ANALYZING TIME-DEPENDENT RELATIONSHIPS: THE IMPACT OF UNEXPECTED AND EXPECTED INFLATION ON STOCK AND COMMODITY MARKETS.

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ABSTRACT

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Abstract

This Master's thesis attempts to analyse and examine the effects of inflation on market returns for different areas. The research analysis is aimed initially at the stock market returns indices within major global economic regions: United States, Euro Zone19 and OECD countries.

This thesis contributes to the academic literature by providing evidence that challenges the traditional inflation – market returns relationship analysis. Based on the analyses evidences, further recommendations are to include in future research analysis more macroeconomic and economic activity variables to incorporate all macroeconomic shocks and global economic events.

Key words

Inflation, unexpected, expected inflation, stock market returns, commodity market returns, VAR analysis.

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1. INTRODUCTION

Inflation and market returns were both subjects of interest amongst the financial institutions and economists over the decades. Moreover, it has become a more significant topic for research from both economic and financial perspectives.

Nowadays, inflation is becoming a significant macroeconomic indicator that has a direct impact on the economy and financial markets. Although stock or commodity returns and inflation are joint research topics in finance and macroeconomics (Zhang, 2021), this needs to be more detailed and examined by the public with no economic background.

As an economic occurrence, inflation can significantly impact the performance of companies, either positively or negatively depending on their specifics. The spikes in the inflation rates in the 70s of the last century has caused economic turmoil and financial crisis across different parts of the globe.

Similarly, a series of economic shocks caused by international events have deepened already weak global economic situation. The European Sovereign crisis, COVID-19 and the Russia-Ukraine war made Governments and Central Banks across the globe develop new measures and execute new plans for unexpected concerns. Unprecedented policy initiatives have been made by central banks and finance ministries worldwide to lessen the effects of the pandemic (Zhang, 2021). Lately, inflation is one the most discussed indicators due to its importance. In many industrialised and emerging economies, high inflation levels have caused an increase in volatility and uncertainty in financial markets. These factors have generated concerns to the relationship between inflation and financial markets. The complex relationship between inflation and industries performances, can have both significant negative and positive economic and financial impacts.

This master's thesis goal is to analyse the influence of inflation on stock market and commodities market returns in different industrial sectors and geographic regions. The thesis also examines how the relationship between inflation and market returns is changing in time. Hence, in the thesis, an investigation and comparison will be performed within different industries or economic sectors. In this research it is used a quantitative approach, utilising econometric techniques to analyse time series inflation and market returns data. As the main contributor, various data, including international organisations, central banks, and financial databases, is used to gather the data. Analysing this indicator through this aspect provides betters insights and a clear perspective on how it affects and how we can attempt to prevent any severe consequences.

1.1. Motivation

All global economies are affected by inflation at one point in time. Weaker economies or those that have just passed a crisis suffer the most from unanticipated inflation. Inflation's influence on market returns is particularly important since investors tend to reduce the negative impacts of inflation on asset returns. Inflation is also an important predictor of market performance, impacting interest rates, currency rates, and consumer purchasing power.

Over the decades, inflation has affected countries to varying degrees. Hachula et al. (2018) state that robust inflation expectations should not be affected by macroeconomic news, only some distortions on a short-term basis. Furthermore, they mention that if an unexpected change in inflation occurs, it might generate grave consecutive end results.

Fama (1981) describes the negative correlation between stock returns and inflation as the consequence of proxy effects; hence this can create some ambiguity in establishing the real relationship between the market returns and the inflation.

Inflation is the rate at which the price of goods and services are rising over the time. The result of this is decreasing the purchasing power of money, and therefore, a loss of real value in the medium of exchange. When the expected inflation rate increases, it can lead to higher longer-term interest rates and a higher cost of borrowing for businesses or population. On the contrary, deflation represents a decline in the prices of goods and services. This can lead to country's economic growth. Therefore, if central banks or business have a clear understanding of the current situation, they can come up with the solutions that are intended to boost their performance.

Another important statement highlighted by Kaul (1987, 1990) and which is considered in this paper suggests that changes in monetary policies affect directly the correlation between stock returns and inflation. Also, when monetary policies are countercyclical, there is no correlation or a negative one between assets returns and inflation (Zhang, 2021). Clearly, monetary policies have substantial impact on indicators either positively or negatively.

It is easier to understand the performance of publicly listed companies or the anticipated global economic growth if we understand how inflation, stock market returns, and other macroeconomic factors work. Besides, it would be easier to understand the overall cost of living trend if we could better grasp how inflation works. Thus, this Master's thesis aims to contribute to the literature and offer novel insights into the complex correlation between inflation and market returns.

1.2. Research Questions

This Master's thesis attempts to analyse and examine the effects of inflation on market returns for different areas. The objective is to estimate how the expected and unexpected inflation affect stock market indices, and which indices benefit or lose from this. The research analysis is aimed initially at the stock market returns indices within major global economic regions: United States, Euro Zone19 and OECD countries. The analysis is oriented to the commodity returns in the latter part. The main research questions proposed for this master thesis are:

- *What is the behaviour of the stock market and commodity indices in relation to expected or unexpected inflation rate changes over time?*

- *Which indices benefit and which loose due to changes in the inflation rates?*

These questions will help investigate the trends in the indices' behaviour in relation to inflation forecasts. Furthermore, it will help to understand how decomposed inflation affects indices in different economic regions.

1.3. Research Methods

The data used for analysis in this thesis is obtained from the Refinitiv (known also as Thomas Reuters) and OECD portals and the FRED St. Louis database. To examine the research questions of the thesis, the Vector Autoregression method is implemented. VAR approach is used to capture the relationship between decomposed inflation, stock market indices and commodities total returns, industrial production growth, volatility index and Three-Month Treasury Bill variables. This thesis adopts a quantitative methodology utilizing rigours econometric analyses.

1.4. Structure of the thesis

This Master's thesis is divided into chapters that define the research stages and the structure of the thesis. The first chapter contains details about the Master's thesis, reasons for choosing the topic and an introduction to it. The first part of Chapter 2, Theoretical Framework, provides a detailed background as well as definitions for major macroeconomic terms. Afterwards, the second part of Chapter 2 provides an elaborate review of existing literature as well as research on this area. Discussion of data sources, collection methods, variables and analytical technique models are contained in Chapter 3. In Chapter 4 – Empirical Analysis, descriptive statistics and empirical results are presented. Also, the last chapter of this Master's thesis contains the conclusion as well as recommendations for further studies on this topic.

