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**Mestrado em Estatística e Gestão de Informação**

Master Program in Statistics and Information Management

## **Volatility Spillover Effects Between S&P 500 Sectors**

The special case of IT sector.

Eduardo José Pereira Mendonça

Dissertation report presented as partial requirement for  
obtaining the Master's degree in Statistics and Information  
Management

NOVA Information Management School  
Instituto Superior de Estatística e Gestão de Informação  
Universidade Nova de Lisboa

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# **Volatility Spillover Effects Between S&P 500 Sectors**

by

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Dissertation report presented as partial requirement for obtaining the Master's degree in Information Management/ Master's degree in Statistics and Information Management, with a specialization in Risk Analysis and Management

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## **ABSTRACT**

The main objective of this dissertation is to study the volatility spillover effect between the Information Technologies sector and the other sectors of S&P 500 index. After many studies and research of volatility spillover effects between developed and emerging stock markets, between markets across different countries or even between different assets indexes it is time to make it between sectors. Deepening this question reflects the importance of this study for investors who invest in stocks of the sectors that compose this index, and therefore, at the same time, these same investors want to diversify their portfolio, thus being a protection strategy against large losses. This study involves the application of three models: VAR model, DCC-GARCH and BEKK-GARCH to help in the scope of this study, which comprises a timeline from January 2012 to December 2021. The results showed that, for instance, volatility spillover effects are more evident in the case between the Information Technologies and Industrials sectors as well as in the case between the Information Technologies and Financials sectors, demonstrating that for example, for Industrials and Financials sectors, the investors that already have stocks on companies of Information Technologies sector may have better options in stocks of companies belonging to other sectors when it comes to invest.

## **KEYWORDS**

Volatility; Spillover effect; VAR model; DCC-GARCH model; BEKK-GARCH model; S&P 500 sectors.

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## 1. INTRODUCTION

In the universe of investors, among many attributes, what makes the difference is the ability to know how to define well at various times throughout the duration of an investment. Among these definitions there are some variables at play, such as risk, duration, type of asset or market in which an investor intends to invest. The last decade was marked by a period of stability in the S&P 500 index, in which, even, there was a growing appreciation, namely on the part of the IT sector, which has registered a great development in the last decades, being today the sector with more value and more weight in the S&P 500 index. With the arrival of the pandemic, instability settled in this index and, consequently, also affected all the sectors that comprise it. But among these sectors there were different reactions to the pandemic. One way to better understand these variations and reactions between sectors is through spillover effects. This can be considered as a measure that assesses the amount of information that is transmitted from one financial asset to another. More specifically, spillover effects occur when changes recorded in each financial asset are propagated and recorded at a later time interval in another financial asset.

The objective of this dissertation is to understand the spillover effects that the IT sector caused in the remaining sectors of the S&P 500, being this sector the most significant among the investments made in this index. In this way, we aim to help investors prepare themselves better before making their investment decisions. Certainly, also with this purpose, several studies have been published over the last few decades, but these have intensified in recent years. Some of these studies on spillover effects encompass sectors in market indexes, like for instance, the spillover effect between stocks of the same sector from different countries or the spillover effect of oil prices on stock markets, but few studies focus the effects on sectors among themselves. Clearly that is a fact which further emphasizes the importance of this study.

In previous literature, the studies that focus on the volatility spillover effects between sectors on the same index, different models have been used, but there is one that is used very frequently. That model is the one created by [\(Diebold & Yilmaz, 2012\)](#) that measure the network connectivity and volatility spillovers, by using vector autoregressive contents. In cases where the objective of the study is to examine the spillover effects across all sectors, this is a good model to implement, but here we used other models like Dynamic Conditional Correlation (DCC) model from [\(Engle, RF., Sheppard, 2001\)](#) and BEKK model from [\(Engle & Kenneth, 1995\)](#). We thought that these models would better fit in our focus of understanding what was the real influence of the IT sector, and only the IT sector, on other sectors during the last decade. This different approach to the study of volatility spillover effects was important to add some knew

conclusions in this subject. In fact, this dissertation ended up proving that there are no volatility spillover effects in all case studies, that is, between IT and all other sectors of the S&P 500 index, and in the cases where this existence is verified, this effect is much clearer in some than others.

The rest of this dissertation is constituted as follows. Section 2 portrays much of the current literature on the topic that fills this dissertation: volatility spillover effects between the same index sectors along with the descriptions of the models and statistical tests that will be used. The next section, Section 3, contains the methodology in which the models and statistical tests, described in the previous section, will be implemented, also including information on the treatment of the data used in this dissertation. Section 4 contains the exposition of the empirical results, derived from the application of the models and statistical tests of the previous section and finally, in section 5, the conclusions are presented together with the necessary explanations.

## **2. LITERATURE REVIEW**

### **2.1. VOLATILITY SPILLOVER PHENOMENON**

Since many years ago, in most types of market analysis, volatility is considered a key variable, because of its importance in understanding the behavior of financial markets and its components. More recently, the volatility spillover effects emerged as a new and interesting study variable. One of the first times that the notion of volatility spillover effect appeared in a research paper was in (Ross, 1989), where the author considered that changes in volatility were caused by the spread of information between markets. Later, (Shen et al., 2018), defined the volatility spillover effect as the second moment in the relationships between financial series, and, that it measure the rate of information flow transmitting between markets.

Over the last decades, volatility transmission occurrences have been registered with greater frequency. As a result, multiple studies were presented to provide answers to the questions that emerged in the face of such facts. In recent years, published studies on this topic have intensified even more and most of them were not carried out only between stock markets. They were also applied to different indices from different countries, with different types of financial assets. Hence, volatility spillovers can also occur between futures markets, bonds, exchange rates, interest rates and many other financial and economic variables (Li & Giles, 2015). For instance, it is possible to determine whether there is a volatility spillover effect between any exchange rate and any futures market, that is, whether there is a transfer of information from the exchange rate to the futures market, affecting the volatility recorded therein. (Zeng et al., 2021) adds that as volatility also symbolizes asset risk, it can be concluded that volatility spillover effect is the transmission of risk.

### **2.2. VOLATILITY SPILLOVER EFFECT BETWEEN SECTORS**

As already mentioned in the introduction section, within the currently existing literature it is not possible to discover many works or studies carried out on the volatility spillover effect between sectors in the same index. Among those that it was possible to find, there are some that stand out. Looking at the case of the work of (Laborda & Olmo, 2021), their goal was to see if it is possible to predict financial crisis with the knowledge of the volatility spillovers between sectors. For that purpose, they used data from seven sectors, (Health Care,

Pharmaceuticals, Biotechnology, Banking/Insurance, Cyclical Sector, Technology and Energy), belonging to the S&P 500 index, and the methodology introduced by (Diebold & Yilmaz, 2012). They reached to the conclusion that volatility spillover effects are important to predict financial crisis. Regarding sector analysis, they found out that Banking/Insurance, Energy, Technology and Biotechnology are the ones that cause more volatility flow to the remaining sectors.

Using the same methodology, (Choi et al., 2021) studied the dynamics of volatility spillover and network connectedness between the sectors of the ASX index, coming to the conclusion that the instability that has been installed in the markets in recent times has increased the transmission of volatility between sectors, especially the financial sector. It should be noted that in this study, the author intended to study the volatility spillover effects of the ASX sectors, through the connectedness between all sectors. This is only possible using the (Diebold & Yilmaz, 2012) model.

Another work that was focused on a similar topic was the one done by (El Hedi Aroui et al., 2011). Here the authors main objective was to analyze the volatility transmission between Oil prices and sectors from the US and Europe stock markets. The S&P 500 sectors, at that time, were divided in ten categories, according to the Global Industry Classification Standard (GICS). But in this work, the authors only considered seven. The sectors considered were Automobile and parts, Financials, Industrials, Basic Materials, Technology, Telecommunication and Utilities.

To arrive at the results, they implemented four different bivariate models. The first, which also served as a benchmark in this study, is VAR-GARCH (1,1). The other three are the CCC-GARCH (1,1), DCC-GARCH (1,1) and BEKK-GARCH (1,1). The methodology of this work is in reality very close to the one that we pretend to implement in this thesis. In (El Hedi Aroui et al., 2011), they reached to the values of conditional variance and covariance between the oil and each of the sectors included in this work. With that it is possible to take conclusions about the spillover effects between these variables. The results showed that the European stock markets, as well as the US stock markets, are affected by the changes in oil markets.

In our thesis, the principle is like the one applied in this work, since we are not working with oil prices or even the Europe markets. Our only focus will be the volatility spillover effects in S&P 500 index sectors and mainly the influence between IT sector and the others.

### 2.3. VOLATILITY SPILLOVER METHODS AND MODELS: PREVIOUS RESEARCH

After the emergence of the volatility spillover effect and the greater interest in this new measure, the need for new models capable of measuring it also began to be greater. Through many studies, research and paper works, a variety of models were used for measuring the volatility spillover effects. The different objectives and purposes among these studies or works made by scholars and investigators, also bring the need to use different models and methods.

Starting by one of the most used models, the VAR model is present in many works. It all began when in 1980, (Sims, 1980) claimed that, at that time, the way in which econometric models were constructed was not appropriate. Thus, in response to these problems, he launched the bases for vector autoregressions model (VAR model). The simplicity and the easy way to obtain and understand the answers that this model offers is stated in the work of (H. Stock & W. Watson, 2001), where the authors stated that: "This simple framework provides a systematic way to capture rich dynamics in multiple time series, and the statistical toolkit that came with VARs was easy to use and to interpret". Given these facts, this model was widely accepted by researchers, not only in studies of macroeconomic variables, but also in other types of studies, such as volatility spillover effects. In (Abidin et al., 2014), used the VAR model to calculate the spillover effects between Australia, China, Hong-Kong, Japan and New Zealand markets. In order to avoid significant cross-correlation between markets that are more closely to each other and to better capture the dynamic relationship between all five markets, they decided to introduce the five markets in VAR model instead of applying the bivariate VAR. They end up concluding that for instance, the one day lagged returns of the Chinese market have a significant impact on stock returns from Australian market, but the inverse was not proved. (Song et al., 2022) used the VAR model to examine the volatility spillover effects between China's carbon trading and energy markets. The results showed that there exists a strong spillover effect between the two markets in study.

Another type of models that added a lot to the study of volatility spillover effects were the Multivariate GARCH models (MGARCH). Once again, the growing need to use multivariate models has led some researchers to release these types of models. (Chevallier, 2012) used some specifications of multivariate GARCH models like BEKK, CCC and DCC because according to the author: "...the class of MGARCH models allows to capture the dynamics of variance and covariance overtime." In (Engle, RF., Sheppard, 2001) the authors revealed this same need by stating the following: "While univariate GARCH models have met with widespread empirical success, the problems associated with the estimation of multivariate GARCH models with time-

varying correlations have constrained researchers to estimating models with either limited scope or considerable restrictions.”

One of the first MGARCH models to be presented was the CCC-GARCH. It was introduced by (Bollerslev, 1990), and it was characterized by having time varying conditional variances and covariances, as well as constant conditional correlations. These constant conditional correlations were calculated based on a constant correlation estimator. However later (Engle, RF., Sheppard, 2001) stated that through this estimator it is not possible to obtain consistent standard errors. Hence, they introduced the DCC-GARCH model, that, was considered as a multivariate specification that also contains conditional variance and correlation but especially contains a time varying correlation matrix. The key was in the transformations that the authors made in the conditional covariance, which allows the possibility of estimating the time varying correlation matrix. This matrix is then important to understand the variance and covariance dynamics that, for example two variables like two different sectors, had over time.

Another famous MGARCH model is the BEKK-GARCH one. This model was proposed by (Engle & Kenneth, 1995) and is also very common in volatility spillover studies. (Cardona et al., 2017) analyzed the volatility spillovers between stock markets of US and six largest Latin American countries, using the BEKK-GARCH model. In (McCullough et al., 2018) the authors investigated the volatility spillover effects between the FTSE/JSE Top 40 index and its corresponding futures contracts. They implemented both BEKK-GARCH and DCC-GARCH models, with the last one being used to confirm the results obtained by the BEKK-GARCH model. (Zeng et al., 2021) focused on the analysis of the dynamic volatility spillover effect between the European Union allowance (EUA) and certified emissions reduction (CER) markets, using both VAR model and a multivariate BEKK-GARCH model. He found out that among some conclusions, it is important to highlight the fact that an existence of asymmetric volatility spillover effect between the EUA and CER markets with a more significant volatility spillover effect on the CER market. In the work of (Song et al., 2022), beyond the VAR model, already mentioned above, the authors also used a BEKK-GARCH model to measure the volatility spillover effects between China’s carbon trading and energy markets.

Turning attention to a different type of methodology, one of the most recent designed methods, the work of Francis X. Diebold and Kamil Yilmaz in 2008 is currently a very widely used method out of other models or methodologies, regarding the measurement of volatility spillover effects. For instance, they were responsible for creating, among other important things, the Spillover Index, which, is built through a VAR model where they take advantage of variance decompositions, which in turn allow them to incorporate spillover effects across

markets. In this specific work they intended to show the divergences in the behavior of returns spillovers and volatility spillovers, using data from nineteen global equity markets. This work was important to really show differences between the two characteristics mentioned above, where volatility spillovers register more sudden changes than return spillovers, proving that after the outbreak of a crisis, there is a large contagion effect ([Diebold & Yilmaz, 2008](#)). It was also important because the implementation of this new method opened new horizons about studies on this topic. On the other hand, this method also had some limitations and the need to obtain new types of information led the authors to design a new method. So, later, in 2012, they presented a model that measure the connectedness and volatility spillovers effect between assets in the US stock, bond, foreign exchange, and commodities markets. It is based on forecast error variance decomposition (FEVD) from a generalized VAR model. Thus, it was possible to make the variance decompositions independent of the ordering of the variables during the process of identifying the VARs, of the Cholesky factor and, also, the fact of being able to obtain information about the directional spillovers instead of a total of spillovers ([Diebold & Yilmaz, 2012](#)). In this work they end proving that after the explosion of the 2007-2008 crisis, the volatility spillovers recorded considerable increases.

Obviously, since the release of this method, many scholars chose to use it to study volatility spillover effects between different things and for different purposes. For instance ([Ari, 2021](#)) carried out a study on the volatility spillover effect between the shares of the health care sector of the ISE index, the exchange rate and precious metal prices, using the model created by ([Diebold & Yilmaz, 2012](#)). He concluded that the connections between these elements increased in the last years, more specifically in the pandemic period, and that the health sector plays an important role in Turkish markets.

## 2.4. ASSUMPTIONS IN FINANCIAL RETURNS

To be able to study volatility spillover effects, it is necessary, in all works on this matter, to calculate the returns, and respective volatility, of the assets in question, in order to carry out

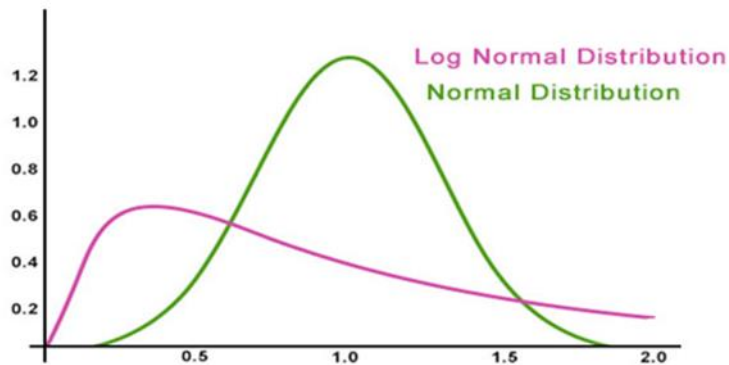


Figure 1 - Log-normal vs Normal distribution graphics

the necessary analyses in the following steps. A return represents the changes of the prices of an asset during a certain period, which can result in losses or gains for investors. One of the most used ways to calculate the returns is through log-returns. The main reason to this fact is that due to the assumption of a log-normal distribution, it is possible to obtain a more realistic and a better representation of the distribution of daily financial returns. The skewed distribution present in the log-normal distribution, as it is possible to see in Figure 1, have a close approximation to the distributions presented by the financial returns, where fatter tails and excess kurtosis are very often visible.

The use of this type of returns also implicate the assumption that the returns are continuous over time which means that returns are divided into infinite sub-periods of time (Miskolczi, 2017).

After calculating the returns, it will then be possible to proceed to the volatility calculation. This one can be described as a measure of uncertainty from the calculations of returns of asset prices (Hull, 2018). There are different ways to calculate volatility, from a simpler formula to more sophisticated models such as the GARCH models.

The family of the GARCH models got its start with (Brown et al., 1975), when he designed and proposed the ARCH (Autoregressive Conditional Heteroskedasticity) model. This was the first model to incorporate a stochastic process, with the objective to change the assumption on constant volatility present in past models and introduce a conditional volatility to better fit to

the reality. This work by Engle opened new horizons in this matter, and since then several other variants have been proposed. Based on Engle's ARCH model, Tim Bollerslev ([Bollerslev, 1986](#)), proposed the GARCH (p, q). In general, GARCH models have some advantages when compared to other stochastic volatility models. Many economists and researchers argue that these models are easier to implement when compared to continuous-time models, due to the discrete-time stochastic differential equations, as well as the likelihood functions (important for estimating some model parameters) that characterize them. The most famous variant and, still one of the most used, is the GARCH (1,1). This model emerged with the aim of being a reference in volatility modeling, but above all, it is also widely used in financial series forecasting and risk management. However, a few years later, it started to reveal some problems, more precisely, in the measure of a variable like asymmetry. This variable has gained greater importance over the last few decades as it helps to explain some reactions of the financial markets to news that are disseminated in society. This means that asymmetry is defined by a trend that occurs very regularly: in response to good news the volatility of returns recorded is lower than when in response to bad news, in which case it registers large increases in volatility. ([Hansen & Lunde, 2005](#)) proved that the GARCH (1,1) model cannot perform asymmetry measurements in the volatility of the returns. They reached to this conclusion by carrying out a study in which they compared this model to others that proved to be efficient in the ability to measure asymmetries. Studies like ([Glosten et al., 1993](#)) and ([Engle & Ng, 1993](#)) revealed the importance of including an asymmetry factor in financial models, which incorporate time series.

One of the most used models for measuring asymmetry is the APARCH (Asymmetric Power Autoregressive Conditional Heteroscedasticity) model. This model was launched by ([Granger & Engle, 1993](#)) and it is going to be important in for the development of this dissertation. One of its advantages is the fact that it is possible to estimate the equation related to the conditional variance through the information contained in the time series. Another good characteristic of this model is the fact that it can accommodate other models that were proposed, also having as a major objective, the inclusion of an asymmetric parameter to allow for a better measurement and evaluation of this variable. One example of a model in these conditions is the GJR-GARCH of Glosten, Jagannathan and Runkle, having been proposed in ([Glosten et al., 1993](#)).

In the next section, the statistical tests and models that are important for the purpose of this dissertation, will be exposed and explained, to explain better the interactions between them throughout the study.

### 3. DATA AND METHODOLOGY: STATISTICAL TESTS AND MODLES

#### 3.1. DATA

The study in question in this dissertation comprises the use of data relating to the sectors of the S&P500 (^GSPC) index so that it is possible to measure the volatility spillover effects between them. Altogether, there are eleven sectors that make up this index. Next, these same 11 different sectors are indicated, along with their respective ticker symbols. The first will play a central role in this study as it is the sector with which the remaining sectors will be compared. It is the Information Technology sector (^SP500-45). The other sectors are Industrials (^SP500-20), Financials (^SP500-40), Utilities (^SP500-55), Health Care (^SP500-35), Consumer discretionary (^SP500-25), Materials (^SP500-15), Energy (^GSPE), Communication services (^SP500-50), Consumer Staples (^SP500-30) and Real Estate (^SP500-60). All these sectors represent an important part of the economy of a society, and, currently, some have more weight than others. For this example, there is nothing better than the Information Technologies (IT) sector, which currently has great weight in the S&P 500 index.

The choice of these sectors was not made by chance. To be able to carry out this study based on the different sectors of the index mentioned above, it was necessary to use the classification made by the Global Industry Classification Standard (GICS). This system was created and launched by Morgan Stanley Capital International (MSCI) and Standard & Poor's (S&P) together in 1999. According to (Stevens, 2022), each company is classified by a hierarchy divided in four tiers: sector, industry groups, industries and sub-industries. The main tier is the sector one, which is also the one that will be used in this study, while the other tiers show a more distilled classification as one descends further in their hierarchy. The development of this classification system was based on the need to follow up in more detail the evolution of companies belonging to different economic areas. This way investors would have more and better information to consolidate their investments, being at the same time more attractive to them.

Also according to (Stevens, 2022), this classification system has undergone some changes in its tiers over the years. At the sector tier level, there is only one change to be noted. In 2016, some companies were withdrawn from the Financials sector to be allocated to the newly formed Real Estate sector, thus increasing the number of sectors to eleven.

Finally, regarding the origin of the data, they were extracted, in the form of adjusted closing prices (for the index and each sector) from the Yahoo Finance website, and the time interval established for this study lasts for 10 years. It is contained in the following dates: from 01/01/2012 to 31/12/2021. The choice of a time interval with a size of 10 years is enough to

give credibility to the results of this study. Besides that, this package of data also encompasses the years of economic and financial recovery after the 2008-2010 crisis and, more recently, the period of crisis caused by the pandemic. In this sense, it will also be interesting to understand the impact of this pandemic crisis on volatility spillover effects between the IT sector and the rest of the S&P 500 index sectors.

## **3.2. METHODOLOGY**

In this section, the models, and statistical tests that, we will use for the implementation of this study will be presented. It is important to state that all these models and statistical tests were implemented in the R program, using some packages and functions of it to get to the results.

