hand, the equally weighted portfolio shows an F-Value of 0.474211 with a p-value of 0.623577. The high p-value suggests that there is no significant evidence to reject the null hypothesis for the equally weighted portfolio, implying that the model for the portfolio appears to be correctly specified.

For a better visualization, below is a graph of p-values and the mean of all p-values with colors representing the same cases as explained for the RESET test plot:

Reset test: p-values of companies and portfolio- EW



The RESET test null hypothesis is, therefore, rejected for 7 out of the 26 stocks, indicating the possibility of omitted variables (that we address below with the introduction of additional regressors), structural breaks (that we address below with the use of the Chow test) or the presence of non-linearities.

4.2. White test

In order to assess the presence of heteroscedasticity in our regression models, we conducted the White test. In the context of our analysis, it challenges the hypothesis of the Gauss-Markov theorem that the residuals are homoscedastic which underpins the theorem's implication that the OLS estimator is the linear unbiased estimator with minimum variance. This diagnostic test helps evaluate whether the variance of the errors is constant across all levels of the independent variables.

The null hypothesis (**H0**) assumes homoscedasticity, where the variance of errors is constant, while the alternative hypothesis (**H1**) suggests the presence of heteroscedasticity, indicating varying error variances. A refusal of the null hypothesis implies that the OLS estimators are no longer the Best Unbiased Linear Estimators and that the standard errors of the estimators are biased, therefore making our hypothesis testing on the coefficients invalid.

The results of the White test, presented in the table below, provide insights into the potential heteroscedasticity across individual equities and the equally weighted portfolio. (The lower p-values (under 2%) in the chart are in orange)

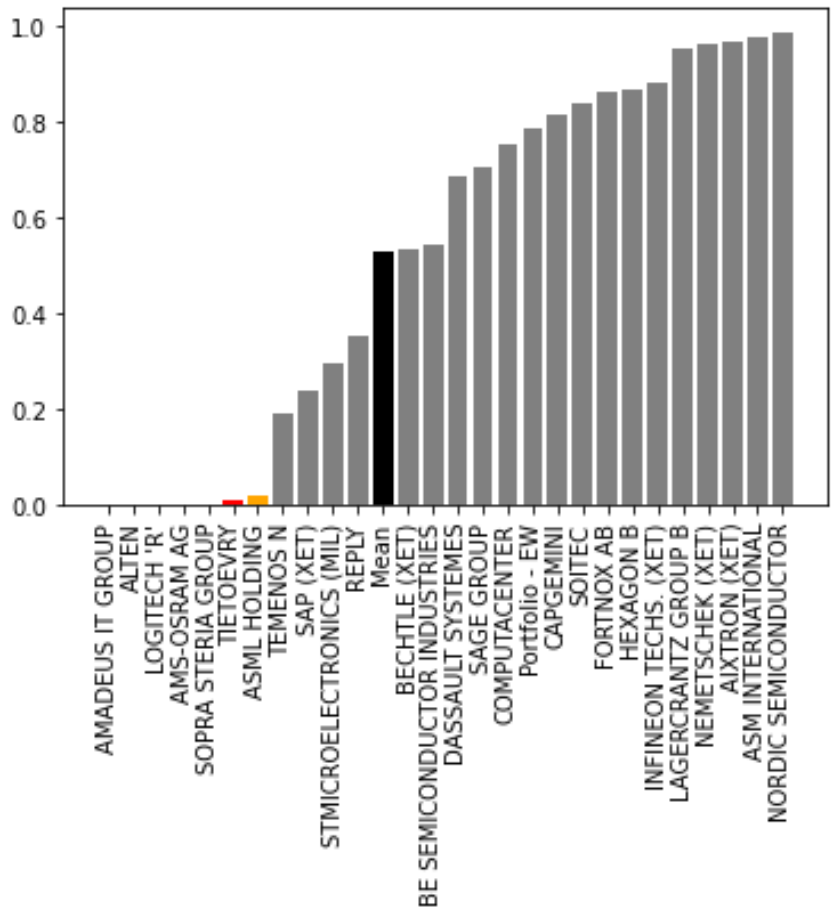
	F-Value	**p-value**
NORDIC SEMICONDUCTOR	0,0125201	0,9875593
ASM INTERNATIONAL	0,027552	0,9728304
NEMETSCHEK (XET)	0,0380848	0,9626433
AIXTRON (XET)	0,0386503	0,9620994
LAGERCRANTZ GROUP B	0,0495157	0,9517101
INFINEON TECHS. (XET)	0,124079	0,8834261
HEXAGON B	0,1414296	0,8682645
FORTNOX AB	0,1500906	0,8607955
SOITEC	0,177614	0,8374909
CAPGEMINI	0,2089027	0,8117762

Portfolio - EW	0,2438994	0,7839638
COMPUTACENTER	0,282556	0,7543673
SAGE GROUP	0,3540769	0,7025704
DASSAULT SYSTEMES	0,3791511	0,6852801
BE SEMICONDUCTOR INDUSTRIES	0,6111336	0,5444586
BECHTLE (XET)	0,6278236	0,5355406
Mean	3,3220543	0,5261434
REPLY	1,0524675	0,3523564
STMICROELECTRONICS (MIL)	1,2399911	0,2931613
SAP (XET)	1,4476048	0,2393127
TEMENOS N	1,6862532	0,1896818
ASML HOLDING	4,2641479	0,0163113
TIETOEVRY	4,8425979	0,009537
SOPRA STERIA GROUP	8,3065619	0,0004233
AMS-OSRAM AG	9,413766	0,0001618
LOGITECH 'R'	9,5309765	0,0001463
ALTEN	14,491163	2,384E-06

AMADEUS IT GROUP	29,952858	3,133E-11

We present below a graph that represents the p-values for a better visualization.

White test: p-values of companies and portfolio-EW



Notably, several companies exhibit substantial evidence of heteroscedasticity, as indicated by their low p-values. For instance, AMADEUS IT GROUP, ALTEN, LOGITECH 'R', AMS-OSRAM AG, and SOPRA STERIA GROUP demonstrate F-values ranging from 8.31 to 29.90 with exceptionally low p-values (ranging from 3.25E-11 to 0.00042). These results strongly suggest that the variance of errors in predicting returns for these companies is not constant, highlighting potential challenges on the validity of our hypothesis testing on the parameters and on the conclusion that the OLS estimators are the BLUE estimators. In contrast, certain companies, including BECHTLE (XET), BE SEMICONDUCTOR INDUSTRIES, DASSAULT SYSTEMES, SAGE GROUP, COMPUTACENTER, and the equally weighted portfolio, show F-values with p-values above 0.05 which suggests a lack of strong evidence for heteroscedasticity in their regression models. While the mean p-value is above our significance level of 0.05, the individual company results underscore the importance of considering heteroscedasticity on a case-by-case basis.

As mentioned above, the results of this test were used to inform the type of standard errors that are used in the estimation of the linear regression model.

4.3. Durbin-Watson Test

The Durbin-Watson test is used to detect the presence of first-order autocorrelation in the residuals of a regression model. Autocorrelation occurs when the residuals are correlated with each other, violating the assumption of independence of the Gauss-Markov theorem and with similar consequences for the presence of heteroskedasticity presented above. The test statistic ranges from 0 to 4, with critical values that have to be recovered from tables.

For this reason, we used the critical values (**DL** representing the lower critical value and **DU** representing the upper critical value) at 1% and 5% confidence level for a model with 100 observations (in our sample we have 120), one regressor and an intercept. We divided the test results, for clarity purposes, into two cases:

1) The null hypothesis (**H0**) is the absence of **positive autocorrelation** in for which if the value **d** of the test statistic is:

a) d < DL: there is statistical evidence that the error terms are positively autocorrelated.

b) d > DU there is **no** statistical evidence that the error terms are positively correlated.

c) DL < d < DU the test is inconclusive.

2) The null hypothesis (**H0**) is the absence of **negative autocorrelation** in for which if the value **d** of the test statistic is:

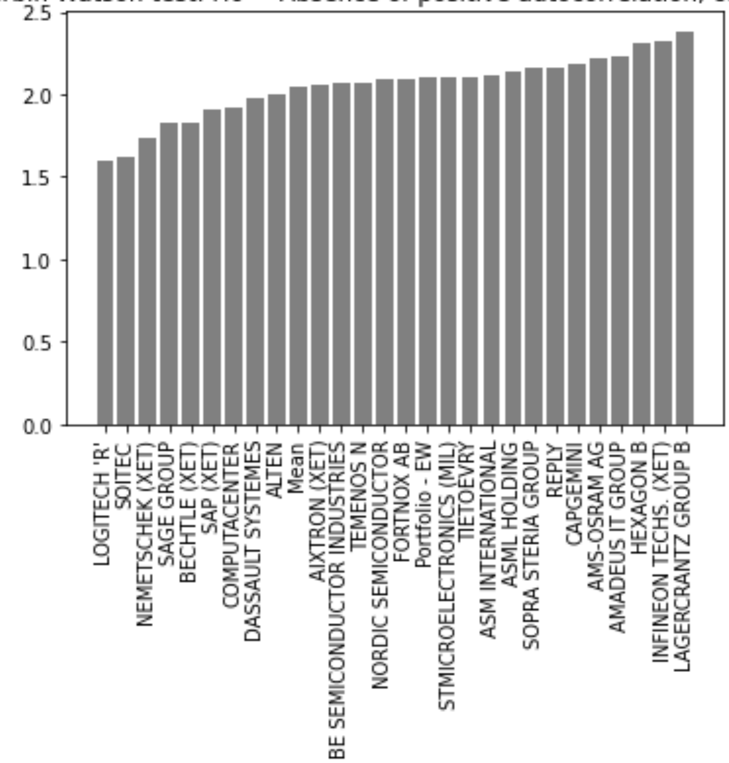
a) (4-d) < DL: there is statistical evidence that the error terms are negatively autocorrelated.

b) (4-d) > DU there is **no** statistical evidence that the error terms are negatively correlated.

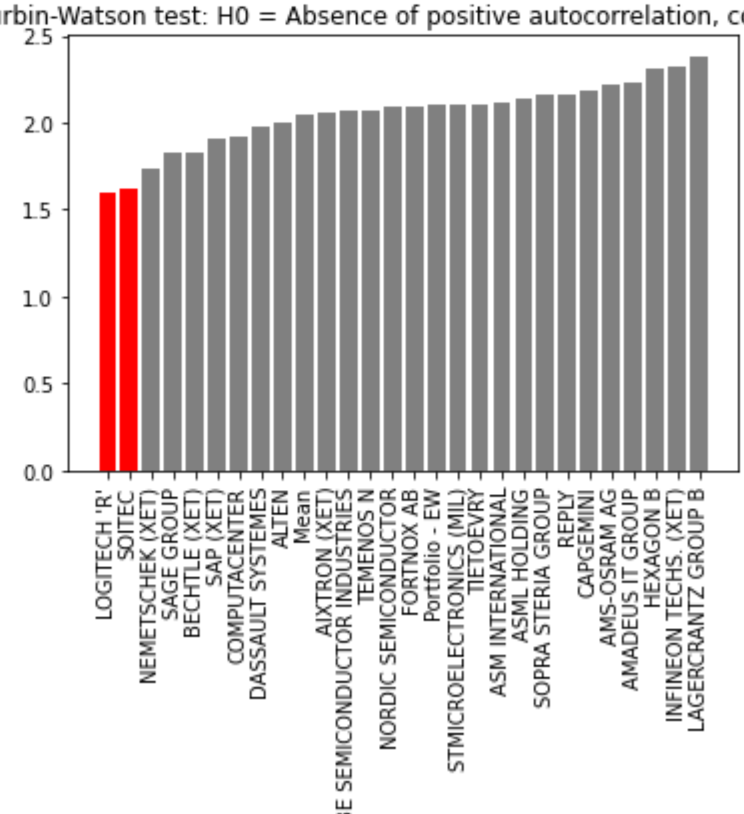
c) DL < (4-d) < DU the test is inconclusive.

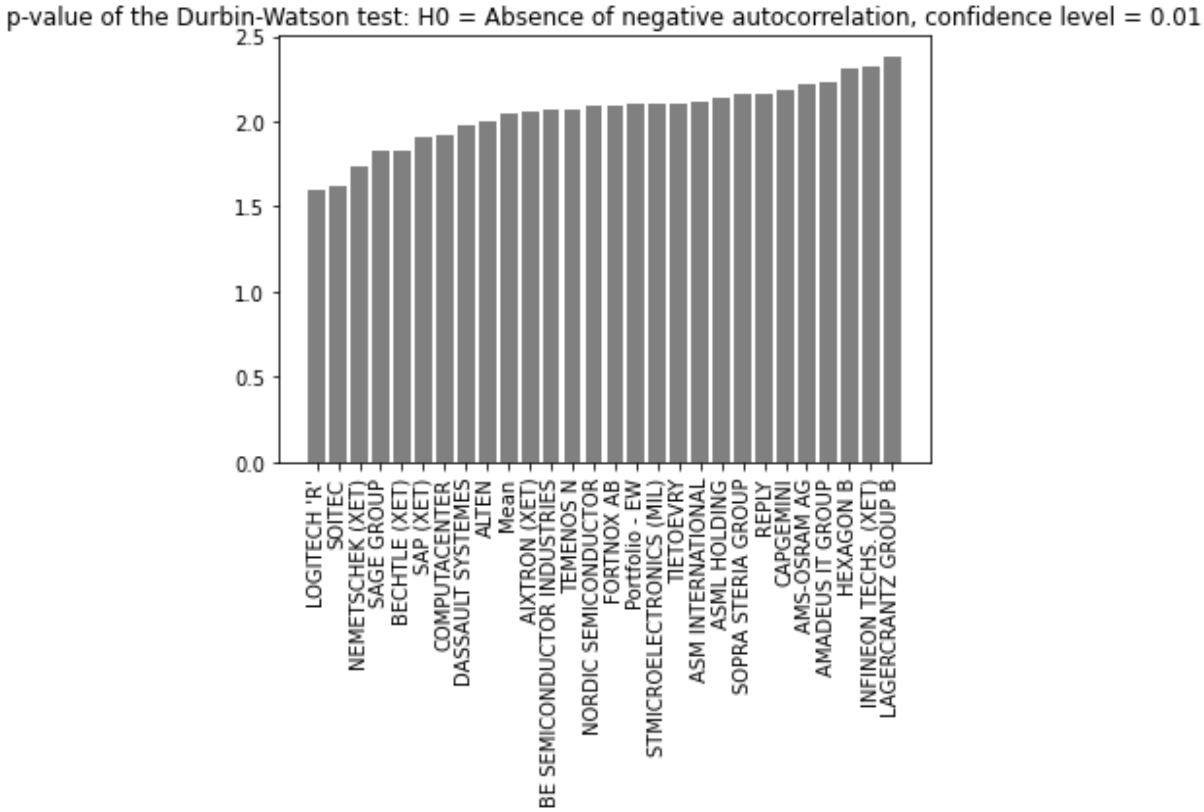
For a visual representation, we present the following plots, in which the color red indicates that we reject the null hypothesis at the confidence level specified in the title of the plot, the color gray indicates that we do not reject the null hypothesis and the color blue indicates that the test is inconclusive.

