**TRINITY COLLEGE**

**BUSINESS SCHOOL**

**"Project 3 - Herding"**

**Module**: Financial Modelling & Analysis

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**MSc** **Programme**: Business Analytics

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1.- Data:

The data used for the analysis have been the prices of 10 assets, five of them are tokens, created and developed to operate on a blockchain, i.e. cryptocurrencies, while the other five are traditional securities from the technology sector. The assets are:

* BTC
* ETH
* BNB
* AAVE
* UNI
* AAPL
* MSFT
* TSLA
* NVDA
* INTC

In addition, in order to model and try to describe the behavior of these assets, five variables were taken into account:

* CPI (inflation)
* IP (industrial Production)
* Stock Market Index
* Interest Rate
* Unemployment rate

The first step was to import the data of the analyzed assets from Yahoo Finance, the time horizon is from October 3, 2020 to May 1, 2023, approximately 3 years. The time horizon is reduced since several of the analyzed cryptocurrencies have a very short lifetime. The time frequency of the data is daily and the calculations referring to these prices are made with this time frequency although later in the construction of the model they are transformed to monthly data since they have to necessarily square with the data of the factors used (which many of them use that time frequency) and it is explained later.

Once the data were imported into the R environment, the returns of all the assets were calculated with the difference of the logarithms of the prices and the first observation that is lost when performing this calculation was eliminated.

Subsequently, observations (days) with NA values, derived from the difference between the stock market and the cryptocurrency market at the opening on weekend days, were removed.

Additionally, the data of the factors that were used as variables in the modeling process and in the descriptive and predictive analysis of the assets were imported. The FRED (Federal Reserve Economic Data) database was used for this purpose. The time horizon is the same as that of the assets and the time frequency is monthly for all of them, although the Stock Market Index and the Interest Rate have daily data, the rest of the indexes are updated on a monthly basis, so it was decided to carry out the analysis with a monthly time frequency for all the variables to be introduced in the model.

Once all the data necessary for the analysis had been imported and the NA values had been processed, an analysis of the assets was carried out prior to the construction of the model; this analysis included the calculation of correlations between assets, causality and volatility.

To calculate the correlation between assets, a variance and covariance matrix was created, from which the following conclusions can be drawn:

* Cryptocurrency vs. Technological Stocks: The correlations between cryptocurrencies and technological stocks (AAPL, MSFT, TSLA, NVDA, INTC) are generally weaker compared to the correlations within cryptocurrencies. This suggests that the movements of cryptocurrencies are not strongly correlated with the movements of technological stocks, indicating potential diversification opportunities between these asset groups.
* High Correlations within Technological Stocks: Among the technological stocks, there are moderate to strong positive correlations. For example, AAPL and MSFT have a correlation of 0.739, indicating a relatively strong positive relationship between these two stocks. Similar correlations can be observed between other technological stocks.
* Sector-Specific risks: the strong positive correlations within cryptocurrencies suggest that the overall performance of the cryptocurrency sector may have a significant impact on the returns of individual cryptocurrencies. Similarly, the correlations within technological stocks indicate that sector-wide factors can influence the performance of individual stocks within the technology sector.

In order to calculate the volatility of the assets, the GARCH model was estimated for each one of them:

* The analysis of the GARCH (1,1) model fitted to Bitcoin (BTC) returns reveals that BTC returns do not exhibit a significant drift in mean. However, there is evidence of volatility persistence, indicating that past squared returns have a significant impact on BTC's conditional volatility. The model's goodness-of-fit measures suggest a reasonable fit to the data, with no evidence of serial correlation or significant autoregressive conditional heteroscedasticity effects in the residuals.
* Ethereum's GARCH model indicates that the volatility of ETH returns is influenced by its own past volatility, as well as by the squared residuals of the previous period. The estimated parameters suggest that ETH returns have positive autocorrelation and are persistent, with an estimated alpha (0.120) and beta (0.814) higher than those of Bitcoin. However, the estimated mean (mu) is close to zero, indicating that the average return of ETH is not significantly different from zero. The log-likelihood value is positive, indicating that the model provides a good fit for the data. Overall, Ethereum exhibits   
    
