**Department of Economics and Finance**

Chair of Empirical Finance

# A sensitivity analysis of the Perceived Risk Index©


**Supervisor**

Prof. Giacomo Morelli

**Co-supervisor**

Prof. Stefano Marzioni

**Author**

Luca Mequio

748991


**Academic Year 2022-2023**

I would love to dedicate this work this work to all the people who supported me during this fantastic experience

First of all, special thanks go to my supervisor, Giacomo Morelli, and my colleagues at Enel Spa, Chiara De Polis and Kleber Santiago Tapia Becerra, for their patience, advices and availability throughout the writing of the thesis

I thank my family, who always supports me in every choice and gives me support in difficult moments, probably without them I would have not made it

Last but not least, I thank my friends, who made this journey unique and unforgettable

## Table of Contents

# Abstract

The objective of this thesis is to first analyse individually and then as a whole all the factors that make up the Perceived Risk Index©, an indicator for which Enel SpA holds the copyright of ownership, so as to be able to specifically understand their response both immediately and in the medium term to a given event, to understand how they are affected by the stress of these situations, and finally to be capable to classify their sensitivity and how they behave in relation to the different sectors analysed, thus being able to make a complete comparison between them.

This is calculated by analysing the data of three economic sectors during two major crises through specific models, observing the data one month before the event, i.e. at a time when they were still 'in equilibrium', up to four months later, in order to create a complete picture of the situation and make an analysis of the results in the best possible way.

# Introduction

During my internship at Enel Spa, I had the opportunity to work with the Perceived Risk Index©, a financial indicator, developed by the company itself, which holds the copyright of ownership, that aims to assess the risk perceived by a company and quantify it, so as to understand the exposure that a company has towards a defined risk, which among many could be political, systemic or credit risk.

I was immediately interested in this topic because of the new approach that Enel Spa wanted to give to controlling the risks and situations of its competitors and others.

Therefore, I decided to analyse it more specifically in my thesis, setting myself the goal of understanding how sensitive this indicator and its component variables are to moments of market stress due to major crises.

This paper is structured as follows: at the beginning, a first overview of the financial markets can be found, with an explanation of where the Perceived Risk Index© wants to place itself in this world, then the process of developing this financial indicator is analysed and its three variables, Credit Default Swap, Implied Volatility and Inverse Stock Price, are defined.

After providing an explanation of all three components of this financial indicator and an assessment of their strengths and weaknesses, the document turns to the description of the stock market sectors that were considered, on which the data analysis and subsequent comparison of results will be carried out.

The study of these data is done by the use of three different empirical functions, which are: the Autocorrelation Function, the Partial Autocorrelation Function and the GARCH.

Through these functions, the correlation and volatility of the variables and of the Perceived Risk Index© itself in the two crisis events are studied for all three sectors.

Once the results of these functions are obtained for the two periods taken into consideration, i.e. COVID-19 and the Russian invasion of Ukraine, the results are analysed and commented on according to the different movements they had and how they behaved during these difficult times.

# 1. Perceived Risk Index©

## 1.1. *An overview*

Financial markets include any place or system where exchanges of financial assets, such as shares, bonds, derivatives, cash, mutual funds or bank deposits, take place and consists of the institutions that regulate it, the instruments of the market and its participants.

The financial market plays a key role in the global economy, as it enables all its participants both to invest and to raise capital for their own businesses through its complex and active ecosystem, which is a dynamic network of linked firms that includes investors, issuers, intermediaries, regulators, processes, products and services, all working together with the final goal of creating liquidity to allow businesses to grow, to raise money for ventures, to reduce the overall risk by improving the available information and to enhance confidence to achieve better economies.

Investors include both individuals and institutions that buy and sell financial instruments, while issuers are those entities that, in order to finance their activities, issue the financial instruments that are traded in the market.

The intermediaries, on the other hand, are those who facilitate the meeting between investors and issuers and thus allow the market to operate at its best and have as many participants and capital as possible at its disposal, while regulators, such as the Security and Exchange Commission or the Federal Reserve Board, are those who oversee that market dynamics are fair and that everyone follows the rules, which change according to local, regional and global regulations.

The financial market is constantly evolving, with its characteristics and structures changing and adapting to new methods of trading and new instruments traded, as are its participants, who are always informed and ready to manage their portfolios and related strategies in the best possible way according to their situations and objectives.

The financial market, being so globally important, provides significant information and signals on the circumstances and conditions of all its players, which are studied daily by analysts in order to understand and predict the future.

Enel SpA has developed an indicator whose purpose is to understand market conditions and to be able to interpret both the current and future performance of the companies under analysis through the study of risk perception of investors, so as to obtain data that is then compared between the company itself and its competitors and not, in order to best forecast and adapt to all market changes.

This financial indicator was called “Perceived Risk Index©”, it is an indicator for which Enel SpA holds the copyright of ownership, and it is a forward-looking measure, as it considers three different variables that reflect the risk component experienced by investors and markets.

These three are the input variables of the Perceived Risk Index©:

- Credit default swap;
- Implied volatility;
- Inverse stocks price.

An indicator of perceived risk assesses and quantifies the level of risk that is associated with a company during a situation or event, this data is calculated to understand the exposure that the business has to a well-defined risk, which for example could be a political, systemic or credit risk.

The analysis of risk perception is carried out using objective data, to keep it as close to reality as possible and not distort it with subjective impressions that could alter its understanding and interpretation.

The analysis of this indicator is useful for understanding and managing unexpected situations that may arise in the market and can also provide useful hints for better forecasting it.

Enel SpA has been operating this indicator since early 2019 and it is used to calculate the business risk perceived by financial markets.

The companies included in the analysis are 40, divided into 6 different sectors: Automotive, Consumer Goods, Electricity, Oil & Gas, Software, Technology.

The Perceived Risk Index© of each company as of 31/12/2018 has a base year of 100%, as this date is used as a benchmark, so that all other calculated dates move according to this starting point.

Enel SpA considers the Perceived Risk Index© a key indicator for understanding a company's financial situation, as it provides it with relevant data on the performance of both the market and all the companies considered in this study.

The results obtained from these businesses are compared with those of Enel SpA and an analysis is made both strictly on the sector and main peers of the latter, and in general with all the other firms, to have the best possible picture of the company's financial situation also in relation to its direct competitors and not.

Periodically, the Perceived Risk Index© of each company is calculated using data taken from Bloomberg and all the comparisons and analyses of the moment are made, so that the data is always up-to-date and in step with the market and its changes.

The Perceived Risk Index© was vital during periods of maximum market stress and volatility, thanks to this tool, Enel SpA was able to keep track of the results the market was recording and see if they were in line with its own, to understand whether the contractions and instability of the moment were a phenomenon that everyone was experiencing or if there were more serious problems that needed to be looked for in the company.

### *1.2. The development process*

During the process of developing the Perceived Risk Index©, the risks that were identified as the main ones to be avoided through the use of this indicator were financial and strategic risks.

Financial risks represent the category of risks that are immediately perceived by companies, since they are closely linked to the essence of the business and can have a significant impact on it if verified.

Financial risks include three different categories:

- Credit risk, which indicates the possible loss resulting from a counterparty's failure to settle a claim it has taken on, i.e. an outstanding receivable;

- Market risk, concerning market trends, occurs when there is an unexpected change either in prices, such as commodity prices, or in interest or exchange rates;

- Liquidity risk, which refers to a company's difficulty in obtaining monetary resources or liquidating assets on the market, rendering the business unable to meet the expenses associated with its operations.

Strategic risks are those risks that could threaten the competitiveness and achievement of the company's objectives, i.e. whether the company will be able to meet its expected results, they are closely linked to macroeconomic variables and the economic and financial system.

Through the use of the Perceived Risk Index©, Enel SpA is able to have a clearer understanding of these risks, as this indicator provides it with a better perspective of the situation both inside and outside the company and allows it to better manage risks, thus decreasing the chances of being exposed and damaged by them.

The factors that are used to analyse all risks that could affect the company are: Credit Default Swap (5Y), Implied Volatility (3 months), Inverse Stock Price.

The Credit Default Swap (5Y) was selected as the factor to be analysed and integrated into the study as it provides valuable data on a company's chances of default and financial distress, it was decided to select 5 years as the time horizon as it allows for the right balance between flexibility and interest rates, it will also provide an average market spread.

The market spread, i.e. the difference between the price paid when buying or selling the CDS and the market price on that day, is related to the tenor of a Credit Default Swap, i.e. the time remaining before the expiry of the contract, which the longer its tenor, the greater the spread.

So choosing a CDS, which can have a duration of 1 month up to 10 years, with a life of 5 years, will give an intermediate value among all possible options.

Implied volatility (3 months) was incorporated into the Perceived Risk Index© analysis given its usefulness in measuring market expectations and its role in option pricing.

It was decided to choose 3-month implied volatility, as this time frame was considered a good compromise in terms of elasticity and predictive ability among the various time horizons available, which can vary from 1 month to over 1 year.

This indicator predicts the probability of a price movement, so the more distant a forecast is from the present the more uncertain its occurrence is.

Therefore, it was decided to use 3 months as the time horizon, in order to maintain a fair distance in terms of time to make the analysis as coherent and prospective as possible and at the same time maintain a high probability of determining option volatility.

The Inverse Stock Price was included as a variable in the Perceived Risk Index© calculation because it provides the investors' valuation of the company.

It has been used in reverse as a matter of convenience and homogeneity with the direction of the other two factors, so that the rise and fall of these values can be interpreted in the same way.

Although it is a market-influenced variable, the data it provides for analysis is all too important and valuable, as it not only reflects the impressions, sentiment and conditions of the market and its investors, but also offers short-term evaluations of the company, market patterns and trends, and is another indicator of the volatility of the companies being analysed.

In addition, it provides immediate data on the impact that a piece of news or risk has on the market, thus ensuring that a strategy is created as promptly as possible.

Once the credit default swap, implied volatility and inverse stock price have been calculated individually, these three variables are used in the calculation of the Perceived Risk Index©, which then provides a percentage of the perceived riskiness of each company included in the analysis.

This percentage is useful for making comparisons between the various companies and the sectors they are associated with, and the three variables that make up this indicator then allow for more in-depth analysis, as they provide specific information, such as volatility, default probability or market trends.

The data provided by this analysis are multiple and it also happens that the same data is provided, but obtained with a different calculation method, which then allows for a more complete view and a possibility of comparison even with the single, objective final result.

All this highlights the ductility and usefulness of the Perceived Risk Index©, underlining its potential breadth and depth of analysis.

The interpretation of the data is less complex than in other financial instruments, and the understanding of indicators such as beta, a coefficient that defines the measure of systematic risk of a financial asset, is clear from the outset, which once again highlights the good work done in the development of the indicator and in the proper inclusion of the various factors that are complementary to one another.

This indicator still has room for improvement, especially when considering the inclusion of ESG factors, a much-discussed topic in today's world, but the starting point and the growth it has undergone to date make it appear solid and enable Enel SpA to make a quantum leap in monitoring the financial performance of both the company itself and its competitors and others.

### *1.3. Credit Default Swap*

A credit default swap (CDS) is a derivative contract which is a financial instrument that allows one investor to swap or compensate its credit risk with that of another, it is a bilateral agreement between two parties, a buyer and a seller of credit protection.

A credit default swap came into existence in 1994 and it is used to transfer the financial exposure of fixed income commodities.

In a CDS contract, the protection buyer agrees to make periodic payments until the maturity of the contract to the protection seller, and in return, the seller, in the event of default by the third party, makes a payment to the buyer of the contract.

A credit default swap can have three different maturities: three, five or ten years, with the five-year maturity being the most common choice.

The profit gained by the Credit Default Swap buyer, during the life of this financial instrument, can be estimated as follows:

$$Profit\ to\ buyer\ of\ CDS = \Delta CDS \times N \times D$$

Where:

**ΔCDS**: it is the basis point change in credit spread,

**N**: it is the notional amount,

**D**: it is the duration of the bond

The buyer gains when the default spread grows over the term of the Credit Default Swap, while if the spread decreases, then it is the seller to gain.

The choice of the settlement type of the CDS, which can be physical or cash, is determined when the contract is concluded.

The contract specifies all the obligations and rights of the parties, and also defines the situations that are considered as 'credit events', which are: bankruptcy, default, debt moratorium, debt repudiation or debt restructuring.

The payment made by the CDS seller to the buyer, once the occurrence of a credit event has been established, is calculated as follows:

$$Payout\ Amount = N \times Payout\ Ratio = N \times (1 - Recovery\ Rate)$$

Where:

**N**: it is the notional amount,

The payout ratio is the loss suffered by a bondholder as a percentage of the nominal value of the bond, equal to 1 minus the recovery rate, i.e. the percentage of the amount due that is recovered from the bondholder during the insolvency proceedings.

CDS is mostly used for speculative purposes, hedging or as a form of arbitrage, usually those who use this type of derivative do so to hedge against the risk of default of a debt instrument or to speculate on the credit of a said borrower.

It is possible to close or unwind a CDS before its maturity in order to monetise or extract market value, to do so requires the agreement of both parties.

Credit Default Swaps played an important role both in the Great Recession of 2008, due to the lack of a legal framework regulating the market, and in the European debt crisis of 2010.

This lack of market transparency became a concern for regulators who decided to entrust the supervision of this financial instrument to the Securities and Exchange Commission and the Commodity Futures Trading Commission since 2009 with the Dodd-Frank Act in the US, while in Europe they have been regulated since 2012 and are overseen by the European Securities and Markets Authority (ESMA).

In general, CDS are a useful tool for risk management in the financial markets, but they should always be used with caution and a thorough understanding of how they work.

### ***1.3.1.*** *Impact of the CDS*

CDS contracts are complex financial instruments that have many strengths but are also subject to limitations and the creation of risks, such as liquidity, basis or systemic risk, which contribute to financial instability in the market.

The major strengths of credit default swaps are:

- Utility in risk management, with CDS contracts an investor can transfer the default risk he owns, so as to be protected in case there is a default of a third party;

- Flexibility in the management of the contract, CDS are liquid instruments and this allows investors to enter and exit their positions with relative ease, thus increasing their flexibility and use not only when dealing with credit exposure;

- Being adaptable to situations, credit default swaps are often modified according to the specificity of the situation, thus allowing investors to better protect themselves from the risks they are facing and thus align with their investment strategies.

In addition to their strengths, credit default swaps also have weaknesses, the most important of which include:

- Risk of counterparty default, CDSs are bilateral agreements, in which the buyer relies on the seller for protection in case there is a default of a third party, when the seller defaults on the contract, thus not compensating the buyer, the buyer exposes himself to counterparty risk, thus not receiving the payment he is due;

- Lack of transparency, credit default swaps are financial instruments that are often traded over-the-counter, resulting in limited transparency, and they do not always have public prices or even standardised contract terms, making their fair valuation more complex;

- Market influence, CDS prices can be influenced by market perceptions, e.g. in times of high stress, spreads and CDSs can increase significantly, thus increasing the cost of protection, which may no longer be as effective;

- Speculation, credit default swaps are also used a lot for speculative purposes, leading in the most extreme cases to market distortions, thus creating misperceptions of some companies and a general instability of the entire financial organism.

There are solutions to these weaknesses or limitations that CDS have, for example, the Securities and Exchange Commission and the Commodity Futures Trading Commission in America and the European Securities and Markets Authority in Europe are keeping an increasingly close watch on every single trade, so that they can keep them as transparent as possible and if there is something wrong, they can intervene immediately and not leave these contracts free in the market.

The two bodies that supervise these contracts are also doing meticulous work to prevent any fraud or speculation for inappropriate purposes in the market, so that this financial instrument is not influenced or changed by illicit actions and can be used for the right reasons for which it was created.

As far as counterparty risk is concerned, there are more and more court rulings on which the buyer can rely in the event that a seller does not fulfil the contract, so that he can protect himself in this circumstance as well.

Despite everything, therefore, CDSs remain efficient and very important credit derivative instruments for all developments and evolutions in the various financial markets and for all uses for both protective and speculative purposes of investors.

### *1.4. Implied volatility*

Implied volatility is one of the fundamental pillars of the options market forecasting and refers to the future volatility in price of a given asset, it is a forward-looking measure that takes into account the market's expectations of future option price movements.

Implied volatility calculates how much the price of an asset will fluctuate over a certain period in the future, based on current market prices and not on historical data, thus referring to a metric that captures the likelihood of changes in the price of a specific security.

It is often regarded as a proxy for market risk and is expressed using percentages and standard deviations over a given time horizon.

Implied volatility (IVOL), using the Black-Scholes-Merton model, can be estimated in the following way, proposed by Corrado and Miller in 1996:

$$\sigma \approx \frac{\sqrt{2\pi/T}}{Y+X} \times (C - \frac{Y-X}{2} + \sqrt{\left(C - \frac{Y-X}{2}\right)^2 - \frac{(Y-X)^2}{\pi}})$$

Where:

**T**: it is the remaining life of the option,

$$Y = Se^{-yT}$$

With **S**: being the price of the underlying security,

**e**: being the natural exponent of the stock dividend multiplied by the remaining life of the option,

$$X = Ke^{-rT}$$

With **K**: being the strike price defined on the option,

**e**: being the natural exponent of the discount factor,

**C**: is the call option price.

Investors use it to predict future market movements, the supply and demand for a security, to price option contracts and it is also used by traders to assess the risk and potential return of options in the market.

In the case of high implied volatility, the market expects large changes in the price of a security, thus making an option relatively expensive.

Conversely, when there is low implied volatility, the market expects small changes in the price of an option, thus making it relatively cheap.

Changes in implied volatility in option prices also indirectly and significantly influence the price of option contracts and the values of option portfolios.

In general, implied volatility is a key concept in the securities market, as it provides valuable information on the next trend and this makes it possible to create strategies to anticipate these future option movements, but one must always bear in mind that these calculations are based on assumptions and expectations and options do not always reflect the behaviour that is predicted by studies.

### *1.4.1. Utility of Implied volatility*

Implied volatility plays a key role in the market due to its usefulness in measuring the market's expectations and its role in option pricing, but at the same time it is a relatively influential and market-dependent instrument.

The strengths of implied volatility are:

- Importance in pricing, implied volatility is used to price option contracts, as incorporating it into the pricing method results in better market expectations of future volatility, thus contributing to greater accuracy and fairness, hence avoiding perceived risk and price fluctuation;

- Predicting the market, implied volatility is used to understand the market's expectations of future movements, the level of risk and uncertainty of securities so that investors can make decisions on their strategies based on accurate information;

- Uncovering undervalued options, implied volatility can help a trader understand which option is undervalued, this can be done by looking at implied volatility in relation to historical volatility, by doing so an investor can find discrepancies in the market that will allow him to exploit them to his advantage;

- Investment capacity, implied volatility provides useful information to understand how much the price of an option will move, the investor is thus helped to get an idea of how much to invest, based on a higher or lower deviation of the security.

However, implied volatility also has some weaknesses and limitations:

- Limited predictive ability, implied volatility is based on market expectations, which can change rapidly, thus making actual volatility predictions inaccurate or wrong, thus leading investors to make choices that are not congruent with future market trends;

-Arbitrariness, implied volatility is determined by the market and its prices, which are influenced by trading dynamics, making it dependent on the market and sensitive to any unexpected news, this phenomenon has a not insignificant impact on its value and consequently that of the securities linked to it, as well as on investors' market strategies, so this variable may be distorted and misinterpreted, thus creating erroneous expectations and potential untrue judgements;

- Mean reversion, implied volatility tends to alternate between periods of high variance and periods where instability is lower, which can complicate the prediction of timing accuracy and market variability, creating potential problems for investors in planning strategies;

- Relation to option pricing, implied volatility is one of the key components in determining the price of options, which is why its variations and misvaluations can have a significant impact on the value of options, which therefore may not always reflect their true and accurate valuation;

- Weak specificity, implied volatility provides information on the high or low movement of an option, but does not specify its direction, which could lead investors to make decisions that later turn out to be wrong.

Solutions can be found to these limitations and weaknesses of implied volatility. For example, for the limited predictive capacity, an investor or analyst can add the analysis of implied volatility to that of other financial instruments, so that he does not base his strategy solely on the study of one variable, so that if it is not right or has inaccuracies, his investment does not suffer greatly.

The same approach can be taken for the problem of the arbitrariness of implied volatility, which can be influenced by the market and its news, so it should be attached to a broader study where other variables independent of the speculations of the market and its participants are also present, so that one can realise when the implied volatility is biased and then readjust one's strategy accordingly.

For the limitations given by mean reversion and the relationship with option pricing, one can use a unique solution, i.e. both of these weaknesses have the problem of potential wrong or inaccurate timing calculations and values, thus creating possible inaccurate strategies or misinterpretations, so to overcome this difficulty one must work in more detail on the pricing models and the dynamicity of this variable, so as to be able to increase the effectiveness and efficiency of calculations and the accuracy of the values obtained.

One solution to solve the limitation of low specificity, on the other hand, is to combine the study of this variable with that of other variables, so as to obtain a complete picture of both the volatility of the option and its direction in the future, in order to better predict its trend and create the best possible strategy with the data available.

Implied volatility remains one of the most important fundamentals for forecasting the options market, and although it has limitations, to which, as one has just read, solutions can be found, investors and all those involved in the financial market prefer to include it in their analysis rather than not, precisely because of the valuable additional information it brings to the understanding of options performance.

### *1.5. Inverse stock price*

Inverse stock price is the inverse of the company's share price.

It is calculated by doing: $Inverse\ \ Stock\ Price = {}^{1}/_{Share\ Price}$

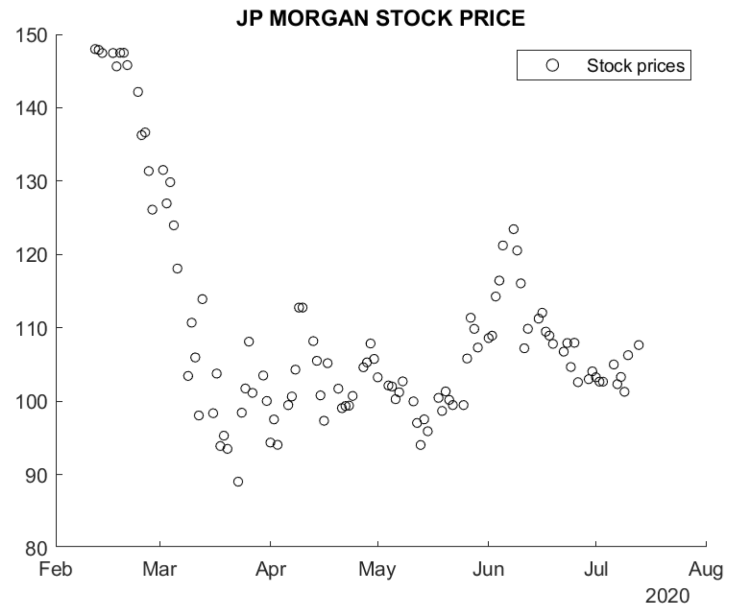



*Figure 1.1: JP Morgan Stock prices*

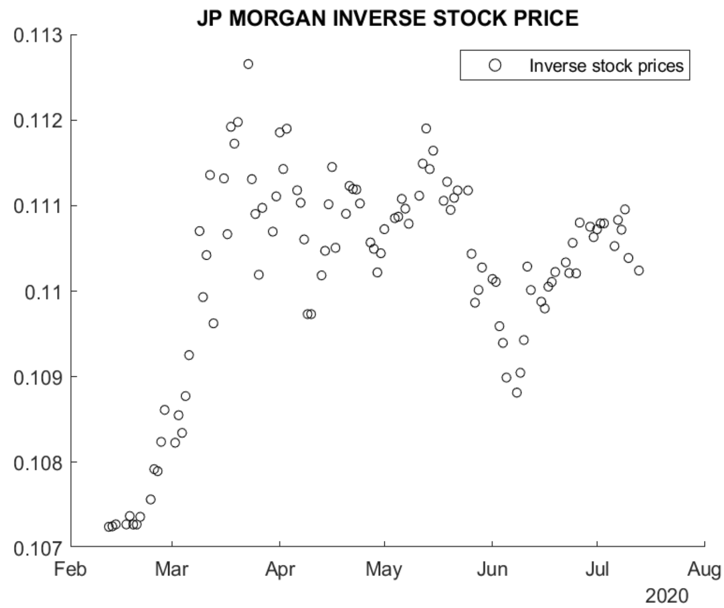



*Figure 1.2: JP Morgan Inverse Stock prices*

In the two graphs it can be seen that the trend of the inverse stock price, the figure on the right, is completely opposite to that of the stock price, the figure on the left, emphasising the concept of inverse.

This can be seen here for the values of JP Morgan, a company in the financial sector, from mid-February 2020 to mid-July 2020.

This method is often used for a matter of convenience, such as in the calculation of the Perceived Risk Index©, so as to have the changes in the same direction as the other elements in the analysis, since both the CDS and the implied volatility, as their values increase, the company's situation worsens and vice versa, and to obtain the same trend, the inverse of the stock price is used.

Stock price refers to the price of a share that is traded on the market, i.e. it is the value that ideally reflects the valuation that investors have of that company.

The price is not fixed, it can change depending on how the company's performance is viewed, so it can rise or fall depending on market conditions.

The value of a share is determined when the company enters the public market, i.e. when the company is going through an IPO, an initial public offering.

During the IPO, the price of the stock is set according to the amount of demand in relation to the company's offer.

After its entry into the public market, the stock price will be influenced by several factors, such as economic changes, political events or wars, but also by the pure activity of the company itself, in fact, changes in management or production, the uniqueness of the products or services that the company offers and even the notoriety of the business itself have a great impact on the price of its shares.

News that refers to a company's financial data is well regarded by the market, if it beats its own forecasts, this leads to a rise in the price, just as the health and integrity of the company leads to the same result, while scandals or underperformance lead to a fall in the value of the shares.

The price of a share, however, does not always reflect the intrinsic value of a business, as sometimes the value that buyers and sellers give it is wrong and this may affect its rise or fall in price.

Businesses usually want their share price to go up so that they can gain more prestige, discourage third-party takeovers and also generate more revenue so that they can have more money to invest in new projects and the growth of the company itself.

Companies encourage growth and the purchase of its shares, which then leads to greater demand and a subsequent increase in price, through the payment of dividends, which attracts new investors and strengthens the relationship with old ones.

A company, however, may also want its share price to fall, this is often achieved through a stock split, i.e. the division of the shares themselves, this decreases the value of the share itself, but does not alter the market capitalisation of the company.

Companies that take this route do so because they believe that the high share price discourages the average investor from buying, and by doing so they are able to attract more investment than a company with a high share value.

Traders constantly use the stock price in their market analysis, so that they can find stocks that are undervalued and profit from them.

The stock price remains a key figure and should always be taken into account in a market analysis, as it reflects how much an investor is willing to pay to own a piece of a company, a key figure if one wants to understand how the market reasons.

### ***1.5.1.*** *Influence of Inverse stock price*

Inverse stock price is widely used in financial market analysis, it is a variable that has both strengths and weaknesses, like any other financial instrument, but if properly understood and framed it can offer good insights for one's investment strategy.

Among its strengths are:

- Reflection of the company's value, the inverse stock price gives an immediate insight and understanding of a company's value, as the more a company is worth and its services or products are valuable to investors, the higher its share price will be, so this can give an understanding of the company's valuation at first glance;

- Investor's opinion, the inverse stock price is also determined by the law of supply and demand, i.e. the more investors want a certain stock, the more the stock will be worth and vice versa. So if a lot of people want to own a part of a company, this means that this company is considered capable and valuable, the opposite is the case if the demand for the shares of a business is low. This information helps to understand the market's opinion of a certain company and is a non-negligible detail in a financial analysis;

- Finding undervalued companies, investors often add the inverse stock price to their market analysis when they want to find shares that are undervalued by the market, also through this variable they can find shares that do not reflect the real intrinsic value of the company.