2. THEORETICAL FRAMEWORK

In the today's global economy context, the relationship between inflation and the stock market return plays a significant importance. The objective of the theoretical framework chapter is to explain the macroeconomic factors that are responsible for inflation's level trends and their changes. Also, it explores how the inflation impact the stock and commodity markets. Initially, I examine the current theoretical background, as research papers and articles, and the already known definitions and theorems. The second part of this chapter is dedicated to review and discuss the already existing results from previous research papers. This approach aims to highlight existing theories and pave the way for analysing the role of inflation related to stock and commodity market returns.

2.1. Key definitions and background

2.1.1. Consumer Price Index

Mishkin (2019), defines inflation rate as the growth of the aggregate price level. Inflation, as the macroeconomic indicator denotes the rate at which the price of goods and services change over time. Thereby, it is exerting an impact on the purchasing power. Purchasing power, in essence, can be explain as the quantity of goods and services that can be purchased with a certain amount of money within a particular timeframe. Consequently, when the inflation increases, customers will experience a lower ability to purchase the same products for the same amount of money.

One of the most widely and commonly used standard inflation measurements is the Consumer Price Index or CPI, which measures the average price change paid by urban consumers over time (Mishkin, 2019). The formula to determine the inflation rate in a specific country, is equal to the percentage change in the CPI between the price of the basket of goods and services at the present value and the annual price change in subsequent years.

Inflation Rate = $(CPI_{\text{Present Value}} - CPI_{\text{Past Value}}) / CPI_{\text{Past Value}} \times 100\%$

The basket of goods and services included in the Consumer Price Index reflect the average spending on household food, housing, transportation, and entertainment. Typically, these prices are gathered nationwide and calculated by the national bureau of statistics of the respective country. Subsequently, these calculations are utilized to calculate the average inflation level of the nation. Furthermore, the CPI indicator is handful instrument that can be used as a benchmark for inflation targeting by the government and central banks.

2.1.2. Producer Price Index

Another way to measure inflation is using the Producer Price Index (PPI) indicator. Similar to the CPI indicator that was defined above, the PPI indicator is calculated by a national bureau of statistics but measures the average level of the wholesale price (Mishkin, 2019).

Producer Price Index is typically used to measure inflation by calculating the average change specific goods and services prices over the time; however, the calculation estimation is for a specific goods or services group. The main advantage of this index is that it gives the opportunity to calculate inflation at the beginning when the prices for goods and services are just starting to change. Producer Price Index can be considered an indicator that can predict the future direction of inflation. If the PPI is increasing, this can show that consumer prices will also increase in the future too. If the PPI is decreasing, this can indicate that the consumer level will decrease too. Companies use this index to determine the possible future price of goods and services. Same time, economists use it to forecast inflation and analyse the overall economic conditions of a country. Nonetheless, a significant disadvantage of the PPI is that it does not consider the effect of trade on the domestic economy, as it measures only the price changes for products produced and sold domestically. Moreover, it cannot display an accurate change in the cost of living for customers since it needs to consider the quality of goods and services. From a general perspective, Producer Price Index is a good indicator if it is considered only at the initial products' stage or at the wholesale level that is traded internally. Otherwise, PPI has limitations in predicting inflation at a more comprehensive level.

2.1.3. GDP Price Deflator

Another alternative to the Consumer Price Index indicator to calculate the inflation rate is the GDP Price Deflator. It is an indicator that measures and shows how the changes in the prices affect the change in the GDP level. The GDP deflator is explained by Mishkin (2019) as the nominal GDP divided by the real GDP. He also mentions how the GDP deflator may inflate or deflate a nominal amount into a real amount. Like the other indexes, this is essential for policymakers to analyse and forecast the overall economic status and adopt the most relevant macro and monetary policies. Inflation can be measured widely and in detail with the GDP deflator, which gives a superior advantage over the CPI. Instead of calculating the price changes of consumer goods and services from a fixed and static basket of goods, the GDP price deflator is more flexible and grasps the prices of goods outside that respective fixed basket of goods. This makes it a more accurate measure of overall inflation. An important example that can characterise the difference between CPI and GDP Price Deflator is that the new goods and services or changes in consumption habits are reflected in the latter but not in the CPI.

Furthermore, GDP Price Deflator can be used to compare a country's economic activity and performance over time. This measure that is linked to the Gross Domestic Product, offers an understanding in future economic trend.

However, it is worth noting that the GDP Deflator is harder to calculate, due to the scope size of the "basket" prices used in calculations. Therefore, for a more accurate result, it requires a considerable amount of time and effort. Moreover, the GDP deflator includes the production of goods and services instead of the consumption or purchase of goods and services.

In this current paper, Consumer Price Index will be the only indicator based on which the inflation rate is measured or calculated. One of the reasons is its accuracy which includes only goods and services consumed by individuals. Additionally, CPI is a common indicator that was used in the measurement of inflation in other studies (see Ciccarelli & Mojon, 2010; Browne & Cronin, 2010; Humpe & Macmillan, 2009).

2.2. Consumer Price Index and Inflation

Inflation, a significant term in both macroeconomics and finance, can impact different aspects of the economy. It may cause a decrease in consumer purchasing power and an increase in business costs.

Understanding the causes and effects of inflation implies digging into various economic theories and models. Different theories can be more or less applicable depending on the economic conditions, and inflation is a complex phenomenon influenced by many factors.

Many economists suggest that inflation tends to go up when the country's money supply grows faster than its economy. In the USA, especially during COVID-19 lockdowns, the stimulus offered to people has increased the overall money supply in the country. Based on the post-COVID-19 inflation activity, economists are more interested in the correlation between stock returns and inflation (Zhang, 2021).

2.2.1. Cost-push inflation

There are multiple known factors that drive the growth of inflation. In the post-COVID era, the current circumstances are characterized by cost-push inflation. The cost-push inflation describes an increase in the cost of producing goods and services, consequently resulting in an increase in final prices.

One of the reasons that come from the energy sector and that can cause the cost increase is because the energy resources are not enough or the prices are increasing all the time. The current war in Ukraine can cause these issues since the export of natural resources from Russia has been cancelled. Cost-push inflation can occur in different industry sectors and can be caused by numerous factors, including supply chains, natural disasters or changes in government activities and policies. From the energy sectors or metals industries - the fluctuations of the oil and natural gas prices or the metal raw materials can also impact the production, distribution or increased demand costs. These changes can have an impact on the electricity, fuel and other inputs price changes.

