Università degli Studi di Padova

Master Degree Course in Computational Finance

Regression and Time Series Models

Group Work 1 - Regression with CAPM Model

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Assignment 2

Equity Returns

In this section, we analyze the relationship between the excess returns of individual stocks and those of the sector market using scatter plots. The objective is to explore whether linear relationships exist, as assumed by the CAPM model. Scatter plots are used to visually assess the correlation between variables and to identify potential deviations. Particular focus is given to outliers and non-linear trends, as these could suggest the need for deeper analysis or alternative approaches. The scatter plots reveal a clear relationship between the excess returns of most stocks and the sector market. For instance, stocks like Johnson & Johnson, Pfizer, and Medtronic show a well-defined linear trend, indicating a strong correlation with market returns. These results suggest that the CAPM model can effectively describe the variability in returns for these stocks, supported by significant β coefficients and high R^2 values. However, some stocks, such as Boston Scientific and Cigna, display more scattered data points around the trendline, pointing to weaker correlations and the influence of unique factors that the CAPM might not capture. In addition, outliers observed in stocks like Revvity and Labcorp Holdings could reflect extraordinary events, such as regulatory changes or R&D results, which may reduce the model's effectiveness for these cases. The slope of the trendline offers further insights: for example, Eli Lilly and Teleflex demonstrate steeper slopes, suggesting a high β and greater sensitivity to market movements, while flatter slopes, as observed in Humana, indicate lower exposure to systematic risk. Overall, our observations suggest that the CAPM model effectively explains the behavior of most stocks analyzed. However, instances of high dispersion or the presence of significant outliers underscore the need for further evaluation, which will be undertaken in subsequent stages of the analysis.