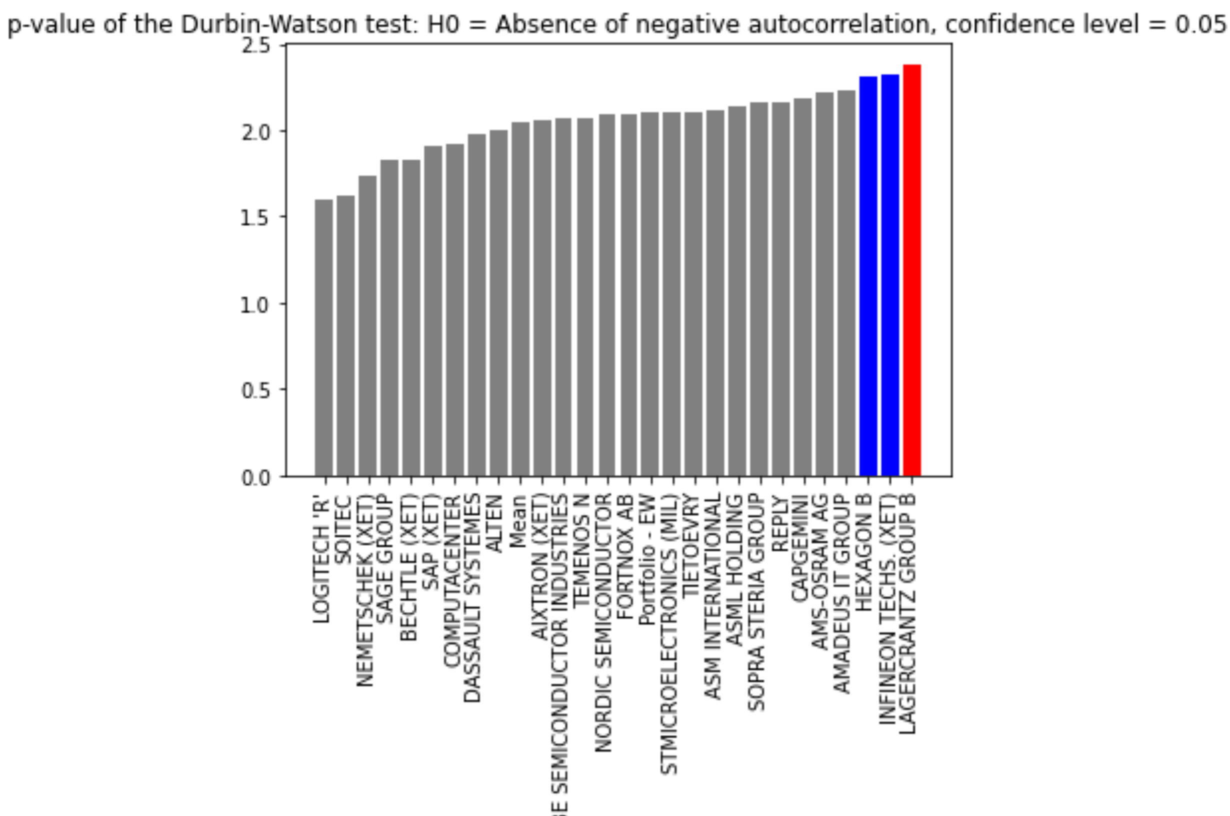
p-value of the Durbin-Watson test: H0 = Absence of positive autocorrelation, confidence level = 0.01



p-value of the Durbin-Watson test: H0 = Absence of positive autocorrelation, confidence level = 0.05




p-value of the Durbin-Watson test: H0 = Absence of negative autocorrelation, confidence level = 0.01
2.5
2.0
1.5
1.0
0.5
0.0
LOGITECH 'R'
SOITEC
NEMETSCHEK (XET)
SAGE GROUP
BECHTLE (XET)
SAP (XET)
COMPUTACENTER
DASSAULT SYSTEMES
ALTEN
Mean
AIXTRON (XET)
BE SEMICONDUCTOR INDUSTRIES
TEMENOS N
NORDIC SEMICONDUCTOR
FORTNOX AB
Portfolio - EW
STMICROELECTRONICS (MIL)
TIETOEVRY
ASM INTERNATIONAL
ASML HOLDING
SOPRA STERIA GROUP
REPLY
CAPGEMINI
AMS-OSRAM AG
AMADEUS IT GROUP
HEXAGON B
INFINEON TECHS. (XET)
LAGERCRANTZ GROUP B


p-value of the Durbin-Watson test: H0 = Absence of negative autocorrelation, confidence level = 0.05
2.5
2.0
1.5
1.0
0.5
0.0
LOGITECH 'R'
SOITEC
NEMETSCHEK (XET)
SAGE GROUP
BECHTLE (XET)
SAP (XET)
COMPUTACENTER
DASSAULT SYSTEMES
ALTEN
Mean
AIXTRON (XET)
BE SEMICONDUCTOR INDUSTRIES
TEMENOS N
NORDIC SEMICONDUCTOR
FORTNOX AB
Portfolio - EW
STMICROELECTRONICS (MIL)
TIETOEVRY
ASM INTERNATIONAL
ASML HOLDING
SOPRA STERIA GROUP
REPLY
CAPGEMINI
AMS-OSRAM AG
AMADEUS IT GROUP
HEXAGON B
INFINEON TECHS. (XET)
LAGERCRANTZ GROUP B

From the images above, we conclude that we have 3 stocks that exhibit serial correlation in the residuals at a 5% confidence level, indicating the need to use HAC standard errors for those stocks. However, due to the inconclusive nature of the test for some of the stocks, there is the need for further analysis on the possible presence of serial correlation among the residuals.

4.4. Breusch-Godfrey Test

The Breusch-Godfrey test is, in a way, an extension of the Durbin-Watson test for the detection of higher-order autocorrelation, making it a valuable tool in assessing the overall autocorrelation structure in our residuals. The null hypothesis of the Breusch-Godfrey test is that there is no serial correlation in the residuals of the regression model, while the alternative hypothesis of the test is that there is serial correlation in the residuals. However, in this case, we can detect autocorrelation also of order higher than 1 by including further lagged values of the residuals in the auxiliary regression.

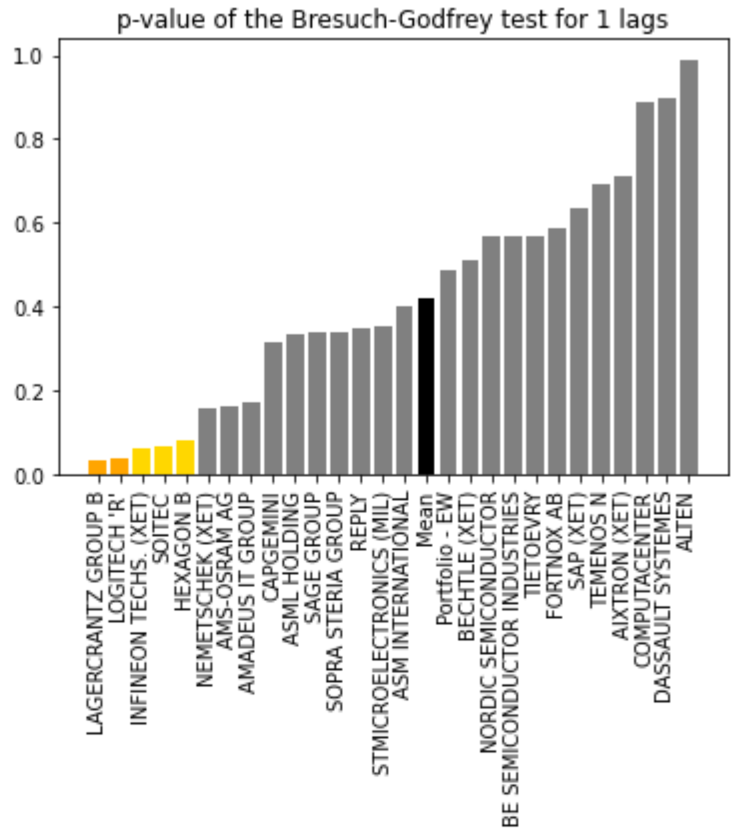
The results are the following:

	F-Value	**p-value**
ALTEN	0.00015	0.99011
DASSAULT SYSTEMES	0.01663	0.89759
COMPUTACENTER	0.02021	0.88719
AIXTRON (XET)	0.13650	0.71244
TEMENOS N	0.15846	0.69130

SAP (XET)	0.22925	0.63296
FORTNOX AB	0.29787	0.58625
TIETOEVRY	0.32966	0.56695
BE SEMICONDUCTOR INDUSTRIES	0.33095	0.56620
NORDIC SEMICONDUCTOR	0.33121	0.56605
BECHTLE (XET)	0.43569	0.51050
Portfolio - EW	0.49012	0.48525
Mean	1.27423	0.41754
ASM INTERNATIONAL	0.70651	0.40231
STMICROELECTRONICS (MIL)	0.87743	0.35083
REPLY	0.89333	0.34652
SOPRA STERIA GROUP	0.91726	0.34016
SAGE GROUP	0.92835	0.33727
ASML HOLDING	0.94943	0.33187
CAPGEMINI	1.02266	0.31397

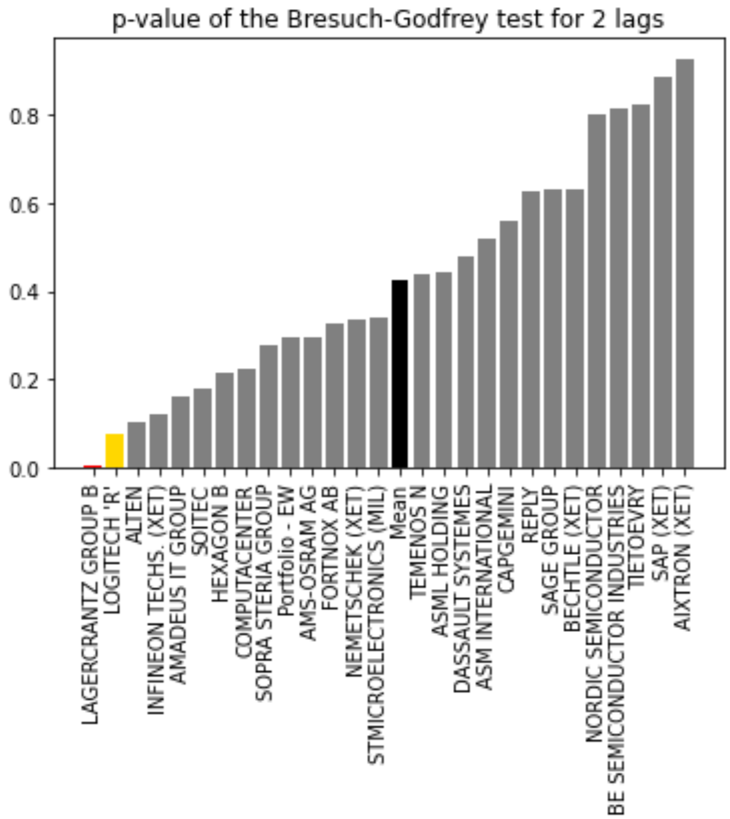
AMADEUS IT GROUP	1.89314	0.17147
AMS-OSRAM AG	2.00930	0.15899
NEMETSCHEK (XET)	2.05550	0.15432
HEXAGON B	3.13332	0.07931
SOITEC	3.51855	0.06317
INFINEON TECHS. (XET)	3.55362	0.061896
LOGITECH 'R'	4.56174	0.03477
LAGERCRANTZ GROUP B	4.60733	0.03390

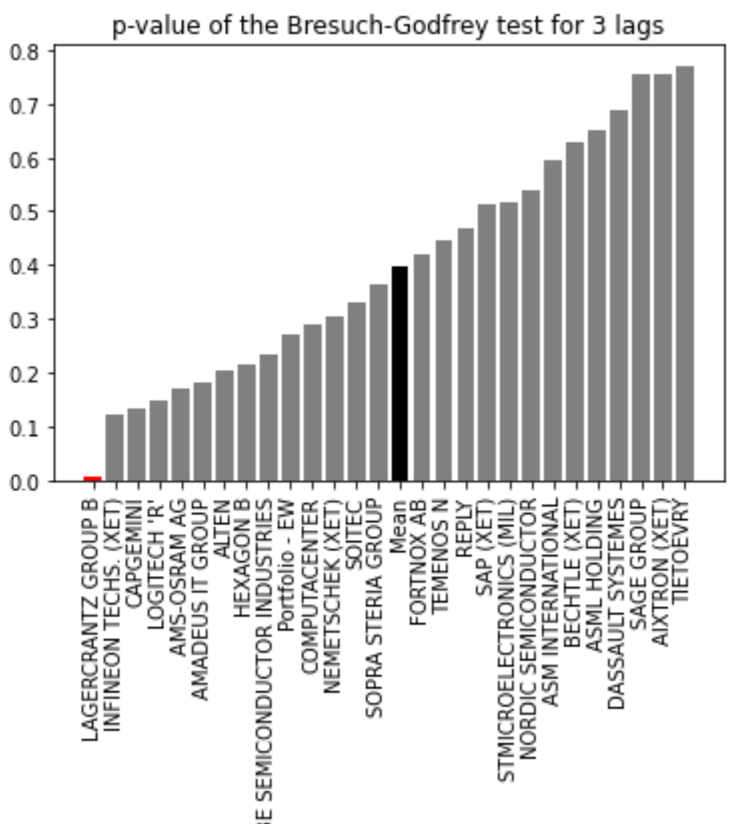
The following plot shows the results of the Breusch-Godfrey test with just one lag of the residual included in the auxiliary regression:



We can see from the results some parallels with the Durbin-Watson test, as the stocks for which the null hypothesis is rejected at a confidence level of 10% are the same for which the null hypothesis of the DW test was rejected at a 5% confidence level or for which the test was inconclusive.

