

Louvain School of Management

**The impact of uncertainty on the financial market:
How does uncertainty in the US financial market impact the
performance of the US portfolios
between 2001 and 2025 ?**

Simon Christmann

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Leonardo Inia

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1. Abstract

Uncertainty is known as a risk on the financial markets. It can increase or decrease the return on the stock markets. Usually, the uncertainty is compared to the volatility. In this research, the purpose is to predict the return of US portfolio on three years by adding seven indicators like inflation, price of oil, price of gold, euro/dollar rate, EPU¹ and interest rate to find if these macro-financial indicators have an impact on the predicted returns and are synonym of uncertainty on the financial market while their rates increase or decrease. The research is based on quantitative data. The prediction starts at the beginning of 2023 and finishes at the end of 2025. The portfolios are composed on the S&P 500. We found that most of the volatility of the macro-financial indicators are pertinent for our study. We used the significant indicators to predict the returns of the different sector over three years.

¹ Economic Policy Uncertainty

2. Introduction

The relationship between uncertainty and financial markets has been a subject of great interest and research for many years. Financial market uncertainty is often caused by a variety of factors, including geopolitical events, changes in government policies, fluctuations in exchange rates, and sudden changes in investor sentiment. These uncertainties create a sense of unpredictability in the financial markets, which can result in significant volatility and risk premiums that can affect the performance of various investment portfolios.

Investors, analysts, and policymakers are keenly interested in understanding the relationship between uncertainty and portfolio performance. This is because the financial market plays a vital role in the economy, and its performance affects individuals, businesses, and governments at both local and global levels. The relationship between uncertainty and portfolio performance is especially important in today's increasingly interconnected and complex financial markets, where a single event in one market can have ripple effects throughout the entire system.

Given the significant impact of uncertainty on financial markets and portfolio performance, it is essential to develop reliable methods to measure and manage uncertainty. A variety of measures can be used to quantify uncertainty, including the CPI, and other macroeconomic indicators. However, identifying the most effective indicators and developing robust models that can accurately capture the relationship between uncertainty and portfolio performance remains an ongoing challenge.

Therefore, this research aims to examine the impact of uncertainty on the performance of US portfolios from 2001 to 2022, using various indicators of uncertainty, including the CPI, and other macroeconomic and microeconomic indicators. We will analyze how different types of portfolios in different sectors such as consumer sector, manufacturing sector, high-technology sector, healthcare sector and other sector, are affected by uncertainty.

The results of this research will provide valuable insights into the relationship between uncertainty and portfolio performance, which can be used to inform investment decisions, risk management strategies, and policy interventions. Moreover, this study can contribute to the existing literature by providing a comprehensive analysis of the impact of uncertainty on

different types of investment portfolios over an extended period, which can help investors and policymakers better understand the dynamics of financial markets and the role of uncertainty in shaping portfolio performance.

The different indicators used in this research are the Consumer Price Index, which is used as indicator of inflation rate, the oil price, which is converted in oil rate, the gold price which is converted in gold rate, the EUR/USD exchange rate, the interest rate and finally the economic policy uncertainty rate which calculated the number of times the word ‘economic crisis’ appears in press. The volatility index (VIX) is not used on this study because it is calculated thanks to the return of the portfolio. So, it is sure that it is correlated to the portfolio returns.

Moreover, based on our analysis of the impact of uncertainty on portfolio performance using various indicators, we did a prediction on three years to see the impact of these relevant indicators on the portfolio returns. The prediction starts at the beginning of 2023 and finishes at the end of 2025.

3. Literature

3.1 Uncertainty and its effects

Uncertainty and risk are important concepts in finance and economics, with significant impacts on financial market behavior and investor decisions. While these two terms are often used interchangeably, there is a crucial difference between them. Risk refers to situations in which the potential outcomes and their probabilities can be estimated, while uncertainty refers to situations in which the potential outcomes and their probabilities cannot be known in advance.

In this context, uncertainty can have a significant impact on financial markets, leading to increased volatility and changes in investor behavior. This can have significant implications for economic activity and growth, as well as for the decisions of policymakers and regulators.

Researchers have developed a range of measures and indicators to try and quantify uncertainty, including text-based and econometric-based measures. Understanding these measures and their implications is crucial for investors, policymakers, and anyone seeking to understand the behavior of financial markets in times of uncertainty.

3.1.1 The notion of uncertainty

Uncertainty is defined as a situation in which nothing is known in advance, and which cannot be predicted in the near or distant future. According to Knight (1921)², a distinction is made between uncertainty and risk. The difference between the two concepts is that risk can be predicted in the future. This means that it is possible to estimate all the possibilities and to associate a probability of realization to them.

For example, when we flip a coin, there are two possibilities: either heads or tails. The result is not known in advance, but we know the two possibilities. Moreover, there is a one-in-two chance of getting heads or tails, so the probability is also known in advance, unlike

² Knight, F.H. (1921). *Risk, Uncertainty, and Profit*. Hart, Schaffner, and Marx Prize Essays, No. 31. Houghton Mifflin, Boston and New York.

uncertainty. In the notion of uncertainty, it is impossible to know the probability and the possibilities in advance, hence the difference between risk and uncertainty.

This statement defines the terms "risky" and "uncertain" as they are used in this context. An event is considered "risky" if the outcome is unknown, but there is knowledge of the potential outcomes and their likelihoods. In contrast, an event is considered "uncertain" if the outcome is also unknown, but there is no knowledge or understanding of the distribution of potential outcomes.

By linking this notion to the economy, it is possible to show that economic agents are not able to predict future events. During the covid period, uncertainty was present in the financial markets because it was impossible to predict how events would unfold in the short or long term.

From a macroeconomic point of view, the notion of uncertainty is very broad and is sometimes confused with risk. It is then referred to a mixture between uncertainty and risk. This similarity between the two concepts gave birth to the VIX. This indicator corresponds to the volatility index that was used by Bloom (2009)³ to measure uncertainty.

3.1.2 How does uncertainty impact the stock market?

Uncertainty is a parameter related to macroeconomics. Macroeconomics is defined as a global vision of the economy with several components such as the unemployment rate, inflation, the performance of industries, etc. When the economy is in goes wrong, the notion of uncertainty appears. According to Bloom (2009)⁴, after each economic shock related to an oil embargo, an economic crisis, a war, etc. a situation of uncertainty in the economy and financial markets is felt. Our research focuses on the U.S financial markets.

When uncertainty is present in the economy, financial markets tend to be in the red. There are several reasons for this phenomenon. The first is that the behavior of investors in times of uncertainty changes. According to Beers (2022), their behavior becomes more and

^{2,3} Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3), 623-685.

more pessimistic. Each bad news impacts their decisions more and more negatively. This leads to a withdrawal of capital and a fall in the financial markets.

Then, in a situation of uncertainty, volatility in the financial markets is very high. According to Andersen et al (2006, p.781), “*the volatility is defined as the (instantaneous) standard deviation (or "sigma") of the random Wiener-driven component in a continuous-time diffusion model*”. Andersen et al (2006) conducted research that demonstrated a positive correlation between volatility and uncertainty. On the other hand, Andersen et al (2006) examined risk through measuring return volatility, while measuring uncertainty by considering the degree of disagreement among professional forecasters, with different weights assigned to each forecaster. Moreover, one study showed that volatility and uncertainty are related, while another study looked at how to measure risk and uncertainty using different methods. Volatility is measured by the Volatility Index (VIX). This indicator is considered as an asset in the notion of uncertainty. When this indicator is high, volatility is very high and causes large upward or downward movements in the financial markets.

Finally, financial markets are linked to the macroeconomy. Stock market indices such as commodity prices, the S&P 500... are indices that can influence the financial markets. These indices are considered like benchmarks and represent the health of the market. The S&P 500 is a stock market index that tracks the performance of 500 large companies listed on stock exchanges in the United States. When the S&P 500 is in the red, it generally means that the stock prices of the companies that make up the index have decreased, which could be due to a variety of factors such as negative economic news, poor corporate earnings reports, geopolitical events, or market uncertainty. A decline in the S&P 500 does not necessarily indicate a recession or a bear market, but it can be an indicator of market volatility or a shift in investor sentiment.

Financial markets are complex and when they are in periods of uncertainty, prices are volatile, and investors' decisions are no longer coherent... which leads to a decline or even a crash.

3.1.3 Uncertainty and risk factor measures

Over time, researchers tried to find a way to measure and quantify uncertainty. According to the study of Danilo Cascaldi-Garcia et al (2021), they divided the measurement

of uncertainty into four categories: text-based, survey-based, econometric-based, and market-based measures. The text-based and econometric-based are useful for research. Unfortunately, market-based measures are useless for research because they are constructed with financial markets data. It is therefore logical that these measures will be correlated to uncertainty.

The text-based methodology uses text data and new articles to measure uncertainty and risk. This method counts the number of occurrences of a keyword in the text. The method has created several indicators such as Monetary Policy Uncertainty, Economic Policy Uncertainty, Word Uncertainty, Geopolitical risk...etc.

The other methodology is econometric-based measures. According to Danilo Cascardi-Garcia et al (2021, p.21), *“Uncertainty is equated with lack of predictability of aggregate activity under this approach. Related to this, researchers have used quantile regressions to estimate the value of aggregate economic activity that is « at risk »”*. The two indicators are macroeconomic uncertainty index (MUI) and value-at-risk (VaR). Jurado, Ludvigson, and Ng (2015)⁵ conducted research and concluded that when macroeconomic uncertainty increases, there is a significant decline in real economic activity in the United States. Additionally, they argue that macroeconomic uncertainty acts as an amplifier of recessions rather than being the direct cause of them. Moreover, the study suggests that when there is more uncertainty in the macroeconomic environment, it can make an existing recession worse, rather than being the initial cause of the recession itself.

Concerning value-at-risk, it is the quantile of the conditional portfolio distribution, and it is considered as a risk-reporting measure (Andersen et al., 2006). The problem with Value at Risk (VaR) is that it only provides information about the likelihood or probability of experiencing a loss beyond a certain threshold, but it does not indicate the expected magnitude or size of the loss that may occur on the days when the VaR is exceeded or breached. VaR cannot estimate the amount of loss in the event of occurrence, and this limitation can be a significant issue for risk management and decision-making.

Another indicator of the risk is the Expected Shortfall (ES). Andersen et al., (2006, p.792) defined the expected shortfall as *“the expected loss on the days when losses are larger*

⁵ Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3), 1177–1216.

than the VaR”. Also, it is sensitive to the shape of the tail of the distribution of returns on portfolio. Expected shortfall is calculated by averaging all the returns in the distribution that are worse than the VaR of the portfolio at a given level of confidence. For instance, for a 95% confidence level, the expected shortfall is calculated by taking the average of returns in the worst 5% of cases.

Finally, the last indicator is the downside risk. Kenton (2022) provides a definition of the downside risk: *“Downside risk is an estimation of a security's potential loss in value if market conditions precipitate a decline in that security's price. Depending on the measure used, downside risk explains a worst-case scenario for an investment and indicates how much the investor stands to lose. Downside risk measures are considered one-sided tests since the potential for profit is not considered”*. Downside risk measures are typically used to estimate a worst-case scenario for an investment, allowing investors to understand how much they could potentially lose. It's important to note that downside risk measures are one-sided tests, meaning that they only consider the potential for loss and don't factor in the potential for profit.

3.2 The uncertainty response on different economic factors

In this section, it explains the relationship and link between economic factors and uncertainty. The different economics factors used in this research are gold, oil, asset pricing, monetary policy, long-term interest rate and inflation.

All these factors have a more or less close relationship with uncertainty but their reactions each impact the market differently. They selected for this research because they are the factors most likely to have an impact on financial markets in times of uncertainty.

3.2.1 Gold as a safe haven in times of uncertainty

Jones and Sackley (2016)⁶ conducted research to explore the relationship between gold price fluctuations and economic policy uncertainty. Their study showed that when there is high economic policy uncertainty, the price of gold tends to increase. In a similar vein, Gao and Zang

⁶ Jones A.T, and Sackley W.H. (2016). An uncertain suggestion for gold-pricing models: The effect of economic policy uncertainty on gold prices. *Journal of Economics and Finance* 40, 367–379.

(2016)⁷ investigated how economic policy uncertainty affects the correlation between the UK stock market and the gold market. They found that uncertain economic policies result in moderate correlation, while certain economic policies are associated with high correlation.

Balcilar, Gupta, and Piedzioch (2016)⁸ also conducted research on the factors that affect gold price dynamics, specifically economic, macroeconomic, and financial uncertainties. Their study revealed that macroeconomic and financial uncertainties play a critical role in determining gold returns and volatility. In summary, these studies demonstrate that economic policy uncertainty, along with macroeconomic and financial uncertainties, have significant impacts on the behavior of gold prices and their relationships with other markets.

The purpose is to find whether gold performs the function of hedge and a safe haven property under different gold market scenarios and diverse uncertainty episodes. It seems that there are some periods when gold and uncertainty are positively correlated. Thanks to the quantile-based approaches, the research shows that the gold is a safe haven if gold is positively correlated with uncertainty when the uncertainty is high.

The research uses different shades of uncertainty such as low, middle or high, but we will use only the low or high uncertainty for this work. The results come from the quantile-on-quantile regression (QQR) approach (Sim and Zhou, 2015)⁹. It can be useful in assessing the dependence structure between gold returns and uncertainty. The QRR (quantile regression relationship) model is capable of capturing the dynamic relationship between gold returns and uncertainty, taking into account different market conditions such as bearish or bullish periods.

When macroeconomic uncertainty is high and the gold market is bearish, there is positive response. The gold returns increase. Concerning microeconomic uncertainty, when gold market is bearish and uncertainty is high, there is also a positive response. The gold returns

⁷ Gao, R., and Zhang, B. (2016). How does economic policy uncertainty drive gold–stock correlations? Evidence from the UK. *Applied Economics*, 48 (33), 3081-3087.

⁸ Balcilar, M., Gupta, R., and Piedzioch, C. (2016). Does Uncertainty Move the Gold Price? New Evidence from a Nonparametric Causality-in-Quantiles Test. *Resources Policy*, 49, 74-80.

⁹ Sim, N., and Zhou, A. (2015). Oil Prices, US Stock Return, and the Dependence Between Their Quantiles. *Journal of Banking and Finance*, 55, 1-8.

increase too. Moreover, the response of gold returns to the economic policy uncertainty seems positive when the uncertainty is high and under bear gold market.

About the financial uncertainty, there is a positive response with the gold returns in period of high uncertainty and bull gold market. But when uncertainty is low, the response seems also positive. In the bearish market, the relationship appears negative whatever the uncertainty level.

The impact of political uncertainty on gold prices demonstrates that there is a clear positive correlation between the level of uncertainty and gold returns. Specifically, when political uncertainty is at its highest and the gold market is bearish, there tends to be a strong response in gold returns. So, when there is more uncertainty in the political landscape, investors may turn to gold as a safe haven asset, driving up its price.

It appears that the research has found that gold can serve as a safe haven during uncertain times, but its effectiveness as a hedge may be limited to political uncertainty. Additionally, the relationship between gold returns and uncertainty is positive and strong, but nonlinear. This may be due to a variety of factors such as the mood of gold traders, supply and demand in the gold market, price fluctuations of other assets, and unconventional monetary policies. Overall, it seems that gold can play an important role in a diversified investment portfolio, particularly during times of heightened uncertainty.

3.2.2 The complex relationship between oil prices and stock returns

In the literature, there are various views on the relationship between crude oil price changes and stock returns. For instance, Kling (1985)¹⁰ suggested that crude oil price increases are associated with stock market declines, while Chen et al. (1986)¹¹ found no effect of oil price changes on asset prices. Jones and Kaul (1996)¹² reported a stable negative relationship between

¹⁰ Kling, J. L. (1985). Oil Price Shocks and Stock-Market Behavior. *Journal of Portfolio Management*, 12, 34–9.

¹¹ Chen, N.-F., Roll, R., and Ross, S. A. (1986). Economic Forces and the Stock Market, *Journal of Business*, 59, 383–403.

¹² Jones, C., and Kaul, G. (1996). Oil and the Stock Markets. *Journal of Finance*, 51, 463–91.

oil price changes and aggregate stock returns. Huang et al. (1996)¹³ did not find a negative relationship between stock returns and changes in the price of oil futures. Wei (2003)¹⁴ concluded that the 1973-1974 oil price increase could not explain the decline in U.S. stock prices in 1974.

The impact response of stock returns appears to be driven by fluctuations in expected real dividend growth and by fluctuations in expected returns associated with a time-varying risk premium, regardless of the shock. Sadorsky (1999)¹⁵ notes that the relative importance of demand and supply shocks in the crude oil market evolves over time, leading to regressions that relate stock returns to innovations in the price of oil that may find no significant statistical relationships or unstable relationships over times.

Kilian and Park (2009) show that the effects of demand and supply shocks in the crude oil market on U.S. macroeconomic aggregates are qualitatively and quantitatively different, depending on whether the oil price increase is driven by oil production shortfalls, by a booming world economy, or by shifts in precautionary demand for crude oil that reflect increased concerns about future oil supply shortfalls. As such, it is natural to expect similar differences in the effect of these shocks on stock returns.

The common view in the literature is that oil price increases affect the U.S. economy and the U.S. stock market through their effect on the cost of producing energy-intensive goods, as noted by Kilian and Park (2009). The cost of producing these goods explains why stock returns of companies in the chemical industry are often expected to be particularly sensitive to disturbances in the crude oil market because these companies heavily rely on oil products as raw materials.

Kilian and Park (2009) find that the response of aggregate stock returns can vary considerably depending on the cause of the oil price shock. The negative response of stock prices to oil price shocks, often referred to in the financial press, is only observed when the

¹³ Huang, R., Masulis, R. and Stoll, H. (1996). Energy Shocks and Financial Markets. *Journal of Futures Markets*, 16, 1–27.

¹⁴ Wei, C. (2003). Energy, the Stock Market, and the Putty-Clay Investment Model. *American Economic Review*, 93, 311–23.

¹⁵ Sadorsky, P. (1999). Oil Price Shocks and Stock Market Activity. *Energy Economics*, 21, 449–69.

price of oil rises due to an oil-market-specific demand shock, such as an increase in precautionary demand driven by concerns about future crude oil supply shortfalls. In contrast, crude oil production disruptions have no significant effect on cumulative stock returns. Furthermore, higher oil prices driven by an unanticipated global economic expansion have persistent positive effects on cumulative stock returns within the first year of the expansionary shock. This result arises because a positive innovation to the global business cycle will stimulate the U.S. economy directly, while at the same time driving up the price of oil, thereby indirectly slowing U.S. economic activity.

Finally, Dohyoung (2019) notes that oil supply and demand shocks have significant negative effects on emerging stock returns, whereas aggregate demand shocks cause a sustained rise of returns. Economic uncertainty shocks in the U.S lead to a substantial decline of emerging equity returns. In particular, the impacts of oil shocks on emerging stock returns are amplified by the endogenous response of US economic uncertainty.

3.2.3 Relationship between risk, uncertainty, and asset pricing

Anderson, Ghysels and Juergens (2009) measure risk by the volatility of return and uncertainty by the degree of disagreement of professional forecasters. Anderson, Ghysels and Juergens (2009) wish to examine the risk-return trade-off and the uncertainty-return trade-off. The risk-return trade-off is a well-established concept in finance that suggests that the expected excess return on investment should increase in proportion to the level of market volatility. This concept is so fundamental that it is considered as the ‘first law of finance’. Recent studies suggest that asset pricing should take into account not only risk, but also uncertainty.

The relationship between conditional volatility and expected return has been studied by several researchers. Baillie and DeGennaro¹⁶, French, Schwert, and Stambaugh (1987)¹⁷, and Campbell and Hentschel (1992)¹⁸ have found a positive but mostly insignificant relationship.

¹⁶ Baillie, R. T., and DeGennaro, R. P. (1990). Stock Returns and Volatility. *Journal of Financial and Quantitative Analysis*, 25, 203–214.

¹⁷ French, K. R., Schwert, G. W., and Stambaugh, R. F. (1987). ‘Expected Stock Returns and Volatility. *Journal of Financial Economics*, 19, 3–29.

¹⁸ Campbell, J. Y., and Hentschel, L. (1992). No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns. *Journal of Financial Economics*, 31, 281–318.

On the other hand, Campbell (1987)¹⁹, Nelson (1991)²⁰, and Brandt and Kang (2004)²¹ have found a significantly negative relationship. Glosten, Jagannathan, and Runkle (1993)²² and Turner, Startz, and Nelson (1989)²³ find that the relationship between conditional volatility and expected return can be both positive and negative depending on the estimation method used. Finally, Ghysels, Santa-Clara, and Valkanov (2005)²⁴ use Mixed Data Sampling (MIDAS) estimation methods and find a significant and positive relationship between the market return and conditional volatility.

The proposed method for measuring agents' uncertainty in mean returns is to use the level of disagreement among professional forecasters. This is because the predictions of forecasters are seen as a good representation of the range of ideas that agents in the economy are exposed to, and it's likely that agents partially base their beliefs on these predictions. If professional forecasters all have similar expectations for returns, then uncertainty is likely to be low. However, if there is a high level of disagreement among forecasters, then agents are more likely to be unsure about mean returns, and uncertainty is high.

The empirical analysis conducted by Anderson, Ghysels and Juergens (2009) investigates both risk and uncertainty in time series and cross-section. The authors have found that uncertainty is a more significant factor than risk in determining the expected market excess returns in the time series. Moreover, the expected returns of an asset could be influenced by the degree of covariance, or the extent to which changes in the uncertainty of the asset are related to changes in the market as a whole. In other words, if there is a strong relationship between

¹⁹ Campbell, J. Y. (1987). Stock Returns and the Term Structure. *Journal of Financial Economics*, 18, 373–399.

²⁰ Nelson, D. B. (1990). ARCH Models as Diffusion Approximations. *Journal of Econometrics*, 45, 7–39.

²¹ Brandt, M. W., and Kang, Q. (2004). On the relationship between the conditional mean and volatility of stock returns: A latent VAR approach. *Journal of Financial Economics*, 72, 217–257.

²² Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, 48(5), 1779–1801.

²³ Turner, C. M., Startz, R., and Nelson, C. R. (1989). A Markov Model of Heteroskedasticity, Risk, and Learning in the Stock Market. *Journal of Financial Economics*, 25, 3–22.

²⁴ Ghysels, E., Santa-Clara P., and Valkanov, R. (2005). There is a Risk–Return Tradeoff After All. *Journal of Financial Economics*, 76, 509–548.

the uncertainty in the asset and the uncertainty in the market, this could have an impact on the expected returns of the asset. This relationship is likely to be examined in empirical research as a potential factor affecting asset pricing.

The approach of Merton (1980)²⁵ and Foster and Nelson (1996)²⁶ have shown that it is possible to estimate volatility accurately by sampling returns over very short time periods. Therefore, assuming that volatility is known is not an unreasonable assumption. However, in practice, there are certain characteristics of high-frequency data, such as leptokurtosis, intra-daily deterministic patterns, and market microstructure features like price discreteness, nonsynchronous trading, and bid-ask spread, which can affect the data used in empirical research. These factors can further complicate the estimation of volatility in real-world applications.

Based on the analysis conducted by Anderson, Ghysels and Juergens (2009), the uncertainty measure developed by the researchers shows a correlation coefficient of 0.28 with the market excess return. In addition, the uncertainty measure is positively correlated with the Small Minus Big (SMB) factor, which means that greater uncertainty is associated with higher returns for smaller firms relative to larger ones. However, the uncertainty measure is insignificantly negatively correlated with the High Minus Low (HML) factor, which implies that there is no significant relationship between uncertainty and for returns growth stocks relative to value stocks.

Finally, uncertainty plays a significant role in explaining the cross-sectional variation in stock returns. Specifically, stocks that are more exposed to uncertainty tend to have higher average returns than those with lower exposure, with the highest uncertainty portfolios having the largest returns on average. However, it is important to note that these portfolio returns are not statistically distinguishable from each other, meaning that the differences could be due to chance. Nevertheless, the economic implications of these findings are substantial, with high

²⁵ Merton, R. C. (1980). On Estimating the Expected Return on the Market: An Exploratory Investigation. *Journal of Financial Economics*, 8, 323–361.

²⁶ Foster, D. P., & Nelson, D. B. (1996). Continuous Record Asymptotic for Rolling Sample Variance Estimators. *Econometrica*, 64 (1), 139-174.

uncertainty portfolios having returns that are on average 200 basis points greater per quarter than low uncertainty portfolios.

3.2.4 The relationship between monetary policy and the stock market

In their analysis of the relationship between monetary policy and the stock market, Bernanke and Kuttner (2005) emphasize that the most direct and immediate effects of monetary policy actions are felt in the financial markets. Policymakers aim to modify economic behavior by affecting asset prices and returns in ways that will help to achieve their ultimate objectives.

However, Bernanke and Kuttner (2005) also note that the market may not react significantly to changes in the Federal funds rate that are already anticipated by futures market participants. In addition, they suggest that unexpected funds rate increases may lead to declines in stock prices due to several factors, such as a decrease in expected future dividends, a rise in expected real interest rates, or an increase in expected excess returns associated with holding stocks. The authors argue that simple regressions of equity return on surprise changes in the Federal funds rate are not sufficient to disentangle the various effects, and a more structured approach is required.

Bernanke and Kuttner (2005) also find that the reactions to monetary policy surprises tend to differ across industry-based portfolios, with the high-tech and telecommunications sectors exhibiting a response half again as large as that of the broad market indices. However, they caution that monetary policy surprises are responsible for only a small portion of the overall variability of stock prices.

Bernanke and Kuttner (2005) suggest two potential channels through which tight monetary policy could affect the stock market. First, it could directly increase the riskiness of stocks by, for example, raising the interest costs or weakening the balance sheets of publicly owned firms. Second, it could reduce the willingness of stock investors to bear risk.

Finally, Bernanke and Kuttner (2005) offer an alternative interpretation of their findings. They suggest that the large movements in excess returns associated with monetary policy changes may reflect an excess sensitivity or overreaction of stock prices to policy actions. In conclusion, while the authors find that there is an effect of monetary policy on the stock market,

they argue that this effect is not directly attributable to policy's effects on the real interest rate, but rather on expected future excess returns or expected future dividends.

3.2.5 Long-term interest rates and inflation expectations

Gürkaynak, Sack, and Swanson (2005) noticed that many macroeconomic models assume constant and perfectly known long-run characteristics of the economy, such as inflation and the real interest rate. This assumption leads to the expectation that short-term nominal interest rates will remain relatively fixed after a macroeconomic or monetary policy shock.

However, Gürkaynak, Sack, and Swanson (2005) note that forward rates at longer horizons actually move in the opposite direction to short-term rates following such shocks. The authors argue that this behavior can be explained by financial market concerns about long-term inflation, which causes the private sector to adjust its expectations of the long-run level of inflation in response to macroeconomic and monetary policy surprises.

Gürkaynak, Sack, and Swanson (2005) also note that while the steady-state real interest rate may vary over time, changes alone do not seem sufficient to explain the term structure evidence. Instead, it is the private sector's adjustment of its long-run inflation expectations that appears to be the most plausible explanation.

Gürkaynak, Sack, and Swanson (2005) suggest that while the Federal Reserve has achieved remarkable economic performance over the sample period, there may be scope for improvement in stabilizing long-term forward rates and inflation expectations. The authors suggest that one way to achieve this could be for the Federal Reserve to credibly commit to an explicit inflation target.

4. Empirical study

4.1 Methodology

First, we perform several tests on the data. We convert the return to log-return for each portfolio and indicators. The first test is to check if the portfolios are stationary. Then, the second test is to check if there is a normalization of the residuals. Finally, we perform a test of autocorrelation on the portfolios.

Quantitative methodologies were used in this study to scrutinize the potential correlation between stock returns and macro-financial indicators. In order to assess the correlation between each indicator and stock returns, we used the GARCH model in order to measure the volatility when we add macro-financial indicator to the dependent variables.

Following this, the primary objective of this study was to forecast future returns over a triennial duration, commencing from the onset of 2023 until the conclusion of 2025. In order to achieve this objective, 3 distinct models were assessed, commencing from the most elementary and progressively advancing to the more intricate. The initial statistical model used in our analysis was the seasonal Autoregressive Integrated Moving Average and Generalized Autoregressive Conditional Heteroskedasticity models.

In our study, we used the Recurrent Neural Network, which is deemed the most intricate model, to examine the progression of yield prognostications and establish the partiality of each model with the intention of discerning the most pragmatic model.

According to our research results, the Recurrent Neural Network emerged as the most plausible model. The model facilitated the integration of pertinent indicators into our analysis, thereby enhancing the precision of our forecasts and giving us the opportunity to assess the role played by these indicators in the uncertainty of portfolio returns.

4.1.1 Test

4.1.1.1 Test of Stationarity

To check whether the time series are stationary, we use the ADF test. In this case, the ADF statistic for each portfolio is negative and the p-value is very small (less than 0.05) for all

portfolios. Therefore, we reject the null hypothesis that the time series is non-stationary and conclude that all five portfolios are stationary. This means that there is no significant trend or seasonality in the data, and the statistical properties of the data remain constant over time.

4.1.1.2 Test of normalization of residuals

We used the Jarque-Bera test to find if the residuals are normalized. The null hypothesis is that the residuals are normally distributed. For each portfolio and macro-financial indicators, we reject the null hypothesis that the residuals are not normalized. We try to solve the issue by using a boxcox. Even with this method the p-value rejects the null hypothesis, but it has a small impact on the results.

4.1.1.4 Test of heteroscedasticity of residuals

We used the Breusch-Pagan test to determine whether the residuals are homoscedastic. The null hypothesis is that the residuals are homoscedastic (constant variance). In this case, the Breusch-Pagan test for each portfolio is negative and the p-value is very high (less than 0.05) for all portfolios. Therefore, we can't reject the null hypothesis that the time series are homoscedastic and conclude that all five portfolios are homoscedastic.