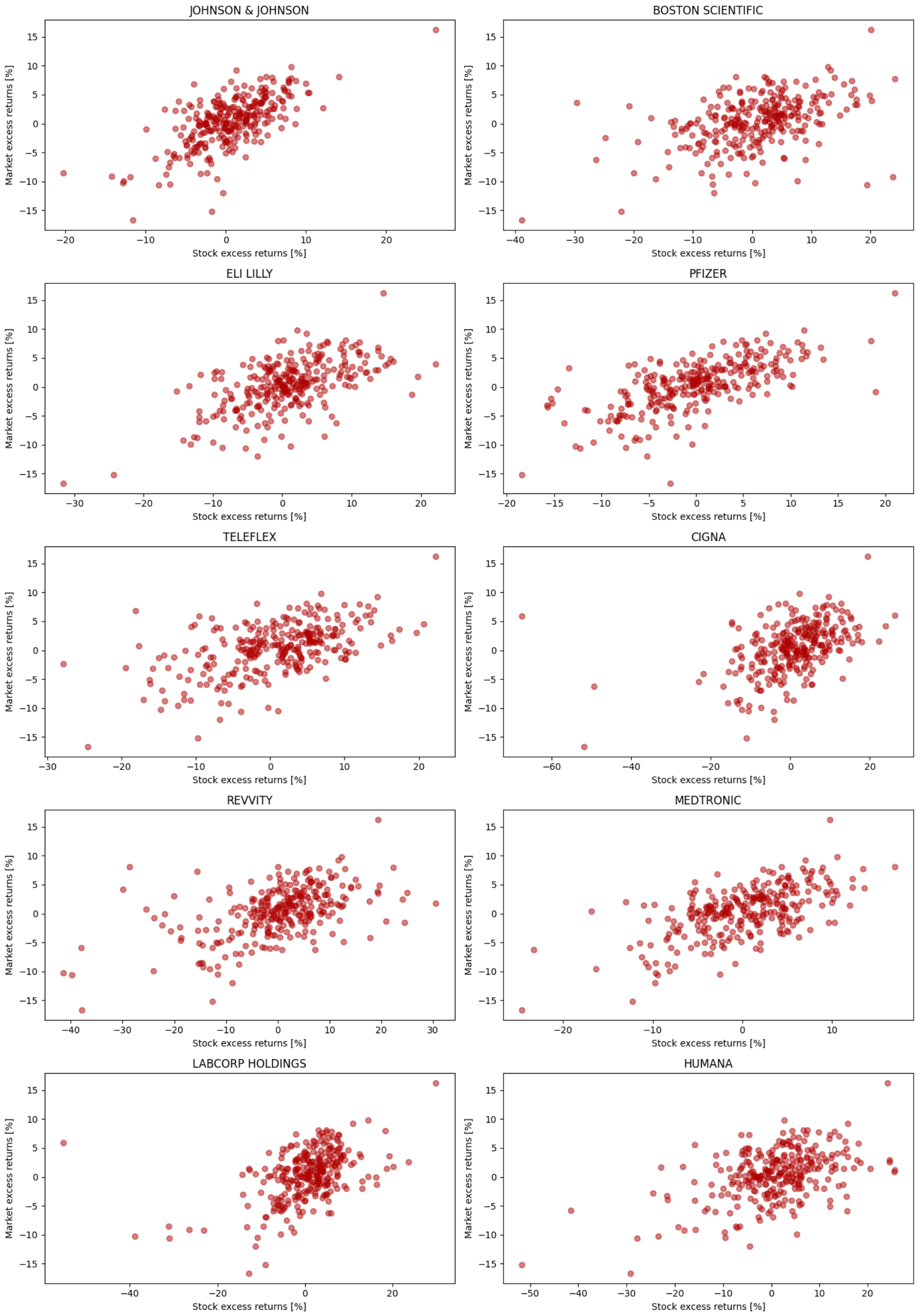

Fig. 2.1: Scatterplot of equities' log-returns against excess market returns.

Assignment 3

Linear Regression

In this section, we analyze the relationship between the excess returns of individual stocks and those of the sector market using scatter plots. The objective is to explore whether linear relationships exist, as assumed by the CAPM model. Scatter plots are used to visually assess the correlation between variables and to identify potential deviations. Particular focus is given to outliers and non-linear trends, as these could suggest the need for deeper analysis or alternative approaches. The scatter plots reveal a clear relationship between the excess returns of most stocks and the sector market. For instance, stocks like Johnson & Johnson, Pfizer, and Medtronic show a well-defined linear trend, indicating a strong correlation with market returns. These results suggest that the CAPM model can effectively describe the variability in returns for these stocks, supported by significant β coefficients and high R^2 values. However, some stocks, such as Boston Scientific and Cigna, display more scattered data points around the trendline, pointing to weaker correlations and the influence of unique factors that the CAPM might not capture. In addition, outliers observed in stocks like Revvity and Labcorp Holdings could reflect extraordinary events, such as regulatory changes or R&D results, which may reduce the model s effectiveness for these cases. The slope of the trendline offers further insights: for example, Eli Lilly and Teleflex demonstrate steeper slopes, suggesting a high β and greater sensitivity to market movements, while flatter slopes, as observed in Humana, indicate lower exposure to systematic risk. Overall, our observations suggest that the CAPM model effectively explains the behavior of most stocks analyzed. However, instances of high dispersion or the presence of significant outliers underscore the need for further evaluation, which will be undertaken in subsequent stages of the analysis.