### **3.2.1. Log-returns**

After extracting all the necessary data, it is time to implement practices related to the scope of this dissertation that will lead to results that can be scrutinized. The first procedure is to analyze the ten years of prices movements registered by the S&P 500 index and its eleven sectors. Therefore, to begin this analysis the returns of these same prices must be calculated. To calculate returns, assuming they have a log-normal distribution, we will use the following formula for log-returns:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Equation 1 - log-returns calculation formula

where  $r_t$  represents the log-return and  $P_t$  the adjusted closing price in time  $t$ .

After the calculations of the returns some tests need to be done to get a better information of the data. The explanations of the utility of those tests will be given in the next steps.

### **3.2.2. Normality in Index/Sectors returns**

Although, earlier in this dissertation, it was mentioned that, in relation to the returns, they have a log-normal distribution, the normality test will be carried out. The reason for this fact comes from the need to have evidence that the returns are not normally distributed. Therefore, for this purpose, the Jarque-Bera test will be used. This is a test that is easily applicable, demonstrates effectiveness at an asymptotic level, being distributed as  $\chi^2_{(2)}$  (chi-squared

distribution) and it was built through a derivation of the Lagrange multiplier method (Jarque & Bera, 1987). The null hypothesis of this test represents the evidence of normality in the tested observations and is rejected if, for  $\alpha$  significance level, the Jarque-Bera test statistic obtained is greater than  $\chi^2_{(2)}$ .

Hence the Jarque-Bera test is defined through the following equation:

$$JB = n * \left( \frac{(\widehat{\sqrt{b_1}})^2}{6} + \frac{(\widehat{b_2} - 3)^2}{24} \right)$$

Equation 2 - Jarque-Bera LM test statistic equation

Where  $(\widehat{\sqrt{b_1}})^2 = \frac{\widehat{\mu_3}}{(\widehat{\mu_2})^3}$ ,  $\widehat{b_2} = \frac{\widehat{\mu_4}}{(\widehat{\mu_2})^2}$  and n representing the sample size. It is also important to mention that  $(\widehat{\sqrt{b_1}})^2$  and  $\widehat{b_2}$  are respectively the estimates of Skewness and Kurtosis.

### 3.2.3. Stationarity in Index/Sector returns

The next parameter to be evaluated is the stationarity of the data of the returns obtained for the S&P 500 Index and its eleven sectors. Stationarity is very important when it comes to time series analysis. The term stationarity, in this context of time series, indicates, in the case of its existence, an independence in relation to time, that is, more specifically that its variance does not vary as a function of time. The absence of stationarity in these cases can lead to problematic situations when interpreting the results of such a study (Savit & Manuca, 1996). In order to test for stationarity, the ADF (Augmented version of the Dickey-Fuller) test was chosen. Like in this dissertation, where we work with multiple time series, in the work of (Thangamuthu et al., 2022), the authors stated that: "To avoid spurious regression by regressing one random walk time series data on another random walk time series data, a stationarity test was conducted using the Augmented Dickey-Fuller (ADF) unit-root test." Besides this fact, with this test is also possible to avoid serial correlation. To achieve that it is necessary to include lagged terms that are established by minimizing a given Information Criteria.

Hence the ADF test is stipulated so that the null hypothesis represents evidence of non-stationarity. Therefore, if this hypothesis is rejected, the time series in question presents stationarity. For this parameter, the calculation of log returns is of fundamental importance, because for the models and tests in this dissertation, like for instance the VAR model, to provide

credible results. In this sense, it is necessary to work with stationary time series, and only the time series of log returns can guarantee this particularity with much more certainty.

### 3.2.4. ARMA model

When it comes to the study of time series, the Autoregressive Moving Average (ARMA) model has always been an important factor for this purpose. It is very often related to the studies of financial markets to make short-term forecasting based on past movements of those markets and, it is characterized by the incorporation of a conditional mean equation. (Tang, 2021) stated that: “The ARMA model (p, q) is currently the most commonly used model for fitting stationary time series, which considers the autoregression of financial market indicators and considers the interference of random fluctuations, making it possible to predict the short-term trend with a low error rate.” The conditional mean equation of the ARMA (p, q) model can be analyzed separately, that is, it has a part dedicated to autoregression AR(p), where p represents the number of autoregressive terms, and, another part related to the moving average MA(q), with q being the number of lagged moving average terms. According to (Tang, 2021), this model represents the junction of two different models: the AR(p) and the MA(q) where AR(p) model is more dedicated to catch the momentum and mean reversion effects, helping to show how much the returns are related to the past and the MA(q) is responsible for measuring the shock effects observed in the white noise terms giving information about the relationship between returns and past random shocks. Given this, the ARMA (p, q) model is defined by the following equation:

$$y_t = \mu + \varphi_1 y_{t-1} + \dots + \varphi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q}$$

Equation 3 - equation of the ARMA (p, q) model

Where  $\mu$  represents the mean of the past returns,  $y_{t-i}$  a return at time  $t - i$  and  $\varepsilon_t$  a white noise process.

With this information, the next challenge will be figuring out how to correctly estimate the values of p and q. The answer to this situation lies in the “auto.arima” function from “forecast” package in the R program language. With these tools it is possible to fit, in a faster and simpler way, the univariate time series of log-returns to an ARIMA (p, d, q) model with  $d = 0$  that is equivalent to an ARMA (p, q) model. But before implementing this function of R, it is necessary to decide which is the best Information Criterion to use for this purpose. In this sense, we chose to use the Akaike Information Criterion (AIC) rather than Bayesian Information Criterion (BIC),

considering the conclusions of (Vrieze, 2012), that despite carrying out the study directly for an area such as psychology, some of that conclusions can still be applied in other types of study such as this one. The main conclusion of this author, which makes the difference here, is the fact that although the BIC is more consistent and more effective when one of the candidate models is the one that best fits the data, it does not have the ability, in finite size observations, to minimize as much risk as possible of choosing the wrong model. This idea can be confirmed by these words wrote by the author in the work already mentioned in the last page: “In other words, while AIC may not be asymptotically consistent in selecting the true model, when N is finite, it will not select a bad model—but the BIC may. This property is termed minimax rate of convergence in risk; AIC minimizes the maximum possible risk in model selection.”, where N is the number of the observations.

After the estimates have been made, it is necessary to verify that they are well adapted to the model. This verification results from the application of the Portmanteau test. This test was launched in the work of (Ljung & Box, 1978) and, will precisely test the independence of the residuals, that is, if the residuals do not show autocorrelation. The estimate of this test is presented as follows:

$$\tilde{Q} = n(n + 2) \sum_{k=1}^m \frac{\rho_k^2}{n - k}$$

Equation 4 - Statistic estimation of the Portmanteau test

Where n is the size of the sample, m the number of lags and  $\rho_K$  is the autocorrelation for the k lag.

Lastly, the null hypothesis, of this statistic test, that here represents the presence of serial correlation, is rejected if, for  $\alpha$  significance level,  $\tilde{Q} > \chi_{1-\alpha, m}^2$ . As this is not desirable for studies such as this one, it is expected that the null hypothesis will not be rejected.

### 3.2.5. ARCH test

As mentioned before, this study involves an adjustment to the log-return data of a GARCH-type model, more specifically, the APARCH model. Taking the mean equations of the ARMA models mentioned in the previous section, the fact of estimating their parameters and correctly fitting the model to the data is not in itself sufficient to guarantee evidence of heteroscedasticity in these same data. Also, to take advantage of the capabilities of GARCH type models to be able

to expose time varying volatility records, it is necessary to perform a statistical test to verify the existence of conditional heteroscedasticity. This statistical test is the ARCH test, that is a Lagrange Multiplier test that was introduced by (Brown et al., 1975) and consists of measuring the significance of a chi-squared statistic.

Like all statistical tests, this one also includes two hypotheses. Here, the null hypothesis represents the lack of an ARCH effect, meaning that if it is rejected, the GARCH models type can be adjusted to the data without facing problems of autocorrelation and expose the evidence of time varying volatility. Obviously, the verification of the existence of these facts are desirable on a study like this one.

### **3.3. METHODOLOGY: MODELS**

In the next section, the intricacies of the models to be implemented in this study will be explored. The first model to be examined is the VAR model, followed by the analysis of two Multivariate GARCH models: the DCC-GARCH model and the BEKK-GARCH model.

#### **3.3.1. VAR Model**

When it comes to econometric regression models, it is impossible not to mention the VAR model and its wide use by practitioners. In some studies, the VAR model is put into practice to forecast between different economic and financial variables. On the other hand, in other works it is also used to study the dynamics between multiple time series, such as the effects that a period of high volatility in financial markets may have on the relationship between 2 or more time series. Following a similar idea, but with a different objective, the VAR model, more specifically the bivariate strand, is used in this study to better analyze the connections among the returns time series of the IT sector and the other sectors of the S&P 500.

In general, this is the equation that defines the multivariate VAR(q) model:

$$y_t = \mu + X_1 y_{t-1} + \dots + X_q y_{t-q} + \varepsilon_t$$

Equation 5 - Multivariate VAR model equation.

Where  $y_t$  represents the observed values of the stationary variables,  $\mu$  represent the matrix of the intercept terms,  $X_{1,\dots,q}$  constitute the matrices of coefficients to be estimated and lastly, the  $\varepsilon_t$  is presented as the random error term.

With the aim of carrying out a better examination to the features of this model, a few diagnostic multivariate tests will be introduced. Two of these tests have already been introduced in this dissertation. One is the Portmanteau test to assess the existence of serial correlated errors and to verify the statistical evidence of conditional heteroscedasticity, the ARCH LM test is applied. Then come the two news. The first refers to the CUSUM test. This test was introduced by (Brown et al., 1975) and for a brief description it is enough to say that this test seeks to assess the stability of the VAR model in question.

### 3.3.2. DCC-GARCH model

Due to the evolutions that the financial markets have undergone, the need for models with greater capacity to measure variations over time has emerged. Volatility spillover effects are an example of these variations. In this way, and because they have this capability, the MGARCH models have gained increasing interest. One of the MGARCH models that best presents this capability is the DCC-GARCH model (Dynamic Conditional Correlation GARCH model). But the process of using this model, and especially in this study, demonstrates a particularity, which is, before applying the features of this model to the data set, it is necessary to estimate a univariate GARCH model for each sector. Therefore, only after applying this estimation process to the returns of each sector is it possible to estimate the parameters of the DCC-GARCH model. For this, it is necessary to resort to the transformed residuals of the estimation process of the univariate GARCH models of each sector. In this dissertation, the univariate model that was chosen to fit the data is the APARCH (Asymmetric Power ARCH) model. This model of (Granger & Engle, 1993) have special particularities that distinguishes it from other GARCH models. One of them is the possibility of being able to estimate the power parameter ( $\delta$ ) of the time varying volatility instead of having to be imposed in the model equation. The other difference is related to the fact that a parameter ( $\gamma$ ), with the ability to capture the asymmetric volatility present in the time series returns under study, was added to the model. This addition was made in order to improve the distribution of data volatility (Olowe & Ayodeji, 2009). Also about this topic, in the working paper of (Longmore & Robinson, 2004) the authors stated that: "...the assumption of normality, which restricts  $d$  to either 1 or 2, is often unrealistic due to significant skewness and kurtosis." With these facts, we concluded that this APARCH model is the one that better describes the variations of the data.

Regarding the lag of the parameters  $p$  and  $q$  of the APARCH model, the value for them will be the value 1. This decision is related to the fact that the study of (Hansen & Lunde, 2005) exposed that models that incorporate bigger lags does not have a better performance than the models with the (1,1) lag. More concretely, in their study, those models registered worst performances than the models with (1,1) lag.

The APARCH ( $p,q$ ) model is defined by the following equation:

$$\sigma_t^\delta = \omega + \sum_{i=1}^p \alpha_i (|\varphi_{t-i}| - \gamma_i \varphi_{t-i})^\delta + \sum_{j=1}^q \beta_j \sigma_t^\delta$$

Equation 6 - APARCH model equation

Where  $\omega > 0$ ,  $\delta > 0$ ,  $\alpha_i \gg 0$  for  $i = 1, \dots, p$ ,  $\beta_j \gg 0$  for  $j = 1, \dots, q$ . Besides that  $-1 < \gamma_i < 1$  for  $i = 1, \dots, p$ . This model will constitute the variance model within the DCC-GARCH one implementation. However, it is also important to mention that for the implementation of the DCC-GARCH model it is also necessary to estimate a mean model, which in this case is represented by the ARMA model mentioned previously in section 3.2.4. In practice, for each sector, estimated an APARCH (1, 1) model and an ARMA ( $p, q$ ) model that precisely form the variance model and the mean model of each sector. This will be crucial to apply the DCC-GARCH model between the IT sector and the other sectors.

Returning to the process of estimating the parameters of the DCC-GARCH model, the main objective lies in obtaining the values of the time varying correlation matrix ( $R_t$ ):

$$R_t = X_t^{-1} Q_t X_t^{-1}$$

Where

$$Q_t = (1 - \gamma_1 - \gamma_2)M + \gamma_1 Q_{t-1} + \gamma_2 \epsilon_{t-1} \epsilon'_{t-1}$$

Equation 7 - Equations of the estimation process of DCC-GARCH model

With  $\gamma_1, \gamma_2 > 0$  and  $\gamma_1 + \gamma_2 < 1$  which means the guarantee of non-negativity and stationarity of the  $Q_t$  matrix, and consequently of the  $R_t$  one. A very important detail is the fact all the calculations during the estimation process of the DCC-GARCH model must be done according to the non-negativity and stationarity rules established in the GARCH methodology processes. That's why it is also important to mention that  $Q_t$  is a positive-definite matrix,  $X_t$  is a diagonal matrix where its values represent the square root of the diagonal terms in  $Q_t$  and  $M$  represents the unconditional covariance matrix of the variable  $\epsilon_t$ , which in its turn is the standardized innovation vector. With this process concluded, the conditional variance is estimated. The next

step consists in the estimation of the covariance matrix  $H_t$ . This matrix is obtained through the following process:

$$H_t \equiv A_t R_t A_t$$

Equation 8 - Process of the estimation of the covariance matrix.

Where  $A_t$  is a diagonal matrix and, the values in that diagonal are, in this study, the coefficients of the conditional correlation between the S&P 500 sectors and they are represented by  $g_{i,t}$  in the following equation:

$$g_{i,t} = \alpha_{i,0} + \sum_{k=1}^{K_i} \alpha_{i,k} r_{i,t-k}^2 + \sum_{z=1}^{Z_i} \delta_{i,z} g_{i,t-z}$$

Equation 9 - Equation used to obtain the diagonal values of matrix A.

After exposing the features of the DCC-GARCH model, it is also necessary to show that, according to some authors, this model shows some weaknesses. Despite presenting a good capacity in the calculation of dynamic correlations between variables, this model simultaneously presents flaws in the demonstration of the asymptotic properties of the estimated parameters (Caporin & McAleer, 2013). Bearing in mind these facts, which somehow detract from the credibility of the DCC-GARCH model, we decided to follow the methodology that suggests using this model as a diagnostic supplement for the BEKK-GARCH model. This methodology was suggested precisely by (Caporin & McAleer, 2013) and was used in the work developed by (McCullough et al., 2018). Then, in the next section, the nuances of the BEKK-GARCH model are presented.

### 3.3.3. BEKK-GARCH model

The (Baba-Engle-Kraft-Kroner) BEKK-GARCH model is one more case of the models that belong in the MGARCH models group. A version of this model was developed by (Engle & Kenneth, 1995) continuing the work previously developed by themselves and by other authors such as Baba and Kraft, who, by the way, together, these four authors give the model its name. The great interest in this model for the study of volatility spillovers is largely due to its virtues. Very briefly, this model manages to guarantee the positive definiteness of the variance-covariance matrix and at the same time also guarantees greater simplicity since, compared to other

models, this one has few parameters to be estimated. It aims to calculate a conditional variance matrix ( $H_t$ ) and, in its general form, the BEKK-GARCH (p, q) is defined by the following equation:

$$H_t = CC' + \sum_{i=1}^q A_i(\varepsilon_{t-i}\varepsilon'_{t-i})A_i' + \sum_{j=1}^p B_j H_{t-j} B_j'$$

Equation 10 - BEKK-GARCH (p, q) equation

Where  $C$  is a lower triangular matrix with intercept terms,  $A$  is a matrix that contains ARCH coefficients,  $\varepsilon_t$  represents a random error vector matrix and the GARCH effects caused by GARCH coefficients are presented in matrix  $B$ . In practice this means that the values of matrix  $A$  give information about the shocks in the mean equations, while the values of matrix  $B$  convey information about the variance and covariance. But in this case, as in the DCC-GARCH model where the APARCH variant is used, it is also important to incorporate a parameter such as asymmetry. With this parameter it is possible to obtain more refined information about volatility spillover effects. Taking this parameter into account, the new equation of the BEKK-GARCH (p, q) model is as follows:

$$H_t = CC' + \sum_{i=1}^q A_i(\varepsilon_{t-i}\varepsilon'_{t-i})A_i' + \sum_{j=1}^p B_j H_{t-j} B_j' + \sum_{w=1}^w G_w(v_{t-w}v'_{t-w})G_w'$$

Equation 11 – BEKK-GARCH (p, q) equation with asymmetric parameters.

Where  $G$  is the matrix with asymmetric coefficients and  $v_{t-w} = \varepsilon_{t-i} \circ I_{\varepsilon < 0}(\varepsilon_{t-i})$  with  $\circ$  being the Hadamard product.

As stated earlier for the other GARCH models used in this study along with the due reasons, for the BEKK-GARCH model the terms  $p$  and  $q$  will be equated to the value 1. As the IT sector will be individually compared with each of the other sectors of the S&P 500, the binary version of the BEKK-GARCH (1, 1) will be implemented. Therefore, given these facts, the matrices of this model format are presented next, together with the equations that characterize each of the elements of the conditional variance matrix ( $H_t$ ):

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix}, C = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix}, A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, G = \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}$$

Where

$$\begin{aligned} h_{11,t} &= c_{11}^2 + (a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{12}^2 \varepsilon_{2,t-1}^2) \\ &+ (b_{11}^2 h_{11,t-1} + 2b_{11}b_{12}h_{12,t-1} + b_{12}^2 h_{22,t-1}) \\ &+ (g_{11}^2 v_{1,t-1}^2 + 2g_{11}g_{12}v_{1,t-1}v_{2,t-1} + g_{12}^2 v_{2,t-1}^2) \end{aligned}$$

$$\begin{aligned}
h_{22,t} &= c_{22}^2 + (a_{21}^2 \varepsilon_{1,t-1}^2 + 2a_{21}a_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{22}^2 \varepsilon_{2,t-1}^2) \\
&+ (b_{21}^2 h_{11,t-1} + 2b_{21}b_{22,t-1} h_{12,t-1} + b_{22}^2 h_{22,t-1}) \\
&+ (g_{21}^2 v_{1,t-1}^2 + 2g_{21}g_{22} v_{1,t-1} v_{2,t-1} + g_{22}^2 v_{2,t-1}^2)
\end{aligned}$$

$$\begin{aligned}
h_{12,t} &= c_{11}c_{21} + [a_{11}a_{21} \varepsilon_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22}) \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{12}a_{22} \varepsilon_{2,t-1}^2] \\
&+ [b_{11}b_{21} h_{11,t-1} + (b_{12}b_{21} + b_{11}b_{22}) h_{12,t-1} + b_{12}b_{22} h_{22,t-1}] \\
&+ [g_{11}g_{21} v_{11,t-1} + (g_{12}g_{21} + g_{11}g_{22}) h_{12,t-1} + g_{12}g_{22} h_{22,t-1}]
\end{aligned}$$

Equation 12 - Equations of the variance-covariance matrix

After exposing the equations that define the terms of the matrix  $H_t$ , it is important to explain the meaning that the terms of these equations have in the study of volatility spillover effects, bearing in mind that A is the matrix where information about previous shocks (ARCH effects) can be found, while in B is the previous increase in sectors returns variance (GARCH effects). The G matrix contains information about asymmetric effects, which means, how a negative shock in both sectors returns will affect the two sectors covariance returns.

A good way to explain this is with a practical example of this study and in this sense, we consider that variable 1 is represented by the IT (Information Technology) sector and that variable 2 is represented by the Ene (Energy) sector. Following this thought, it's easy to see that the terms  $h_{11,t}$  and  $h_{22,t}$  represent the conditional variances of the IT and Ene sectors respectively. For example, taking into account that the objective is to study the spillover effects in the IT sector in the Ene sector, the focus should be on the  $a_{12}$  and  $b_{12}$  coefficients, because, remembering what was said earlier about them, while the first measures the ARCH Effects of the IT sector on the Ene sector the second measures the GARCH effects of the IT sector on the Ene sector. If the objective is the opposite, do the same but now for the variables  $a_{21}$  e  $b_{21}$ .

Thus, the presentations of the models and statistical tests to be used in this study end, and in the next section the results obtained through the application of the methodologies discussed here will be exposed and analyzed.

## 4. RESULTS ANALYSIS

### 4.1. GRAPHICAL ANALYSIS AND DESCRIPTIVE STATISTICS

In almost all studies like this one, that is, with the same objectives as this one, the analysis section begins with an examination of the data, in this case the time series, which give life to this study. Thus, in Figure 2, there is a graphic image of the daily adjusted closing prices of the S&P 500 index, over the 10-year time covered by this study.