Instead, the weaknesses of the inverse stock price are:

- Shares on the market, the inverse stock price is strongly linked to the number of shares on the market, in fact two companies can have the same market capitalisation but two totally different prices and this is due to the number of shares that each company decides to issue on the market, therefore the price of a share is not very reliable for a correct market analysis;

- Changes due to the will of the company, the company can influence the price of its shares, e.g. through the payment of dividends it can attract new investors, who increase the demand for the company's shares, thus increasing their value, while through a stock split the company can decide to make its shares worth less. These are just two techniques that companies use to influence the price of its shares, which may then be out of line with the true value of the company itself;

- Market influence, the inverse stock price is greatly influenced by the market, by news, both good and bad, and by speculation; in fact, stock prices can be very volatile depending on the information that is published about a certain company or even by external factors such as wars or political crises, which are not directly related to a company but which indirectly change the value of its shares. For this reason, this variable is not so stable and solid to be a key component on which to base an investment strategy;

- Not reflecting intrinsic value, the inverse stock price may not reflect the true value of a company, since a certain company that is, for example, in the early stages of launching its product or service that may prove to be revolutionary, or that is making cutbacks in its workforce so that it can save money in order to be able to flourish, are viewed inaccurately by the market and so its share price does not reflect the true value of the project that this business has espoused in order to become large and successful. Thus, this indicator can have a wrong valuation, which could create investment strategies that are not as exact as one imagines.

However, solutions can be found to these limitations of the inverse stock price.

For example, for the problem of shares on the market, in addition to analysing the share price, one must also take into account the market capitalisation and the number of shares that the company has decided to issue, in order to have a more complete and truthful view of the company.

With regard to the company's desired changes in value, on the other hand, an investor must also analyse the managerial decisions that are made and the influence that the company wants to have on its share price, so as to understand its psychology and the method with which it approaches the market, so as to have a full understanding of what the choices of the business are and thus be able to integrate them into its analysis for the creation of an optimal investment strategy.

One solution to the problem of market influence is to add market-independent variables to one's analysis, so as to be capable to distinguish between results that are influenced by the market and those that are not.

The last but not least of the weaknesses is that of not reflecting the intrinsic value. One way to overcome this problem is to study the company you want to invest in in greater detail, because the more you know about a company, the more you will have an understanding of its real value, so that if it is under- or over-valued, you can act accordingly and design a profitable investment strategy.

The inverse stock price is considered one of the most important and comprehensive indicators to include in a financial analysis, although it has limitations and weaknesses, which, as can be seen, can be overcome.

Many aspects of the company are taken into account to determine its value, which makes it relevant and meaningful for investors as it provides them with valuable information in several areas.

# 2. Data and Methodologies

## *2.1. Stock market sectors analysis*

The stock market can be subdivided into different sectors, depending on the characteristics of the companies that make it up.

In this thesis, three different and not very correlated sectors were examined in order to obtain data as independent as possible, so as to be able, through the analysis of the three variables of which these data are a part, to find singular and objective results.

In fact, each sector is influenced in a different way by the macroeconomic variables, such as cyclicality, that make up the market, and it was on this particularity that the choice was mainly based.

The sectors that are studied are: Automotive, Financial and Oil & Gas.

In the automotive sector, we find all companies involved in the design, development and sale of vehicles.

It is a sector in continuous development and change, which has recently seen the advancement of electric vehicles, to the detriment of traditional vehicles with combustion engines, and the integration of autonomous driving.

It is precisely because of this revolution that it is undergoing that it was chosen for this study, since it is interesting to note how the Perceived Risk Index© and its components have moved and interpreted the different market situations during the events under analysis.

The selected companies are: Volkswagen, Porsche, Stellantis, BMW, General Motors and Tesla.

The financial sector is a very broad category that includes all companies that are involved in capital management, lending and the provision of financial services.

It is a sector that is highly regulated by laws and is always under scrutiny by government companies because of its crucial importance and because of the vast amounts of capital that are managed by the companies that are part of it, which, if inappropriately administered, could create significant damage to a country's economy and citizens.

The financial sector was examined precisely because of the importance and impact it has in today's world and also because it is one of the sectors that is not currently part of the Enel SpA Perceived Risk Index© study, so with the inclusion of these new companies, this thesis aims to contribute to broadening the view that this indicator provides of the market.

The selected companies are: JP Morgan & Chase Co, Citigroup Inc., Bank of America Corp, Morgan Stanley, HSBC, Banco Santander

The Oil & Gas sector encompasses all companies engaged in the exploration, production, refining and distribution of oil and gas products.

This is a very critical sector, as it is closely linked to the energy needs of every single person in the world and is also influenced by various factors, both geopolitical and technological, due to its global presence.

In recent years, this sector has been at the centre of criticism for its impact on the world's flora and fauna, which has led companies to undertake a transition towards renewable energies that has seen the involvement of a lot of capital, both human and financial.

For this reason and because of its relationship to the utilities sector, with which it shares the common aspect of energy distribution and to which Enel SpA belongs, the Oil & Gas sector was chosen for this analysis.

The objective of the study of this sector is precisely to verify how, during the crisis events that were taken into consideration, the variables have moved given the great change that the companies that are part of it are undergoing.

The selected companies are: Repsol, Eni, Total Energies, Exxon Mobil, British Petroleum and Shell.

These three sectors, as previously mentioned, are different and also the economic variables that influence them have different impacts on each, for example the financial sector is considered a leading sector, therefore sensitive to changes in interest, which tends to anticipate market lows and highs, as opposed to a sector such as the automotive one which is marked as lagging, therefore sensitive to the demand for goods, and which tends to lag the general market trend.

The sensitivity these sectors have to inflation or interest rates also changes, with the financial sector benefiting from low inflation and thus falling interest rates, while the Oil & Gas sector, given its link to commodities, benefits more from times of high inflation and thus rising interest rates.

All this underlines the distinctiveness present in the study, which makes the analysis more varied and multifaceted, thus opening up the thesis to multiple insights to be explored.

### *2.2. Methodologies used*

#### ***2.2.1.*** *Autocorrelation Function*

The autocorrelation function (ACF) is a statistical tool that is used for the purpose of measuring the correlation between values of the time series, a collection of sample values related to different random variables, at different lags h, indicating amplitude and length of the memory of the process.

The ACF can be defined as:

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)} = Corr\ (X_{t+h}, X_t) \qquad h \in R$$

Where:

$$\gamma(h) = Cov\ (X_{t+h}, X_t) \qquad h \in R$$

$$\gamma(0) = \sigma^2$$

With $\boldsymbol{\sigma}^2$ indicating the Var ($X_t$)

This formula is particularly used for stationary processes, i.e. models with restrictions on their heterogeneity, so as to avoid excessive variability of $X_t$, favouring a more homogeneous probabilistic structure.

The autocorrelation function is usually only studied for its positive time intervals, since its characteristics that $\gamma(h)=\gamma(-h)$ e $\rho(h)=\rho(-h)$ make it an even function, symmetric with respect to zero, and thus the time distance between $X_t$ and $X_{t-h}$ is equal to that between $X_t$ and $X_{t+h}$.

The value of this function fluctuates between $-1< \rho(h) < 1$, since it is a correlation.

For a time series without autocorrelation, the estimated values of the ACF must lie in the range $\pm\ {}^{1,96}/_{\sqrt{n}}$, and in this situation they can be considered zero, whereas if they lie outside this interval, then the time series would show a correlation between its values, which are considered significantly different from zero.

This function is mostly used to find the presence of systematic patterns or dependencies in time series, i.e. to understand whether, for example, the data are random or white noise, to detect the presence of trends or seasonality.

The ACF provides help in selecting the appropriate time series model, since, through the analysis of its graph, it is possible to understand the details of the autoregression and moving averages of the data, to be able to extrapolate and interpret them in the best possible way.

### *2.2.2. Partial Autocorrelation Function*

The partial autocorrelation function (PACF) measures the autocorrelation between $X_t$ and $X_{t+h}$, without taking intermediate values into account, in other words, it represents the correlation between the current value and its value at time h, adjusted by the influence of previous lags.

This function is used as a way of measuring the direct contribution of each individual value to the time series and simultaneously being able to control the influence of intermediate lags.

The partial autocorrelation function is defined as:

$$\phi_{hh} = Corr(X_t, X_{t+h} | X_{t+1}, X_{t+2}, \dots, X_{t+h-1})$$

Where:

Considering a regression model where $X_{t+h}$ is the depended variable regressed against $X_{t+h-1}$,$X_{t+h-2}$,..,$X_t$ and it is defined as:

$$X_{t+h} = \phi_{h1}X_{t+h-1} + \phi_{h2}X_{t+h-2} + \dots + \phi_{hh}X_t + e_{t+h}$$

With $\mathbf{e_{t+h}}$: being the uncorrelated shock.

At this point, both sides are multiplied by $X_{t+h-j}$ and the expected values taken are equal to:

$$\rho(j) = \phi_{h1}\rho(j-1) + \phi_{h2}\rho(j-2) + \ldots + \phi_{hh}\rho(j-h)$$

Now we obtain the following system of equations, known as Yule-Walker equation, for j=1,2,…,h:

$$\rho(h) = \phi_{h1}\rho(h-1) + \phi_{h2}\rho(h-2) + \ldots + \phi_{hh}\rho(0)$$

After some computation, this is what we get from this system:

$$\phi_{hh} = \frac{\begin{vmatrix} 1 & \rho(1) & \rho(2) & \ldots & \rho(h-2) & \rho(1) \\ \rho(1) & 1 & \rho(1) & \ldots & \rho(h-3) & \rho(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \rho(h-1) & \rho(h-2) & \rho(h-3) & \ldots & \rho(1) & \rho(h) \end{vmatrix}}{\begin{vmatrix} 1 & \rho(1) & \rho(2) & \ldots & \rho(h-2) & \rho(1) \\ \rho(1) & 1 & \rho(1) & \ldots & \rho(h-3) & \rho(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \rho(h-1) & \rho(h-2) & \rho(h-3) & \ldots & \rho(1) & 1 \end{vmatrix}}$$

The partial autocorrelation function provides insight into the specific relationships of the lags and how each of them contributes to the overall structure of the autocorrelation.

The PACF is a useful tool for selecting models for time series, facilitating their prediction, identification and dependence.

It also provides support in recognising the order of autoregressive patterns, since by showing the direct effect of each value on the observation, it allows a more precise determination of an autoregressive model.

### *2.2.3. GARCH*

The GARCH model was first proposed by Bollerslev in 1986 and was created to overcome the problem of parameterisation of models with a low number of observations, as the ARCH model is able to fit time series that have a high parameterisation.

The GARCH, which stands for Generalized Autoregressive Conditional Heteroskedasticity, is thus able to fit time series with a low number of observations and best captures their volatility over time.

The model is defined as follows:

$$r_t = \sqrt{\sigma_t^2 \times z_t} \qquad z_t \sim D(0,1)$$

Where:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2$$

With $\omega > 0$, $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$

**$z_t$**: it is a white noise distributed as a normal with mean equal to 0 and variance equal to 1.

The quantity $\alpha + \beta$ is the persistence of the model and it defines several properties in the GARCH, such as the decay of autocorrelation.

This model is important to study because, in addition to the low number of observations required, it assumes that the conditional variance of a time series depends not only on its past values, but also on the quadratic residuals and past conditional variances.

This view of conditional volatility makes it possible to observe the persistence of the shock in the time series, as it takes into account heteroskedasticity, thus making it possible to study more accurately the dependence between the conditional variance and the shocks of past volatilities and the dynamics of the underlying volatilities.

Furthermore, using this process better captures volatility clustering, i.e. the phenomenon in which periods of high volatility tend to be followed by other periods of high volatility, which allows for better modelling and analysis of changing volatility patterns.

This model is also flexible and adaptable to different volatility dynamics, allowing the capture of both short- and long-term dependencies, their averages and more complex characteristics that could not be captured by other processes.

In addition to observing the past phenomena of a time series, the GARCH model also makes it possible to make predictions of volatility and option prices, and it is precisely the incorporation of the view of past volatilities into the study that helps to provide more detailed and meticulous predictions than models that do not take this into account in their analysis.

# 3. Events analysed

## 3.1. COVID-19

The first of the two crisis events taken into consideration is the COVID-19 pandemic, a health crisis that broke out during March 2020, precisely the 12th was chosen as the official day of the outbreak, and that placed the world economy in serious difficulty.

The three variables and economic sectors in the months from February to July will be analysed to see how they performed and a comparison will be made between them to see the differences in movements.

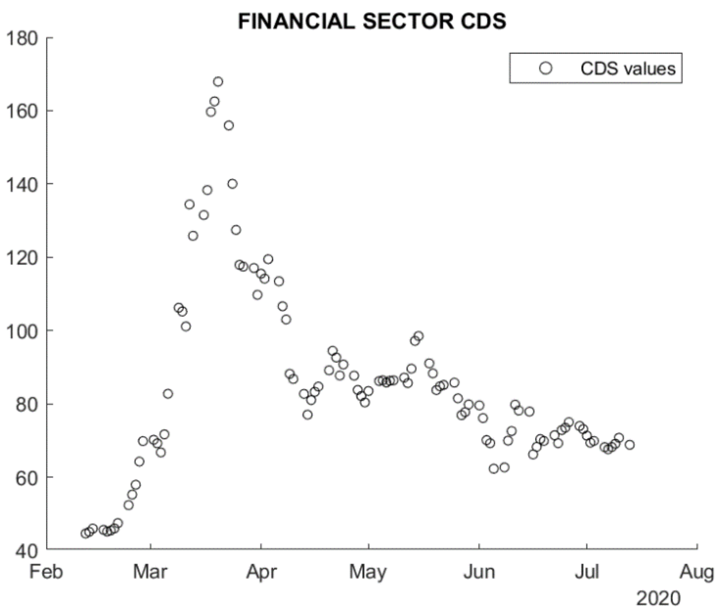



*Figure 2.1: Financial sector CDS values*

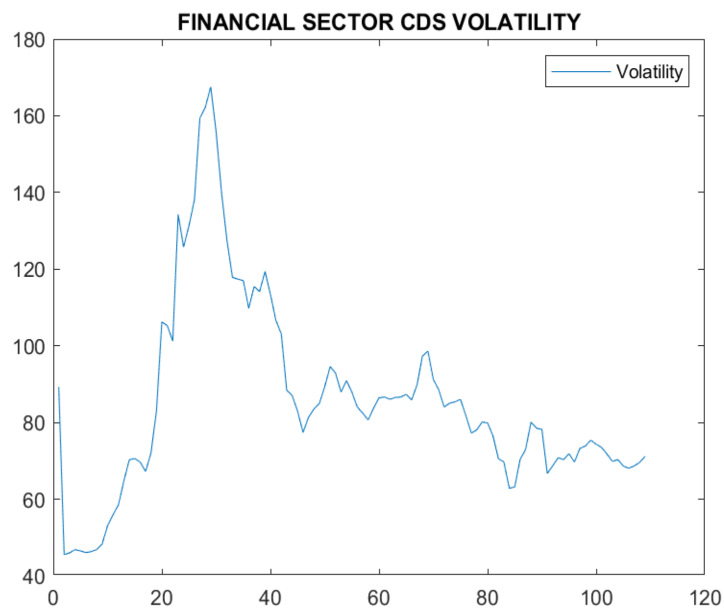



*Figure 2.2: Volatility of Financial sector CDS*

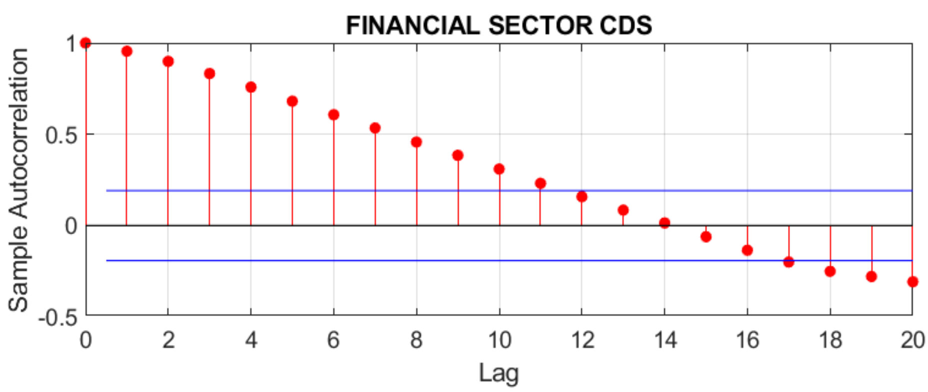



*Figure 2.3: Financial sector CDS Autocorrelation function*

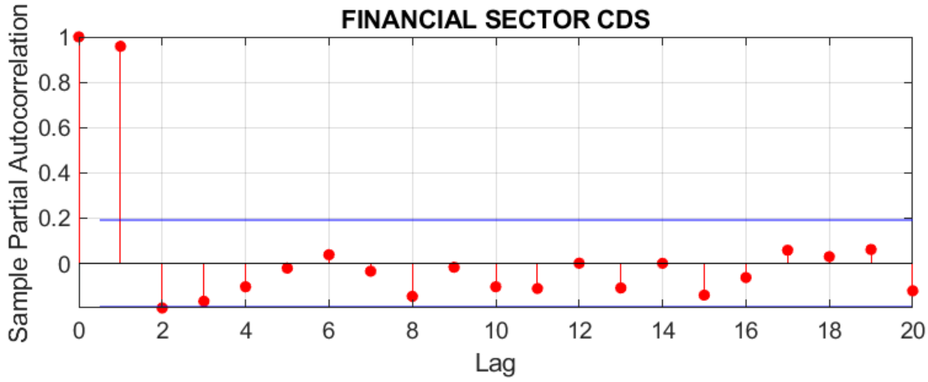



*Figure 2.4: Financial sector CDS Partial Autocorrelation function*

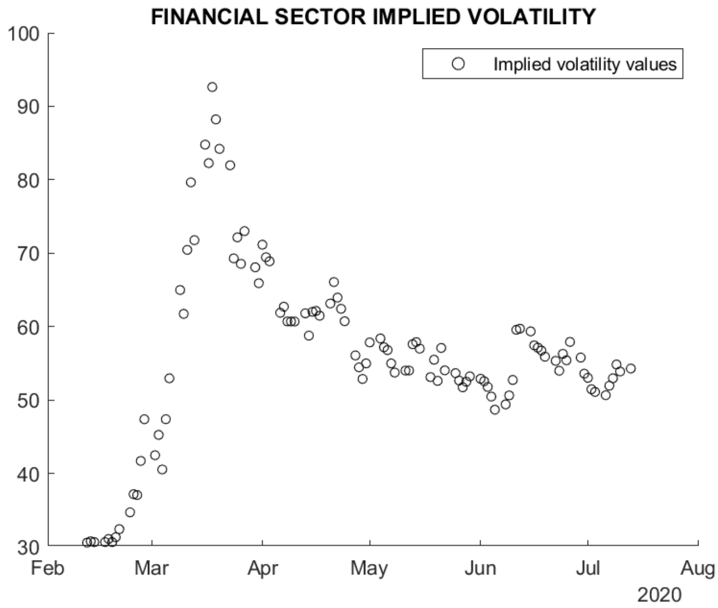



*Figure 3.1: Financial sector Implied Volatility values*

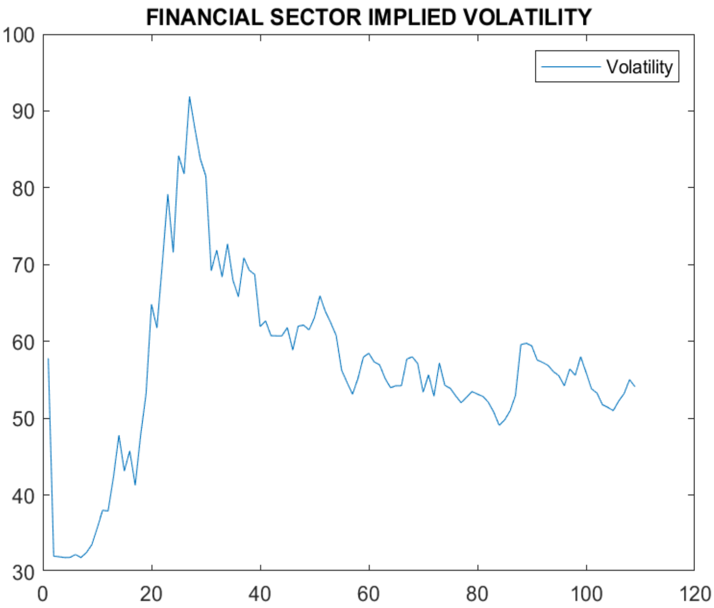



*Figure 3.2: Volatility of Financial sector Implied Volatility*

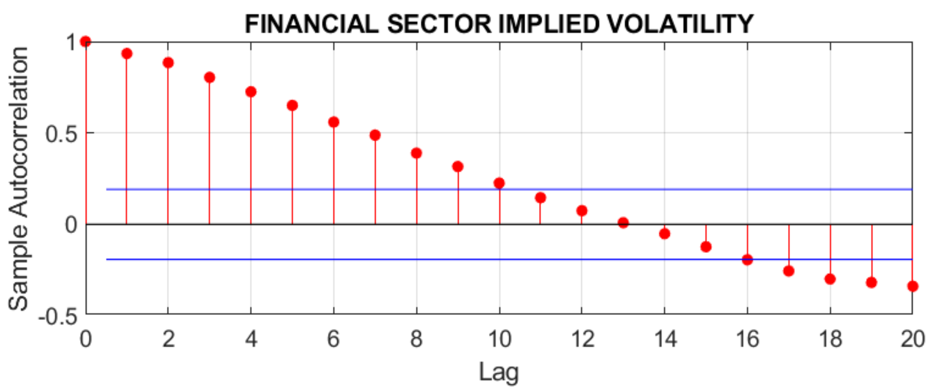



*Figure 3.3: Financial sector Implied Volatility Autocorrelation function*

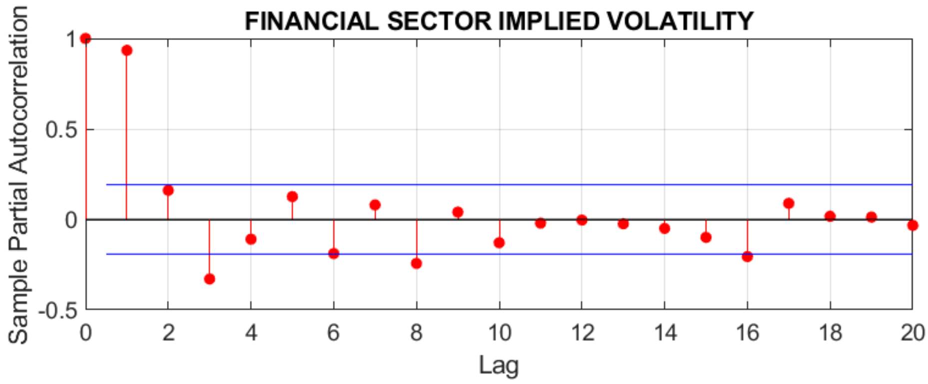
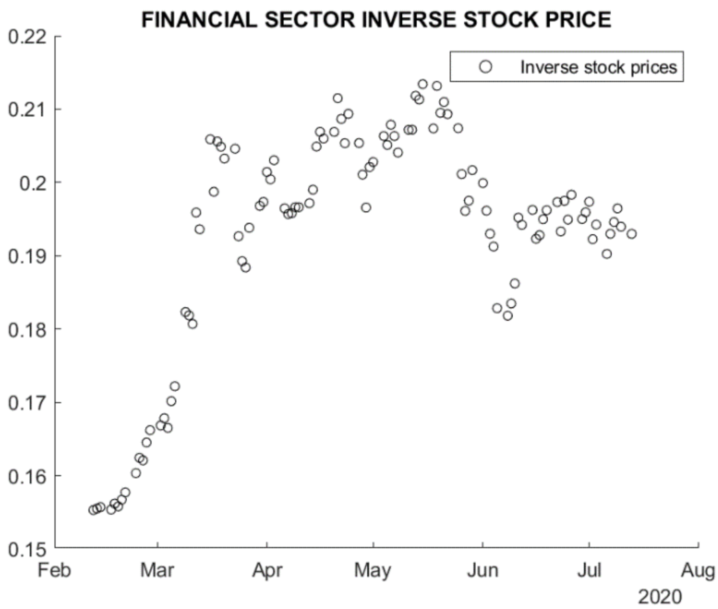



*Figure 3.4: Financial sector Implied Volatility Partial Autocorrelation function*



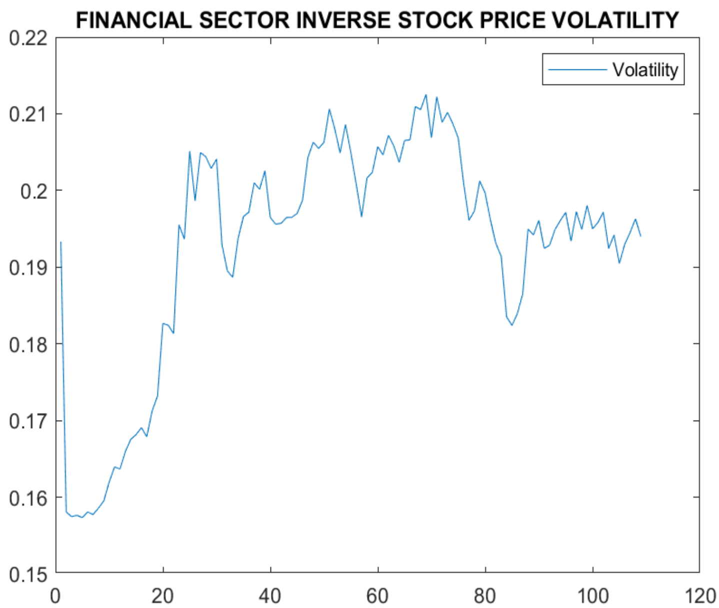




*Figure 4.1: Financial Sector Inverse Stock prices*

*Figure 4.2: Volatility of Financial sector Inverse Stock Price*

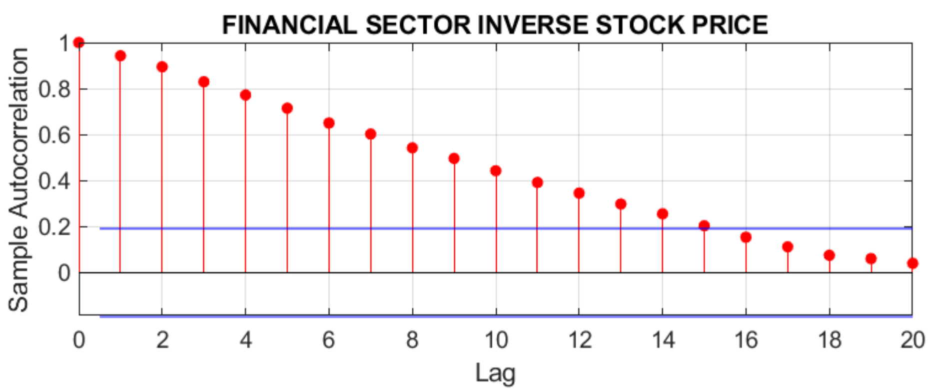



*Figure 4.3: Financial sector Inverse Stock Price Autocorrelation function*

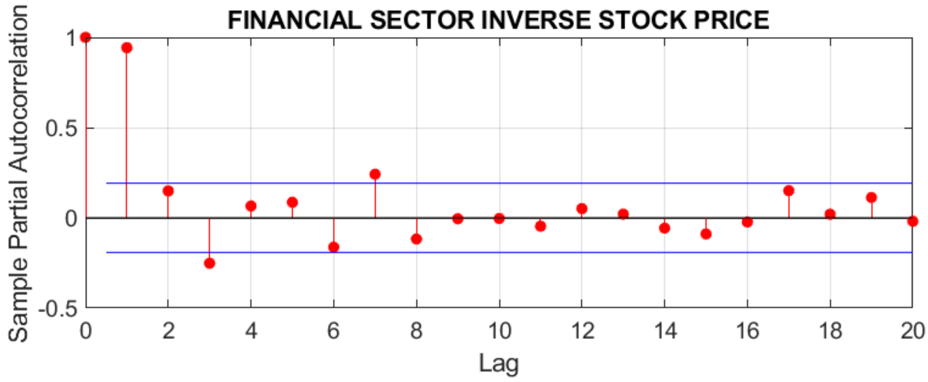



*Figure 4.4: Financial sector Inverse Stock Price Partial Autocorrelation function*

The financial sector during the COVID-19 pandemic saw significant instability and high volatility, as can be seen from the values of the three variables that have been taken into account for this thesis.