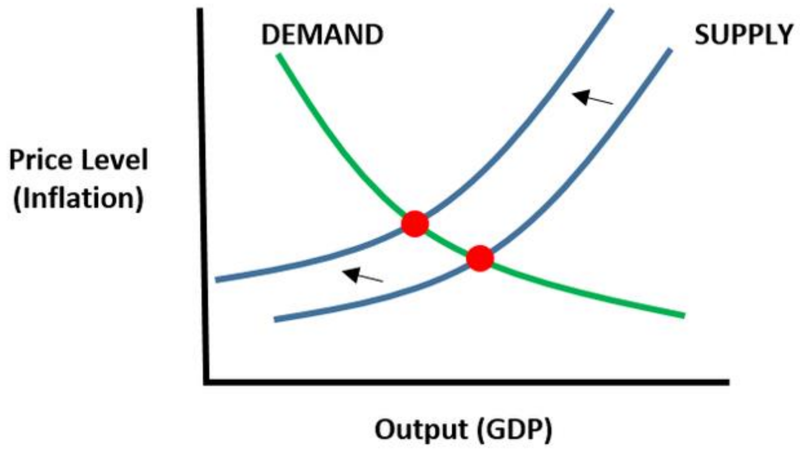

Figure 1 Interaction between Demand and Supply in the Cost-Push Inflation scenario

Inflation caused by cost-push inflation can influence stock market returns. Figure 1 shows that when there is a decrease in supply will lead to higher prices and less demand for the goods and services.

If the production costs increase, goods and services will respectively be more expensive, and this will cause companies' profitability to decrease, which respectively will lead to stock market declines.

According to the classical approach, cost-push inflation is temporary, would eventually subside, and the market will rebalance. It has contended that the drop in demand brought on by the price increase will push companies to lower their pricing. Inflation will eventually reach its average pace as a result of this. According to this approach, cost-push inflation reduces stock market returns because investors may lose faith in the market and may sell their positions.

The oil crisis of the 1970s is one of the most notable examples of cost-push inflation affecting stock market returns. Because of the Arab-Israeli war and the Iranian Revolution, the price of oil increased significantly during this period. This has resulted in an increase in energy costs led by the higher prices for goods and services (Brandt & Wang, 2003). Inflation increased significantly, resulting in an overall decline in stock market performance. Recently, the global pandemic of Covid-19 has demonstrated how cost-push inflation affects stock market returns, a well. Many companies have faced increased production costs, as a result of disruptions in supply chains. Moreover, another reason was due to because of the rising labour costs. Thus, stock prices declined, and stock market returns decreased.

2.2.2. Demand-pull inflation

Demand-pull inflation, in contrast to cost-push inflation, occurs when the lack of goods and services results in an upward surge in inflation. This eventually is distinguished by an increase in the price index from the lack of availability of a particular product.

The occurrence of this phenomenon can be attributed to various factors, some are changes in the consumer preferences and economic expansion. As a consequence, companies are compelled to increase their prices in order to be align with the increased demand.

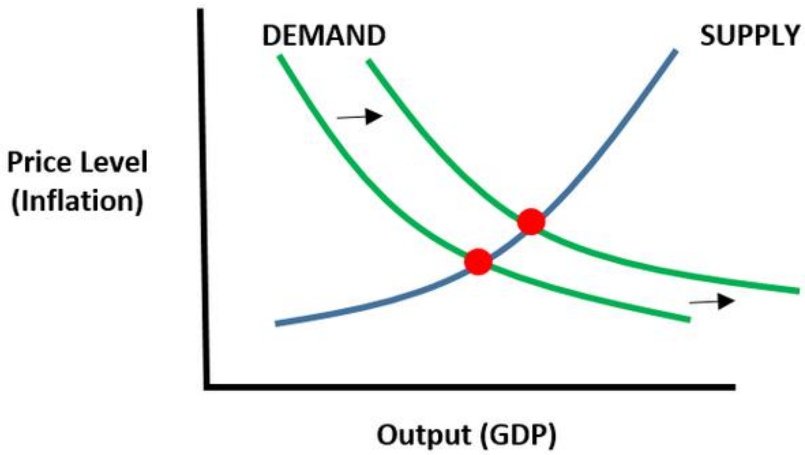

Figure 2 Interaction between Demand and Supply in the Demand-Pull Inflation scenario

When the demand for the companies' products increases, it can positively affect earnings and investor confidence. Figure 2 shows the demand-pull inflation scenario. It describes the case, where an increase in the demand will result in higher prices and higher output. This will later result in increased sales and profits. However, this also can have a negative impact, since it is possible for prices to increase to a point where the investors start doubting the correctness of the earnings, or how it can impact the economy. This respectively, will result in stock prices plunging; hence, the stock market returns will decline.

Demand-pull inflation can also be viewed as a threat to stock market stability, because might deteriorate consumers' purchasing power. This will result in a lower demand for goods and services. Companies will earn less money and stock prices will drop. Furthermore, higher interest rates from demand-pull inflation can also reduce the availability of investment capital on the stock market.

In the technology industry, for instance, there are some cases that can be used to demonstrate demand-pull inflation and how it affects stock market returns. The dot-com bubble has seen a significant rise in stock at the end of 90's. This growth was caused by new technologies such as e-commerce and the rapid expansion of the internet. After the dot-com bubble burst, many stock prices have declined sharply, because those were overpriced. This resulted in major losses made by investors.

The dot-com boom and subsequent fall exemplifies cost-push inflation leading to market instability. This rise in prices resulted from increased consumptions and expenditures on technology-related goods and services, lowered these two variables at once. The stock market became unstable because of the decreased demand. This has also caused technology companies' earnings and stock values to decline.

The cryptocurrency bubble from 2017 has also impacted the stock market returns. The cryptocurrencies companies stock market prices increased significantly, because of the increase in demand for digital coins like Bitcoin and Ethereum.

The negative side is that stock and commodity prices can drop fall rapidly when the bubble bursts. This will leave the investors with substantial financial losses.