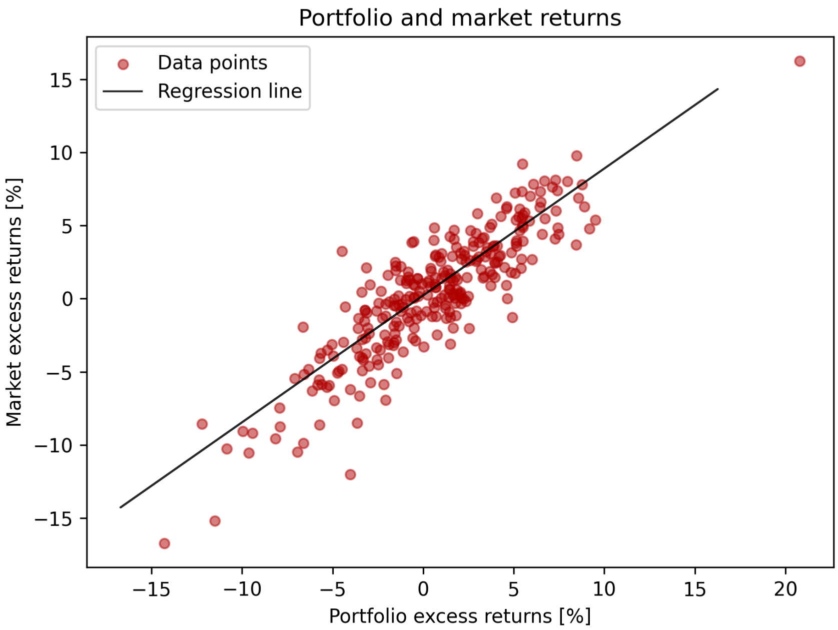

Fig. 3.1: Scatterplot of portfolio's returns against excess market returns, with linear regression.

Assignment 4

Diagnostic Tests

This section validates the reliability of the CAPM model through diagnostic tests. These tests aim to ensure that key assumptions, such as constant residual variance (homoscedasticity) and the absence of autocorrelation, are satisfied. When violations are detected, adjustments, such as robust standard errors, are applied to improve the reliability of the results. The results confirm that the CAPM model effectively explains the returns of many stocks in the Healthcare sector. For example, Johnson & Johnson (β=0.752, p¡0.01) and Pfizer (β=0.953, p¡0.01) show significant β coefficients, indicating their sensitivity to market movements. High R^2 values suggest that a substantial portion of the return variability is explained by the model. However, for stocks like Cigna and Labcorp Holdings, lower R^2 values point to the potential influence of idiosyncratic factors not captured by the CAPM. The diagnostic tests highlight some limitations. For instance, the White Test identifies heteroscedasticity in stocks such as Johnson & Johnson and Humana, indicating that residual variance is not constant. To address this issue, we applied robust standard errors (HAC). Additionally, the Breusch-Godfrey Test reveals autocorrelation in the residuals for Labcorp Holdings, requiring further adjustments to ensure the validity of the model. Despite these challenges, the F-statistics and regression p-values confirm the overall significance of the model. The analysis of the equally weighted portfolio further supports these results. Diversification reduces idiosyncratic risk and enhances the stability of parameter estimates. Compared to individual stocks, the portfolio demonstrates a stronger and more consistent linear relationship with market returns, reinforcing the applicability of the CAPM model at an aggregate level.

Assignment 5

Chow Test

5.1 Structural Breaks and Chow Test

In this section, we employ the Chow test to assess whether a significant structural change occurs in the regression models at specific points in time. To ensure the robustness of our analysis, we first established a minimum data subset size for the unrestricted models, setting it to 10% of the total dataset, in order to maintain statistical validity while preserving sufficient data for meaningful comparisons. Subsequently, the Chow test was systematically applied to all linear regressions conducted on the selected equities, allowing us to identify potential structural breaks across the dataset, that is, significant changes in the regression parameters caused by external shocks, market-wide events, or company-specific factors. These structural breaks may reflect shifts in the relationship between excess returns and market behaviour, such as changes in systematic risk (β) or the presence of unexplained excess returns (α) due to macroeconomic conditions, regulatory adjustments or sector-specific developments. To identify these structural breaks, we analyzed the p-values obtained from the Chow test for each equity over time: a p-value below the threshold of 0.01 was interpreted as evidence of a structural break at that particular point in time, signaling that the CAPM parameters had changed significantly. In this analysis, only periods of at least two consecutive months with p-values below the threshold were considered as break dates, ensuring that the identified breaks reflect sustained shifts rather than noise or transient fluctuations.