As far as Credit Default Swaps are concerned, the financial sector has seen a significant upsurge in values since well before the official outbreak of the crisis, in fact, as can be seen in Figure 2.1, an upward trend in CDS can already be seen since the last weeks of February.

This trend is also seen in volatility, which gradually increases until it reaches a peak on 20 March 2020, after which it begins to decrease, but always maintaining an irregular trend.

From Figure 2.2, no clustering of volatility can be discerned, but what can be defined are the large fluctuations that occur in the most concentrated phase of the pandemic, i.e. from the end of February to mid-April, where the CDS registers an inordinate rise and subsequent fall in a short period of time, and then calms down from May until the end of the summer period, with volatility becoming much more moderate compared to the previous months, always remaining relatively high.

The correlation during this period of crisis is strong, as Figure 2.3 also demonstrates. In fact, during the period from February to May, a trend can be seen that underlines a great positive correlation of CDS values, which slowly decline.

At the end of figure 2.3, we can see a negative correlation between the values and this emphasises how a positive return has a high probability of being followed by a negative return, a phenomenon that can also be seen in figure 2.1, where we can see that, at the end of June and in July, the returns tend to be more irregular with an alternation of positive and negative.

In Figure 2.4, we can see that the partial autocorrelation function is not really relevant as all values are in the 5% range, hence negligible, suggesting that there is no correlation in the financial sector CDS net of observations without intermediates.

The implied volatility of the financial sector, unlike the other two variables taken into account, suffers slightly later from the effects of the pandemic, as can be seen in Figure 3.1.

Values do not start to rise until the end of February, before falling slightly and then rising suddenly.

Volatility also behaves in the same way, as can be seen in Figure 3.2, where one can see, after a slight drop, a sudden rise, which will then keep volatility high in subsequent periods.

No volatility clusters can be seen, but an irregular pattern can be identified that continues throughout the observations.

In Figure 3.3, on the other hand, a strong positive correlation can be seen, which decays relatively early compared to that of the other variables.

As in the ACF of the CDS, a negative correlation occurs in the last lags, suggesting that there is a weak tendency to reverse the previous day returns.

The partial autocorrelation function has only few significant returns, indicating that there is a low dependence between the returns from which intermediate values are removed.

The inverse stock price of the financial sector is in all likelihood the variable, among the three used to calculate the Perceived Risk Index©, that most felt the impact of the pandemic, in fact, its values increased dramatically and remained high throughout the post-crisis period analysed, as can be seen in Figure 4.1.

The volatility of the inverse stock price from the earliest lags of the analysis is high, and in contrast to the volatility of CDS and Implied Volatility, it remains high throughout the analysed period.

Figure 4.2 shows the high values found during the crisis, it is not possible to identify a volatility cluster, but an irregular trend can be seen throughout the horizon under consideration, with a sudden spike due to the outbreak of illness, which is actually recorded during the month of March.

The inverse stock price of the financial sector has a strong positive correlation, as can be seen in Figure 4.3, with the values of the first 8 lags being significant.

The autocorrelation decays very slowly, with a clear positive trend that underlines the strong dependence that the returns have on each other, this pattern is usually associated with periods of high and persistent volatility, a prediction that turns out to be accurate.

The partial autocorrelation function has very few lags that are statistically different from zero, indicating that there is a weak dependence between the observations without the intermediate values taken into account.

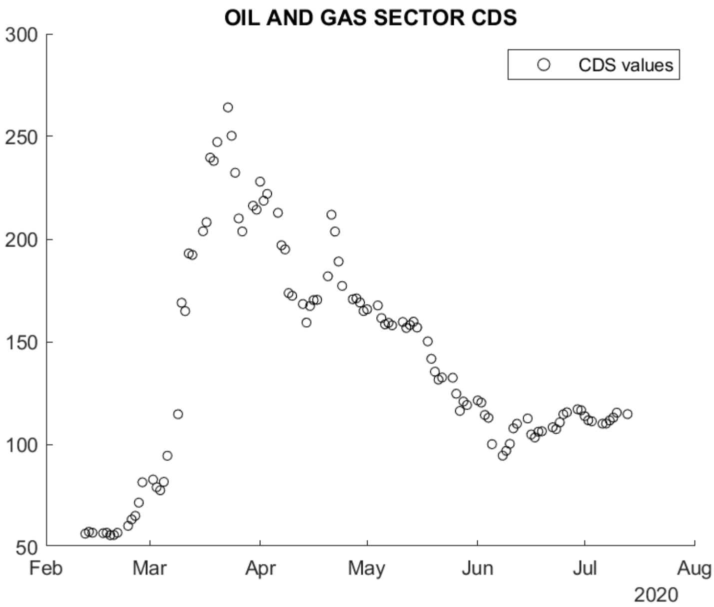



*Figure 5.1: Oil & Gas sector CDS values*

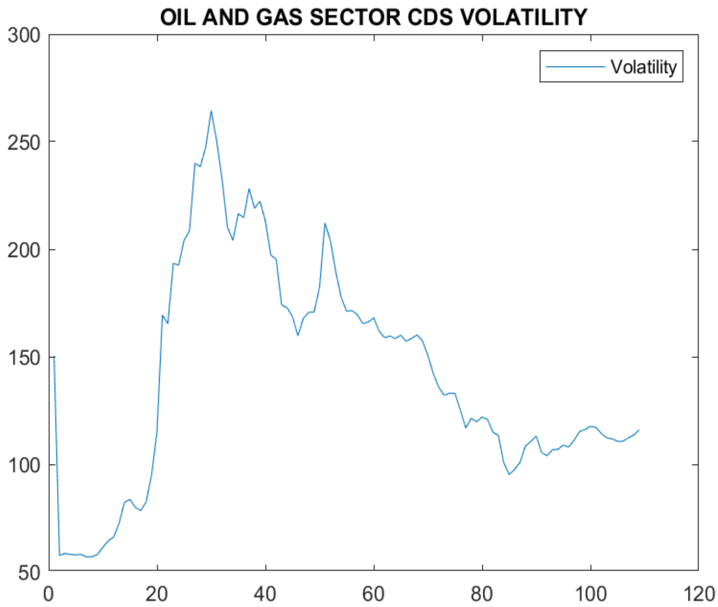



*Figure 5.2: Volatility of Oil & Gas sector*

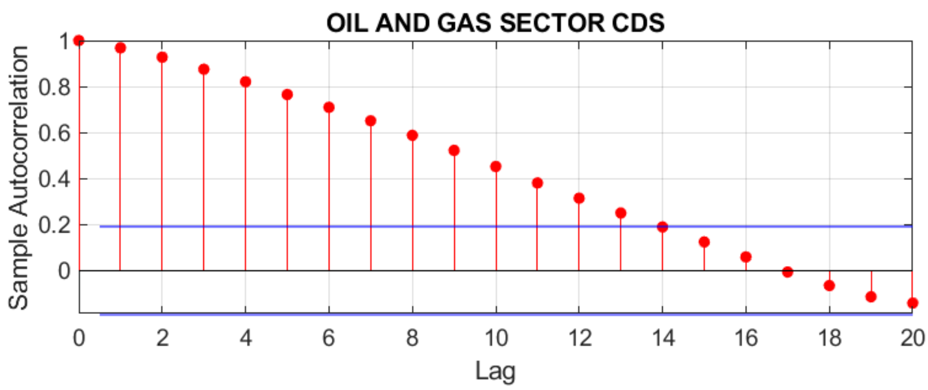



*Figure 5.3: Oil & Gas sector CDS Autocorrelation function*

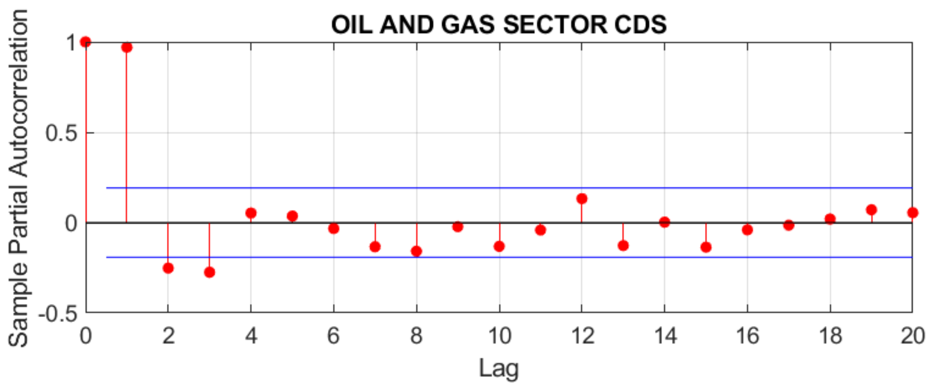
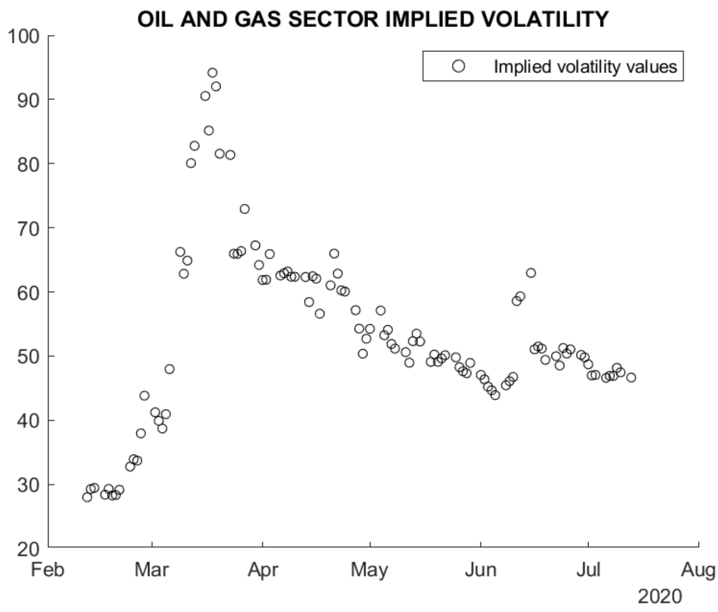



*Figure 5.4: Oil & Gas sector CDS Partial Autocorrelation function*



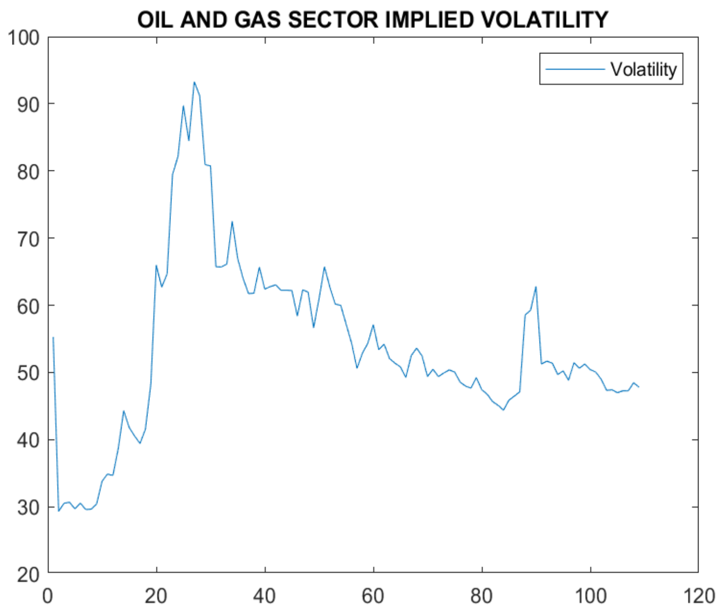




*Figure 6.1: Oil & Gas sector Implied Volatility values*

*Figure 6.2: Volatility of Oil & Gas sector Implied Volatility*

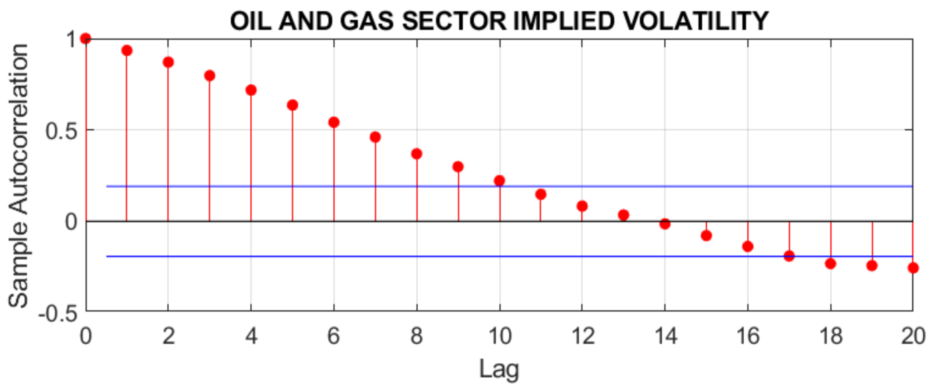



*Figure 6.3: Oil & Gas sector Implied Volatility Autocorrelation function*

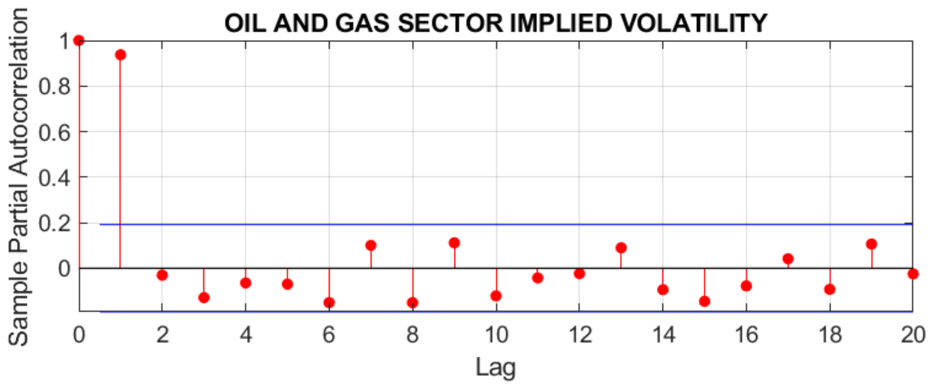



*Figure 6.4: Oil & Gas sector Implied Volatility Partial Autocorrelation function*

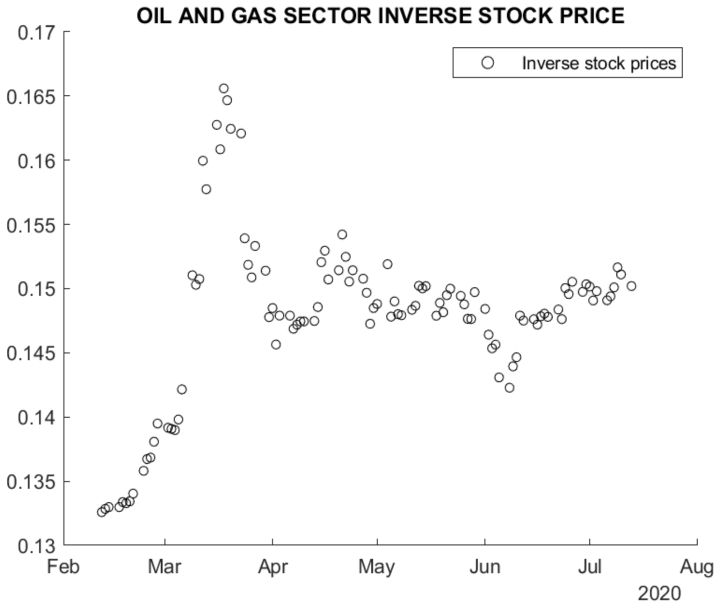



*Figure 7.1: Oil & Gas sector Inverse Stock prices*

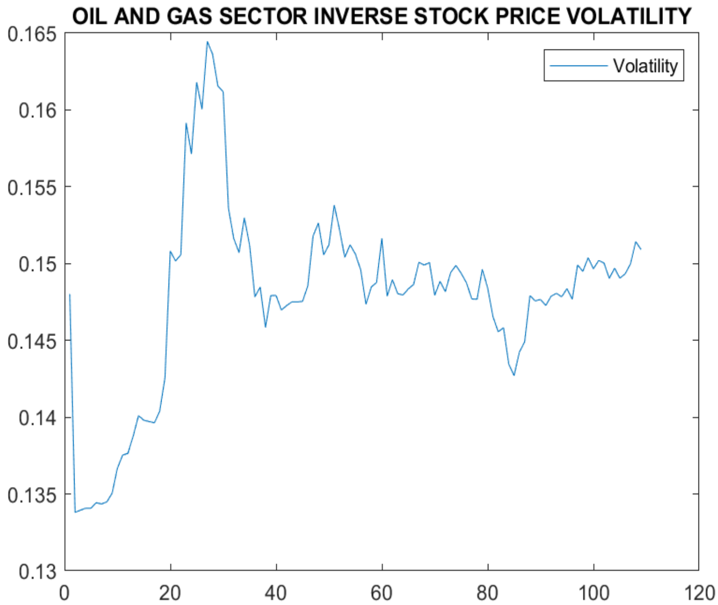



*Figure 7.2: Volatility of Oil & Gas sector Inverse Stock Price*

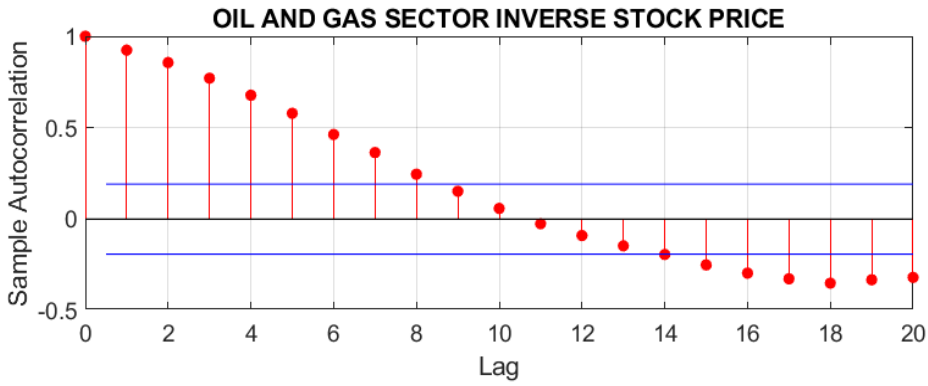



*Figure 7.3: Oil & Gas sector Inverse Stock Price Autocorrelation function*

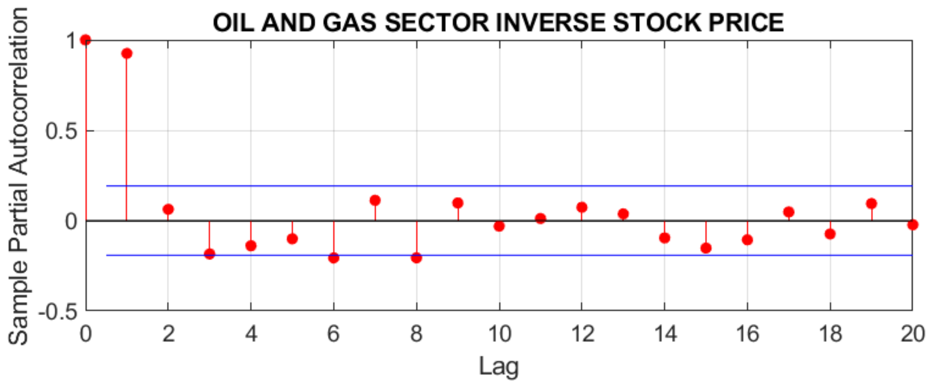



*Figure 7.4: Oil & Gas sector Inverse Stock Price Partial Autocorrelation function*

The oil and gas sector during the COVID-19 pandemic was exposed to very high volatility and significant capital losses.

This can be seen from the graphs of the three variables that were taken into account for this study.

As can be seen from Figure 5.1, the CDS values saw a sudden increase at the beginning of March 2020 and thereafter there were many fluctuations, which underlines the uncertainty of the market in the hot period of the crisis, where any positive forecast was contradicted by less reassuring news and vice versa.

Only since June there has been a decline in CDS values, brought about by greater confidence in the situation that had been defined.

CDS volatility was high for more than half of the period under consideration, as can be seen in Figure 5.2.

One can see the various shocks with which the CDS was affected, with the greatest at the beginning of the pandemic, followed by smaller fluctuations, most likely due to the release of uncertain news about the epidemiological condition.

It was only at the end of the period under consideration that volatility returned to relatively lower levels than at the outbreak of the pandemic, underlining a greater certainty of the picture of the situation that was forming.

Figure 5.3 instead shows the autocorrelation function of the CDS values, where a strong positive dependence can be observed, with a slow decay, usually found in periods of strong volatility, which remains persistent for several periods, a prediction that is accurate when looking at Figure 5.2.

This strong positive trend, which can be observed at the beginning of Figure 5.3, underlines a significant correlation between the CDS values, which becomes less relevant during the last lags considered for the analysis.

The partial autocorrelation function is indeed weak, as can be seen in Figure 5.4, since only the first four lags are significant, while the rest, falling within the 5% range, are of little impact, so it is possible to say that there is a low correlation between these values.

With regard to the values of the implied volatility of the oil and gas sector, Figure 6.1 shows that it is only in late March that we have the sudden increase due to the crisis, which leads to a significant rise, which calms down in a relatively short time if we compare it with the CDS data.

Volatility, as can be seen in Figure 6.2, has a large initial shock, which is followed by smaller movements, but which nevertheless remain irregular throughout the period under analysis.

From Figure 6.2 it is not possible to define a volatility cluster, but it can be seen that volatility remains high throughout the period, underlining the uncertainty that the market was experiencing during those months.

The autocorrelation function of the implied volatility shows a strong positive correlation, which however decays relatively soon, as can be seen in Figure 6.3.

This solid positive trend is succeeded by a negative one in the last lags examined, which emphasises that a positive return is very likely to be succeeded by a negative one, a phenomenon that can be observed in Figure 6.1, where irregular and uneven results are observed in the last period.

The partial autocorrelation function of the implied volatility demonstrates a weak, almost negligible correlation, since as can be seen in Figure 6.4, apart from the first two lags, the rest are all in the 5% range, which underlines their low significance in the correlation of values.

The inverse stock price of implied volatility was greatly affected throughout the period analysed for the pandemic, as can be seen in Figure 7.1.

In fact, as early as the beginning of March, values rose sharply, and then remained at those levels throughout the months under consideration, unlike the other two variables, which had seen a slight decrease in values during the summer months.

Volatility also remained high, as can be seen in Figure 7.2, after an initial big shock, smaller up and downs followed, but which always helped to keep it at high values.

The trend was erratic during all the months analysed, so it is not possible to define a cluster for volatility, but it can be seen from the very uncertain movements how this reflected the lack of confidence in the market during the pandemic.

The ACF of the inverse stock price shows a short but strong positive correlation in the early lags, which decay very quickly, as can be seen in Figure 7.3.

Still in this figure, we can observe the significant negative correlation of the last lags, which underlines the high probability that a positive return is followed by an opposite one and vice versa, which can also be observed in figure 7.1, where the returns are inconstant in the last period of the analysis, confirming the good prediction that this model provides.

In Figure 7.4, on the other hand, one can observe the partial autocorrelation function and its not particularly relevant values, which emphasise the low and weak correlation between the values, net of their intermediates, of the inverse stock price.