4.1.1.3 Test of autocorrelation of residuals

We used the Ljung-Box test to find if the residuals are autocorrelated. The null hypothesis is that there is no autocorrelation in the residuals. In this case, the Ljung-Box test for each portfolio is negative and the p-value is very high (less than 0.05) for all portfolios. Therefore, we can't reject the null hypothesis that the time series are no autocorrelated and conclude that all five portfolios are no autocorrelated.

A plot of the distribution of standardized residuals is a useful tool for checking the assumption of normality in a statistical model. It allows to visually inspect how well the model fits the data and identify potential problems with the model.

4.1.2 *S-ARIMA : Seasonal Autoregressive Integrated Moving Average*

According to Hyndman and Athanasopoulos (2018), S-ARIMA models are an extension of ARIMA models that can handle time series data with a seasonal component. ARIMA stands for Auto-Regressive Integrated Moving Average, and it is a powerful statistical model used for

time series forecasting. S-ARIMA models incorporate additional seasonal components that capture repeating patterns in the data over fixed periods of time. These seasonal components are specified using three additional hyperparameters: the seasonal period, the seasonal difference order, and the seasonal order of the autoregressive and moving average terms.

The SARIMA model can be defined using the following notation:

$SARIMA(p,d,q)(P,D,Q)_m$

where:

- p : the order of the autoregressive (AR) component
- d : the degree of differencing required to make the time series stationary
- q : the order of the moving average (MA) component
- P : the order of the seasonal autoregressive (SAR) component
- D : the degree of seasonal differencing required to make the time series stationary
- Q : the order of the seasonal moving average (SMA) component
- m : the number of time steps in each seasonal period (e.g., 12 for monthly data with a yearly seasonality)

Box, Jenkins, Reinsel and Ljung (2015)²⁷ found that SARIMA model combines these components to capture both the non-seasonal and seasonal patterns in the data, and can be expressed using the following equation:

$$y(t) = c + AR(p) + MA(q) + SAR(P,m) + SMA(Q,m) + e(t)$$

where:

- $y(t)$ is the value of the time series at time t
- c is a constant term
- $AR(p)$ is the autoregressive component of order p
- $MA(q)$ is the moving average component of order q

²⁷ Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time series analysis: forecasting and control, 5th edition. *John Wiley & Sons*.

- SAR(P,m) is the seasonal autoregressive component of order P, with a period of m
- SMA(Q,m) is the seasonal moving average component of order Q, with a period of m
- $e(t)$ is the error term at time t

The equation for a S-ARIMA model is as follows:

$$y(t) = c + \Phi_1 y(t-1) + \Phi_2 y(t-2) + \dots + \Phi_p y(t-p) + \theta_1 e(t-1) + \theta_2 e(t-2) \\ + \varphi_1 y(t-s) + \varphi_2 y(t-2s) + \dots + \varphi_p y(t-ps) + \theta_1 e(t-s) \\ + \theta_2 e(t-s) + \dots + \theta_p e(t-qs) + e(t)$$

Where:

- $y(t)$ represents the time series at time t
- c is a constant
- $\Phi_1, \Phi_2, \dots, \Phi_p$ are the autoregressive terms of the model of order p
- $\theta_1, \theta_2, \dots, \theta_p$ are the moving average terms of the model of order q
- $e(t)$ is the error term at time t
- $\varphi_1, \varphi_2, \dots, \varphi_p$ are the seasonal autoregressive terms of the model of order P
- $\theta_1, \theta_2, \dots, \theta_p$ are the seasonal moving average terms of the model of order Q
- s is the seasonal period (e.g., 12 for monthly data with yearly seasonality)

According to Hyndman and Athanasopoulos (2018), the SARIMA model is fitted to the time series data using maximum likelihood estimation, and the optimal hyperparameters are chosen based on the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC).

4.1.3 GARCH : Generalized Autoregressive Conditional Heteroskedasticity

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) is a statistical model used to analyze and forecast time series data with changing variance over time, also known as heteroskedasticity. The model was first proposed by Robert F. Engle in 1982²⁸ as an extension of the ARCH (Autoregressive Conditional Heteroskedasticity) model.-

²⁸ Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 50(4), 987-1007.

The GARCH model allows for the conditional variance of a time series to depend on its own past values as well as the past values of its squared error terms. This makes it a powerful tool for modeling and forecasting financial data, where the volatility of asset returns can change over time.

The GARCH model can be defined as follows:

$$\varepsilon(t) = \sigma(t) * z(t)$$

$$\sigma^2(t) = \omega + \alpha * \varepsilon^2(t - 1) + \beta * \sigma^2(t - 1)$$

where:

- $\varepsilon(t)$ is the error term at time t
- $\sigma(t)$ is the conditional standard deviation of $\varepsilon(t)$
- $z(t)$ is a random variable with mean 0 and variance 1

ω , α , and β are the model parameters, with ω representing the constant term, α representing the autoregressive term, and β representing the moving average term

According to Bollerslev, T. (1986)²⁹, the GARCH model is fitted to the time series data using maximum likelihood estimation, and the optimal values of the parameters ω , α , and β are chosen based on the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC).

4.1.4 RNN : Recurrent Neural Network

According to Hochreiter and Schmidhuber (1997), RNN (Recurrent Neural Network) is a type of neural network architecture that is widely used in deep learning. Unlike feedforward neural networks, RNNs are designed to process sequential data, such as time series. The main advantage of RNNs is their ability to capture the temporal dependencies of input data, making them suitable for applications such as language translation, speech recognition, and time series forecasting.

²⁹ Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3), 307-327.

The basic building block of an RNN is the recurrent cell, which is a network of neurons that receives an input and an internal state (also known as a hidden state) from the previous time step. The internal state serves as a memory that enables the network to store information about the past inputs and use it to make predictions about the future. The internal state is updated at each time step using a set of learnable parameters that are optimized during the training process.

The most popular variant of RNN is the Long Short-Term Memory (LSTM) network, which was introduced by Hochreiter and Schmidhuber in 1997. LSTM is designed to address the problem of vanishing gradients in traditional RNNs, which can occur when the network is trained on long sequences. The LSTM network uses a set of gating mechanisms that control the flow of information through the network, allowing it to selectively retain or discard information at each time step.

The equation for the LSTM cell with a forget gate is as follows:

$$f_t = \sigma_g (W_f x_t + U_f h_{t-1} + b_f)$$

$$i_t = \sigma_g (W_i x_t + U_i h_{t-1} + b_i)$$

$$o_t = \sigma_g (W_o x_t + U_o h_{t-1} + b_o)$$

$$\bar{c}_t = \sigma_c (W_c x_t + U_c h_{t-1} + b_c)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \bar{c}_t$$

$$h_t = o_t \odot o_h(c_t)$$

where:

- $x_t \in \mathbb{R}^d$ is the input vector to the LSTM unit at time t
- $f_t \in (0,1)^h$ is the forget gate's activation vector at time t, which determines how much information from the previous state is retained
- $i_t \in (0,1)^h$ is the input gate's activation vector at time t, which determines how much new information is added to the cell state
- $o_t \in (0,1)^h$ is the output gate's activation at time t, which determines how much information is output from the cell state
- $h_t \in (-1,1)^h$ is the hidden state vector at time t also known as output vector of LSTM unit

- $\bar{c}_t \in (-1,1)^h$ is the cell input activation vector at time t
- $c_t \in \mathbb{R}^h$ is the cell state vector at time t

$W \in \mathbb{R}^{h \times d}$, $U \in \mathbb{R}^{h \times h}$ and $b \in \mathbb{R}^h$ is weight matrices and bias vector parameters which need to be learned during training where the superscripts d and h refer to the number of input features and number of hidden units.

Concerning the activation function:

- σ_g is the sigmoid function
- σ_c is the hyperbolic tangent function
- σ_h is the hyperbolic tangent function where $\sigma_h(x) = x$

Moreover, Hochreiter and Schmidhuber (1997) found that during training, the parameters of the LSTM network are optimized using backpropagation through time (BPTT), which is a variant of the standard backpropagation algorithm that is designed to handle sequential data. BPTT involves unrolling the network over time and computing the gradients of the loss function with respect to the parameters at each time step. These gradients are then used to update the parameters using an optimization algorithm such as stochastic gradient descent (SGD).

Finally, Hochreiter and Schmidhuber (1997) explained that RNNs have been used extensively in time series forecasting, where they have been shown to outperform traditional time series models such as ARIMA and GARCH. They have also been used in natural language processing tasks such as language translation and text generation. However, RNNs are computationally expensive to train and can be prone to overfitting, particularly when the training data is limited.

4.2 Data

It is an existing data. The data comes from the Kenneth R. French for the portfolio industry. We selected the data between 2001/01/01 to 2022/12/01.

Concerning the other macro-financial indicators as inflation, price of oil,... The data is also an existing data and come from the federal reserve bank of St-Louis. The macro-financial

indicators have also been transformed in log-return for each portfolio. We selected the data between 2001/01/01 to 2022/12/01.

5. Results

In our analysis, we estimated the best model to use. The best models with the lower AIC are the GARCH (1,1) and the S-ARIMAX (2,0,2) (0,1,1). These parameters do not change throughout the analysis. The GARCH (1,1) model has a zero mean. The purpose of the SARIMAX model was to determine whether there were heteroscedasticity and autocorrelation in the model. And, whether the residuals were normalized. We calculated the residuals of the dependent variables with the exogenous variables. Then, we used the conditional volatility of the residuals from the SARIMAX model which we inserted in the GARCH model. For the aim of this study, we are more interested in the GARCH results because it models volatility, which is synonymous with uncertainty, but we looked at when it was necessary to the results of the SARIMAX model when there was confusion in the interpretation of the results.

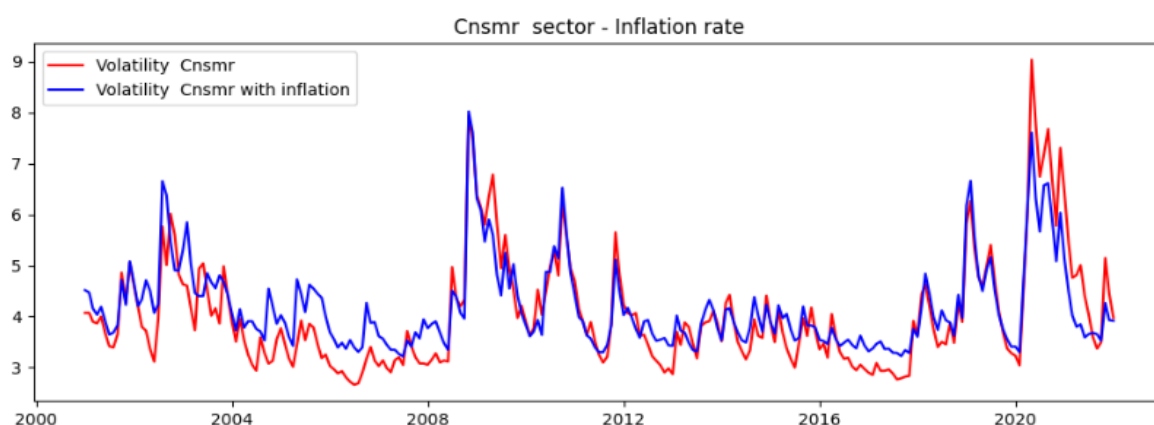
5.1 Dependent variables and exogenous variables

5.1.1 The relationship between dependent variables and inflation rate

In this section, the purpose is to determine whether there is a significant relationship on volatility between the inflation rate and the dependent variables. To do so, we use a SARIMAX model. Then, we use a GARCH model to get an overview of the volatility. The GARCH model takes the residuals from the SARIMAX model to calculate the results. Each graph represents the conditional volatility of the dependent variables with the inflation rate and the conditional volatility of each dependent variable.

5.1.1.1 The effect of inflation rate on the consumer returns

After analyzing the volatility of consumer returns with and without the inflation rate using the GARCH model, we observed that the two curves follow each other closely. This suggests that the volatility of the inflation rate may be correlated to the volatility of consumer returns, but it is only an assumption.



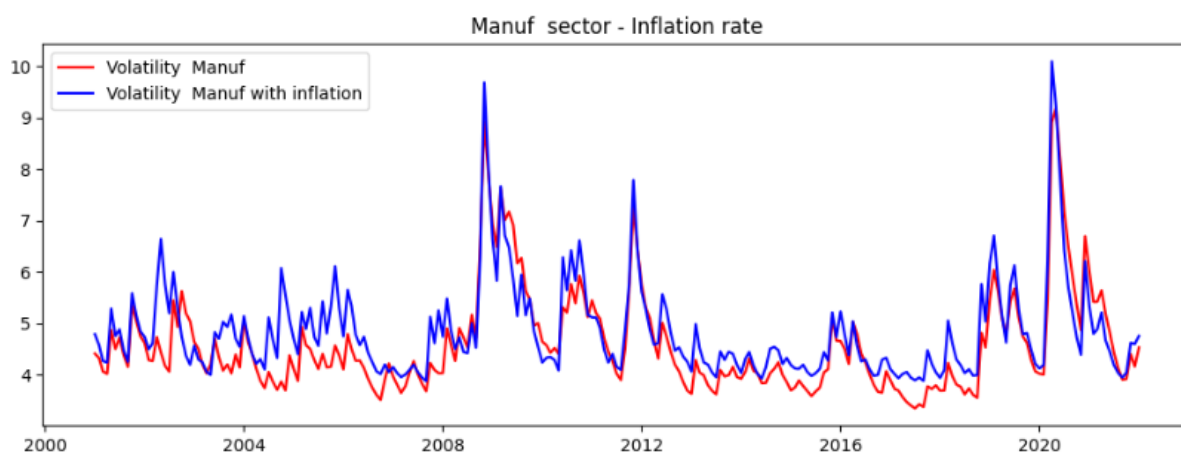
The GARCH model also shows that the inflation rate has a significant effect on the volatility of consumer returns. The omega coefficient is positive and statistically significant at the 5% level, indicating that volatility has a constant non-zero mean. The alpha coefficient is positive and statistically significant, suggesting that past shocks to consumer returns have a persistent effect on future volatility. The beta coefficient is positive and statistically significant, implying that volatility tends to persist over time.

Based on these results, we suggest that the volatility of the inflation rate can have a significant impact on the volatility of consumer sector returns based on the GARCH model.

5.1.1.2 The effect of inflation on manufacturing returns

After analyzing the volatility of the manufacturing returns with and without the inflation rate using GARCH model, we observe that the two curves follow each other closely. This suggests that the volatility of inflation rate may have a significant impact on the volatility of manufacturing returns.

But the results of the GARCH model showed that the estimated coefficients of both alpha and beta were not statistically significant at conventional levels, indicating that past volatility had no significant impact on current volatility. On the other hand, the estimated coefficient of omega was also not statistically significant, implying that the conditional variance of manufacturing returns was not significantly different from zero.

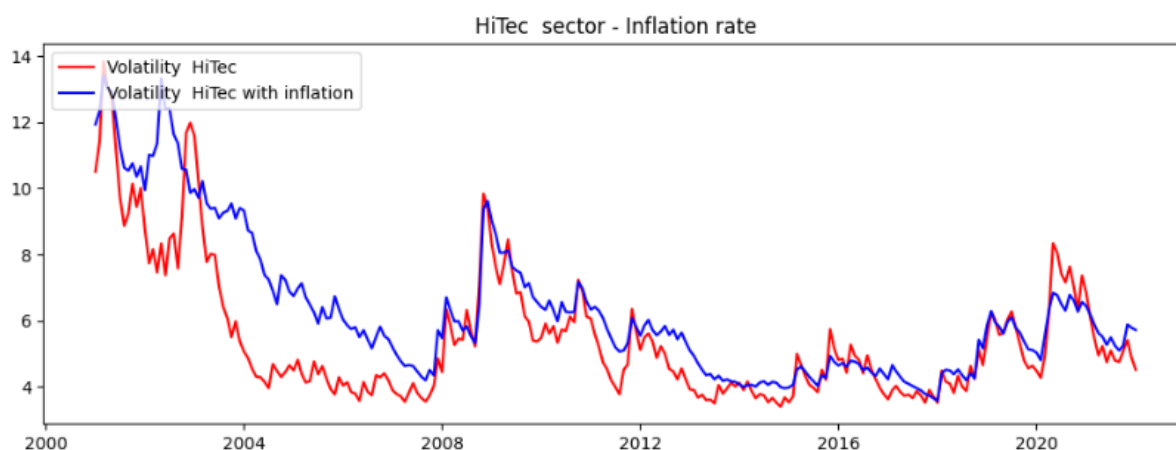


Therefore, based on the model results, we conclude that the volatility of CPI rate may not have a significant impact on the volatility of manufacturing returns.

5.1.1.3 The effect of inflation rate on the high-technology returns

The SARIMAX model captures the dynamic properties of the CPI rate and their potential influence on the high-technology sector, while the GARCH model allows us to model the volatility of the high-technology industry returns.

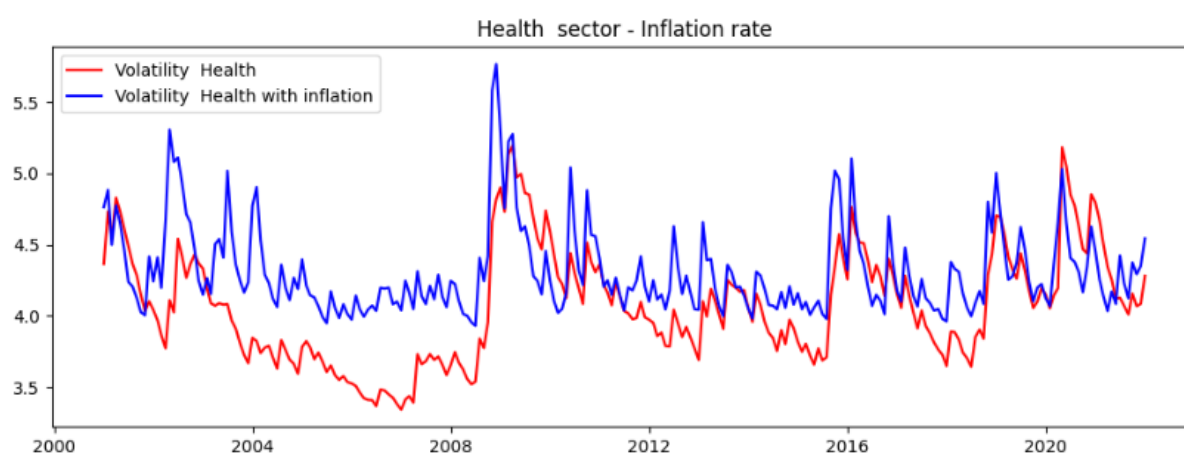
The GARCH model revealed that the volatility of the high-technology industry returns is influenced by past shocks, with a statistically significant coefficient of beta. Moreover, we observed that the two curves follow each other closely. This suggests that the volatility of the inflation rate may have a significant impact on the volatility of manufacturing sector returns.



In conclusion, this study shows that the volatility of CPI can have a significant impact on the volatility of high-technology industry returns.

5.1.1.4 The effect of inflation on the healthcare returns

Moving on to the GARCH results, we observe that the coefficient of the omega parameter is 6.2603 with a standard error of 5.565 and a p-value of 0.261. The alpha parameter has a coefficient of 0.0812 with a standard error of 0.05276 and a p-value of 0.124, while the beta parameter has a coefficient of 0.5837 with a standard error of 0.322 and a p-value of 0.06965.



When comparing the volatility of healthcare sector returns with inflation to the volatility of healthcare sector returns alone, we can see that the volatility of healthcare returns with inflation does not follow the red line. This suggests that the volatility of inflation rate has less impact on the healthcare returns.

From the results of GARCH model, the volatility of CPI rate may not have a significant impact on the healthcare returns.

5.1.1.5 The effect of inflation rate on the other sector returns

When we look at the GARCH model, we can see that the beta coefficient for the CPI rate is significant at the 5% level, indicating that changes in the CPI rate may have a significant impact on the volatility of the other sector returns.

Furthermore, if we compare the volatility of other sectors' returns and the volatility of other sectors' returns with inflation, we can see that the volatility of other sectors' returns with

inflation almost follows the red line. This suggests that the volatility of inflation rate may have an impact on the volatility of other sectors' returns.



In conclusion, our models suggest that the volatility of CPI rate can have a significant impact on the returns of other sectors.

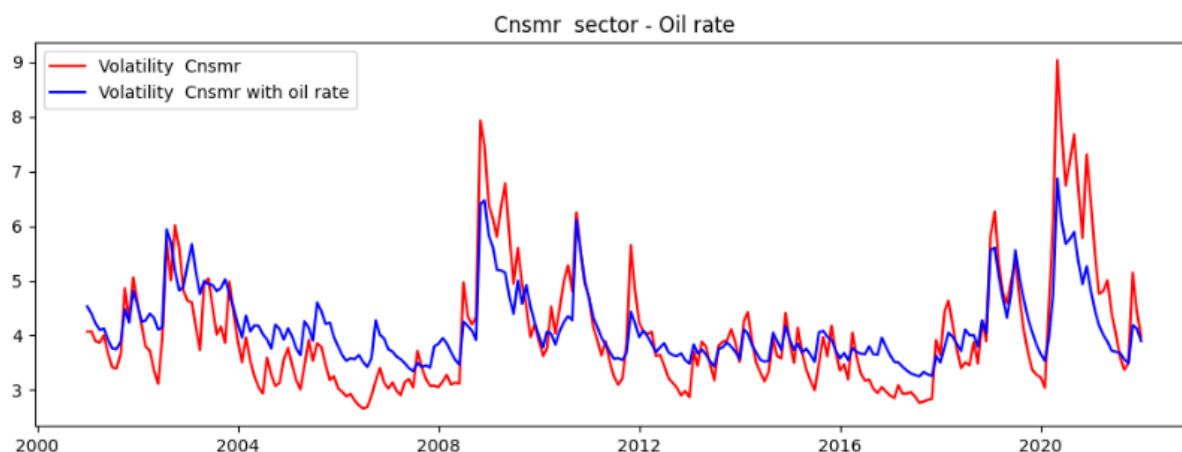
5.1.2 The relationship between dependent variables and oil price rate

In this section, the purpose is to determine if there is a significative relation on the volatility between oil rate and the dependent variables. To do that, we use a SARIMAX model. Then, we use a GARCH model to have an overview about the volatility. The GARCH model takes the residuals of the SARIMAX model to calculate the results. Each graph represents the conditional volatility of the dependent variables with oil price rate and the conditional volatility of each dependent variables.

5.1.2.1 The effect of the oil price rate on the consumer returns

With the GARCH model, the coefficients for omega, alpha, and beta are 2.6931, 0.1204, and 0.7288, respectively. The p-values for these coefficients suggest that only beta may be statistically significant at the 10% level. However, the coefficient for beta is positive, which indicates that past values of the consumer sector return and the oil price rate are positively related, meaning that an increase in the oil price rate is associated with an increase in the volatility of the consumer sector return.

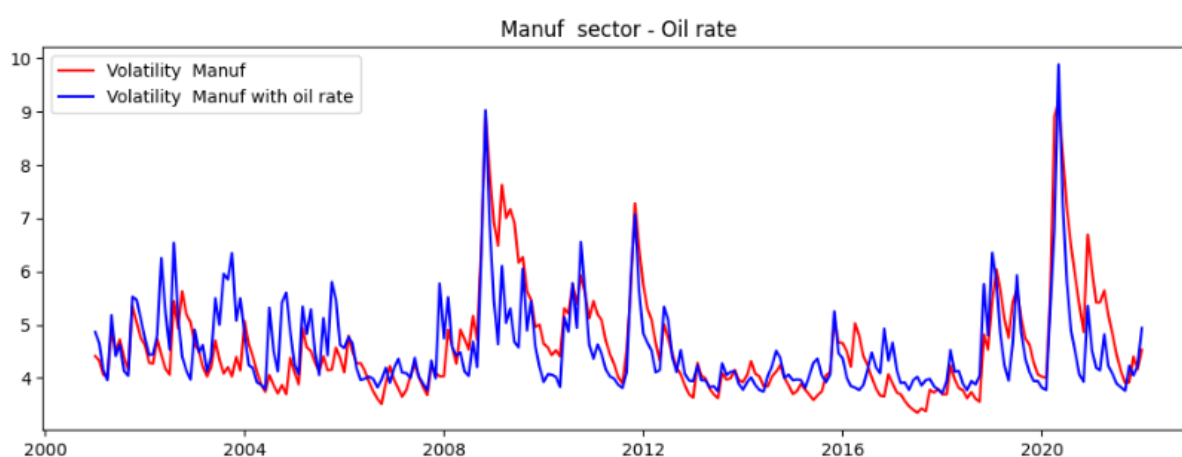
Furthermore, if we compare the volatility of the consumer returns with and without the oil price rate, we can see that the volatility of the consumer returns with the oil price rate follows more or less the volatility of the consumer returns without the oil price rate. This suggests that the volatility of the oil price rate may have an impact on the volatility of consumer returns.



In conclusion, the GARCH model suggests that the volatility of the oil price rate may have a significant impact on the consumer returns. An increase in the volatility of the oil price rate is associated with an increase in the volatility of the consumer returns.

5.1.2.2 The effect of the oil price on the manufacturing returns

Based on the GARCH model results, the coefficient for the oil price rate is not statistically significant at the 5% level. This suggests that the oil rate may not have a significant impact on the volatility of the manufacturing sector return.



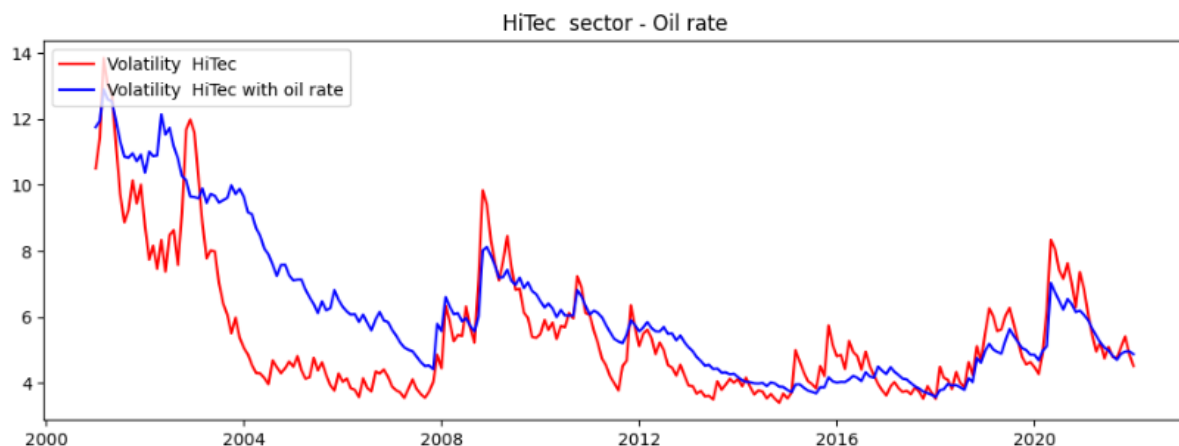
If we compare the volatility of the manufacturing sector returns with the volatility of the manufacturing returns with oil price rate, we can see that the volatility of the manufacturing returns with oil price rate almost perfectly follows the red line, suggesting that the oil price rate may have an impact on manufacturing returns.

In conclusion, while the GARCH model suggests that oil price volatility may not have a significant impact on the volatility of the manufacturing returns.

5.1.2.3 The effect of the oil price rate on the high-technology returns

The GARCH model shows that the volatility of the high-technology returns is significantly influenced by the past volatility of the sector, with a high beta coefficient of 0.8954. However, the omega coefficient of 0.8564 and alpha coefficient of 0.0742 are not statistically significant, suggesting that there is no persistent long-term trend or significant short-term changes in the sector volatility.

Comparing the volatility of the high-technology returns with the oil rate to the volatility of the high-technology returns alone, we find that the volatility of the sectors' returns with the

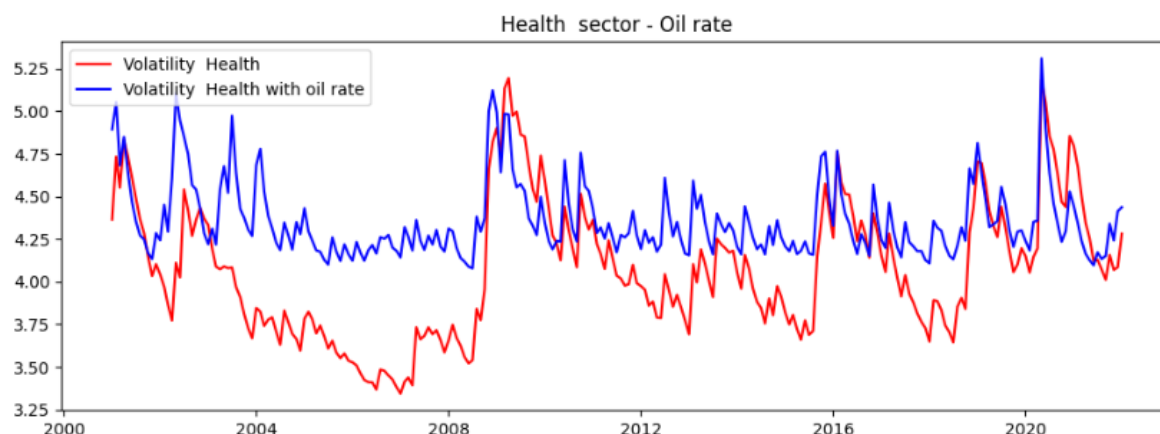


oil rate doesn't follow the red curve. This suggests that the volatility of the oil rate may not have an impact on the high-technology returns.

In conclusion, the GARCH model suggests that the volatility of oil rate may have a significant impact on the volatility of high-technology sector return.

5.1.2.4 The effect of the oil price rate on the healthcare returns

We have plotted the volatility of healthcare returns and the volatility of healthcare returns with oil price rate. We can see that the volatility of healthcare sector returns with oil price rate doesn't follow the red line, which suggests that the volatility of the oil price rate may have no impact on the volatility of the healthcare returns.