Additionally, we can detect whether there is autocorrelation of higher order by including additional lags in the auxiliary regression.

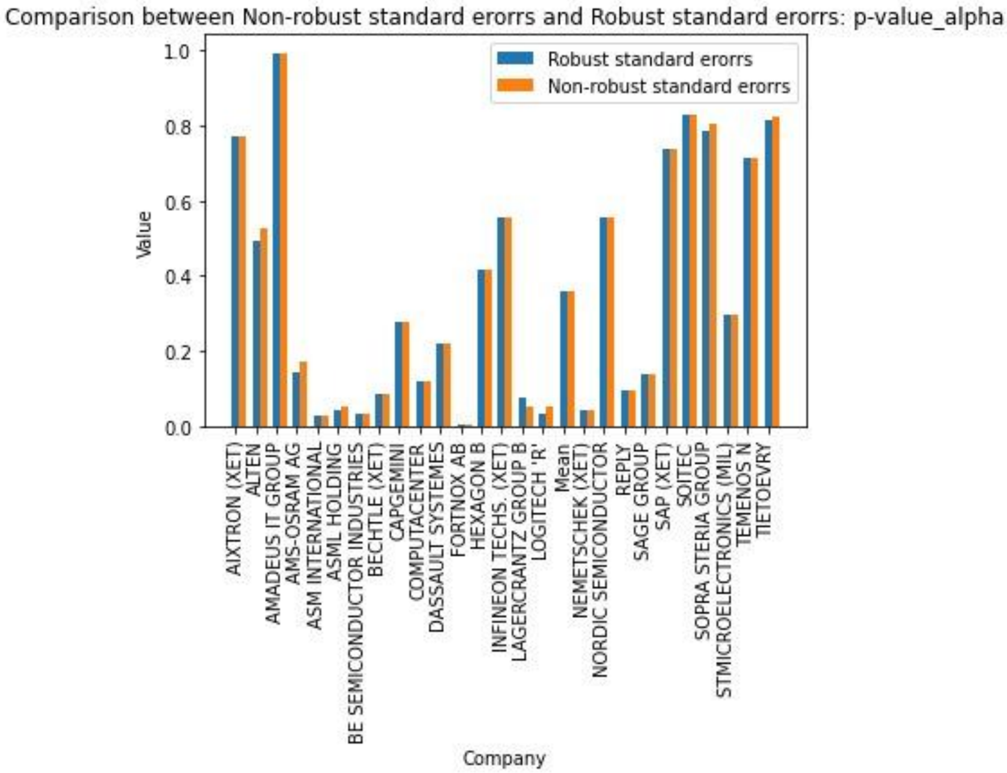

p-value of the Bresuch-Godfrey test for 2 lags
0.0
0.2
0.4
0.6
0.8
LAGERCRANTZ GROUP B
LOGITECH 'R'
ALTEN
INFINEON TECHS. (XET)
AMADEUS IT GROUP
SOITEC
HEXAGON B
COMPUTACENTER
SOPRA STERIA GROUP
Portfolio - EW
AMS-OSRAM AG
FORTNOX AB
NEMETSCHEK (XET)
STMICROELECTRONICS (MIL)
Mean
TEMENOS N
ASML HOLDING
DASSAULT SYSTEMES
ASM INTERNATIONAL
CAPGEMINI
REPLY
SAGE GROUP
BECHTLE (XET)
NORDIC SEMICONDUCTOR
BE SEMICONDUCTOR INDUSTRIES
TIETOEVRY
SAP (XET)
AIXTRON (XET)

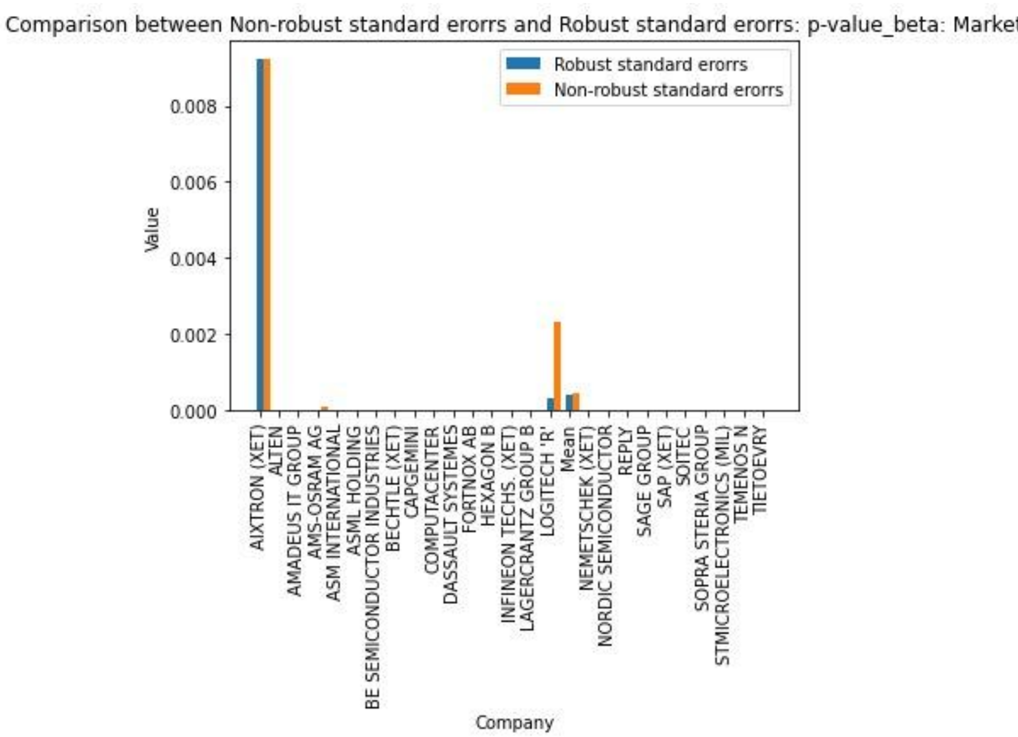

p-value of the Bresuch-Godfrey test for 3 lags
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
LAGERCRANTZ GROUP B
INFINEON TECHS. (XET)
CAPGEMINI
LOGITECH 'R'
AMS-OSRAM AG
AMADEUS IT GROUP
ALTEN
HEXAGON B
BE SEMICONDUCTOR INDUSTRIES
Portfolio - EW
COMPUTACENTER
NEMETSCHEK (XET)
SOITEC
SOPRA STERIA GROUP
Mean
FORTNOX AB
TEMENOS N
REPLY
SAP (XET)
STMICROELECTRONICS (MIL)
NORDIC SEMICONDUCTOR
ASM INTERNATIONAL
BECHTLE (XET)
ASML HOLDING
DASSAULT SYSTEMES
SAGE GROUP
AIXTRON (XET)
TIETOEVRY

From the plots above, we can see that for some of the stocks the autocorrelation is of order higher than 1 which should inform the choice of how many lags we should include for the estimation of the HAC standard errors. However, we proceeded with the inclusion of just one lag, and this could affect the validity of the inference on the two stocks for which a serial correlation among the residuals of order higher than one was detected.

*4.5. **Robust vs non-robust standard errors***

When we use Ordinary Least Squares (OLS) to estimate values in a regression, we assume certain conditions, one of which is that the variability of errors (differences between predicted and actual values) is constant and absence of serial correlation. If these assumptions are violated, meaning the variability isn't constant (heteroskedasticity), or serial correlation is present, OLS estimates might not be as efficient as they could be. To solve this issue, we can use a different method to calculate standard errors, one that's more robust to issues like heteroskedasticity and serial correlation. The method we used is the HAC (Heteroscedasticity and Autocorrelation Consistent) estimator. This method adjusts standard errors to be more reliable in the presence of these issues. To solve this problem, in the OLS estimation we implemented a verification using White test and Breusch Godfrey, so if the p-values are <0.05 then robust estimators are used.





From the plots above we can see that we have some changes in the p-value of the significance test of the parameters as a result of using HAC standard errors. This shows that without the use of these robust standard errors our inference is not valid as a result of the estimators for the standard errors of the parameters being inefficient and biased.

5. Analysis of the model, adding explanatory variables

5.1. Fama French Model

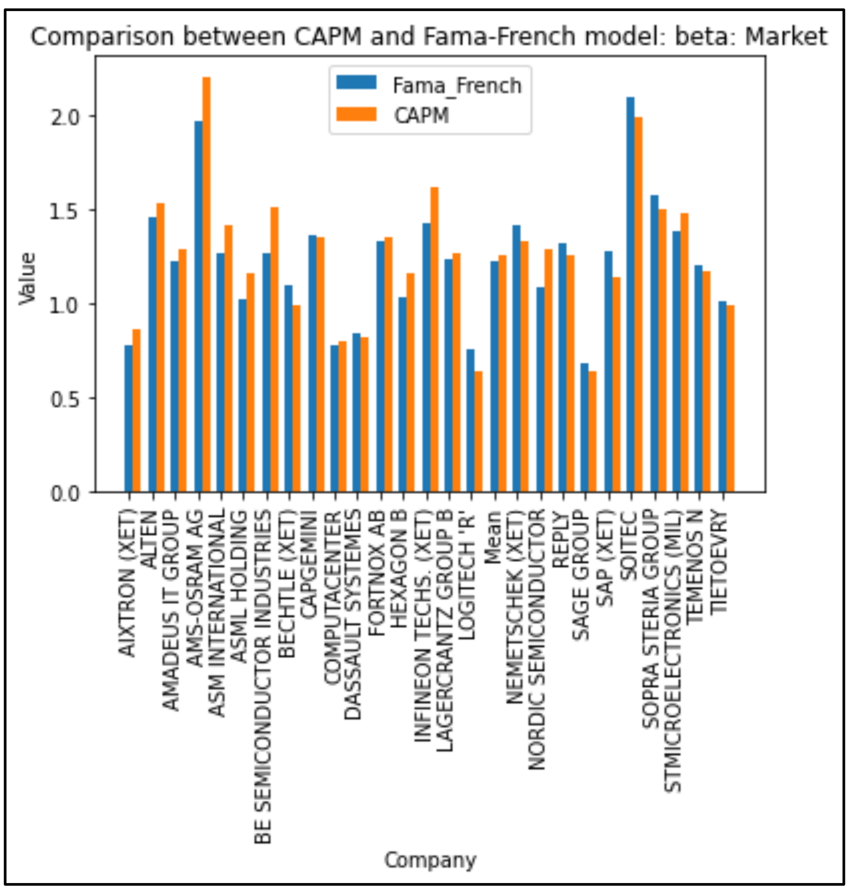
The Fama-French model is an asset pricing model that extends the Capital Asset Pricing Model (CAPM) by incorporating additional factors to better explain the returns on stocks. It was developed by economists Eugene Fama and Kenneth French in the early 1990s. The Fama-French model suggests that the expected return on a stock is influenced not only by the overall market risk but also by additional factors. The factors that we decided to download from the Kenneth France website were:

- **SMB**: (Small Minus Big size factor) This factor captures the historical tendency of smaller companies to outperform larger ones. It suggests that small-capitalization stocks tend to have higher returns than large-capitalization stocks over time.
- **HML**: (High-Minus Low) This factor reflects the historical tendency of value stocks (those with a low price-to-book ratio) to outperform growth stocks (those with a high price-to-book ratio). It suggests that stocks with lower valuation metrics may provide higher returns.
- **MOM**: The momentum factor was introduced to capture the tendency of stocks that have performed well in the past to continue performing well, and vice versa.
- **RMW**: The Robust Minus Weak factor measures the performance difference between companies with robust profitability (high operating profitability) and those with weak profitability.

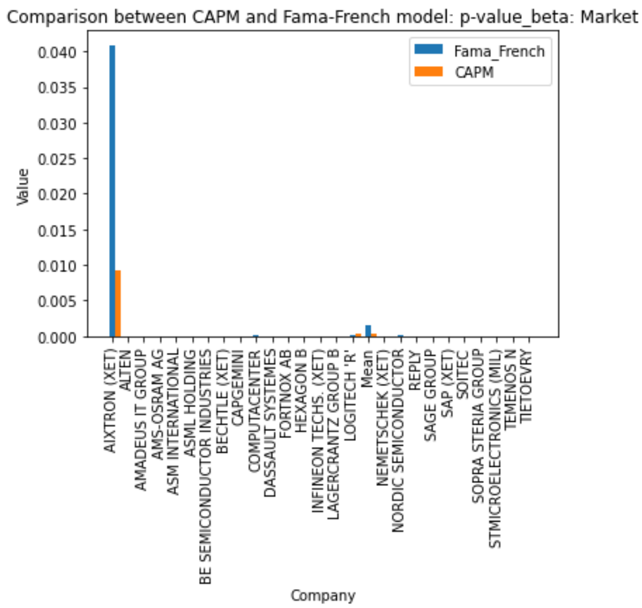
- **CMA:** The Conservative Minus Aggressive factor measures the performance difference between companies that are conservative in their investment policies and those that are aggressive.