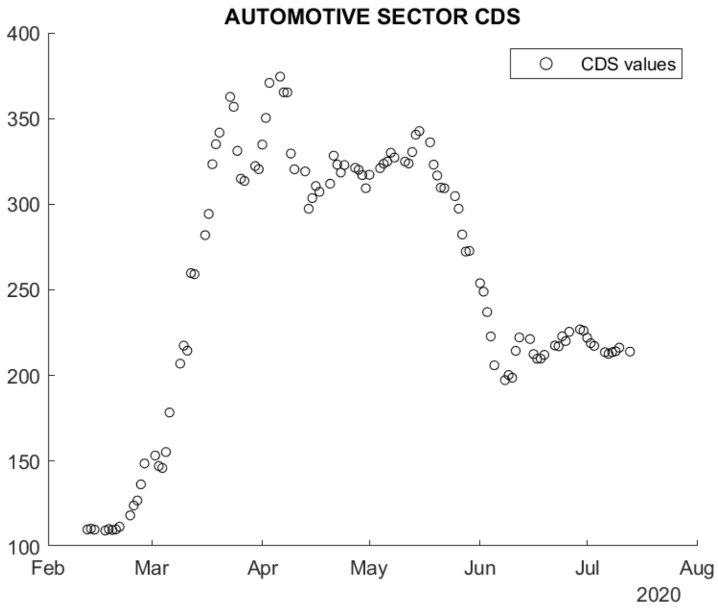



Figure 8.1: Automotive sector CDS values

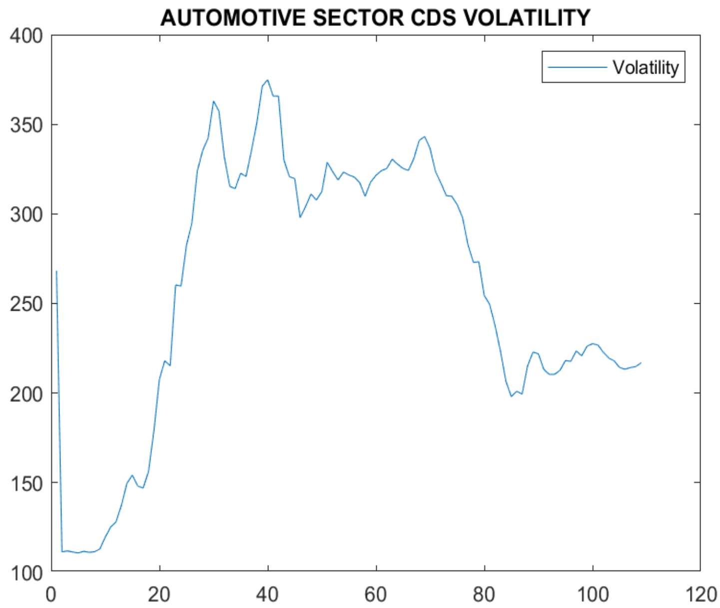



Figure 8.2: Volatility of Automotive sector CDS

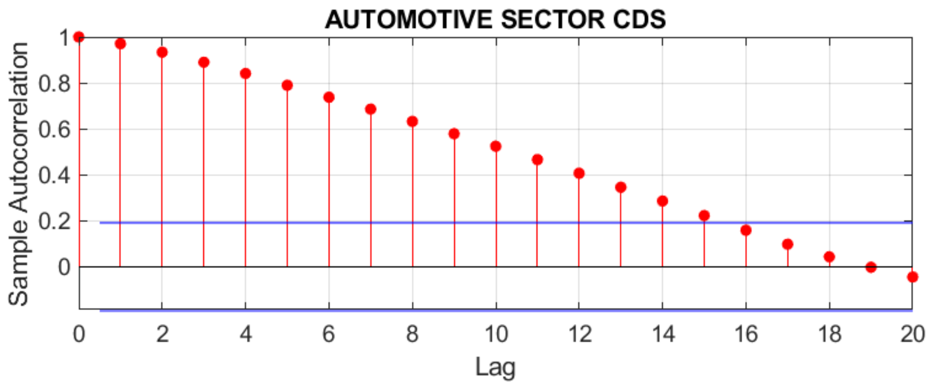



Figure 8.3: Automotive sector CDS Autocorrelation function

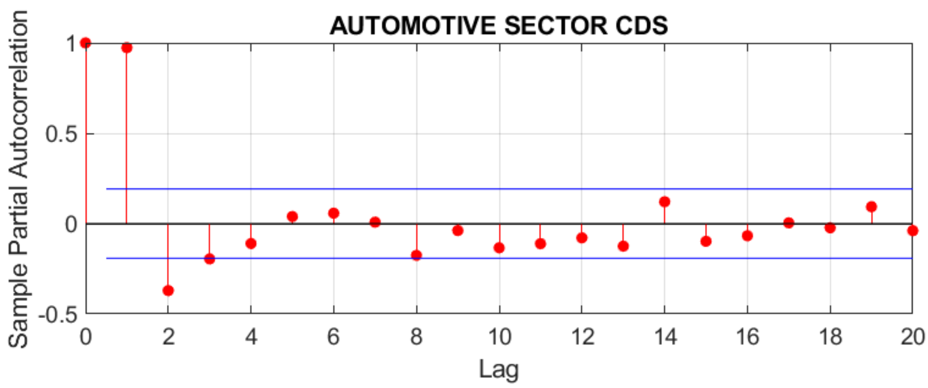



Figure 8.4: Automotive sector CDS Partial Autocorrelation function

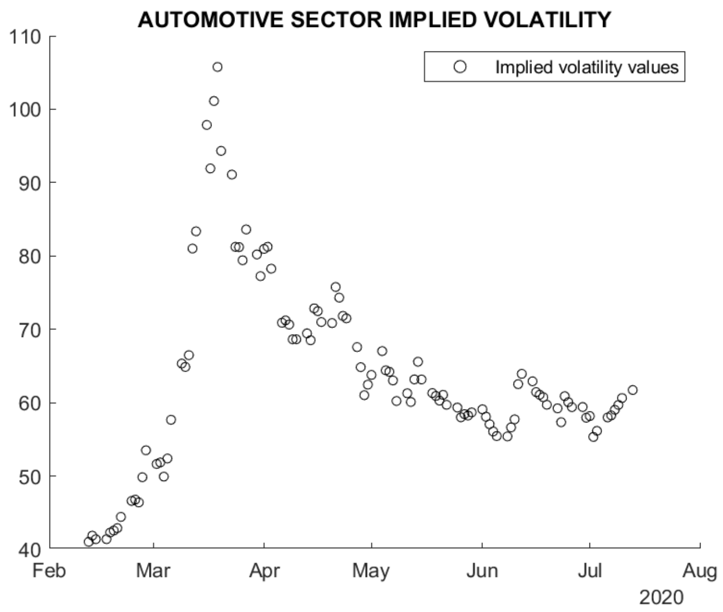



*Figure 9.1: Automotive sector Implied Volatility values*

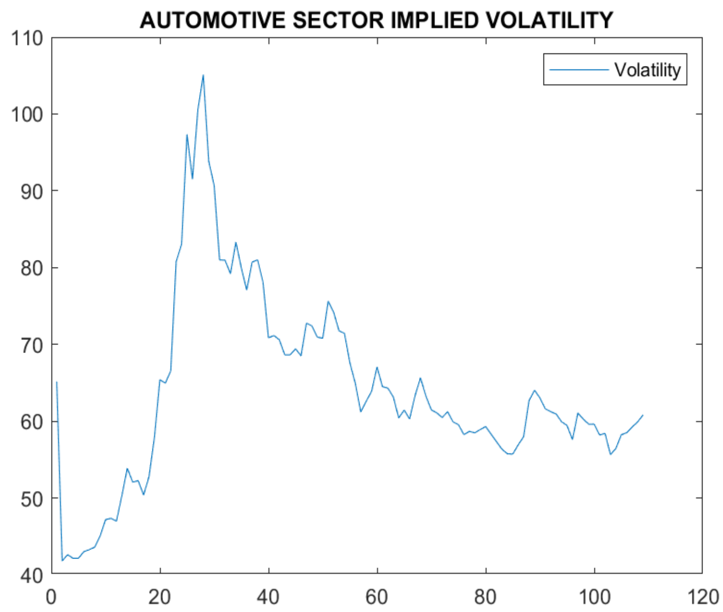



*Figure 9.2: Volatility of Automotive sector Implied Volatility*

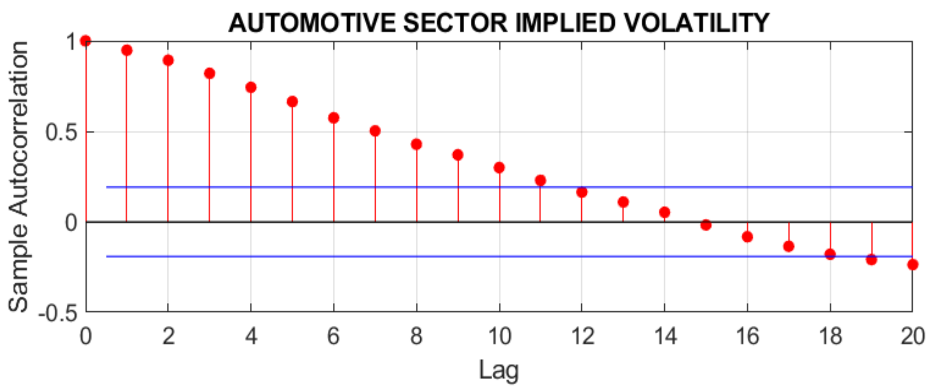



*Figure 9.3: Automotive sector Implied Volatility Autocorrelation function*

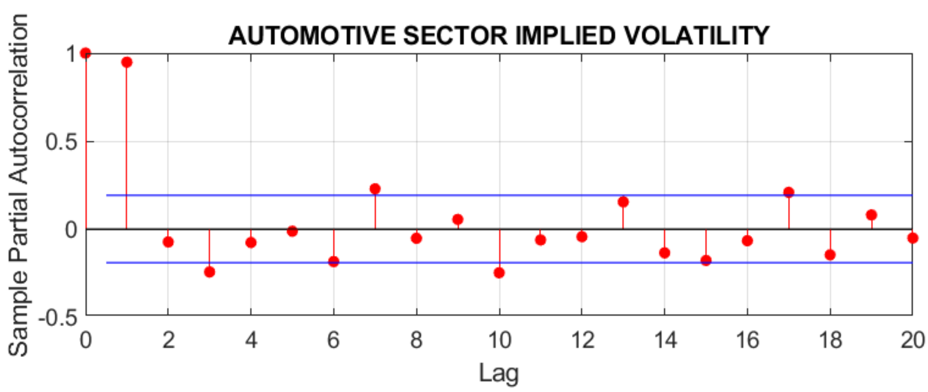



*Figure 9.4: Automotive sector Implied Volatility Partial Autocorrelation function*

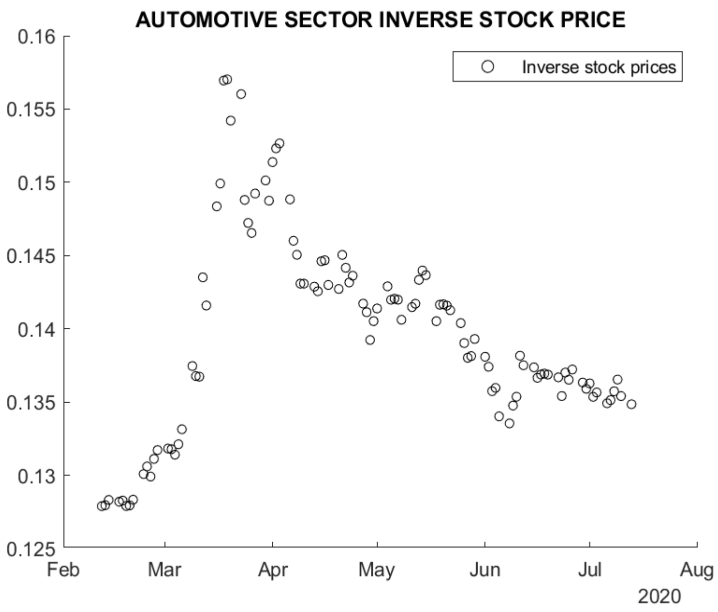



*Figure 10.1: Automotive sector Inverse Stock*

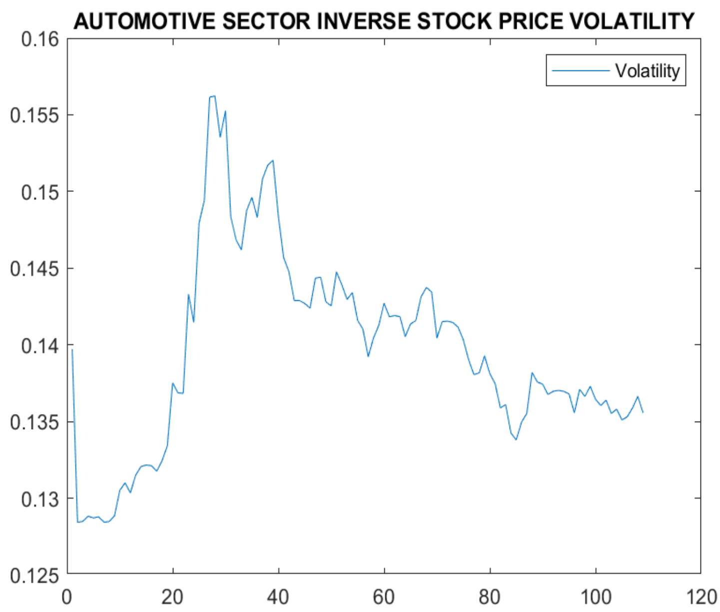



*Figure 10.2: Volatility of Automotive sector Inverse Stock*

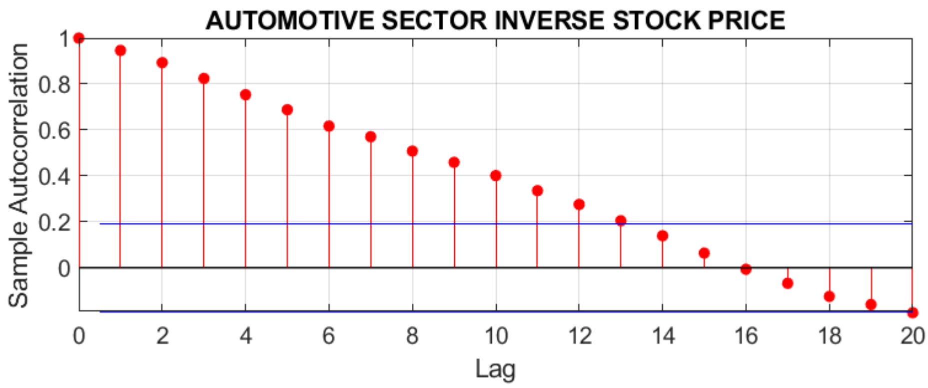



*Figure 10.3: Automotive sector Inverse Stock Price Autocorrelation*

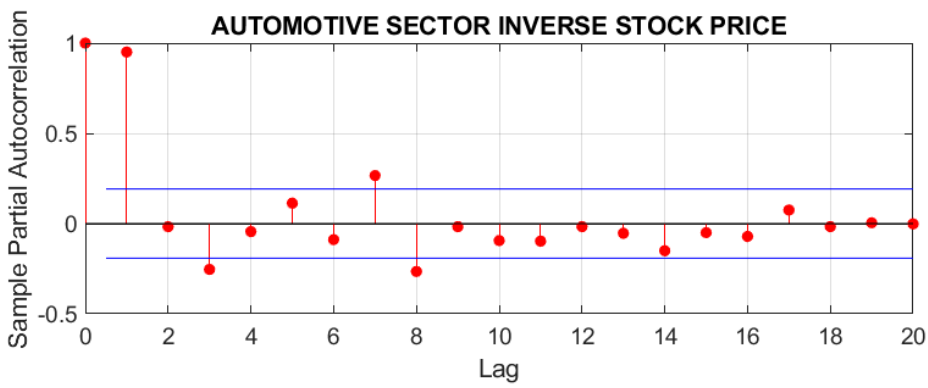



*Figure 10.4: Automotive sector Inverse Stock Price Partial Autocorrelation*

The automotive sector is probably the one of the three sectors taken into account that suffered the greatest impact during the COVID-19 crisis, as can be seen from the graphs above, which show significant volatility and strong correlation during the period under analysis.

Going into more detail, one can see in Figure 8.1 how CDS values soared during the pandemic and did not hint at decreasing before June.

This suggests that the automotive market was in dire straits and that the companies in it had to go through some really tough times, especially in March, April and May.

Only in June there was a decrease in CDS values, due to the growing confidence in the markets.

The volatility of the CDS, as can be seen in Figure 8.2, increased markedly, with an initial shock that affected its growth dramatically, taking it to very high levels, on which it remained for almost the entire period analysed.

After the first big shock, volatility has experienced various, relatively small fluctuations, which have always kept it high.

Only in recent lags has volatility seen a slight decrease.

In Figure 8.3, the autocorrelation function of the CDS can be observed, where a positive trend can be seen very clearly, emphasising a strong correlation between the values, and which has a very slow decay.

This pattern is often linked to moments of high volatility that remains high and persistent for subsequent periods, as can be seen in Figure 8.2, the volatility remains high and sustained over almost the entire period analysed, so the forecast provided by the ACF is true and well-founded.

The partial autocorrelation function, as can be seen in Figure 8.4, has only the first three lags that are significant, while all the others are negligible, indicating that there is a weak correlation between the CDS values net of their intermediates.

As far as implied volatility is concerned, as can be seen from Figure 9.1, there is a sudden increase in values at the beginning of March, which, however, unlike the CDS, is not lasting, in fact, it can be observed that already in April the values are much lower and go down more and more towards the end of the period under analysis.

Volatility likewise has an increase in the first lags of the analysis and then slowly goes down, as can be seen in Figure 9.2.

This shows how the car market, after an initial big shock by which it was caught off guard, has stabilised and revised all its forecasts, expecting a slow recovery, which, as can be seen in the last lags of the analysis, is happening.

Figure 9.3 shows the trend of the autocorrelation function, which is very significant in the early lags and decays relatively quickly.

The positive trend, which is denoted in the first 10 lags, demonstrates a strong dependence and correlation between the values of the implied volatility, which becomes much less relevant in the last 10 lags, all of which are in fact in the 5% range, demonstrating that they are negligible values for the definition of correlation.

The partial autocorrelation function, as can be seen in figure 9.4, on the other hand, is not very meaningful, since in addition to the first two lags, it has only two others that are outside the range of insignificance, while all the others are within it.

One can therefore denote a weak correlation of the values of the implied volatility net of its intermediates.

The inverse stock price of the automotive sector lags somewhat in being affected by the crisis, compared to CDS and implied volatility.

As can be seen in Figure 10.1, it is only in the second half of March that there is the sudden rise in values, which also occurred in the other two variables examined, but much earlier.

The values remain high until well into May, and it is only at the beginning of June that there is a decrease in them.

Volatility is high from almost immediately and remains there for most of the period under analysis, with an irregular trend and various fluctuations, as can be seen in Figure 10.2.

Again, in the figure 10.2, we can see how the first big shock is followed by many up and downs, which are contained in the oscillation, but which perfectly summarise the uncertainty in the market and the resulting price volatility.

The autocorrelation function is strong and its decay is slow, the positive trend that characterises it underlines the significant correlation that exists between the values of the inverse stock price, as can be seen in figure 10.3.

This trend again emphasises a high volatility, which can also be seen in Figure 10.2, confirming the correct analysis made in the ACF.

In Figure 10.4, we can observe a partial autocorrelation function that has only 5 relevant lags and that make a difference to the measurement of the correlation of values, while all the others are negligible.

The correlation of the values of the inverse stock price net of its intermediates is weak and not very relevant.

Now that all the variables have been studied for the three sectors under analysis, it is time to take an overview in order to see the movements and behaviour during this period of crisis, and then make a comparison between them.

The first variable that will be analysed is the Credit Default Swap.

The CDS saw a sudden increase during the pandemic in all three sectors analysed.

The rise in values in the financial sector was earlier than in the other two, with the financial sector seeing a significant surge in the last week of February, and the other two only in early March.

As for the first big shock, it was the same in all three sectors, and the irregular trend with various fluctuations, which kept it always high in value, was also repeated for all three case studies.

For both the automotive, financial and oil & gas sectors, a significant decrease only began in June, meaning that the values remained high for almost the entire period analysed.

The volatility of the CDS for all three sectors has experienced an initial big shock, which led to a disproportionate rise in values, which then remained high for most of the analysed period.

Immediately after the official outbreak of the pandemic, values were already high for all three sectors, and volatility remained persistent until almost the end of the period under analysis, underlining that during the first months of the crisis, uncertainty was high.

The many fluctuations were due to the news that came out daily on the situation, which remained uncertain and therefore no precise strategies could be devised.

Only in the last few lags, CDS volatility has seen a decrease, reflecting the increasing certainty in the markets and the averting of the probability of default for most companies.

The autocorrelation function saw a strong positive trend in all three sectors, confirming a strong correlation between CDS values.

This positive trend is also often a prediction of high and persistent volatility over several periods, an assumption that proves to be correct as volatility remains really high in the months studied.

The ACF of the financial sector has significant values in the last lags, meaning that a positive return will most likely have been succeeded by a negative return, and as can be seen, this is what actually happened, with very erratic returns in the last month under analysis.

Correlation during a period of crisis tends to increase due to panic and general uncertainty, and for an instrument like the CDS, which is traded a lot in this type of situation, it is relatively normal.

The Partial autocorrelation function, on the other hand, is irrelevant for all three sectors, as there are not many significant lags to be taken into account in the analysis.

The reason for this high CDS for so many months lies in the fact that the Credit Default Swap is a much-used instrument in times of crisis, especially by those who bet on company defaults, and in a pandemic full of uncertainty, where many companies had to remain closed and therefore unable to produce, the risk of insolvency increased dramatically for many businesses and the markets were very volatile, the risk of default was alive for many companies and this therefore led to a protraction of high CDS values.

The Credit Default Swap is therefore a good indicator of market uncertainty and its prolongation, thus facilitating the identification of the crisis period and consequently the approach to be taken.

The implied volatility after a large initial shock, where it registers a sudden increase, decreases slightly almost immediately, and then settles halfway between the pre-pandemic values and the values found during the initial shock.

These values decrease more and more in the last two months under analysis.

Implied volatility thus behaves differently from CDS, where values remain high for almost the entire period under analysis.

Implied volatility has a large initial increase, but then decreases more slowly.

In all three sectors analysed, the pattern is very similar, with the initial big shock being followed by smaller fluctuations, with many up and downs, which always keep volatility relatively high and erratic in its results.

This inconstant trend highlights the uncertainty of the markets during such a period of crisis when there is no security to rely on.

The autocorrelation function presents similar results in all three sectors analysed.

In all sectors, there is a strong positive trend, which decays relatively soon, in fact this strong correlation is only found up to about the tenth lags for all the case studies.

After the tenth lag, the values begin to be negligible because they fall within the 5% range, thus negligible.

There is one detail, however, for both the financial sector and the oil & gas sector, the last 4 and 3 lags respectively are significant and negative and emphasise that there is a high probability that a positive return will be followed by a negative return, which we can see again in the values of the implied volatility, where in the final for both these two sectors it shows an inconstant trend.

The partial autocorrelation function, on the other hand, is not particularly relevant for all three sectors, having most values in the 5% range, thus making them negligible and approximating 0, thus indicating a weak correlation between the values of implied volatility net of their intermediates.

Such fluctuating values of implied volatility during the pandemic were mainly caused by the uncertainty that existed at such a time, the sudden shock that spilled over into the financial markets, creating panic selling and irrational behaviour, and the systemic risk, thus generating an extraordinary market situation.

Implied volatility thus turns out to be a useful tool for tracking systemic risk, which the Perceived Risk Index© aims to help indicate and avoid, and investors' general expectations of the future, thereby creating a dynamic indicator of perceptions at a complicated time of great stress for the economy, therefore establishing itself as a fundamental in predicting the market even in tough times.

The inverse stock price is probably the variable most affected by the crisis, with a sharp increase in values that then remained high until almost the end of the period analysed, unlike the other two variables which had a decrease in their values by around May.

In fact, the pattern of the inverse stock price in all three sectors was very similar, with a sudden increase at the beginning of March which then maintained high values throughout the period under analysis.

The volatility of the inverse stock price increased immediately and remained high throughout the period studied.

In all three sectors, we find this sudden rise and subsequent persistence, with a very irregular trend and small fluctuations, due to the uncertainty in the market and the lack of confidence investors had during the pandemic period.

The correlation of the inverse stock price is strong and positive, denoting a serial dependence of the results, as can be seen from the results of the autocorrelation function.

The positive trend is found in all three sectors, with a slow decay in the financial and automotive sectors and a faster decay in the oil & gas sector.

This tendency found in the automotive and financial sectors is a sign of a high and persistent volatility in the variable under analysis, a phenomenon that is true when analysing the volatility of the inverse stock price.

The autocorrelation function of the Oil & Gas sector has a final negative trend, which underlines a high inconstancy in returns, with a succession of positive and negative results.

The partial autocorrelation function has negligible values, so concluding that there is a weak and not really relevant correlation between the values of the inverse stock price.

The high values of the inverse stock price are due more to the reduced business activity that the pandemic has brought, which has caused less revenue for companies and consequently less capital to pay off its debts, making it more prone to default, thus causing its stock price to deteriorate.

Another cause of such high values has been the suspension or decrease in dividends, which has led to a departure of investors and consequently capital.

Another reason was the general uncertainty and insecurity that was present in the market, which led all investors to sell off the assets they owned, causing a general depreciation of companies' shares.

It can therefore be said that the inverse of the share price is a good measure of investors' perceptions of companies, especially in times of crisis, where it can really show how market participants feel, thus making the analysis even more specific.

In terms of sectors, however, it can be seen that the financial sector anticipated the impact of the crisis and came out of it relatively earlier than the other two sectors analysed, which confirms why it is considered a leading sector.

This phenomenon is due to the fact that the markets, both stock and bond markets, moved earlier, having perceived the danger of the situation that was about to unfold, which is why it can be seen that the falls in stocks and movements towards bonds considered safer have been happening since before the official outbreak of the pandemic.

Investors and analysts, both because of their analytical skills and because of the considerable information they had access to, were able to move earlier in order to ensure a faster recovery from the hard times that were occurring.

The oil & gas sector only really felt the effects of the crisis when the first nation lockdowns were being announced.

These shutdowns led to a lower demand for oil, which caused a general surplus, which then led to a cutback in production, thus creating a very uncertain situation for most of the companies surveyed.

The lockdown also changed the demand for energy and also its use, thus leading to a change in the global economic environment, which did not allow an easy recovery for the companies in this sector.

One can therefore define the oil & gas sector as a lagging sector, i.e. a sector that is very sensitive to market demand and takes longer to show market trends.

Also in the same category is the automotive sector, which experienced the true impact of the pandemic only when the first national lockdowns were happening.

These led to a general decrease in demand for passenger cars, causing a significant drop in sales.

The lockdown also led to the closure of factories and thus an inability to produce, which then caused a slow recovery as companies had no vehicles to sell once demand was returning.

The sector therefore struggled to pull itself out of the early months of the pandemic and compared to the other two sectors, had a slower recovery.

The financial sector therefore proves useful in being able to make market forecasts, since, as anticipated, it predicts the impacts that a situation may have on the economy, whereas the oil & gas and automotive sectors, although slower to perceive the impacts of a crisis, in the long run better reflect what the real market conditions are.

### *3.2. Russian Invasion of Ukraine*

The second crisis event that was analysed was the Russian invasion of Ukraine, a geopolitical crisis that began at the turn of February and March 2022 and had much more serious repercussions worldwide than expected.

For this crisis, as for the previous one, the three variables and economic sectors in the months of February to July will be analysed, so as to see the movements they have had and to be able to compare them.