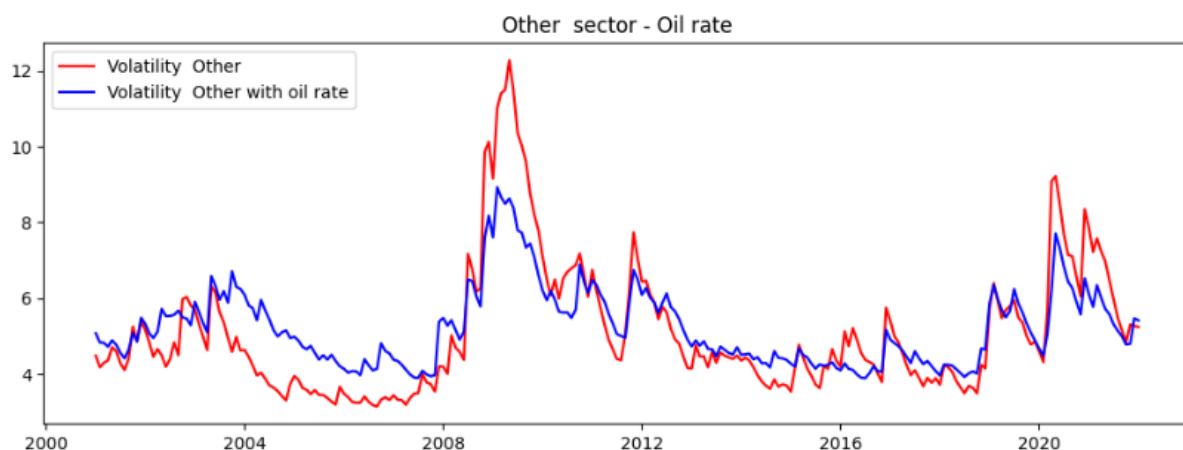


Meanwhile, the GARCH model results suggest a significant positive relationship between the volatility of the oil rate and the volatility of healthcare returns. Overall, our analysis suggests that the volatility of the oil price rate may have an impact on the volatility of healthcare returns.

5.1.2.5 The effect of the oil price rate on the other sector returns

The GARCH model results show that the volatility model's coefficients are all statistically significant except for omega. The alpha coefficient is positive and statistically significant at the 5% level, indicating that past squared errors have a positive effect on current volatility. The beta coefficient is also statistically significant at the 1% level, indicating that past volatility shocks have a positive effect on current volatility.

When we compare the volatility of other sector returns with and without oil price rate, we can see that the red line in the graph for the other sector return with oil price rate follow the red line for the other sector returns without oil price rate. This observation suggests that volatility of oil price rate may have an impact on the other sector's returns.



Therefore, based on the GARCH model and the comparison of volatility between the Other sector return with and without oil price rate, we can conclude that the volatility of the oil price rate may have a statistically significant impact on the other sector returns.

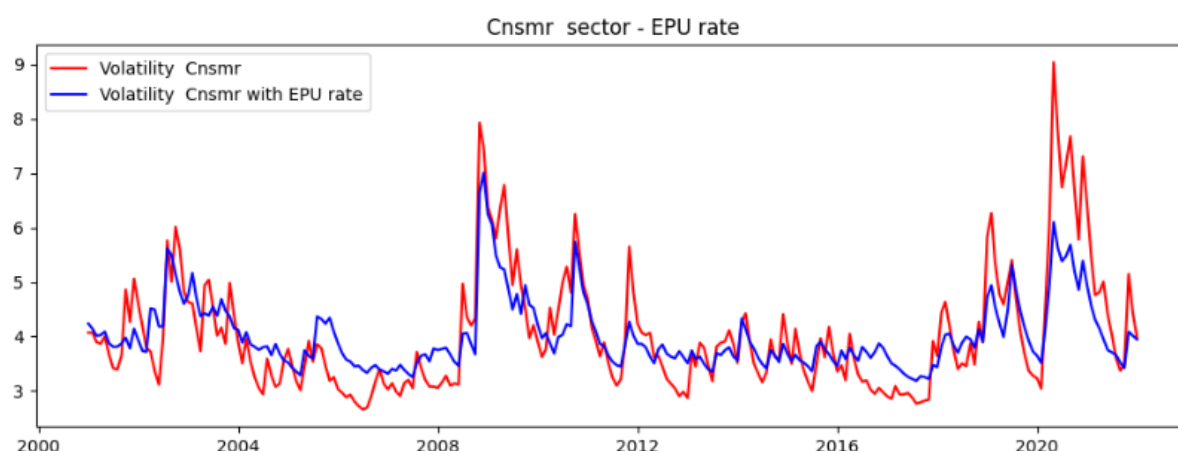
5.1.3 *The relationship between dependent variables and economic policy uncertainty*

In this section, the purpose is to find if there is a significative relation on the volatility between economic policy uncertainty rate and the dependent variables. To do that, we use a SARIMAX model. Then, we use a GARCH model to have an overview about the volatility. The GARCH model takes the residuals of the SARIMAX model to calculate the results. Each graph represents the conditional volatility of the dependent variables with EPU rate and the conditional volatility of each dependent variables.

5.1.3.1 The effect of the economic policy uncertainty on the consumer returns

Based on the GARCH model results, we can see that the coefficients of the omega, alpha, and beta parameters are significant at the 5% level. This indicates that the volatility of the consumer sector return is affected by its own past volatility, as well as the past volatility of the EPU rate.

By comparing the volatility of the consumer sector return with and without the EPU rate, we can see that the volatility of the consumer returns with the EPU rate follows the red line, indicating that the volatility of EPU rate may have an impact on the consumer returns.

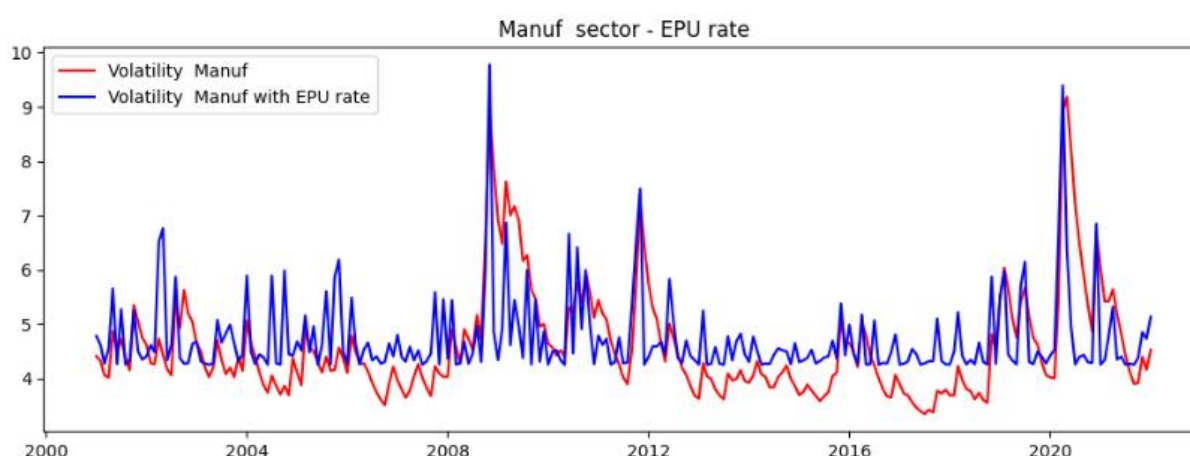


In conclusion, the analysis suggests that the volatility of EPU rate may have a significant impact on the consumer returns.

5.1.3.2 The effect of the economic policy uncertainty on the manufacturing returns

In the GARCH model, the coefficient of alpha is significant at the 5% level, but omega and beta are not significant.

Looking at the volatility plots, we can see that the volatility of the manufacturing returns with EPU rate does not follow the red line, indicating that there may be not significant impact of EPU rate on the manufacturing sector return.

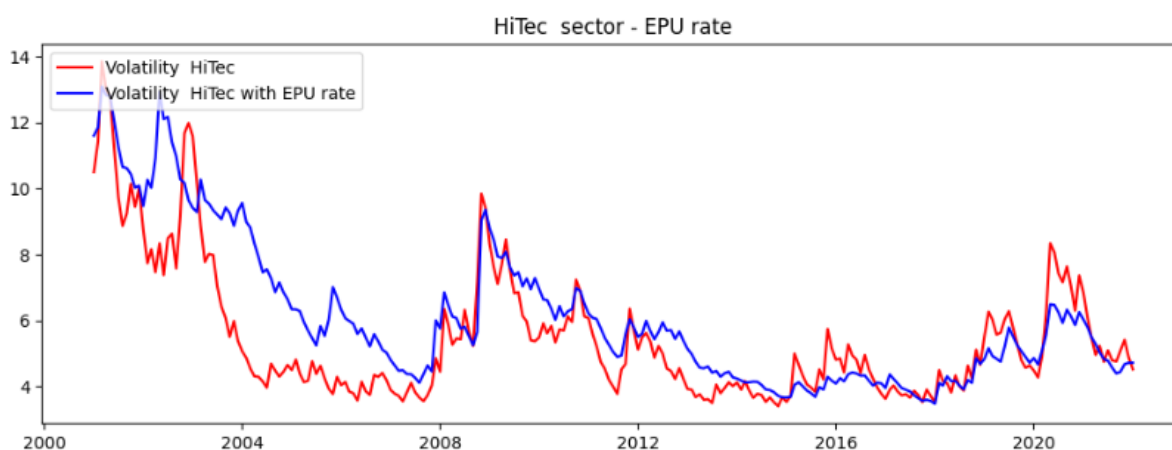


Overall, based on the results of the model and the volatility plots, we can conclude that the volatility of EPU rate may have not significant impact on the volatility of the manufacturing returns.

5.1.3.3 The effect of the economic policy uncertainty on the high-technology returns

Based on the results of the GARCH model, we can see that the alpha coefficient is not statistically significant at the 5% level (p-value of 0.259), while the beta coefficient is highly significant (p-value of 5.042e-23). This suggests that there is a strong and significant effect of past volatility on current volatility in the high-technology returns. .

Furthermore, when comparing the volatility of the high-technology sector return and the volatility of the high-technology sector return with EPU rate, we can see that the volatility of the high-technology returns with EPU rate almost follows the red line. This suggests that the volatility of EPU price rate may have an impact on the high-technology returns.

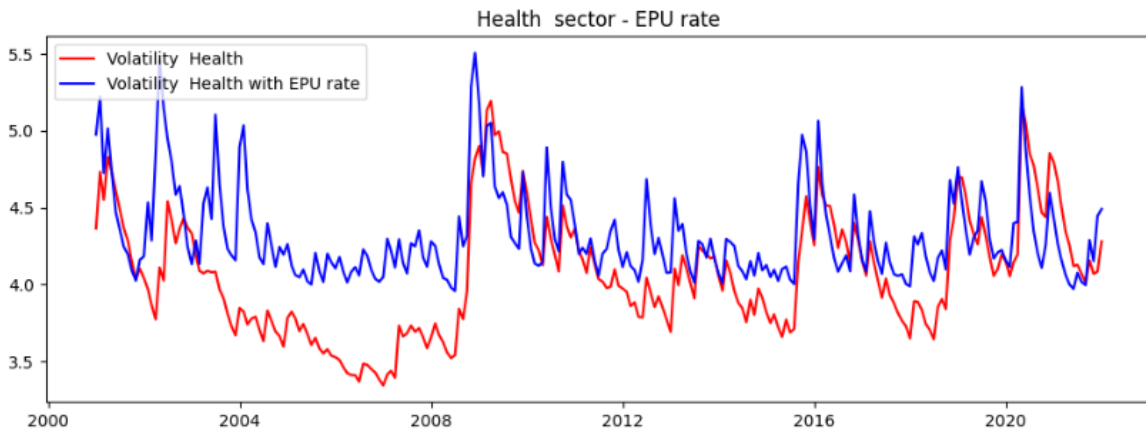


In conclusion, based on the results of the GARCH, the volatility of EPU price rate may have an impact on the high-technology returns.

5.1.3.4 The effect of the economic policy uncertainty on the healthcare returns

In the GARCH model, we can see that the alpha and beta coefficients are both positive, but only the beta coefficient is statistically significant at a 0.129 level. This suggests that there is some persistence in the volatility of the healthcare returns, but the impact of the EPU rate on this volatility is not clear.

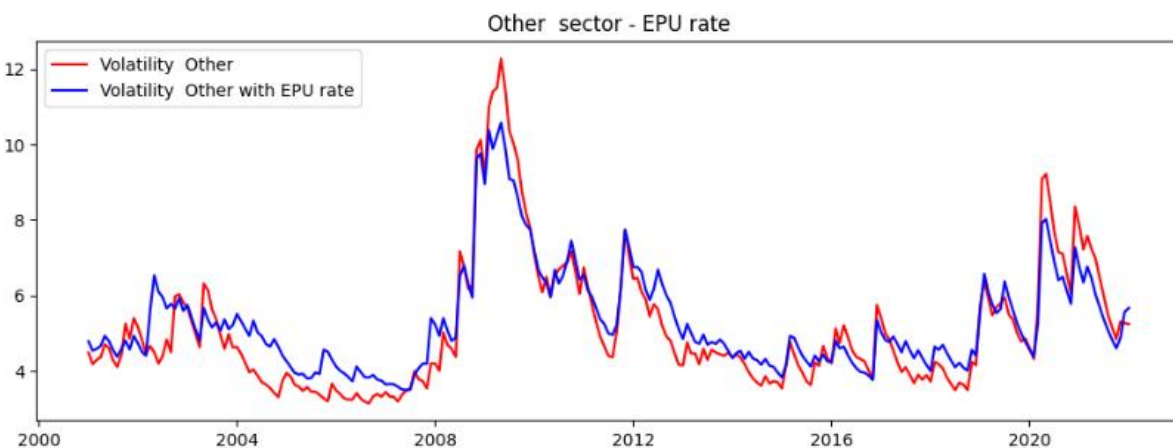
When we compare the volatility of the healthcare returns with and without the EPU rate, we can see that the volatility with the EPU rate does not follow the red line as closely as the volatility without the EPU rate. This suggests that the EPU rate may indeed have no impact on the healthcare returns.



Overall, while there is some evidence to suggest that the EPU rate has an impact on the healthcare sector return, the results are not entirely conclusive. The non-significant coefficient in the GARCH model suggest that there may be some uncertainty around this relationship. We will not use this relationship for the forecasting.

5.1.3.5 The effect of the economic policy uncertainty on the other sector returns

Based on the GARCH model, we can observe that the volatility model has a significant impact on the other sector's returns. The coefficients for the omega, alpha, and beta parameters have p-values of 0.122, 0.023, and $1.575e-40$, respectively. The coefficient for alpha suggests that past volatility has a positive effect on current volatility, whereas the coefficient for beta suggests that shocks to the variance are persistent.



The graph comparing the volatility of other sector returns and the volatility of other sector returns with EPU price rate shows that the volatility of the other sector returns with EPU

price rate almost follows the red line, indicating that the volatility of EPU price rate may have an impact on the volatility of other sector's returns.

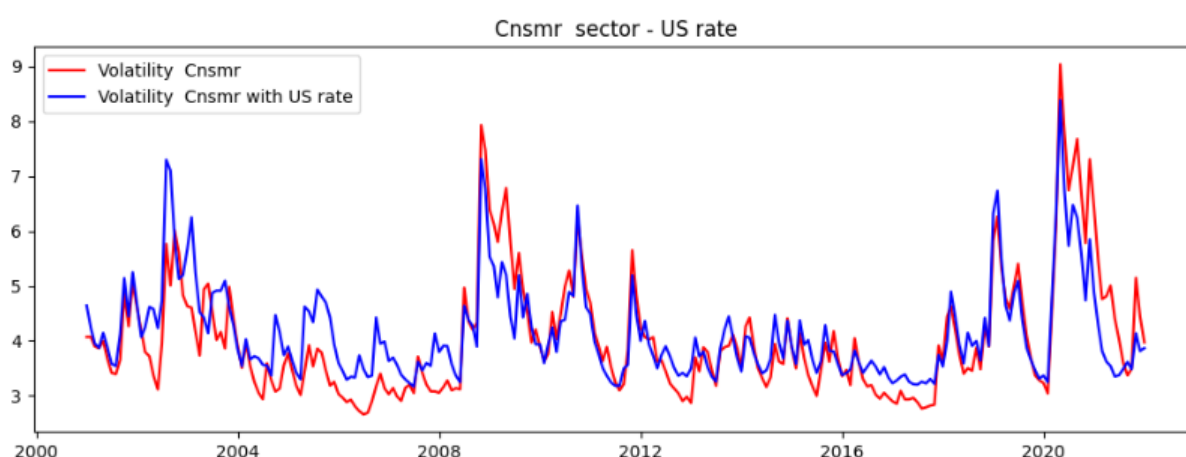
In conclusion, based on the results of the GARCH model, the EPU rate may have a significant impact on the volatility of other sector returns.

5.1.4 The relationship between dependent variables and EUR/USD rate

In this section, the purpose is to determine if there is a significative relationship on the volatility between the EUR/USD rate and the dependent variables. To do so, we use a SARIMAX model. Then, we use a GARCH model to have an overview about the volatility. The GARCH model takes the residuals of the SARIMAX model to calculate the results. Each graph represents the conditional volatility of the dependent variables with EUR/USD rate and the conditional volatility of each dependent variables.

5.1.4.1 The effect of the EUR/USD rate on the consumer returns

The GARCH model results suggest that the volatility of the consumer returns is influenced by its own past volatility as well as by past shocks to the system. The estimates for alpha and beta are both statistically significant, indicating that past shocks have a persistent effect on the volatility of the consumer sector return, and that the volatility tends to revert to its long-term average. The estimate for omega is also statistically significant, indicating that there is a constant level of volatility in the consumer returns that is not explained by past shocks.



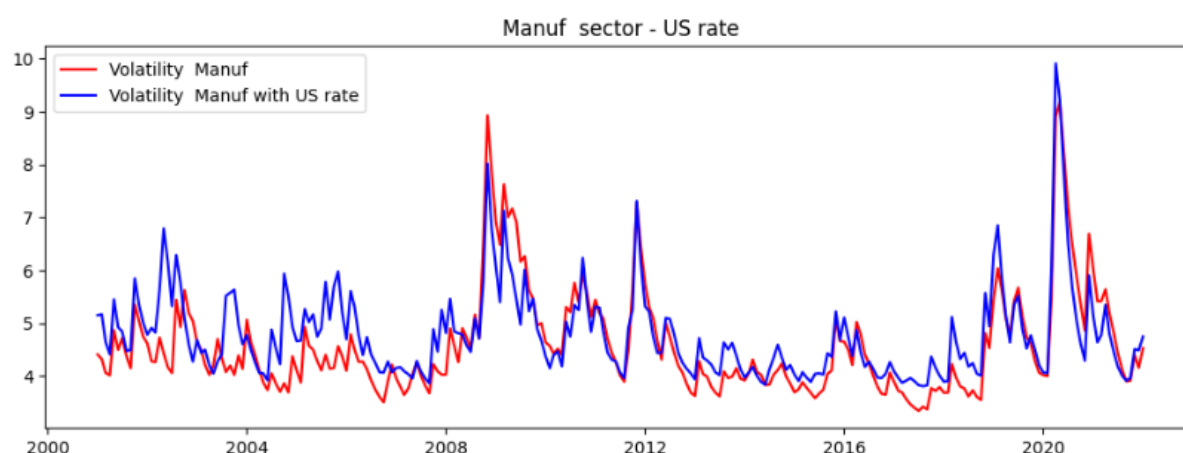
Comparing the volatility of the consumer returns with and without the EUR/USD rate, we can see that the volatility of the consumer returns with the EUR/USD rate follows the same

pattern as the red line, suggesting that the volatility of the EUR/USD rate may have an impact on the consumer returns.

In summary, our analysis suggests that GARCH model has been able to capture the behavior of the consumer sector return. The results show that changes the volatility of EUR/USD rate may have a significant impact on the volatility of the consumer returns.

5.1.4.2 The effect of the EUR/USD rate on the manufacturing returns

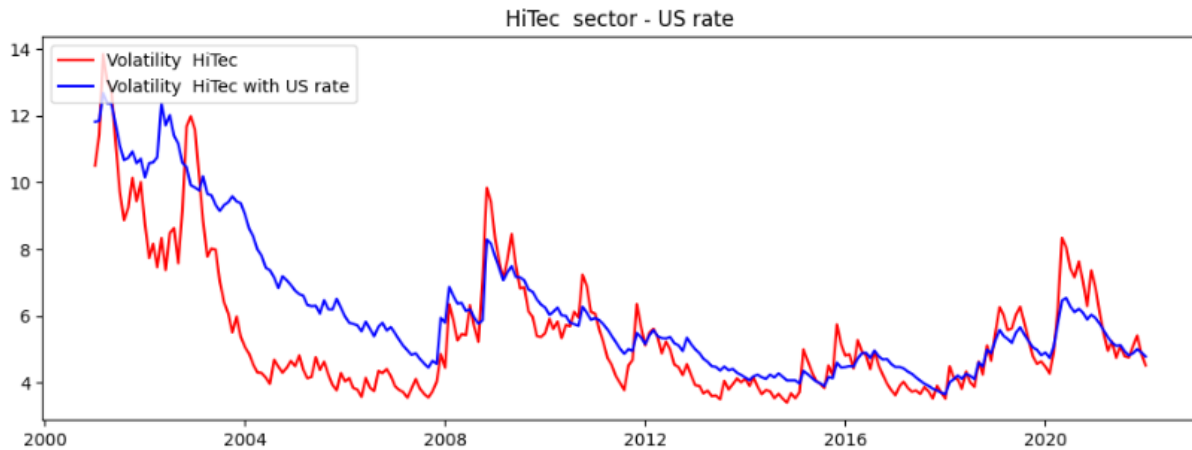
Comparing the results of the GARCH model, it seems that the GARCH model has more impact in predicting the volatility of the manufacturing returns. However, the GARCH model suggests that the alpha and beta coefficients are not statistically significant, while the omega coefficient is positive but not significant. Overall, the comparison between the volatility of manufacturing returns and the volatility of manufacturing sector return with EUR/USD rate shows that the volatility of EUR/USD rate may have an impact on the manufacturing returns.



We can conclude from the GARCH model that the volatility of the EUR/USD rate may have no impact on manufacturing returns.

5.1.4.3 The effect of the EUR/USD rate on the high-technology returns

GARCH model indicates that only the variance of the high-technology returns is significantly affected by the model's parameters. Comparing the volatility of the high-technology returns with and without EUR/USD rate, it appears that the volatility of the sector's return with the EUR/USD rate doesn't perfectly follow the red line, which suggests that the EUR/USD rate may have no an impact on the high-technology returns.

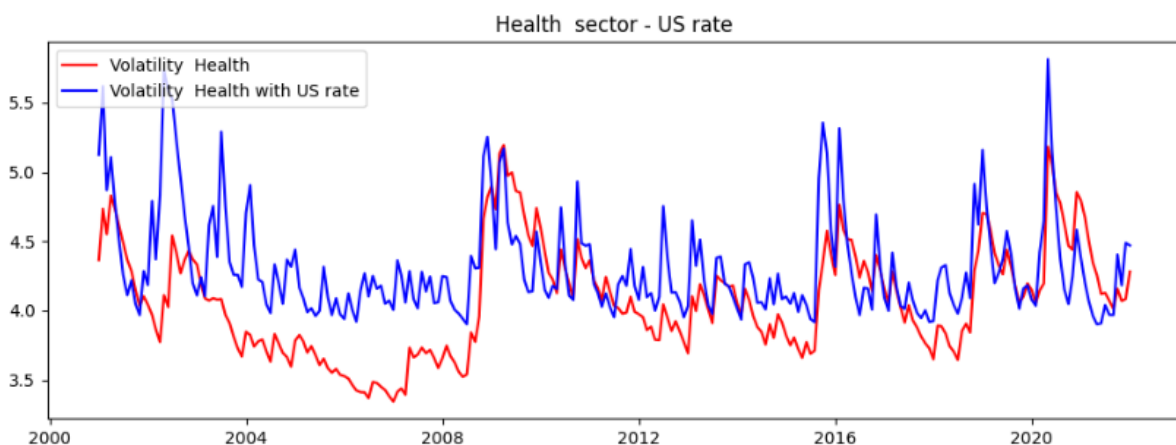


Therefore, we can conclude that the volatility of EUR/USD rate is not significant in our model, and it may not affect the high-technology returns.

5.1.4.4 The effect of the EUR/USD on the healthcare returns

The GARCH model indicates that the volatility of healthcare returns is affected by the EUR/USD rate, as the inclusion of the EUR/USD rate variable in the model improves its fit.

When comparing the volatility of healthcare returns with and without the EUR/USD rate, we observe that the volatility of healthcare returns with the EUR/USD rate does not follow exactly the expected pattern, indicating that the EUR/USD rate may have no impact on healthcare returns.



In conclusion, by considering the results of the GARCH model, We can see that the volatility of EUR/USD rate may have an impact on the volatility of healthcare returns.

5.1.4.5 The effect of the EUR/USD rate on the other sector returns

The GARCH model indicates that the coefficients for alpha and beta are significant, suggesting that the volatility of the data has an autoregressive and moving average component. Moreover, the volatility of other sectors' returns with the EUR/USD rate follows more or less the red line, indicating that the volatility of the EUR/USD rate may have an impact on other sectors' returns. Thus, the volatility of the EUR/USD rate is significant in our model and may have an impact on the volatility of other sectors' returns.



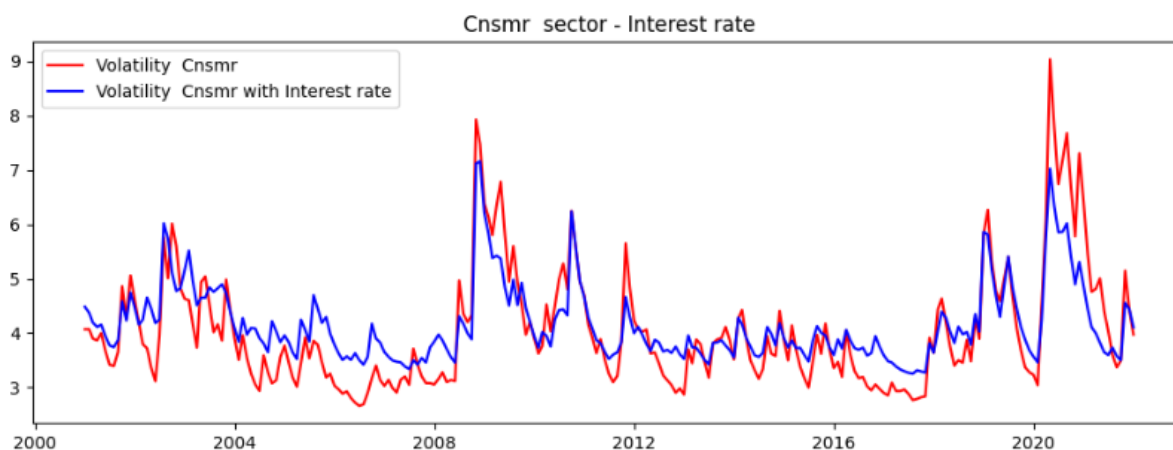
5.1.5 The relationship between dependent variables and interest rate

In this section, the purpose is to find whether there is a significative relationship on the volatility between interest rate and the dependent variables. To do that, we use a SARIMAX model. Then, we use a GARCH model to have an overview about the volatility. The GARCH model takes the residuals of the SARIMAX model to calculate the results. Each graph represents the conditional volatility of the dependent variables with interest rate and the conditional volatility of each dependent variables.

5.1.5.1 The effect of the interest rate on consumer returns

Based on the GARCH model results, we can see that the alpha coefficient, which represents the impact of past squared errors on current volatility, is statistically significant at the 5% level. This indicates that there is some persistence in the volatility of consumer sector returns. The beta coefficient, which represents the impact of past conditional variances on current volatility, is also statistically significant at the 5% level, suggesting that past volatility has an impact on current volatility.

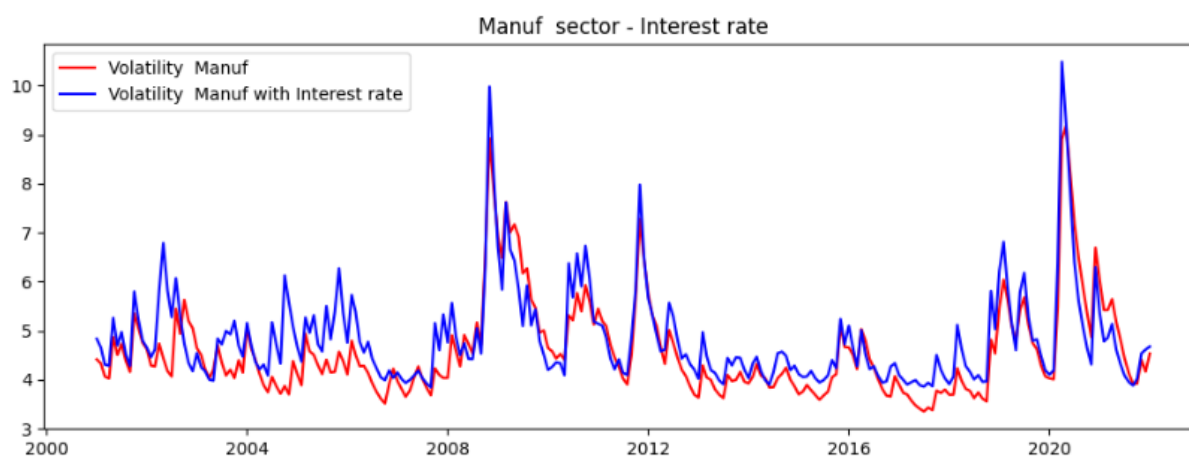
If we compare the volatility of consumer sector returns and the volatility of consumer sector returns with interest rate, we can see that the volatility of consumer sector returns with interest rate follows almost exactly the red line. This suggests that the volatility of the interest rate may have an impact on the volatility of consumer sector returns.



Overall, the GARCH model suggests that there is some persistence in the volatility of consumer returns. Therefore, it is possible that the interest rate may have an impact on the consumer returns.