5.2. Comparison of the coefficients

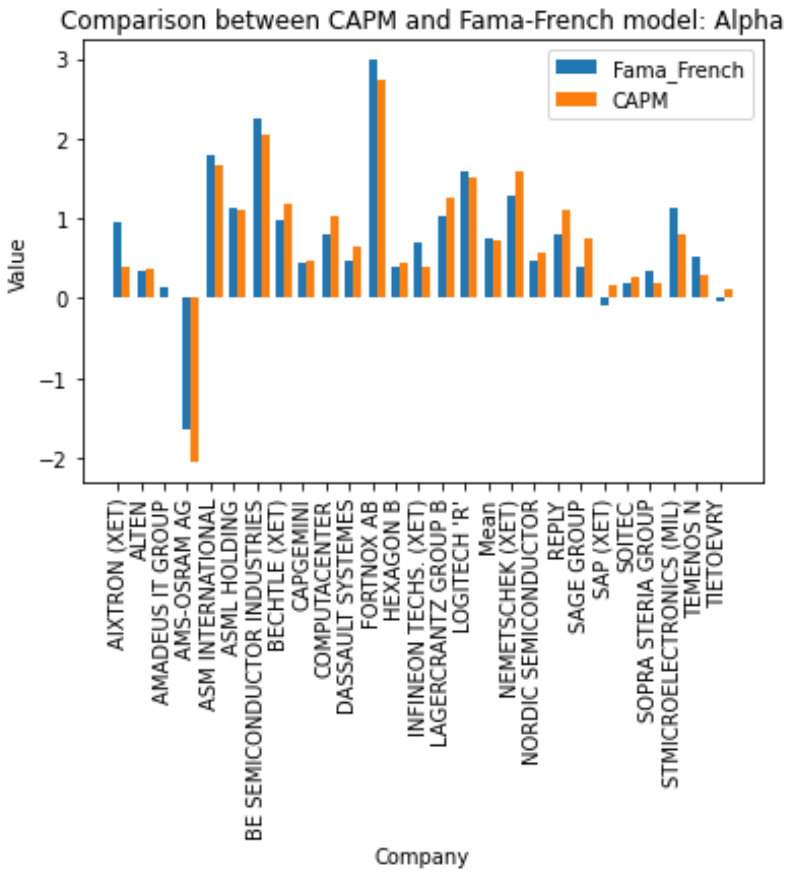
After conducting Ordinary Least Squares (OLS) regression with the expanded model incorporating additional factors, we evaluated the beta coefficients associated with the market factor, contrasting them with our original Capital Asset Pricing Model (CAPM). We can see some differences arising, but no discernible overall pattern on whether the inclusion of additional factors reduces or increases the beta associated with the Market factor.



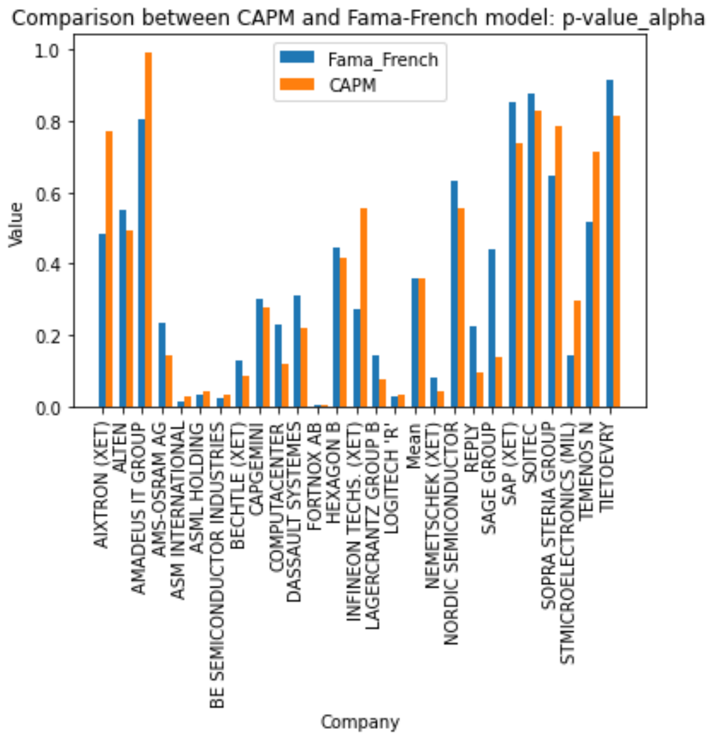
Additionally, the p-values for the new factors remain consistently low, like those observed in the CAPM model, suggesting statistical significance for each equity.



Moreover, a similar analysis was conducted for the alpha values, leading to the generation of the following plot:

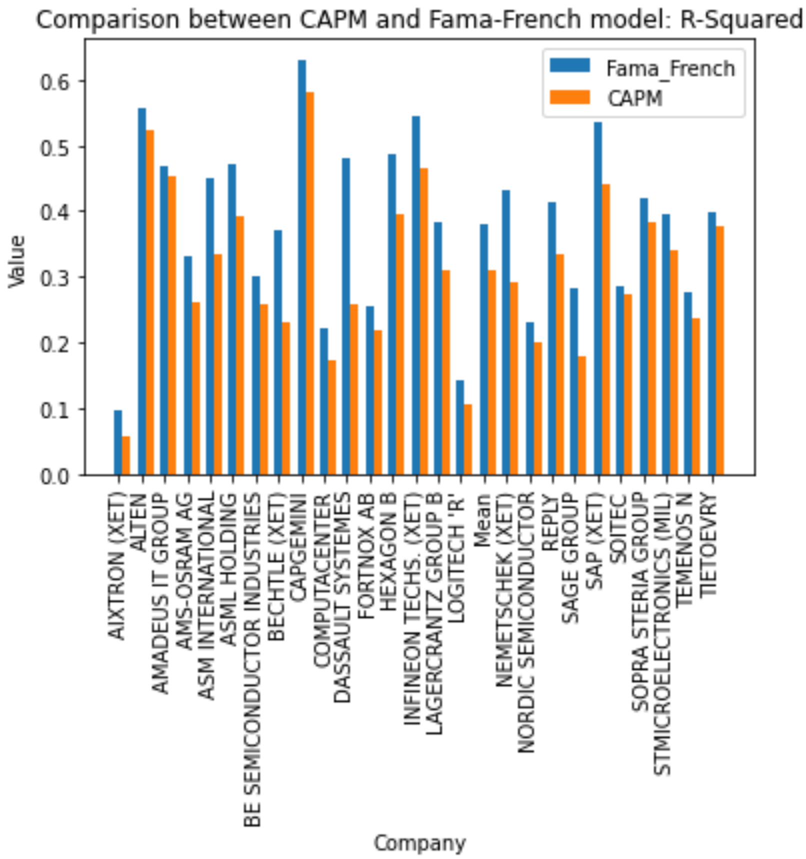


Again, seeing the p-values we can realize that the values are still very high, accepting the null hypotheses.



The Fama-French model includes more factors compared to the simple CAPM, providing a better framework for explaining the variation in the returns. As a result, the model may better explain the observed variation in returns, leading to an increase in R-squared (That we remember is a measure of the fit of the model)

This is what we expected in theory, and is what we obtained, showing it in the following plot:



5.3. Irrelevant variables

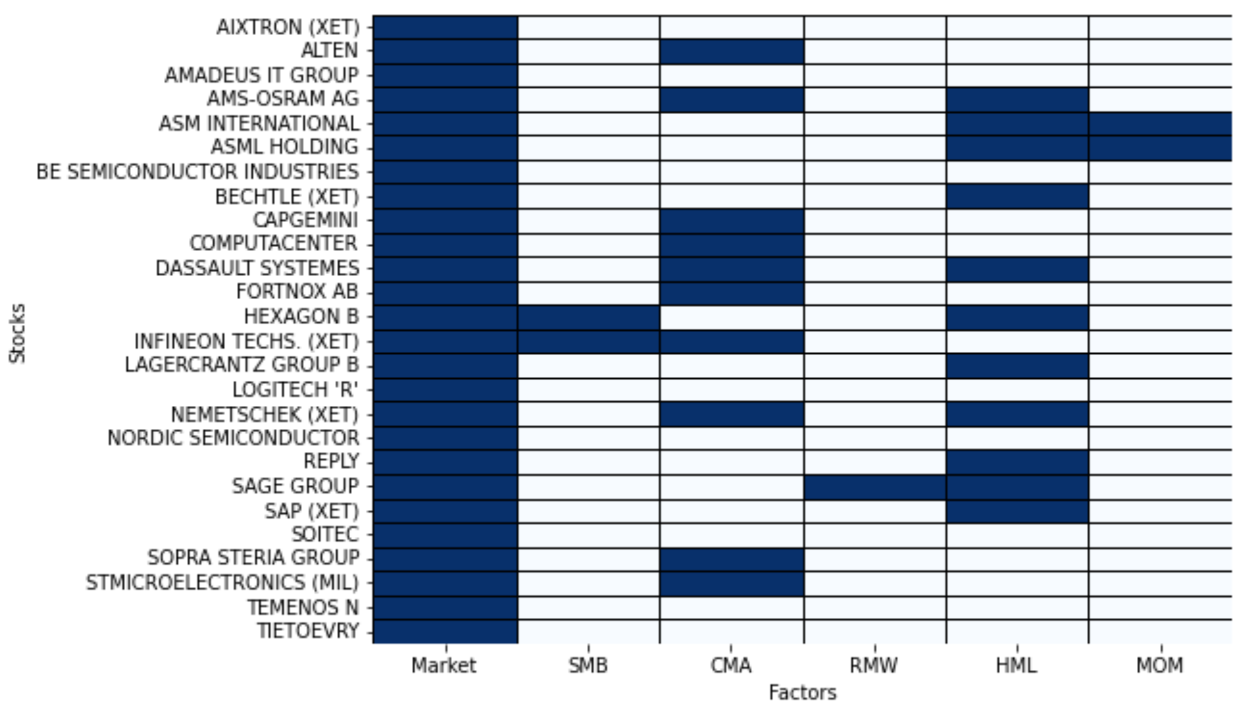
However, seeing as the Fama-French model is estimated using a linear regression model with multiple covariates, we have to take into account the possible presence of irrelevant variables. Therefore, we proceeded with the following algorithm to eliminate the irrelevant variables for each stock which mimics the GETS procedure.

- We estimated the model for each stock using all the factors.
- For every company looked at the factor (HML, MOM…) with the highest p-value and if the p-value is lower than 0.05 we re-estimated the model without that factor.
- In order to choose between the two possible specifications, we used the BIC (Bayesian Information Criterion): as we know, BIC penalizes models with more parameters, making

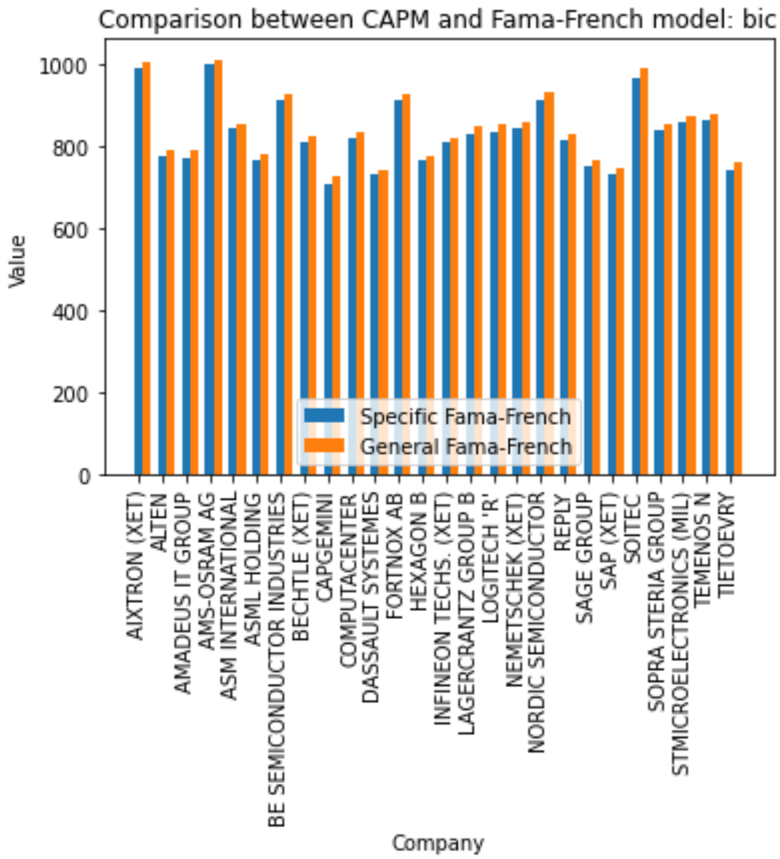
it useful for selecting a model that fits the data well while avoiding overfitting. Lower BIC values indicate a better trade-off between goodness of fit and model complexity.

- If the BIC of the model with one less parameter is smaller, the BIC of model with all the parameters.
- The process stops when there’s no improvement in the fit or there isn’t any more variable whose coefficient has a T-test with p-value smaller than 0.05.

The result is that, for each stock, we can have a different set of factors based on which of the original 6 factors help explain the variability of the log stock returns. The plot below shows the result of this procedure:



As we can see, the market factor is included in the regressors for every stock, highlighting the importance of considering the correlation of a stock with the market when analyzing its risk-return profile. Additionally, we show the plot of the BIC value for the Fama French model with all the factors versus the one resulting from the procedure.