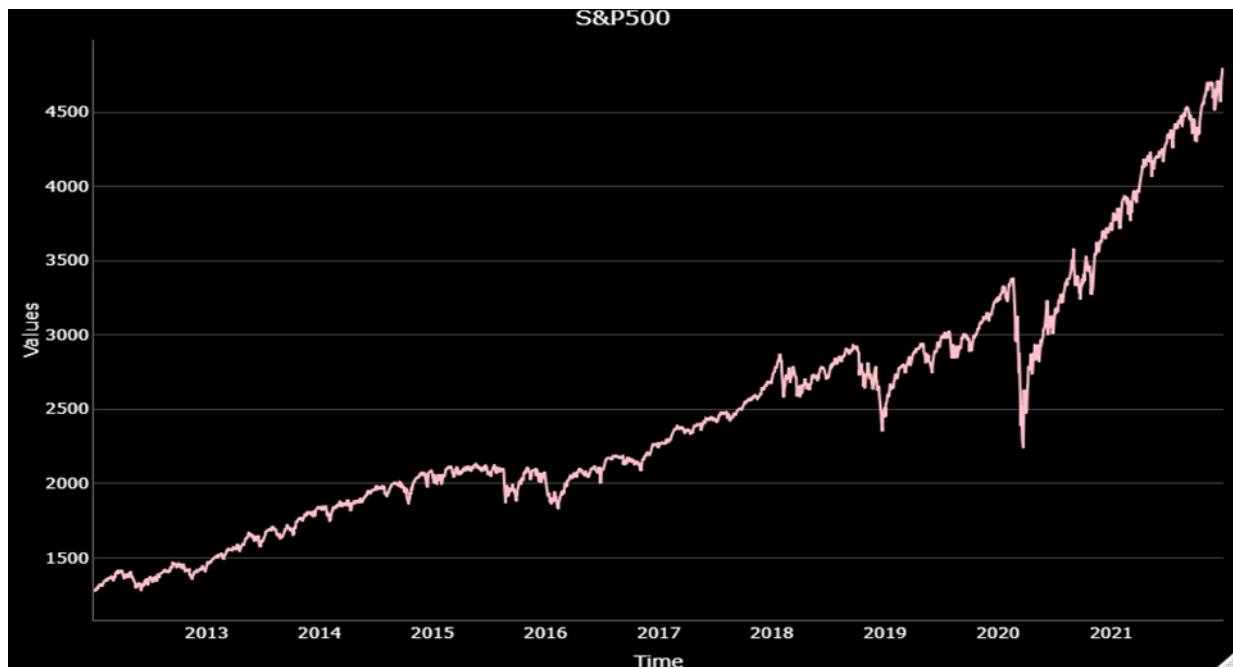


Figure 2 - Adjusted closing prices of S&P 500 index.

The information that can be extracted from this graph is that it clearly reflects what the global economic and financial situation of the last decade was like. This starts with a gradual recovery of economic activity after what happened in 2008, that is, the global financial crisis. In fact, this was a truly historic decade in the sense that this growth trend continued until the end of 2021. Despite these facts, it is important to note that in 2020 the pandemic implied an interruption in the trend growth observed until then, causing even initially a slight fall in the valuation of the index. Even so, with the resumption of economic activity, this fall was quickly reversed, thus also resuming the growth trend.

In relation to the behavior of the sectors in the same period, they generally follow the trend shown by the S&P 500 index. Observing the IT sector graph, in Figure 3, this is almost a copy of the S&P 500 index graph. The graphics of the other sectors that present are placed in Annex A.

Despite this apparent generalist behavior across sectors, there is one exception, that is the Energy sector. When looking at the graph of this sector in Figure 3, the behavior it has shown

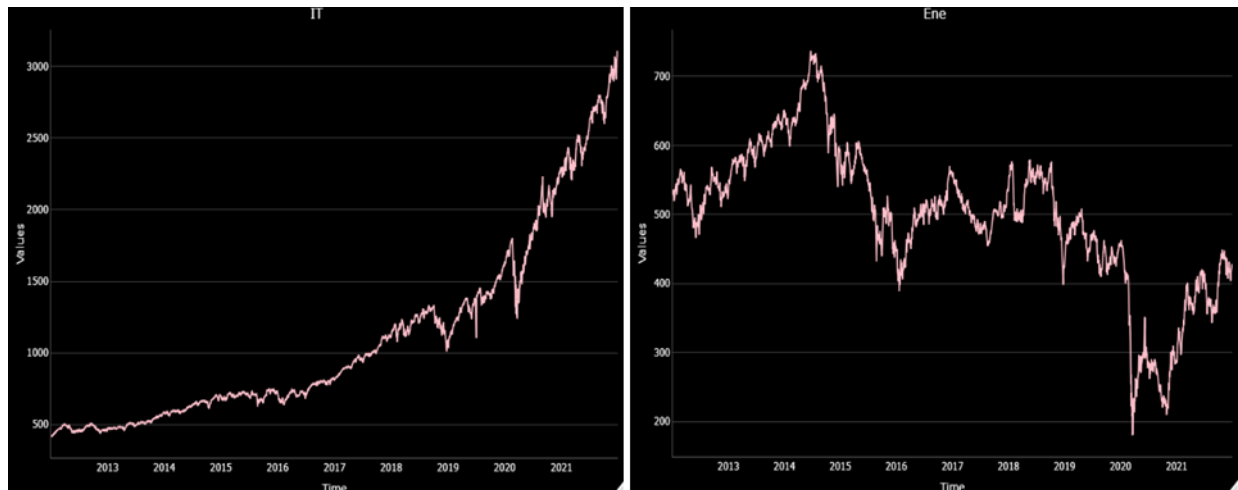


Figure 3 - Adjusted closing prices of IT sector (left) and Energy sector (right).

over the last decade reflects a downward trend in its adjusted closing prices values. After observing the graphs with movements of the adjusted closing prices and registering the presence of a stochastic trend in all of them, it is necessary to eliminate it to guarantee stationarity, which is very important to ensure a good implementation of the models discussed in the previous sections. To avoid these problems caused by non-stationarity, we took the adjusted closing prices and proceeded to calculate the log-returns using the formula exposed in section 3.2.. After obtaining the log-returns, they were graphed to get a better idea of their behavior. Figure 4 and 5 shows the log-returns charts of the S&P 500 index and the IT and

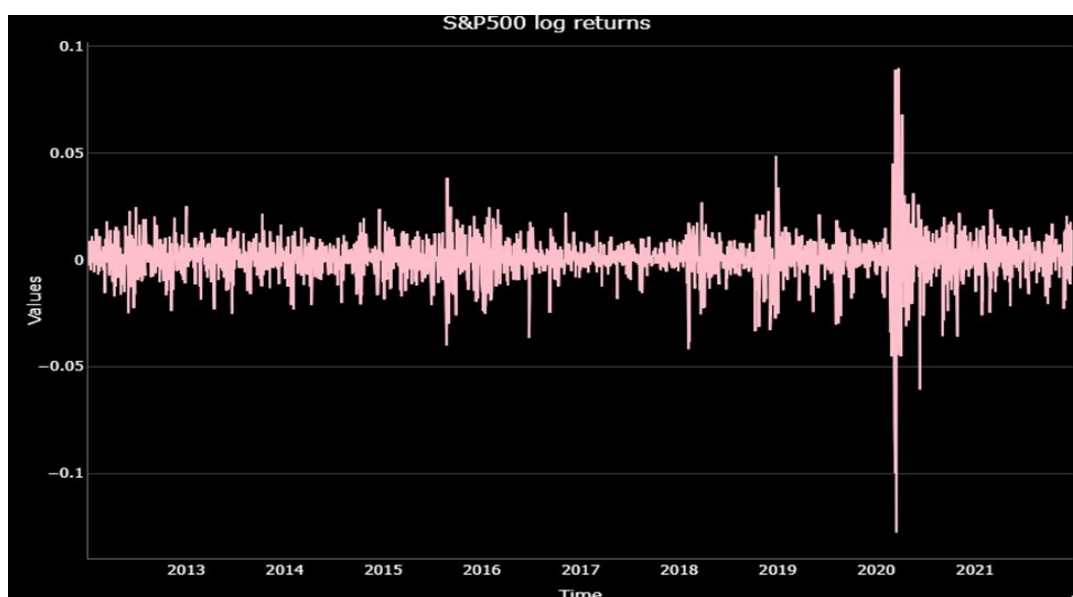


Figure 4 - Log-returns of S&P 500 index.

Energy sectors respectively. The charts with the log-returns of the other sectors are displayed in Annex B.

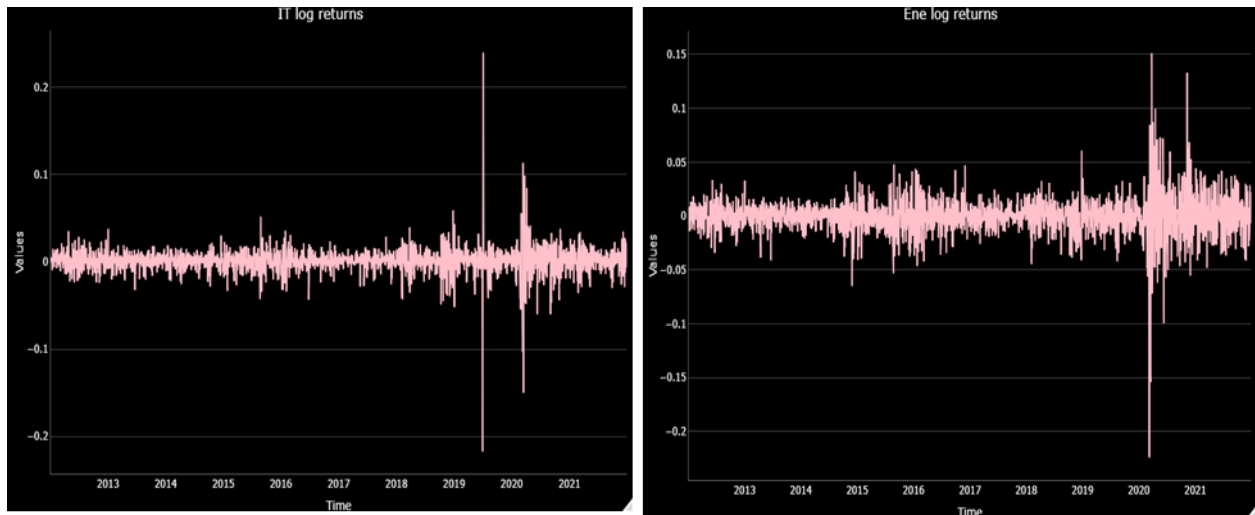


Figure 5 - Log-returns of the IT and Energy sectors.

In the case of log returns, like what happens with adjusted closing prices, the behavior of the sectors when compared to their index is also similar. Looking at the graphs of the log-returns belonging to the index and the sectors, the trends seen in the adjusted closing prices graphs ended up being eliminated, with the log-returns graphs showing a convergence to a constant value. It is also necessary to highlight the differences between some sectors regarding the dispersion of log-returns values. For example, between the IT and Energy sectors, whose graphs are in Figure 5, this difference is clearly visible. The IT sector has a smaller dispersion than the Energy sector. To finish this analysis of the log returns charts, it is verified the existence of some factors related to volatility such as volatility clustering. This means that it is possible to identify periods of high volatility, in this case occurring more specifically during the period of the pandemic crisis, as well as periods with records of low volatility.

After the conclusions drawn through the analysis of the charts, it is time to turn attention to the analysis of some statistical values about the S&P 500 index and the eleven sectors presented in table 1.

Examining the values in table 1, and starting with the first statistical parameter, it is possible to conclude that the mean returns all have positive values, except for the Energy sector, which in this case has a value of -0,0000937. These values make sense considering the graphical analysis done previously, which show a growth trend except for the Energy sector, which exhibited a negative trend. The highest value among the sectors was the value recorded by the IT sector, which is a strong indicator of the growing appreciation and weight that this sector has within

the S&P 500 index. In relation to extreme values, in this case the maximums and the minimums, the sectors present a greater disparity between them. It should be noted that the highest values to be recorded for the maximums are in the IT and CD sectors, which on the one hand explains once again the great development that the IT sector has registered and which, on the other hand, also explains a little of what the characteristics are. from the sector CD. The activity of this sector is based on industries that because they do not produce products and goods, let's say necessities, are more vulnerable to a more difficult economic and financial situation and

	S&P 500	IT	Ind	Fin	Uti	HC	CD	Mat	Ene	CS	TS	RS
Mean	0,00052	0,00079	0,00044	0,00051	0,00028	0,00056	0,00065	0,00038	-9,37E-05	0,00034	0,00029	0,00036
Maximum	0,09	0,24	0,18	0,22	0,19	0,19	0,24	0,11	0,15	0,13	0,088	0,083
Minimum	-0,13	-0,22	-0,18	-0,20	-0,18	-0,18	-0,22	-0,12	-0,22	-0,11	-0,11	-0,18
Std. Dev.	0,01	0,015	0,01292402	0,015	0,01	0,012	0,013	0,013	0,017	0,009	0,011	0,012
Skewness	-0,999	-0,037	-0,5416806	-0,22	0,08	-0,050	-0,099	-0,54	-0,97	0,095	-0,53	-1,56
Kurtosis	24,91	60,91	43,97392	46,78	57,78	58,55	92,06	16,51	24,65	39,84	12,41	31,29
Jarque-Bera	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16
ADF test	< 0,01	< 0,01	< 0,01	< 0,01	< 0,01	< 0,01	< 0,01	< 0,01	< 0,01	< 0,01	< 0,01	< 0,01

Table 1 - Statistics of Log-returns.

therefore, also present greater volatility in their returns. Another proof of this is that when the minimum values are observed, the smallest minimums are recorded by this sector (CD), and by the IT sector and the Energy sector, with the values for these two sectors being understandable for the reasons already mentioned about them. Table 1 also shows standard deviation values are all very close to 0 in the eleven sectors and in the index, confirming what had already been observed during the graphical analysis, that is, that in general they present a low dispersion in the values of returns. Regarding the skewness values, these are negative for all sectors and index, which indicates that, in general, during the observed period, these, despite presenting some significant losses, recorded many small gains. Speaking now of the values related to kurtosis, values above three were registered for all sectors and for the index, indicating the presence of leptokurtosis in the observed data. This fact agrees with the results obtained with the Jarque-Bera test, in which the p values were all lower than 1%, thus rejecting the null hypothesis and confirming the absence of normality in the returns.

Finally, using the "uruga" package from R program, we carry out the ADF test, and like the results of the Jarque-Bera test, the results of the ADF test were also unanimous, with p-values below 1%. In this way, the null hypothesis is rejected precisely for a significance level of 1%, thus guaranteeing the stationarity of the observed returns.

## 4.2. ESTIMATING ARMA MODEL

In this next step involves the estimation of the ARMA (p, q) model for all the time series of log returns for each sector. The ADF test results that are displayed in the Table 1 confirmed the stationarity of the time series of log returns and so it is possible to proceed with the conditional mean estimation using ARMA (p, q) model. In this sense, we follow the idea that we set out in section 3.2.4. of the Methodology that implies the application of the "auto.arima" function in R program, taking into account the AIC (Akaike Information Criterion), which will determine the ARMA (p, q) model that best suits the univariate time series of each sector. The estimation of the ARMA (p, q) models are shown in Table 2 for all sectors, along with the results (p-values) of the Ljung-Box test, for up to tenth order serial correlation and the results (p-values) of ARCH test.

Looking at table 2, we can see that, except for the TS sector, the estimated models are well suited to the time series of returns. The reason for this is explained by the column of p-values of the Ljung-Box tests, where all values, except for the TS sector, are greater than at least an  $\alpha$

	IT	Ind	Fin	Uti	HC	CD	Mat	Ene	TS	CS	RS
ARMA (p, q)	(4, 3)	(5, 4)	(5, 4)	(4, 4)	(4, 5)	(0, 3)	(3, 4)	(2, 4)	(1, 1)	(4, 1)	(4, 2)
Ljung-Box test	0,88	0,99	0,99	0,47	0,97	0,92	0,61	0,022	1.101e-10	0,19	0,92
ARCH test	0	0	0	0	0	0	0	0	0	0	0

Table 2 - ARMA model estimations with Ljung-Box tests and ARCH tests for all sectors.

significance level of 1%, thus indicating, for these cases, not rejecting the null hypothesis. However, for the TS sector, the null hypothesis is rejected, thus verifying that the estimated ARMA model does not fit in the best way to the log-returns time series. Therefore, we conclude that some of the details of the correlation incorporated in the time series of this sector were not completely transferred to the ARMA model. In this way, we went looking for a different ARMA model, with higher values for p and q, that is, an ARMA model that incorporates more variables. Therefore, after increasing the p and q values and testing these models, the ARMA format (3, 3) was the one that registered the best suitability to the fit, with a p-value for the Ljung-Box test of 0, 53. Thus, the null hypothesis is rejected, and, it is concluded that the residuals of the time series of the returns of the TS sector do not show signs of autocorrelation. This means that this model is already able to incorporate much more details of the correlation contained in the TS sector time series.

Lastly, about the ARCH tests, they were unanimous in demonstrating that the log-returns time series verify the existence of conditional heteroscedasticity, which means, the presence of time

varying volatility. For all sectors, the null hypothesis was rejected for an alpha significance level of 1%, thus allowing greater confidence in the estimation of the APARCH model later.

### 4.3. VAR MODEL

#### 4.3.1. VAR Model results

So far, in this dissertation, both the statistical tests on the data of the closing adjusted prices and then on the log-returns, as well as the application of the ARMA model, were carried out at the univariate level. In the following sections, the study will be carried out at the multivariate level, with the implementation of the models discussed above, starting with the VAR. Therefore, to satisfy the needs of this study to analyze the spillover effects between the IT sector and the rest, ten VAR models and the consequent diagnostic tests were implemented. First, it was necessary to estimate the number of lags, or rather, the number of p terms for each of these ten VAR(p) models, which, in this case was  $p = 9$  for all. These estimates were obtained using the "VARselect" function contained in the "vars" package of the R program. Table 3 shows the values for the covariance and correlation between the IT sector and the other models obtained through the implementation of the VAR model.

	IT vs Ind	IT vs Fin	IT vs Uti	IT vs HC	IT vs CD	IT vs Mat	IT vs Ene	IT vs TS	IT vs CS	IT vs RS
Covariance	0,000142	0,000151	0,0000916	0,000126	0,000159	0,000128	0,000118	8,95E-05	9,04E-05	8,52E-05
Correlation	0,7951	0,7457	0,5396	0,7912	0,8872	0,7278	0,4923	0,5723	0,6974	0,518

Table 3 - Covariances and Correlations estimated through the VAR model.

In a first instance, in the analysis of the covariance values, the values close to zero between the IT sector and the CS, TS and RS sectors are clearly noticeable. This means that between the IT sector and these 3 sectors there is great independence. On the other hand, the CD sector is the one that shows a greater dependence on the IT sector since it is the sector with the highest covariance. Regarding the correlation values, these are relatively close, being the value for the Energy sector the one that most differs from the others and at the same time the lowest value among the ten registered. This fact was to some extent expected considering the differences found in the analysis of the graphs carried out in section 4.1., especially in the trends that the time series of the adjusted closing prices of the IT and the Energy sector showed.

Note that the VAR model only provided unique covariance and correlation values, unlike the two models that will be analyzed below, which provide what the covariance and correlation values were over the ten years on which this study is based.

### 4.3.2. Diagnostic tests of the VAR model

Again, diagnostic tests play an important role in this study. In this case, it will be important to check some important parameters of the VAR model. The first parameter to be addressed is stability. This is important to ensure that there are no disturbances in the linear regressions of each of the estimated models. The test that was adopted for this situation is the CUSUM test based on recursive residuals. The results dictated that for all ten models there is stability because, in all graphs such as the one in Figure 7, the red lines, above and below, are never exceeded. The graphs in Figure 7 refer to the relationship between the IT and Industrial sectors, the rest of which are available in Annex D. To a certain extent, the stability found in this type of test was already predictable because, when estimating the VAR models for the 10 cases under study, all of them presented polynomial roots with values between 0 and 1.

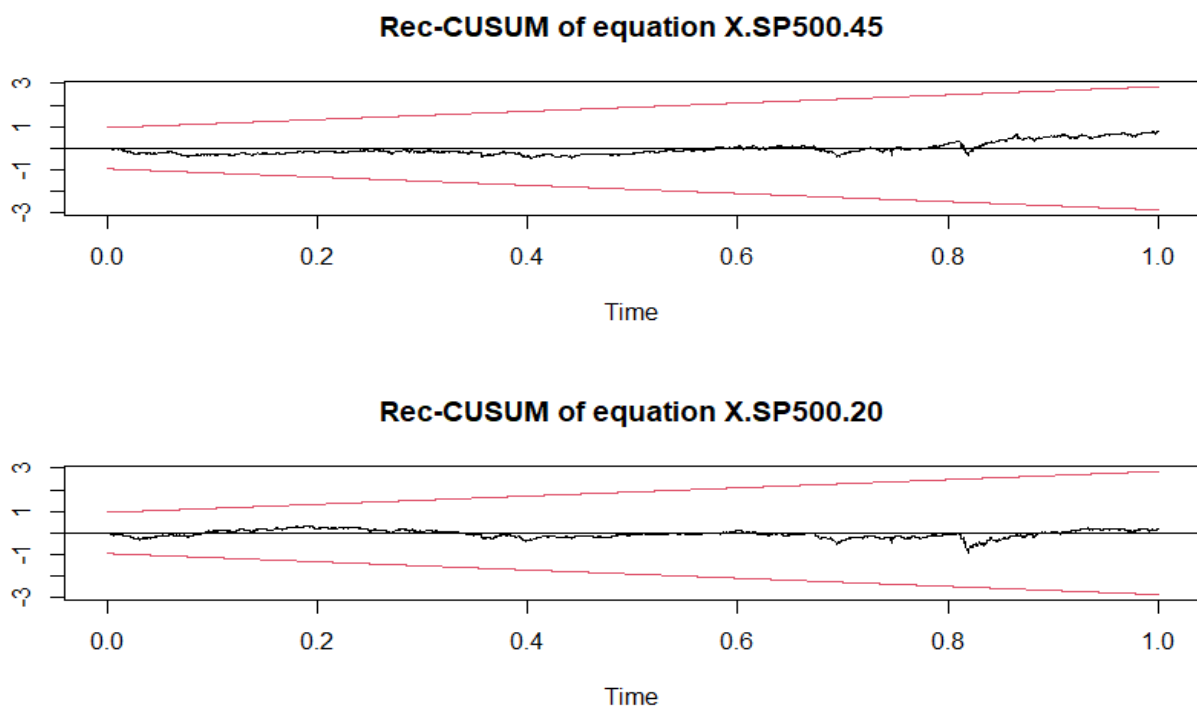


Figure 6 - Graphics of Rec-CUSUM test for IT and Industrials sectors.