2.2.3. Built-in inflation

The third type that describes the inflation growth causes is built-in inflation. This spiral effect started at the employees level within a company, usually a large company, with a more significant effect on the local market. This describes the effect when the employee asks for a higher salary to cover the increased living costs. Afterwards, the company increases their product prices to counteract the rising wages. Economic conditions, monetary policy, and past inflation can be among the factors that can contribute to it.

2.3. Theoretical Review: Inflation and Stock Market Returns

One of the macroeconomics subjects that has received significant attention both theoretically and empirically is the question of the welfare costs of inflation (Fountas & Karanasos, 2007). Numerous empirical research has been conducted to analyse the complex relationship between inflation and stock market performance.

Academics, financial experts, and monetary policymakers are continually interested in and concerned about the impact of inflation on the stock market (Liu & Serletis, 2022). There are several factors related to inflation that can impact the stock markets returns, some of them are such as, changes in the price of goods and services, interest rates.

This Master's thesis aims to investigate the historical responses of stock and commodity market indices to forecasted unexpected and expected inflation changes over time. Additionally, it will analyze which indices benefit and which loose due to changes in the inflation rates.

In order to analyse the impact of inflation on different components, the initial approach requires diving into the well-known Fisher hypothesis. This economy theory states that the nominal interest rate equals the real interest rate plus the anticipated inflation rate. According to the Fisher Model, expected nominal rates of return on assets should follow expected inflation (Boudoukh et al., 1994).

According to the Fisher effect, an increased nominal interest rate is correlated to a higher inflation rate. Thus, a higher nominal interest rate can lead investments to decline. Furthermore, a rise in inflation can also be the reason for the decreasing the consumer purchasing power. Consequently, this phenomenon will simultaneously decrease the demand for various products and services, therefore reducing the profitability of companies. Lately, more and more researchers have proven, based on the empirical evidence, that the hypothesis does not hold. (see, Lintner (1975), Bodie (1976), Fama and Schwert (1977), and Kaul (1987)).

According to Geetha et al. (2011), the interest rate correlates positively with inflation to adjust for the differences in the real value of nominal interest payments. Interest rates reflect more expected inflation rather than current inflation (Geetha et al., 2011).

Monetary policies significantly influence inflation. Sellin (2001) states that monetary policy directly affects inflation through financial markets. Central banks can control and maintain prices by managing the money supply and interest rates. For instance, in times when there is high rate of inflationary pressures, central bank might decide to adopt a contractionary monetary policy by raising interest rates; hence reducing amount of money in circulation. Changes implemented on monetary policies (through money and the bond markets) result into fluctuations in the levels of interest rates hence affecting both real economic activity and the level of inflations (Sellin, 2001).

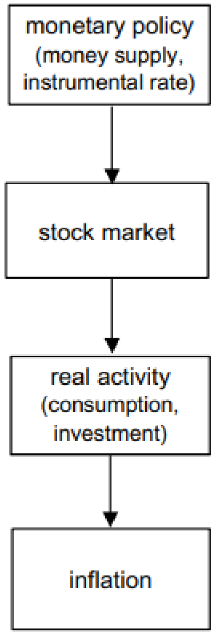

Figure 3 The stock market channel. (Sellin, 2001)

Central banks have become interested in the stock market's implications and how monetary policies can be transmitted through those (Sellin, 2001). The stock return-inflation relationship is more adverse when a nation's central bank pursues a more assertive countercyclical monetary policy. Also, the outcomes vary depending on the monetary policy framework (Zhang, 2021).

Alternatively, a very tight monetary policy or a quick hike in interest rates might lead to a decline in economic activity and poor stock market performance. This is because increased interest rates make the borrowing expensive. Therefore, this will discourage investments and slow down economic growth. Monetary policies can affect the stock market in either direct or indirect ways.

By decreasing demand for stocks, for instance, a monetary policy raising interest rates can lower stock market returns directly. As per Zhang (2021), when inflation rises, the central banks will lift their policy rate if they are oriented on maintaining price stability and conducting countercyclical monetary policy. This is because higher interest rates make borrowing more expensive, discourage investment and lowers the net present value of the equities (Zhang, 2021).

When investors expect high inflation, they also anticipate higher interest rates and a hold in economic growth, both of which possess the potential to adversely impact on the stock market. On the contrary, the expectations for a low inflation, might trigger a favourable climate for investments and bestow a positive influence upon the stock market. Brandt & Wang (2003) mention that there is a relationship between expected and unexpected inflation and real asset prices.

Although the inflation can have both positive and negative effects on an economy, unexpected inflation can cause he problems for individuals and businesses. Unexpected inflation occurs when the rate of inflation surpasses the inflation expectations from the financial markets, producers or consumers. This could result from several factors such as increased money supply; reduced availability of goods and services; or sudden rise in consumer demand. The relationship between economic growth and unexpected inflation is positive in many studies as well as in various theoretical accounts that introduce costs of adjustment (Brandt & Wang 2003). Additionally, Brandt & Wang's (2003) research paper establish a clear and strong connection between overall risk aversion and unexpected inflation.

A nation can experience an unexpected inflation because of an unexpected increase in demand for goods and services from abroad. For example, if the exports of a country are in high demand, this demand can cause prices to rise and thus lead to inflation. If central bank decides to raise money supply to stimulate the economy to grow, because of the rising demand for goods and services, prices could be higher and hence inflation would rise too. On the contrary, if the central banks fail to control money supply efficiently, this could cause a sudden surge in inflation rate. In wealthy nations, real stock values have historically declined during periods when the inflation increases (Zhang 2021). Due to this factor, stock market returns might decrease within such sectors. Unexpected changes in interest rates caused by unexpected inflation can affect the cost of borrowing for both individuals and businesses. Usually, the relationship between unexpected inflation and real asset prices is easier to identify in interest rates movements (Brandt & Wang, 2003). Consumer spending may also be affected by higher interest rates since people with lower incomes are not able to spend additionally on goods or services. This may impact the profitability of businesses across a range of industries and decrease stock prices.

2.4. Literature Review

Inflation is one of the important macroeconomic variables. Investors, financial experts or economics, they are interested in the stock market and inflation relationship. In order to make a fully correct investment decision, they have to know the information regarding stock market performance and how this performance is affected.

Companies in areas such as health care, services and hospitality may be less affected by inflation than those operating in areas such as materials, technology and energy. Hence, investors might require different investment strategies for each industry to minimize the impact of inflation on their portfolio. Also, economic variables such as economic growth rates or the government policies influence the interaction of inflation and the stock market. For instance, high-interest rates limit borrowing and therefore, reduce the corporate profitability of firms which in turn affects their chances of credit.