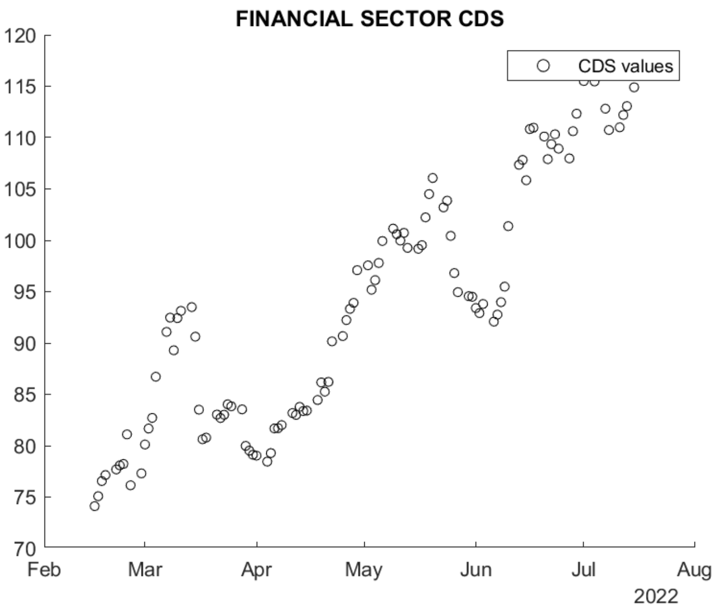



*Figure 11.1: Financial sector CDS values*

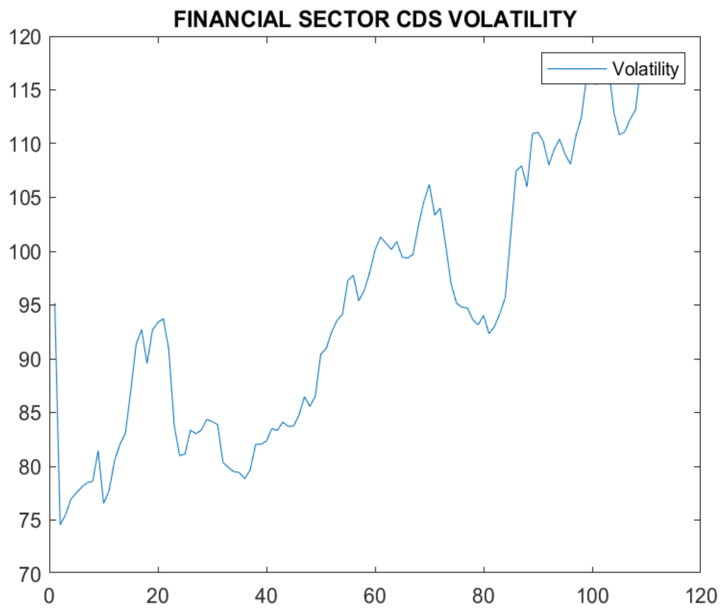



*Figure 11.2: Volatility of Financial sector CDS*

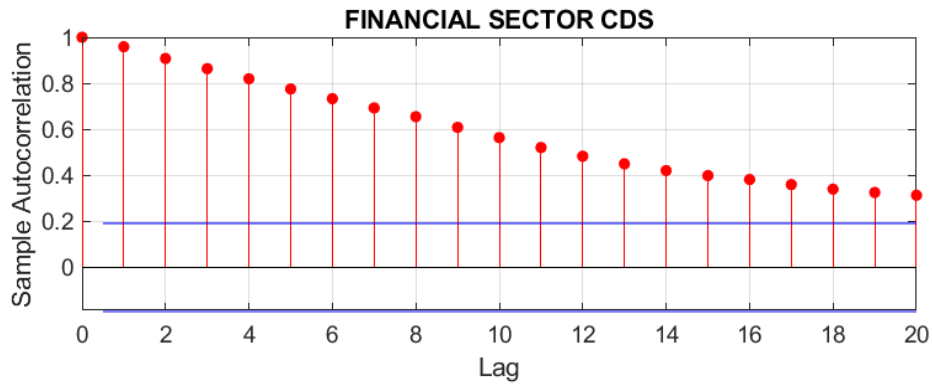



*Figure 11.3: Financial sector CDS Autocorrelation function*

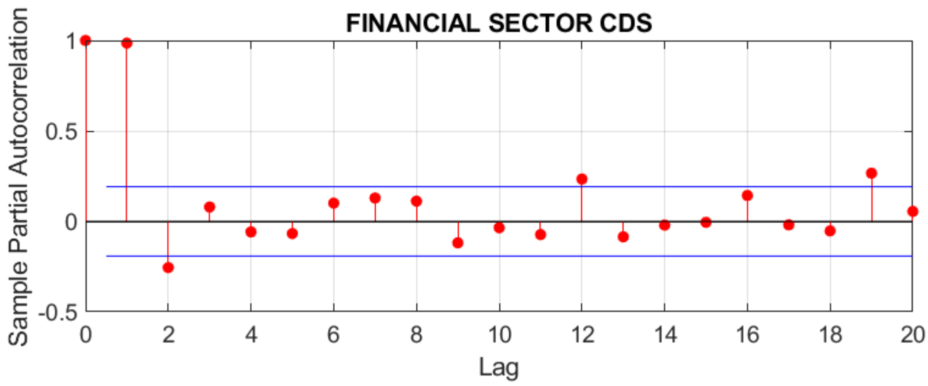



*Figure 11.4: Financial sector CDS Partial Autocorrelation function*

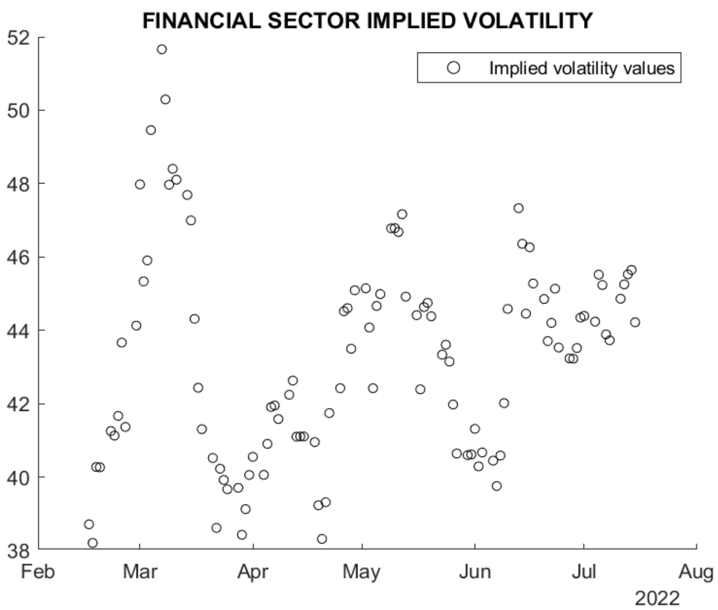



*Figure 12.1: Financial sector Implied Volatility values*

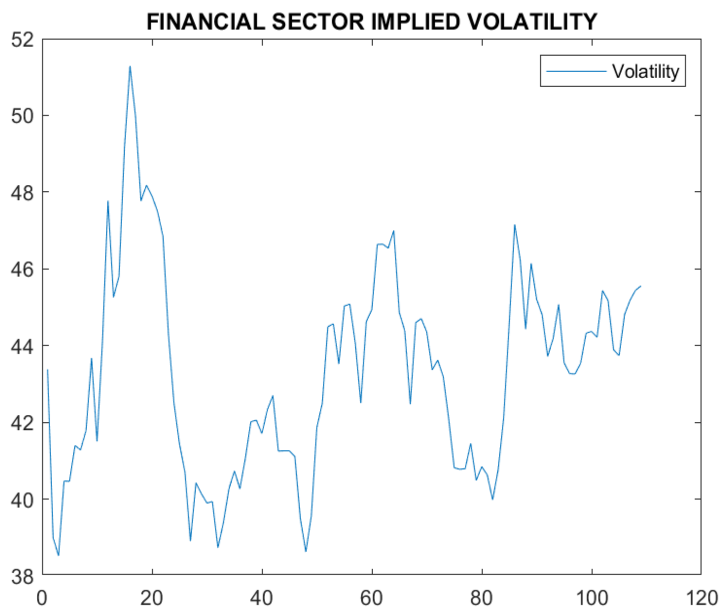



*Figure 12.2: Volatility of Financial sector Implied Volatility*

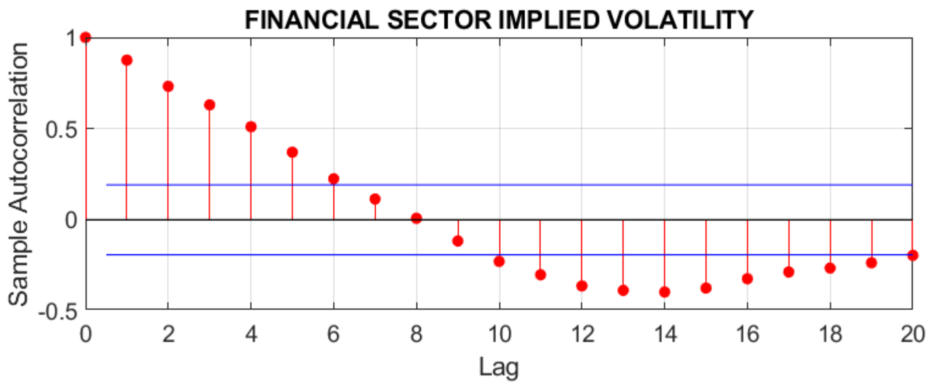



*Figure 12.3: Financial sector Implied Volatility Autocorrelation function*

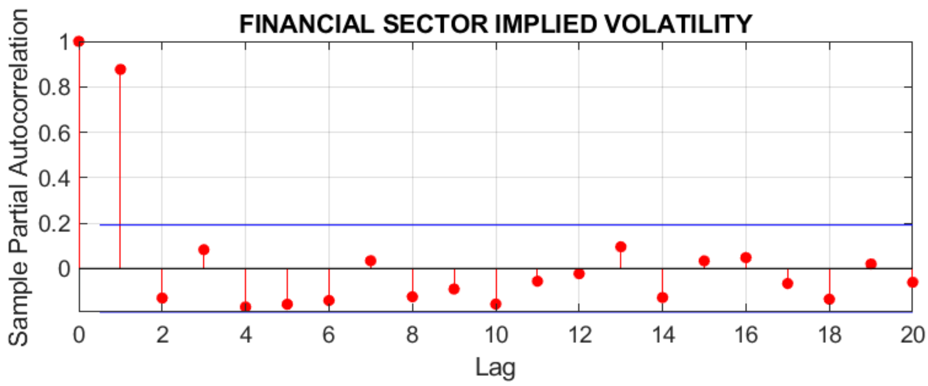



*Figure 12.4: Financial sector Implied Volatility Partial Autocorrelation function*

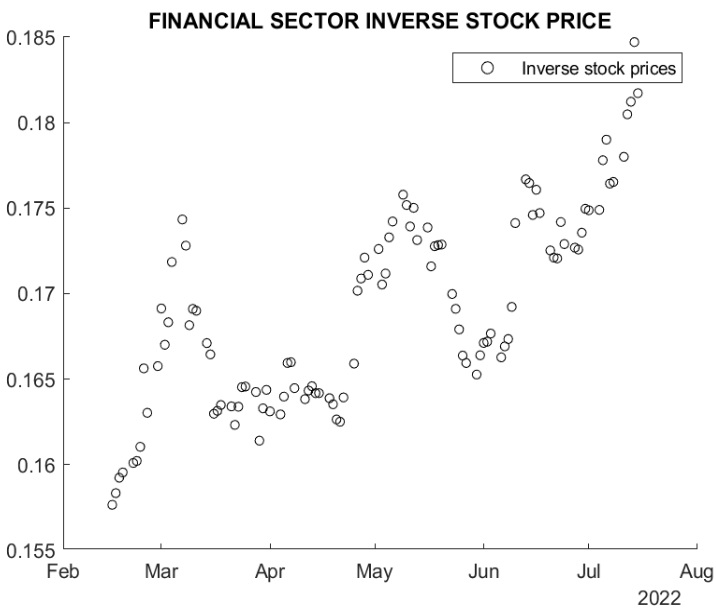



*Figure 13.1: Financial sector Inverse Stock prices*

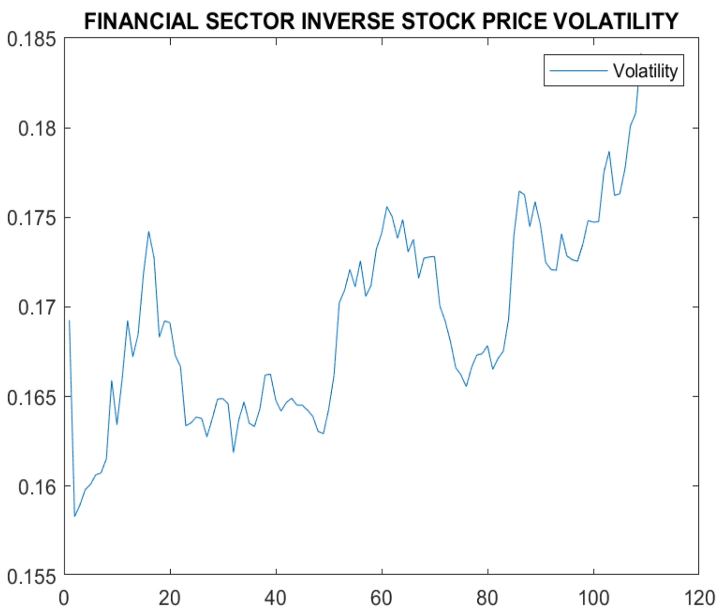



*Figure 13.2: Volatility of Financial sector Inverse Stock Price*

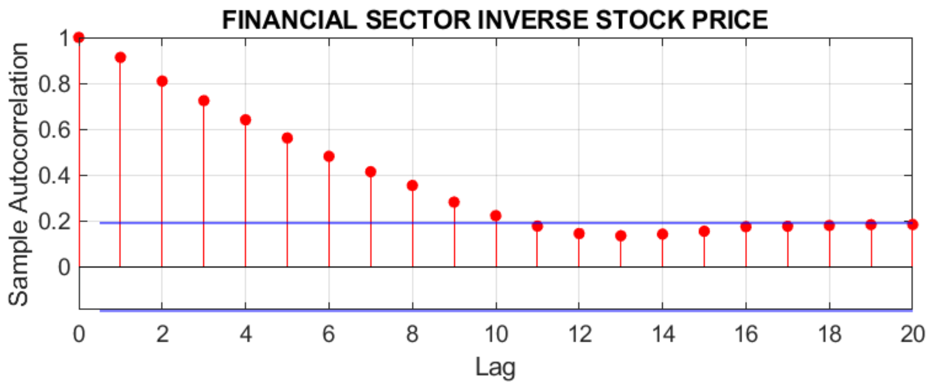



*Figure 13.3: Financial sector Inverse Stock Price Autocorrelation function*

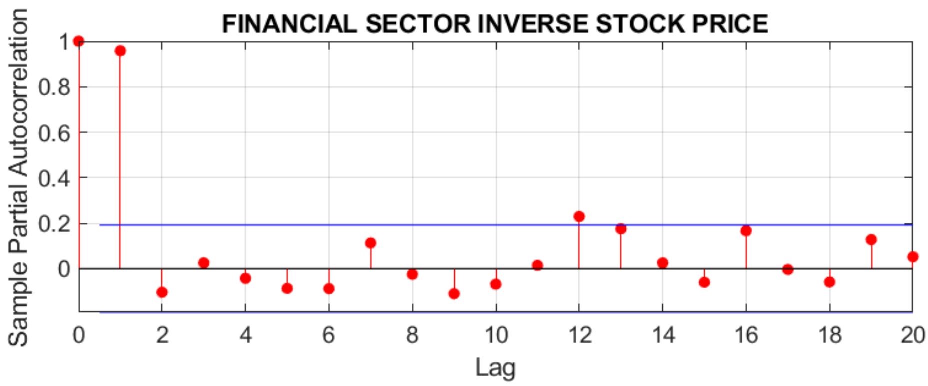



*Figure 13.4: Financial sector Inverse Stock Price Partial Autocorrelation function*

The financial sector during the Russian invasion of Ukraine saw a great deal of instability, especially in the months following the outbreak of war, with volatility increasing and market uncertainty becoming more and more rampant.

The Credit Default Swap, in the months analysed, saw a great increase in its values, especially in the latter part of the period analysed.

As can be seen from Figure 11.1, the CDS had a small fluctuation at the start of the war, which led to an increase in values, but these fell shortly afterwards, underlining the fact that the market did not expect a great impact from this event.

It can be seen, however, that from April onwards values rose steadily until the end of the months analysed, which shows how the market was mistaken about the effects this crisis could bring and how it suffered.

Volatility, as can be seen in Figure 11.2, has an initial shock, which, however, does not affect the values too much, since almost immediately it returns to being low, only later can be seen a trend that brings it to being high and persistent throughout the second part of the period analysed.

This shows the great uncertainty that existed in the markets, due to the not very reassuring news about the war and the world mechanics that it had triggered, leading to serious shortages of raw materials and consequently losses for many companies.

The autocorrelation function, as can be seen in Figure 11.3, shows a positive trend that highlights a strong and serial dependence between the values of the financial sector CDS.

This trend, which underlines a significant correlation with a very slow decay as lags increase, is often linked to moments of high and long-lasting volatility of the variable being analysed, a prediction that turns out to be correct if one observes Figure 11.2 on volatility itself.

The partial autocorrelation function has few significant lags, as can be seen in Figure 11.4, indicating that the CDS values, net of its intermediates, have a low and weak correlation with each other.

As far as the Implied Volatility of the financial sector is concerned, it can be seen in Figure 12.1, how, unlike the CDS, it suffered a shock as early as the outbreak of war, which led to a sudden increase, not very long-lasting, since by the end of March the values had already returned to the same levels as before the event.

This phase was short-lived, because as early as April there was another rise, which was also to be seen in the following months, with peaks of decline that were immediately cancelled out by a further shock and subsequent rise soon afterwards.

Volatility, as can be seen in Figure 12.2, as well as returns, has an initial large shock that causes its values to increase disproportionately, but then subsequently decreases, for only a few lags however, since it then registers shocks, with several large fluctuations, which cause it to remain high throughout the period analysed.

Volatility therefore has an irregular trend, with many fluctuations that highlight an uncertain market with few certainties to rely on.

In Figure 12.3, it can be observed the autocorrelation function, which is significant in the first lags, but decays quickly, and then from the tenth lag onwards gives way to a very consistent negative trend.

The first lags show a strong correlation between the values of the implied volatility in the financial sector, while the second half of the figure on the ACF, with this negative trend, emphasises a high probability that positive returns are followed by negative returns, which is demonstrated by Figure 12.1, where one can see large price fluctuations, much inconstancy and results that are not at all homogeneous, as proof of the correct reading of the ACF.

The partial autocorrelation function, as can be seen in Figure 12.4, once the first two lags have been removed, has the remainder within the 5% interval, and therefore considered irrelevant and equal to zero, from which it can therefore be noticed that there is no correlation between the values of implied volatility in the financial sector.

The inverse stock price of the financial sector developed very erratically during the Russian invasion of Ukraine.

During the period analysed, as can be seen in Figure 13.1, there were many ups and downs, but the values rose steadily, thus underlining how the companies in this sector saw their stocks deteriorate more and more due to the war.

The volatility of this variable, as can be seen in Figure 13.2, had various shocks and fluctuations, but it can be seen that there was an upward trend, which caused it to be more persistent and its values to become increasingly higher as the lags passed.

The autocorrelation function had a positive trend that decayed very slowly, because even though, as can be seen in Figure 13.3, after the tenth lags the values dropped a lot, they still remained significant and made a difference in the inference of the correlation between the values of the inverse stock price of the financial sector.

A strong dependence between these values over the period analysed can thus be defined, showing how the results were worse as time passed.

The partial autocorrelation function has negligible values, as can be seen in Figure 13.4, underlining how weak the correlation is between the inverse stock price values.

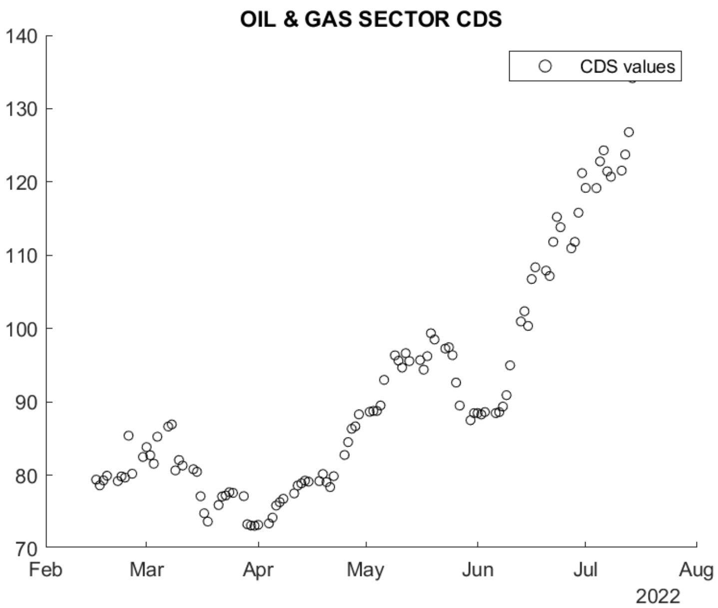



*Figure 14.1: Oil & Gas sector CDS values*

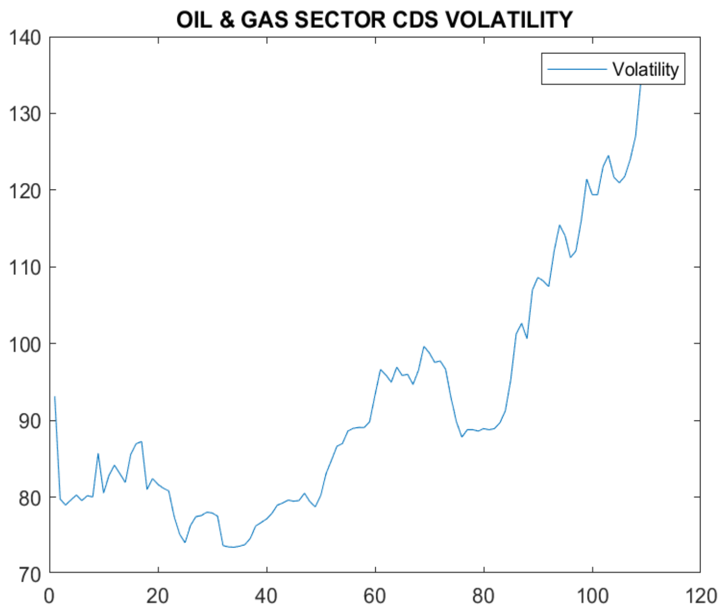



*Figure 14.2: Volatility of Oil & Gas sector CDS*

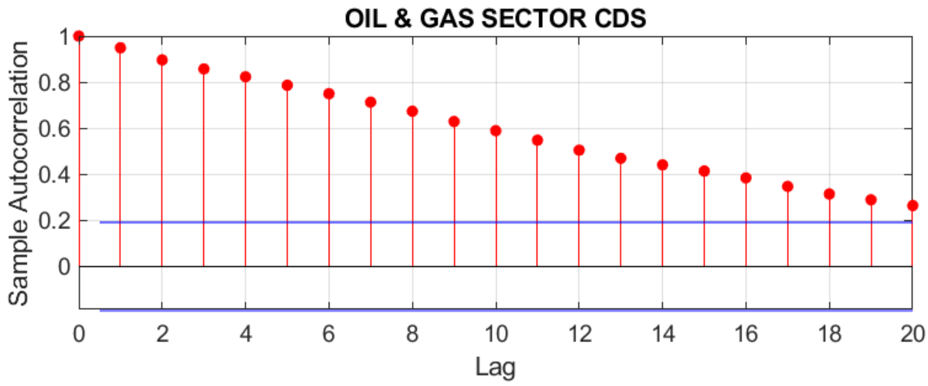



*Figure 14.3: Oil & Gas sector CDS Autocorrelation function*

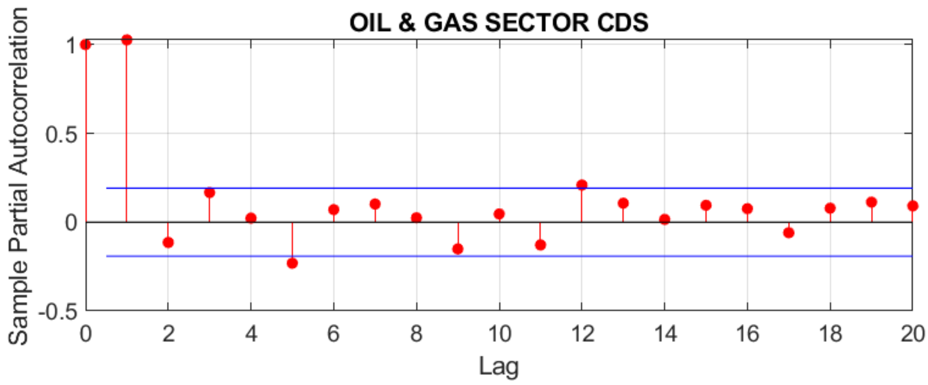



*Figure 14.4: Oil & Gas sector CDS Partial Autocorrelation function*

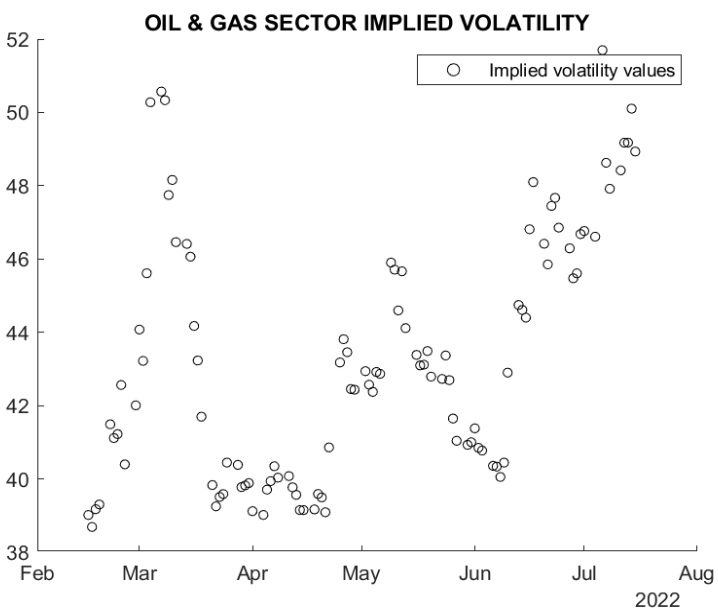



*Figure 15.1: Oil & Gas sector Implied Volatility values*

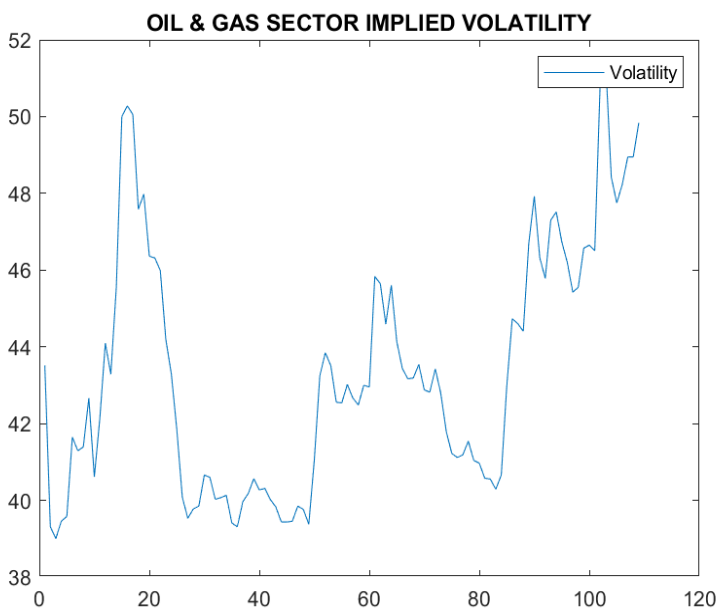



*Figure 15.2: Volatility of Oil & Gas sector Implied Volatility*

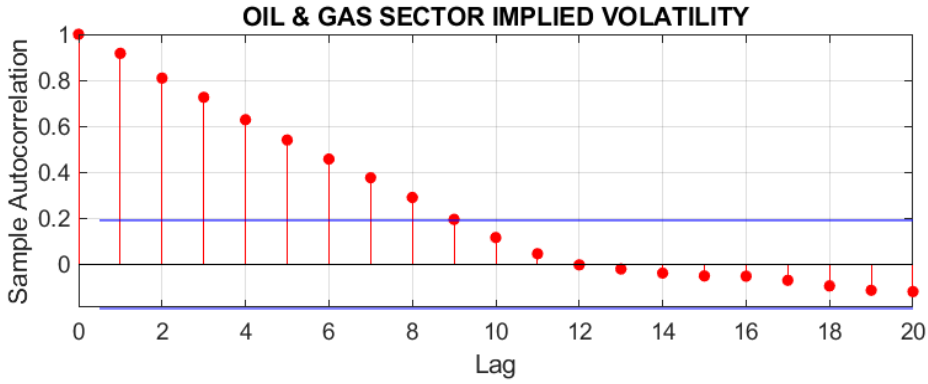



*Figure 15.3: Oil & Gas sector Implied Volatility Autocorrelation function*

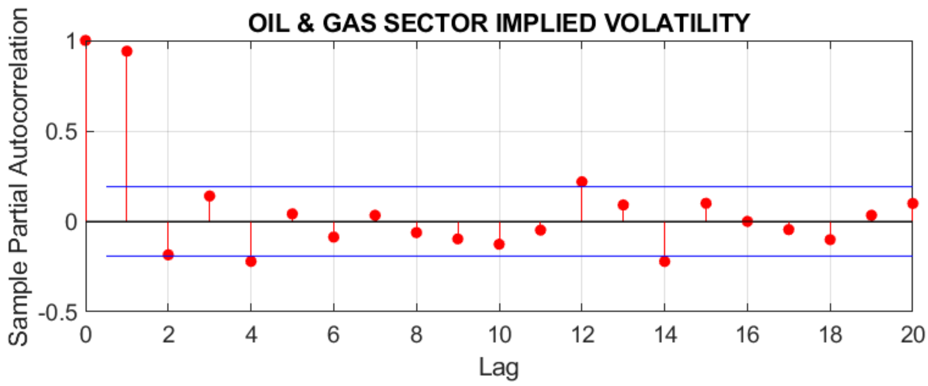



*Figure 15.4: Oil & Gas sector Implied Volatility Partial Autocorrelation function*

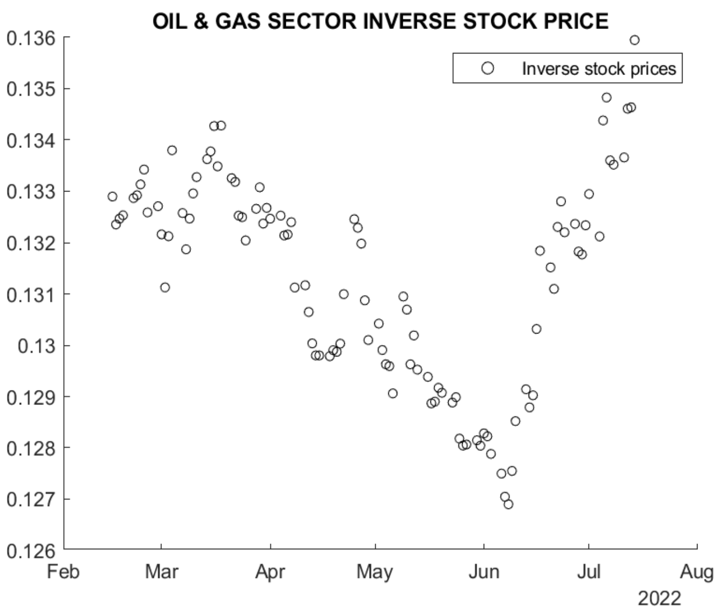



*Figure 16.1: Oil & Gas sector Inverse Stock prices*

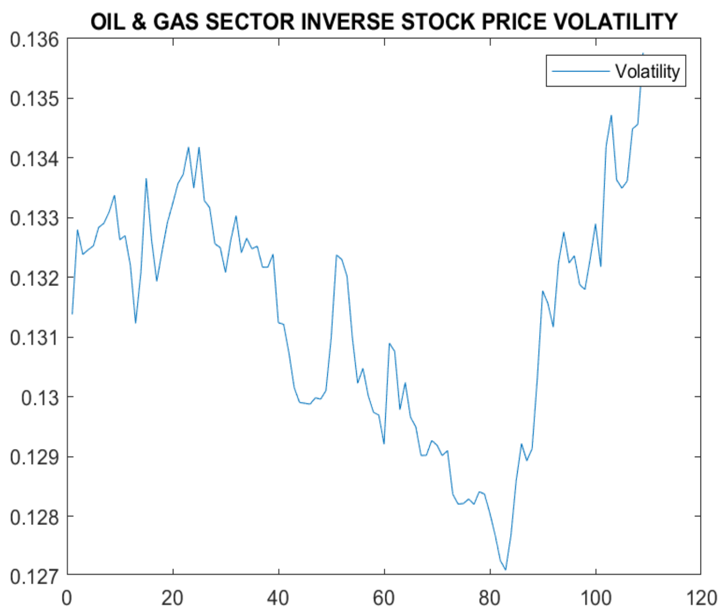



*Figure 16.2: Volatility of Oil & Gas sector Inverse Stock Price*

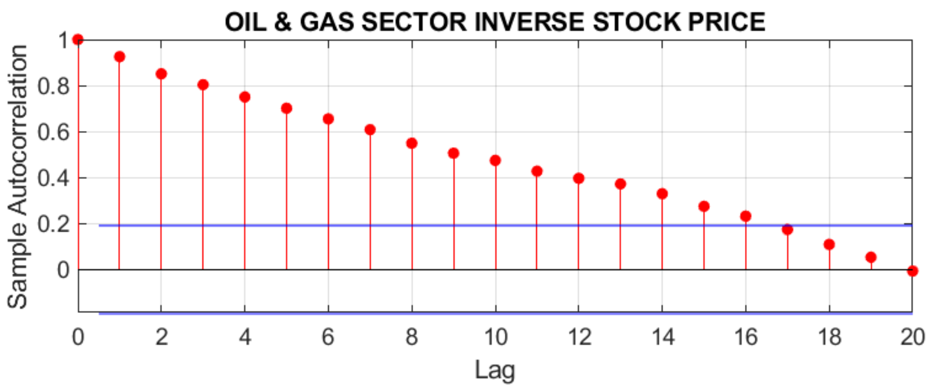



*Figure 16.3: Oil & Gas sector Inverse Stock Price Autocorrelation function*

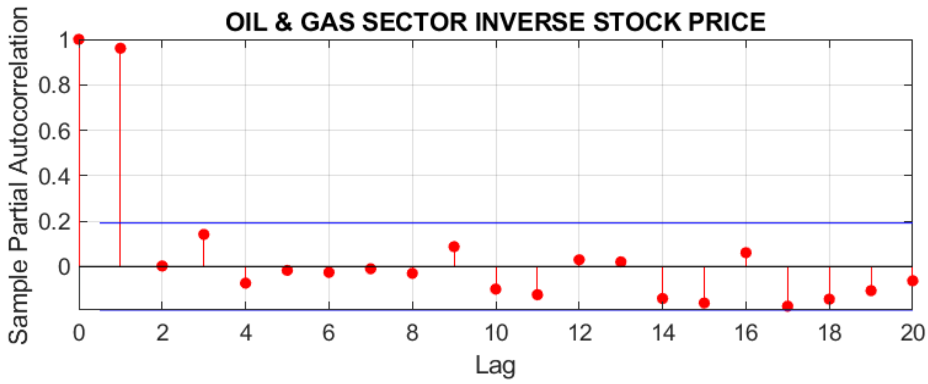



*Figure 16.4: Oil & Gas sector Inverse Stock Price Partial Autocorrelation function*

The Oil & Gas sector during the Russian invasion of Ukraine, experienced large losses in both raw materials and capital, as countries such as Russia and Ukraine are among the largest gas producers in the world and their lack created significant difficulties for all companies involved in this sector.