The results of this analysis are displayed in Figure 5.1, highlighting that different

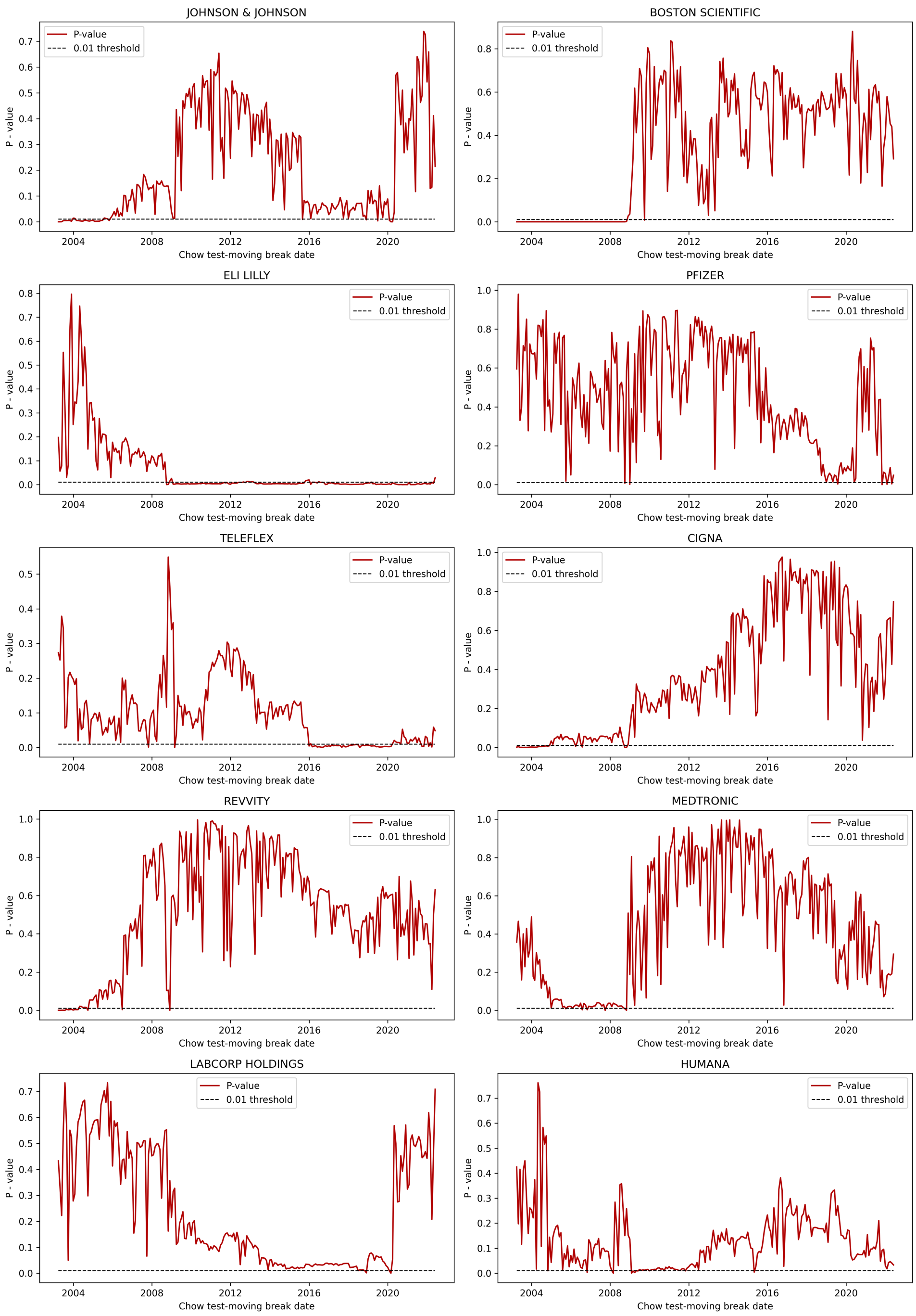

Fig. 5.1: Chow Test performed for all equities in search of structural breaks.

equities exhibit fundamentally distinct behaviors. Notably, certain equities, such as *Eli Lilly*, *Boston Scientific*, and *Teleflex*, show p-values consistently below the 0.01 threshold for extended periods, indicating prolonged structural breaks; this raises the question of whether the CAPM relationship for these equities in these periods is truly linear or whether a different modeling approach may be warranted.

5.2 Periods of Shared Structural Breaks

Despite these observations, no clear or consistent pattern of structural breaks emerges across all equities; to explore potential commonalities further, an additional histogram was generated (Figure 5.2), which illustrates the frequency and overlap of structural breaks shared among different equities.