5.1.5.2 The effect of the interest rate on the manufacturing returns

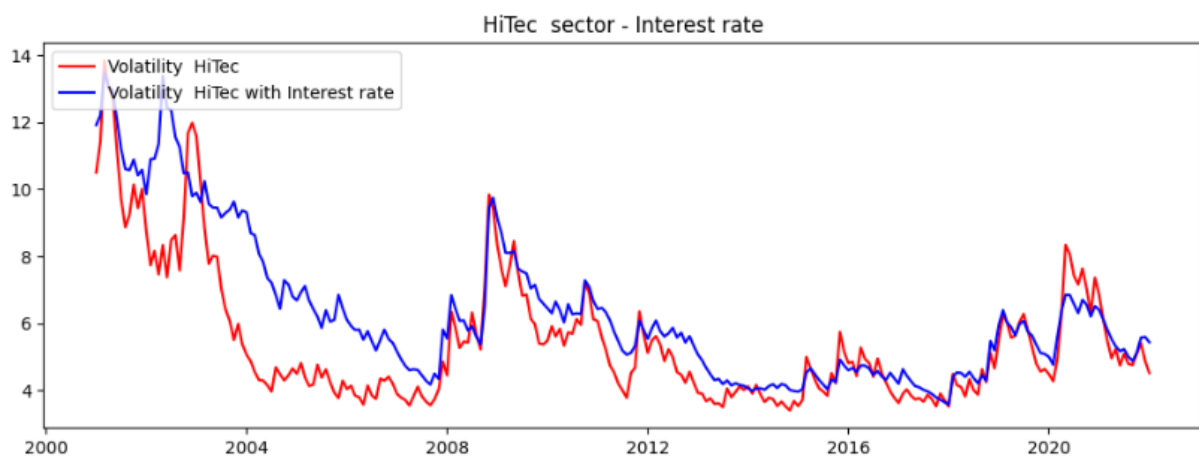
The GARCH model indicates that the coefficients for omega, alpha and beta are not significant. But the volatility of the manufacturing sector return with the interest rate follows the red line, indicating that the volatility of interest rate may have an impact on the volatility of manufacturing returns. Thus, the volatility of the interest rate is not significant in our model. So, the volatility of interest rate may not have an impact on the manufacturing returns.



5.1.5.3 The effect of the interest rate on the high-technology returns

After analyzing the curves of the volatility of high-technology returns and the interest rate, we can observe that the volatility of the high-technology sector returns with interest rate follows more or less the exact path of the red line, indicating that the volatility of interest rate may have an impact on the high-technology returns.

On the other hand, the GARCH model shows that the coefficients for the omega, alpha, and beta parameters are 1.3668, 0.1032, and 0.8552, respectively, and the p-values for these coefficients indicate that they are statistically significant at a significance level of 5%.



Based on these results, we can conclude that the volatility of interest rate may have an impact on the volatility of high-technology returns

5.1.5.4 The effect of the interest rate on the healthcare returns

After analyzing the curves of the volatility of healthcare returns and the interest rate, it can be observed that there is no correlation between them. The volatility of healthcare returns



with interest rate doesn't follow exactly the red line, which suggests that the volatility of interest rate may have an impact on the healthcare returns.

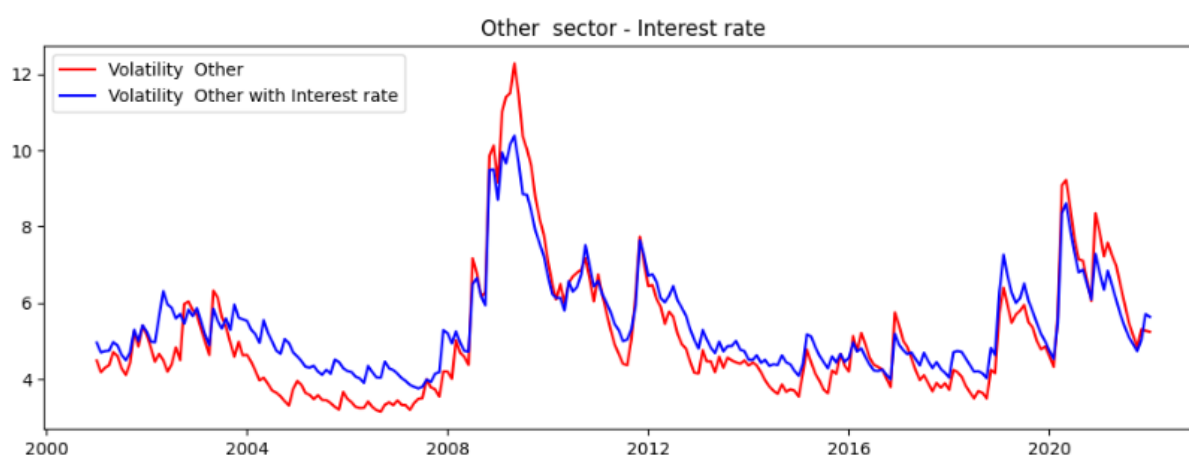
Furthermore, the GARCH model was used to model the volatility of the healthcare returns and found that the alpha and beta coefficients are positive and statistically significant. This suggests that there is a persistent effect of shocks to the healthcare sector return and that past volatility has a positive impact on current volatility.

In conclusion, the volatility of interest rate may have a significant impact on the healthcare returns.

5.1.5.5 The effect of the interest rate on the other sector returns

On the other hand, the GARCH model results suggest that the interest rate has a significant impact on the volatility of the other sector return. The coefficients for alpha and beta are statistically significant at the 5% level ($P < |t| = 0.036$ and $P < |t| = 2.559e-21$, respectively), indicating that past volatility and past shocks have a persistent effect on the current volatility of the other sector return.

When comparing the volatility of the other sector returns with the interest rate to the volatility of the other sector returns without the interest rate, we can observe that the former follows almost the red line, suggesting that the volatility of interest rate may have an impact on the volatility of other sector returns.



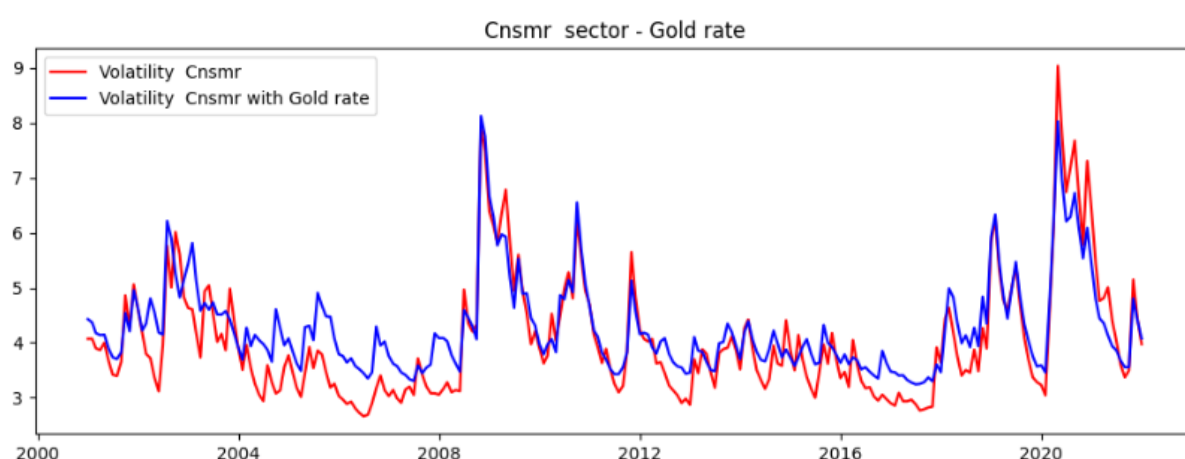
Therefore, based on the GARCH model and the comparison of the volatility curves, we can conclude that the volatility of interest rate may have a significant impact on the volatility of other sectors' returns.

5.1.6 The relationship between dependent variables and gold price rate

In this section, the purpose is to find if there is a significative relationship on volatility between gold price rate and the dependent variables. To do that, we use a SARIMAX model. Then, we use a GARCH model to have an overview about the volatility. The GARCH model takes the residuals of the SARIMAX model to calculate the results. Each graph represents the conditional volatility of the dependent variables with interest rate and the conditional volatility of each dependent variables.

5.1.6.1 The effect of the gold price rate on the consumer returns

Regarding the GARCH model, the coefficients of omega, alpha and beta are all significant at the 10% level, indicating that the model is well specified. The estimated coefficient for alpha is positive, meaning that past squared error terms have a positive effect on future volatility, while the estimated coefficient for beta is positive, indicating that past conditional variances have a positive effect on future conditional variances. The GARCH model has also helped us to capture the volatility clustering effect that is typical of financial time series.



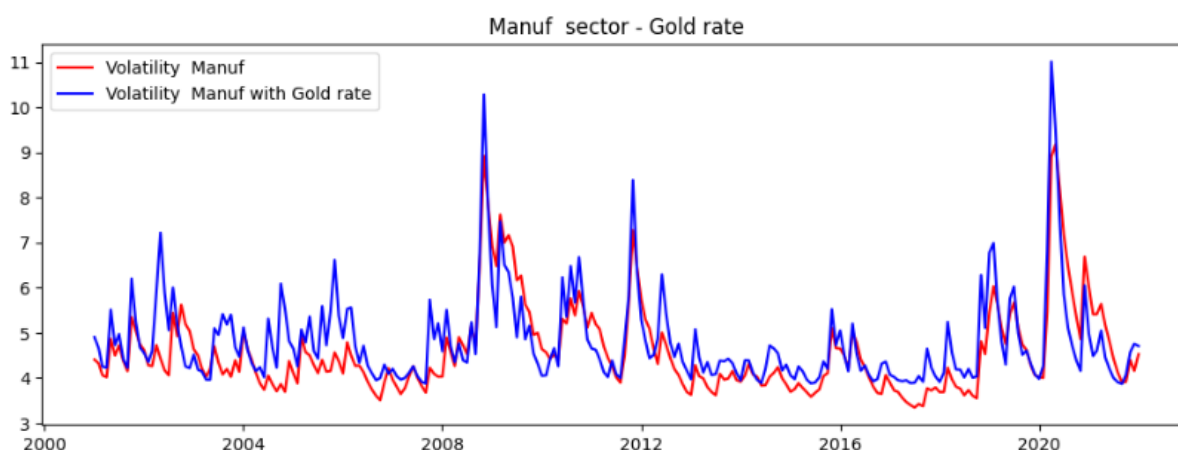
Regarding the volatility of consumer returns with gold rate, we can see that it follows almost exactly the red line, indicating that the volatility of the gold rate may have an impact on

the consumer returns. This is further supported by the GARCH model results, which suggest that past volatility and past squared errors may have a positive effect on future volatility, indicating the presence of volatility clustering.

Overall, we can conclude that the gold price rate may have a significant impact on the consumer returns.

5.1.6.2 The effect of the gold price rate on manufacturing returns

The GARCH model results show that the variance of the manufacturing sector's return is influenced by its past values, as well as by the lagged values of the squared residuals. The coefficients of the GARCH model suggest that the current variance of the manufacturing sector's return is positively influenced by the past variance and the past squared residuals. The alpha coefficient is also significant, indicating that the model has detected some volatility clustering in manufacturing returns, but beta is not significant.



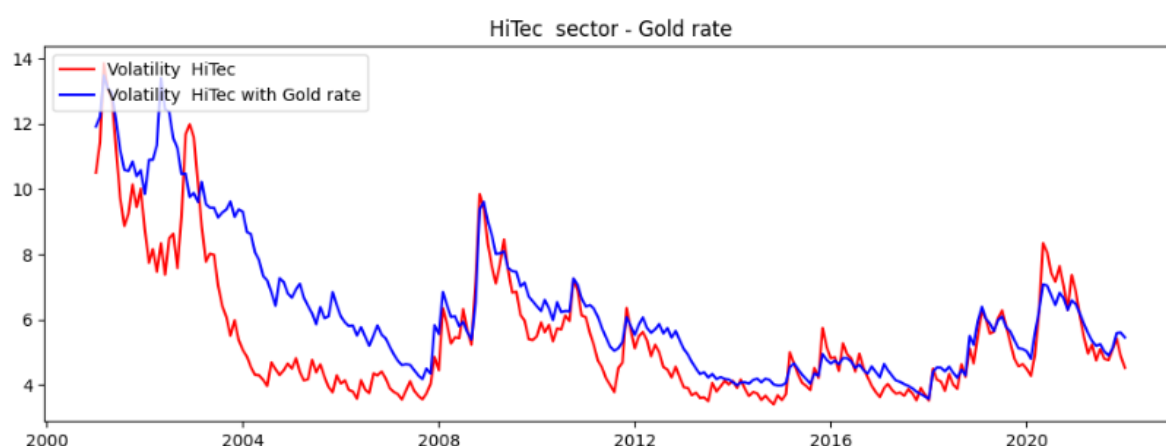
The findings suggest that the manufacturing sector's return is influenced by its past values and the lagged values of the squared residuals, indicating that volatility clustering is present. However, the impact of the volatility of gold rate on the volatility of the manufacturing returns may not be statistically significant. Therefore, it may not be accurate to conclude that the gold rate may have significant impact on the manufacturing returns based on these results.

5.1.6.3 The effect of the gold price rate on the high-technology returns

The results of the GARCH model suggest that the volatility of the high-technology returns is affected by past volatility and shocks to the system. The coefficient for the alpha parameter, which measures the impact of past volatility on current volatility, is positive but not statistically significant (p-value of 0.195), while the coefficient for the beta parameter, which

measures the impact of shocks to the system on current volatility, is also positive and statistically significant (p-value of $6.473e-22$). Additionally, the omega parameter, which measures the constant level of volatility, is positive but not statistically significant (p-value of 0.168).

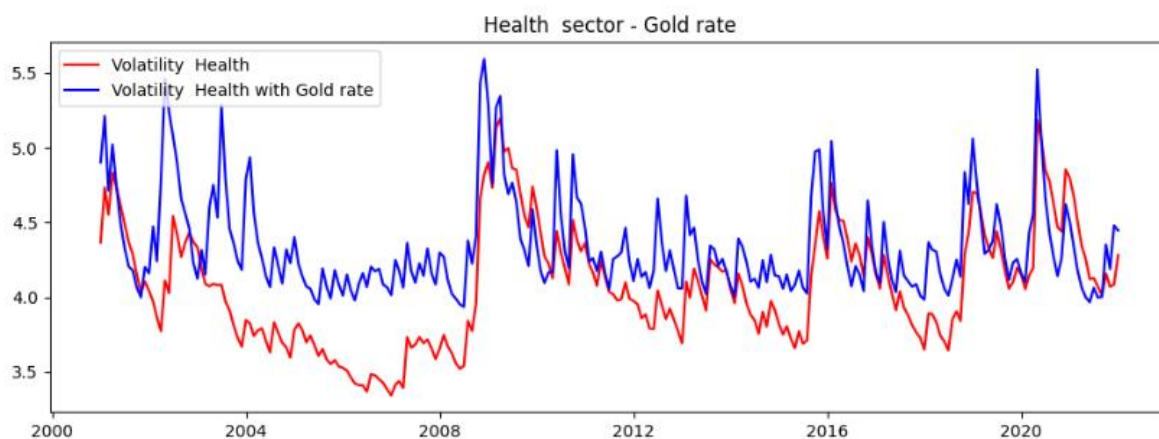
When comparing the volatility of the high-technology returns with the gold price rate to the volatility of the high-technology returns without the gold price rate, we can observe that the former follows almost the red line, suggesting that the volatility of gold price rate may have an impact on the volatility of high-technology returns.



Overall, the findings suggest that while the volatility of gold price rate may not have a direct impact on the returns of high-technology returns.

5.1.6.4 The effect of the gold price rate on the healthcare returns

The GARCH model suggests that the volatility of the gold price rate may not have an impact on the healthcare sector, with a not significant coefficient for the beta parameter (0.5902,



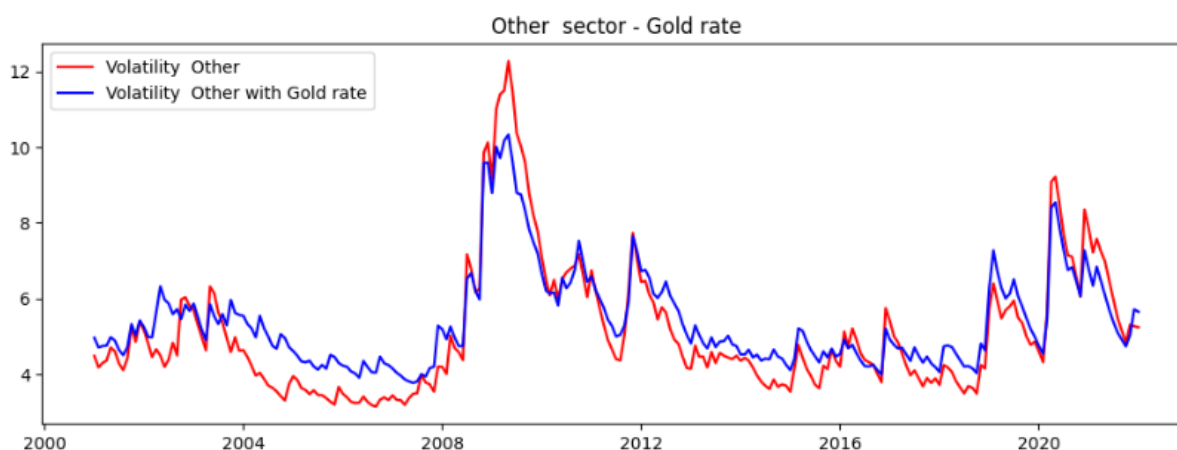
$p < 0.05$). The model also estimates an omega parameter of 6.1592, indicating that there is some volatility in the healthcare sector that cannot be explained by the volatility of gold price rate alone.

When comparing the volatility of the healthcare returns with the gold price rate to the volatility of the healthcare returns without the gold price rate, we can observe that the former doesn't follow the red line, suggesting that the volatility of gold price rate may have an impact on the volatility of the healthcare returns.

In conclusion, the findings from the GARCH model provide evidence that the volatility of gold price rate may have no significant impact on the healthcare returns.

5.1.6.5 The effect of the gold price rate on the other sector returns

The GARCH model results indicate that the volatility of gold rate variable has a significant impact on the volatility of the other sector return. The coefficients of both the alpha and beta terms are statistically significant, indicating that the past squared errors and past volatility have a significant impact on the current volatility. Additionally, the omega coefficient, which represents the constant term in the volatility equation, is positive but not statistically significant at the conventional 0.05 level.



When comparing the volatility of the healthcare returns with the gold price rate to the volatility of the other sector returns without the gold price rate, we can observe that the former follows the red line, suggesting that the volatility of gold price rate may have an impact on the volatility of the other sector returns.

In conclusion, GARCH model indicates that the volatility of gold price may have a significant impact on the volatility of the other sector returns.

5.3 Forecast on the dependent variables by integrating the relevant explicative variables.

The forecast has been made using the RNN model. The relevant macro-economic indicators have been added to the forecast for each different sector. The prediction was made from January 2023 to December 2025.

5.3.1 Forecast of the consumer returns

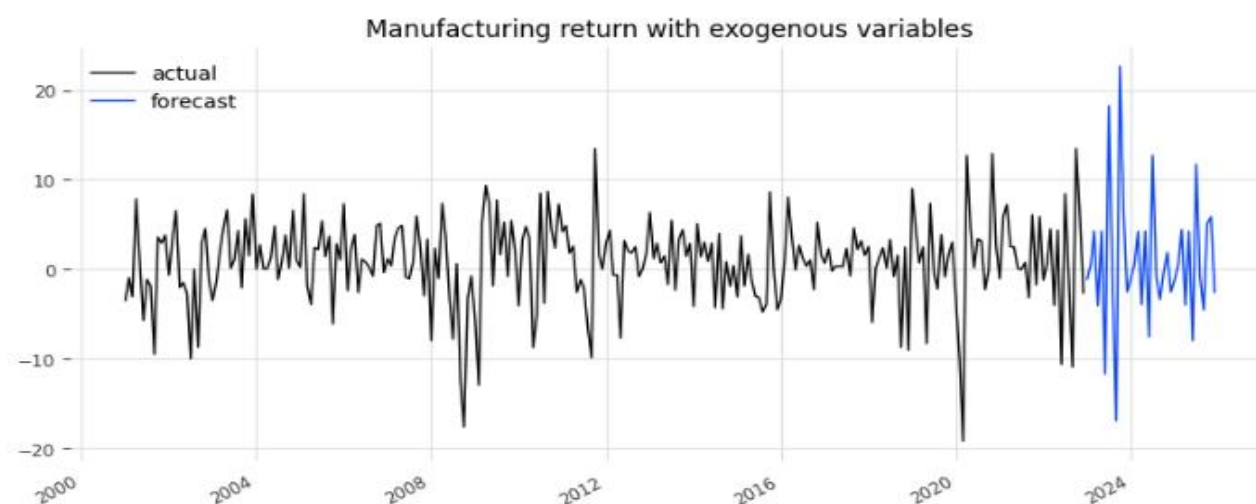
Our analysis has shown that the volatility of the inflation rate, the oil price rate, the rate of economic policy uncertainty, the EUR/USD rate, the interest rate, and the gold price rate are relevant to predict the return of consumer sector between January 2023 to December 2025.



We can see that when we add all these indicators to the model, the prediction for the return between January 2023 and December 2025 is very volatile until 2024. After 2024, the returns look stable for the consumer sector.

5.3.2 Forecast of the manufacturing returns

Through our analysis, we saw that the volatility of inflation, oil price, economic policy uncertainty, EUR/USD, the interest rate, and the gold price are not relevant to predict the return of the manufacturing sector between January 2023 to December 2025.



We can see that by adding no indicators to the model, the prediction for the return between January 2023 and December 2025 is very volatile until 2025. It seems that the year of 2024 for the manufacturing sector will have a negative return according to our prediction.

5.3.3 Forecast of the high-technology sector

Through our analysis, we have seen that the volatility of inflation, the oil price, economic policy uncertainty and the interest rate, are relevant to predict the return of the high

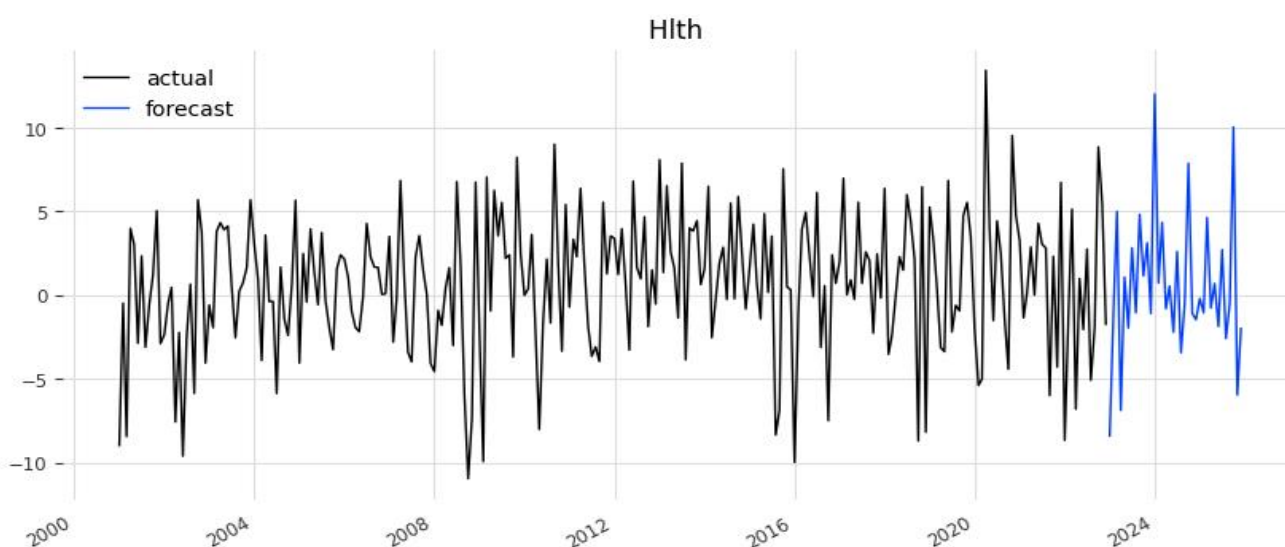


technology sector between January 2023 and December 2025. Unfortunately, the volatility of the EUR/USD rate and the gold price rate are not significant to predict the return of high-technology sector.

We can see that when we add all these indicators to the model, the return prediction between January 2023 and December 2025 is very volatile until 2025. It seems that the year 2025 for the high-technology sector will have a positive return according to our prediction.

5.3.4 Forecast of the healthcare sector

Through our analysis, we have seen that the volatility of oil price rate, the EUR/USD rate and the interest rate are relevant to predict the return of the healthcare sector between January 2023 and December 2025. The volatility of the inflation rate, the rate of economic policy uncertainty and the rate of the gold price rate are not added to the model prediction as they are not relevant for the healthcare sector.



We can see that when we add all these indicators to the model, the prediction for the return between January 2023 and December 2025 is very volatile until 2025. The returns increase and decrease during all the predicted periods.

5.3.5 Forecast of the other sector

Through our analysis, we have seen that inflation volatility, oil price, economic policy uncertainty, EUR/USD, interest rate, and gold price are relevant to predict the return of the other sector between January 2023 and December 2025.



We can see that when we add all these indicators to the model, the prediction for the return between January 2023 and December 2025 is very volatile until 2025. Returns increase and decrease in all the predicted periods.

6. Conclusion

The conclusion of this research is that the volatility of macroeconomic indicators has a real impact on the returns of certain economic sectors. These findings suggest that investors should pay particular attention to fluctuations in these macroeconomic indicators when making investment decisions related to these sectors.

We found that consumer sector returns are impacted by the volatility of the inflation rate, the oil price rate, the rate of economic policy uncertainty, the gold price rate and finally by the volatility of the interest rate. The significance of this indicator in relation to consumer returns can be explained by the fact that the consumer sector is highly sensitive to changes in commodity prices and that gold is often considered a safe haven asset in times of economic uncertainty. Therefore, changes in the gold price rate may signal changes in the overall economic environment, leading to changes in consumer sector returns.

In the manufacturing sector, we have seen some shocking results. None of the macro-financial indicators are relevant to the impact of returns in this sector. Based on what we know, the volatility of the inflation rate, the interest rate and the EUR/USD rate should normally have an impact on manufacturing returns. Inflation can impact production costs, which can lead to an increase in the cost of manufacturing goods. This increase in costs can lead to a decrease in demand for goods, which can have a negative impact on manufacturing returns. In addition, when interest rates rise, the cost of borrowing increases, which can lead to a decrease in business investment and consumer spending. This can lead lower demand for manufactured goods, which can have a negative impact on manufacturing returns. Finally, the EUR/USD is likely to be significant as many manufacturing companies operate in several countries and rely on international trade. Changes in exchange rates can impact the cost of importing raw materials or exporting finished goods, which can affect the profitability of the manufacturing sector. We have based our analysis on the results of our model, although the results are not satisfactory.

Then, we found that high-technology sector returns are impacted by the volatility of the inflation rate, the oil price rate, the rate of economic policy uncertainty and finally by the volatility of the interest rate. The volatility of the EUR/USD rate and the gold rate are not significant on the returns of the high-technology sector. This can be explained by the fact that the high-technology sector is often global in nature, meaning that companies in this sector have

operations and sales in several countries. This international exposure can help mitigate the impact of exchange rate fluctuations on their returns. While fluctuations in the EUR/USD rate may affect the value of their foreign exchange contracts, the overall impact may be limited due to the ability of companies to hedge against currency risk.

In terms of healthcare sector performance, we found that volatility in oil prices rate, the EUR/USD rate and interest rates have an impact on the return of healthcare sector. The volatility of inflation rate, economic policy uncertainty rate and gold price rate are not significant for the return of healthcare sector. This could be explained by the fact that the healthcare sector is a defensive sector, which means that it is less affected by economic cycles and market fluctuations. Therefore, factors such as the inflation rate, the level of economic policy uncertainty and the price of gold, which are more sensitive to market fluctuations, may not have a significant impact on the healthcare sector's returns.

On the other hand, the healthcare sector is highly dependent on oil, which is used in various medical products such as pharmaceuticals and medical devices. Therefore, the volatility of oil price rate can have an impact on the returns of the healthcare sector. Additionally, the healthcare sector is often subject to international trade and cross-border transactions, which makes it more sensitive to exchange rate fluctuations such as the EUR/USD rate. Finally, the healthcare sector is also affected by interest rate movements, as changes in interest rates can affect the cost of borrowing for healthcare companies and influence their investment decisions.

Finally, we found that the return of other sector is affected by the volatility of the volatility of inflation rate, the oil price rate, the economic policy uncertainty rate, the EUR/USD rate, the interest rate, and the gold price rate. The return of the other sectors includes all sectors except the consumer sector, the manufacturing sector, the high-technology sector, and the healthcare sector. This could be due to the diversity of industries and companies that make up this sector. Volatility in inflation, oil prices, economic policy uncertainty, the EUR/USD rate, interest rates, and the price of gold can all affect the various companies in this sector differently, leading to an overall impact on the sector's returns. In addition, the "other" sector may include companies that are particularly sensitive to changes in multiple macroeconomic factors, which may further explain why a wide range of indicators have an impact on returns of this sector.

To conclude this research, we are aware that the predictions that have been made are only predictions and that other economic factors than those used may change them. Furthermore, we

have selected only 6 macroeconomic indicators that we believe are the most best-known and most relevant to our research, but we are aware that there are others that could also have an impact on our results. Finally, the model we used is used to model volatility, but it sometimes gave us results that were not significant when they should normally have been. We have applied the results of the model to the letter for the sake of consistency.