  similar volatility characteristics to Bitcoin, with some differences in the estimated parameters.
* The GARCH model for Binance Coin suggests that BNB returns are influenced by both its own past volatility and squared residuals. The estimated parameters indicate positive autocorrelation in returns and a persistence of volatility. The estimated alpha (0.183) and beta (0.809) values are higher than those of Bitcoin, indicating that BNB returns have higher volatility and are more sensitive to shocks in the market. The log-likelihood value is positive, indicating a good fit of the model. Overall, BNB exhibits similar volatility patterns to Bitcoin, with higher estimated parameters suggesting higher volatility and sensitivity to market shocks.
* The GARCH model for Uniswap reveals that UNI returns are influenced by its own past volatility and squared residuals. The estimated parameters suggest negative autocorrelation in returns and a high persistence of volatility. The alpha (0.061) and beta (0.920) values are relatively high compared to Bitcoin, indicating higher volatility and sensitivity to market shocks. The log-likelihood value is positive, indicating a good fit of the model. UNI exhibits similar volatility characteristics to Bitcoin, but with higher estimated parameters suggesting greater volatility and sensitivity to market fluctuations.
* The GARCH model for Aave indicates that AAVE returns are influenced by both its own past volatility and squared residuals. The estimated parameters suggest positive autocorrelation in returns and a persistence of volatility. The alpha (0.029) and beta (0.725) values are lower than those of Bitcoin, indicating lower volatility and sensitivity to market shocks. The log-likelihood value is positive, indicating a good fit of the model. AAVE exhibits similar volatility patterns to Bitcoin, but with lower estimated parameters suggesting lower volatility and sensitivity to market fluctuations.
* En cuanto a los resultados de los valores de empresas tecnológicas:
* The volatility of AAPL, as measured by the GARCH model, indicates a moderate level of volatility. The estimated parameters suggest that the conditional variance of AAPL returns is best captured by an sGARCH(1,1) model. The persistence of volatility is relatively low, with an alpha parameter of 0.0603. This implies that shocks to AAPL returns dissipate rather quickly. Comparing the volatility of AAPL to cryptocurrencies, such as BTC and ETH, the traditional asset exhibits lower volatility. This is expected, as cryptocurrencies are known for their higher volatility due to various factors, including speculative trading and market inefficiencies. Among the traditional assets, AAPL's volatility is comparable to MSFT and NVDA, but lower than TSLA and INTC.
* MSFT (Microsoft Corporation): The volatility of MSFT, as estimated by the GARCH model, is relatively low. The model suggests that an sGARCH(1,1) specification adequately captures the conditional variance dynamics of MSFT returns. The estimated parameters indicate a low level of persistence in volatility, with an alpha parameter of 0.0603. When comparing MSFT's volatility to cryptocurrencies, MSFT exhibits significantly lower volatility. Among the traditional assets considered, MSFT's volatility is similar to AAPL and NVDA, but lower than TSLA and INTC.
* TSLA (Tesla, Inc.): TSLA exhibits high volatility, as indicated by the GARCH model. The estimated parameters of the sGARCH(1,1) model show a higher level of persistence in volatility, with an alpha parameter of 0.1197. This suggests that shocks to TSLA returns have a more lasting impact on future volatility. Comparing TSLA's volatility to traditional assets, TSLA's volatility is significantly higher. This is consistent with the reputation of TSLA as a high-growth, high-risk stock. Among the traditional assets considered, TSLA has the highest volatility.
* NVDA (NVIDIA Corporation): The volatility of NVDA is moderate, as estimated by the GARCH model. The model suggests that an sGARCH(1,1) specification adequately captures the conditional variance dynamics of NVDA returns. The estimated parameters indicate a moderate level of persistence in volatility, with an alpha parameter of 0.1834. Comparing NVDA's volatility to cryptocurrencies, NVDA exhibits lower volatility. Among the traditional assets considered, NVDA's volatility is similar to AAPL and MSFT, but lower than TSLA and INTC.
* INTC (Intel Corporation): The volatility of INTC, as measured by the GARCH model, is relatively low. The estimated parameters of the sGARCH(1,1) model indicate a low level of persistence in volatility, with an alpha parameter of 0.1834. Comparing INTC's volatility to cryptocurrencies, INTC exhibits significantly lower volatility. Among the traditional assets considered, INTC's volatility is similar to AAPL, MSFT, and NVDA, but lower than TSLA.

2.- Estimate a statistical factor model:

In order to carry out this analysis, a Principal Component Analysis or PCA model was constructed. It is a statistical technique used to reduce the dimensionality of a data set, preserving its essential structure. This is achieved by transforming the original variables into a new set of uncorrelated variables called principal components. These principal components are linear combinations of the original variables and are ordered such that the first component captures the maximum amount of variation in the data, the second component captures the maximum remaining variation, and so on.

PCA is a useful analysis when estimating a statistical factor model, as it helps to identify the underlying factors driving the variation in a set of assets. By performing PCA on asset returns, you can determine the principal components that explain most of the variance in the data. These principal components can be interpreted as common factors that influence asset returns. By identifying these factors, you can gain insight into the underlying structure of asset returns and potentially build a factor model that explains their behavior.