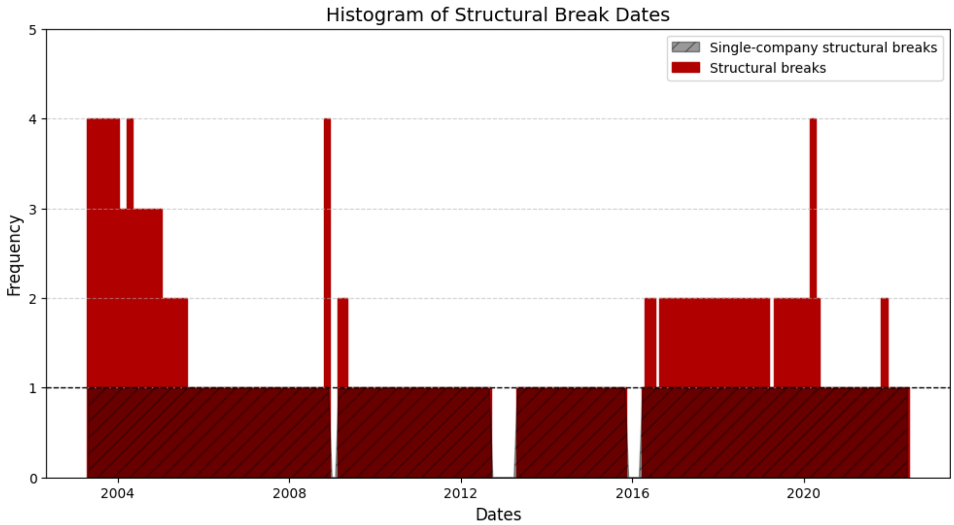

Fig. 5.2: Frequency of months identified as structural break points.

Figure 5.2 highlights two important aspects of the data: first, there is no single period that constitutes a break date for all equities; the maximum number of companies sharing a structural break at any given time is in fact 4. Nonetheless, the break dates identified as significant changes to the regression parameters align closely with expectations, in fact the data reveal break dates significantly relevant in three distinct periods of time:

- **2003**: Structural breaks are observed throughout most of the year, coinciding with the SARS epidemic. This period also aligns with economic and legislative developments, including the introduction of the Medicare Modernization Act, which reshaped healthcare policy and access in the United States.

- **October and November 2008**: These months mark the onset of the 2008/2009 financial crisis.

- **February and March 2020**: Structural breaks during this time correspond to the emergence of the COVID-19 pandemic and the widespread implementation of precautionary measures.

An important observation is that the structural breaks identified in 2003 extended over a prolonged period, spanning multiple consecutive months, whereas the impact of the COVID-19 pandemic appears to have been more concentrated and shorter in duration. The prolonged effect in 2003 could reflect the gradual adjustment of the healthcare market to the SARS epidemic and concurrent economic and legislative changes. In contrast, the shorter duration of structural breaks during COVID-19 may suggest that lessons learned from the SARS outbreak, including the implementation of precautionary measures and improved epidemic preparedness, helped mitigate the impact of subsequent epidemics on the healthcare market. Alternatively, the healthcare market may have simply grown so significantly in size and diversification over time that it developed a level of resilience that enables it to absorb and adapt to substantial disruptions in the economic landscape. This growth, coupled with advancements in technology, expanded infrastructure, and more robust financial mechanisms, might have contributed to the market's ability to withstand even major shocks, such as those caused by the 2008 crisis and te COVID-19 pandemic. This explanation also accounts for the observation that the majority of equities were not significantly impacted during these events: the increased resilience and diversification of the healthcare market may have allowed many companies to maintain stability despite the broader economic disruptions.

5.3 Chow Test on Portfolio

In order to further investigate the impact of significant events in the economic environment, the same Chow test was performed on the excess returns of the portfolio. This approach aggregates the behavior of individual equities into a single measure, allowing for the identification of systemic disruptions across the healthcare market.

The results, displayed in Figure 5.3, reveal two distinct periods where structural breaks in the portfolio's return dynamics are particularly significant: these are the beginning of 2009, likely reflecting the aftermath of the 2008 financial crisis, and the final months of 2023, which may indicate the presence of recent economic or sector-specific disruptions affecting the healthcare market.