In emerging markets, inflation may have a greater impact on the stock market. This can result in adverse effects on the stock markets in terms of increased cost borrowing, decreased confidence among investors and loss of value of currency. Under such circumstances, investors might need to seek other methods of investment like investing in industries that are less vulnerable to the inflationary pressures or countries with lower inflation rates for example. On top of this, the impact on share markets can shift depending on different types of inflation. For example, this kind can be highly detrimental to manufacturing and construction sectors whose primary inputs include labour and raw materials if there is increase in their costs because this is referred as cost-push inflation. However, companies in retailing business and consumer products might benefit from demand-pull inflation which refers to situation when there is an increased purchase for goods and services by customers.

Sectors with a high degree of global supply chains integration, like manufacturing and technology, where input costs are rising quickly, may be more susceptible to inflation. This may result in supply chain interruptions, increased production costs, and decreased profitability for businesses working in these areas.

Manufacturing and technology sectors, which have a high exposure to the global supply chains are likely to be more vulnerable to inflationary pressures. These factors can lead to disruptions in the supply chains or higher production expenses. Therefore in the end the profitability of those companies will decrease in time. This might lead to disruptions in the supply chains, higher production expenses and thus lower the profitability of those companies.

The energy sector is one of most vulnerable to inflation on a worldwide scale. Price increases may result from inflationary pressures since oil and gas are crucial inputs for many enterprises in the sector. For energy companies, this might entail higher production costs, poorer profitability, and lower stock prices. Inflation can be beneficial to the energy industry in some instances.

To overcome climate change challenges more successfully, the renewable sector could take advantage of increasing government investment in clean energy initiatives in order to lower CO_2 emissions. Reduced pace of economic growth may prompt less demand for oil, and gas that will have a negative influence on stock prices of energy companies.

Boudoukh et al. (1994) investigated the cross-sectional relation between industry-sorted stock returns and expected inflation and found that the relationship is linked to cyclical movements in industry output.

Zhang (2021) mentions that the stock market is presently being used by economic scholars and investors to hedge against inflation.

In the 20th century, it was not clear what made the inflation increase; today, however, economists are responding differently. According to Lintner (1975); Fama & Schwert (1977) and Fama (1981), nominal returns on stock negatively impact on inflation in developed countries. It came out that Baker et al (2003) and Pastor & Veronesi (2003) show that inflation directly affects stock prices and the monetary policies adopted to combat it. Therefore changes in share prices may also affect aggregate demand and overall economic stability. In this regard, central banks have been concerned with price stability besides taking into account inflation implications for the national economy.

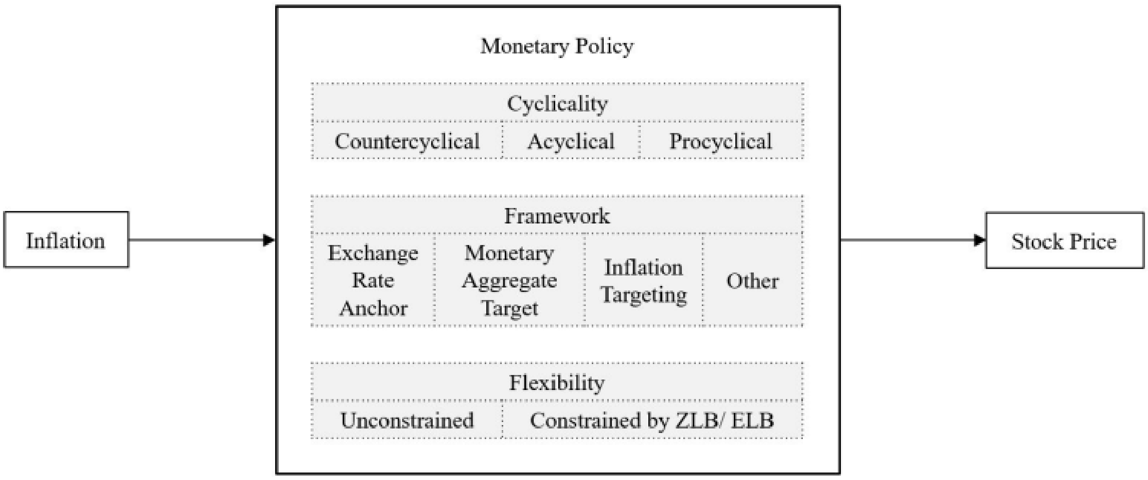

Figure 4 Key Monetary Policy Elements that Affect Stock Returns and Inflation. (Zhang, 2021)

In his findings Zhang (2021) highlights that central banks of developing countries should closely watch over unexpected growths in money supply because it could lead to inflation as well as bursting of bubbles within a country's capital markets- both representing serious threats towards stability of financial systems. To avoid the development of stock market bubbles, they can think about instituting monetary policies that encourage stability, such as limiting the expansion of the money supply.

Kaul (1987, 1990) suggests that policies' actions can directly impact the relationship between stock returns and inflation. According to him this is caused by an equilibrium process in the monetary sector. Kaul's theory emphasizes just how essential the financial sectors are in influencing the stock market. The changes in stock returns are result of interactions between various elements of the monetary sectors, such as inflation rates, money supply and interest rates. It states that changes in economic variables like inflation affects entirely the monetary environment which consequently leads to changes in stock returns.

Katz et al. (2017) examine the reason for the slow response of local stock markets to fluctuations in local inflation. Their research demonstrates that investors in the local stock market see a decline in the actual returns on local equities when the rate of local inflation rises. According to the findings of Katz et al. (2017), local investors of stock exchanges tend to have outdated inflation expectations which makes them react slower to local inflation rate changes. This affects the effectiveness of the regional stock market since the investors can't determine the value of investments when inflation is not determined in the correct way. Investors could earn lower returns due to them needing to appreciate the importance of keeping their inflation expectations.

LeBlanc & Chinn (2004) conducted an analysis where they studied quarterly data from the United States, United Kingdom, France, Germany, and Japan between Q1 1980 and Q4 2001. The authors focused on the impact of oil price shocks to inflation across several advanced countries. Their analysis also captured the unique oil price increase witnessed in 2000 where oil prices went higher than the previous nominal peaks that took place in 1973, 1979 and 1990.