Looking at the PCA results, we can observe the following:

Standard deviation: this represents the amount of variation captured by each principal component. The larger the standard deviation, the more variation the component explains. PC1 has the highest standard deviation of 0.5402, indicating that it captures a significant portion of the total variation in the data.

Proportion of Variance: This indicates the proportion of total variance explained by each principal component. PC1 explains 94.55% of the total variance, which is quite high. As we move to the next components, the proportion of variance explained decreases. PC2 explains 3.44% of the variance, PC3 explains 0.67%, and so on.

Cumulative Proportion: This shows the cumulative proportion of variance explained by each principal component. It helps determine how many components are needed to capture a desired level of variance. The first two components (PC1 and PC2) explain approximately 97.98% of the total variance, and the first five components explain 99.50%.

Based on these results, it can be concluded that the first principal components capture a substantial amount of the variance in asset returns. This suggests the presence of common factors influencing asset returns. These components can potentially be used as factors in a statistical factor model to explain and predict asset returns, which is what we will do in the next section.

3.- Economic factor model:

the development of this model, the first step was the selection of the factors that a priori could be common to both sectors and to all assets:

* Inflation: Inflation is a major factor affecting the value of financial assets, including cryptocurrencies (BTC, ETH, BNB) and technology stocks (AAPL, MSFT, TSLA, NVDA, INTC). Inflation can influence investor demand and purchasing power, which in turn can affect the prices of these assets. In addition, inflation can have an impact on monetary and fiscal policies, which can affect the overall economic environment in which these assets operate.
* Production index: The production index is an indicator that measures economic activity and the production of goods and services in an economy. This factor can be relevant for technology stocks (AAPL, MSFT, TSLA, NVDA, INTC) as their performance is related to the production and sale of technology products and services. An increase in the production index may indicate an increase in the demand for technology and, therefore, have a positive impact on the performance of these stocks.
* Stock market index: The stock market index, as a general indicator of market performance, can have an impact on all of the above stocks. General market movements can influence investor confidence and demand for financial assets. In addition, technology stocks (AAPL, MSFT, TSLA, NVDA, INTC) can have a particularly strong correlation to the stock market index, as these companies often have significant weight in technology indexes.
* Unemployment rate: unemployment rate is a key indicator of the health of the labor market and the economy in general. It can affect both cryptocurrencies (BTC, ETH, BNB) and technology stocks (AAPL, MSFT, TSLA, NVDA, INTC). A high unemployment rate may indicate economic weakness and a decrease in demand for goods and services, which could negatively affect asset prices. On the other hand, a low unemployment rate may indicate a strong economy and increased consumer spending power, which could have a positive impact on asset prices.
* Interest rate: The interest rate is a factor that can influence the cost of financing and investment decisions of economic agents. Both cryptocurrencies (BTC, ETH, BNB) and technology stocks (AAPL, MSFT, TSLA, NVDA, INTC) can be affected by changes in interest rates. For example, an increase in interest rates may make equity investments less attractive.

After selecting the factors that would act as independent variables in the model, a multivariate regression model was constructed, and the results are as follows:

When analyzing the coefficients, it can be seen that most of the predictor variables do not have statistically significant effects on asset prices. In other words, these variables do not provide substantial explanatory power for asset behavior. The p-values associated with the coefficients are generally high, indicating that the null hypothesis (no effect) cannot be rejected.

However, there are some exceptions where some variables show a degree of significance. For example, the design\_matrixDGS10 variable (representing the 10-year Treasury bond yield) appears to have a positive effect on BTC.USD.Close, ETH.USD.Close, BNB.USD.Close, and NVDA.Close, with statistically significant coefficients. This suggests that changes in 10-year Treasury bond yields may have some influence on these asset prices.

In addition, the design\_matrix variableGSPC.Close (representing the closing price of the S&P 500 index) shows a positive effect on BTC.USD.Close, BNB.USD.Close and NVDA.Close, with statistically significant coefficients. This implies that the performance of the S&P 500 index may be associated with the price movements of these assets.

Other variables such as design\_matrixINDPRO (industrial production index) and design\_matrixUNRATE (unemployment rate) show mixed results, with some assets showing positive coefficients and others showing negative coefficients. However, these effects are generally not statistically significant, indicating that the relationship between these economic indicators and asset prices is weak or non-existent.

4.- Prediction of the prices with Monte Carlo Simulation:

For the development of this point, a series of parameters were adjusted, such as the number of iterations to be performed and the number of periods to be predicted. In this case the number of simulations is 1000 and a total of 30 periods will be predicted.

In the R file, only the BTC asset has been run, but it can be run with any of the assets in the portfolio. In the case of BTC, the prediction is as follows:

A graph showing the price of bitcoin

Description automatically generated with low confidence