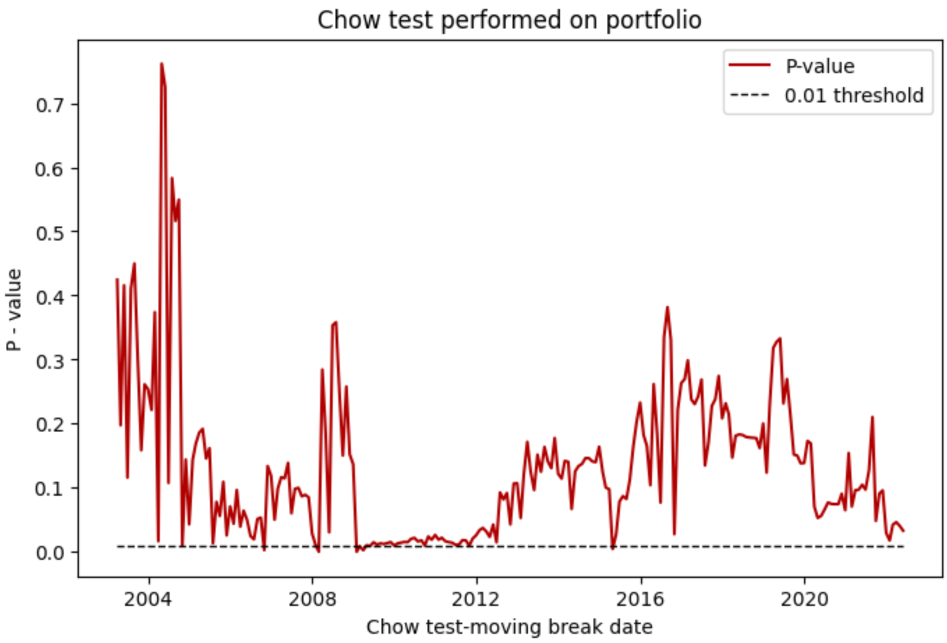

Fig. 5.3: Frequency of months identified as structural break points.