The statistical tests that were applied again were the Portmanteau asymptotic, to test the evidence of serial correlation, the ARCH test to verify the existence of time-varying volatility and finally the Jarque-Bera test to assess the evidence of normality in the VAR models. Table 4 shows the p-values of these three tests for each of the ten VAR models in question.

	IT vs Ind	IT vs Fin	IT vs Uti	IT vs HC	IT vs CD	IT vs Mat	IT vs Ene	IT vs TS	IT vs CS	IT vs RS
PT.asymptotic	0,7508	0,4807	0,3002	0,4667	0,7509	0,5907	0,08595	0,5185	0,06579	0,4835
ARCH test	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16
Jarque-Bera test	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16	< 2,2e-16

Table 4 - P-values of the PT.asymptotic test, ARCH test and Jarque-Bera test for the 10 VAR models.

Starting with the results of the Portmanteau test, they clearly show a positive sign, the absence of autocorrelation in the models, because for these p-values, the null hypotheses were not rejected for an  $\alpha$  significance level of 5%. The next test, the multivariate ARCH test, once again had a unanimous result for all cases. The null hypotheses were all rejected for an  $\alpha$  significance level of 1% and, therefore, time-varying volatility exists in all VAR models.

Finally, the p-values of the Jarque-Bera tests performed were all very close to 0, thus rejecting, once again, the null hypotheses for a  $\alpha$  significance level of 1% and, therefore, it is possible to affirm that the existence of Normality. Still on this topic of Normality, it is important to mention that as it was rejected, it is necessary to decide on the choice of a distribution that is the most adequate for these data. In this sense, in the next section, when implementing the APARCH (variance) model, we will test two distributions that we think are the most appropriate and understand which of the two best fits the situation.

## 4.4. DCC-GARCH MODEL

### 4.4.1. Distribution choice and APARCH parameters estimation

The theme of this section will start by recalling what was said in the previous section about the rejection of normality for the time series under study, it is necessary to adjust a distribution that fits them, when fitting the APARCH model to the univariate time series of each sector. Bearing this in mind, using the "rugarch" package from the R program, we fitted, for each sector, a variance model, the APARCH (1, 1), and a mean model, the ARMA (p, q) models that were estimated before, in section 4.2., for each sector. This was repeated twice for each sector, the difference being that at first it was done with the student-t distribution and at a second time it was done with the Normal skew distribution. The fact that these two distributions were considered for this study is related to the observations made by (Mandelbrot, 1963) in which the author identified the fat tails and greater values for kurtosis as one of the main characteristics of returns distributions in financial markets. Therefore, as the two distributions that we implemented in the study present these characteristics, we decided to test them and, through this test, choose the one that best fits. As decision factors for this choice, the values of the AIC criterion and the Log-likelihood are considered. In this sense, in Table 7 the results of this fit are visible, with the values of these two parameters.

	IT	Ind	Fin	Uti	HC	CD	Mat	Ene	TS	CS	RS
Snorm: AIC	-6,1749	-6,3522	failed	-6,4858	-6,5627	-6,3775	-6,2569	-5,8082	-6,3399	-6,9654	-5,9947
Snorm: Log-Likelihood	7778,905	8003,949	failed	8170,864	8268,544	8029,693	7881,995	7316,782	7985,396	8770,994	7551,347
t-Student: AIC	-6,3301	-6,509	-6,2598	-6,5708	-6,6662	-6,5483	-6,2978	-5,8337	-6,4041	-7,0637	-6,8488
t-Student: Log-Likelihood	7974,125	8201,095	7887,756	8277,817	8398,758	8244,48	7933,499	7348,895	8066,093	8894,649	8625,38

Table 5 - AIC and Log-Likelihood values for Snorm and t-Student distributions.

Before going to the analysis of all the numerical results, it is necessary to observe the Fin sector case, which registered a failure to obtain values for the AIC and for the Log-likelihood of the Normal skew distribution in the case of the Fin sector. The R program could not reach a result because it registered a failure when trying to invert the Hessian matrix during the process. More specifically, this fact indicates that this matrix is not positive definite and therefore it is impossible to invert it. Therefore, in the case of the Fin sector, the t-Student distribution is chosen depending on the problem registered.

Regarding the remaining obtained results, the choice in the t-Student distribution is clear as water. In the values for the AIC criterion, the t-Student distribution always registers lower values than the Snorm distribution, which indicates that the models are better fitter under t-Student distribution. Another factor that reinforces this statement is that the values of the Log-

Likelihood are superior, in all cases, under the t-Student distribution when compared to the Snorm distribution. Hence, with the knowledge of these facts, obviously the choice fell on the t-Student distribution. In fact, the effect that this choice will have in the next section, where the the implementation of the DCC-GARCH (1, 1) model will be done, is that as this model is multivariate, the distribution that will be used is the multivariate t-Student and not the univariate version of this distribution.

Finally, in relation to the APARCH parameters that were estimated, there are also some undesirable values to be noted, since not all parameters referring to the GARCH processes have statistically significant estimates. This statement can be confirmed by consulting the tables that are available in Annex E.

#### 4.4.2. GRAPHICAL ANALYSIS OF THE DCC-GARCH (1, 1) RESULTS

In this section, the graphics of the time-varying conditional correlations (left) and covariances (right) between the IT sector and the other sectors, to better understand the variations in the relationships and influences between them that occurred over the ten years of study. For this, it was necessary to resort to the "rmgarch" package of the R program to obtain these same graphs.

But before going to the graphical analysis, it is important to make a brief reference to the joint estimates of the ten cases DCC-GARCH (1, 1) models. The values of these parameters are displayed in Table 9 and as it can be seen they are all positive and statistically different from 0. This fact is proof that in this model the existence of the notion of time-varying conditional

	IT vs Ind	IT vs Fin	IT vs Uti	IT vs HC	IT vs CD	IT vs Mat	IT vs Ene	IT vs TS	IT vs CS	IT vs RS
DCC(a)	0,1350	0,1061	0,0441	0,0910	0,0807	0,0809	0,0939	0,0940	0,0619	0,0658
DCC(b)	0,7587	0,8373	0,8979	0,8070	0,8480	0,8269	0,8575	0,8725	0,8817	0,8585

Table 6 - DCC(a) and DCC(b) joint estimates.

correlations is verified.

Starting this analysis with the pair of sectors IT and Ind, the Figure 7 shows the relation during the time interval that was chosen for this study. In this case, there is mostly a positive correlation between these two sectors, with values around 0,7. Despite some low correlation peaks registering values close to 0 and even negative values, for instance in mid-2013, these two sectors show a certain connection over time, with strong influences between them, and it can even be said that there is an effect volatility spillover between these two sectors. In the

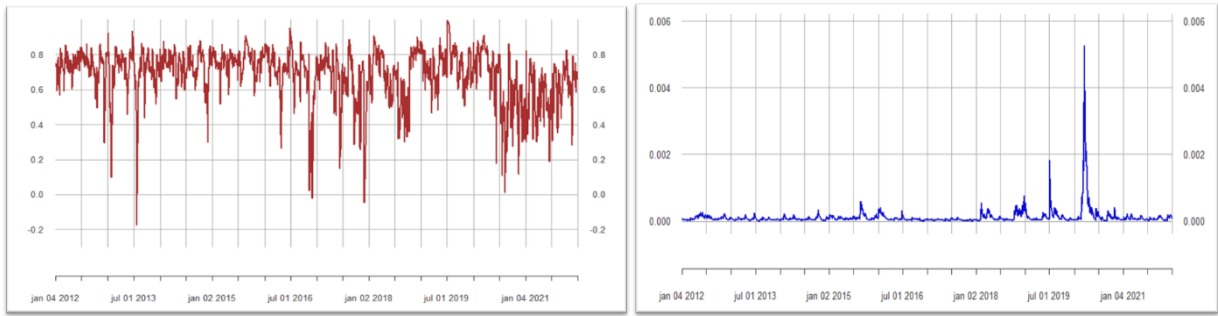


Figure 7 - Time-varying covariances and correlations between IT and Ind sectors.

covariances graphic, the values are very close to 0 until mid-2019 and then on 2020 year, where it is visible two peaks of covariance.

The second case, visible in Figure 8, is between the IT and Fin sectors. Here, there are some similarities with the IT vs Ind case, mainly up to 3/4 of the sample, with large flow of information between these two and with some low correlation peaks, even surpassing the barrier of -0.2, but mostly with values close to 0.7. But, towards the end of 2019 and beginning of 2020 (arrival of the pandemic) onwards the correlation values became lower. Despite this, the idea that exists a volatility spillover effect between these two sectors seems correct. Relatively to the covariance values, Figure 9 is very similar to Figure 8, which means that Fin and Ind sectors have a similar behavior in the relationship with IT sector.

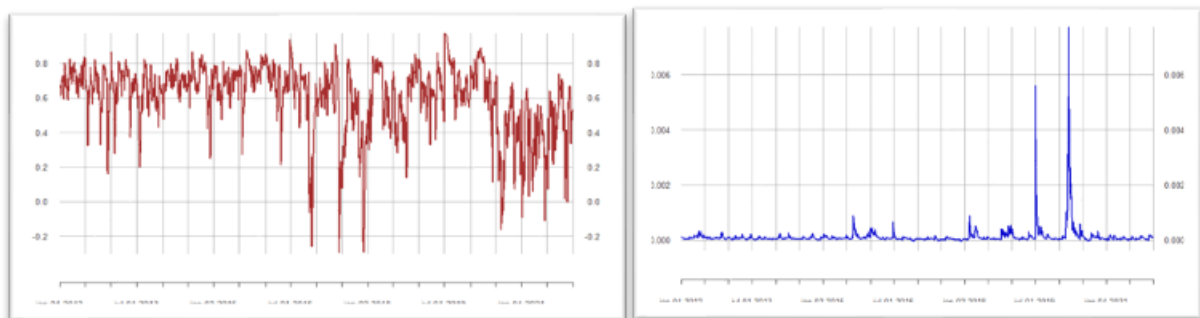


Figure 8 - Time-varying covariances and correlations between IT and Fin sectors.

Then, Figure 9 shows the time-varying conditional correlation between IT and Uti sectors. In this case, it is already possible to point out many differences in relation to the first two cases. The correlation is practically always positive, with one or two exceptions, for example in mid-2018, but on average the correlation between the IT and Uti sectors is almost always very close to 0.3. Therefore, here it is already possible to state that if there is a spillover effect, it will be weaker. For the covariances between these 2 sectors show that there's no covariance in most of the time except in mid-2019 and in 2020.

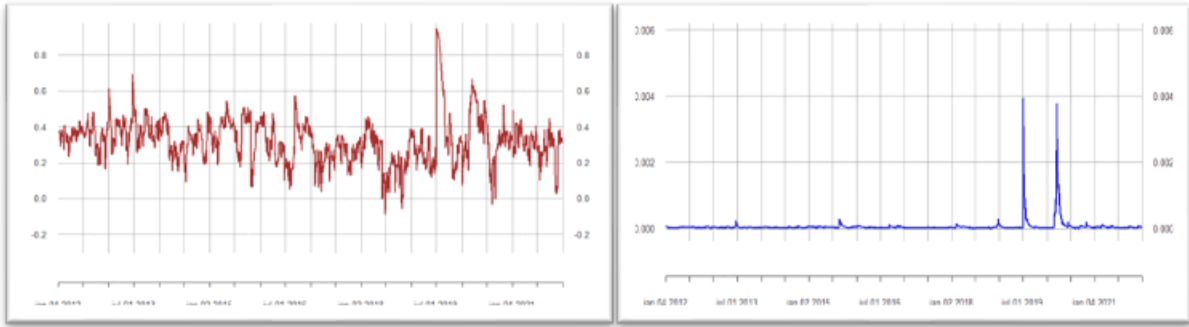


Figure 9 - Time-varying covariances and correlations between IT and Uti sectors.

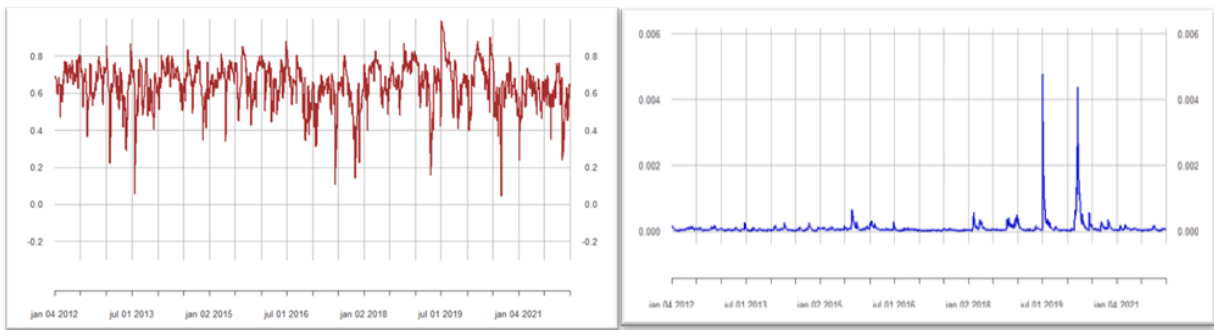


Figure 10 - Time-varying covariances and correlations between IT and HC sectors.

In Figure 10, the graphic of the IT and HC time-varying conditional correlation is shown. Between these two sectors, the relationship of "proximity" between them is clear, since the correlation between them is always positive over time, indicating the existence of a spillover effect. Here the covariances variations are very similar to the ones observed for the Fin sector case.

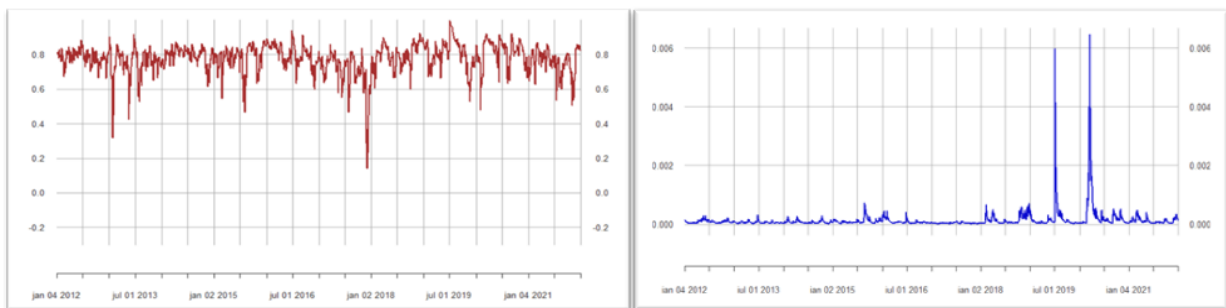


Figure 11 - Time-varying covariances and correlations between IT and CD sectors.

In the case of IT and CD sectors correlations relationship, the Figure 11 presents the graphic with the variations of the correlation between them over the ten years and the conclusion is easy to compute because it is the same for the case between the IT and HC sectors. So, it can be sad that a spillover effect also exists in this case. The covariances are also very similar except

in the case of the CD sector the peaks of the covariance are higher than the ones registered for the HC and Uti sectors.

In the relationship with the Mat sector, what happened with the Ind and Fin sectors happens again, with a strong correlation being observed over time, with the exception of a low correlation peak, indicating the presence of a spillover effect between IT and Mat sectors. Like the correlations, the time-varying covariances graphic in Figure 12 is also very similar when compared to Ind and Fin sectors graphics.

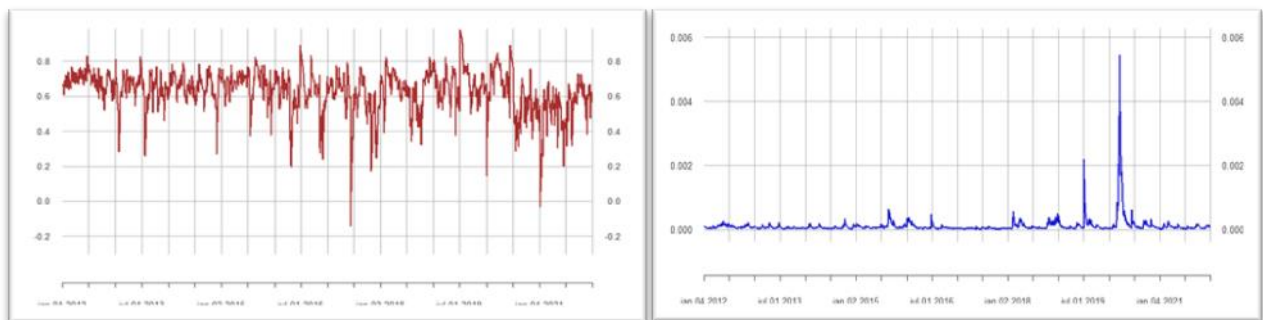


Figure 12 - Time-varying covariances and correlations between IT and Mat sectors.

In the Energy sector, when compared with the cases of other sectors, it has been possible to observe since the beginning of this study that it is the one that has registered more disparities with the IT sector. The graph in Figure 13 is the mirror image of that. Here the correlation shows many variations between positive and negative levels and when the pandemic arrived, the average values of the correlation became lower. The spillover effect in this case will not be very significant. In the covariances, the only notable record is verified in 2020, with values very close to 0 in the rest of the time. In the covariance graphic, the conclusion is simple because the Energy sector never followed trends in the IT sector except during the pandemic crisis.

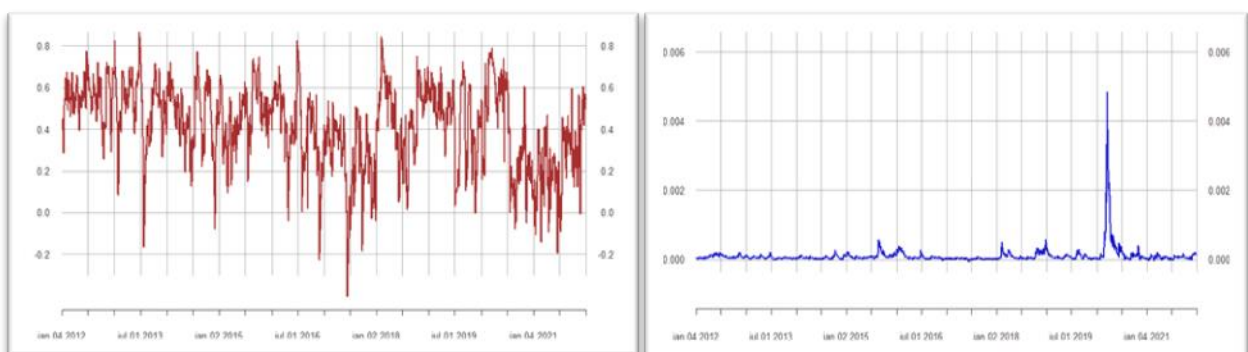


Figure 13 - Time-varying covariances and correlations between IT and Ene sectors.

Finally, in the correlated relationship between the IT sector and the last three sectors (TS, CS and RS), the graphs in Figures 14, 15 and 16 have very similar shapes between them. In addition to showing lower correlation values over time, they also record one or another negative value. This indicates that the spillover effects between the IT sector and these 3 sectors are not very significant. In the covariances side, the graphics for these three sectors reveal some differences between them. In the TS sector, it was found the only negative value among all the sectors in this study, showing that at that time, mid-2019, there was an inverse trend between the behavior of the IT and TS sectors returns. In CS sector there are two peaks of covariance, with the graphic of this sector showing a parallel form to the Ind one. Lastly, the RS sector covariances demonstrate only one high peak in 2020, following the trend that have been seen in all sectors, that in this this year (year of the explosion of pandemic) all the sectors had similar behavior to the IT one.

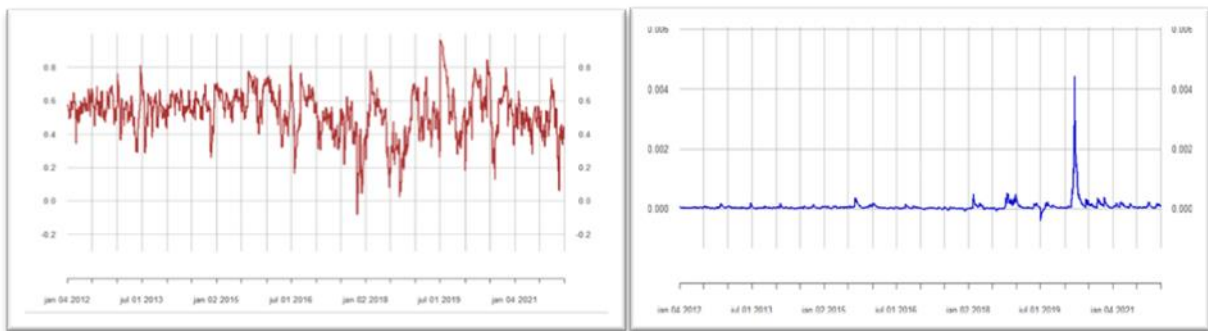


Figure 14 - Time-varying covariances and correlations between IT and TS sectors.