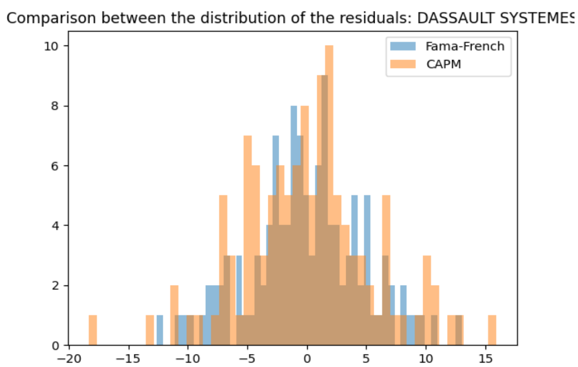
As we can see from the plot, for every stock the procedure has yielded a lower value of the BIC, resulting in a better balance between the increase in fitness that an additional regressor adds and the additional complexity it introduces.

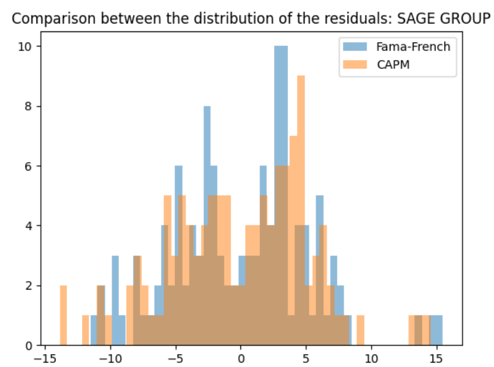
5.4. ***Comparison of the correlation among residuals and their distribution***

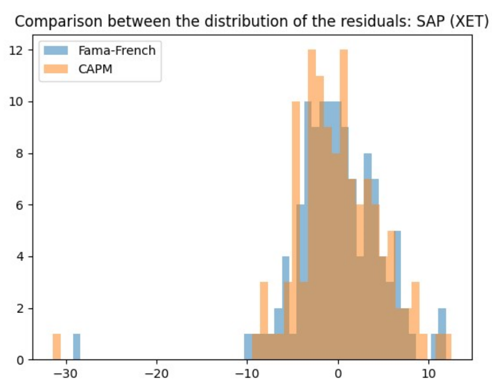
What we did for evaluating the residuals of the new model was to compare their level and distribution with the ones from the CAPM model.

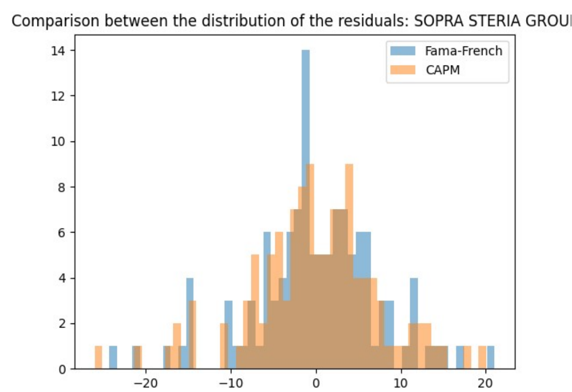
For what concerns the distribution, what we expect for the residuals in this case is something similar to what we had with the CAPM model, as having 0 mean by construction, this is something that we can easily see graphically comparing the distributions of the 2 models.

Mean zero of residuals: This assumption is built into the model because, any deviations from the predicted returns are expected to be random and should balance out to zero over time. Here we put some examples of the histograms produced by comparison between CAPM and Fama-French models.







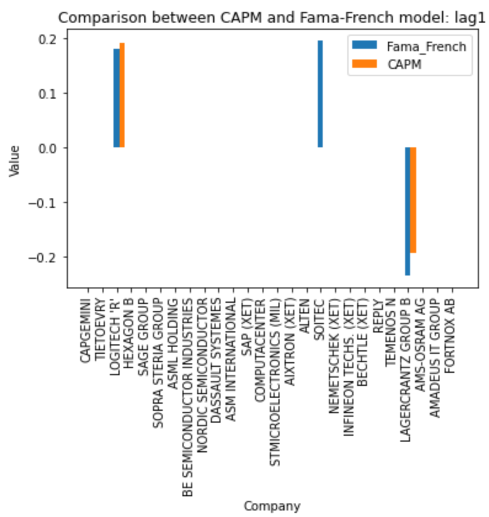


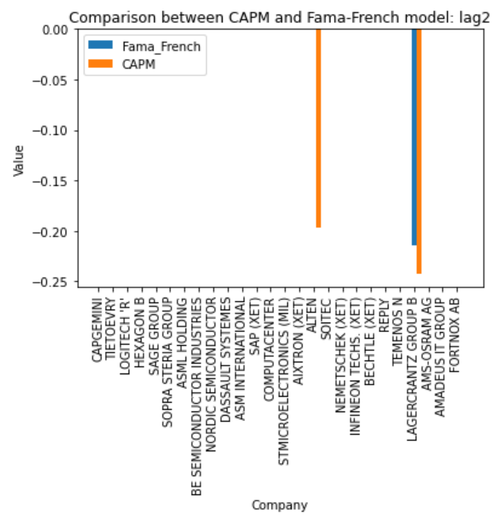
The histograms are following the expected behavior, overlapping in a good way to the ones of the CAPM model, in some of them is more evident, while in others the distribution can have a longer tail to the right or left.

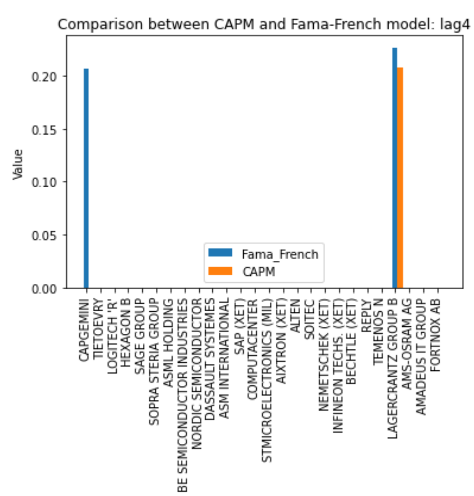
Then we compared the values of the correlations between the residuals. Increasing the lag in this context involves extending the temporal analysis to look for potential variations in residuals over longer periods or with larger time delays.

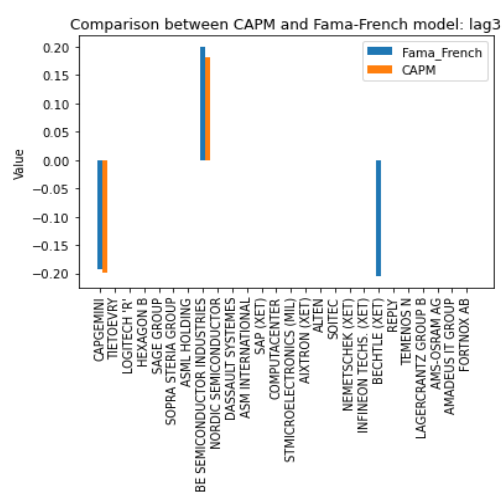
We estimated the correlation coefficient using the PACF applied to the residuals we obtained from the estimation of the two models for each stock. We analyzed the PACF coefficients for the first 4 lags and we considered whether they were or not different from zero by looking at their confidence intervals.

The results are shown in the following plots, from which we can see that for that the values for the correlations are near to 0 for most of the equities, changing in relation to the number of lags:









6. Chow Test

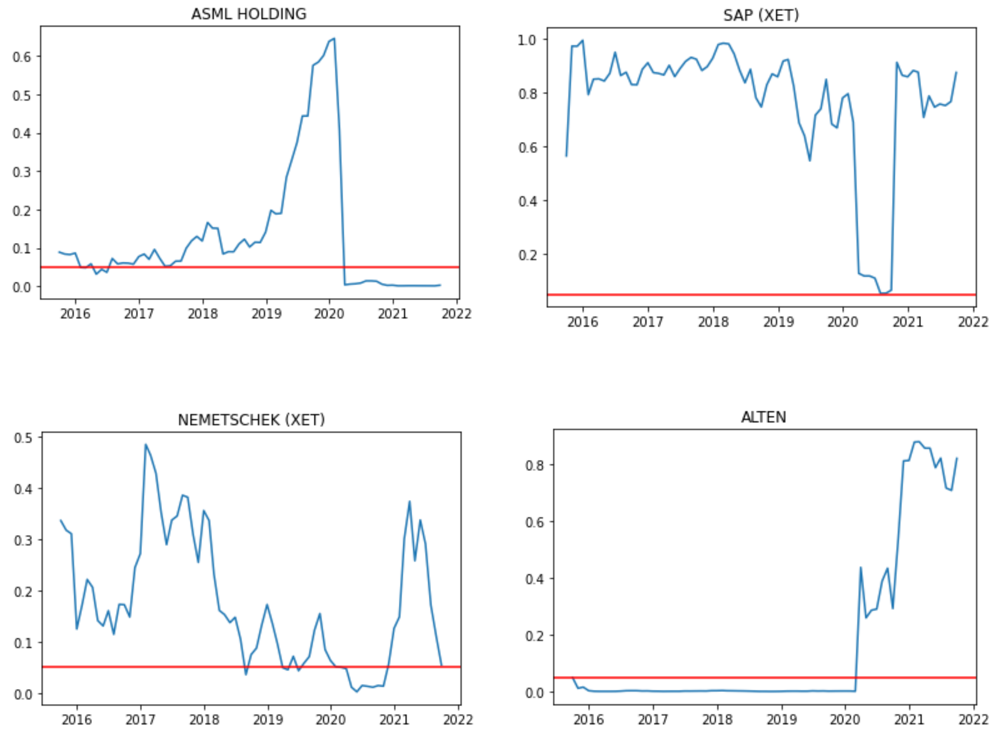
6.1. CAPM Model

The Chow test is a statistical test used to detect whether there is a structural break in a time series regression model. A structural break occurs when there is a significant change in the relationship between the dependent variable and the independent variables.

We conducted the Chow test for structural breaks in the following manner:

- We divided the sample in a first subsample comprising the first 20% of the observations and a second one comprising the remaining 80%.
- We estimated the test statistic for the Chow test and the corresponding p-value.
- We then added the next observation in chronological order to the first subsample while removing it from the second subsample and repeated the step above.
- We kept going until we obtained two subsample that are the mirror image of the starting distribution.

The plots tracking the evolution of the p-value of the test statistic for each possible break date, presented below, reveal that certain equities exhibit apparent break dates while others do not. Some plots for equities with identified break dates are reported. Upon visual inspection, it can be deduced that break dates falling between 2020 and 2021 may be attributed to the impact of the COVID-19 pandemic in some way.

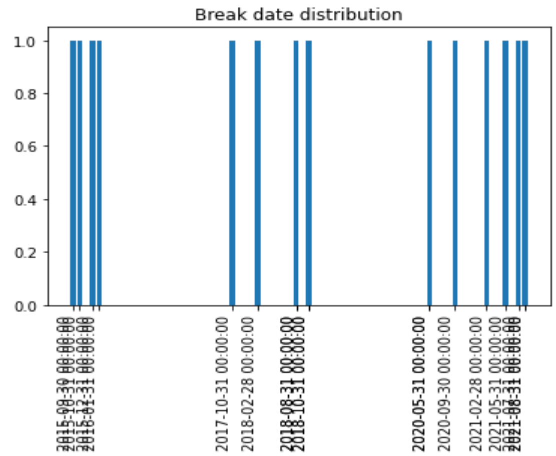


6.2. Finding the Break Dates

In order to find potential break dates, we implemented the following procedure:

- For each stock, we looked at the values of the p-value from the Chow test at each date and found the minimum value.
- If this value was lower than 0.05, then this is our first break date.
- We then re-estimated the Chow test statistic following the above procedure for the remaining sample, if the remaining sample has at least 22 observations.
- Keep going until either we don't find any p-values of the Chow test statistic lower than 0.05 or we don't have enough observations to estimate the Chow test statistic.

To be more specific here we have a plot showing the break date distribution, we can see that they are concentrated in very specific periods of time, 2015, 2017/18 and 2020/21, maybe this can be related to a big change in the market due to external causes.