Assignment 6

Rolling CAPM Stability Analysis

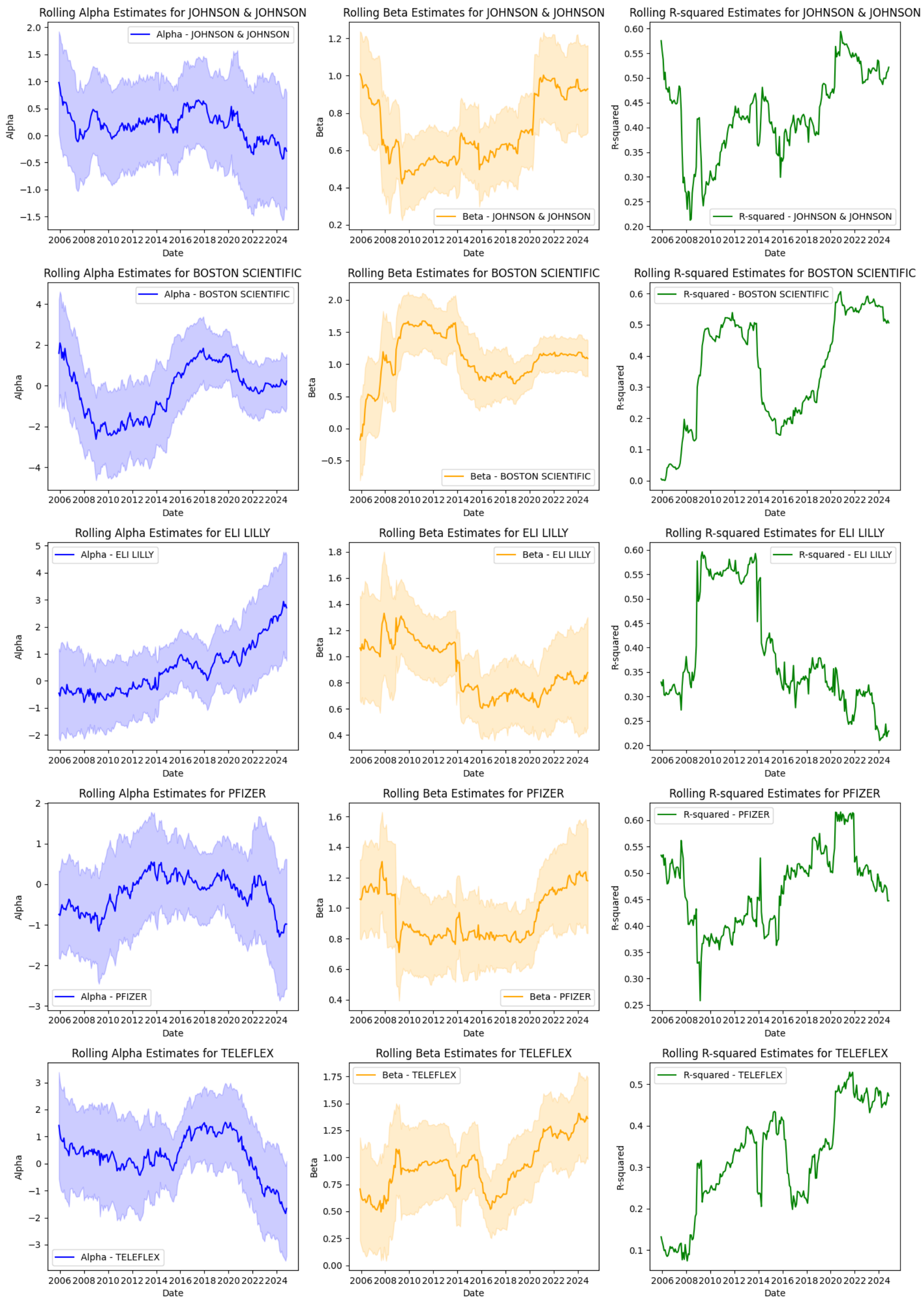

Fig. 6.1: Rolling quantities computed an all equities as an alternative of the Chow Test in search for structural breaks (1).