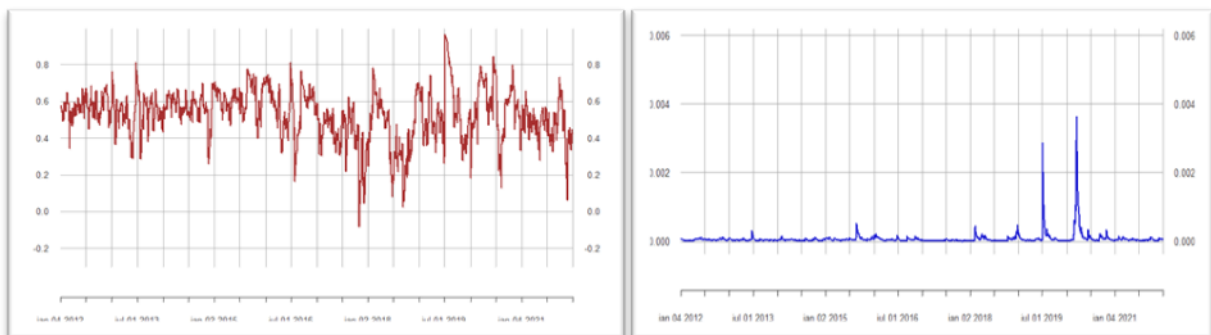


Figure 15 - Time-varying covariances and correlations between IT and CS sectors.

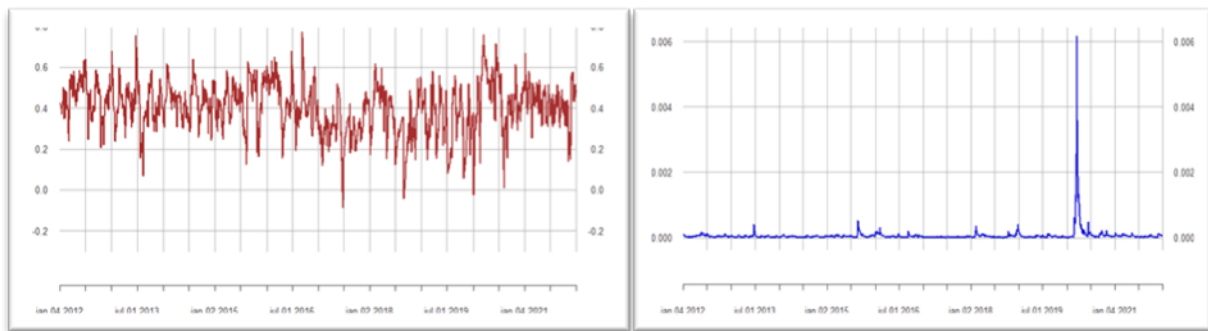


Figure 16 - Time-varying covariances and correlations between IT and RS sectors.

#### 4.5. BEKK-GARCH (1, 1) MODEL RESULTS ANALYSIS

In this section, the graphical and numeric analysis of the values obtained through the implementation of the BEKK-GARCH (1, 1) model will be performed. The analysis will be made for each pair of sectors (IT vs other sectors) through the observation of the time-varying conditional correlation graphs as was done for the DCC-GARCH (1, 1) model and the values of the matrixes of the BEKK-GARCH (1, 1) model that were calculated in this process, which provide important information about volatility spillover effects. This model was simpler and faster to compute, when compared to the DCC-GARCH (1, 1), by using the “BEKKs” package in R program.

To start this analysis process, let’s look to Table 7, that contains the values calculated for matrixes C, A, B and G to each pair of sectors in study and to Table 8 that contains the statistic t-values of the estimates presented in Table 7.

	IT vs Ind	IT vs Fin	IT vs Uti	IT vs HC	IT vs CD	IT vs Mat	IT vs Ene	IT vs TS	IT vs CS	IT vs RS
C(1, 1)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
C(1, 2)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
C(2, 1)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
C(2, 2)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
A(1, 1)	0,05	0,08	0,28	0,00	0,25	0,04	0,26	0,21	0,04	0,31
A(1, 2)	-0,19	-0,19	0,02	-0,17	-0,04	-0,10	-0,02	-0,02	-0,12	0,04
A(2, 1)	0,05	0,08	-0,03	0,10	0,13	0,26	0,05	-0,08	0,04	-0,11
A(2, 2)	0,36	0,37	0,17	0,31	0,34	0,38	0,32	0,21	0,27	0,22
B(1, 1)	0,60	0,65	0,66	0,33	0,00	0,83	0,45	0,10	0,39	0,22
B(1, 2)	0,44	0,53	0,23	0,10	-0,08	0,50	0,04	0,16	0,17	-0,03
B(2, 1)	-0,11	-0,14	-0,32	0,17	0,26	-0,55	-0,05	0,22	0,14	0,16
B(2, 2)	-0,03	-0,02	0,04	0,35	0,32	-0,33	0,24	0,17	0,23	0,35
G(1, 1)	0,98	0,96	0,87	0,99	0,88	0,95	0,94	0,95	1,00	0,95
G(1, 2)	0,03	0,00	-0,06	0,02	-0,06	-0,01	-0,02	-0,03	0,03	0,00
G(2, 1)	-0,10	-0,08	0,06	-0,10	0,02	-0,09	0,00	0,06	-0,14	-0,03
G(2, 2)	0,86	0,87	1,00	0,87	0,94	0,91	0,91	0,95	0,86	0,91

Table 7 - Values of matrixes estimated through BEKK-GARCH (1, 1) model.

	IT vs Ind	IT vs Fin	IT vs Uti	IT vs HC	IT vs CD	IT vs Mat	IT vs Ene	IT vs TS	IT vs CS	IT vs RS
C(1, 1)	18,29	18,50	18,15	15,56	13,47	14,57	12,39	0,18	7,79	11,65
C(1, 2)	17,62	18,41	2,47	11,73	9,46	10,96	4,98	0,16	9,58	7,06
C(2, 1)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
C(2, 2)	9,26	13,70	0,00	8,70	9,45	5,65	13,94	0,01	0,00	8,86
A(1, 1)	1,79	4,40	10,70	0,00	5,09	1,74	14,85	13,76	1,56	12,65
A(1, 2)	8,03	9,39	1,13	8,59	1,18	5,62	1,49	2,26	7,07	2,24
A(2, 1)	3,20	7,06	1,02	3,64	2,07	12,79	2,30	4,21	1,02	4,31
A(2, 2)	17,69	24,49	7,49	12,22	8,25	21,32	15,52	14,23	8,93	10,71
B(1, 1)	26,68	28,46	15,11	17,34	0,00	29,52	9,08	2,80	19,28	4,90
B(1, 2)	13,35	16,93	9,20	3,75	1,11	16,97	0,92	4,61	7,48	0,99
B(2, 1)	3,39	5,46	4,96	5,07	1,90	12,14	0,93	5,46	3,51	3,23
B(2, 2)	0,61	0,56	1,01	8,28	4,23	6,56	5,77	4,01	5,79	9,84
G(1, 1)	204,43	188,56	70,37	184,30	49,16	117,61	143,34	285,47	183,40	155,60
G(1, 2)	4,61	0,23	7,90	3,53	5,32	1,39	2,84	6,90	5,08	0,60
G(2, 1)	12,21	11,98	6,74	8,93	0,69	8,81	0,24	7,21	9,57	1,96
G(2, 2)	95,96	107,48	194,67	78,08	56,61	111,84	93,23	160,88	78,80	97,68

Table 8 - t-values of the matrixes estimated values through BEKK-GARCH (1, 1).

Now that Table 7 is available, and from an analytical perspective that in relation to ARCH effects, the values of the term A(1, 2) are all negative, with the exception of the cases IT vs Uti and IT vs RS. This indicates that these were the only two sectors that were not negatively affected at times when the IT sector suffered a shock. In the case of the term A(2, 1), the values are mostly positive, with the exception of the IT vs Uti, IT vs TS and IT vs RS cases, indicating that the only cases in which the IT sector was more negatively affected happened when the sectors Uti, TS and RS suffered a shock.

Regarding the GARCH effects, for the calculation of  $B(1, 1) \cdot B(1, 2)$ , only the IT vs RS case presented negative values, meaning that only in this case does an increase in the variance of the IT sector returns resulted in a decrease in covariance returns between these sectors. Also in this calculation exists a 0 value in IT vs CD sector, meaning that in this case there are no types of ARCH effects. Conversely, the calculation of  $B(2, 1) \cdot B(2, 2)$  only gave a negative result in the cases IT vs Uti and IT vs Ene, indicating that only in these two cases there was a decrease in the returns covariance following an increase in returns variance in the Utilities and Energy sectors.

Looking now at the values in Table 8, the statistical t-values of the estimated values indicate that most of the values in Table 7 are statistically significant following (Prusty, 2010) thinking that t-values greater than 2 or less than -2 can be considered- if statistically significant, justifying this with the fact that the higher the t-values (in absolute value) the greater the confidence that the estimate made is the most correct.

Let's start with the relationship between the IT and Ind sectors, Figure 17 shows the graphs with the time-varying conditional correlations and conditional standard deviation for IT and Ind sectors. Looking at the conditional correlation graph in Figure 17, the correlation here is always positive, showing a stronger connection between these two sectors. The conditional standard deviation graphs indicate that these two variables have similar performances in this parameter suggesting an existence of a spillover effect.

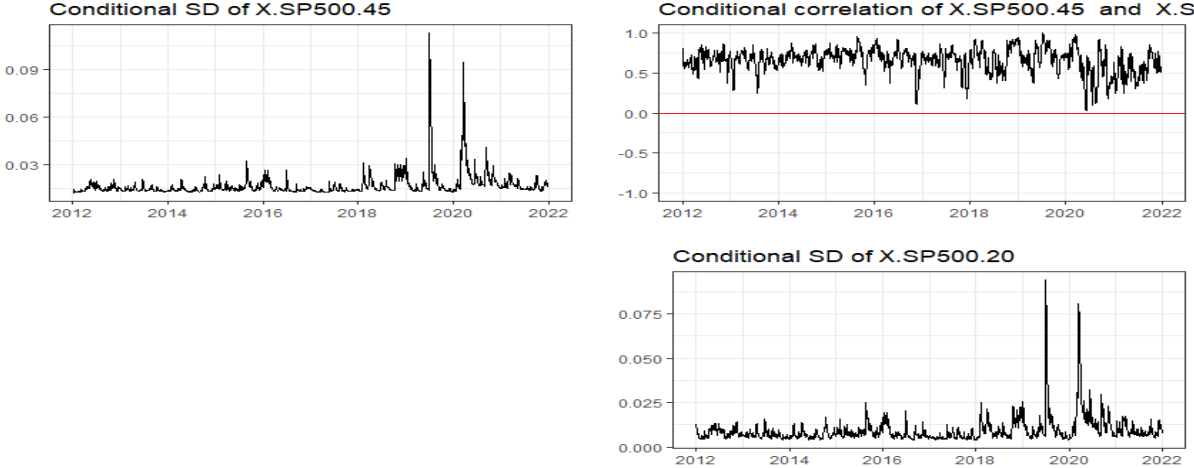


Figure 17 - Conditional SD values and Conditional Correlations for IT and Ind sectors.

For the pair IT vs Fin sectors, the conditional correlation graphic in Figure 18 shows similar curves to the one determined through the DCC-GARCH (1, 1) model, except in the final quarter of the observation where there's a lot of variations between negative and positive values. With the conditional standard deviation graphics, the conclusions are the as the ones obtained for IT vs Ind sectors.

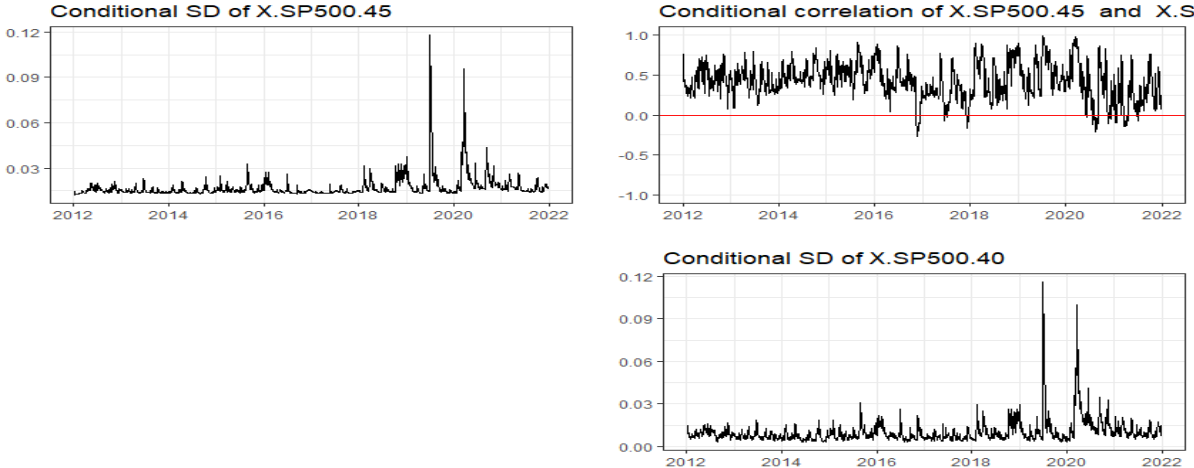


Figure 18 - Conditional SD values and Conditional Correlations for IT and Fin sectors.

Regarding the graphics presented in Figure 19 for the case IT vs Uti, once again the conclusions for the conditional standard deviation are the same as the ones made for the last two cases, since the graphics are very similar among the three cases. In the conditional correlation situation, the estimations made here match the ones made through the DCC-GARCH (1, 1) model, showing that the possible existent volatility spillover effects are weak.

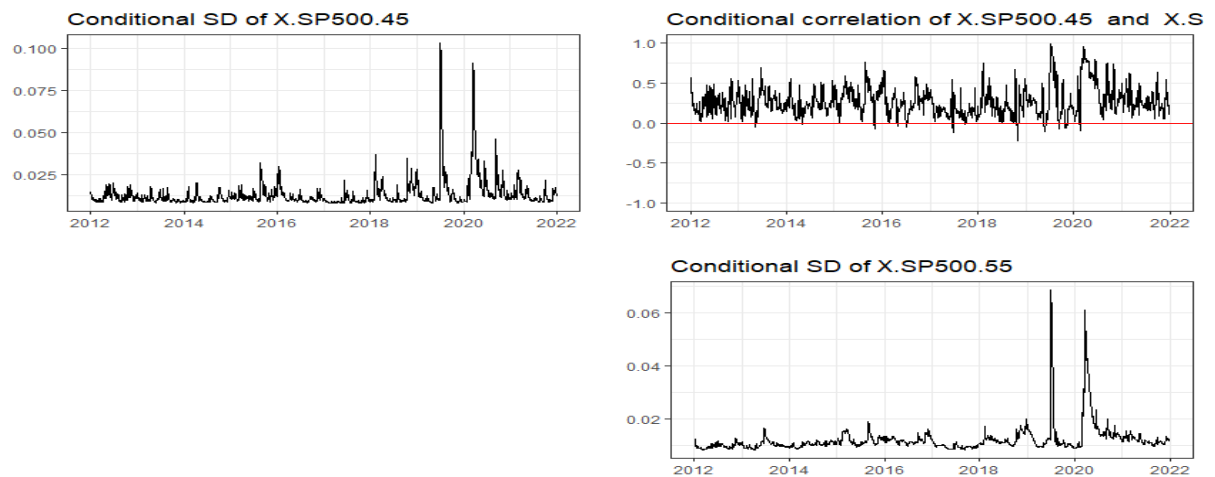


Figure 19 - Conditional SD values and Conditional Correlations for IT and Uti sectors.

On the IT vs HC case, as in the previous three cases, the conditional standard deviations graphics in Figure 21 present similar forms. Also in Figure 20, in the conditional correlation graphic, the IT and HC sectors present a strong correlation during time.

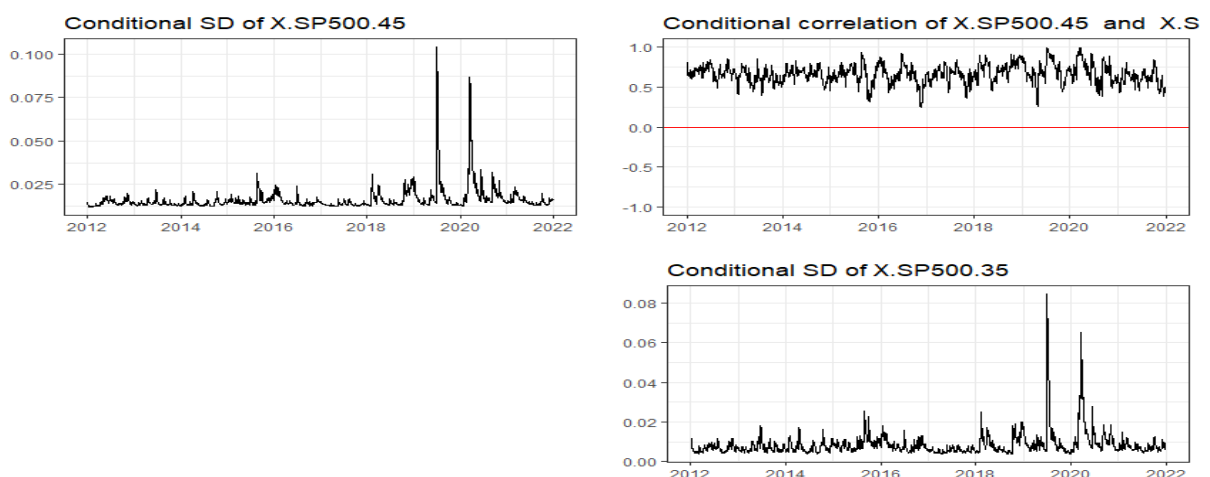


Figure 20 - Conditional SD values and Conditional Correlations for IT and HC sectors.

Relatively to Figure 21, the conditional standard deviation for each IT and CD sectors stays equal to last cases. The graphic for conditional correlation demonstrates a lot of variations across time, so, if there exists a spillover effect, that will not be a stronger one.

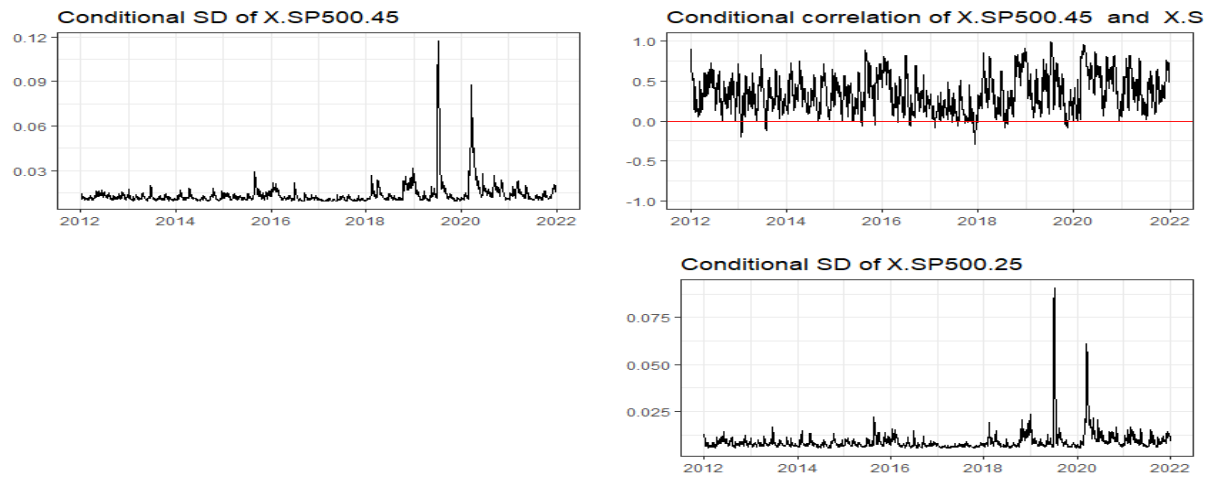


Figure 21 - Conditional SD values and Conditional Correlations for IT and CD sectors.

In the case IT vs Energy sector, there is probably the most singular case among all the cases involved in this study. Looking at Figure 22, the conditional standard deviation of IT sector is different when it is compared when compared to the cases that have been seen so far. It means that when this parameter is explained by the values of the Energy sector instead of others, the results change. The values for the conditional correlations are also shows some particularities. In general, the values are small which implicates a weak spillover effect between these two sectors. It also reveals a strong negative peak before the arrival of the pandemic, which increased the values in conditional standard deviations.

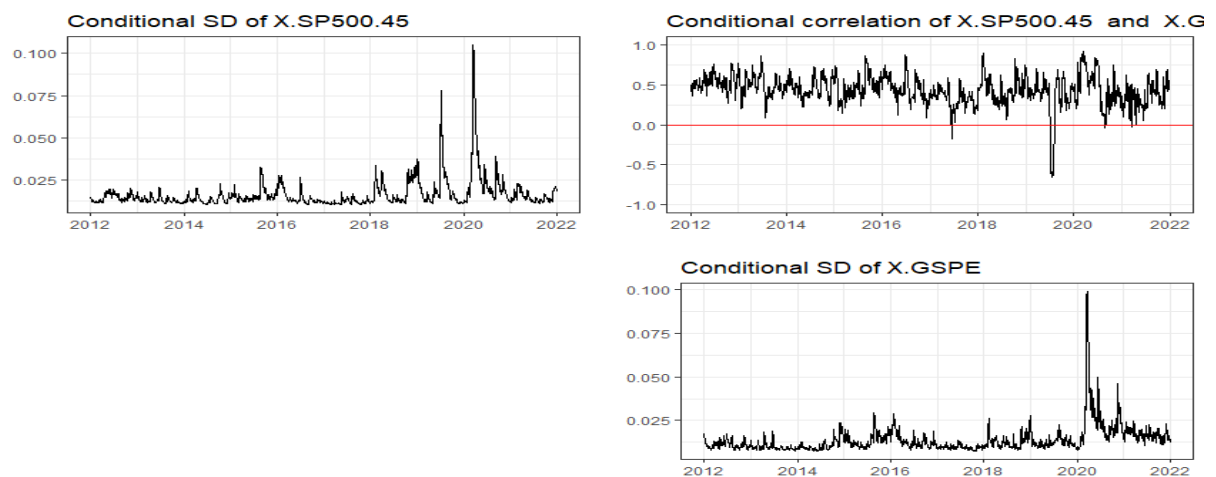


Figure 22 - Conditional SD values and Conditional Correlations for IT and Ene sectors.