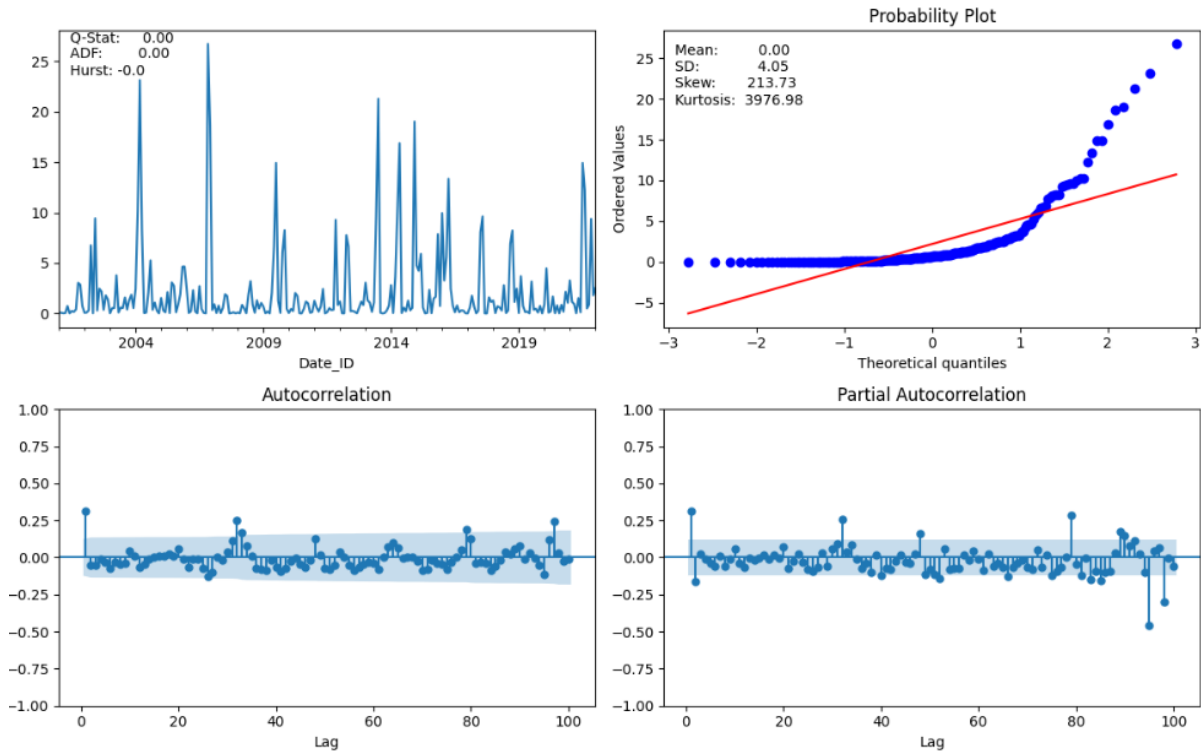
7. Annexes

7.1 Dependent and Independent Variables (Graphs)

7.1.1 Correlogram of dependent variables

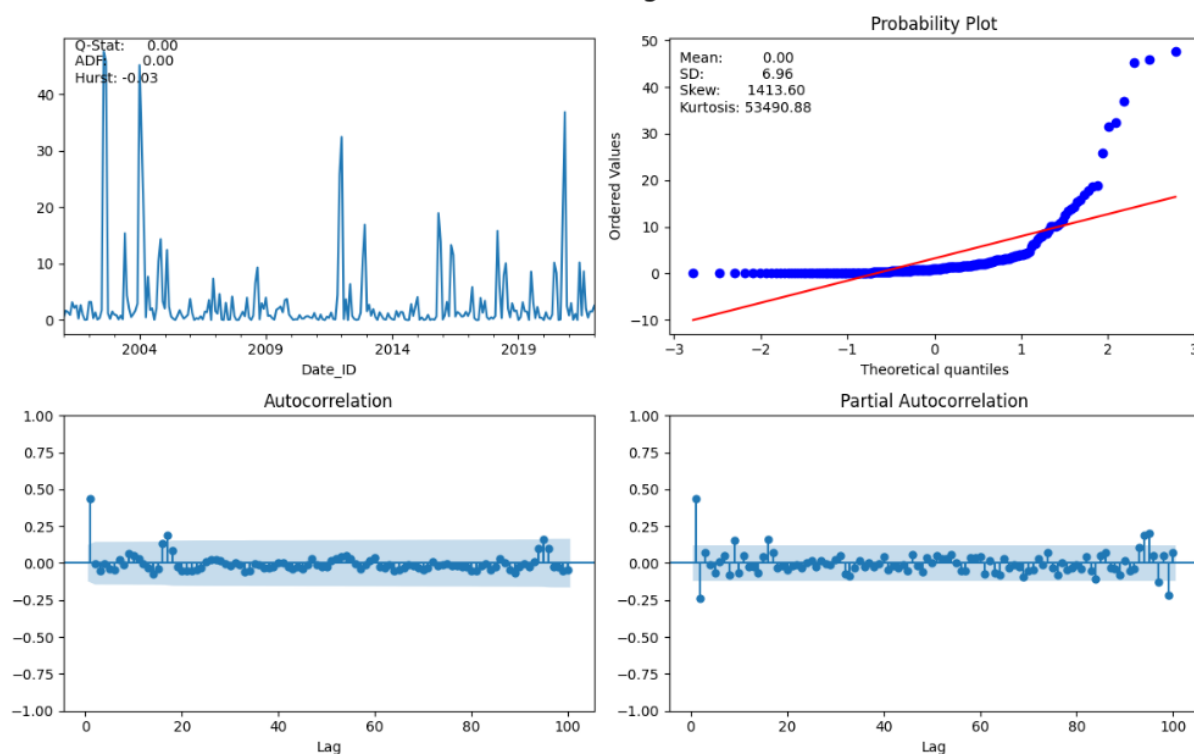
7.1.1.1 Consumer sector

Consumer sector



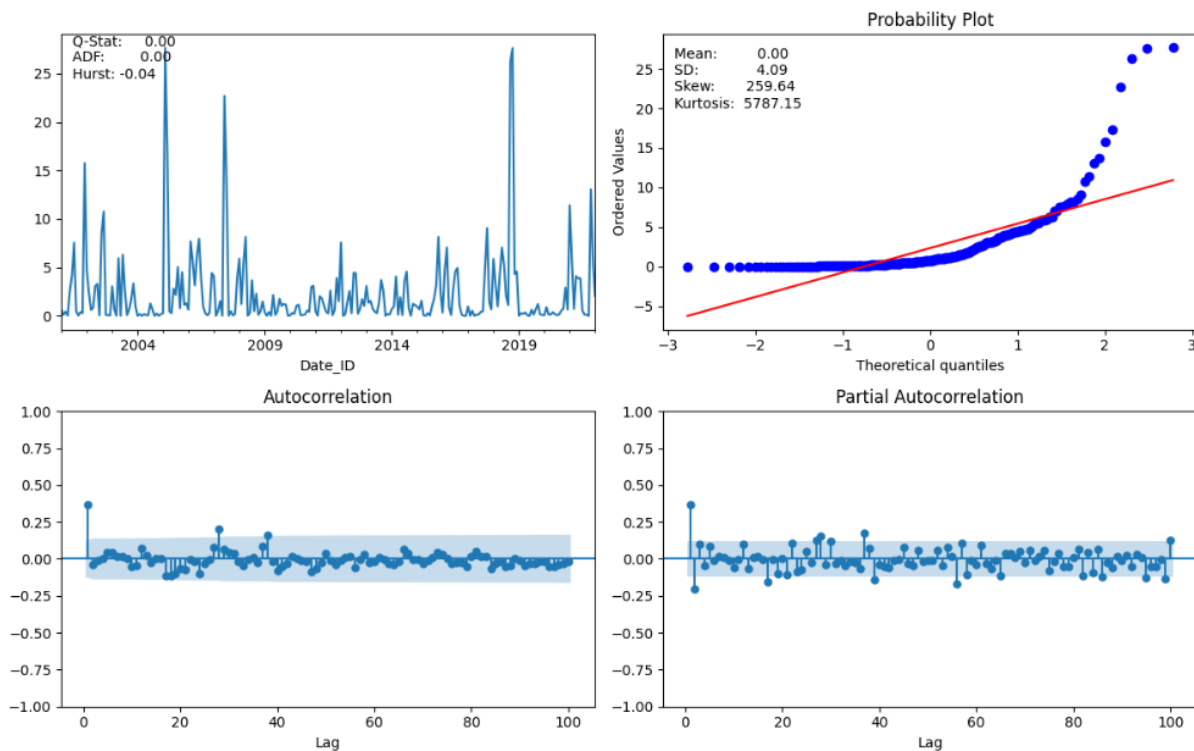
7.1.1.2 Manufacturing sector

Manufacturing sector



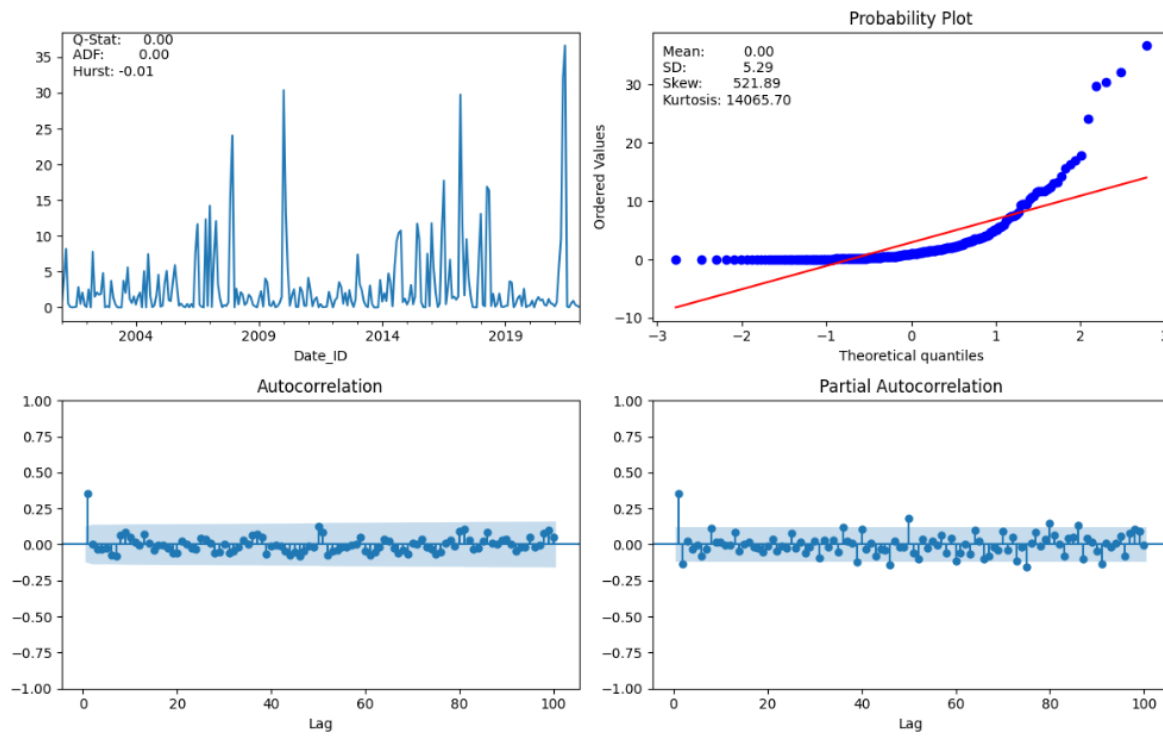
7.1.1.3 High-technology sector

High Technology sector



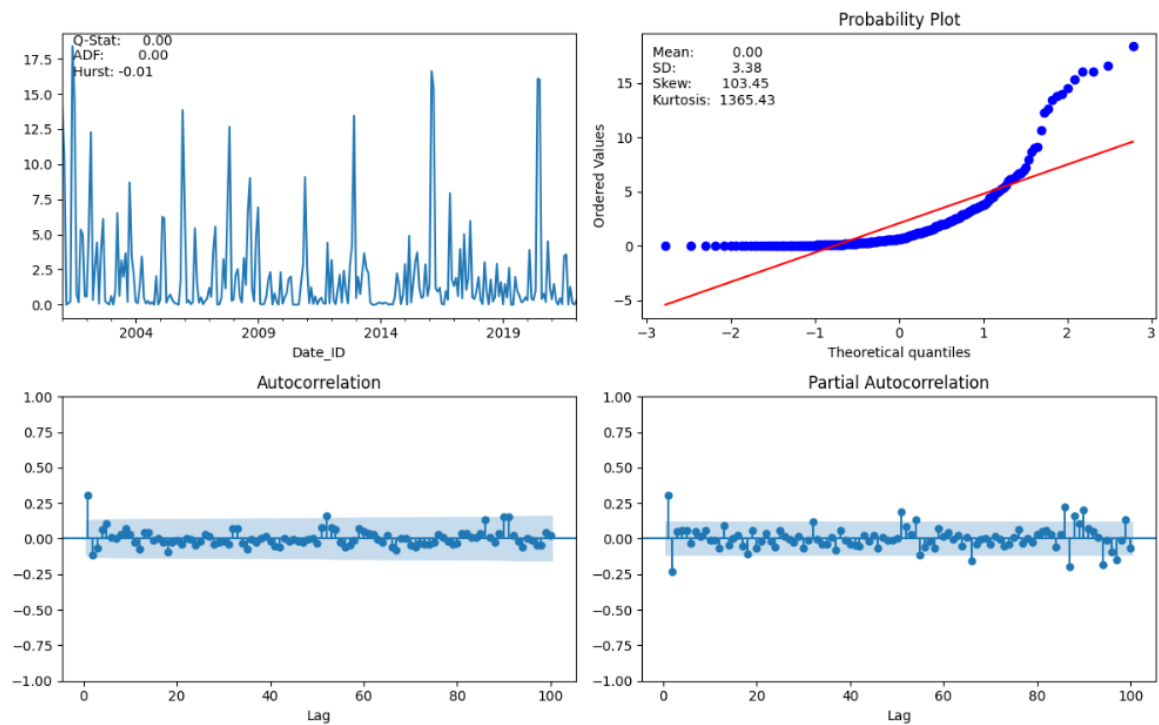
7.1.1.4 Healthcare sector

Healthcare sector



7.1.1.5 Other sector

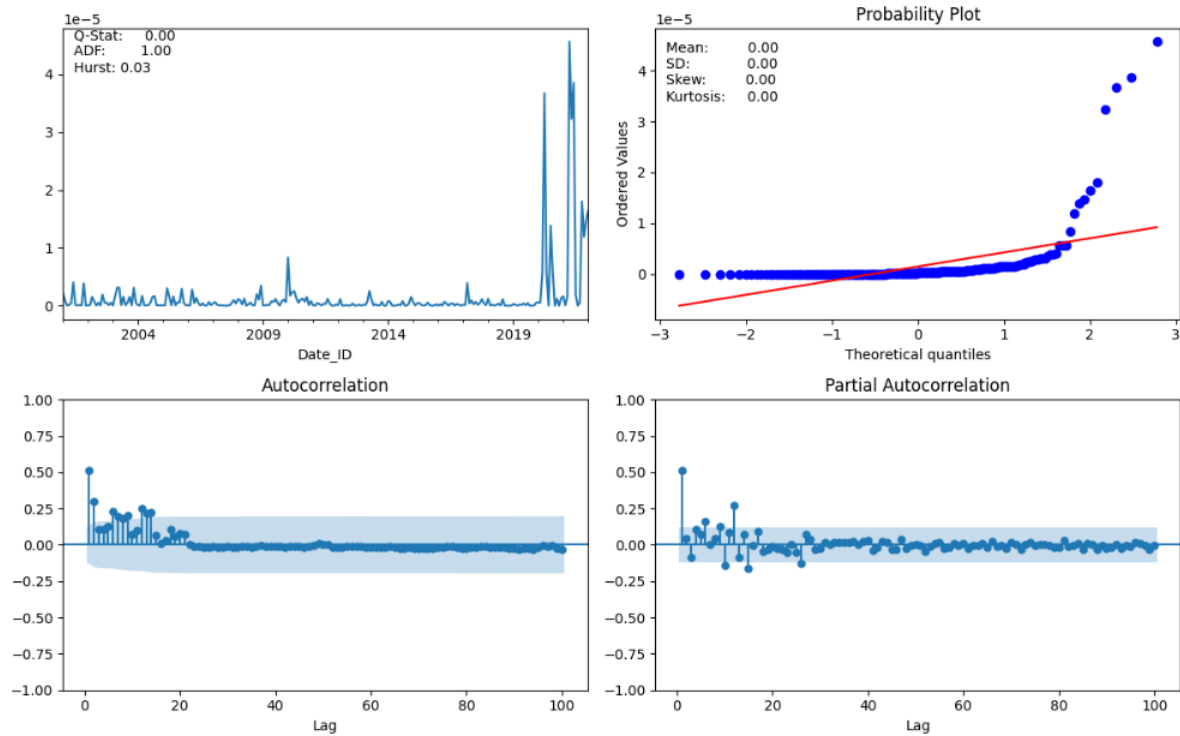
Other sector



7.1.2 Correlogram of independent variables

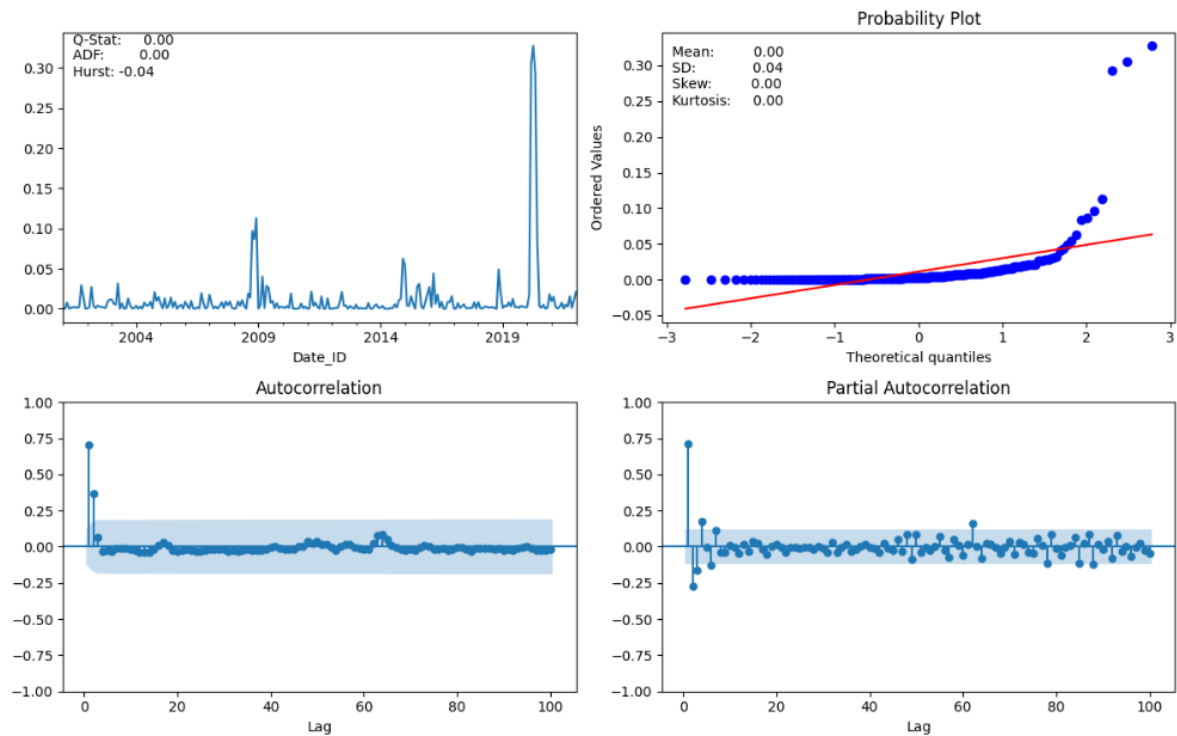
7.1.2.1 Inflation rate

Inflation



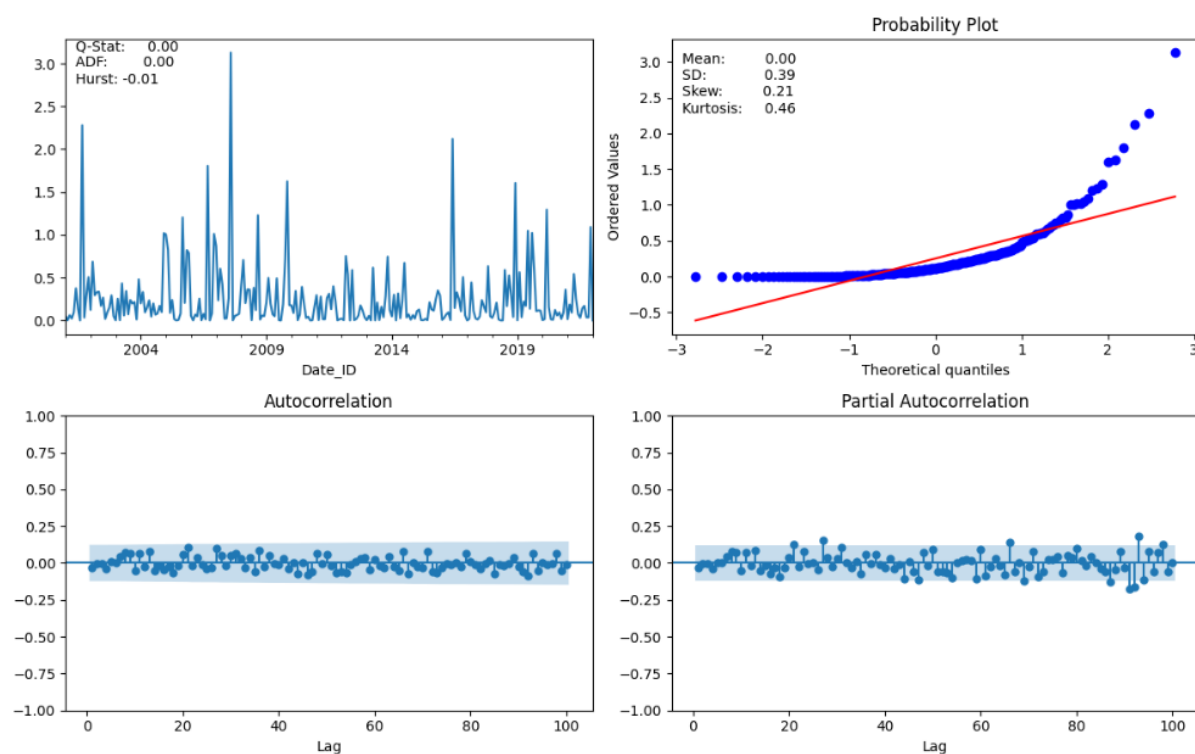
7.1.2.2 Oil rate

Oil rate



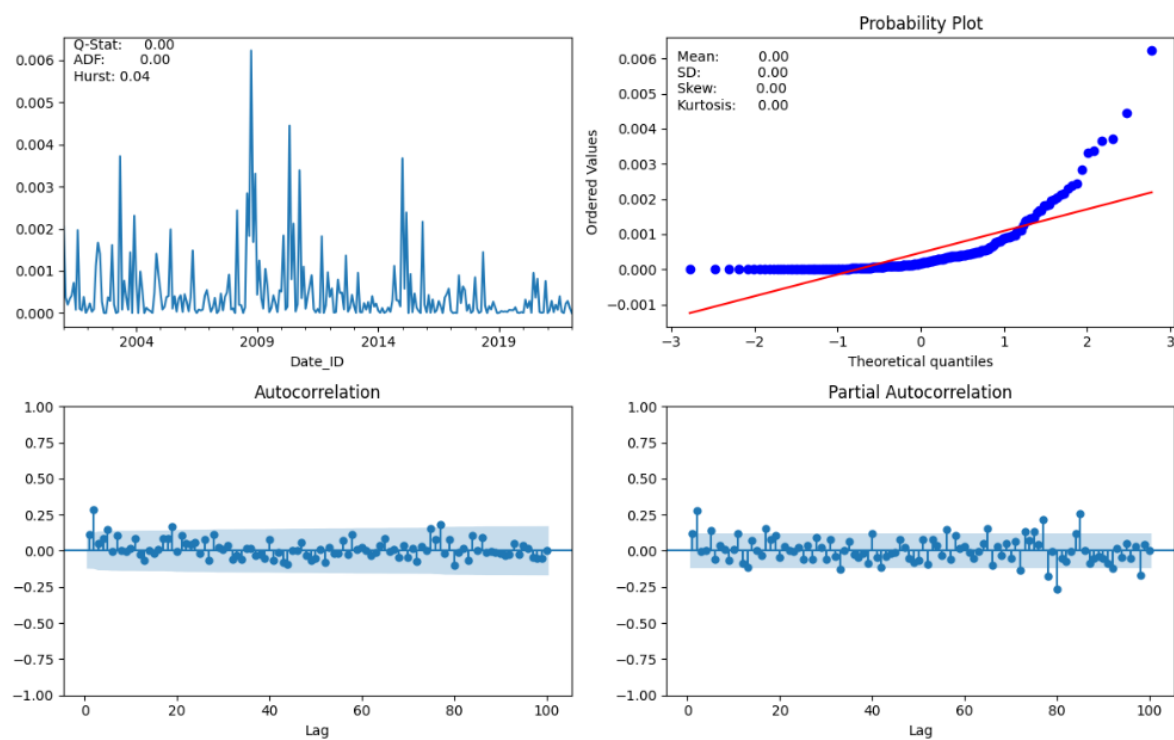
7.1.2.3 Economy policy uncertainty rate

EPU rate



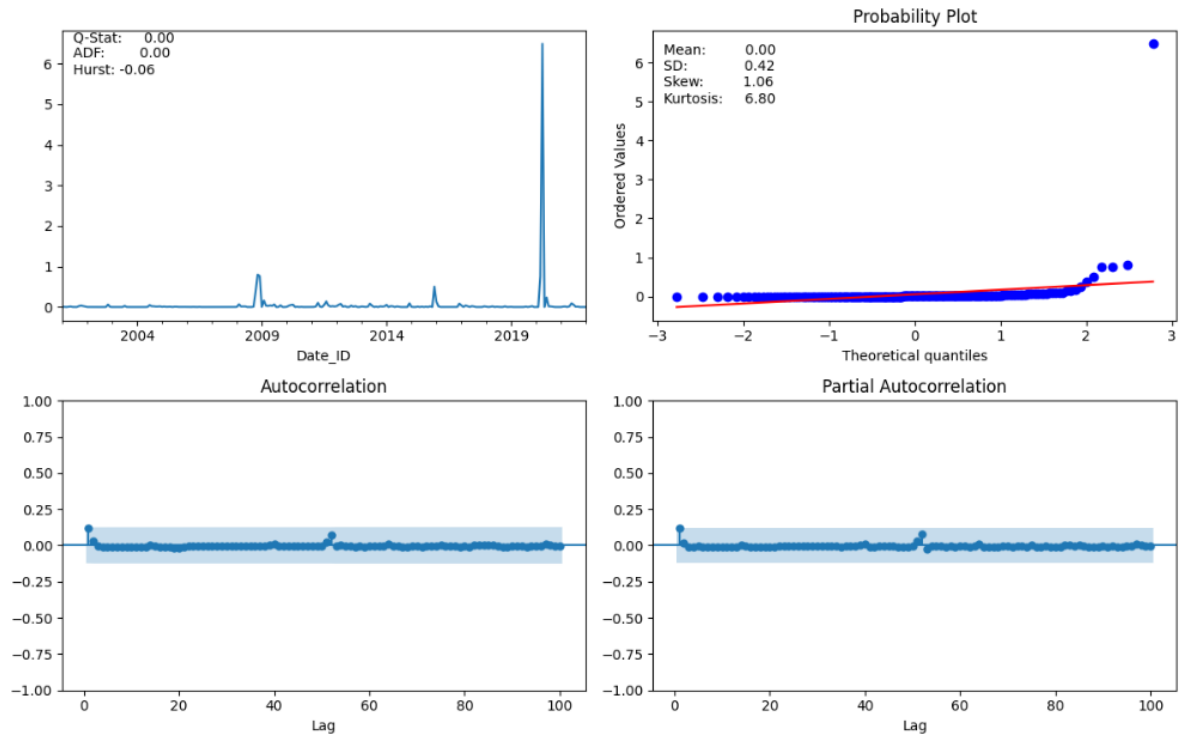
7.1.2.4 EUR/USD rate

EUR/USD rate



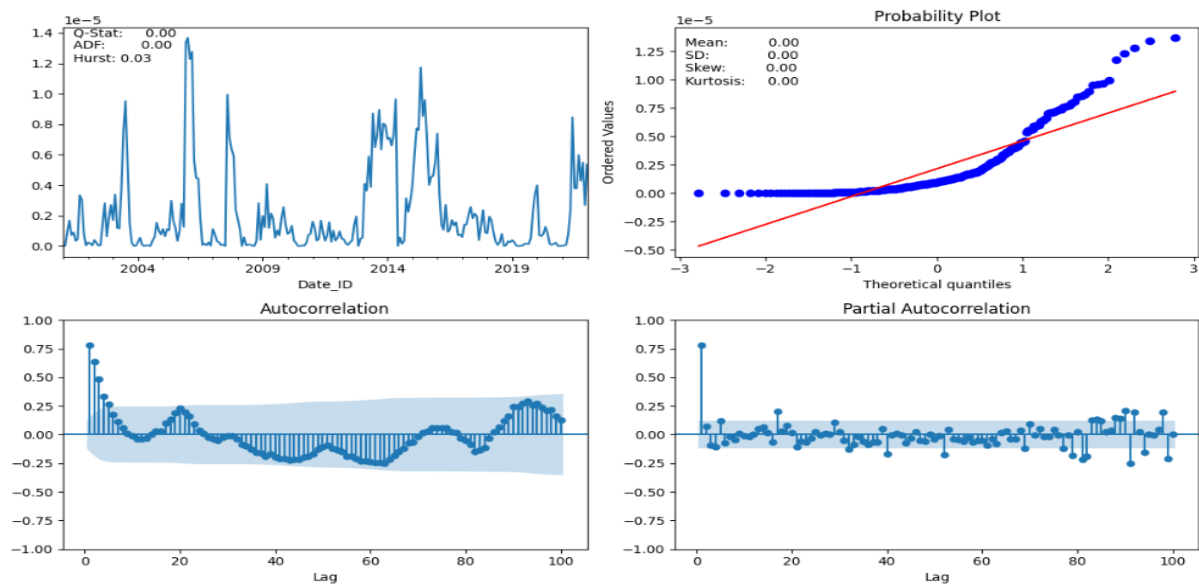
7.1.2.5 Interest rate

Interest rate



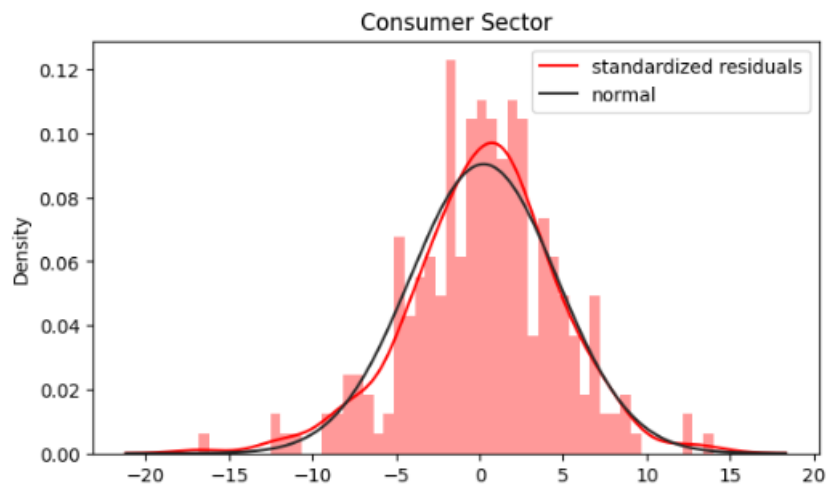
7.1.2.6 Gold rate

Gold rate

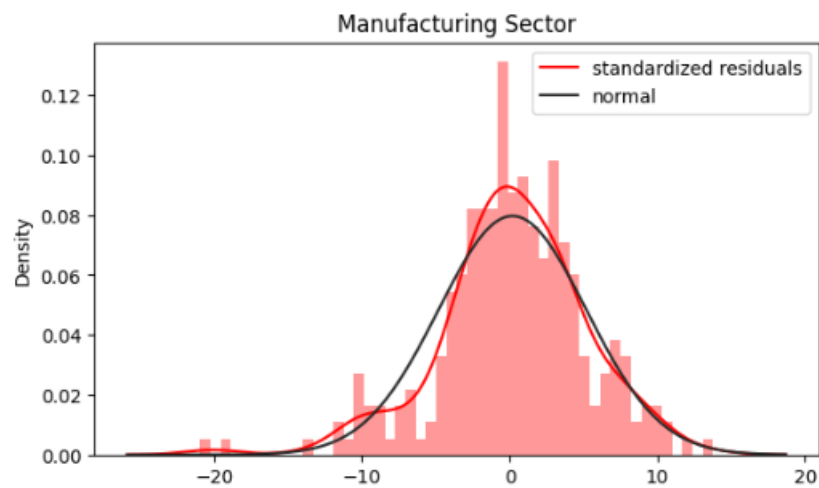


7.1.3 Standardized residuals of dependent variables

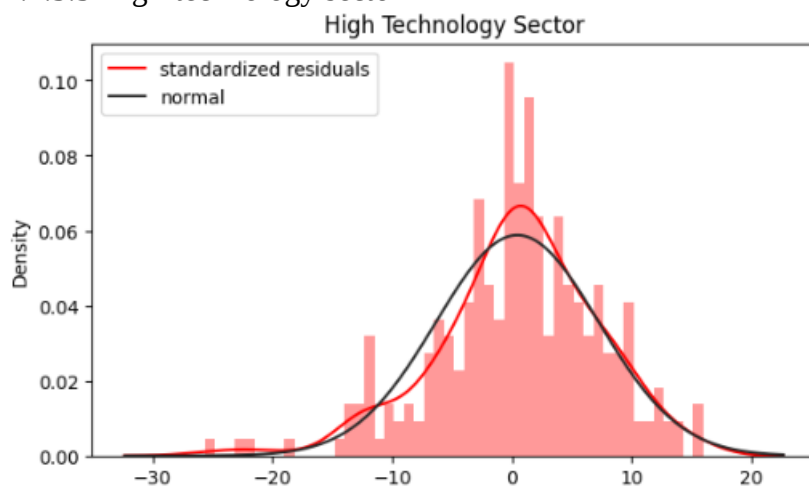
7.1.3.1 Consumer sector



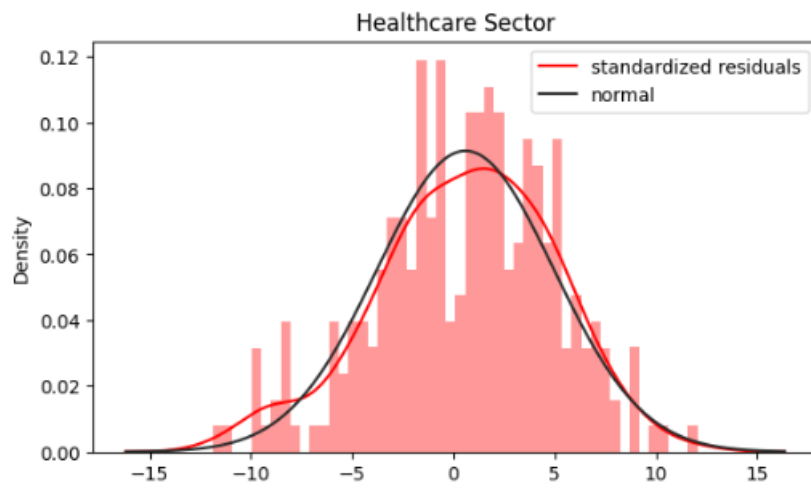
7.1.3.2 Manufacturing sector



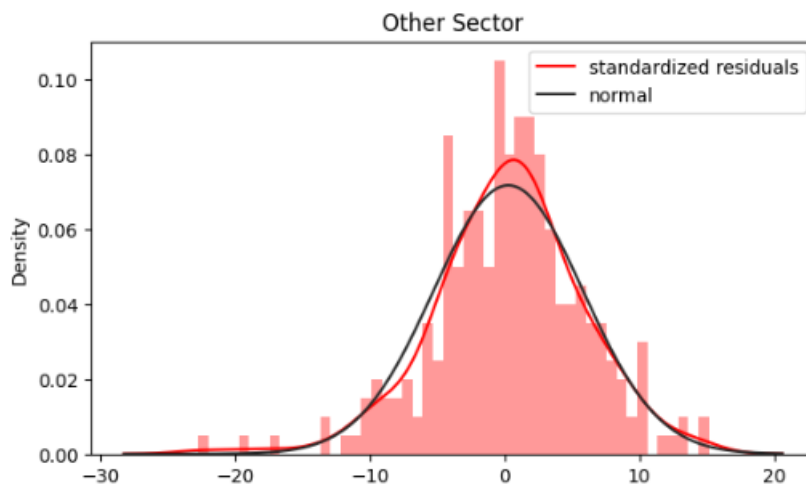
7.1.3.3 High-technology sector



7.1.3.4 Healthcare sector

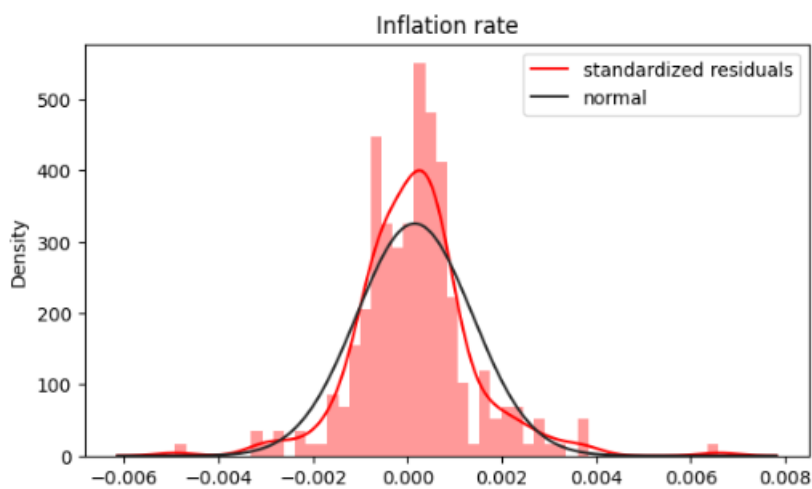


7.1.3.5 Other sector

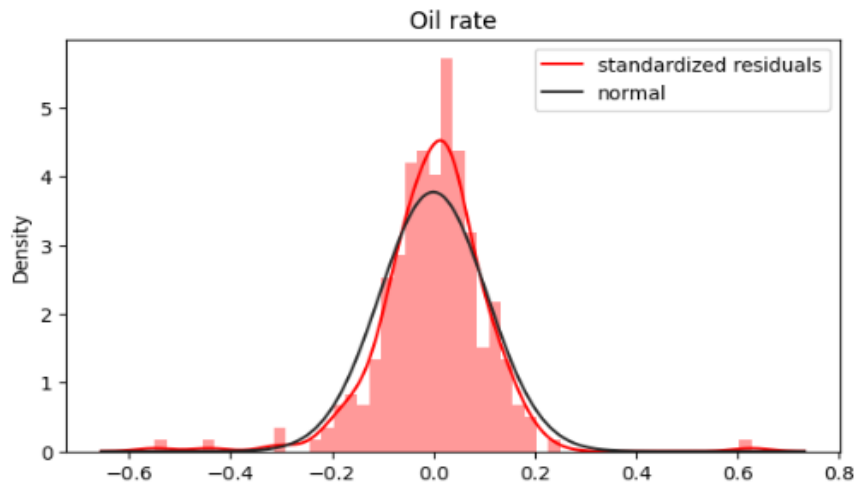


7.1.4 Standardized residuals of independent variables

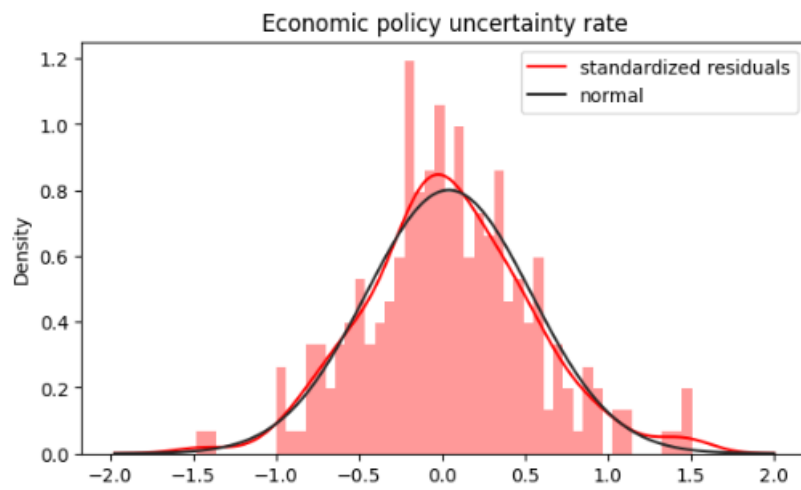
7.1.4.1 Inflation rate



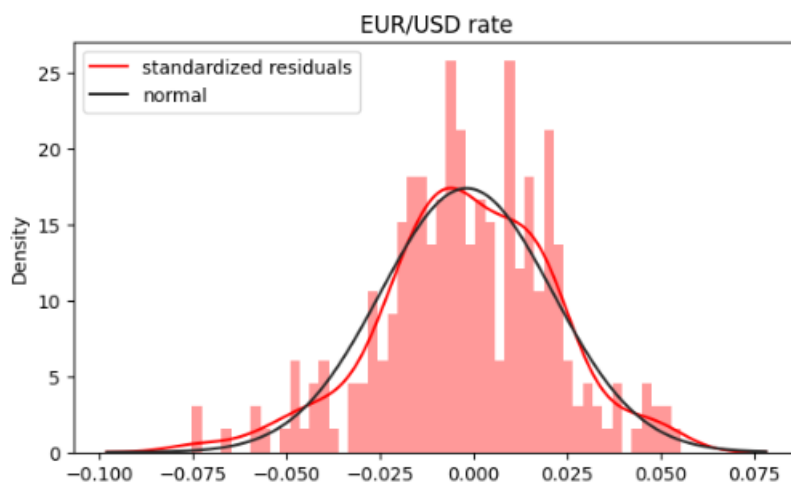
8.1.4.2 Oil rate



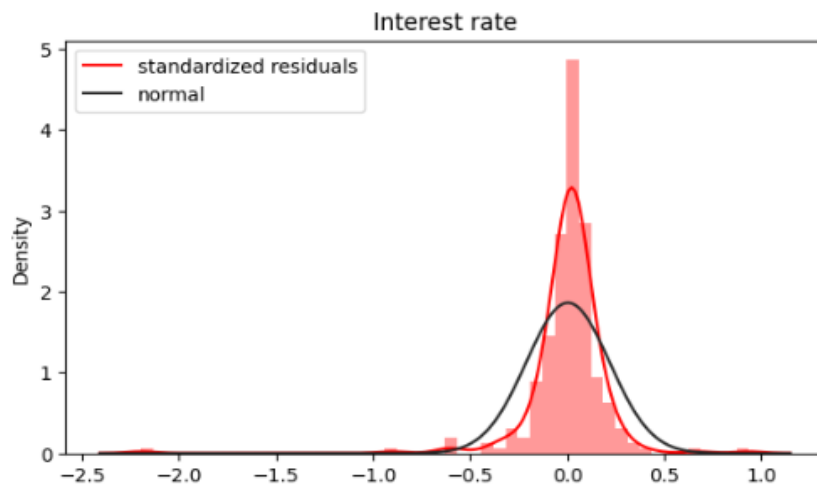
8.1.4.3 Economy policy uncertainty rate



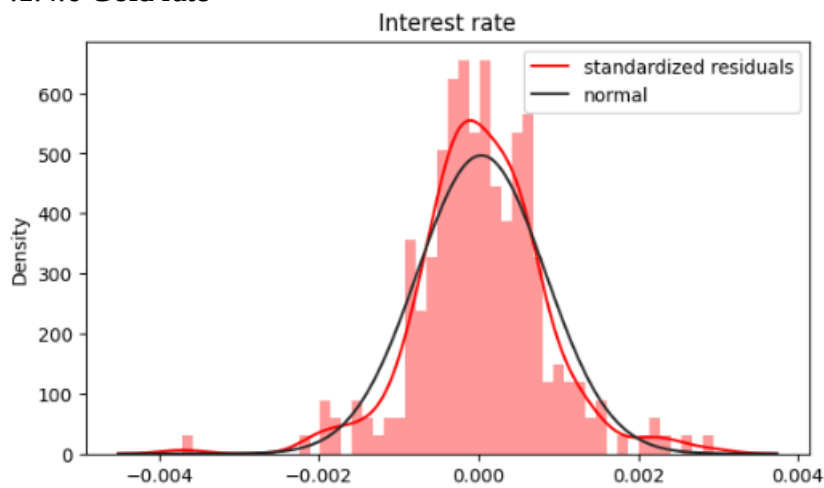
7.1.4.4 EUR/USD rate



7.1.4.5 Interest rate

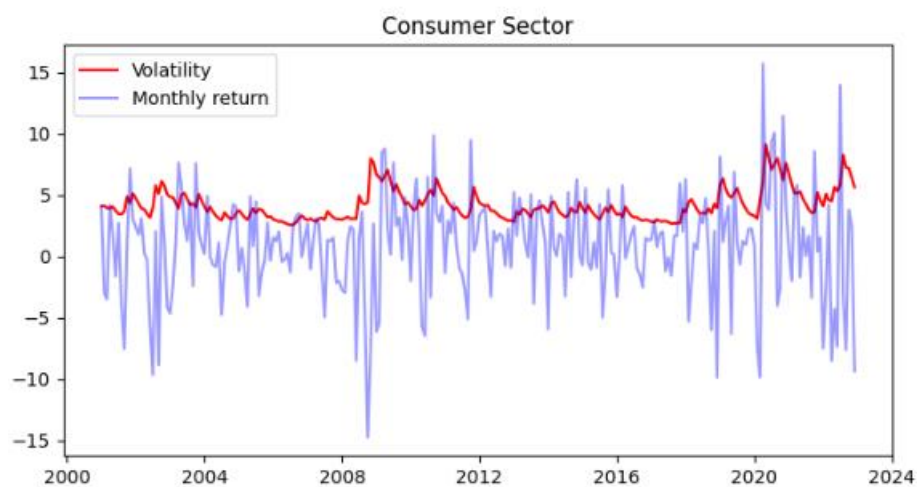


7.1.4.6 Gold rate

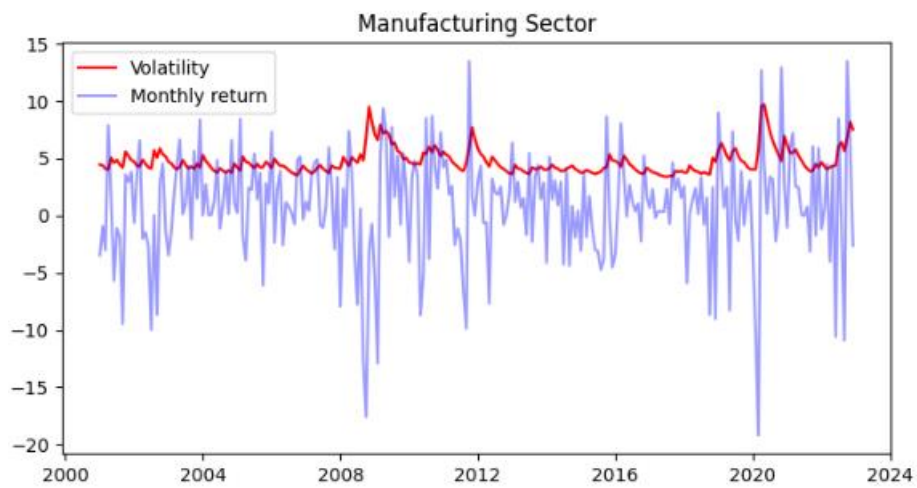


7.1.5 Volatility of dependent variables

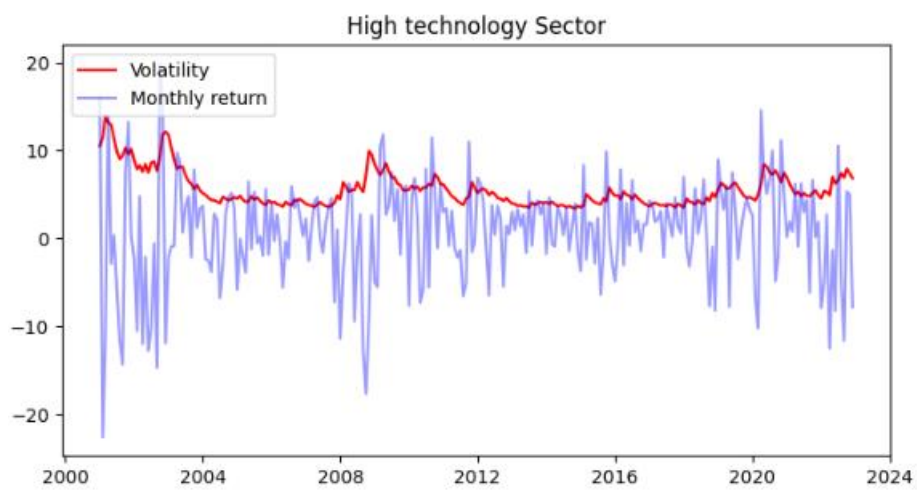
7.1.5.1 Consumer sector



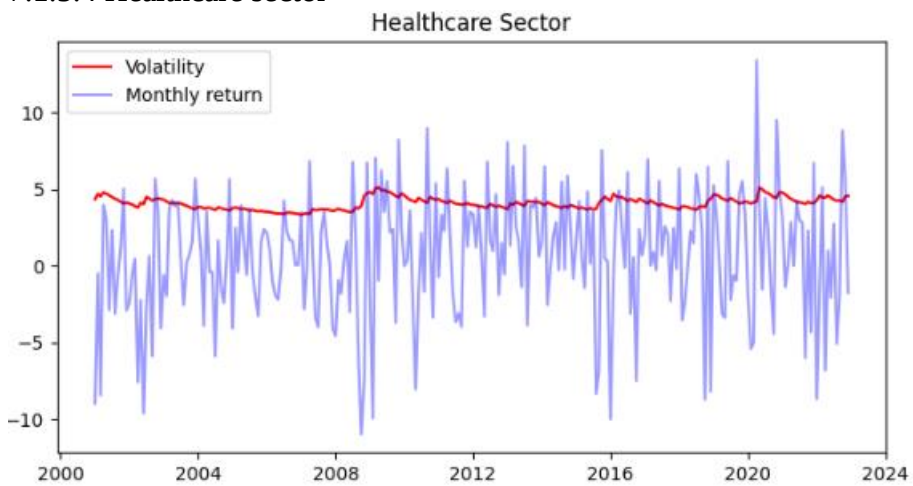
7.1.5.2 Manufacturing sector



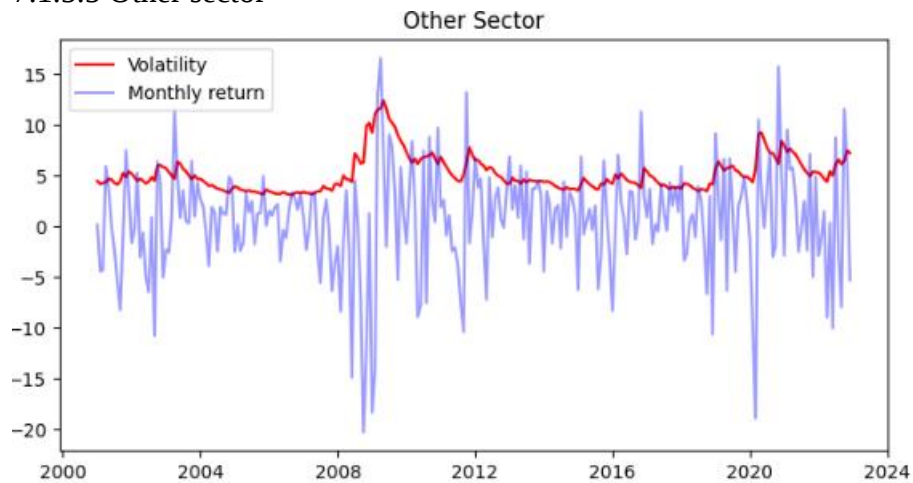
7.1.5.3 High-technology sector



7.1.5.4 Healthcare sector

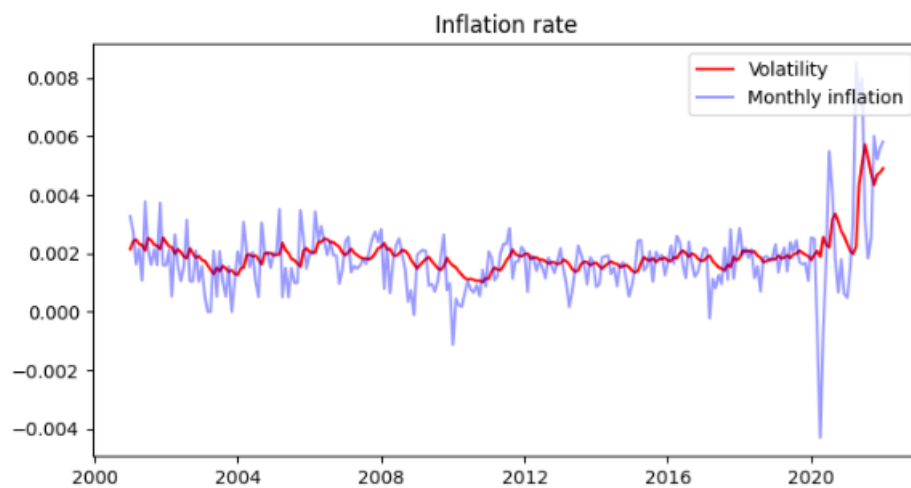


7.1.5.5 Other sector

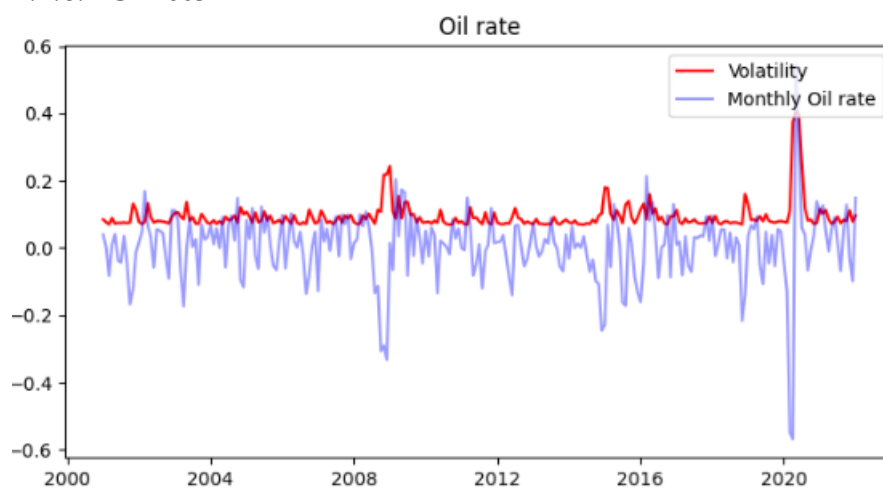


7.1.6 Volatility of independent variables

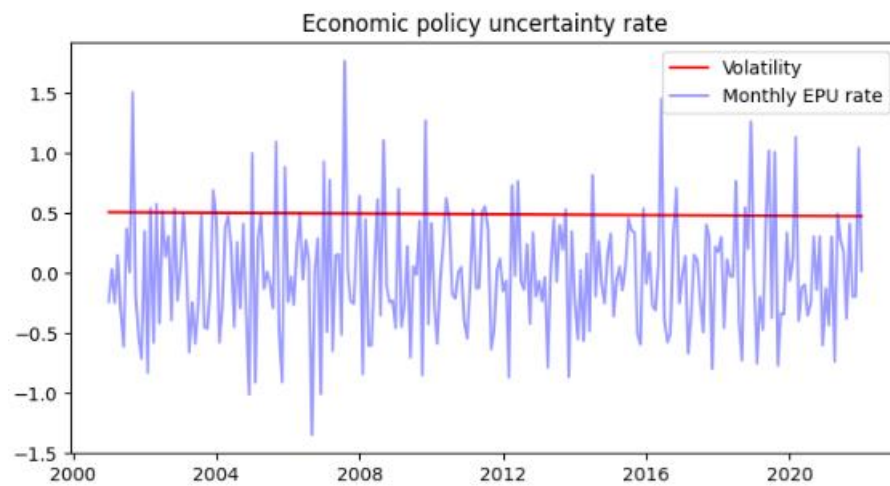
7.1.6.1 Inflation rate



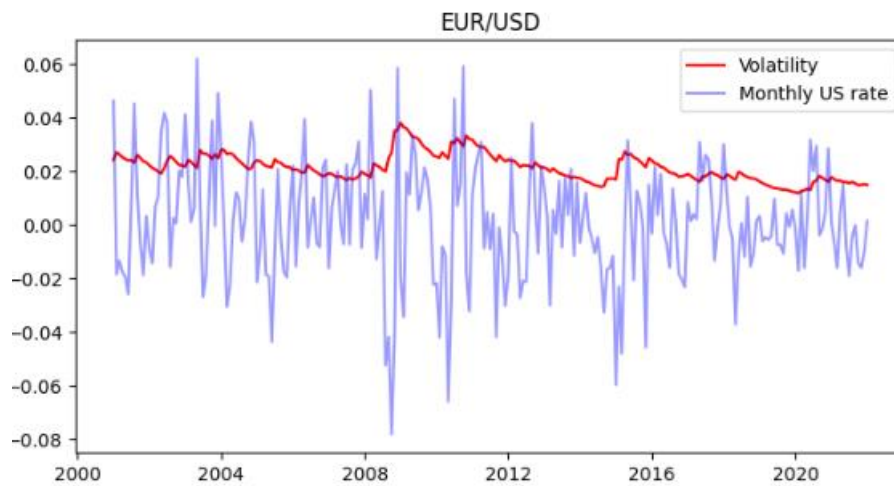
7.1.6.2 Oil rate