They used augmented Phillips curves to estimate the impacts of a 10 per cent increase in oil prices on inflation. The study showed that such an increase in oil prices leads to inflationary increases ranging from 0.1-0.8 percentage points. Nevertheless, there were differences in these effects' intensity between the US, Japan, and Europe. In addition to that, such trends were found to be similar in the United States and the European Union with regard to the pass-through of these effects. The same authors think that inflation in Europe is more sensitive to oil prices for two main reasons. First, European counterparts are more successful at securing pay raises in response to rising energy prices. Secondly, due to less intense competition in product markets, European producers are more likely to pass on higher labour costs to consumers, resulting in higher prices.

In economies with a high degree of specialization, changes in the price of one commodity, like oil, can have more substantial spillover effects, raising inflation. In a similar manner, manufacturers may have more price power and be better able to pass on increased costs to customers in less competitive marketplaces.

Furthermore, in a study by Chen (2009), he notes that oil price increases have become less impactful to overall price levels due to improved monetary policies and increased trade.

Blanchard & Gali (2007) used VAR analysis for several industrialized countries such as US, France, UK Germany, Italy and Japan. The research aimed to analyse how oil price shocks affect inflation and economic activity over time. According to the paper, the consequences of oil price shocks have steadily declined with time.

According to Peersman and Van Robays (2012), shocks to the global economy's oil demand led to transitory economic activity increases and considerable inflation across all nations. Nonetheless, the importance of oil and energy is critical in evaluating how exogenous shocks to the oil supply will affect the economy.

De Gregorio et al.' (2007) using enhanced Phillips curves with data from advanced and emerging nations, they noted of a weakened relationship between oil prices and domestic inflation. According to their research, this weakend relationship is most pronounced in advanced economies. This finding is explained by the reduction of oil intensity and the extent of currency exchange rate influence.

The current oil shocks have had a very different impact on the world economy than earlier ones. Economic activity has not suffered considerably, and inflation has stayed under control; today, the global economy seems more robust. The majority of conventional calculations of the economic impact of oil have been modified to account for recent developments. According to their study, this enhanced resilience results from countries using less oil, which lowers the effects of rising oil prices on inflation and output. Moreover, the volatility in the currency rate that frequently follows oil shocks has softer inflationary impacts, necessitating a softer monetary policy response. This element has been a pivotal contributor to earlier economic downturns brought on by oil shocks. Last but not least, unlike in the past when there were supply constraints, the high oil prices of recent years resulted from rising demand.

Laopodis (2006) carried out a study to examine the connection between inflation and stock market performance. The findings suggested that there was some sort of negative relationship between these two variables, signifying that the stock market can serve as an inflation hedge tool. Moreover, the Federal Funds rate, which is an interest rate at which banks lend money to one another, and also stock returns were analysed in this research. In the 1970s, the bivariate results showed a weak correlation between them, while they showed that their association was linearly negative during the 1990s. Nevertheless, multivariate analysis discovered a significant short-term association in the 1970s as well as this same unidirectional linkage in the 1990s. This implies that stocks returns do not respond positively to monetary easing carried out during 1990's or negatively to monetary tightening. The dynamic relationship between monetary policy and stock prices was inconsistent. These findings are inconsistent with Fama's (1981) proxy theory who claimed that while real activity and real stock returns are positively related, inflation is negatively associated with real activity.

Using Fisher's theory, Madsen (2004) undertook research so to analyse the relationship between stock market returns and inflation. The Fisher hypothesis is evaluated with reference to the inflation process, inflation expectations, and time aggregation of the data. The findings changed depending on the model used, time scale of the data, inflation persistence in the sample and instruments used for expected inflation. For dependent variables including nominal share returns, the results were more supportive of the Fisher hypothesis when inflation was constant. Madsen's study also highlights the difficulties in validating Fisher's theory on the relationship between inflation and stock market performance. The findings further show that factors such as model specification, time aggregation, inflation persistence, and dependent variables amongst other can have significant impact on the accuracy of hypothesis in the study.

Wei (2009) researched the correlation between stock performance and unexpected inflation. His findings showed that over a business cycle, there was a correlation between unexpected inflation and the nominal equity return of Fama-French book-to-market and size portfolios. He drew two important conclusions from the study. First, during periods of economic recessions, equity returns tend to respond more adversely to inflation shocks than during periods of expansion. Second, the equity returns of medium sized companies with low book-to-market ratios show a stronger negative relationship with unexpected inflation. These results support the idea that unexpected inflation is significant and should be incorporated in the investment decision making process, especially during a recession. Also, it suggests that the investors should change their portfolio strategies when is needed.

In their research, Erb & Harvey (2006) similarly decompose inflation into the same two components – expected and unexpected. Moreover, they will use the same approach to get the unexpected inflation, which results from the difference between actual and expected inflation. Erb & Harvey (2006) mention that commodities account for approximately 40 per cent of the weightage of the CPI, and the rest of the services carry 60 per cent. Therefore, analysing the relationship between commodities returns and inflation becomes meaningful.

They find that the annual inflation rate can explain 43 per cent of the time-series variation of S&P GSCI's annual excess return since 1969. Furthermore, S&P GSCI has a positive correlation with the actual inflation, although it is not statistically significant. On the other hand, S&P GSCI positively correlated with unexpected inflation and was statistically significant. There could be some individual commodities that can serve as good hedge instruments for inflation, but it cannot be said that a whole group of commodities serves as a good hedge against inflation (Erb & Harvey, 2006).

Commodities prices were relatively steady and statistically significant indicators of overall inflation during the 1970s and early 1980s (Furlong & Ingenito, 1996). They mentioned that since the early 1980s, commodity prices have generally lost their strength as inflation indicators, especially regarding non-oil commodity prices. These were relatively strong and statistically significant, leading indicators of overall inflation for the 1970s and early 1980s. Nonetheless, these started to perform poorly afterwards. A decline in overall inflation also characterizes this period, while commodity prices have become more volatile. Furlong & Ingenito (1996) offer some of the possible reasons for the deterioration of the relationship between commodity prices and overall inflation. Some of the reasons they are offering are the decline in the commodities in total output, the lesser use of commodities as a hedge against inflation or countervailing monetary policy responses that need to be completed.