For the IT vs Mat relationship, it appears to reveal some similarities to previous cases in conditional standard deviations graphics of Figure 23. Also in this Figure, the conditional correlations are, in general, positive, which indicates an existence of a strong connection between these two sectors.

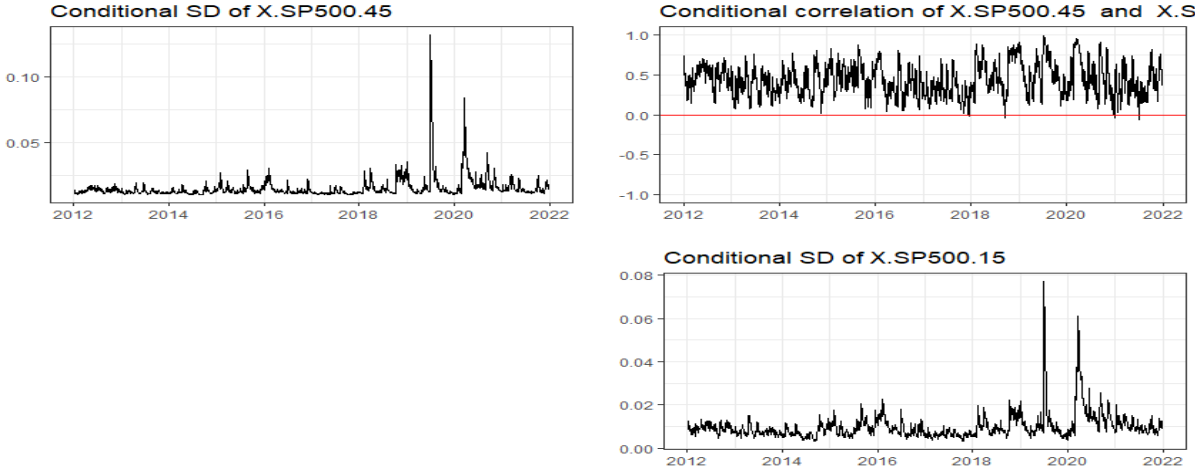


Figure 23 - Conditional SD values and Conditional Correlations for IT and Mat sectors.

For IT vs TS and IT vs CS cases, the graphics are displayed in Figures 24 and 25. For IT vs TS case the conditional correlation is very disperse, with very high and low values, meaning that these two have not a strong consistent relation. This fact can also be proved by the observation of the conditional standard deviation graphics because these display different shapes. On the other hand, the IT vs CS conditional correlation graphic reflects a strong correlation, and the conditional standard deviation shows very similar shapes.

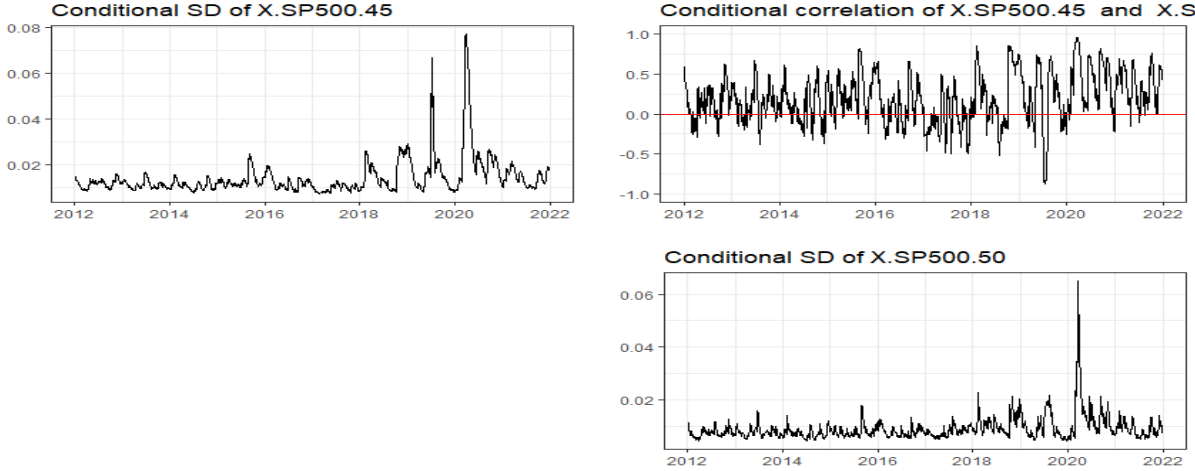


Figure 24 - Conditional SD values and Conditional Correlations for IT and TS sectors.

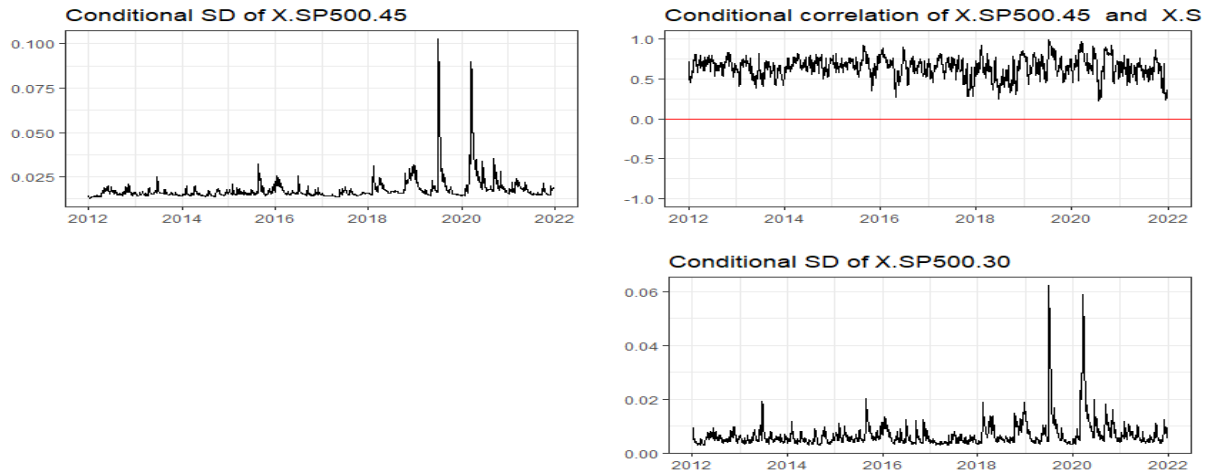


Figure 25 - Conditional SD values and Conditional Correlations for IT and CS sectors.

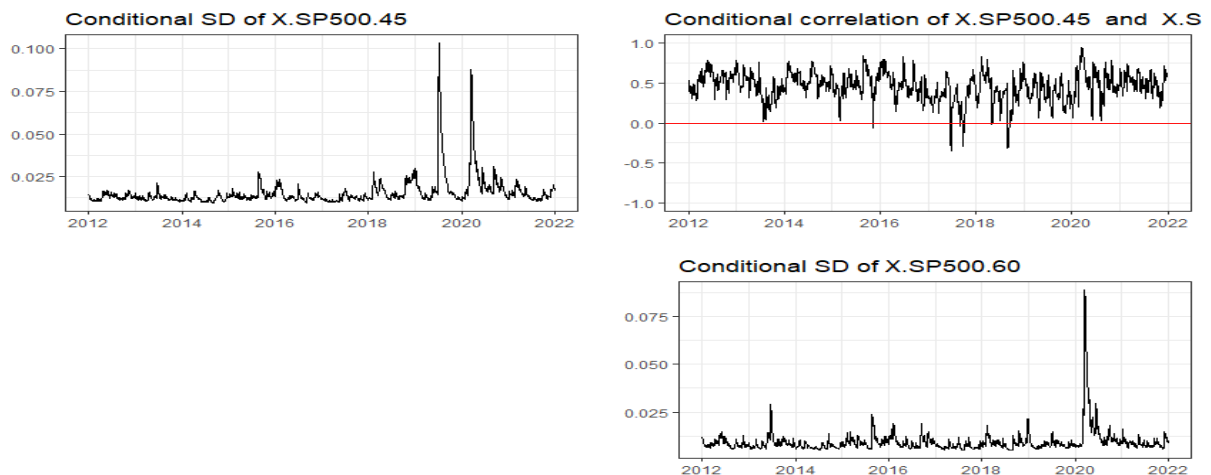


Figure 26 - Conditional SD values and Conditional Correlations for IT and RS sectors.

Lastly, the IT vs RS case reveals some disperse conditional correlation values, also showing relationship that is not consistent. Also, in the conditional standard deviation graphics in Figure 26, there is evidence of the differences in the behavior of these two sectors during the ten years of observations.

Finally, for the analysis of the asymmetric parameters estimated through the BEKK-GARCH (1, 1) model, Table 10 will make it clear.

The objective of the calculation that was computed is to understand if when each pair of sectors have a shock at the same time, the returns covariance of them will record an increase in its value. As it can be seen in Table 10, the values of this calculation are all positive and closer to 1, which means that this fact is verified to all pairs of sectors in study.

	IT vs Ind	IT vs Fin	IT vs Uti	IT vs HC	IT vs CD	IT vs Mat	IT vs Ene	IT vs TS	IT vs CS	IT vs RS
$G(1, 2)*G(2, 1) + G(1, 1)*G(2, 2)$	0,8413	0,8286	0,8598	0,8626	0,8266	0,8675	0,8519	0,9043	0,8602	0,8681

Table 9 – BEKK-GARCH (1, 1) asymmetric parameters calculations for analysis.

## **5. DISCUSSION OF THE RESULTS**

In this section of results discussion, to better organize all the thoughts and observations made, the discussion has been divided into parts. Each of these parts will talk about each of the ten cases to which this study applies. Therefore, the first case is the relationship between IT and Ind sectors.

### **5.1. IT AND IND SECTORS**

Starting with the results obtained by the VAR model, they showed a correlation close to 0.8, which represents a considerable value for a correlation value and a covariance of 0.0001419, and despite being a value close to 0, it was the third highest value among all 10 cases. With this information alone, it is already possible to predict the possible existence of a volatility spillover effect between these two sectors, largely because of the strong correlation and high dependence due to covariance value. With the application of the DCC-GARCH model, the demonstration that these two sectors present a high correlation between them continued with the observation of the graph in Figure 7. This fact was confirmed after the implementation of the BEKK-GARCH model provided the graphs in Figure 17 confirming the high correlation relationship between these two sectors, adding the fact that the conditional standard deviation graphs are equal, meaning that they registered similar values of volatility during the ten years, which also explains the close relationship between these two sectors. The values from Table 7 also showed that Ind sector tended to follow the variations of the IT sector in both ARCH effects and GARCH effects in the ten years of study. Therefore, it can be said that there are volatility spillover effects between the IT and Ind sectors.

### **5.2. IT AND FIN SECTORS**

This case is similar to the previous IT vs Ind one. The VAR model indicated a correlation value of 0,7457 and a covariance of 0,0001509, this being the second highest value for the covariance recorded among the ten cases under study. The proof of this is that, despite some low peaks, the DCC-GARCH model graphic in Figure 8, revealed, in general, high correlation values for these two sectors, and later, the BEKK-GARCH model confirmed this statement with the conditional correlation and similar conditional standard deviation graphics in Figure 18. The values in Table 7 also demonstrate the influence that IT sector has in this sector, following its variations both in the event of shock (ARCH effects) and an increase in the variance of returns (GARCH effects). In the end, it seems correct to state that there exist volatility spillover effects between these two sectors.

### **5.3. IT AND UTI SECTORS**

In this case, the correlation and covariance from the VAR model were lower when compared to the values from the two previous cases. A covariance of 0,0000916 and a correlation of 0,5396 reflect this conclusion. From Figure 9 it is possible to confirm the lower conditional correlation estimated from the DCC-GARCH model, thus matching the VAR estimate and, a 0 conditional covariance values during most of the time of the study, showing a very low dependence between these two sectors. The results of the BEKK-GARCH model confirmed these facts, with the Uti sector showing an inverse trend in the ARCH effects, that is, when the IT sector suffered a shock, this did not negatively affect the Uti sector as in GARCH effects, meaning that when the variance of the returns of the Uti sector increased, the returns covariance of both returns decreased. These facts confirm the idea that exists a certain independence of Uti sector from IT sector and, hence, there is no evidence of a volatility spillover effect from IT sector on Uti sector.

### **5.4. IT AND HC SECTORS**

In the IT vs HC case, the higher values for covariance and correlation are back, as it is shown by the VAR model estimates, 0,000126 and 0,7912 respectively. Figure 10 present the DCC-GARCH model conditional correlation and conditional covariance graphics for this case, which in their turn corroborate the VAR model estimations, reflecting a homogenous correlation. Then, in the Figure 20 BEKK-GARCH model conditional correlation graphic demonstrate a high correlation between these two sectors and the conditional standard deviation graphics of each sector being equal. The values in Table 7 showed that in both ARCH and GARCH effects, the HC sector follows the same tendency of Ind and Fin sectors. In this sense, despite a not so higher conditional covariance, there is evidence of volatility spillover effect in this case.

### **5.5. IT AND CD SECTORS**

This is the easiest case to analyze in this study. This case contains the highest VAR model estimates for covariance (0,0001587) and correlation (0,8872). These facts demonstrate the proximity and dependence between IT and CD sectors. From Figure 11 it is possible to confirm this theory because when looking to DCC-GARCH conditional correlation graphic it is visible the high correlation values during most of the time and the conditional covariances of the same model display the highest peaks that can be seen in this study. Obviously, after these statements, the BEKK-GARCH model continued to reinforce this theory. By the observations of the BEKK-GARCH model graphics in Figure 21, despite showing a lower mean conditional covariance, this is still positive and considerable. The conditional standard deviation graphics

are equal which, indicates a very similar performance during sample time and, one more time, reinforce the idea that seems too obvious: there is a spillover effect between IT sector and CD sector. But the values from Table 7, specially those that measure the GARCH effects, demonstrated that when IT sector returns variance increased, it didn't increase nor decrease the returns covariance of both sectors. Despite this fact, analyzing all the results, seems correct to assume an existence of a volatility spillover effect between IT and CD sectors.

## **5.6. IT AND ENE SECTOR**

This a particular case in this study but not because of the same reasons of the previous one. Even though the VAR model covariance is not one of the lowest (0,0001178), this case presents the lowest VAR model correlation (0,4923). The DCC-GARCH graphics in Figure 13 and the BEKK-GARCH graphics in Figure 22, reflect the VAR model estimates for the conditional correlation in both models and for the conditional covariance in DCC-GARCH. On the other hand, the conditional standard deviation graphics in Figure 22 show a different performance across the ten years of study, which helps to build a theory that these two sectors have not a strong connection. On the other hand, the results in Table 7 show the existence of both ARCH and GARCH effects of the IT sector in Energy one. With this, is not easy to reach a clear conclusion since this way, is not possible to guarantee that a spillover effect doesn't exist here, but, in the case of existence, it is a very weak one.

## **5.7. IT AND MAT SECTOR**

Relatively to this case, the VAR model estimates of covariance and correlation are 0,000128 and 0,7278 respectively, which are one of the highest values in this study for both parameters. The referring conditional correlation graphics to the DCC-GARCH and BEKK-GARCH models seems very similar, with positive correlation during most of the time, thus validating the VAR result as the conditional covariance graphic, in DCC-GARCH. The conditional standard deviation graphics in BEKK-GARCH model also show a lot of similarities and additionally the fact that ARCH and GARCH effects have been verified between these two sectors, there is no doubt to conclude that in this case exists a spillover effect between IT and Mat sectors.

## **5.8. IT AND TS SECTOR**

Between these two sectors, the VAR model estimates were different from the seven cases that was aborded until this point. The correlation value of 0,5723 is not that different from the previous cases but the covariance value of 8,95E-05 denotes a certain independence between these two sectors. The DCC-GARCH models graphics of conditional correlation and conditional covariance in Figure 14 confirm the considerable value of correlation but in the conditional

covariance this is the case that contains the only negative value, showing that at that time these two sectors were in an inverse relation meaning that were moving in different directions. In the BEKK-GARCH model graphics in Figure 24, the conditional correlations are very dispersed, which means that were times that these two sectors had a strong relation and in other times they had the opposite. In the conditional standard deviation these sectors also had differences in their variations, which doesn't reinforce the connection between them. In the opposite direction, Table 7 results showed an existence of ARCH and GARCH effects from IT sector to TS one. Hence, once again the conclusion is not clear and because of that, we will assume that in case of existence, there is a weak spillover effect in IT vs TS sector.

### **5.9. IT vs CS SECTOR**

In the VAR estimates for this case, the values are similar to the IT vs TS sector one, with 9,04E-05 for the covariance and 0,6974 for correlation, that in reality is considerable value. The DCC-GARCH and BEKK-GARCH models results all stated that IT and CD sectors have strongly associated. Despite the conditional correlation graphics of DCC-GARCH and BEKK-GARCH reveal some differences, the second one shows constant high values for this parameter. Then the equal conditional standard deviation graphics between these two sectors and the existence of ARCH and GARCH effects from IT sector on CS one, proved by the values in Table 7, increases even more the theory that exists a spillover effect in this case.

### **5.10. IT vs RS SECTOR**

In this case, the VAR model estimates are very similar to the two previous cases, with 8,52E-05 for the covariance and 0,518 for correlation. The DCC-GARCH model graphics doesn't reflect a strong conditional correlation and regarding the conditional covariance there is only one big peak of it in time of pandemic arrival, showing that in this time these two sectors were in high tune. This fact is corroborated by the BEKK-GARCH model conditional standard deviation graphics like in the case of the conditional correlations. Additionally, the Table 7 results indicate a clear opposite trend between these two sectors, both in ARCH and GARCH effects. In conclusion, these two sectors don't present volatility spillover effects.

## 6. CONCLUSIONS

Interest in the way information circulates among the various players in the financial markets has increased over the last few decades and it is called volatility spillover effects. This interest is due to the need to invest more safely, considering the information on whether a variable suffers from a large or small influence of another variable. In this sense, this dissertation aims to study volatility spillover effects between sectors of the S&P 500 index, trying to understand how this effect develops between them after having already studied the spillover effects between, for example, different types of markets and indices.

For this purpose, three different models were implemented: VAR, DCC-GARCH (1, 1) and BEKK-GARCH (1, 1). The first two models served as complement to the BEKK-GARCH (1, 1), being the latter a more robust model than the VAR model and presenting less complexity in its processes when compared to the DCC-GARCH in general. The data cover the period from January 2012 to December 2012 and were taken for each sector of the S&P 500 index and its own.

In general, all sectors seem to receive a minimum of influence from the IT sector but as seen in the previous sections this influence is more noticeable in some sectors than others. The most evident cases are those of the Ind, Fin, HC, CD, Mat and CS sectors, and the others are either not as evident as these or even show that doesn't exist a volatility spillover effect. In this respect, the most considerable cases are those of the Energy and TS sector. After drawing these conclusions, the important factor of analysis from the investor's point of view comes in, because when it comes to investing in the IT sector, it is possible to perceive that the Ind, Fin, HC, CD, Mat, and CS sectors have a certain tendency to follow the movements of this sector. Therefore, to diversify their investments, the investor should take this information into account. To give a more specific and practical example, if an investor already has in his investment portfolio shares of a company in the IT sector, it might not be a good idea to invest in shares of, for example, companies belonging to the Ind or Fin sector, as these sectors show a certain tendency to follow the movements of the IT sector, in case there is a devaluation of the shares of this sector, this will not be compensated as the shares of the Ind and Fin sectors will also devalue. By investing in sectors that do not appear to be influenced by the IT sector, the investor will be able to avoid greater losses.

Another important fact is the effect of the pandemic impact that is transversal to all the cases under study. When this impact arrived, in all cases the conditional covariances and correlations values increased, obviously showing that the shock reached the sectors in a similar way. Before that, from 2012 to around 2017/2018/2019, a low covariance is also visible in all cases,

reflecting the stability experienced in the financial markets in this period. After that, there are already some differences between the ten cases. In almost all cases where the spillover effect is evident, in the conditional covariance graphs of the DCC-GARCH model, peaks of high covariance are visible around the year 2019, before the peaks of the impact of the pandemic. This fact reinforces the idea of a spillover effect between the sectors involved in these cases and at the same time indicates the opposite in the remaining sectors.

In sum, it is important to recognize that volatility spillover effects are quite useful in helping investors looking for assets that ensure and increase the advantages of asset diversification leading to better portfolio construction and management.

## 7. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORKS

Regarding the limitations pointed out to this study, it is related to the models that were used in this context. As it was possible to observe, the VAR model, despite being easy to implement, does not perform such in-depth analyzes of the covariance and correlation values and hence it was used as a complement. Then, the DCC-GARCH model, despite already having the ability to carry out deeper analyzes on these parameters, has rather complex construction and value estimation processes, with the need to estimate a variance model and a mean model, and not even it was possible in this study to analyze the estimates of the final equation of this model because the R program did not provide them. In this sense, it is recommended that in the future a study similar to this can be carried out using another type of models, such as the [\(Diebold & Yilmaz, 2012\)](#). Another interesting study would be to compare the performance of two different models to understand which one presents, for example, less time spent in estimation or which one, in the face of reality, presented the closest results. Another suggestion for further research would be to carry out a study like the one done in this dissertation but having as variables the market sectors of a small-cap index. At this level, it would be interesting to see whether the effects of volatility spillovers seen in big-cap markets also persist in small-cap markets.