7.1.6.3 Economy policy uncertainty rate



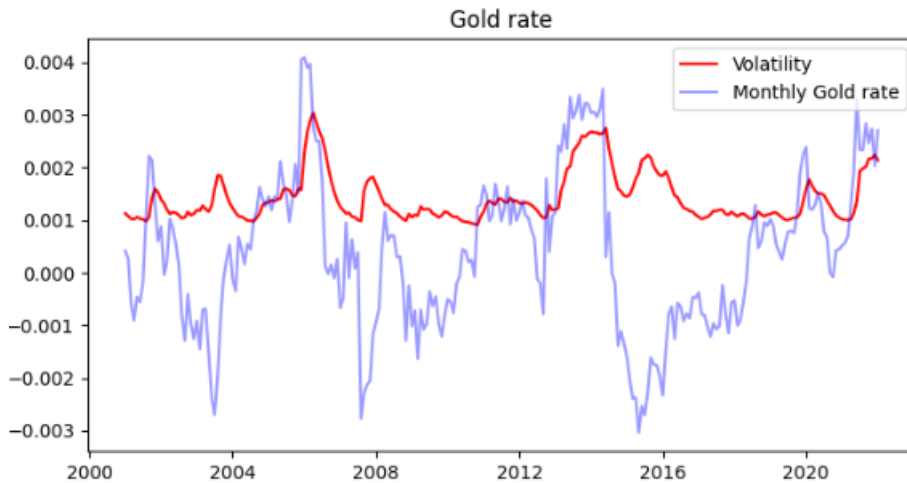
7.1.6.4 EUR/USD rate



7.1.6.5 - Interest rate



7.1.6.6 gold rate



7.2 S-ARIMA and GARCH models (Results)

7.2.1 Independent variables

7.2.1.1 Consumer sector - Inflation rate

```

Zero Mean - GARCH Model Results
=====
Dep. Variable:          None          R-squared:          0.000
Mean Model:            Zero Mean     Adj. R-squared:     0.004
Vol Model:             GARCH         Log-Likelihood:    -716.390
Distribution:          Normal        AIC:               1438.78
Method:               Maximum Likelihood BIC:              1449.38
Date:                 Thu, May 11 2023 No. Observations:  253
Time:                 07:02:01       Df Residuals:      253
                               Volatility Model Df Model:      0
=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----+-----+-----+-----+-----+-----
omega        3.6535      1.482        2.464    1.372e-02    [ 0.748, 6.559]
alpha[1]      0.1842    7.048e-02      2.614    8.958e-03    [4.607e-02, 0.322]
beta[1]       0.6196      0.106        5.847    5.009e-09    [ 0.412, 0.827]
=====

Covariance estimator: robust

SARIMAX Results
=====
Dep. Variable:          Cnsmr          No. Observations:  253
Model:                 SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood    -689.251
Date:                  Thu, 11 May 2023 AIC               1392.503
Time:                  07:02:01       BIC               1416.896
Sample:                - 01-01-2001   HQIC              1402.330
                               - 01-01-2022
Covariance Type:       opg
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----+-----+-----+-----+-----+-----
CPI_Rate_Simple_Return -161.0882    155.047     -1.039    0.299    -464.975    142.798
ar.L1                  -0.5478      0.031    -17.901    0.000     -0.608     -0.488
ar.L2                  -0.9499      0.030    -31.577    0.000     -1.009     -0.891
ma.L1                   0.6160      0.041    14.861    0.000      0.535      0.697
ma.L2                   0.9967      0.109      9.155    0.000      0.783      1.210
ma.S.L12               -0.9987      4.042     -0.247    0.805     -8.922      6.924
sigma2                 15.1570      60.843      0.249    0.803    -104.093    134.407
=====

Ljung-Box (L1) (Q):      0.32      Jarque-Bera (JB):      20.61
Prob(Q):                 0.57      Prob(JB):              0.00
Heteroskedasticity (H):  1.70      Skew:                  -0.28
Prob(H) (two-sided):     0.02      Kurtosis:               4.32
=====