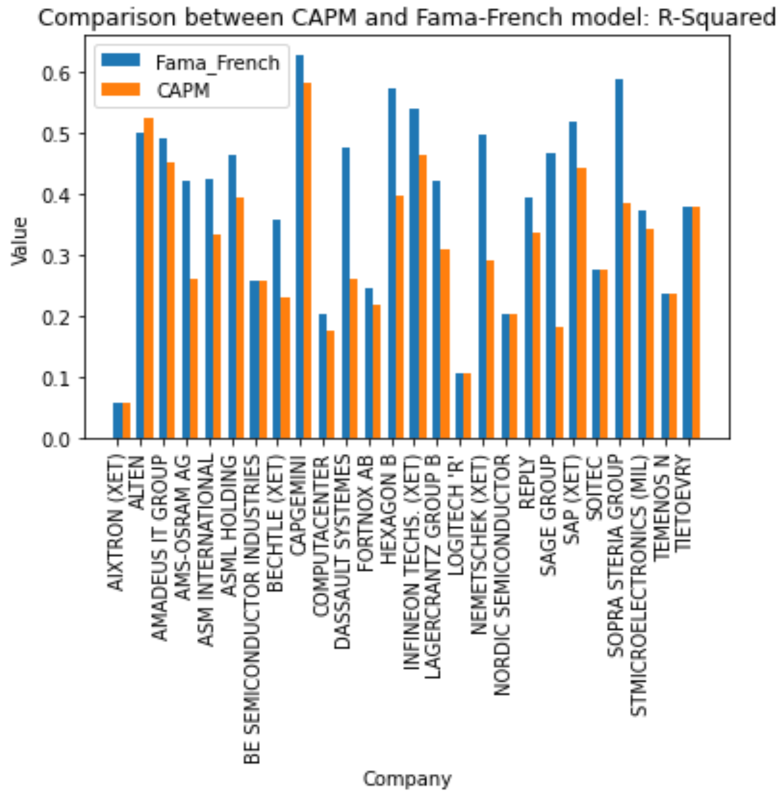
6.3. Fama-French Model

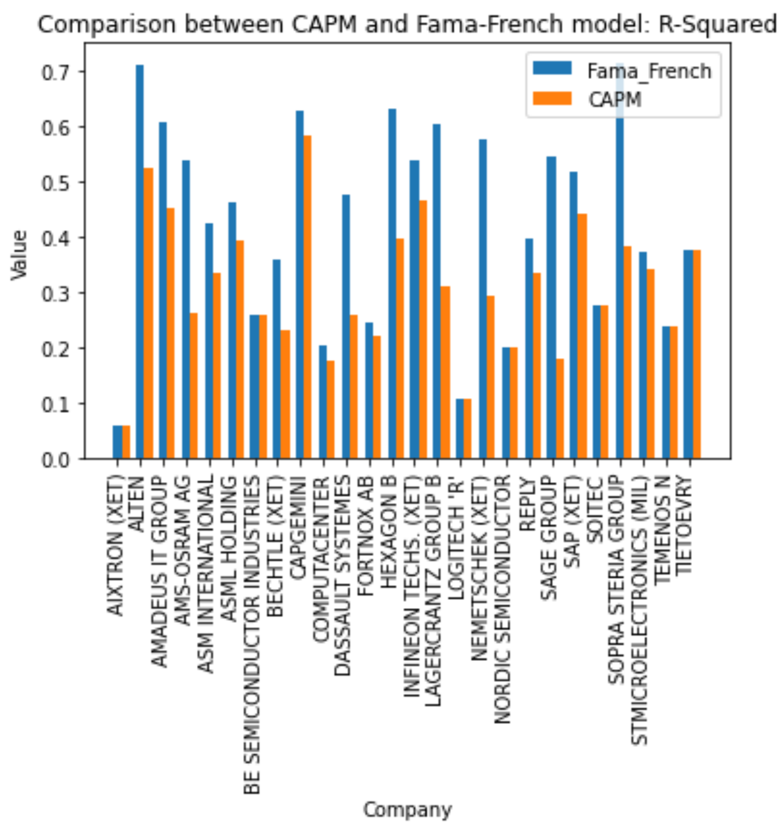
We also looked for break dates for the Fama-French model. For every break date found with the procedure presented above, we did an iterative process that:

- If a break date is found, re-estimating the model from the beginning of the sample to the break date, eliminating the irrelevant values as we explained in the procedure that mimics the GETS procedure.
- Then, we look whether there is an additional break date using the above procedure and if one is found, then we remove the irrelevant variables following the usual procedure.
- We keep going until we don’t find any more break dates, or we don’t have sufficient data for the estimation of the Chow test statistic.

In the end we will store the results of the models estimated and optimized in each interval according to their break dates, in which we could have a different model for every period, being in theory the best model we could find.

We put the plots of the companies shown before to show the improvement in the fitness of the model compared with the CAPM:


Comparison between CAPM and Fama-French model: R-Squared
Fama_French
CAPM
Value
0.0
0.1
0.2
0.3
0.4
0.5
0.6
AIXTRON (XET)
ALTEN
AMADEUS IT GROUP
AMS-OSRAM AG
ASM INTERNATIONAL
ASML HOLDING
BE SEMICONDUCTOR INDUSTRIES
BECHTLE (XET)
CAPGEMINI
COMPUTACENTER
DASSAULT SYSTEMES
FORTNOX AB
HEXAGON B
INFINEON TECHS. (XET)
LAGERCRANTZ GROUP B
LOGITECH 'R'
NEMETSCHEK (XET)
NORDIC SEMICONDUCTOR
REPLY
SAGE GROUP
SAP (XET)
SOITEC
SOPRA STERIA GROUP
STMICROELECTRONICS (MIL)
TEMENOS N
TIETOEVRY
Company


Comparison between CAPM and Fama-French model: R-Squared
Fama_French
CAPM
Value
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
AIXTRON (XET)
ALTEN
AMADEUS IT GROUP
AMS-OSRAM AG
ASM INTERNATIONAL
ASML HOLDING
BE SEMICONDUCTOR INDUSTRIES
BECHTLE (XET)
CAPGEMINI
COMPUTACENTER
DASSAULT SYSTEMES
FORTNOX AB
HEXAGON B
INFINEON TECHS. (XET)
LAGERCRANTZ GROUP B
LOGITECH 'R'
NEMETSCHEK (XET)
NORDIC SEMICONDUCTOR
REPLY
SAGE GROUP
SAP (XET)
SOITEC
SOPRA STERIA GROUP
STMICROELECTRONICS (MIL)
TEMENOS N
TIETOEVRY
Company

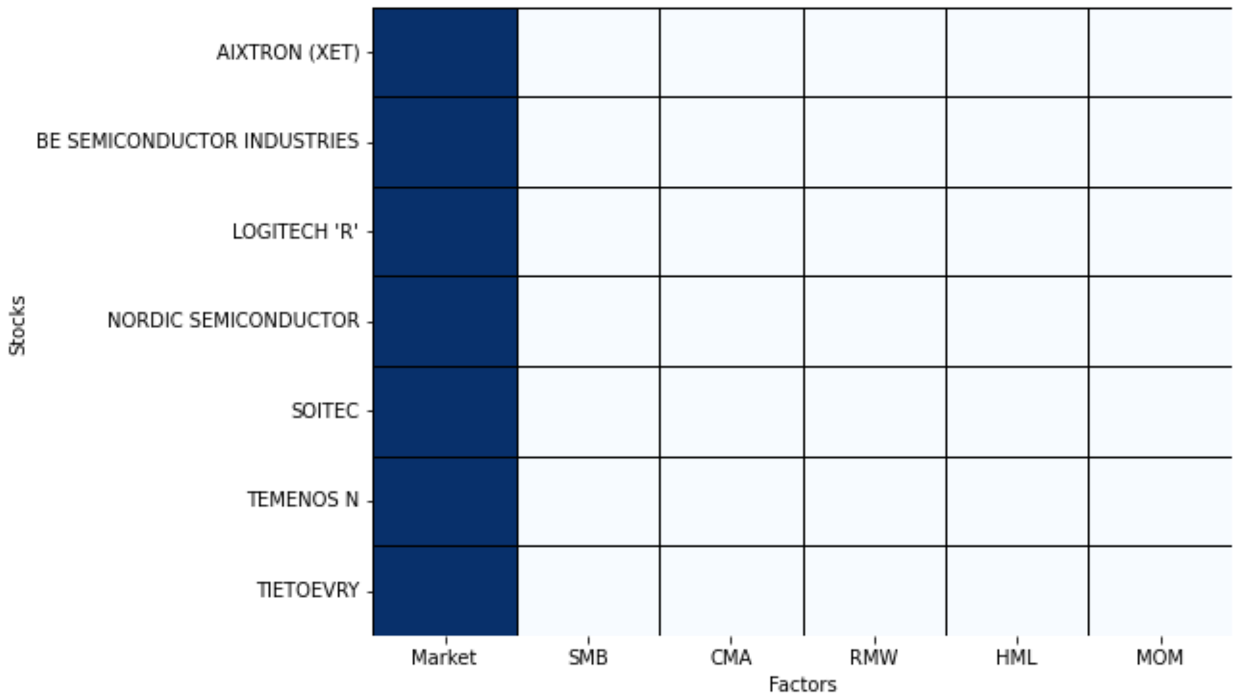
As a result, we have that for each stock we have **n + 1 models** with **n being the number of breaks found**, in order to compare the goodness of the fit between the CAPM and the models we obtained with these procedures we used two approaches:

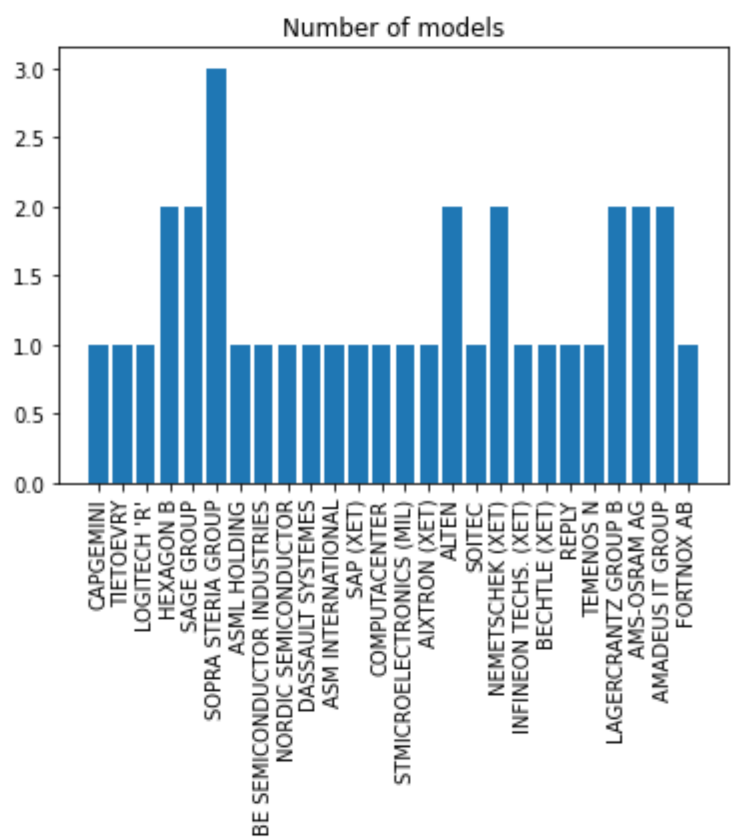
1) We looked at the average value of the R-Squared obtained across the n + 1 models.
2) We looked at the maximum value of the R-Squared obtained across the n + 1 models.

In both plots we can see that we obtained an improvement for all but 6 stocks, which are:

- AIXTRON (XET)
- BE SEMICONDUCTOR INDUSTRIES
- LOGITECH 'R'
- NORDIC SEMICONDUCTOR
- SOITEC
- TEMENOS N
- TIETOEVRY

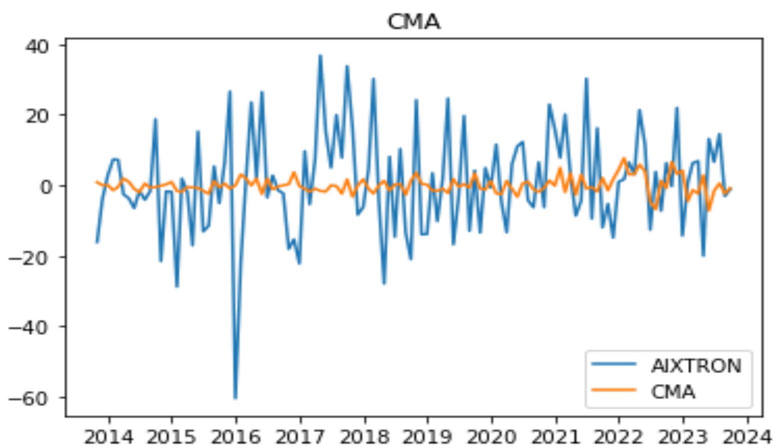
Analyzing as to why that is, we can see from the following two plots that they have 1 model, which means that no structural break was detected and that all the additional Fama-French factors were found to be irrelevant.

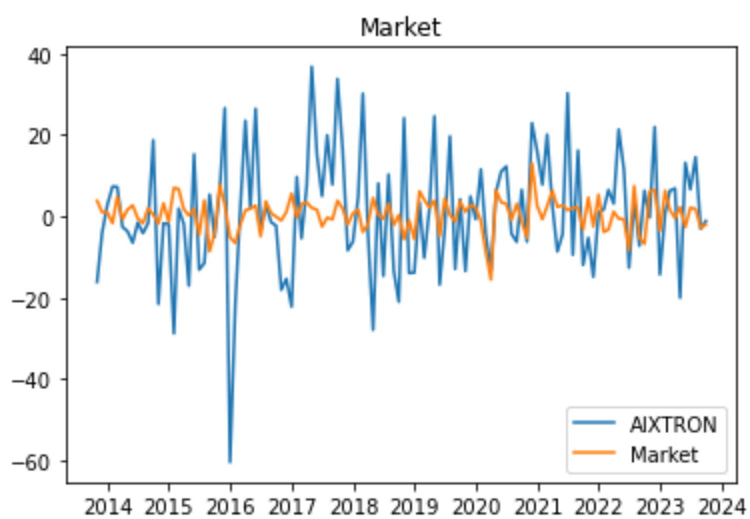

AIXTRON (XET)
BE SEMICONDUCTOR INDUSTRIES
LOGITECH 'R'
NORDIC SEMICONDUCTOR
SOITEC
TEMENOS N
TIETOEVRY
Stocks
Market
SMB
CMA
RMW
HML
MOM
Factors

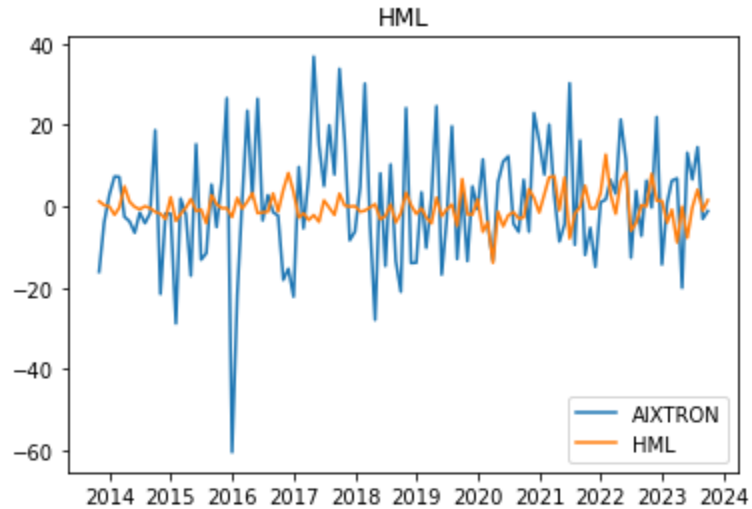

Number of models
0.0
0.5
1.0
1.5
2.0
2.5
3.0
CAPGEMINI
TIETOEVRY
LOGITECH 'R'
HEXAGON B
SAGE GROUP
SOPRA STERIA GROUP
ASML HOLDING
BE SEMICONDUCTOR INDUSTRIES
NORDIC SEMICONDUCTOR
DASSAULT SYSTEMES
ASM INTERNATIONAL
SAP (XET)
COMPUTACENTER
STMICROELECTRONICS (MIL)
AIXTRON (XET)
ALTEN
SOITEC
NEMETSCHEK (XET)
INFINEON TECHS. (XET)
BECHTLE (XET)
REPLY
TEMENOS N
LAGERCRANTZ GROUP B
AMS-OSRAM AG
AMADEUS IT GROUP
FORTNOX AB

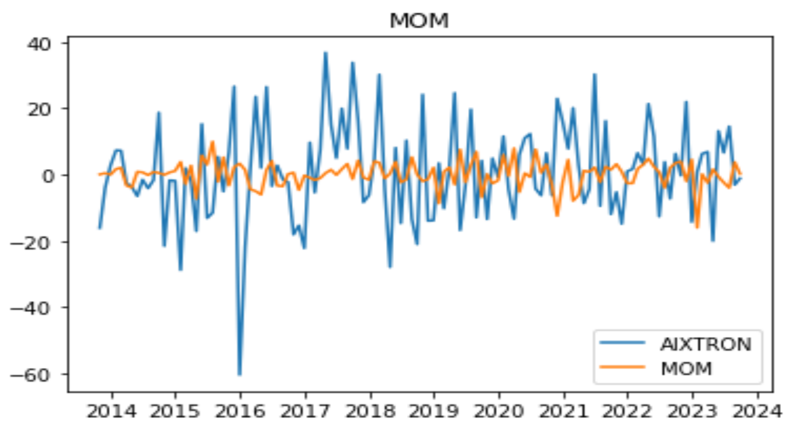
This leads us to conclude that, in order to improve our ability to explain the variability of the log returns for these stocks, we either have to include additional factors, maybe of economic nature, or including the predicted volatility of the stock as an additional factor.