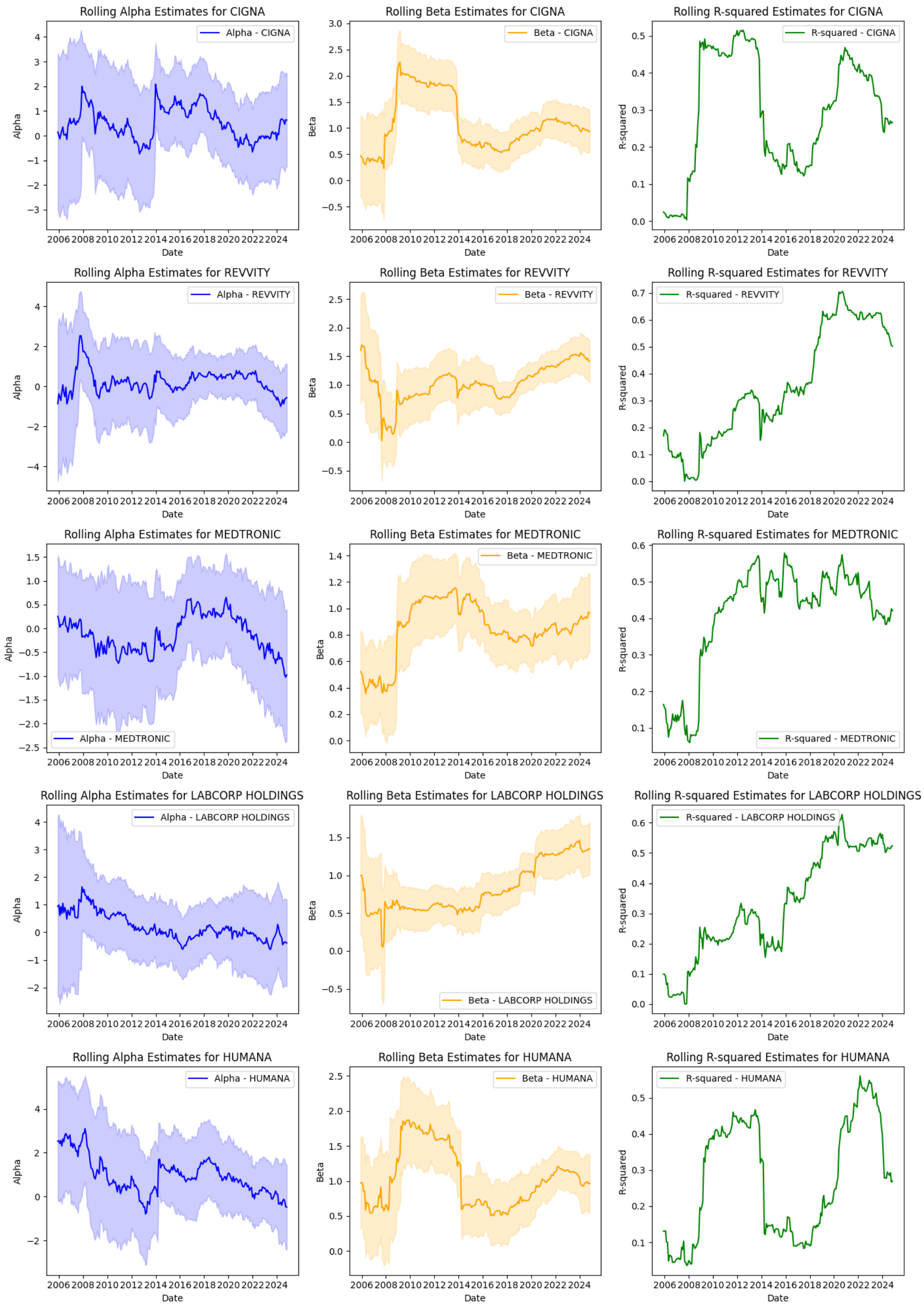

Fig. 6.2: Rolling quantities computed an all equities as an alternative of the Chow Test in search for structural breaks (2).

Assignment 7

Multivariate Regression

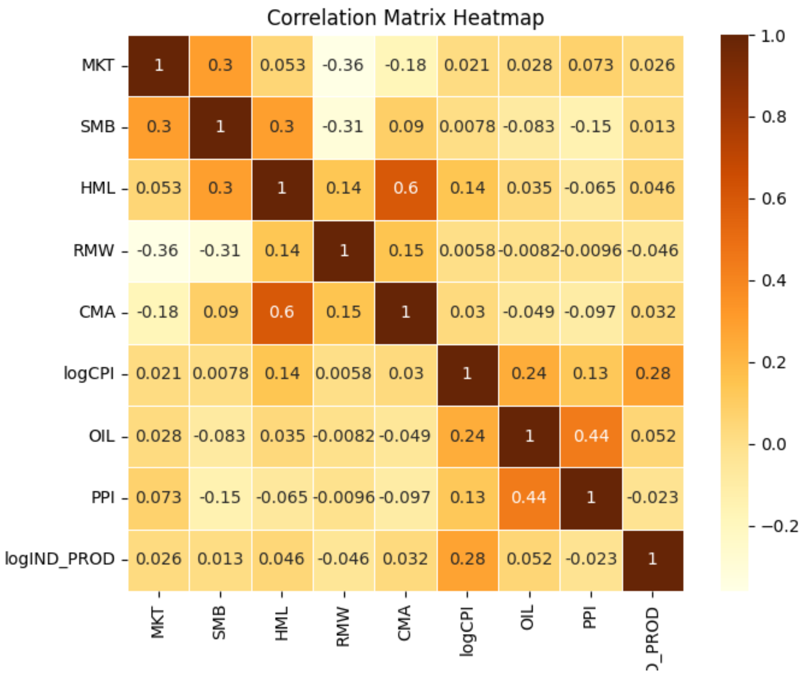

Fig. 7.1: Heatmap of the correlations between the chosen explanatory variables.

Assignment 8

Appendix

Assignment 9

Summary of Group Members' Contribution

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