```

7.2.2.2 Consumer sector - Oil rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:      None      R-squared:      0.000
Mean Model:        Zero Mean  Adj. R-squared:  0.004
Vol Model:         GARCH      Log-Likelihood: -715.217
Distribution:       Normal     AIC:            1436.43
Method:            Maximum Likelihood BIC:            1447.04
No. Observations:  253
Date:              Thu, May 11 2023 Df Residuals:      253
Time:              06:45:14      Df Model:         0
Volatility Model

=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----
omega         2.6931      4.994      0.539      0.590      [-7.095, 12.481]
alpha[1]       0.1204      0.152      0.791      0.429      [-0.178, 0.419]
beta[1]        0.7288      0.409      1.781      7.489e-02 [-7.319e-02, 1.531]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:      Cnsmr      No. Observations:  253
Model:             SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood     -683.492
Date:              Thu, 11 May 2023 AIC                  1380.984
Time:              06:45:15      BIC                  1405.378
Sample:            01-01-2001      HQIC                  1390.812
                  - 01-01-2022
Covariance Type:    opg

=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
OIL_Rate_Simple_Return      5.7065      1.371      4.164      0.000      3.020      8.393
ar.L1                       -0.0920      0.016     -5.611      0.000     -0.124     -0.060
ar.L2                       -0.9932      0.011    -92.327      0.000     -1.014     -0.972
ma.L1                        0.0627      0.024      2.583      0.010      0.015      0.110
ma.L2                        0.9937      0.059     16.760      0.000      0.878      1.110
ma.S.L12                    -0.9981      2.628     -0.380      0.704     -6.150      4.153
sigma2                      14.3884     36.898      0.390      0.697    -57.931     86.708
=====
Ljung-Box (L1) (Q):      0.00      Jarque-Bera (JB):      21.62
Prob(Q):                 0.95      Prob(JB):              0.00
Heteroskedasticity (H):  1.53      Skew:                  -0.01
Prob(H) (two-sided):     0.06      Kurtosis:              4.47
=====

```

7.2.2.3 Consumer sector - Economy policy uncertainty rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:      None      R-squared:      0.000
Mean Model:        Zero Mean  Adj. R-squared:  0.004
Vol Model:         GARCH      Log-Likelihood: -707.506
Distribution:       Normal     AIC:            1421.01
Method:            Maximum Likelihood BIC:            1431.61
No. Observations:  253
Date:              Thu, May 11 2023 Df Residuals:      253
Time:              11:24:00      Df Model:         0
Volatility Model

=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----
omega         2.4223      1.922      1.260      0.208      [-1.344, 6.189]
alpha[1]       0.1107      5.940e-02      1.863      6.240e-02 [-5.735e-03, 0.227]
beta[1]        0.7443      0.147      5.055      4.293e-07 [ 0.456, 1.033]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:      Cnsmr      No. Observations:  253
Model:             SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood     -679.158
Date:              Thu, 11 May 2023 AIC                  1372.317
Time:              11:24:00      BIC                  1396.710
Sample:            01-01-2001      HQIC                  1382.145
                  - 01-01-2022
Covariance Type:    opg

=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
EPU_Rate_Simple_Return      -2.0117      0.504     -3.988      0.000     -3.000     -1.023
ar.L1                       -0.0889      0.026     -3.379      0.001     -0.141     -0.037
ar.L2                       -0.9707      0.026    -36.796      0.000     -1.022     -0.919
ma.L1                        0.0345      0.037      0.924      0.356     -0.039      0.108
ma.L2                        0.9474      0.054     17.431      0.000      0.841      1.054
ma.S.L12                    -0.9818      0.253     -3.881      0.000     -1.478     -0.486
sigma2                      14.2401      3.096      4.600      0.000      8.173     20.308
=====
Ljung-Box (L1) (Q):      0.00      Jarque-Bera (JB):      29.13
Prob(Q):                 0.98      Prob(JB):              0.00
Heteroskedasticity (H):  1.71      Skew:                  -0.31
Prob(H) (two-sided):     0.02      Kurtosis:              4.59
=====

```

7.2.2.4 Consumer sector - EUR/USD rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-713.449			
Distribution:	Normal	AIC:	1432.90			
Method:	Maximum Likelihood	BIC:	1443.50			
Date:	Thu, May 11 2023	No. Observations:	253			
Time:	12:48:26	Df Residuals:	253			
	Volatility Model	Df Model:	0			
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	3.8987	1.415	2.755	5.869e-03	[1.125, 6.672]	
alpha[1]	0.2057	7.991e-02	2.574	1.006e-02	[4.906e-02, 0.362]	
beta[1]	0.5825	0.106	5.518	3.431e-08	[0.376, 0.789]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	Cnsmr		No. Observations:	253		
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)		Log Likelihood	-685.217		
Date:	Thu, 11 May 2023		AIC	1384.433		
Time:	12:48:27		BIC	1408.827		
Sample:	01-01-2001		HQIC	1394.261		
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
US_Rate_Simple_Return	28.3079	10.302	2.748	0.006	8.116	48.500
ar.L1	-0.5399	0.030	-17.743	0.000	-0.600	-0.480
ar.L2	-0.9534	0.033	-29.306	0.000	-1.017	-0.890
ma.L1	0.6130	0.126	4.873	0.000	0.366	0.860
ma.L2	0.9988	0.396	2.523	0.012	0.223	1.774
ma.S.L12	-0.9996	11.497	-0.087	0.931	-23.533	21.534
sigma2	14.5735	167.604	0.087	0.931	-313.924	343.071
Ljung-Box (L1) (Q):	0.64		Jarque-Bera (JB):	13.66		
Prob(Q):	0.42		Prob(JB):	0.00		
Heteroskedasticity (H):	1.55		Skew:	-0.17		
Prob(H) (two-sided):	0.05		Kurtosis:	4.12		

7.2.2.5 Consumer sector - Interest rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-716.132			
Distribution:	Normal	AIC:	1438.26			
Method:	Maximum Likelihood	BIC:	1448.86			
Date:	Thu, May 11 2023	No. Observations:	253			
Time:	13:54:28	Df Residuals:	253			
	Volatility Model	Df Model:	0			
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	3.2494	2.410	1.348	0.178	[-1.473, 7.972]	
alpha[1]	0.1343	7.130e-02	1.883	5.967e-02	[-5.474e-03, 0.274]	
beta[1]	0.6853	0.173	3.956	7.609e-05	[0.346, 1.025]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	Cnsmr		No. Observations:	253		
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)		Log Likelihood	-686.688		
Date:	Thu, 11 May 2023		AIC	1387.377		
Time:	13:54:28		BIC	1411.770		
Sample:	01-01-2001		HQIC	1397.204		
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
Interest_Rate_Simple_Return	0.4188	0.464	0.902	0.367	-0.491	1.328
ar.L1	-0.0898	0.020	-4.583	0.000	-0.128	-0.051
ar.L2	-0.9893	0.014	-72.039	0.000	-1.016	-0.962
ma.L1	0.0549	0.029	1.883	0.060	-0.002	0.112
ma.L2	0.9839	0.042	23.478	0.000	0.902	1.066
ma.S.L12	-0.9026	0.070	-12.859	0.000	-1.040	-0.765
sigma2	15.7018	1.237	12.691	0.000	13.277	18.127
Ljung-Box (L1) (Q):	0.84		Jarque-Bera (JB):	26.45		
Prob(Q):	0.36		Prob(JB):	0.00		
Heteroskedasticity (H):	1.69		Skew:	-0.28		
Prob(H) (two-sided):	0.02		Kurtosis:	4.52		

7.2.2.6 Consumer sector - gold rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:          None      R-squared:          0.000
Mean Model:            Zero Mean  Adj. R-squared:     0.004
Vol Model:             GARCH      Log-Likelihood:     -721.680
Distribution:          Normal     AIC:                1449.36
Method:               Maximum Likelihood BIC:                1459.96
Date:                 Thu, May 11 2023 No. Observations:   253
Time:                 14:47:32      Df Residuals:       253
                               Volatility Model Df Model:          0

=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----
omega          3.2986        1.796        1.836   6.632e-02   [-0.222, 6.820]
alpha[1]        0.1647       7.633e-02        2.158   3.095e-02   [1.509e-02, 0.314]
beta[1]          0.6653        0.135        4.946   7.567e-07   [ 0.402, 0.929]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:          Cnsmr      No. Observations:   253
Model:                 SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood      -695.057
Date:                  Thu, 11 May 2023 AIC                 1404.113
Time:                  14:47:32      BIC                 1428.507
Sample:                01-01-2001    HQIC                1413.941
                               - 01-01-2022
Covariance Type:       opg

=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
Gold_Rate_Simple_Return -332.7256    267.248     -1.245    0.213    -856.522    191.071
ar.L1                   0.2529     1.099      0.230    0.818     -1.901     2.407
ar.L2                   0.5880     0.853      0.689    0.491     -1.084     2.261
ma.L1                   -0.1988     1.088     -0.183    0.855     -2.332     1.935
ma.L2                   -0.5983     0.798     -0.750    0.453     -2.162     0.965
ma.S.L12                -0.9416     0.103     -9.108    0.000     -1.144    -0.739
sigma2                  16.8596     1.509     11.174    0.000     13.902    19.817
=====
Ljung-Box (L1) (Q):      0.02      Jarque-Bera (JB):      24.07
Prob(Q):                 0.89      Prob(JB):              0.00
Heteroskedasticity (H): 1.76      Skew:                  -0.22
Prob(H) (two-sided):     0.01      Kurtosis:              4.48
=====

```

7.2.1.7 Manufacturing sector - Inflation rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:          None      R-squared:          0.000
Mean Model:            Zero Mean  Adj. R-squared:     0.004
Vol Model:             GARCH      Log-Likelihood:     -753.958
Distribution:          Normal     AIC:                1513.92
Method:               Maximum Likelihood BIC:                1524.52
Date:                 Thu, May 11 2023 No. Observations:   253
Time:                 07:02:06      Df Residuals:       253
                               Volatility Model Df Model:          0

=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----
omega          5.9792        7.936        0.753   0.451   [-9.576, 21.534]
alpha[1]        0.1742        0.113        1.536   0.125   [-4.813e-02, 0.397]
beta[1]          0.5817        0.400        1.453   0.146   [-0.203, 1.366]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:          Manuf      No. Observations:   253
Model:                 SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood      -726.844
Date:                  Thu, 11 May 2023 AIC                 1467.687
Time:                  07:02:07      BIC                 1492.081
Sample:                01-01-2001    HQIC                1477.515
                               - 01-01-2022
Covariance Type:       opg

=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
CPI_Rate_Simple_Return -128.7130    277.883     -0.463    0.643    -673.353    415.927
ar.L1                   -0.2185     0.642     -0.340    0.734     -1.478     1.041
ar.L2                   0.5100     0.744     0.686    0.493     -0.948     1.968
ma.L1                   0.2556     0.671     0.381    0.703     -1.060     1.571
ma.L2                   -0.4426     0.777     -0.570    0.569     -1.965     1.080
ma.S.L12                -1.0000     2.77e+04    -3.61e-05 1.000     -5.43e+04    5.43e+04
sigma2                 20.9778     5.82e+05    3.61e-05 1.000     -1.14e+06    1.14e+06
=====
Ljung-Box (L1) (Q):      0.01      Jarque-Bera (JB):      68.50
Prob(Q):                 0.93      Prob(JB):              0.00
Heteroskedasticity (H): 1.53      Skew:                  -0.63
Prob(H) (two-sided):     0.06      Kurtosis:              5.29
=====

```

7.2.2.8 Manufacturing sector - Oil rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:      None      R-squared:      0.000
Mean Model:        Zero Mean  Adj. R-squared: 0.004
Vol Model:         GARCH      Log-Likelihood: -738.999
Distribution:       Normal     AIC:            1484.00
Method:            Maximum Likelihood BIC:           1494.60
Date:              Thu, May 11 2023 No. Observations: 253
Time:              06:45:18      Df Residuals:    253
                    Volatility Model Df Model:          0
=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----+-----+-----+-----+-----+-----
omega        7.4708      6.485        1.152      0.249      [-5.240, 20.181]
alpha[1]     0.2092      0.102        2.042      4.119e-02 [8.365e-03, 0.410]
beta[1]       0.4447      0.342        1.299      0.194      [-0.226, 1.116]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:      Manuf      No. Observations: 253
Model:              SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood -708.155
Date:              Thu, 11 May 2023 AIC            1430.310
Time:              06:45:19 BIC            1454.703
Sample:            01-01-2001 HQIC           1440.138
                    - 01-01-2022
Covariance Type:    opg
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----+-----+-----+-----+-----+-----
OIL_Rate_Simple_Return 17.6489      1.931        9.141      0.000      13.865      21.433
ar.L1                  1.3796      0.046       30.199      0.000        1.290      1.469
ar.L2                 -0.8615      0.042      -20.759      0.000       -0.943     -0.780
ma.L1                 -1.5250      0.129      -11.819      0.000       -1.778     -1.272
ma.L2                  0.9978      0.165        6.051      0.000        0.675      1.321
ma.S.L12              -0.9995     12.857       -0.078      0.938       -26.198     24.199
sigma2               17.7326     227.014        0.078      0.938     -427.206     462.671
=====
Ljung-Box (L1) (Q):      1.62      Jarque-Bera (JB):      22.63
Prob(Q):                 0.20      Prob(JB):              0.00
Heteroskedasticity (H):  1.18      Skew:                 -0.02
Prob(H) (two-sided):     0.47      Kurtosis:              4.50
=====

```

7.2.2.9 Manufacturing sector - Economy policy uncertainty rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:      None      R-squared:      0.000
Mean Model:        Zero Mean  Adj. R-squared: 0.004
Vol Model:         GARCH      Log-Likelihood: -749.966
Distribution:       Normal     AIC:            1505.93
Method:            Maximum Likelihood BIC:           1516.53
Date:              Thu, May 11 2023 No. Observations: 253
Time:              11:24:05      Df Residuals:    253
                    Volatility Model Df Model:          0
=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----+-----+-----+-----+-----+-----
omega        18.1077      9.564        1.893      5.832e-02 [-0.638, 36.853]
alpha[1]     0.2102      0.106        1.976      4.816e-02 [1.699e-03, 0.419]
beta[1]       2.6145e-18      0.406      6.447e-18      1.000      [-0.795, 0.795]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:      Manuf      No. Observations: 253
Model:              SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood -722.055
Date:              Thu, 11 May 2023 AIC            1458.109
Time:              11:24:06 BIC            1482.503
Sample:            01-01-2001 HQIC           1467.937
                    - 01-01-2022
Covariance Type:    opg
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----+-----+-----+-----+-----+-----
EPU_Rate_Simple_Return -1.8120      0.545       -3.326      0.001       -2.880     -0.744
ar.L1                 -0.0216      0.716       -0.030      0.976       -1.425     1.382
ar.L2                  0.5250      0.715        0.734      0.463       -0.877     1.927
ma.L1                  0.0291      0.741        0.039      0.969       -1.424     1.482
ma.L2                 -0.4649      0.743       -0.626      0.531       -1.921     0.991
ma.S.L12              -0.9998     34.962       -0.029      0.977       -69.524     67.525
sigma2               20.1391     703.378        0.029      0.977     -1358.457     1398.736
=====
Ljung-Box (L1) (Q):      0.05      Jarque-Bera (JB):      38.07
Prob(Q):                 0.83      Prob(JB):              0.00
Heteroskedasticity (H):  1.40      Skew:                 -0.45
Prob(H) (two-sided):     0.13      Kurtosis:              4.73
=====

```

7.2.2.10 Manufacturing sector - EUR/USD rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:      None      R-squared:      0.000
Mean Model:        Zero Mean  Adj. R-squared: 0.004
Vol Model:         GARCH      Log-Likelihood: -751.928
Distribution:       Normal     AIC:            1509.86
Method:            Maximum Likelihood BIC:           1520.46
Date:              Thu, May 11 2023 No. Observations: 253
Time:              12:48:29      Df Residuals:    253
Volatility Model:  Df Model:      0

=====
coef      std err      t      P>|t|      95.0% Conf. Int.
-----
omega      5.4640      12.965      0.421      0.673 [-19.947, 30.875]
alpha[1]    0.1662      0.137      1.215      0.224 [-0.102, 0.434]
beta[1]     0.6044      0.658      0.918      0.358 [-0.685, 1.894]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:      Manuf      No. Observations: 253
Model:              SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood -720.709
Date:              Thu, 11 May 2023 AIC 1455.417
Time:              12:48:30 BIC 1479.811
Sample:            01-01-2001 HQIC 1465.245
Covariance Type:    opg

=====
coef      std err      z      P>|z|      [0.025      0.975]
-----
US_Rate_Simple_Return 46.5257      11.648      3.994      0.000      23.696      69.356
ar.L1                 -0.2158      1.619     -0.133      0.894     -3.389      2.957
ar.L2                 0.7407      1.563      0.474      0.636     -2.322      3.804
ma.L1                 0.2489      1.681      0.148      0.882     -3.045      3.543
ma.L2                 -0.7467      1.620     -0.461      0.645     -3.922      2.429
ma.S.L12              -0.9992      7.556     -0.132      0.895     -15.809     13.811
sigma2                19.7163     148.799      0.133      0.895     -271.924     311.357
=====
Ljung-Box (L1) (Q):      0.26      Jarque-Bera (JB):      47.10
Prob(Q):                 0.61      Prob(JB):              0.00
Heteroskedasticity (H): 1.37      Skew:                  -0.51
Prob(H) (two-sided):     0.16      Kurtosis:              4.91
=====

```

7.2.2.11 Manufacturing sector - Interest rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:      None      R-squared:      0.000
Mean Model:        Zero Mean  Adj. R-squared: 0.004
Vol Model:         GARCH      Log-Likelihood: -753.598
Distribution:       Normal     AIC:            1513.20
Method:            Maximum Likelihood BIC:           1523.80
Date:              Thu, May 11 2023 No. Observations: 253
Time:              13:54:31      Df Residuals:    253
Volatility Model:  Df Model:      0

=====
coef      std err      t      P>|t|      95.0% Conf. Int.
-----
omega      6.0346      7.750      0.779      0.436 [-9.155, 21.224]
alpha[1]    0.1855      0.118      1.575      0.115 [-4.529e-02, 0.416]
beta[1]     0.5693      0.394      1.447      0.148 [-0.202, 1.341]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:      Manuf      No. Observations: 253
Model:              SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood -726.622
Date:              Thu, 11 May 2023 AIC 1467.245
Time:              13:54:32 BIC 1491.639
Sample:            01-01-2001 HQIC 1477.073
Covariance Type:    opg

=====
coef      std err      z      P>|z|      [0.025      0.975]
-----
Interest_Rate_Simple_Return -0.9137      1.019     -0.896      0.370     -2.911      1.084
ar.L1                 -0.2048      0.618     -0.331      0.740     -1.416      1.007
ar.L2                 0.4867      0.686      0.709      0.478     -0.858      1.832
ma.L1                 0.2521      0.658      0.383      0.702     -1.037      1.541
ma.L2                 -0.4063      0.722     -0.563      0.573     -1.821      1.008
ma.S.L12              -0.9997     19.034     -0.053      0.958     -38.306     36.306
sigma2                20.9241     397.376      0.053      0.958     -757.919     799.767
=====
Ljung-Box (L1) (Q):      0.00      Jarque-Bera (JB):      75.14
Prob(Q):                 0.95      Prob(JB):              0.00
Heteroskedasticity (H): 1.49      Skew:                  -0.65
Prob(H) (two-sided):     0.08      Kurtosis:              5.40
=====

```

7.2.2.12 Manufacturing sector - gold rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:          None      R-squared:                0.000
Mean Model:            Zero Mean  Adj. R-squared:           0.004
Vol Model:             GARCH      Log-Likelihood:          -752.162
Distribution:          Normal     AIC:                     1510.32
Method:               Maximum Likelihood BIC:                     1520.92
Date:                 Thu, May 11 2023      No. Observations:        253
Time:                 14:47:36              Df Residuals:            253
Volatility Model:                                           Df Model:                 0

=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----
omega        7.6828      7.485        1.026      0.305      [-6.987, 22.352]
alpha[1]     0.2167      0.110        1.974      0.050      [-0.003, 0.432]
beta[1]      0.4679      0.362        1.294      0.196      [-0.241, 1.177]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:          Manuf      No. Observations:        253
Model:                 SARIMAX(2, 0, 2)x(0, 1, [1], 12)  Log Likelihood           -725.871
Date:                 Thu, 11 May 2023      AIC                     1465.742
Time:                 14:47:36              BIC                     1490.136
Sample:               - 01-01-2001      HQIC                    1475.570
Covariance Type:      opg

=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
Gold_Rate_Simple_Return  324.4534      280.058        1.159      0.247      -224.451      873.357
ar.L1                   1.7467      0.121        14.449      0.000        1.510        1.984
ar.L2                   -0.9200      0.110       -8.326      0.000       -1.137       -0.703
ma.L1                   -1.7190      0.117     -14.647      0.000       -1.949       -1.489
ma.L2                    0.9112      0.104      8.771      0.000        0.708        1.115
ma.S.L12                -1.0000      0.068     -14.652      0.000       -1.134       -0.866
sigma2                  21.3955      0.014    1524.105      0.000        21.368        21.423
=====