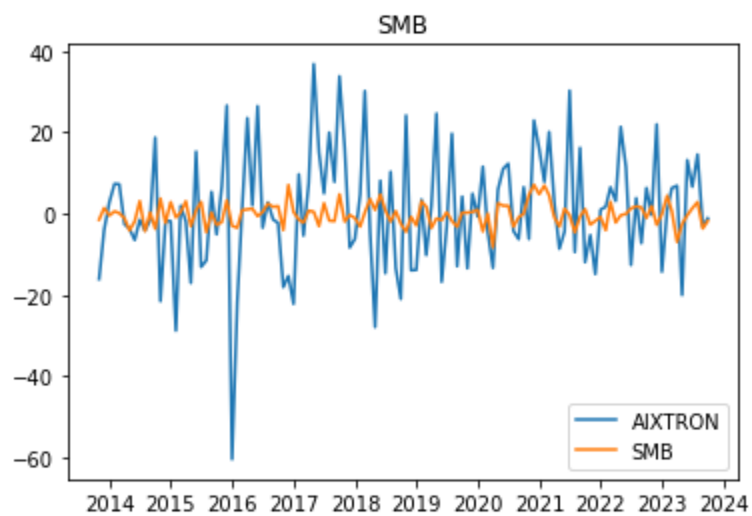
The case for this last possibility can be made by looking, as an example, at the AIXTRON (XET) case, for which we didn't only obtain any improvement through our procedures, but we also obtained an extremely low value for the R-Squared. In fact, by looking at the plots that compare the log returns of this stock and the returns of the market and the portfolios that make up the Fama-French factors, we can see that their volatility pales in comparison to the volatility exhibited by the AIXTRON (XET) stock returns:

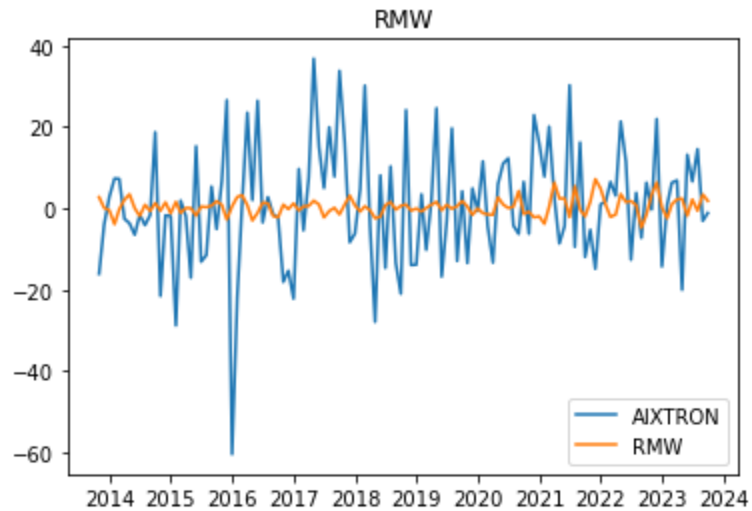





HML
40
20
0
−20
−40
−60
2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024
AIXTRON
HML


MOM
40
20
0
−20
−40
−60
2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024
AIXTRON
MOM


SMB
40
20
0
−20
−40
−60
2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024
AIXTRON
SMB

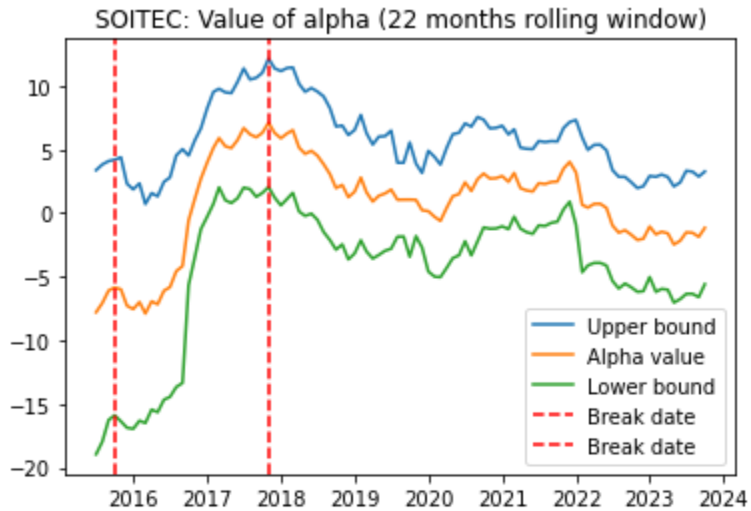


7. Re-estimate the CAPM Model Using a Rolling Window Approach

In this analysis, we employ a rolling window approach to re-estimate the Capital Asset Pricing Model (CAPM) parameters for the selected stocks. The primary objective is to investigate the temporal dynamics of stock returns by employing a moving estimation window and subsequently assessing the stability and significance of the estimated CAPM parameters, namely alpha and beta, along with the R-squared. Due to the presence of multiple breaks at the beginning of the sample, we have estimated these values with both a rolling window of 5 years (60 months) and a rolling window of 22 months to show the possible change in the parameters at the beginning of the sample. This implies that at any given point in time, the CAPM model is re-estimated using a dataset spanning the most recent 5 years or 22 months. The rolling process involved systematically moving the estimation window forward by one month at a time. This step-by-step progression enabled us to examine the dynamic of the CAPM parameters across various time frames and to capture potential changes in the relationships between stock returns and market factors. For the analysis, we are providing plots with Confidence Intervals for alpha and beta in addition to plots without confidence intervals for R-squared.

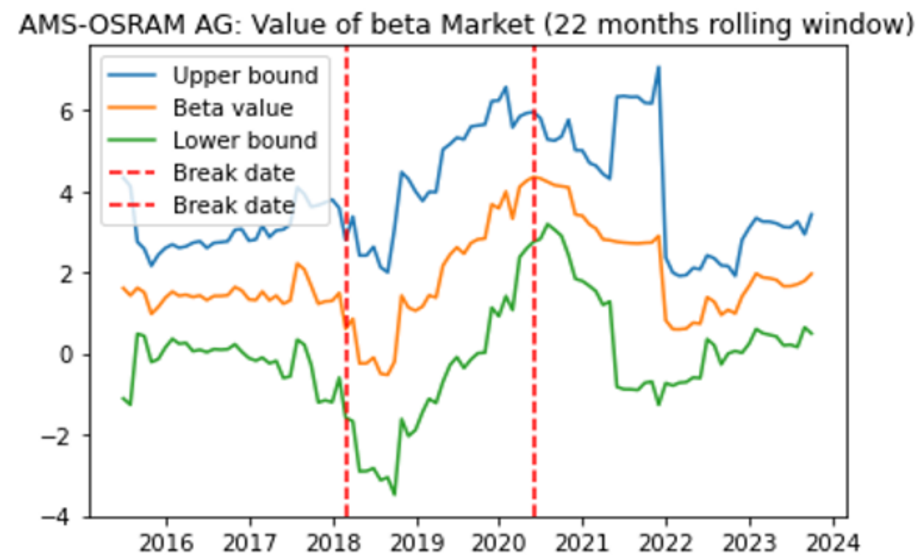
7.1. Alpha Plots

Considering SOITEC, we can see that our procedure identified two distinct breaks, occurring in 2016 and 2018 that marked significant shifts in the behavior of SOITEC's alpha values.



From 2016 to 2018, a substantial increase is observed. This drastic change coincides with the first structural break in the dataset. During this period, the confidence interval for alpha is notably wide, indicative of considerable uncertainty in the model estimates. Following the second break in 2018, a shift in the alpha dynamics is observed. The confidence interval appears relatively narrow, suggesting a higher degree of precision in the estimated alpha values. Alpha remains relatively stable during this period. This stability is reflected in the narrower range between the upper and lower bounds, indicating a more robust estimation of alpha. The relatively steady alpha values post-2018 suggest that the impact of external factors on SOITEC's excess returns may have stabilized, contributing to a more predictable risk-return relationship.

*7.2. **Beta Plots***



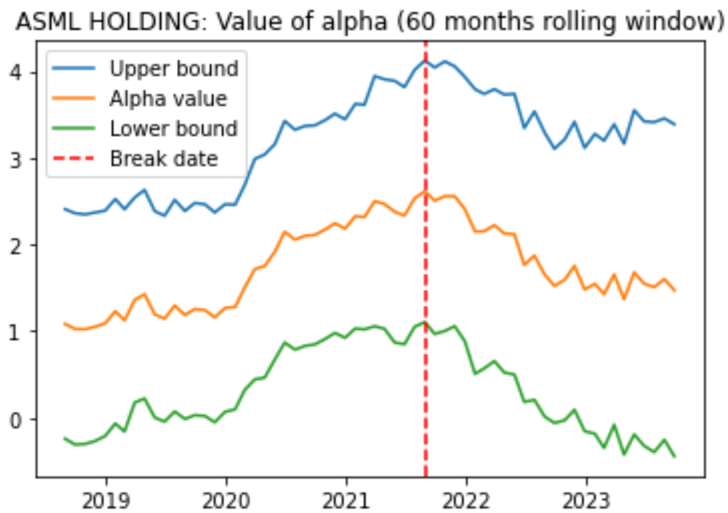
Initially, from 2016 to 2018, the beta values are consistently stable with a narrow confidence interval.

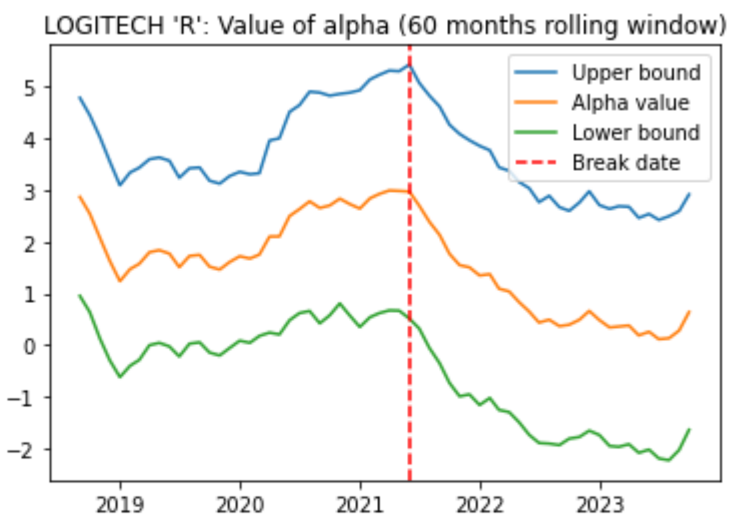
However, a shift occurred in 2018 which has been captured by our choice for the first break, which marked a drop in the beta. Concurrently, the slight widening of the confidence interval may indicate heightened uncertainty or the influence of external factors on the stock's behavior other than the market’s.

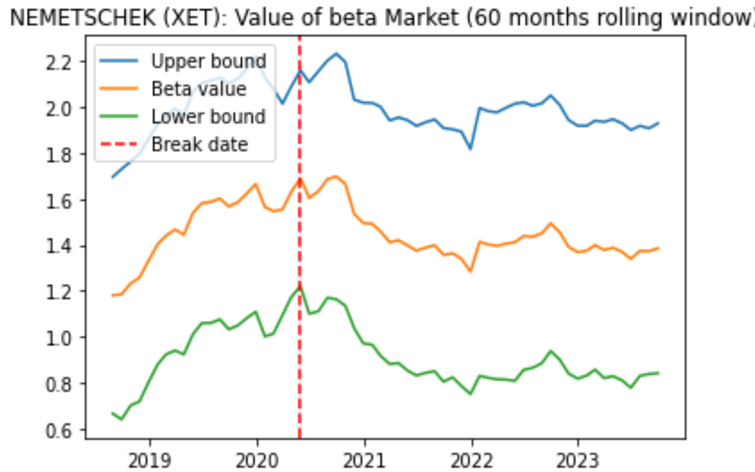
Following this drop, the beta coefficient exhibited an upward movement which suggests that, during this period, ASM-OSRAM AG became more reactive to the market. However, we can see that our procedure does not find in this gradual increase of the coefficient a break.