In his study, Ciner (2011) uses previous studies as a basis for analysis of the link between commodity prices – and inflation. Like prior researches, he examines and validates the hypothesis that financial variables, particularly commodity prices, have some information about inflation. Nonetheless, in interpreting the connection between commodity price and inflation, he does not rule out nonlinear relationships among factors. Moreover, there is also evidence of frequency dependence in this link specifically (Ciner, 2011). Compared to Furlong & Ingenito's (1996) research period and results, Ciner (2011) identifies a positive contemporaneous impact of long-term, permanent shocks in commodity markets on consumer inflation. Moreover, Ciner (2011) suggests that causality from commodity prices to inflation exists only at very low frequencies. The most important finding that is directly related to this master's thesis is that Ciner (2011) does not find any impacts of inflation on commodity prices, and there is no reverse causality from inflation to commodity prices.

Table 1 Summary of the literature review

Authors:	Main Ideas:
Baker et al. (2003); Pastor & Veronesi (2003)	The stock market prices can be directly affected by inflation. Aggregate demand and economic stability can also be affected by the stock market. Central banks ' goal is price stability in relation to countries' economies and their national inflation impact targets.
Blanchard & Gali (2007)	They have used VAR analysis to assess how changes in oil price shocks affected the inflation and economic activity in industrialized countries. They find that oil price shocks impact on the economic activity has declined over time.
Boudoukh et al. (1994)	They investigated the cross-sectional relation between industry-sorted stock returns and expected inflation and found that the relationship is linked to cyclical movements in industry output.
Chen (2009)	Improved monetary policies and increased trade have reduced the impact of oil price increases on overall price levels.
Ciner (2011)	The author investigated whether there is a connection between commodity prices and inflation. It was found a positive long-term impact of commodity prices on the inflation; however, no impact of inflation on the commodity prices. There was detected evidence of nonlinearity and frequency dependence in the influence of inflation caused by the prices of commodities.
Erb & Harvey(2006)	They determined a positive relationship exists between the S&P GSCI index and both expected and unexpected inflation, with the latter measurement being statistically significant. They further noted that certain commodities are useful for inflation hedging while others are not.
De Gregorio et al. (2007)	There is a negative relationship between oil prices and inflation in developed countries due to reduced oil intensity as well as the effects of exchange rates. In recent years, the importance of global economic impacts of oil shocks has declined while their influence on the economy and inflation have faded away as there is less reliance on oil and stabilized exchange rates.
Furlong & Ingenito (1996)	Mostly non-oil commodities were the key inflation indicators in the 1970s and early 1980s. However, since the beginning of the eighties, they have increasingly become less effective as they now account for smaller proportion of total output and are no longer frequently used for hedging purposes.
Katz et al. (2017)	Fluctuations in the local inflation have a delayed effect on local stock markets. Less favourable investment decisions

	are often made by investors based on their outdated expectations of inflation. This emphasizes the need to keep inflation expectations up to date as they influence actual returns from investments.
Kaul (1987, 1990)	Macroeconomic variables, like inflation, directly impact the changes in stock prices. Financial sectors highly influence the stock markets.
Laopodis (2006)	He found a negative relationship between inflation and stock market performance. This implies that stock markets can be used as hedge against inflation. Fama's (1981) proxy theory seems to be contradicted by inconsistency in the dynamic relation between monetary policy and stock prices.
LeBlanc & Chinn (2004)	The intensity of inflation impacts vary between the US, Europe and Japan. In Europe where wage negotiations are more efficient and there is less competition within product markets; oil prices have a greater influence on inflation. A 10 per cent increase in crude oil prices increased the rate of inflation by between 0.1 per cent and 0.8 per cent in those countries.
Lintner (1975); Fama & Schwert (1977); Fama (1981)	Inflation has a direct effect on stock market prices and monetary policies directly affect inflation. Nominal stock market returns negatively impact inflation in developed countries.
Madsen (2004)	Testing the Fisher's theory about the relationship between stock market returns and inflation, it should be noticed that different results may occur depending on model specifications, data aggregations or persistence of inflation. Results support Fisher hypothesis when we use nominal share return cases and there is high persistence of inflation. It brings out the complexities involved in validating Fisher's theory as well as necessitating appropriate.
Peersman & Van Robays (2012)	Shocks to global oil demand caused temporary increases in economic activity and considerable inflation across nations.
Wei (2009)	He studied the correlation between stock performance and unexpected inflation. It was noted that equity returns are more negatively responsive to unanticipated inflation particularly in economic recessions. Companies with medium size and smaller book-to-market ratios were more negatively impacted by unexpected inflation.
Zhang (2021)	The stock market can be used as an inflation hedge. The author mentions the significance of developing nations monitoring money supply to prevent hyperinflation and avert any stock market crash. Again, he advises on monetary policy measures that can foster stability and regulation which would curtail speculative tendencies at the same time providing transparency for informed investment decisions.

3. DATA AND METHODOLOGY

3.1. Data

This research mainly aims to analyse the relationship between inflation, stock market returns and commodities returns, using each country or region's data. Generally speaking, most of the research and prior articles are based on U.S. data and activity; however, it is essential to analyse the data on a wider range of countries. Applying a broader range of countries will give a better understanding of how inflation and indices returns are behaving.

In this thesis, all data are gathered by using monthly observations. As mentioned, I am using the Consumer Price Index (CPI) indicator to calculate inflation, which is also widely used in other academic research papers. The Consumer Index Price for the Euro Area 19[1] is collected using the LSEG – Financial Technology & Data (known as Refinitiv), the USA and OECD World countries[2] data used in this thesis was collected from the OECD database. The sample period is from January 1999 to December 2020.

For the stock market return indicators, I have used the indices market return data – S&P 500 Composite - Total Return, MSCI World - Total Return, S&P GSCI Commodity - Total Return, and their subsequent industry sectors were collected from Refinitiv. The data consists of monthly observations and includes the periods from 1 January 1999 to 31 December 2020. The Stoxx 50 Total Return index includes observations from February 2001 to December 2020. I have decided to use the total return index instead of the price index because the first one includes reinvested dividends, earnings, or interest. Now, we would have a better reflection of the actual returns and a clear understanding of the market returns' performance.

S&P GSCI contains 24 commodities from the United States market, of which six are energy products, five are industrial metals, eight are agricultural products, three are livestock products, and two are precious metals. This index gives us a high level of diversification from all sectors, which allows us to grasp the best financial information on the commodity market returns.