As far as the Oil & Gas CDS is concerned, it can be seen from Figure 14.1 how, at the beginning of the war, the market was not affected, with values even falling in the April period.

It can always be observed, however, that since May there has been a relentless increase in values, probably due to Russian sanctions and the end of Ukrainian production, which has led values to rise more and more, reaching highs in the latter part of the period under analysis.

CDS volatility fluctuated slightly, but remained low in the first 50 lags observed, as can be seen in Figure 14.2.

On the other hand, the behaviour was different in the following lags, where we can observe the emergence of a high and persistent volatility, with an ever-increasing growth that led it to peak in the last lags analysed.

The autocorrelation function, as observed in Figure 14.3, remained significantly high throughout the period analysed, showing a strong correlation between CDS values.

This type of positive trend, with a very slow decay, is often linked to periods of high volatility that remains persistent even in subsequent phases, a phenomenon that is confirmed when looking at Figure 14.2 on CDS volatility.

The partial autocorrelation function has only a few significant lags, as can be observed in figure 14.4, as most fall within the 5% range and can therefore be considered equal to 0.

It can therefore be observed from the PACF that the correlation is weak and negligible over the period under analysis.

The implied volatility of the oil & gas sector, unlike the CDS, has been impacted since the beginning of the war, with a first big shock which saw a sudden increase in values, but which was not lasting, because, as can be seen in Figure 15.1, the values went back down again at the beginning of April.

In May there was another shock that saw values rise again and after a swing in June that caused them to fall only momentarily, they returned to high levels throughout the last period analysed, thus underlining how the prolonged war and the restrictions on Russian production had a considerable impact on the market.

Figure 15.2 shows the trend in volatility, which experienced an initial big shock that saw it rise sharply, then return to lower values after a short time.

The fluctuations became more intense from the fiftieth lag onwards, where oscillations can be seen that made the volatility increasingly high and persistent, especially in the last lags analysed, reflecting the great uncertainty that the market was experiencing.

The autocorrelation function recorded a positive trend which, however, decayed quickly, as can be seen in Figure 15.3, in fact, already at the tenth lag the values fell within the 5% interval and were therefore considered not relevant for the purposes of measuring correlation.

From the first nine lags, it can be noticed that there is a strong and significant correlation between the values of the implied volatility, which, however, becomes weaker in subsequent periods.

The partial autocorrelation function for implied volatility, as it was for CDS, has few significant lags, as can be seen in Figure 15.4, thus underlining a correlation that exists between the values, but which is weak and not very significant.

The inverse stock price of the oil & gas sector has been very erratic throughout the months under analysis.

As can be seen in Figure 16.1, in the first few months there are various fluctuations in the values, but these do not make it rise or fall by much compared to the beginning, only in May a significant decrease is noted, which reaches a minimum in June, and then from there undergoes a significant shock that causes it to rise until it touches the maximum peaks of the period analysed, with high values that highlight the deterioration of the shares of the companies that make up this sector.

Volatility had a similar trend to that of share prices, as can be seen in Figure 16.2, where we note many fluctuations in the first 60 lags, leading volatility to be high but relatively inconstant in its returns.

Between the sixtieth and the ninetieth lag there is a sharp decrease in volatility values, bringing it to be as low as it had ever been in the entire period analysed, but this moment is short-lived, because from that point onwards, there is a shock that makes the values suddenly increase, bringing volatility to be high and persistent for all the remaining lags, this is probably caused by the prolongation of the war and the lack of raw materials that are no longer received by companies and therefore lead them to suffer on the stock market.

In Figure 16.3, the autocorrelation function of the inverse stock price can be seen, where a significant positive trend is observed, which slowly decays.

This trend underlines a strong correlation, which explains the serial dependence between the values, which lasts throughout the period under analysis.

This graph is often associated with periods of persistent volatility that lasts for several phases, a phenomenon that can be confirmed by Figure 16.2, thus highlighting the rightness of the ACF analysis.

There are only two significant lags in the partial autocorrelation function, while all the others can be considered irrelevant, as can be seen in Figure 16.4.

This irrelevance therefore leads to the inference that there is a weak and not particularly relevant correlation between the inverse stock price values of the oil & gas sector, net of their intermediates.

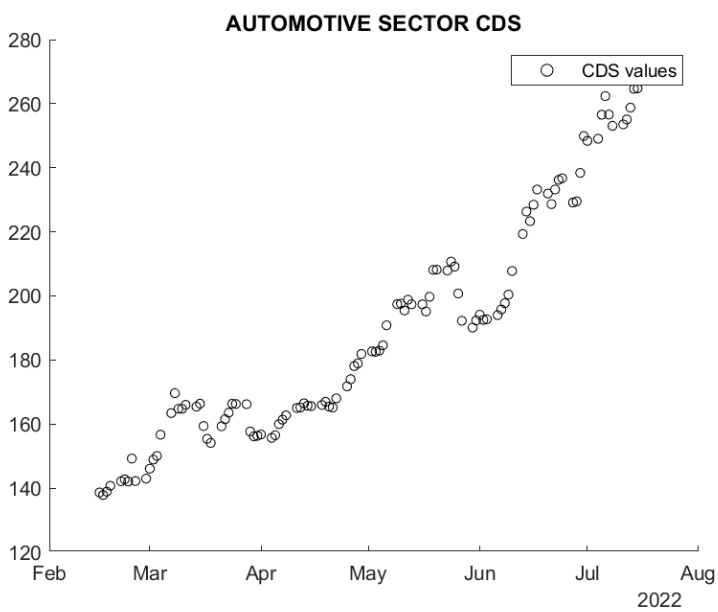



*Figure 17.1: Automotive sector CDS values*

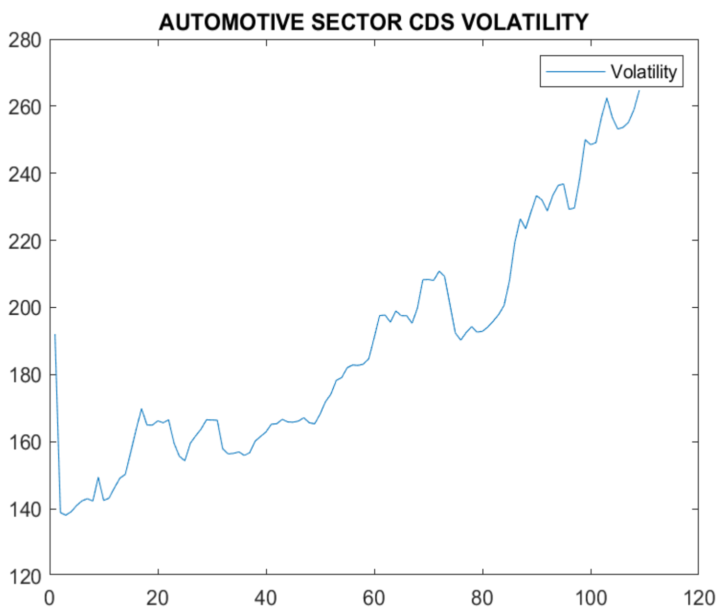



*Figure 17.2: Volatility of Automotive sector CDS*

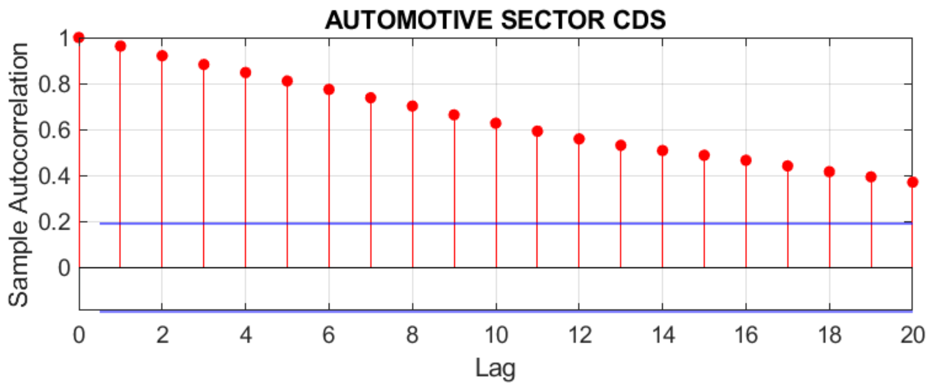



*Figure 17.3: Automotive sector CDS Autocorrelation function*

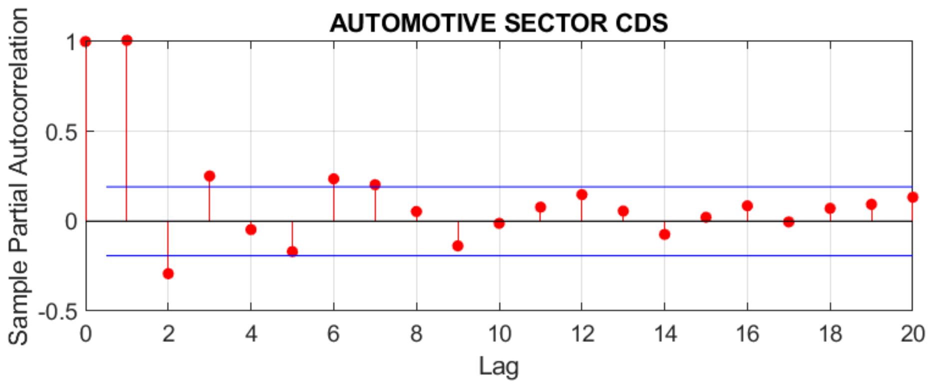



*Figure 17.4: Automotive sector CDS Partial Autocorrelation function*

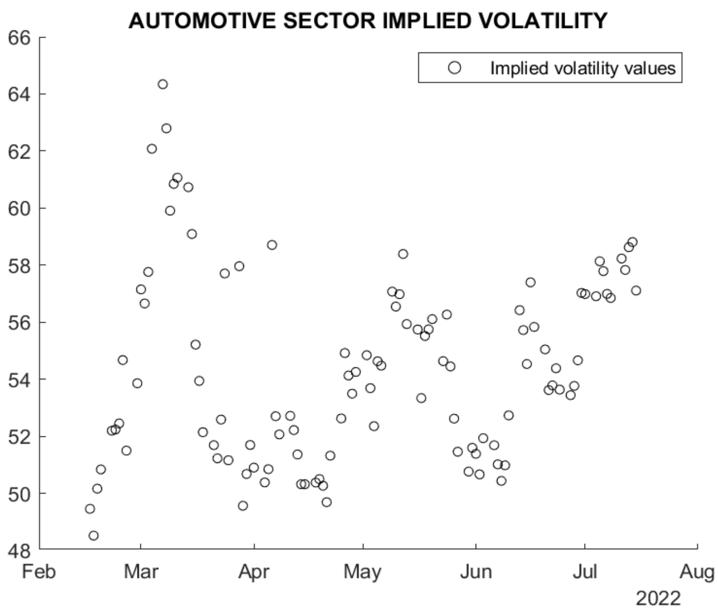



*Figure 18.1: Automotive sector Implied Volatility values*

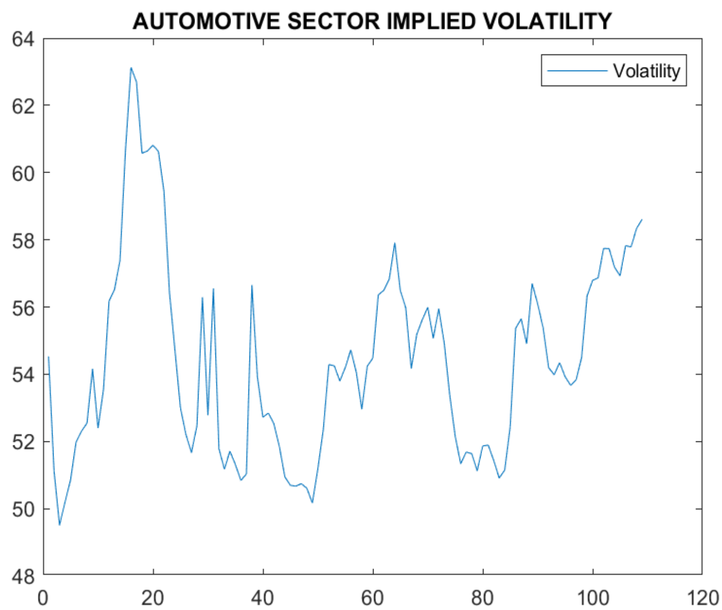



*Figure 18.2: Volatility of Automotive sector Implied Volatility*

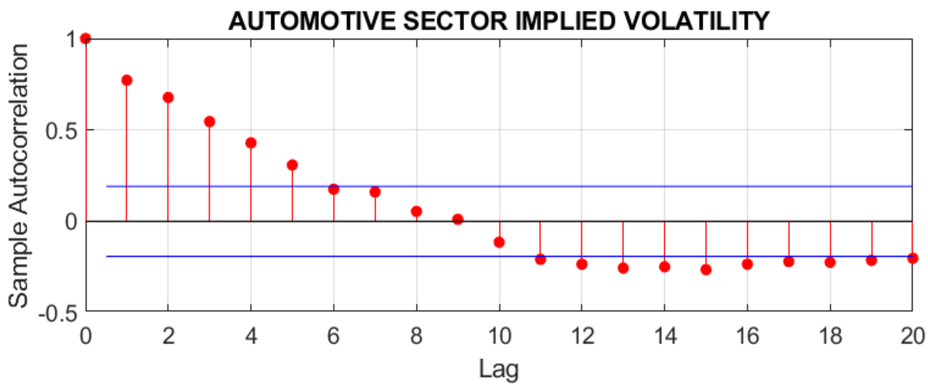



*Figure 18.3: Automotive sector Implied Volatility Autocorrelation function*

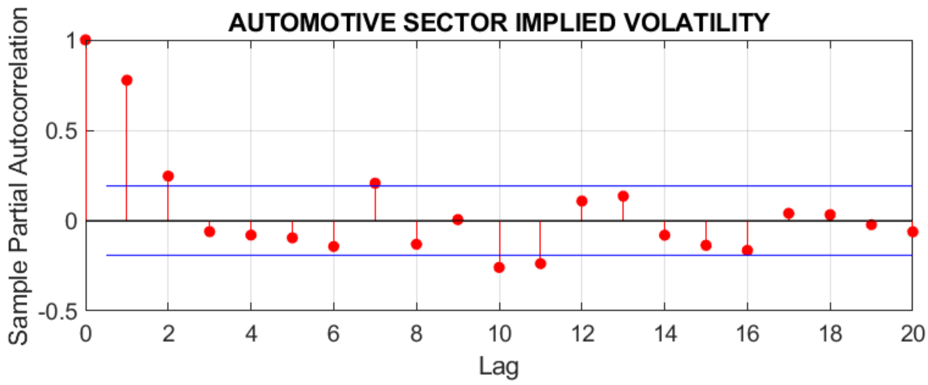



*Figure 18.4: Automotive sector Implied Volatility Partial Autocorrelation function*

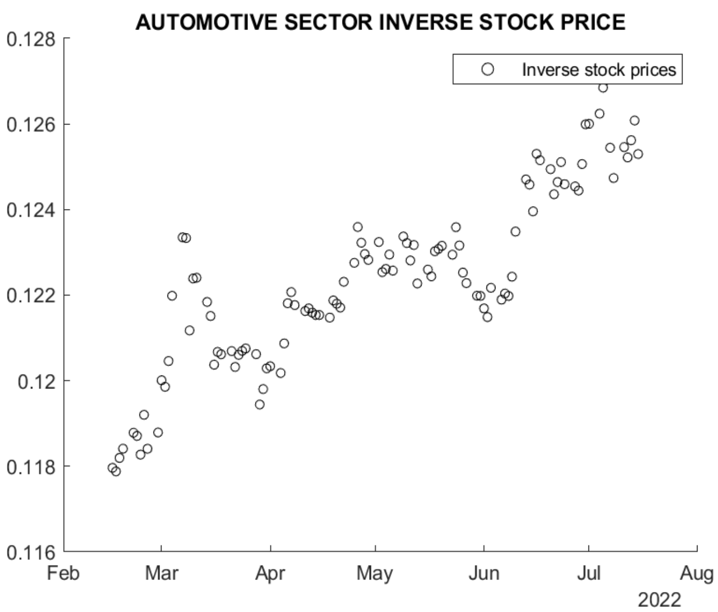



*Figure 19.1: Automotive sector Inverse Stock prices*

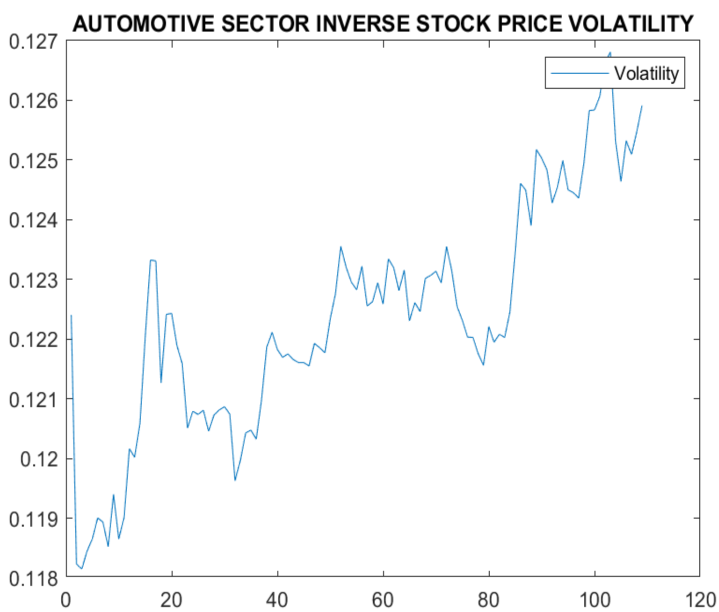



*Figure 19.2: Volatility of Automotive sector Inverse Stock Price*

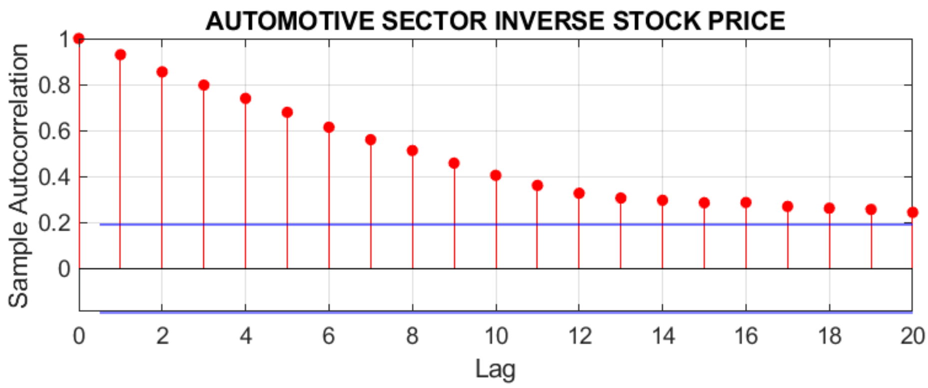



*Figure 19.3: Automotive sector Inverse Stock Price Autocorrelation function*

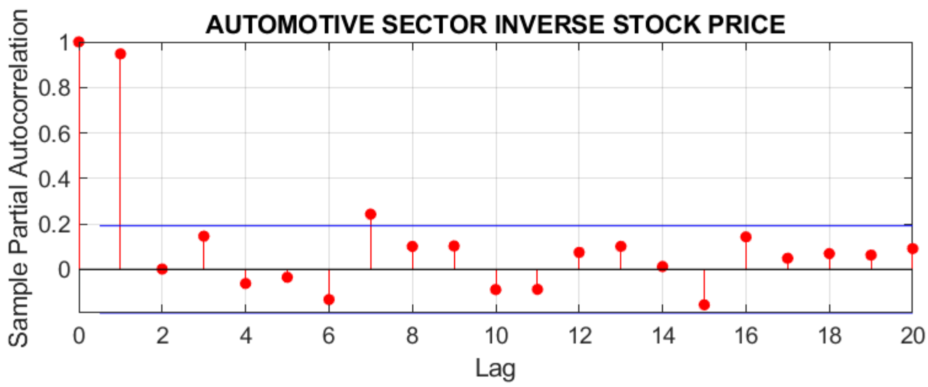



*Figure 19.4: Automotive sector Inverse Stock Price Partial Autocorrelation function*

The automotive sector during the Russian invasion of Ukraine saw significant instability and increasing volatility, as can be seen from the results of the three variables that were analysed.

As far as the Credit Default Swap is concerned, as can be seen in Figure 17.1, the values increased more and more as the months passed, underlining a situation that was worsening as time went on and the war became progressively more destructive, leading to shortages of raw materials that no longer allowed regular production for the companies that made up this sector, with the probability of default therefore becoming increasingly imminent.

Volatility, as can be seen in Figure 17.2, sees an upward trend, with rising values as the lags pass, and thus an increasingly high and persistent volatility.

The volatility trend is always erratic, with many fluctuations, more or less small, leading it to grow as the lags pass, thus highlighting an uncertainty that was in the market and which is becoming more and more rampant as time goes by.

In Figure 17.3, it can be seen that the autocorrelation function registers a significant positive trend in all the lags analysed.

This trend underlines the fact that there is a strong correlation between the CDS values, with a serial dependence between them, which means that a high return is very likely to be followed by another high return.

This type of ACF is often linked to periods of high volatility, which remains persistent for several phases, in fact Figure 17.2 confirms this prediction.

The partial autocorrelation function has few significant lags, as can be seen in Figure 17.4, but these are useful to indicate that there is a correlation between the CDS values net of their intermediates, albeit weak and not too significant.

The implied volatility of the automotive sector had a very irregular and inconstant trend during the period analysed, as can be seen in Figure 18.1.

Its trend over time saw many fluctuations, more or less severe, which always kept it at relatively high levels compared to the period before the outbreak of war.

In fact, it can be seen that during the month of March there is a first large and sudden increase in values, with a subsequent very fast decrease, which has seen the values of implied volatility fluctuate numerous times throughout the time span analysed.

Figure 18.2 shows the volatility of the implied volatility, which registers a large shock at the beginning of the invasion, which causes the volatility values to increase dramatically, subsequently decreasing, but continuing to have more or less intense oscillations throughout the subsequent periods, with volatility becoming more and more persistent as the lags pass.

The autocorrelation function has a brief positive trend in its first few lags that decays very quickly, as can be seen in Figure 18.3, which then gives way from lag eleven onwards to a negative trend that denotes itself until the end of the period under analysis.

This first positive trend can be associated with a significant positive correlation between the values, but it does not last very long, as it soon decays, while from the negative trend in the second half of the lags one can deduce a considerable inconstancy in the results and a high probability that a positive return was followed by a negative one and vice versa, which is true if one observes figure 18.1, where the last section of the returns is very irregular and discontinuous.

The partial autocorrelation function, that can be seen in figure 18.4, has relevant values that can therefore define a correlation between the values, although not very significant, as most lags are in the 5% range, so they can be considered negligible for measuring correlation.

The inverse stock price of the automotive sector went up as the months passed and the war intensified.

As can be seen from Figure 19.1, there has been an upward trend, with many fluctuations and an irregular pattern, but always directed towards a rise in the values of the inverse stock price, bringing it to its highest points in the summer months.

This deterioration underlines how the market saw increasingly severe conditions for the companies in the automotive sector, as they could no longer maintain their production standards.

The volatility of the inverse stock price recorded an initial shock, which saw the values rise sharply, followed by a slight decrease that was only momentary, since from the fortieth lag onwards, as can be seen in Figure 19.2, the volatility became increasingly persistent with values that were each time higher than those of the previous lags, which were confirmed despite the very irregular and fluctuating trend, but which shows a growing trend over time, with peaks of maximum volatility in the last lags analysed.

In Figure 19.3 it can be observed the autocorrelation function, which had a positive trend and all very significant lags, with a decay that in the final part of the period analysed was truly minimal.

This trend in the ACF highlights a strong and notable correlation between the values of the inverse stock price, with this pattern often found in moments of high volatility, as can be seen in Figure 19.2, in fact it is associated with a moment in the market that is very inconsistent and full of uncertainty, as it was during the Ukrainian invasion.

The partial autocorrelation function, as can be seen in Figure 19.4, has few not very significant lags that can contribute to a definition of the correlation of the inverse stock price, as most are in the 5% range and can therefore be considered negligible for the purpose of measuring correlation.