Ljung-Box (L1) (Q):      0.07      Jarque-Bera (JB):        67.83
Prob(Q):                0.79      Prob(JB):                0.00
Heteroskedasticity (H):  1.47      Skew:                   -0.64
Prob(H) (two-sided):    0.09      Kurtosis:                5.26
=====

```

7.2.1.13 High-technology sector - Inflation rate

=====

Zero Mean - GARCH Model Results

=====

Dep. Variable: None R-squared: 0.000

Mean Model: Zero Mean Adj. R-squared: 0.004

Vol Model: GARCH Log-Likelihood: -807.512

Distribution: Normal AIC: 1621.02

Method: Maximum Likelihood BIC: 1631.62

No. Observations: 253

Date: Thu, May 11 2023 Df Residuals: 253

Time: 06:45:21 Df Model: 0

Volatility Model

=====

coef std err t P>|t| 95.0% Conf. Int.

=====

omega 0.8564 0.524 1.633 0.102 [-0.171, 1.884]

alpha[1] 0.0742 5.739e-02 1.292 0.196 [-3.832e-02, 0.187]

beta[1] 0.8954 5.871e-02 15.253 1.584e-52 [0.780, 1.011]

=====

Covariance estimator: robust

SARIMAX Results

=====

Dep. Variable: HiTec No. Observations: 253

Model: SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood -775.251

Date: Thu, 11 May 2023 AIC 1564.502

Time: 06:45:22 BIC 1588.895

Sample: 01-01-2001 HQIC 1574.329

- 01-01-2022

Covariance Type: opg

=====

coef std err z P>|z| [0.025 0.975]

=====

OIL_Rate_Simple_Return 10.1474 2.347 4.324 0.000 5.548 14.747

ar.L1 -0.8854 0.399 -2.219 0.026 -1.667 -0.103

ar.L2 -0.2586 0.372 -0.695 0.487 -0.988 0.470

ma.L1 0.8627 0.411 2.099 0.036 0.057 1.668

ma.L2 0.1308 0.395 0.331 0.741 -0.644 0.905

ma.S.L12 -0.7473 0.060 -12.416 0.000 -0.865 -0.629

sigma2 34.9776 2.901 12.056 0.000 29.291 40.664

=====

Ljung-Box (L1) (Q): 0.04 Jarque-Bera (JB): 10.91

Prob(Q): 0.85 Prob(JB): 0.00

Heteroskedasticity (H): 0.47 Skew: -0.36

Prob(H) (two-sided): 0.00 Kurtosis: 3.75

7.2.2.14 High-technology sector - Oil rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-813.342			
Distribution:	Normal	AIC:	1632.68			
Method:	Maximum Likelihood	BIC:	1643.28			
		No. Observations:	253			
Date:	Thu, May 11 2023	Df Residuals:	253			
Time:	07:02:09	Df Model:	0			
Volatility Model						
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	1.3338	0.863	1.546	0.122	[-0.357, 3.025]	
alpha[1]	0.1005	6.846e-02	1.467	0.142	[-3.372e-02, 0.235]	
beta[1]	0.8587	7.358e-02	11.670	1.817e-31	[0.714, 1.003]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	HiTec		No. Observations:	253		
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)		Log Likelihood	-779.997		
Date:	Thu, 11 May 2023		AIC	1573.993		
Time:	07:02:09		BIC	1598.387		
Sample:	01-01-2001		HQIC	1583.821		
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
CPI_Rate_Simple_Return	-258.7484	260.728	-0.992	0.321	-769.766	252.269
ar.L1	0.0133	0.153	0.087	0.930	-0.286	0.312
ar.L2	0.8584	0.154	5.575	0.000	0.557	1.160
ma.L1	0.0471	0.798	0.059	0.953	-1.517	1.611
ma.L2	-0.9520	0.790	-1.205	0.228	-2.500	0.596
ma.S.L12	-0.7545	0.059	-12.785	0.000	-0.870	-0.639
sigma2	35.6848	27.614	1.292	0.196	-18.437	89.807
Ljung-Box (L1) (Q): 0.13 Jarque-Bera (JB): 19.43						
Prob(Q): 0.72 Prob(JB): 0.00						
Heteroskedasticity (H): 0.57 Skew: -0.59						
Prob(H) (two-sided): 0.01 Kurtosis: 3.74						

7.2.2.15 High-technology sector - Economy policy uncertainty rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-803.824			
Distribution:	Normal	AIC:	1613.65			
Method:	Maximum Likelihood	BIC:	1624.25			
Date:	Thu, May 11 2023	No. Observations:	253			
Time:	11:24:09	Df Residuals:	253			
	Volatility Model	Df Model:	0			
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	1.0635	0.797	1.335	0.182	[-0.498, 2.625]	
alpha[1]	0.0955	8.451e-02	1.130	0.259	[-7.017e-02, 0.261]	
beta[1]	0.8688	8.793e-02	9.881	5.042e-23	[0.696, 1.041]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	HiTec		No. Observations:	253		
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)		Log Likelihood	-772.463		
Date:	Thu, 11 May 2023		AIC	1558.926		
Time:	11:24:09		BIC	1583.320		
Sample:	01-01-2001		HQIC	1568.754		
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
EPU_Rate_Simple_Return	-2.7432	0.752	-3.650	0.000	-4.216	-1.270
ar.L1	-1.0819	0.534	-2.027	0.043	-2.128	-0.036
ar.L2	-0.3060	0.473	-0.647	0.518	-1.234	0.621
ma.L1	1.0640	0.548	1.943	0.052	-0.009	2.137
ma.L2	0.2093	0.511	0.410	0.682	-0.792	1.210
ma.S.L12	-0.7652	0.056	-13.711	0.000	-0.875	-0.656
sigma2	34.0514	2.721	12.515	0.000	28.719	39.384
Ljung-Box (L1) (Q):	0.06		Jarque-Bera (JB):	29.08		
Prob(Q):	0.81		Prob(JB):	0.00		
Heteroskedasticity (H):	0.46		Skew:	-0.55		
Prob(H) (two-sided):	0.00		Kurtosis:	4.29		

7.2.2.16 High-technology sector - EUR/USD rate

Zero Mean - GARCH Model Results

Dep. Variable:	None	R-squared:	0.000
Mean Model:	Zero Mean	Adj. R-squared:	0.004
Vol Model:	GARCH	Log-Likelihood:	-807.729
Distribution:	Normal	AIC:	1621.46
Method:	Maximum Likelihood	BIC:	1632.06
		No. Observations:	253
Date:	Thu, May 11 2023	Df Residuals:	253
Time:	12:48:35	Df Model:	0
	Volatility Model		

	coef	std err	t	P> t	95.0% Conf. Int.	
omega	1.0411	0.597	1.743	8.126e-02	[-0.129, 2.212]	
alpha[1]	0.0726	6.049e-02	1.200	0.230	[-4.595e-02, 0.191]	
beta[1]	0.8902	6.461e-02	13.778	3.464e-43	[0.764, 1.017]	

Covariance estimator: robust

SARIMAX Results

Dep. Variable:	HiTec	No. Observations:	253
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-773.065
Date:	Thu, 11 May 2023	AIC	1560.131
Time:	12:48:36	BIC	1584.524
Sample:	01-01-2001	HQIC	1569.958
	- 01-01-2022		

Covariance Type: opg

	coef	std err	z	P> z	[0.025	0.975]
US_Rate_Simple_Return	36.6365	13.344	2.746	0.006	10.483	62.790
ar.L1	-1.7888	0.026	-69.331	0.000	-1.839	-1.738
ar.L2	-0.9585	0.025	-38.642	0.000	-1.007	-0.910
ma.L1	1.8437	0.076	24.101	0.000	1.694	1.994
ma.L2	0.9916	0.078	12.665	0.000	0.838	1.145
ma.S.L12	-0.8204	0.064	-12.751	0.000	-0.947	-0.694
sigma2	33.6424	3.579	9.400	0.000	26.627	40.657

Ljung-Box (L1) (Q): 0.01 Jarque-Bera (JB): 23.54

Prob(Q): 0.92 Prob(JB): 0.00

Heteroskedasticity (H): 0.50 Skew: -0.60

Prob(H) (two-sided): 0.00 Kurtosis: 3.96

7.2.2.17 High-technology sector - Interest rate

Zero Mean - GARCH Model Results

Dep. Variable:	None	R-squared:	0.000
Mean Model:	Zero Mean	Adj. R-squared:	0.004
Vol Model:	GARCH	Log-Likelihood:	-813.058
Distribution:	Normal	AIC:	1632.12
Method:	Maximum Likelihood	BIC:	1642.72
		No. Observations:	253
Date:	Thu, May 11 2023	Df Residuals:	253
Time:	13:54:33	Df Model:	0

Volatility Model

	coef	std err	t	P> t	95.0% Conf. Int.
omega	1.3668	0.971	1.407	0.159	[-0.537, 3.271]
alpha[1]	0.1032	7.797e-02	1.324	0.186	[-4.960e-02, 0.256]
beta[1]	0.8552	8.570e-02	9.979	1.885e-23	[0.687, 1.023]

Covariance estimator: robust

SARIMAX Results

Dep. Variable:	HiTec	No. Observations:	253
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-779.730
Date:	Thu, 11 May 2023	AIC	1573.459
Time:	13:54:34	BIC	1597.853
Sample:	01-01-2001	HQIC	1583.287
	- 01-01-2022		

Covariance Type: opg

	coef	std err	z	P> z	[0.025	0.975]
Interest_Rate_Simple_Return	-0.6844	1.200	-0.570	0.569	-3.037	1.668
ar.L1	0.0227	0.155	0.147	0.883	-0.280	0.326
ar.L2	0.8641	0.146	5.928	0.000	0.578	1.150
ma.L1	0.0416	0.844	0.049	0.961	-1.613	1.696
ma.L2	-0.9575	0.818	-1.171	0.242	-2.560	0.645
ma.S.L12	-0.7634	0.059	-12.963	0.000	-0.879	-0.648
sigma2	35.5332	28.909	1.229	0.219	-21.128	92.194

Ljung-Box (L1) (Q): 0.05 Jarque-Bera (JB): 19.83

Prob(Q): 0.83 Prob(JB): 0.00

Heteroskedasticity (H): 0.56 Skew: -0.59

Prob(H) (two-sided): 0.01 Kurtosis: 3.77

7.2.2.18 High-technology sector - gold rate

Zero Mean - GARCH Model Results					
Dep. Variable:	None	R-squared:	0.000		
Mean Model:	Zero Mean	Adj. R-squared:	0.004		
Vol Model:	GARCH	Log-Likelihood:	-813.364		
Distribution:	Normal	AIC:	1632.73		
Method:	Maximum Likelihood	BIC:	1643.33		
Date:	Thu, May 11 2023	No. Observations:	253		
Time:	14:47:41	Df Residuals:	253		
		Df Model:	0		
Volatility Model					
	coef	std err	t	P> t	95.0% Conf. Int.
omega	1.3888	1.007	1.380	0.168	[-0.584, 3.362]
alpha[1]	0.1038	8.002e-02	1.297	0.195	[-5.303e-02, 0.261]
beta[1]	0.8541	8.877e-02	9.622	6.473e-22	[0.680, 1.028]
Covariance estimator: robust					
SARIMAX Results					
Dep. Variable:	HiTec	No. Observations:	253		
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-779.813		
Date:	Thu, 11 May 2023	AIC	1573.627		
Time:	14:47:42	BIC	1598.020		
Sample:	01-01-2001	HQIC	1583.454		
	- 01-01-2022				
Covariance Type:	opg				
	coef	std err	z	P> z	[0.025 0.975]
Gold_Rate_Simple_Return	-18.9735	282.298	-0.067	0.946	-572.268 534.321
ar.L1	0.0192	0.140	0.138	0.890	-0.254 0.293
ar.L2	0.8644	0.133	6.519	0.000	0.605 1.124
ma.L1	0.0428	0.179	0.239	0.811	-0.309 0.394
ma.L2	-0.9572	0.136	-7.031	0.000	-1.224 -0.690
ma.S.L12	-0.7624	0.059	-12.966	0.000	-0.878 -0.647
sigma2	35.5565	0.005	7270.360	0.000	35.547 35.566
Ljung-Box (L1) (Q):	0.07	Jarque-Bera (JB):	17.56		
Prob(Q):	0.79	Prob(JB):	0.00		
Heteroskedasticity (H):	0.56	Skew:	-0.56		
Prob(H) (two-sided):	0.01	Kurtosis:	3.70		

7.2.1.19 Healthcare sector - Inflation rate

Zero Mean - GARCH Model Results					
Dep. Variable:	None	R-squared:	0.000		
Mean Model:	Zero Mean	Adj. R-squared:	0.004		
Vol Model:	GARCH	Log-Likelihood:	-728.817		
Distribution:	Normal	AIC:	1463.63		
Method:	Maximum Likelihood	BIC:	1474.23		
Date:	Thu, May 11 2023	No. Observations:	253		
Time:	07:02:13	Df Residuals:	253		
		Df Model:	0		
Volatility Model					
	coef	std err	t	P> t	95.0% Conf. Int.
omega	6.2603	5.565	1.125	0.261	[-4.647, 17.168]
alpha[1]	0.0812	5.276e-02	1.539	0.124	[-2.219e-02, 0.185]
beta[1]	0.5837	0.322	1.814	6.965e-02	[-4.691e-02, 1.214]
Covariance estimator: robust					
SARIMAX Results					
Dep. Variable:	Health	No. Observations:	253		
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-694.822		
Date:	Thu, 11 May 2023	AIC	1403.645		
Time:	07:02:13	BIC	1428.039		
Sample:	01-01-2001	HQIC	1413.473		
	- 01-01-2022				
Covariance Type:	opg				
	coef	std err	z	P> z	[0.025 0.975]
CPI_Rate_Simple_Return	-502.8785	179.591	-2.800	0.005	-854.870 -150.887
ar.L1	0.3050	0.639	0.477	0.633	-0.948 1.558
ar.L2	0.6946	0.511	1.359	0.174	-0.307 1.696
ma.L1	-0.3503	0.528	-0.663	0.507	-1.386 0.686
ma.L2	-0.6148	0.526	-1.168	0.243	-1.646 0.417
ma.S.L12	-1.0000	141.535	-0.007	0.994	-278.404 276.404
sigma2	16.2067	2288.080	0.007	0.994	-4468.347 4500.761
Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	6.84		
Prob(Q):	0.98	Prob(JB):	0.03		
Heteroskedasticity (H):	1.63	Skew:	-0.41		
Prob(H) (two-sided):	0.03	Kurtosis:	3.03		

7.2.2.20 Healthcare sector - Oil rate

Zero Mean - GARCH Model Results					
=====					
Dep. Variable:	None	R-squared:	0.000		
Mean Model:	Zero Mean	Adj. R-squared:	0.004		
Vol Model:	GARCH	Log-Likelihood:	-731.930		
Distribution:	Normal	AIC:	1469.86		
Method:	Maximum Likelihood	BIC:	1480.44		
		No. Observations:	253		
Date:	Thu, May 11 2023	Df Residuals:	253		
Time:	06:45:25	Df Model:	0		
Volatility Model					
=====					
	coef	std err	t	P> t	95.0% Conf. Int.

omega	6.3798	3.688	1.730	8.362e-02	[-0.848, 13.607]
alpha[1]	0.0559	4.562e-02	1.226	0.220	[-3.350e-02, 0.145]
beta[1]	0.6083	0.205	2.970	2.979e-03	[0.207, 1.010]
=====					
Covariance estimator: robust					
SARIMAX Results					
=====					
Dep. Variable:	Health	No. Observations:	253		
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-696.769		
Date:	Thu, 11 May 2023	AIC	1407.538		
Time:	06:45:25	BIC	1431.931		
Sample:	01-01-2001	HQIC	1417.365		
	- 01-01-2022				
Covariance Type:	opg				
=====					
	coef	std err	z	P> z	[0.025 0.975]

OIL_Rate_Simple_Return	2.3778	1.668	1.425	0.154	-0.892 5.648
ar.L1	-0.2012	7.876	-0.026	0.980	-15.637 15.235
ar.L2	0.3499	5.235	0.067	0.947	-9.911 10.611
ma.L1	0.1378	7.867	0.018	0.986	-15.281 15.557
ma.L2	-0.3266	4.742	-0.069	0.945	-9.620 8.967
ma.S.L12	-0.9937	0.690	-1.439	0.150	-2.347 0.359
sigma2	16.4248	11.165	1.471	0.141	-5.459 38.309
=====					
Ljung-Box (L1) (Q):	0.02	Jarque-Bera (JB):	2.88		
Prob(Q):	0.89	Prob(JB):	0.24		
Heteroskedasticity (H):	1.54	Skew:	-0.27		
Prob(H) (two-sided):	0.06	Kurtosis:	3.06		

7.2.2.21 Healthcare sector - Economy policy uncertainty rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-729.505			
Distribution:	Normal	AIC:	1465.01			
Method:	Maximum Likelihood	BIC:	1475.61			
Date:	Thu, May 11 2023	No. Observations:	253			
Time:	11:24:14	Df Residuals:	253			
	Volatility Model	Df Model:	0			
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	6.3145	6.534	0.966	0.334	[-6.492, 19.121]	
alpha[1]	0.0757	6.327e-02	1.197	0.231	[-4.828e-02, 0.200]	
beta[1]	0.5865	0.387	1.517	0.129	[-0.171, 1.344]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	Health	No. Observations:	253			
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-694.081			
Date:	Thu, 11 May 2023	AIC	1402.161			
Time:	11:24:14	BIC	1426.555			
Sample:	01-01-2001	HQIC	1411.989			
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
EPU_Rate_Simple_Return	-1.1046	0.534	-2.070	0.038	-2.151	-0.058
ar.L1	0.3172	0.512	0.620	0.535	-0.686	1.320
ar.L2	0.6823	0.425	1.604	0.109	-0.151	1.516
ma.L1	-0.3816	0.447	-0.853	0.393	-1.258	0.495
ma.L2	-0.5831	0.444	-1.314	0.189	-1.453	0.287
ma.S.L12	-1.0000	201.310	-0.005	0.996	-395.561	393.561
sigma2	16.0945	3235.826	0.005	0.996	-6326.007	6358.196
Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 2.63						
Prob(Q): 0.97 Prob(JB): 0.27						
Heteroskedasticity (H): 1.47 Skew: -0.26						
Prob(H) (two-sided): 0.08 Kurtosis: 3.01						

7.2.2.22 Healthcare sector - EUR/USD rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-728.998			
Distribution:	Normal	AIC:	1464.00			
Method:	Maximum Likelihood	BIC:	1474.60			
		No. Observations:	253			
Date:	Thu, May 11 2023	Df Residuals:	253			
Time:	12:48:40	Df Model:	0			
Volatility Model						
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	6.7413	3.414	1.975	4.830e-02	[5.043e-02, 13.432]	
alpha[1]	0.1015	5.835e-02	1.739	8.196e-02	[-1.287e-02, 0.216]	
beta[1]	0.5375	0.207	2.594	9.487e-03	[0.131, 0.944]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	Health	No. Observations:	253			
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-693.180			
Date:	Thu, 11 May 2023	AIC	1400.359			
Time:	12:48:40	BIC	1424.753			
Sample:	01-01-2001	HQIC	1410.187			
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
US_Rate_Simple_Return	28.6198	10.612	2.697	0.007	7.821	49.419
ar.L1	0.3183	1.042	0.305	0.760	-1.724	2.361
ar.L2	0.6816	0.718	0.949	0.343	-0.726	2.089
ma.L1	-0.3666	0.506	-0.724	0.469	-1.359	0.626
ma.L2	-0.5917	0.500	-1.183	0.237	-1.572	0.389
ma.S.L12	-0.9998	30.313	-0.033	0.974	-60.413	58.413
sigma2	15.9986	470.807	0.034	0.973	-906.765	938.763
Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 3.37						
Prob(Q): 0.99 Prob(JB): 0.19						
Heteroskedasticity (H): 1.47 Skew: -0.28						
Prob(H) (two-sided): 0.09 Kurtosis: 2.84						

7.2.2.23 Healthcare sector - Interest rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:      None      R-squared:      0.000
Mean Model:        Zero Mean  Adj. R-squared: 0.004
Vol Model:         GARCH      Log-Likelihood: -725.456
Distribution:       Normal     AIC:            1456.91
Method:            Maximum Likelihood BIC:            1467.51
Date:              Thu, May 11 2023 No. Observations: 253
Time:              13:54:40      Df Residuals:    253
                               Df Model:      0
                               Volatility Model
=====
               coef      std err      t      P>|t|      95.0% Conf. Int.
-----+-----+-----+-----+-----+-----
omega          7.9206        6.823      1.161      0.246      [-5.451, 21.293]
alpha[1]        0.0817      5.968e-02      1.368      0.171 [-3.531e-02, 0.199]
beta[1]         0.4810        0.404      1.191      0.234      [-0.310, 1.272]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:      Health      No. Observations: 253
Model:              SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood -690.994
Date:              Thu, 11 May 2023 AIC 1395.988
Time:              13:54:41 BIC 1420.381
Sample:            01-01-2001 HQIC 1405.815
Covariance Type:    - 01-01-2022 opg
=====
               coef      std err      z      P>|z|      [0.025      0.975]
-----+-----+-----+-----+-----+-----
Interest_Rate_Simple_Return -2.2949      0.694     -3.307      0.001     -3.655     -0.935
ar.L1                   -1.4149      0.033    -42.341      0.000     -1.480     -1.349
ar.L2                   -0.9517      0.031    -30.587      0.000     -1.013     -0.891
ma.L1                   1.4000      0.042    33.670      0.000      1.319     1.482
ma.L2                   0.9860      0.046    21.339      0.000      0.895     1.077
ma.S.L12                -0.9751      0.166     -5.857      0.000     -1.301     -0.649
sigma2                  15.6765      2.846      5.508      0.000     10.098     21.255
=====
Ljung-Box (L1) (Q):      0.03 Jarque-Bera (JB):      8.96
Prob(Q):                0.87 Prob(JB):      0.01
Heteroskedasticity (H): 1.50 Skew:      -0.47
Prob(H) (two-sided):    0.07 Kurtosis:      3.04
=====

```

7.2.2.24 Healthcare sector - gold rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:      None      R-squared:      0.000
Mean Model:        Zero Mean  Adj. R-squared: 0.004
Vol Model:         GARCH      Log-Likelihood: -730.625
Distribution:       Normal     AIC:            1467.25
Method:            Maximum Likelihood BIC:            1477.85
Date:              Thu, May 11 2023 No. Observations: 253
Time:              14:47:45      Df Residuals:    253
                               Df Model:      0
                               Volatility Model
=====
               coef      std err      t      P>|t|      95.0% Conf. Int.
-----+-----+-----+-----+-----
omega          6.1592        3.635      1.695      9.015e-02      [-0.964, 13.283]
alpha[1]        0.0842      5.070e-02      1.660      9.683e-02 [-1.519e-02, 0.184]
beta[1]         0.5902        0.209      2.822      4.778e-03      [ 0.180, 1.000]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:      Health      No. Observations: 253
Model:              SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood -696.344
Date:              Thu, 11 May 2023 AIC 1406.687
Time:              14:47:46 BIC 1431.081
Sample:            01-01-2001 HQIC 1416.515
Covariance Type:    - 01-01-2022 opg
=====
               coef      std err      z      P>|z|      [0.025      0.975]
-----+-----+-----+-----+-----+-----
Gold_Rate_Simple_Return    79.7036     185.483      0.430      0.667     -283.837     443.244
ar.L1                   0.2712      0.466      0.582      0.561     -0.642     1.185
ar.L2                   0.7054      0.492      1.432      0.152     -0.260     1.671
ma.L1                   -0.3247      0.501     -0.648      0.517     -1.307     0.658
ma.L2                   -0.6324      0.526     -1.203      0.229     -1.663     0.398
ma.S.L12                -1.0000      0.097    -10.359      0.000     -1.189     -0.811
sigma2                  16.3347      0.006    2772.682      0.000     16.323     16.346
=====
Ljung-Box (L1) (Q):      0.00 Jarque-Bera (JB):      4.08
Prob(Q):                0.95 Prob(JB):      0.13
Heteroskedasticity (H): 1.58 Skew:      -0.32
Prob(H) (two-sided):    0.04 Kurtosis:      3.03
=====

```

7.2.2.25 Other sector - Inflation rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-778.626			
Distribution:	Normal	AIC:	1563.25			
Method:	Maximum Likelihood	BIC:	1573.85			
Date:	Thu, May 11 2023	No. Observations:	253			
Time:	07:02:16	Df Residuals:	253			
	Volatility Model	Df Model:	0			
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	2.0787	1.593	1.304	0.192	[-1.044, 5.202]	
alpha[1]	0.1177	5.611e-02	2.098	3.595e-02	[7.718e-03, 0.228]	
beta[1]	0.8167	8.298e-02	9.842	7.396e-23	[0.654, 0.979]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	Other	No. Observations:	253			
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-756.222			
Date:	Thu, 11 May 2023	AIC	1526.445			
Time:	07:02:17	BIC	1550.838			
Sample:	01-01-2001	HQIC	1536.272			
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
CPI_Rate_Simple_Return	119.8899	283.788	0.422	0.673	-436.324	676.104
ar.L1	0.1828	0.712	0.257	0.797	-1.213	1.579
ar.L2	0.4455	0.308	1.447	0.148	-0.158	1.049
ma.L1	-0.0433	0.707	-0.061	0.951	-1.429	1.343
ma.L2	-0.5025	0.400	-1.257	0.209	-1.286	0.281
ma.S.L12	-1.0000	0.070	-14.195	0.000	-1.138	-0.862
sigma2	26.6903	0.003	1.02e+04	0.000	26.685	26.695
Ljung-Box (L1) (Q):	0.12	Jarque-Bera (JB):	38.92			
Prob(Q):	0.73	Prob(JB):	0.00			
Heteroskedasticity (H):	1.77	Skew:	-0.44			
Prob(H) (two-sided):	0.01	Kurtosis:	4.77			

7.2.2.26 Other sector - Oil rate

Zero Mean - GARCH Model Results					
Dep. Variable:	None	R-squared:	0.000		
Mean Model:	Zero Mean	Adj. R-squared:	0.004		
Vol Model:	GARCH	Log-Likelihood:	-772.204		
Distribution:	Normal	AIC:	1550.41		
Method:	Maximum Likelihood	BIC:	1561.01		
		No. Observations:	253		
Date:	Thu, May 11 2023	Df Residuals:	253		
Time:	06:45:30	Df Model:	0		
	Volatility Model				
	coef	std err	t	P> t	95.0% Conf. Int.
omega	1.8194	1.201	1.515	0.130	[-0.534, 4.173]
alpha[1]	0.1032	4.153e-02	2.485	1.297e-02	[2.178e-02, 0.185]
beta[1]	0.8339	5.923e-02	14.080	5.070e-45	[0.718, 0.950]
Covariance estimator: robust					
SARIMAX Results					
Dep. Variable:	Other	No. Observations:	253		
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-745.000		
Date:	Thu, 11 May 2023	AIC	1503.999		
Time:	06:45:31	BIC	1528.393		
Sample:	01-01-2001	HQIC	1513.827		
	- 01-01-2022				
Covariance Type:	opg				
	coef	std err	z	P> z	[0.025 0.975]
OIL_Rate_Simple_Return	13.2634	1.757	7.550	0.000	9.820 16.707
ar.L1	-0.1465	0.061	-2.421	0.015	-0.265 -0.028
ar.L2	-0.9366	0.062	-15.023	0.000	-1.059 -0.814
ma.L1	0.1420	0.088	1.618	0.106	-0.030 0.314
ma.L2	0.8578	0.096	8.938	0.000	0.670 1.046
ma.S.L12	-0.9872	0.385	-2.562	0.010	-1.743 -0.232
sigma2	24.6179	8.913	2.762	0.006	7.150 42.086
Ljung-Box (L1) (Q):	0.01	Jarque-Bera (JB):	8.63		
Prob(Q):	0.94	Prob(JB):	0.01		
Heteroskedasticity (H):	1.27	Skew:	-0.21		
Prob(H) (two-sided):	0.29	Kurtosis:	3.82		

7.2.2.27 Other sector - Economy policy uncertainty rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-772.888			
Distribution:	Normal	AIC:	1551.78			
Method:	Maximum Likelihood	BIC:	1562.38			
Date:	Thu, May 11 2023	No. Observations:	253			
Time:	11:24:18	Df Residuals:	253			
	Volatility Model	Df Model:	0			
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	1.7709	1.145	1.547	0.122	[-0.473, 4.015]	
alpha[1]	0.1222	5.369e-02	2.276	2.286e-02	[1.696e-02, 0.227]	
beta[1]	0.8215	6.163e-02	13.329	1.575e-40	[0.701, 0.942]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	Other	No. Observations:	253			
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-753.151			
Date:	Thu, 11 May 2023	AIC	1520.301			
Time:	11:24:19	BIC	1544.695			
Sample:	01-01-2001	HQIC	1530.129			
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
EPU_Rate_Simple_Return	-1.6504	0.642	-2.571	0.010	-2.909	-0.392
ar.L1	0.1355	0.597	0.227	0.821	-1.035	1.307
ar.L2	0.5414	0.313	1.731	0.084	-0.072	1.155
ma.L1	-0.0307	0.584	-0.053	0.958	-1.174	1.113
ma.L2	-0.5685	0.339	-1.677	0.094	-1.233	0.096
ma.S.L12	-0.9997	14.023	-0.071	0.943	-28.484	26.484
sigma2	26.0733	364.679	0.071	0.943	-688.685	740.832
Ljung-Box (L1) (Q):	0.24	Jarque-Bera (JB):	43.54			
Prob(Q):	0.62	Prob(JB):	0.00			
Heteroskedasticity (H):	1.70	Skew:	-0.45			
Prob(H) (two-sided):	0.02	Kurtosis:	4.87			

7.2.2.28 Other sector - EUR/USD rate

Zero Mean - GARCH Model Results						
Dep. Variable:	None	R-squared:	0.000			
Mean Model:	Zero Mean	Adj. R-squared:	0.004			
Vol Model:	GARCH	Log-Likelihood:	-780.808			
Distribution:	Normal	AIC:	1567.62			
Method:	Maximum Likelihood	BIC:	1578.22			
		No. Observations:	253			
Date:	Thu, May 11 2023	Df Residuals:	253			
Time:	12:48:44	Df Model:	0			
	Volatility Model					
	coef	std err	t	P> t	95.0% Conf. Int.	
omega	2.0722	1.418	1.461	0.144	[-0.707, 4.851]	
alpha[1]	0.0889	3.800e-02	2.341	1.925e-02	[1.447e-02, 0.163]	
beta[1]	0.8425	6.233e-02	13.515	1.270e-41	[0.720, 0.965]	
Covariance estimator: robust						
SARIMAX Results						
Dep. Variable:	Other	No. Observations:	253			
Model:	SARIMAX(2, 0, 2)x(0, 1, [1], 12)	Log Likelihood	-751.631			
Date:	Thu, 11 May 2023	AIC	1517.262			
Time:	12:48:44	BIC	1541.655			
Sample:	01-01-2001	HQIC	1527.090			
	- 01-01-2022					
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
US_Rate_Simple_Return	47.2313	14.020	3.369	0.001	19.753	74.709
ar.L1	0.2448	0.511	0.479	0.632	-0.757	1.247
ar.L2	0.5333	0.274	1.950	0.051	-0.003	1.069
ma.L1	-0.1159	0.497	-0.233	0.816	-1.090	0.859
ma.L2	-0.5986	0.300	-1.996	0.046	-1.186	-0.011
ma.S.L12	-0.9998	23.442	-0.043	0.966	-46.946	44.946
sigma2	25.7474	602.551	0.043	0.966	-1155.230	1206.725
Ljung-Box (L1) (Q):	0.10	Jarque-Bera (JB):	22.94			
Prob(Q):	0.76	Prob(JB):	0.00			
Heteroskedasticity (H):	1.57	Skew:	-0.33			
Prob(H) (two-sided):	0.05	Kurtosis:	4.36			

7.2.2.29 Other sector - Interest rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:          None      R-squared:          0.000
Mean Model:            Zero Mean  Adj. R-squared:     0.004
Vol Model:             GARCH      Log-Likelihood:     -778.514
Distribution:          Normal      AIC:                1563.03
Method:               Maximum Likelihood BIC:                1573.63
Date:                 Thu, May 11 2023 No. Observations:   253
Time:                 13:54:45      Df Residuals:       253
                               Df Model:         0
                               Volatility Model
=====
               coef      std err      t      P>|t|      95.0% Conf. Int.
-----
omega         2.1014      1.642      1.280      0.201      [-1.117, 5.319]
alpha[1]       0.1197     5.712e-02     2.096     3.604e-02 [7.795e-03, 0.232]
beta[1]        0.8140     8.587e-02     9.479     2.559e-21 [ 0.646, 0.982]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:          Other      No. Observations:   253
Model:                 SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood      -756.289
Date:                  Thu, 11 May 2023 AIC                1526.577
Time:                  13:54:45 BIC                1550.971
Sample:                01-01-2001 HQIC               1536.405
                               - 01-01-2022
Covariance Type:       opg
=====
               coef      std err      z      P>|z|      [0.025      0.975]
-----
Interest_Rate_Simple_Return      0.3660      0.927      0.395      0.693      -1.452      2.184
ar.L1      0.1934      0.692      0.280      0.780      -1.162      1.549
ar.L2      0.4600      0.321      1.434      0.152      -0.169      1.089
ma.L1      -0.0587      0.687     -0.086      0.932      -1.405      1.287
ma.L2      -0.5186      0.407     -1.275      0.202      -1.316      0.279
ma.S.L12    -0.9996     13.466     -0.074      0.941     -27.392     25.393
sigma2      26.7540     359.236      0.074      0.941     -677.335     730.843
=====
Ljung-Box (L1) (Q):          0.13 Jarque-Bera (JB):          38.75
Prob(Q):                    0.71 Prob(JB):          0.00
Heteroskedasticity (H):      1.79 Skew:          -0.43
Prob(H) (two-sided):         0.01 Kurtosis:          4.76
=====

```

7.2.2.30 Other sector - gold rate

```

=====
Zero Mean - GARCH Model Results
=====
Dep. Variable:          None      R-squared:          0.000
Mean Model:            Zero Mean  Adj. R-squared:     0.004
Vol Model:             GARCH      Log-Likelihood:     -778.884
Distribution:          Normal      AIC:                1563.77
Method:               Maximum Likelihood BIC:                1574.37
Date:                 Thu, May 11 2023 No. Observations:   253
Time:                 14:47:49      Df Residuals:       253
                               Df Model:         0
                               Volatility Model
=====
               coef      std err      t      P>|t|      95.0% Conf. Int.
-----
omega         2.1196      1.688      1.255      0.209      [-1.189, 5.429]
alpha[1]       0.1193     5.920e-02     2.015     4.386e-02 [3.283e-03, 0.235]
beta[1]        0.8141     8.877e-02     9.171     4.689e-20 [ 0.640, 0.988]
=====

Covariance estimator: robust

=====
SARIMAX Results
=====
Dep. Variable:          Other      No. Observations:   253
Model:                 SARIMAX(2, 0, 2)x(0, 1, [1], 12) Log Likelihood      -756.392
Date:                  Thu, 11 May 2023 AIC                1526.783
Time:                  14:47:50 BIC                1551.177
Sample:                01-01-2001 HQIC               1536.611
                               - 01-01-2022
Covariance Type:       opg
=====
               coef      std err      z      P>|z|      [0.025      0.975]
-----
Gold_Rate_Simple_Return      29.6615     333.003      0.089      0.929     -623.012     682.335
ar.L1      -0.0149      1.152     -0.013      0.990      -2.273      2.243
ar.L2      0.3625      0.442      0.820      0.412      -0.504      1.229
ma.L1      0.1573      1.152      0.136      0.891      -2.101      2.416
ma.L2      -0.3893      0.616     -0.632      0.528      -1.597      0.819
ma.S.L12    -1.0000      0.068    -14.677      0.000     -1.134     -0.866
sigma2      26.7798      0.003     1.05e+04      0.000      26.775      26.785
=====
Ljung-Box (L1) (Q):          0.18 Jarque-Bera (JB):          43.01
Prob(Q):                    0.67 Prob(JB):          0.00
Heteroskedasticity (H):      1.78 Skew:          -0.47
Prob(H) (two-sided):         0.01 Kurtosis:          4.85
=====

```

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