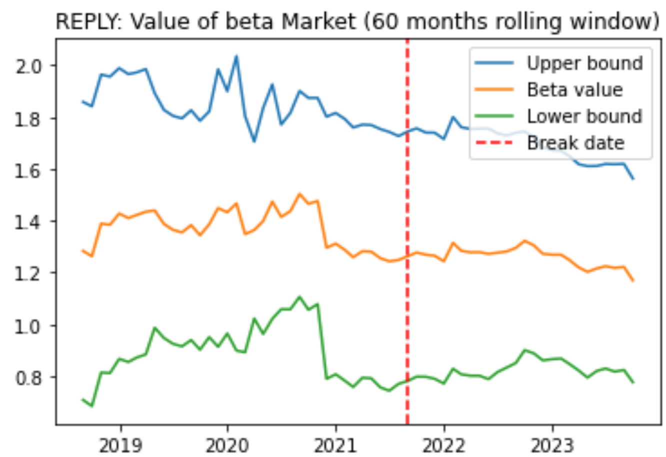
By contrast, we can see that in correspondence with the sharp decline registered at the beginning of 2020, our procedure once again identifies a break. This decline implies a reduced sensitivity to market fluctuations, which may suggest a shift towards a less volatile behavior compared to the earlier period or the presence of idiosyncratic risks brought on by the global pandemic, as does the widening of the confidence interval following the break.

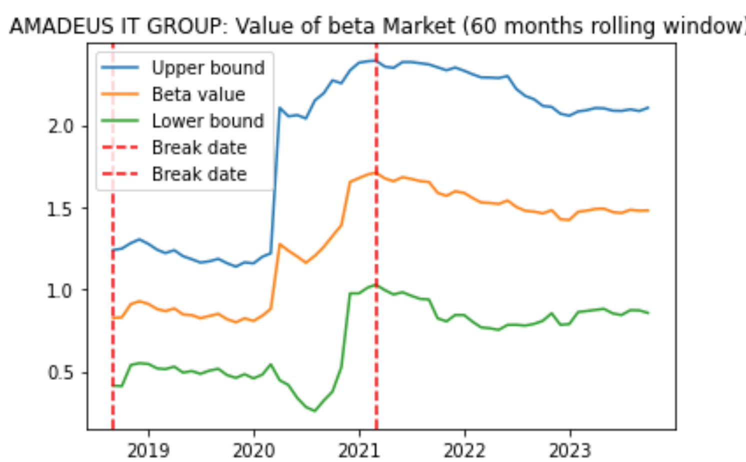
Together with the considerations from the plot of the alpha value of SOITEC, it appears that our procedure for finding break dates is more sensitive to sharp inversions in the behavior of the estimated parameters and less sensitive to gradual increases or decreases in their values. Other examples are the following, in which we can also see that the break dates do not always coincide perfectly with the moment of the inversion in the behavior, showing that our procedure to find break dates could be improved:



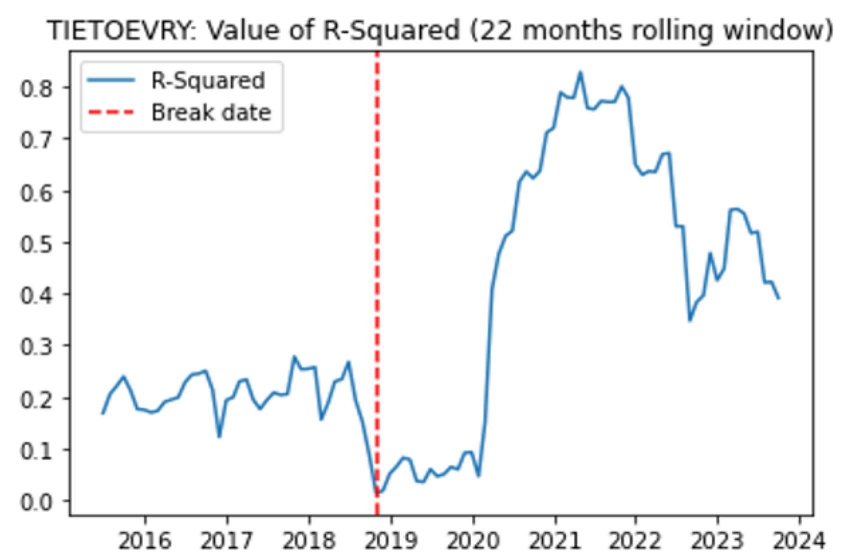



NEMETSCHEK (XET): Value of beta Market (60 months rolling window)
Upper bound
Beta value
Lower bound
Break date
2.2
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
2019
2020
2021
2022
2023

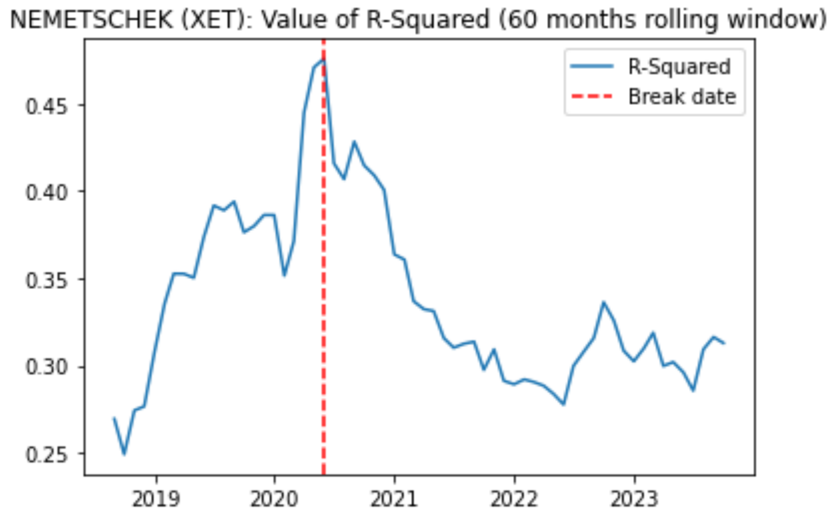

REPLY: Value of beta Market (60 months rolling window)
Upper bound
Beta value
Lower bound
Break date
2.0
1.8
1.6
1.4
1.2
1.0
0.8
2019
2020
2021
2022
2023


AMADEUS IT GROUP: Value of beta Market (60 months rolling window)
Upper bound
Beta value
Lower bound
Break date
Break date
2.0
1.5
1.0
0.5
2019
2020
2021
2022
2023

7.3. R- Squared Plots



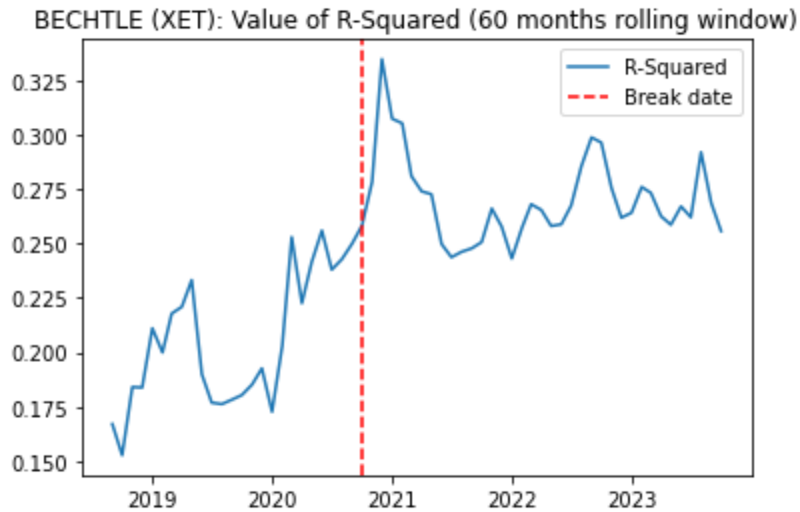
Before the break towards the end of 2018, R-squared values demonstrate relative constancy, fluctuating in the range of 0.2 to 0.3. This period suggests a moderate ability of the CAPM model to capture variations in TIETOEVRY stock returns. A significant shift becomes apparent as 2019 approaches. During this period, R-squared values exhibit a brief moment of stability before experiencing a substantial increase, surpassing 0.8. This surge in R-squared values suggests a remarkable improvement in the CAPM model's ability to explain TIETOEVRY stock returns post-break. The break towards the end of 2018 appears to mark a turning point which leads to a notable enhancement in the CAPM model's explanatory power for TIETOEVRY stock. The increased R-squared values post-break may imply changes in market conditions or the emergence of factors that align more closely with the assumptions of the CAPM model.

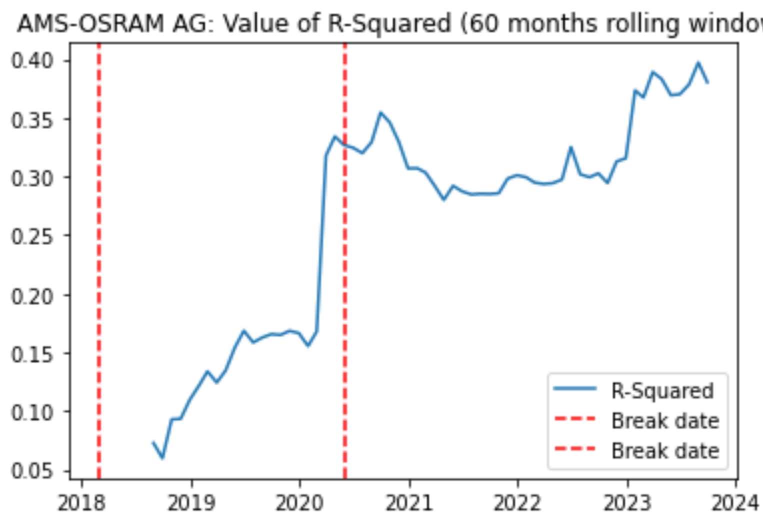


Concerning the R-squared plot for NEMETSCHEK (XET), prior to the break, a discernible trend is observed, with R-squared values gradually increasing from 0.25 to 0.45. This suggests an improving fit of the CAPM model in explaining the stock's returns leading up to the disruption caused by the COVID-19 pandemic in 2020. However, the break in 2020 marks a pivotal moment, resulting in a drastic decline in R-squared values from 0.45 to below 0.3. This sharp decrease indicates a substantial reduction in the model's ability to capture the stock's return variations during this turbulent period, potentially influenced by the unprecedented market conditions associated with the pandemic. In the subsequent years, the R-squared values show a partial recovery, surpassing 0.3 in 2022. This recovery suggests a gradual improvement in the model's explanatory power, but the values remain below pre-break levels, emphasizing the lingering impact of the disruptive event.

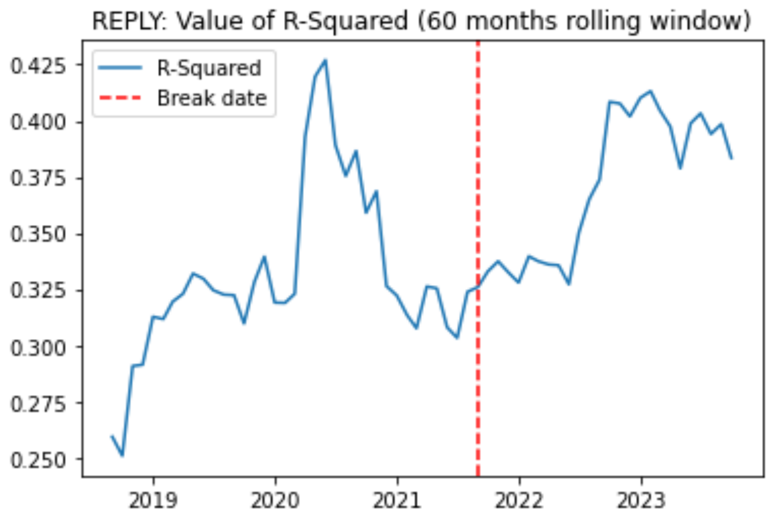
Once again, from these plots, we can infer that our procedure to find breaks position them in periods with sharp inversion in the trend of the behavior of parameters and of the overall goodness of fit of the model. However, we can see that, as far as timing the inversion, the procedure yields once again mixed results. Optimal in the case of NEMETSCHEK, in which case perfectly times the break, but in the case of TIETOEVERY it appears that it is not able to find two breaks where two inversions are really close to each other.

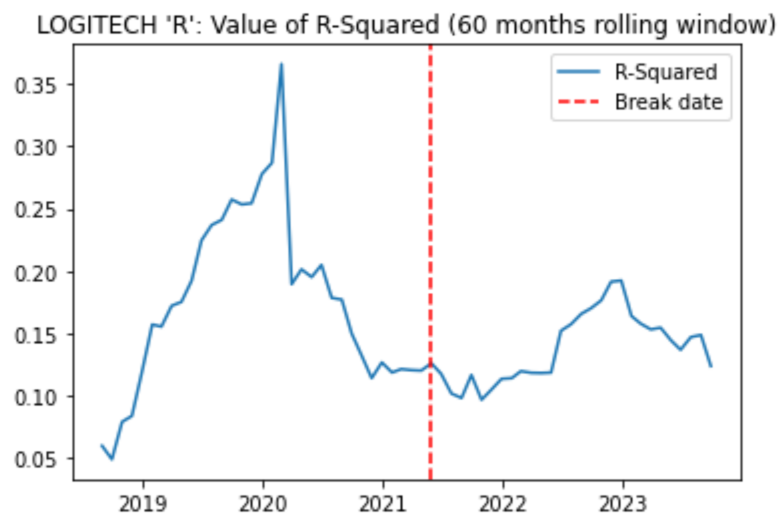
Other two examples of well-timed breaks are the following:





Whereas examples where the breaks appear to be found with some lag are the following:





Additional Plots

For additional plots, please refer to the following Google Drive link:

Homework 1: Additional Plots