It can therefore be detected that the correlation between the inverse stock price values, net of its intermediate values, is weak and not really relevant with a very low dependence.

The overall CDS for all three sectors behaved very similarly, with values that were not greatly affected by the start of the clash, in fact there was only a slight and momentary fluctuation, with a return to normal in April.

However, it was in May that the real impact of the war made itself felt on the markets and on companies, as demonstrated by the rise in CDS values, with increasingly frequent fluctuations that steered the trend of this financial instrument towards an inexorable increase, leading them to touch the period's highs right at the end of the analysis, thus underlining how the lack of raw materials from Russia and Ukraine's inability to produce and export seriously affected all the companies that were analysed and exposed them to the risk of insolvency.

The volatility of the CDS was not greatly affected by the outbreak of war, in fact in all three sectors, the news of the invasion created a shock, but this was contained and only caused values to rise for a very short period.

It is only from around the 40th and 50th lag onwards that the true effect of the war on volatility can be seen, since from this lag onwards in all three sectors an ever greater increase was recorded, which led volatility to be higher and more persistent every day, with a rather irregular trend, but which nonetheless led the values to be the highest recorded in the final part of the study for all three sectors taken into consideration.

The autocorrelation function showed a strong and significant correlation between the CDS values in all three sectors analysed.

In fact, a significant positive trend with a slow decay was always observed, thus underlining how all the returns of this indicator are dependent on each other and that a positive return is very likely to be followed by another positive return and vice versa.

This trend is also associated with periods of high volatility for the sectors that are studied, a prediction that is confirmed by the special study carried out on the latter, which proves its persistence for most of the phases under analysis.

The partial autocorrelation function, on the other hand, recorded irrelevant values in all three sectors analysed, thus highlighting how the correlation between CDS values net of their intermediates is low and therefore negligible.

It can therefore be observed that the Credit Default Swap was traded more actively in the market when the invasion was already well underway, as an increasingly dangerous situation was emerging worldwide from a geopolitical point of view, i.e. this armed assault by Russia created friction between many nations, which consequently also created problems for individual companies.

In addition, both Russia and Ukraine are major producers and exporters of raw materials, and the cessation of these supplying to companies created major production problems and thus increased the likelihood of default by the corporations themselves, thus leading the market to trade this financial instrument more and more linked to the risk of default by businesses throughout the war period.

Implied volatility, unlike CDS, suffered a more pronounced shock at the beginning of the Russian invasion, with a sudden increase in all three sectors analysed.

This increase was momentary, however, as the situation in the markets calmed down in April, causing the values to fall, but from May onwards, given the less than reassuring news and the shortcomings that companies were suffering, the values started to rise again and to be higher month after month, reaching highs in the last phase of the period analysed, reflecting the increasing uncertainty in the markets.

Implied volatility has been very erratic throughout the analysed period, with several shocks keeping it high and persistent, especially in the last lags.

All the fluctuations and the very erratic trend in volatility are a factor in how the insecurities caused by the implied volatility are inherent in the market and in companies, thus provoking many doubts about the future and the survival of businesses.

The autocorrelation function of the implied volatility for all analysed sectors shows a strong positive trend that decays quickly, thus underlining a significant but not too long-lasting correlation between the values of the implied volatility itself.

In contrast to the Oil & Gas sector, both the financial and automotive sectors have the latest lags with a significant negative trend, highlighting how the returns in the second half of the period under analysis are erratic, with positive results followed by negative results and viceversa, thus creating different up and downs in the market that once again highlight the uncertainty brought about by the war.

The partial autocorrelation function of implied volatility shows few significant lags, with most being in the 5% range and thus can be considered negligible, thus defining a weak and negligible correlation between the values.

Implied volatility therefore shows higher values in the second part of the period analysed because it was only in those months that the market really realised the impact of the Russian invasion and consequently perceived an increase in risk, thus translating into higher than normal values due to the less than reassuring news flows and the global political insecurity that was taking shape.

The inverse stock price was very erratic and inconstant throughout the analysed period, with various fluctuations characterising its very fluctuating trend.

However, one can define how there is an ever-increasing trend over time that led the values to be elevated as the months passed, until they reached their maximum peaks in the last phase of the analysed period.

The worsening of the situation coincided perfectly with the news of the Russian invasion, which day by day became increasingly less good, and the various European sanctions did not help companies to take in the already scarce raw materials, placing them in an ever more difficult condition and at risk of collapse.

The volatility of the inverse stock price experienced several shocks during the various lags, which significantly influenced its trend, leading it to be increasingly high and especially persistent as time went by.

All the fluctuations that are present over the months show a great deal of uncertainty in the situation, especially for the companies, which had to endure the political decisions that the invasion had unleashed, as they had no right to counterattack or find alternative ways of receiving the materials they needed.

The autocorrelation function shows a strong positive trend in all three sectors analysed, from which it can therefore be noticed that there is a significant correlation between the values of the inverse stock price, with a serial dependency between them.

All three sectors show a very similar path, which is associated with periods of persistent volatility over several phases, which can be confirmed by the observations of the various volatility graphs of the sectors, thus reinforcing the trend position of the ACF.

The partial autocorrelation function, on the other hand, shows only a few relevant lags that can make a difference when measuring the correlation between values.

Having said this, one can therefore see a weak, almost negligible correlation of the inverse stock price net of its intermediates.

The inverse stock price was probably the variable most affected by the Russian invasion of the three studied, with values remaining high throughout the analysed period and largely influenced by the unstable geopolitical situation and the general scepticism in the market.

All three variables were very useful during the analysis of the Russian invasion of Ukraine, because they all underlined important factors, such as the CDS showed how the risks of a probable default were shaping up during the months analysed, the implied volatility showed the various expectations of investors and what their responses were to the different news coming from around the world, while the inverse stock price, managed to convey the various influences from the different economic elements it was subjected to as best it could.

Among the financial sectors, there was not as much difference as there had been during COVID-19, this was probably due to the more unexpected course of events and the political divisions that have been emerging and impacting the market significantly.

Indeed, the disruption of international trade, whether due to diplomatic reasons, as in the case of Europe with Russia, or for reasons purely related to the war, many Ukrainian factories were destroyed, negatively impacted the normal functionality of the markets, which suffered as they were unable to find alternative ways to make up for these shortcomings.

In addition, there has been volatility in commodities and a flight of capital that has unexpectedly affected any sector, leaving it in dire straits and exposing it to default risks.

Thus, there was no leading or lagging sector among the three taken into analysis, precisely because all three were caught by the news in the same way, thus failing to make predictions, given the great uncertainty both political and financial that was rampant in the world.

# 4. Results

After analysing the three variables that make up the Perceived Risk Index© during the two crisis events, this chapter analyses the results of the Perceived Risk Index© itself and comments on them and how the outcomes varied for the three different sectors and how they behaved during times of stress.

These were the results during the COVID-19 pandemic:

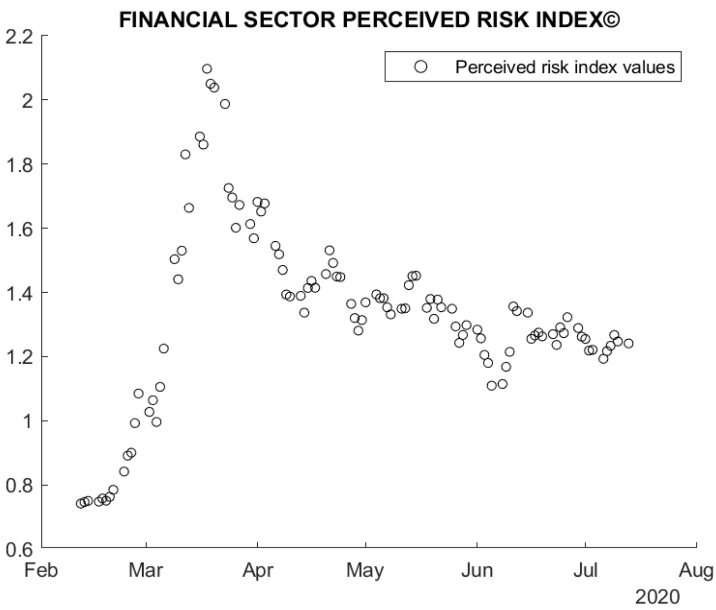



*Figure 20.1: Financial sector Perceived Risk Index© values*

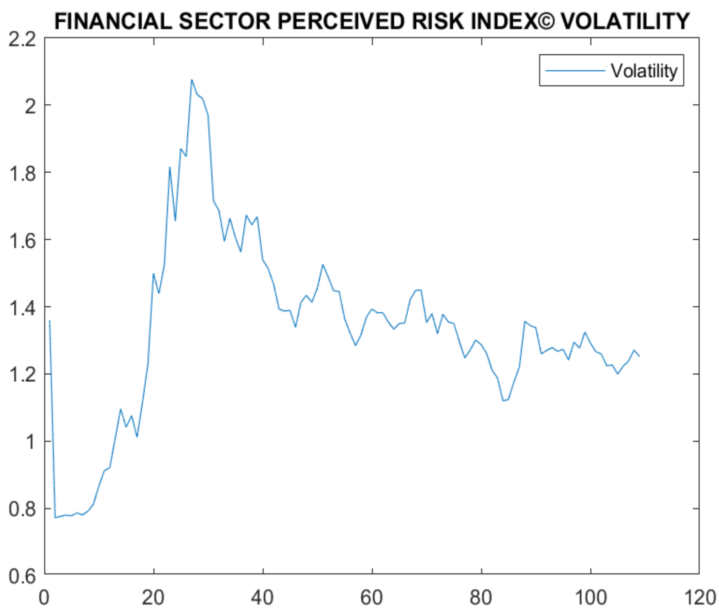



*Figure 20.2: Volatility of Financial sector Perceived Risk Index©*

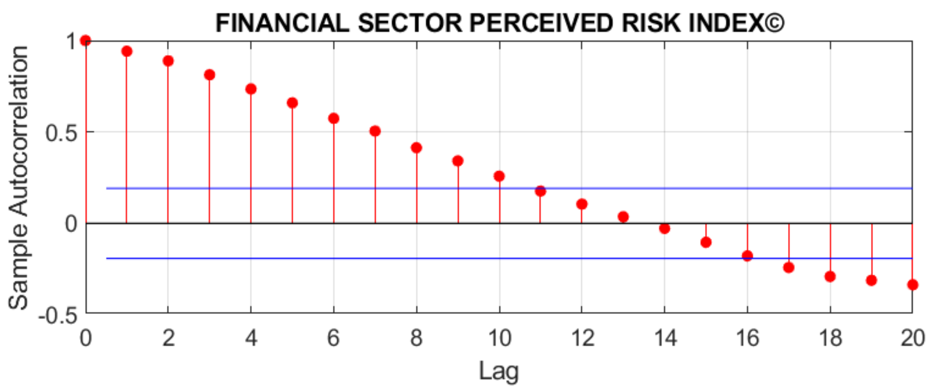



*Figure 20.3: Financial sector Perceived Risk Index© Autocorrelation function*

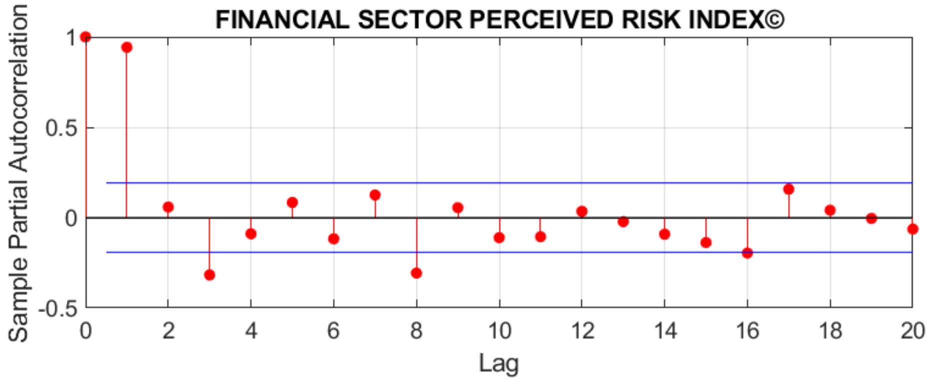



*Figure 20.4: Financial sector Perceived Risk Index© Partial Autocorrelation function*

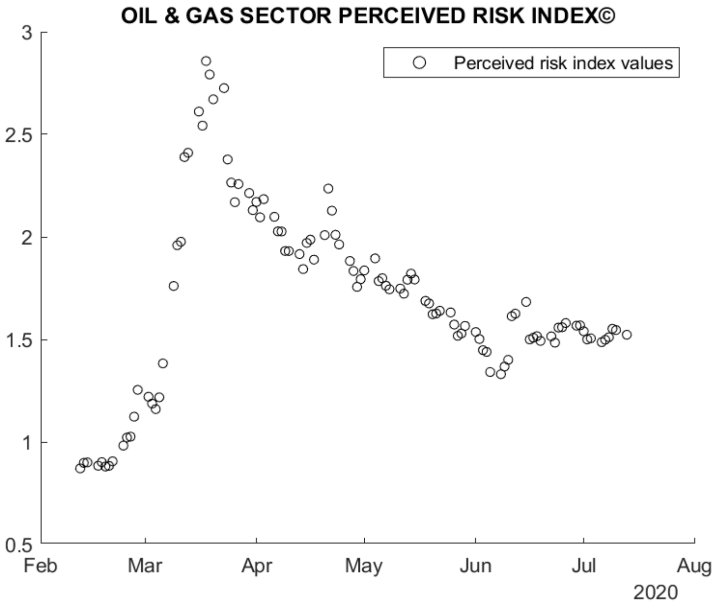



*Figure 21.1: Oil & Gas sector Perceived Risk Index© values*

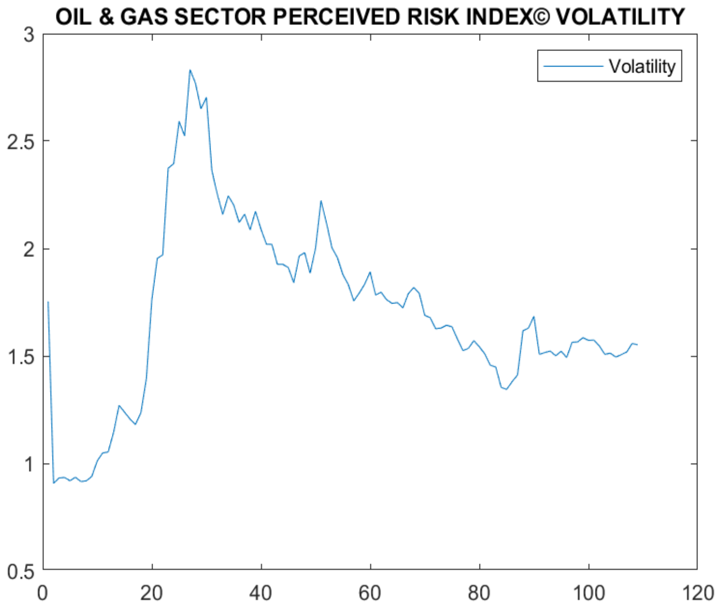



*Figure 21.2: Volatility of Oil & Gas sector Perceived Risk Index©*

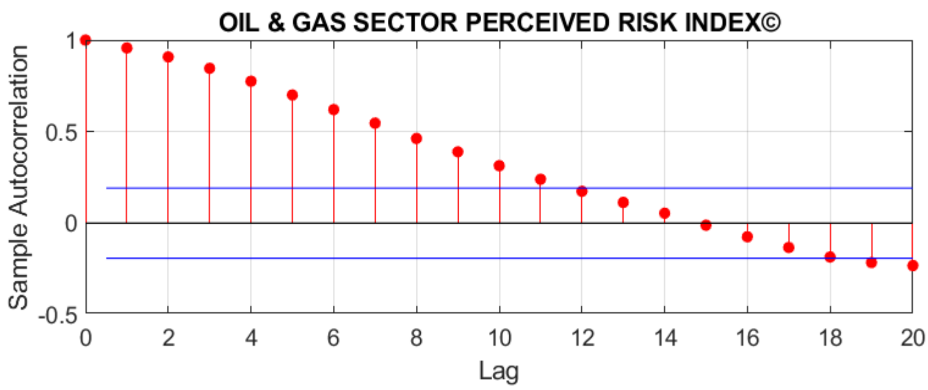



*Figure 21.3: Oil & Gas sector Perceived Risk Index© Autocorrelation function*

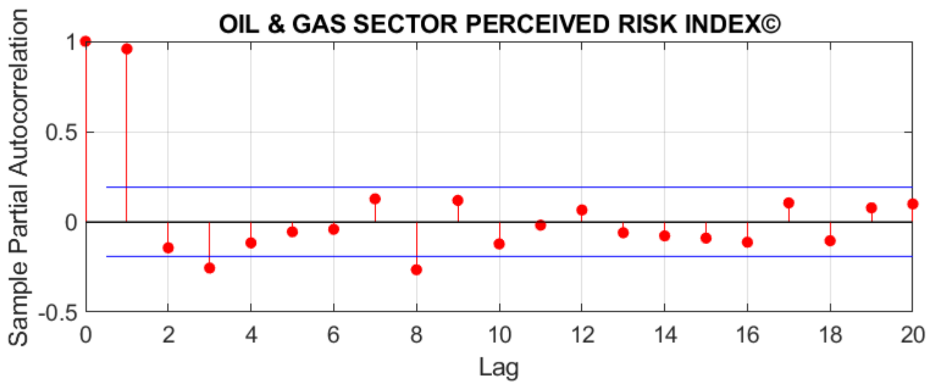



*Figure 21.4: Oil & Gas sector Perceived Risk Index© Partial Autocorrelation function*

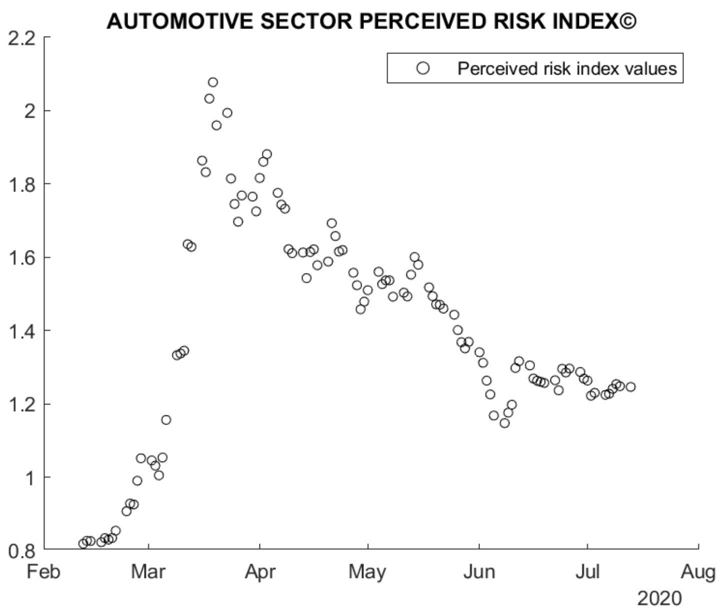



*Figure 22.1: Automotive sector Perceived Risk Index© values*

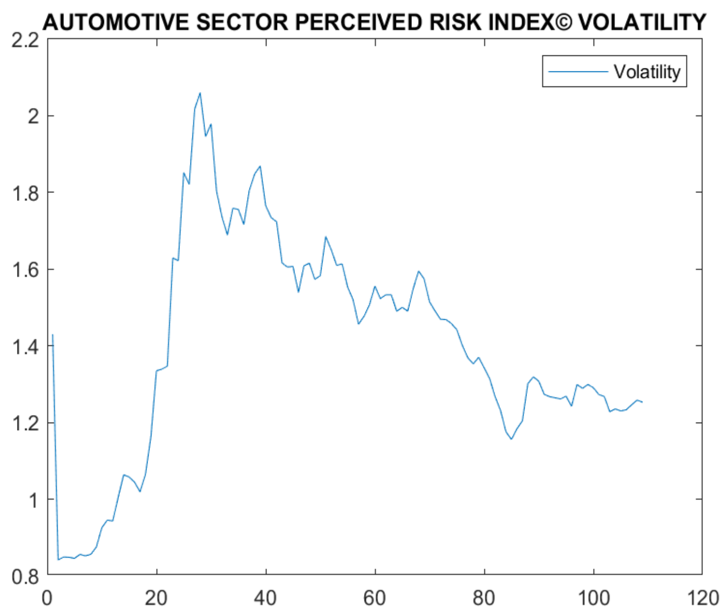



*Figure 22.2: Volatility of Automotive sector Perceived Risk Index©*

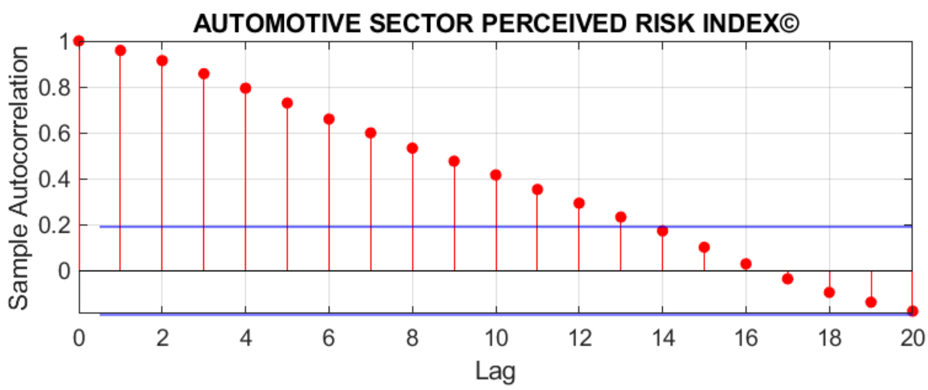



*Figure 22.3: Automotive sector Perceived Risk Index© Autocorrelation function*

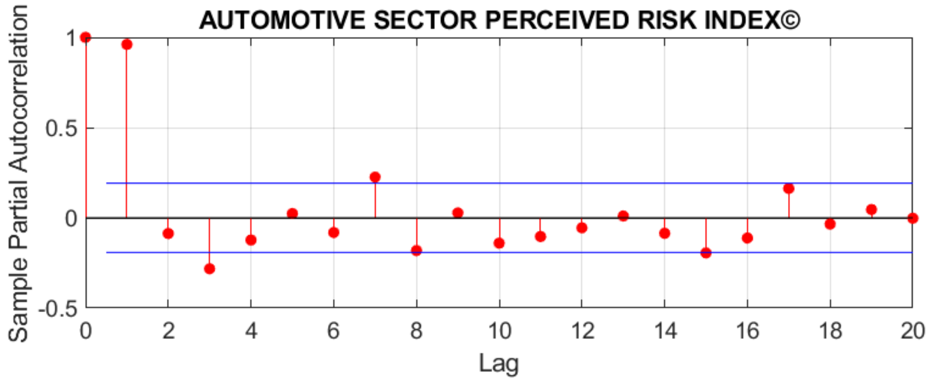



*Figure 22.4: Automotive sector Perceived Risk Index© Partial Autocorrelation function*

The Perceived Risk Index© of the financial sector recorded an increase in its values as early as the end of February, as can be seen in Figure 20.1, this therefore came well before the outbreak of the epidemic and the lockdowns of the various countries.

The first major shock that the financial sector therefore suffers leads it to reach really high levels of this financial indicator, which then tends to decline slowly, until it stabilises at a middle ground between the pre-pandemic values and the peak reached during the total uncertainty.

The trend from April onwards is therefore very irregular, but the Perceived Risk Index© tends neither to fall nor rise during this period, thus remaining stable at these levels.

The volatility of the financial sector was really high in the first 30 lags, as can be seen from Figure 20.2, in fact the market was very unstable in this period due to the precariousness of the news that was being issued.

From around the 40th observation, we can instead see a downward trend in volatility, which still has many fluctuations and irregularities, but nevertheless tends to decrease lag after lag.

In Figure 20.3, one can observe the autocorrelation function of the financial sector, which shows a strong positive trend in the first 10 lags and then declines fairly early.

This trend underlines a significant correlation between the Perceived Risk Index© values for this sector.

In the last part again of this figure, one can see some negative lags in succession, which highlight the fact that the results in the last period are very erratic, with a high probability that a positive return was followed by a negative return and vice versa, a phenomenon that is confirmed if one looks at Figure 20.1, since the last 2 months of the Perceived Risk Index© values are inconstant and discontinuous.

The partial autocorrelation function, observed in figure 20.4, on the other hand, has only four lags that are relevant and make a difference in the measurement of correlation, as the remainder are all within the 5% range and can therefore be considered irrelevant for this purpose.

From the lags analysed, however, it can be observed that there is a correlation between the values net of their intermediates, albeit weak and therefore negligible.

As far as the Perceived Risk Index© of the oil and gas sector is concerned, on the other hand, it can be seen from Figure 21.1 that the values tend to show the true effects of the crisis in late March.

It can be observed how the first lockdowns led the values to soar, in fact it is during this period that the highest peaks of this financial indicator are recorded.

As early as April, however, values begin to decrease, although slowly, with many up and downs, which influence the trend, making it erratic and unstable for all the last months analysed.

Figure 21.2 shows the volatility of the Oil & Gas sector, which from the twentieth observation shows a sudden increase that leads it to be high and persistent for a good period.

Only from around the fiftieth lag does volatility begin to have a significant decrease, leading it to record post-pandemic lows in the last lags analysed.

The autocorrelation function, as observed in Figure 21.3, shows that there is a strong positive correlation with the values, which therefore demonstrate a serial dependence between them.

The ACF does not decay slowly, as already by the twelfth lag, the values are within the 5% range and can therefore be considered poso-significant.

The partial autocorrelation function, which can be observed in Figure 21.4, has the first two lags that are really significant, but of the next two, none is notable, thus showing a negligible correlation, since it is weak and influenced by only two lags.

For the automotive sector, the Perceived Risk Index© underwent a shock, which led it to very high values around mid-March, when the outbreak of the pandemic was made official.

Compared to the other two sectors, the values in the automotive sector remained higher for longer, as can be seen in Figure 22.1, thus struggling to recover from the impact of the crisis, probably due to the halt in car production caused by the lockdowns.

Values only began to decline significantly in May, with the two summer months bringing them to post-pandemic lows.

Volatility from the 20th lag onwards was significantly high, in fact the first major shock caused it to increase immeasurably, as can be seen in Figure 22.2.

It remained high and had many fluctuations and an erratic pattern until around the seventieth observation, from which point onwards it began to have a significant decrease, which saw it stabilise at much lower values in the last lags of the analysis.

The autocorrelation function recorded a strong positive trend that continued for almost all the lags analysed.

As can be seen in Figure 22.3, in fact, the ACF values were significant up to the fourteenth lags, thus underlining a very slow decay.

From this graph it can be noticed that there is a significant correlation between the Perceived Risk Index© values in the automotive sector, with a strong serial dependence between them.

Moreover, this trend is often linked to moments of high and persistent volatility, a phenomenon that is in fact found if one looks at Figure 22.2, confirming how positive correlation leads to several high results in a row.

The partial autocorrelation function has few truly relevant lags that can make a difference in the estimation of correlation, since most are not very relevant, as can be seen in figure 22.4, it can therefore be observed that there is a weak correlation between the Perceived Risk Index© values net of its intermediates.