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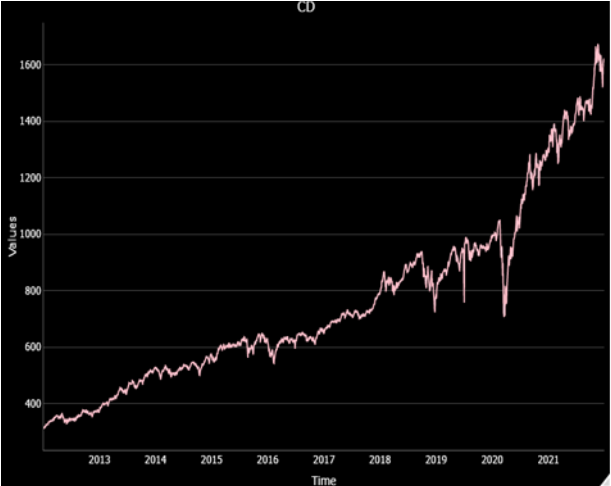
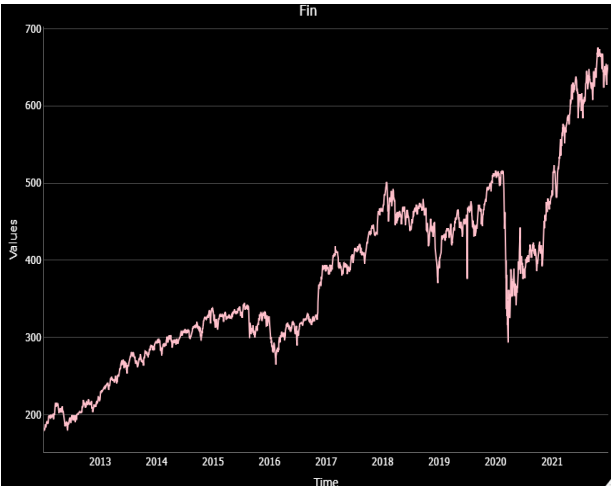
values are indications of low reliability of the predictive power of that coefficient. And a positive t-value indicates a positive relationship between the predictor and the dependent variable. The higher the t-value, the greater the confidence we have in the coefficient as a predictor. Low t-values are indications of low reliability of the predictive power of that coefficient. And a positive t-value indicates a positive relationship between the predictor and the dependent variable.

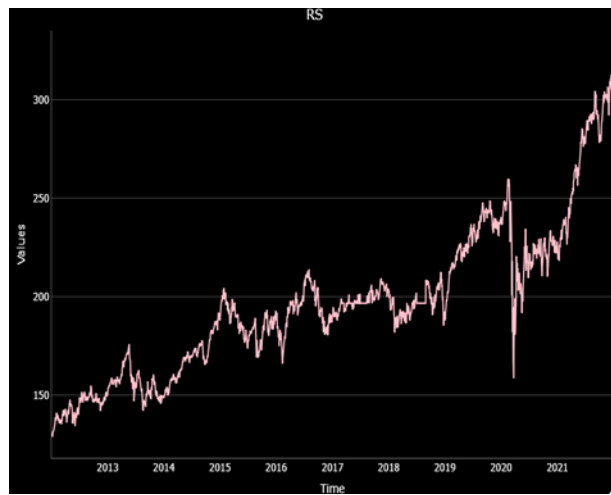
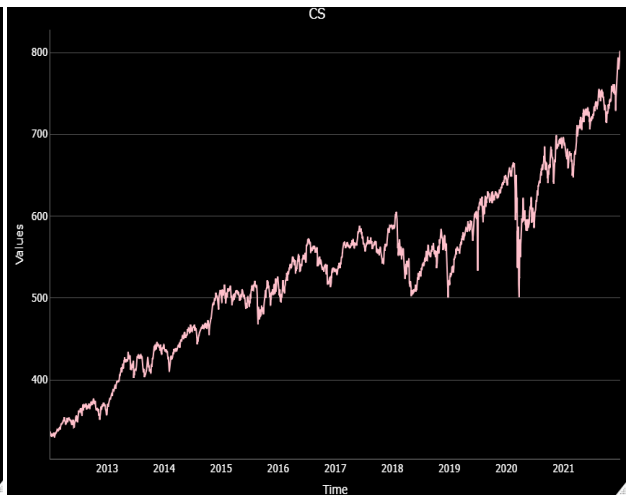
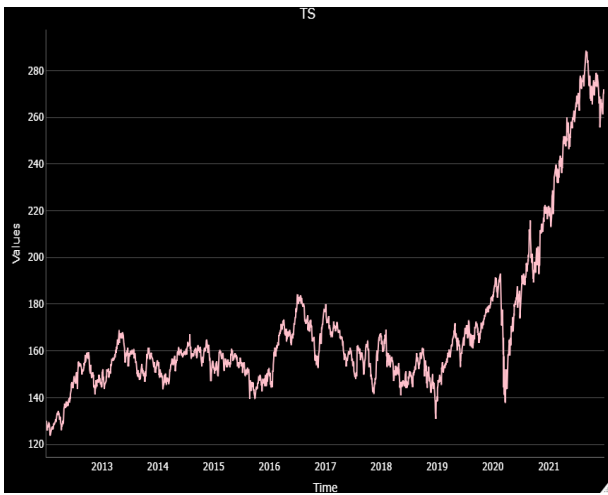
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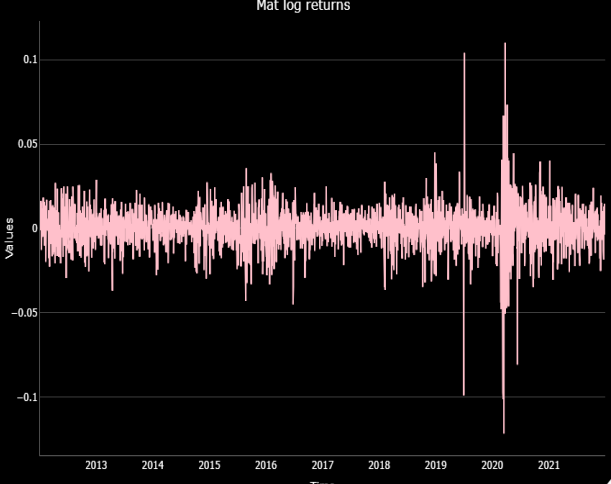
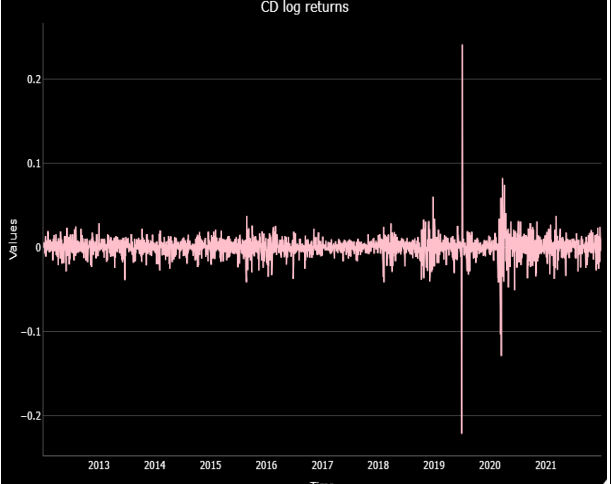
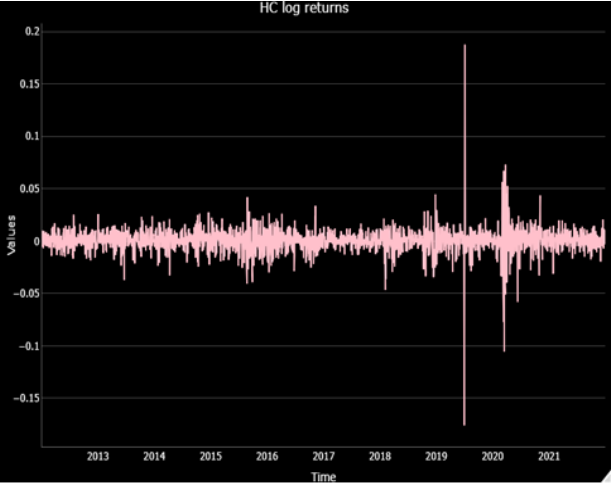
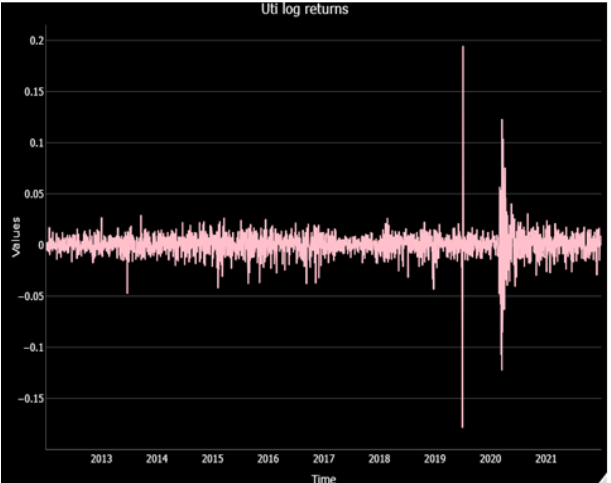
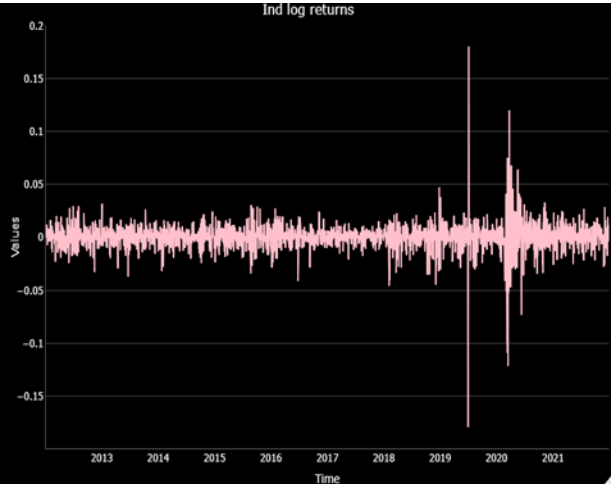
9. ANNEXES

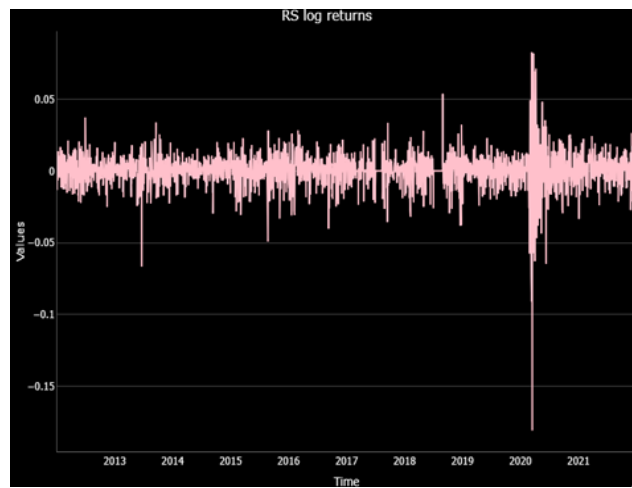
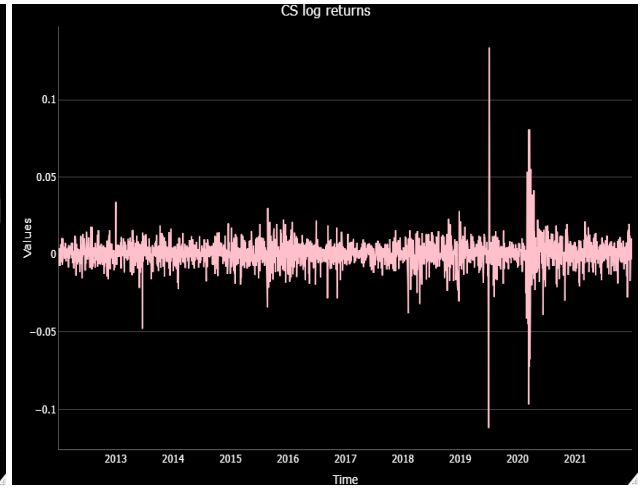
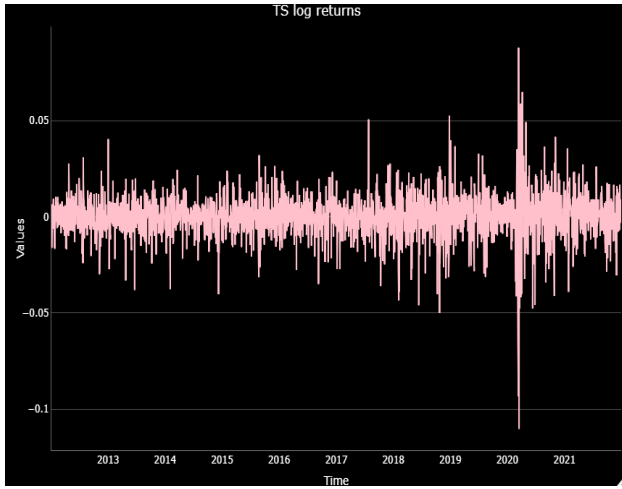
ANNEX A – Adjusted Closing Prices.



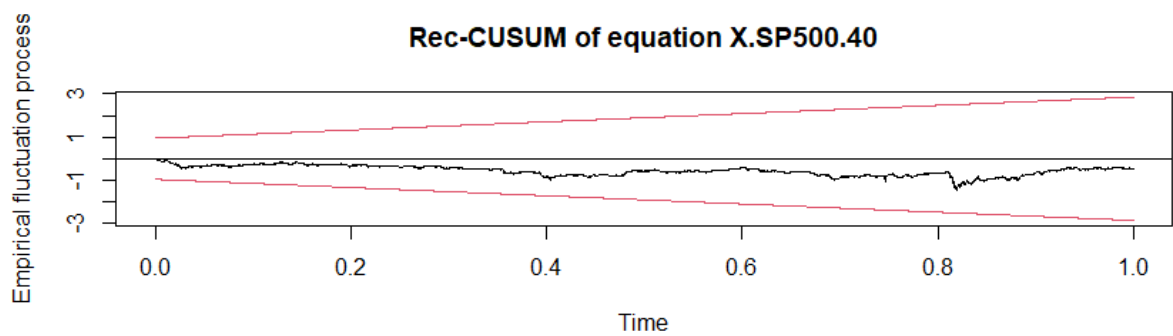
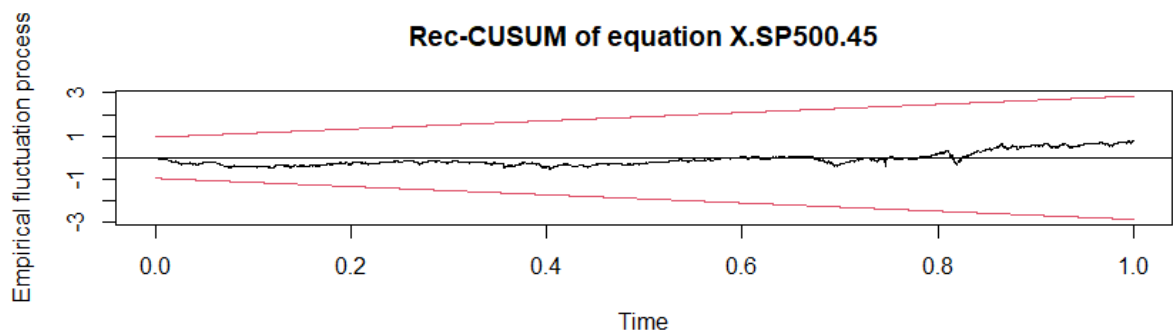
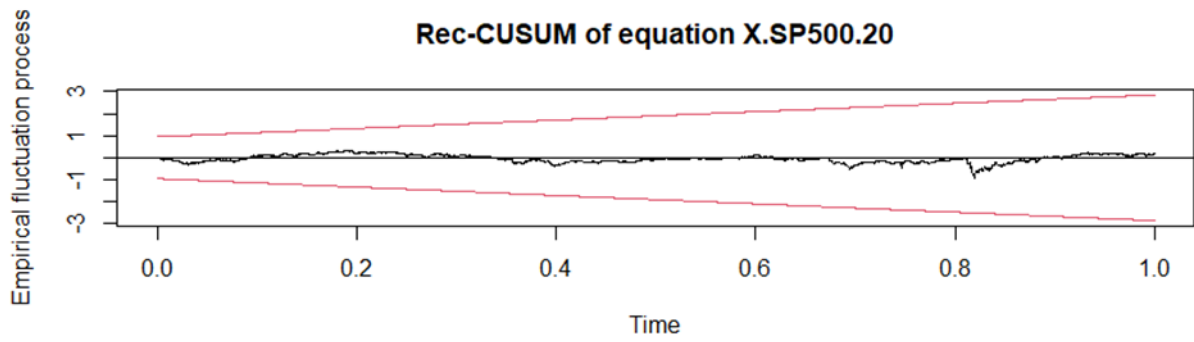
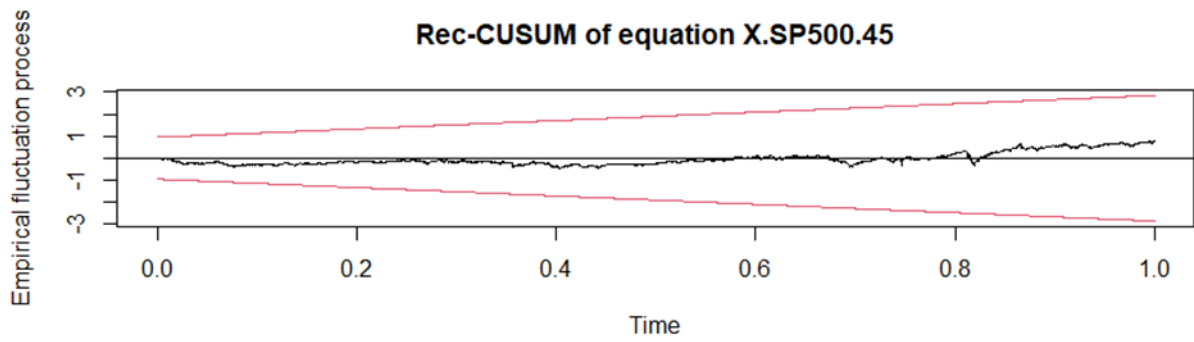


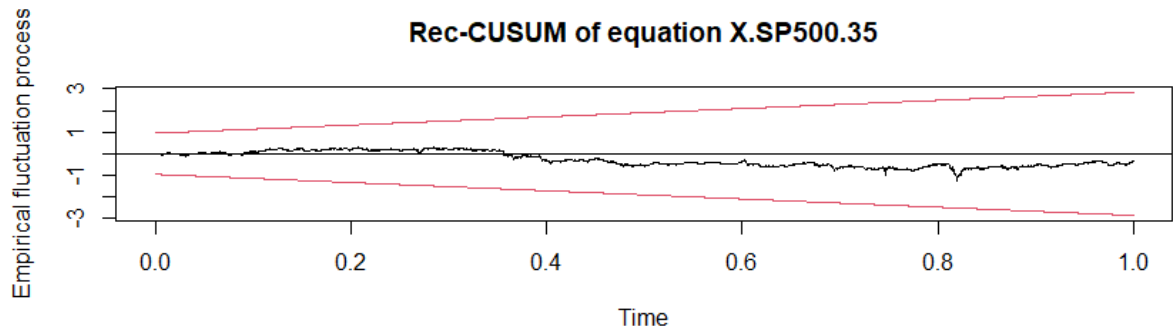
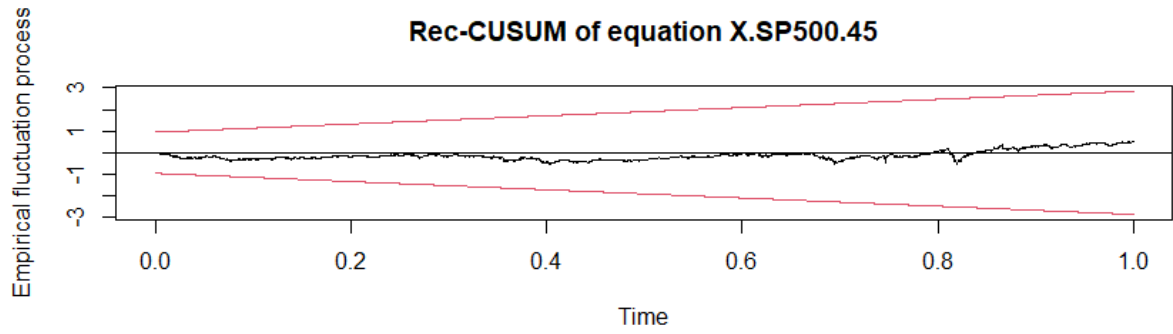
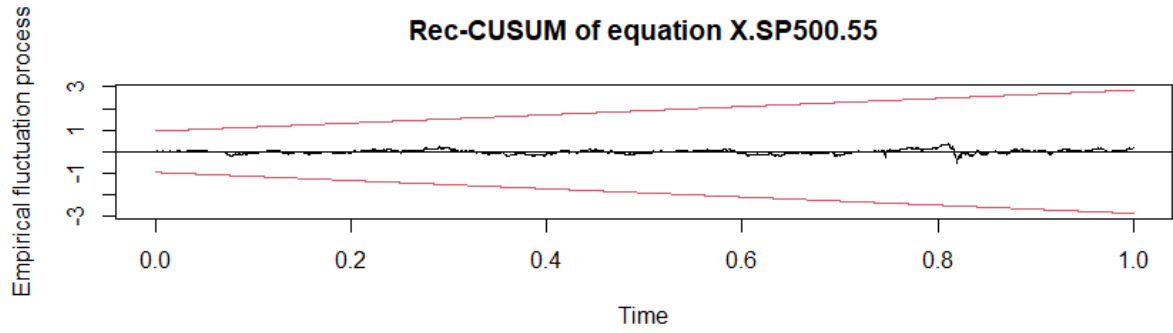
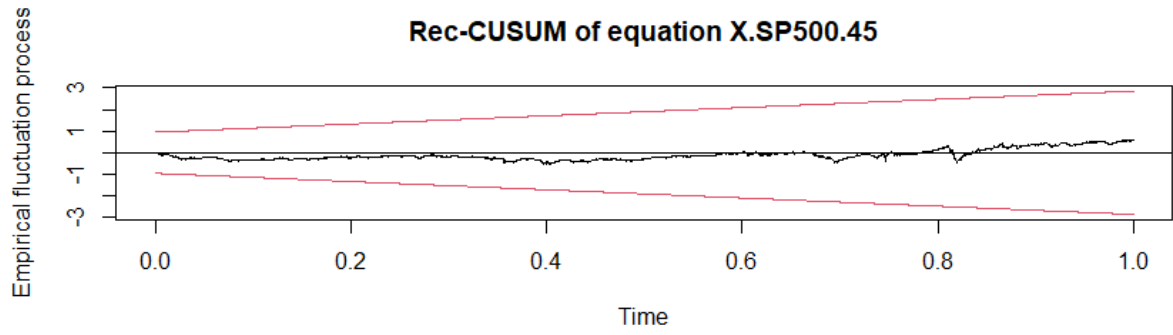
ANNEX B – Log-returns