The following are instead the results during the Russian invasion of Ukraine:

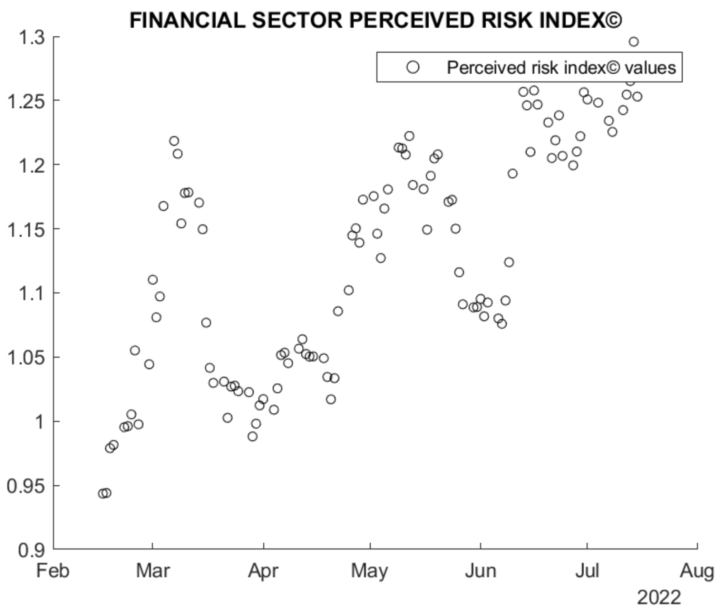



*Figure 23.1: Financial sector Perceived Risk Index© values*

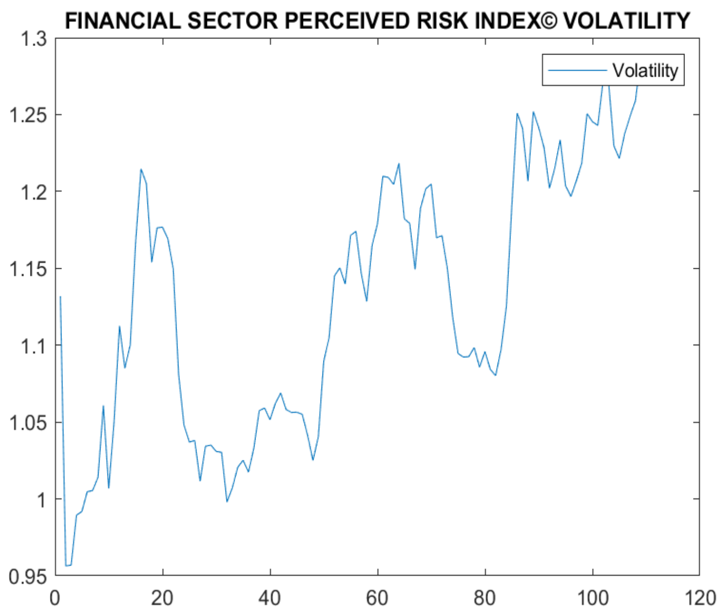



*Figure 23.2: Volatility of Financial sector Perceived Risk Index©*

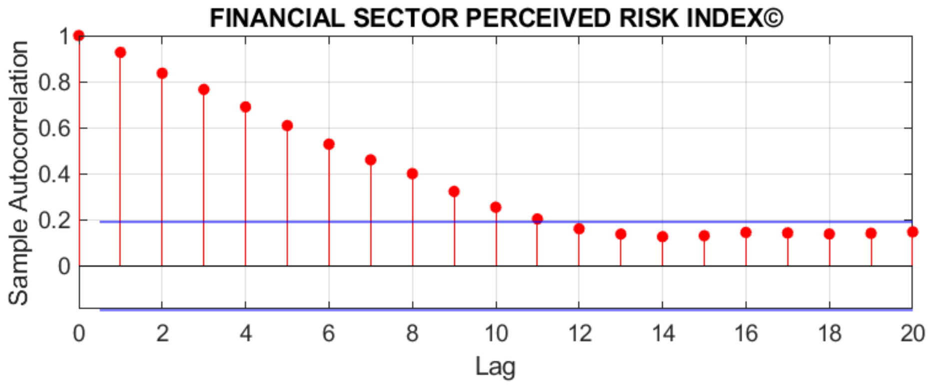



*Figure 23.3: Financial sector Perceived Risk Index© Autocorrelation function*

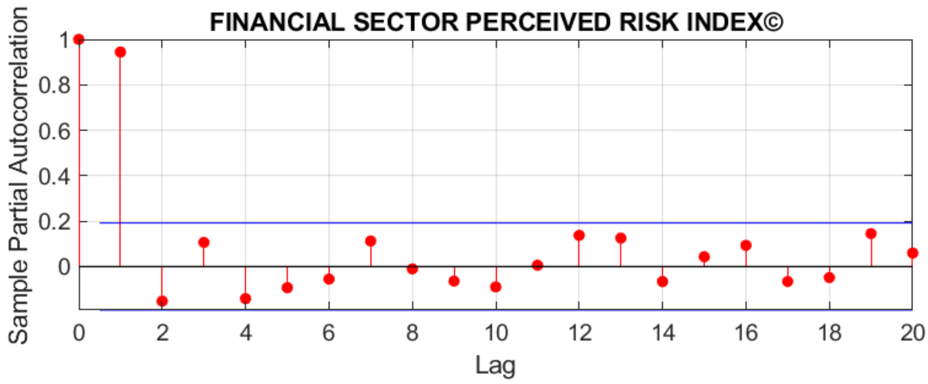



*Figure 23.4: Financial sector Perceived Risk Index© Partial Autocorrelation function*

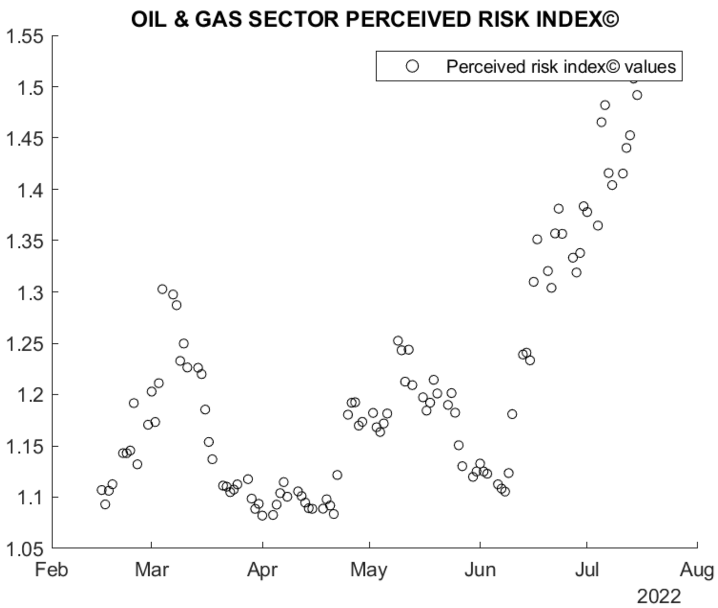



*Figure 24.1: Oil & Gas sector Perceived Risk Index© values*

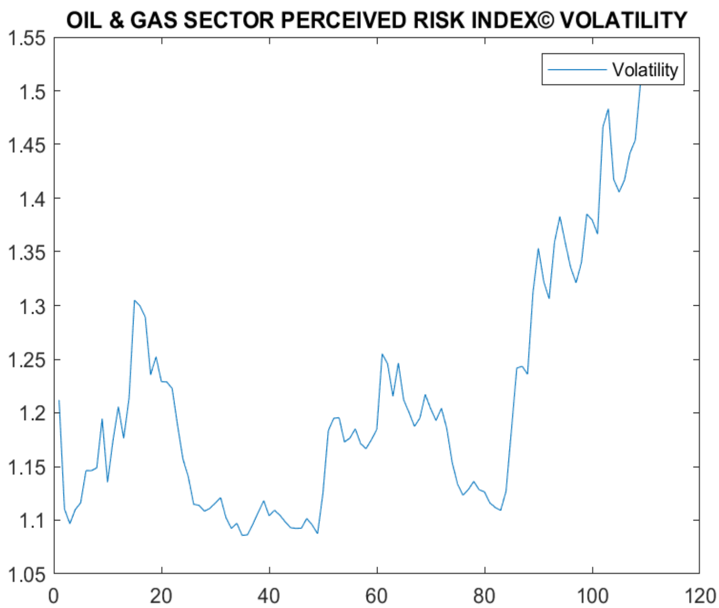



*Figure 24.2: Volatility of Oil & Gas sector Perceived Risk Index©*

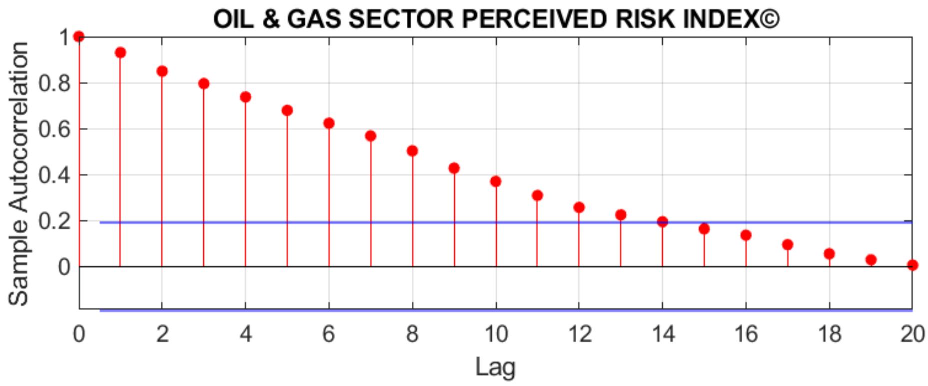



*Figure 24.3: Oil & Gas sector Perceived Risk Index© Autocorrelation function*

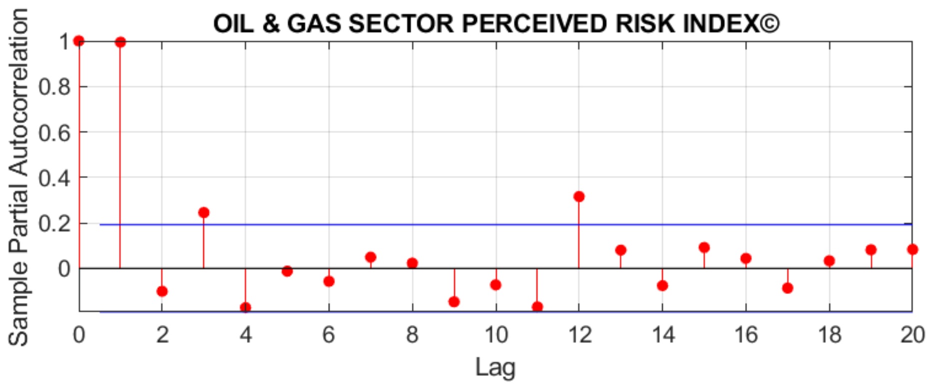



*Figure 24.4: Oil & Gas sector Perceived Risk Index© Partial Autocorrelation function*

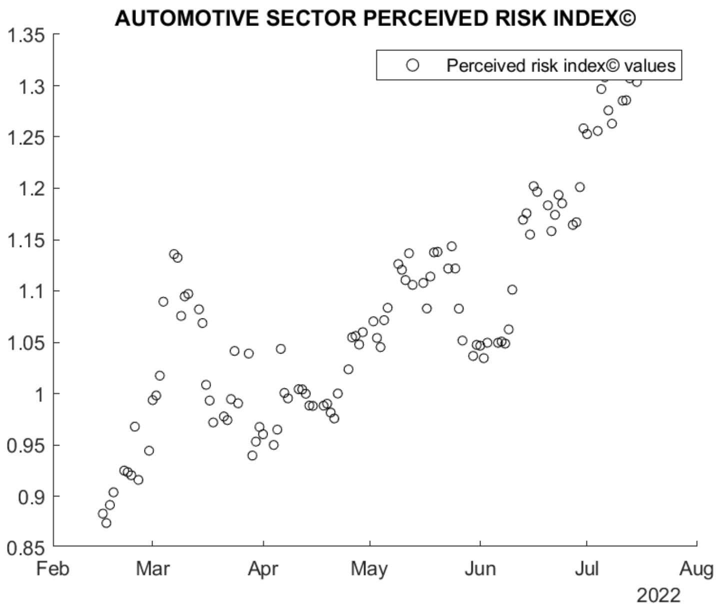



*Figure 25.1: Automotive sector Perceived Risk Index© values*

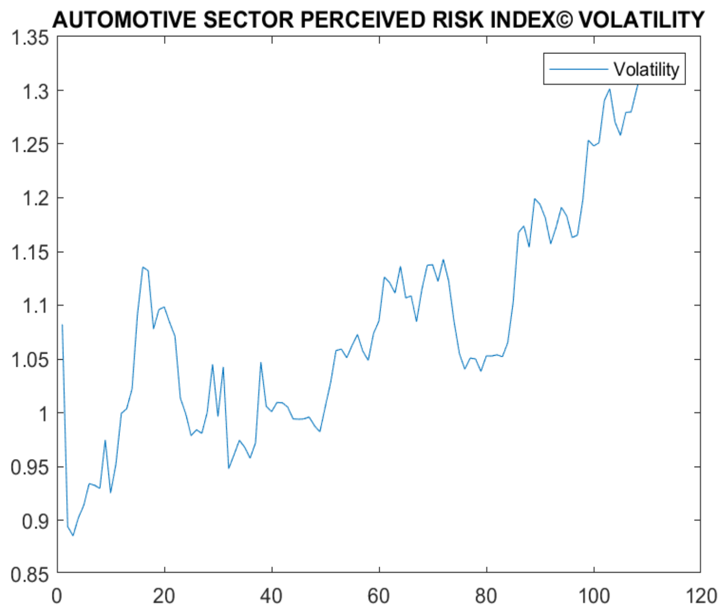



*Figure 25.2: Volatility of Automotive sector Perceived Risk Index©*

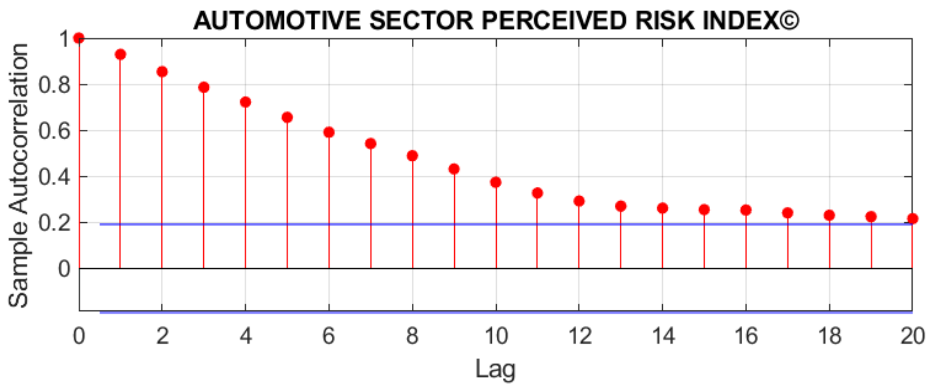



*Figure 25.3: Automotive sector Perceived Risk Index© Autocorrelation function*

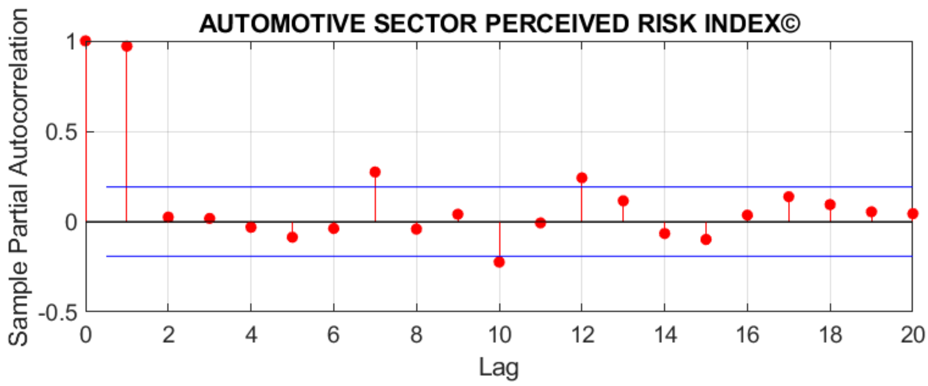



*Figure 25.4: Automotive sector Perceived Risk Index© Partial Autocorrelation function*

The Perceived Risk Index© of the financial sector suffered a major shock at the end of February that caused a sudden increase in values, which, however, declined in a relatively short time, as can be seen in Figure 23.1.

In fact, it can be seen that in April the values are almost in line with those before the outbreak of the war, while from May onwards there is an upward trend that causes values to rise more and more, until they reach their highest peaks at the end of the period analysed.

This behaviour shows how the market did not expect certain results from the invasion of Ukraine, and how political developments have totally changed the game.

The volatility of the financial sector, as can be seen in Figure 23.2, has an initial large fluctuation that causes it to rise only momentarily, however, because around lag thirty, values are low again.

From the fiftieth observation onwards, volatility grows exponentially and remains high and persistent throughout the last period analysed, with slight fluctuations that do not, however, change the final result, i.e. record highs in the last lags analysed.

Figure 23.3 shows the trend of the autocorrelation function, where a strong positive tendency is evident, which slowly decays, thus underlining how the correlation between the values is significant and the dependence is strong.

The partial autocorrelation function, on the other hand, as can be seen in Figure 23.4, has only two relevant lags, while the remaining ones are all negligible, which shows that the values in the financial sector have a weak correlation with each other net of their intermediates.

As far as the Perceived Risk Index© of the oil and gas sector is concerned, it can be seen in Figure 24.1 that, in contrast to the financial sector, the first increase is smaller, with a shock that was therefore felt less by the companies in this sector.

In fact, it can be noticed that in April the values are in line with those prior to the Russian invasion, showing how calm the market really was about the situation.

In May, there is another rise in values, which, however, like the previous one, is only momentary, since at the end of the same month, values are again low.

In June, on the other hand, the Perceived Risk Index© began to rise sharply, with values skyrocketing, peaking in July, precisely the months in which the first sanctions for Russia were enacted, thus damaging the gas trade.

Volatility, as can be seen in Figure 24.2, has been very erratic, with various fluctuations, but this has not kept it high for long.

It is only from the eightieth lag onwards that there is an inordinate increase in volatility, which from time to time is higher and persistent until the end of the period.

The autocorrelation function, as can be seen in Figure 24.3, shows a significant positive trend that decays very slowly, which thus underlines a strong correlation between the values of the Perceived Risk Index© of the Oil & Gas sector.

The partial autocorrelation function has only a few relevant lags, as can be seen in Figure 24.4, from which it can therefore be determined that the oil & gas sector values net of their intermediates have a weak and not particularly relevant correlation.

For the automotive sector, the Perceived Risk Index© had a slight increase during the first period of the Ukrainian invasion, but this was only momentary because the values fell shortly afterwards, as can be seen in Figure 25.1.

In fact, it was not until May that the true results of the war were seen on this sector, with the Perceived Risk Index© rising steadily, with an irregular but increasing trend throughout the last months analysed.

This late impact on the values of the automotive sector was probably due to the increasingly difficult sourcing of raw materials for car production, which were mainly exported from the Ukrainian country itself.

In Figure 25.2, one can observe the volatility of the Perceived Risk Index© of the automotive sector, which shows a very erratic and irregular trend, but which leads it, as the lags pass, to be increasingly high and persistent.

The autocorrelation function shows a relevant positive trend that decays slowly, as can be seen in Figure 25.3, from which it can be observed that the values are significantly correlated with each other and that there is a serial dependence of the same.

This trend is often associated with high volatility that lasts for several phases, a connection that is true in this case, since as can be seen from Figure 25.2, the volatility values are increasingly higher as time passes.

In Figure 25.4, the partial autocorrelation function can be observed, which apart from the first two truly significant lags and two others that are somewhat less relevant, but which nevertheless make a difference, has no other lags worthy of note, from which we can therefore deduce that the correlation of the Perceived Risk Index© values net of their intermediates is weak and not very considerable.

Having analysed both crisis events and their volatilities and correlations for the respective economic sectors, it is time to make comparisons of the different situations that occurred during these events.

The performance of the Perceived Risk Index© for all three sectors was very different in the two events, thus showing how the market was caught by different factors in the two cases.

In fact, during the COVID-19 pandemic, the Perceived Risk Index© of all three sectors shows an initial big shock that causes values to rise disproportionately, which then struggle to fall in the short term, and only in the last month of the period under analysis did they register a significant drop.

The situation is completely opposite during the Russian invasion of Ukraine, where the values of the financial indicator rise at the outbreak of the war, but only moderately, and then fall again in the same month as the invasion.

The significant increase in the Perceived Risk Index© can only be seen from May onwards, thus in the last phase of the period analysed.

It can therefore be concluded that the market's behaviour in relation to these two crisis events was unequal, precisely because in the first case, in which the crisis was of an epidemic nature, the Perceived Risk Index© immediately increased and then decreased with the passage of time, while in the second event, in which the crisis was of a geopolitical nature, the Perceived Risk Index© increased with time, reaching its peak value at the end of the period analysed, a completely opposite evolution to the first case.

One can find an explanation behind these different trends, the market during COVID-19 experienced a period of complete uncertainty, both because there were no historical events to refer to in order to find certainties on which to make forecasts, and because the news coming in from around the world was increasingly serious and doubtful as to how the situation would evolve, which led all companies to experience moments of high risk never experienced before.

During the Russian invasion, on the other hand, the market had various historical events on which to base forecasts and this was probably the reason why it did not respond tremendously to the outbreak of war, if compared to the response it had during the first period of COVID-19, thus keeping the values of the Perceived Risk Index© relatively low, but what really took it by surprise and subsequently sowed chaos and uncertainty in all sectors was the hard political line that was adopted towards Russia and the subsequent delineation that the various most powerful nations of the world adopted.

This situation, added to the scarcity of raw materials that were on the market, caused a haemorrhage in the markets and a general risk of default for the companies analysed, both because of their relations with the Russian country and because they no longer had materials to produce their goods and services, thus exposing them to serious risks.

Having said this, it can therefore be concluded that the response of the Perceived Risk Index©, although different in terms of time, was clear and precise with what this indicator was developed for, i.e. to expose the risks and moments of greatest danger in the market, which came at different times in these two crises, but were captured perfectly by this financial indicator.

Speaking of sectors specifically instead, the financial sector, as could be seen in the study done, managed to anticipate market movements compared to the other two sectors, both during COVID-19 and during the Russian invasion of Ukraine.

In fact, in comparison to the oil & gas and automotive sectors, the financial sector increased as early as the end of February during the pandemic, while the others only increased in late March, whereas during the war, it started to increase significantly as early as the beginning of May, while the other two sectors grew somewhat more slowly.

This newly analysed phenomenon underlines how the financial sector is a leading sector and how it is much more sensitive to events that will take place in the near future, compared to the other two sectors, which are considered as lagging sectors, i.e., those that are slow to follow market trends.

It is therefore important to add this sector to the Perceived Risk Index©, precisely because the indicator is forward-looking, so this fits right in to improve a creation that already lays a solid foundation.

However, this is not to the discredit of the other sectors, because although the financial sector is very useful in predicting market movements in advance, it is a bit of a misleading indicator of when the economy is really starting to recover.

In fact, as can be seen especially during COVID-19, the oil & gas and automotive sectors were slower to recover than the financial sector, thus providing a better view of how the world and markets were still trying to digest and rebuild solid fundamentals for the post-pandemic.

Thus, it can be seen that only the analysis of all sectors put together can provide a more comprehensive and defined reading of the market.

# Conclusions

This thesis presents a comprehensive analysis, both of the Perceived Risk Index© and its three component variables, which was made possible by the completeness of the data that were transposed and the efficiency of the functions used to conduct this study.

In fact, the autocorrelation function and the partial autocorrelation function showed how the correlation of values differed according to the moment of greater or lesser stress that the indicator or variable was facing, while the GARCH framed the trend of volatility and allowed for an analysis of the whole that was not indifferent.

It is clear from the analysis that both credit default swap, implied volatility and inverse stock price are three variables that are sensitive to market movements and can best explain whatever situation the market is going through, thus allowing for valuable information in order to best frame any possible scenario.

As much as these three variables are sensitive to the market, they do not lose their objectivity at times of greatest stress, on the contrary, they remain valid and reliable, thus managing to provide factual data, for which they are precisely analyzed, for example, the CDS gives a complete view of the risk of insolvency of the companies that have been taken into analysis, just as the implied volatility shows the different expectations that investors have and the inverse stock price captures the market's feelings and the various influences to which it was subjected.

All this reliability and seriousness of the three variables, is then reflected in the Perceived Risk Index©, which is therefore a useful indicator, capable of summarizing what is the market situation and the risk that a company or an industry is facing, managing to perform at its best despite the times of great stress it has to endure.

As a result, the Perceived Risk Index© provides an advantage to Enel Spa, precisely because of the possibility it gives the company itself to interpret the market and its movements and to be able to always keep an eye on the trends of its competitors.

In terms of the analysis done of the sectors, what was noted is that the financial sector turns out to anticipate what are the market trends, confirming itself several times as a leading sector, while the oil & gas and automotive sectors, are more of the lagging sectors, that is, they tend to lag the market trend, but, in the long run, they manage to perceive better the recovery phase of the economy, since compared to the financial sector, they are slower to recover, as were the markets after these two big crises.

Thus, the financial sector turns out to be very useful in order to have a forward-looking view of the market, an objective that precisely the Perceived Risk Index© sets itself, and which therefore in my opinion should be attached to the study of this financial indicator.

It turns out, however, that the other two sectors are no less important, since only a detailed and comprehensive study of all the components that make up the financial markets allows for a more defined view of the various scenarios that will emerge over time.

# References


Bailey R. (2005), The Economics of Financial Markets. Cambridge University Press.

Bomfim A. (2005), Understanding Credit Derivatives and Related Instruments. Elsevier Academic Press.

Box G., Jenkins G., Reinsel G., Ljung G. (2016), Time Series Analysis: Forecasting and Control. John Wiley & Sons Inc.

Choudhry M. (2023), The Credit Default Swaps Basis. Bloomberg Press.

Carmona R. (2014), Statistical Analysis of Financial Data in R. Springer.

Christoffersen P. (2016), Elements of Financial Risk Management. Academic Press.

Crouhy M., Galai D., Mark R. (2014), The Essentials of Risk Management. The McGraw-Hill Companie, Inc.

Cryer J., Chan K. (2008), Time Series Analysis. Springer Science+Business Media, LLC.

Culp C., Merwe A., Starkle B. (2018), Credit Default Swaps: Mechanics and Empirical Evidence on Benefits, Costs and Inter-Market Relations. Palgrave Macmillan.

Danielsson J. (2011), Financial Risk Forecasting. John Wiley & Sons Inc.

Dettling M. (2020), Applied Time Series Analysis. Zurich University of Applied Sciences.

Engle R, Patton A. (2001), What good is a volatility model?. Quantitative Finance Volume 1.

Fabozzi F. (2007), Fixed Income Analysis. John Wiley & Sons Inc.

Gabbi G. (2013), Il modello di Black-Scholes-Merton. SDA Bocconi School of Management.

Gastineau G. (2010), The Exchange-Traded Funds Manual, Second edition. John Wiley & Sons Inc.

Hansen P., Lunde A. (2013), Estimating the Persistence and the Autocorrelation Function of a Time Series that is Measured with Error. Cambridge University Press.

Hull J. (2015), Options, Futures, and Other Derivatives 9th edition. Pearson Education Inc.

Iqbal A. (2018), Volatility: Practical Options Theory. John Wiley & Sons Inc.

Linton O. (2019), Financial Econometrics: Models and Methods. Cambridge University Press.

Machina M. (2013), Handbook of the Economics of Risk and Uncertainty:1. North Holland.

Montgomery D., Jennings C., Kulahci M. (2015), Introduction to Time Series Analysis and Forecasting. John Wiley & Sons. Inc.

Natenberg S. (2014), Option Volatility and Pricing: Advanced Trading Strategies and Techniques. McGraw Hill.

Ramsey F. (1974), The Annals of Statistic: Characterization of the Partial Autocorrelation Function. Institute of Mathematical Statistics.

Shiller R. (1992), Market Volatility. Massachusetts Institute of Technology.

Sollis R. (2012), Empirical Finance for Finance and Banking. John Wiley & Sons Inc.

Tze L., Haipeng X. (2010), Statistical Models and Methods for Financial Markets. Springer.

Xekalaki E., Degiannakis S. (2010), ARCH Models for Financial Applications. John Wiley & Sons Inc.

https://www.enelfoundation.org/topics/articles/2022/03/perceived-risk-index

https://www.investopedia.com/

https://www.milanofinanza.it/