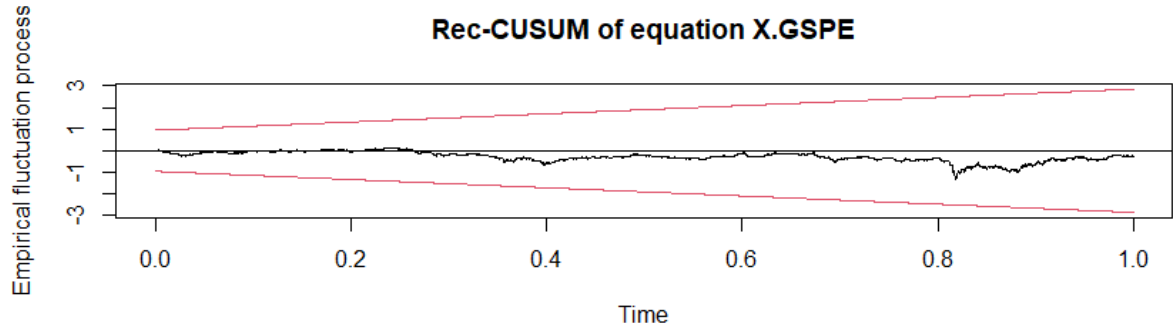
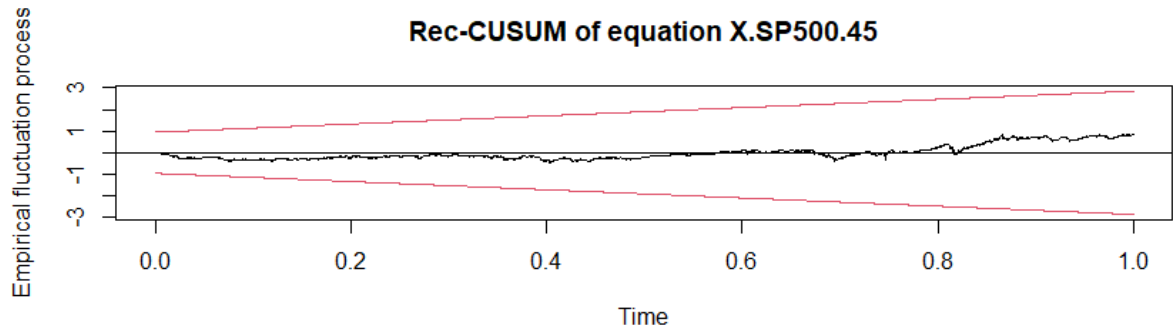
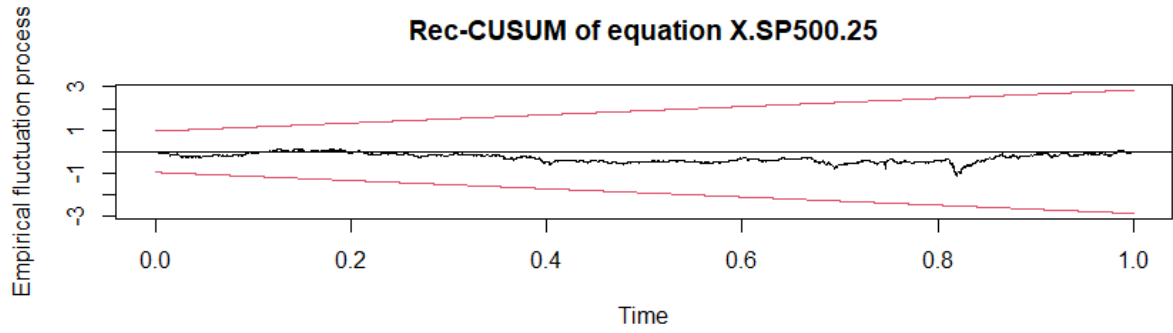
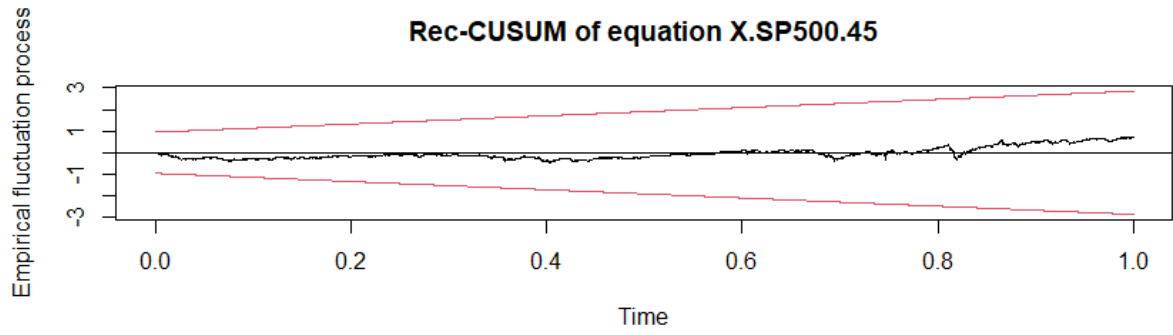


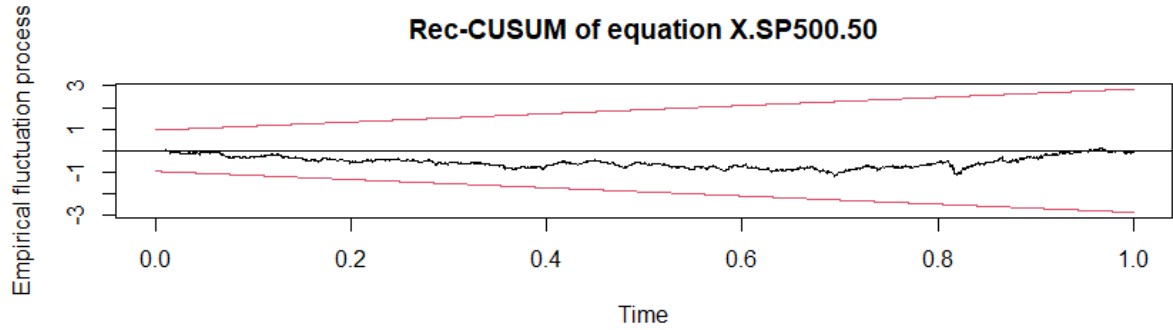
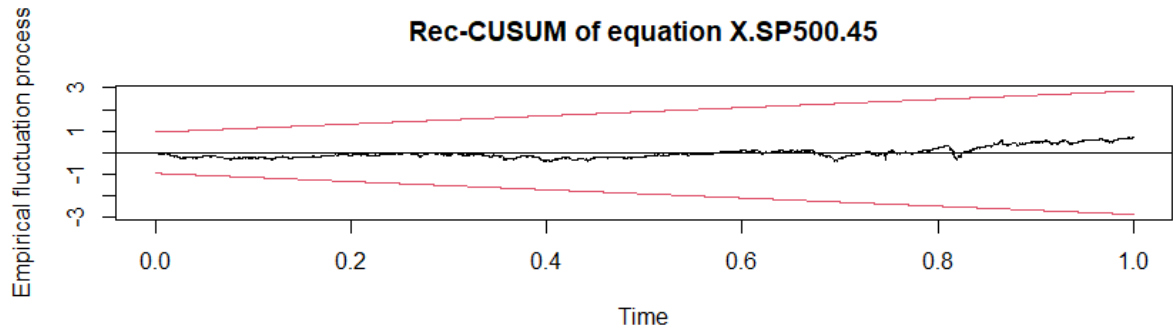
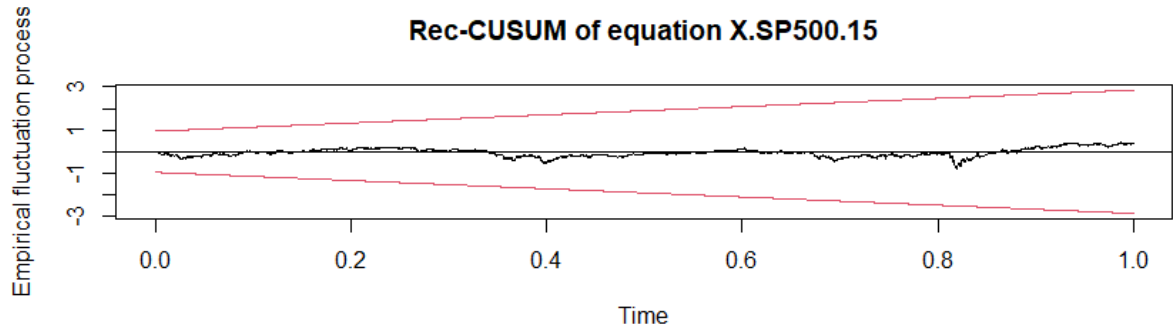
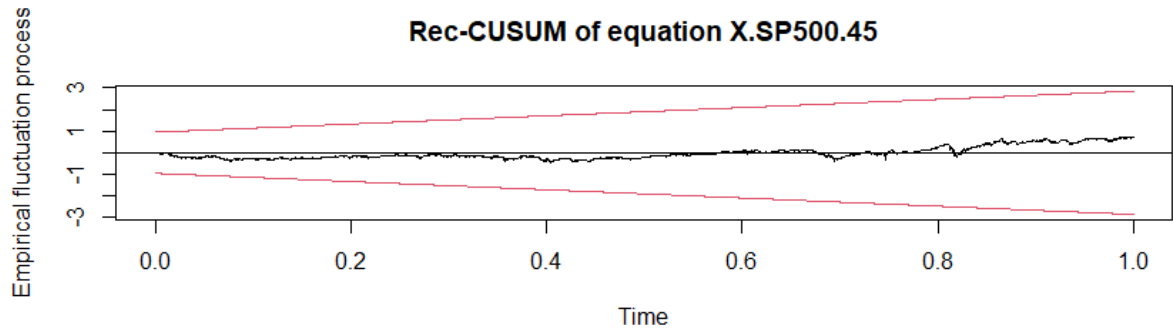


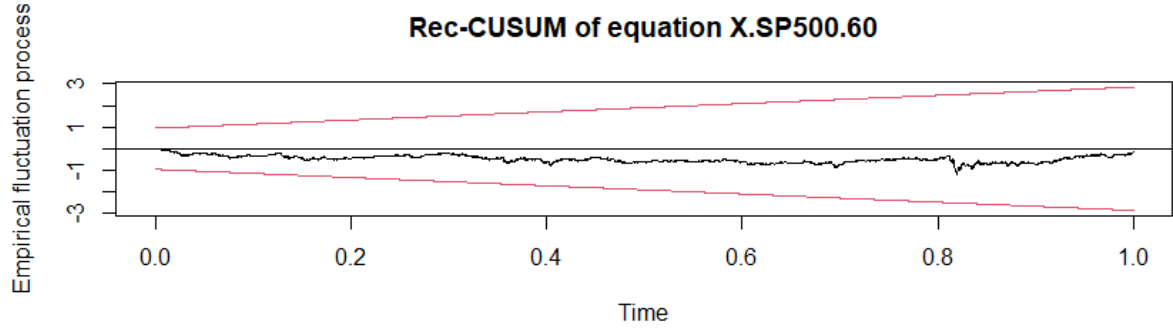
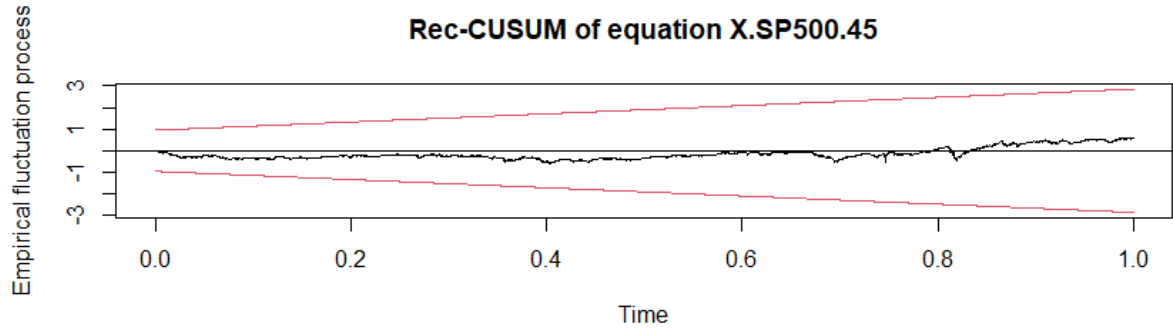
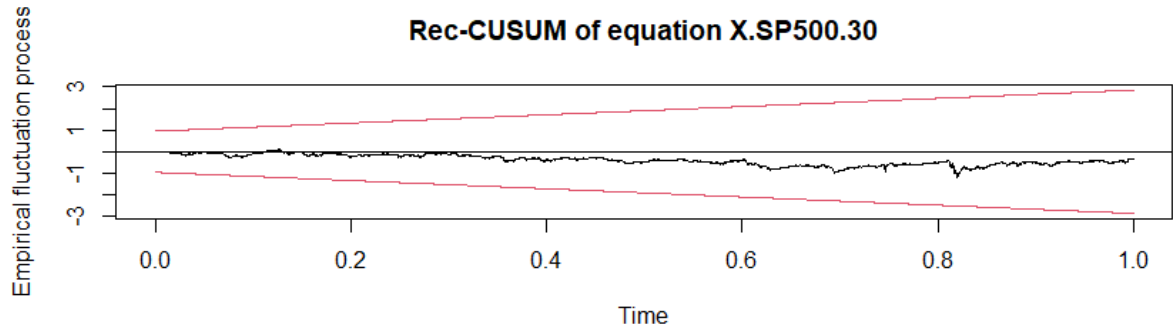
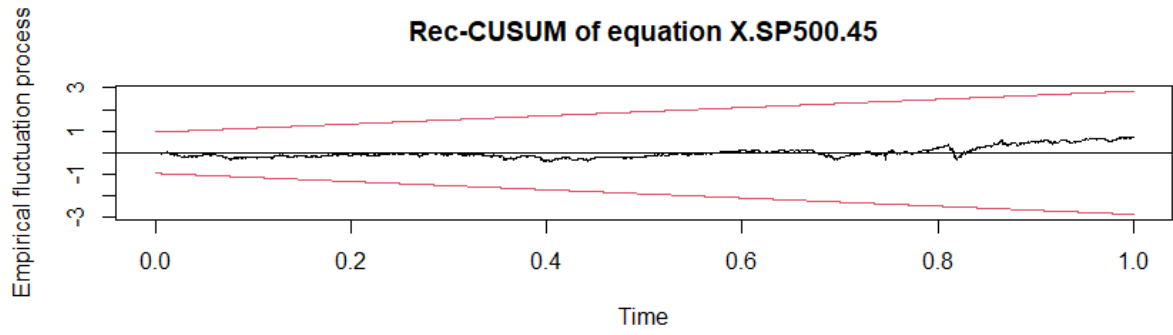
## ANNEX C – CUSUM TESTS











## ANNEX D – APARCH ESTIMATES

IT sector	Estimate	p-value
mu	0,001495	0,006344
ar1	-0,60318	0
ar2	0,573015	0
ar3	0,978173	0
ar4	0,045848	0,000127
ma1	0,571844	0
ma2	-0,58797	0
ma3	-0,95946	0
omega	0,000676	0,035671
alpha1	0,109943	0
beta1	0,886941	0
gamma1	1	0
delta	0,898728	0
shape	4,751181	0

Ind sector	Estimate	p-value
mu	0,000505	0,000804
ar1	-0,088527	0
ar2	0,5106	0
ar3	-0,07093	0
ar4	-1,001458	0
ar5	-0,011136	0,000015
ma1	0,078789	0
ma2	-0,512682	0
ma3	0,075882	0
ma4	0,999136	0,092802
omega	0,000279	0
alpha1	0,08124	0
beta1	0,910037	0
gamma1	1	0
delta	1,012887	0
shape	5,187294	0

Fin sector	Estimate	p-value
mu	0,000675	0
ar1	-0,32292	0
ar2	-0,26781	0
ar3	0,43269	0
ar4	-0,39082	0
ar5	-0,08661	0
ma1	0,271004	0
ma2	0,292805	0
ma3	-0,47538	0
ma4	0,375133	0
omega	0,000002	0,35289
alpha1	0,140962	0
beta1	0,766005	0
gamma1	0,367085	0
delta	2,297641	0
shape	5,599417	0

Uti sector	Estimate	p-value
mu	0,000619	0,000062
ar1	-0,06824	0
ar2	-0,00149	0,963348
ar3	0,099318	0,00162
ar4	-0,82808	0
ma1	0,039467	0,015437
ma2	-0,01361	0,720501
ma3	-0,1228	0,000019
ma4	0,817883	0
omega	0,000155	0,218933
alpha1	0,086331	0
beta1	0,893148	0
gamma1	0,273864	0,024097
delta	1,184759	0
shape	5,859526	0

HC sector	Estimate	p-value
mu	0,000984	0
ar1	0,180266	0,472664
ar2	-0,13182	0,6683
ar3	0,609899	0,002228
ar4	-0,02691	0,892767
ma1	-0,20776	0,394492
ma2	0,136471	0,664931
ma3	-0,66651	0,001191
ma4	0,019729	0,919484
ma5	-0,00855	0,682409
omega	0	0,903057
alpha1	0,043842	0,000218
beta1	0,682722	0
gamma1	0,56672	0,000182
delta	3,369288	0
shape	5,623756	0

CD sector	Estimate	p-value
mu	0,000945	0
ma1	-0,00251	0,903628
ma2	-0,00446	0,831062
ma3	-0,04344	0,033565
omega	0	0,52689
alpha1	0,092981	0,000194
beta1	0,795604	0
gamma1	0,393731	0,001839
delta	2,572484	0
shape	5,23273	0

Mat sector	Estimate	p-value
mu	0,000525	0
ar1	-1,04098	0
ar2	0,78624	0
ar3	0,913599	0
ma1	1,006568	0
ma2	-0,85648	0
ma3	-0,94724	0
ma4	0,004437	0
omega	0,000001	0,644058
alpha1	0,078918	0,324546
beta1	0,850556	0
gamma1	0,360737	0,002606
delta	2,374947	0
shape	7,160096	0

Ene sector	Estimate	p-value
mu	0,000005	0,97799
ar1	1,658304	0
ar2	-0,838365	0
ma1	-1,679106	0
ma2	0,88426	0
ma3	-0,062089	0
ma4	0,045302	0
omega	0,000198	0,22687
alpha1	0,063471	0
beta1	0,943096	0
gamma1	0,684584	0
delta	0,907834	0
shape	8,038055	0

TS sector	Estimate	p-value
mu	0,000506	0,001092
ar1	-0,85405	0,001997
ar2	0,475139	0,332525
ar3	0,755268	0,006617
ma1	0,830924	0,001163
ma2	-0,50143	0,270703
ma3	-0,78245	0,002538
omega	0	0,87263
alpha1	0,040263	0,04816
beta1	0,864754	0
gamma1	0,292477	0,012442
delta	2,911137	0
shape	5,047426	0

CS sector	Estimate	p-value
mu	0,000497	0,000006
ar1	-0,82313	0
ar2	-0,06484	0,018699
ar3	-0,04955	0,060251
ar4	-0,06321	0,003035
ma1	0,770627	0
omega	0	0,850116
alpha1	0,095325	0,001771
beta1	0,7838	0
gamma1	0,22589	0,001649
delta	2,82697	0
shape	5,126994	0

RS sector	Estimate	p-value
mu	0,000742	0
ar1	0,482283	0
ar2	0,382665	0
ar3	0,040455	0,049676
ar4	-0,02434	0,151127
ma1	-0,51871	0
ma2	-0,39652	0
omega	0	0,958195
alpha1	0,064529	0,000847
beta1	0,848839	0
gamma1	0,129028	0,006906
delta	2,996068	0
shape	5,506658	0