1 EURO Area 19 countries list consists of: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Portugal, Slovakia, Slovenia, Spain, the Netherlands. Disclaimer: Croatia joined Eurozone in 2023 and is not part of the list.

2 OECD World list consists of 37 countries: Austria, Australia, Belgium, Canada, Chile, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States.

Following variables and their abbreviations are used in my analysis. These can be found in figures, tables, and other parts of this thesis:

USCPI	*United States Consumer Index Price*
USSP	*S&P 500 Composite Index - Total Return*
EUROCPI	*Harmonised Index of Consumer P7rices (Euro Area 19)*
EUSTOXX	*Euro Stoxx 50 Index - Total Return*
OECDCPI	*Harmonised Index of Consumer Prices (OECD 37)*
MSCIWorld	*MSCI World Index - Total Return*
SPGSCI	*S&P GSCI Commodity - Total Return*
USIP	*United States Industrial Production*
EUROIP	*Harmonised EURO Area 19 Industrial Production*
WorldIP	*Harmonised OECD 37 Industrial Production*
NominalEUROLIR	*Nominal Euro Area 19 Long-Term Interest Rate*
NominalUSLIR	*Nominal United States Long-Term Interest Rate*
TB3M	*Three-Month Treasury Bill Secondary Market Rate, Discount Basis*
VIX	*CBOE Volatility Index: VIX, Index, Monthly, Not Seasonally Adjusted*

A list of all the variables used in the thesis can be found in the Annex.

As per S&P 500 factsheet, as of November 2023, the combined weightings of the information technology, health care and financial sectors make up to 50 per cent of the total S&P 500 index. Therefore, these sectors are playing a major role in the index's price movement.

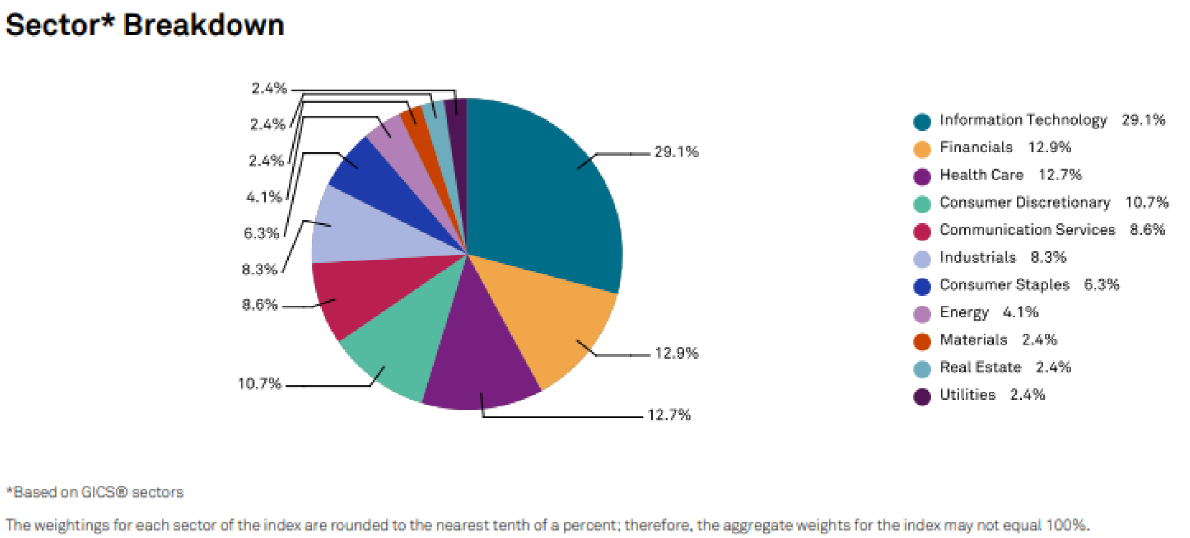

Figure 5 The weightings of the 11 sectors in the S&P 500 index on 30th of November 2023. (S&P Dow Jones Indices LLC, 2023)

In MSCI World, as of November 2023, Information Technology has a lower weight in the total index compared to the S&P 500 Composite. Moreover, the next four sectors have relatively similar sector weights, and the smallest ones, again, are closer to each other.

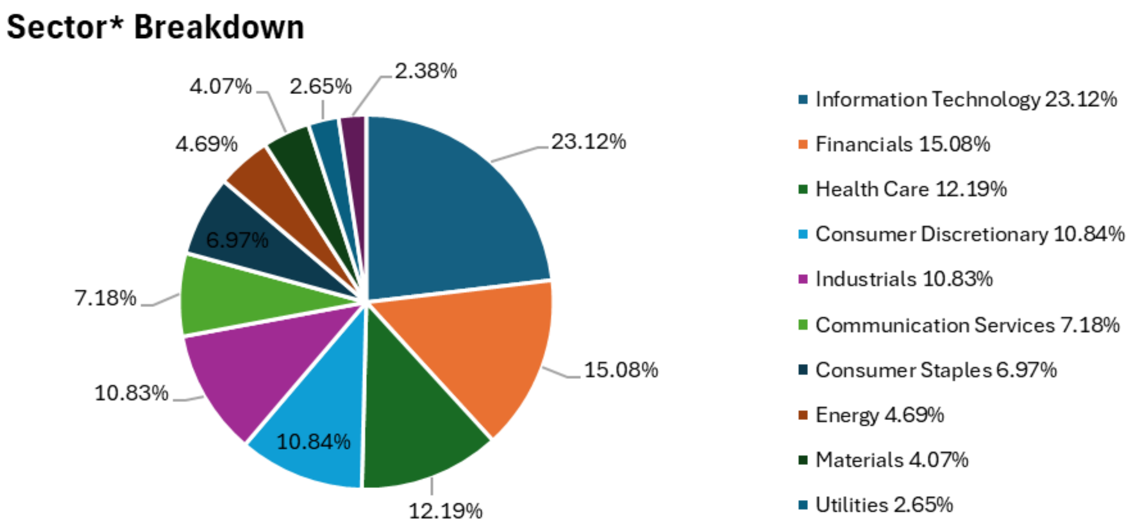

Figure 6 The weightings of the 11 sectors in the MSCI World index on 30th of November 2023. (MSCI Inc., 2023)

A significant observation regarding MSCI World index, is the country weights, where United States has 70.07 per cent from the total. Therefore, United States sectors and companies play a more significant role than the rest of the world combined.

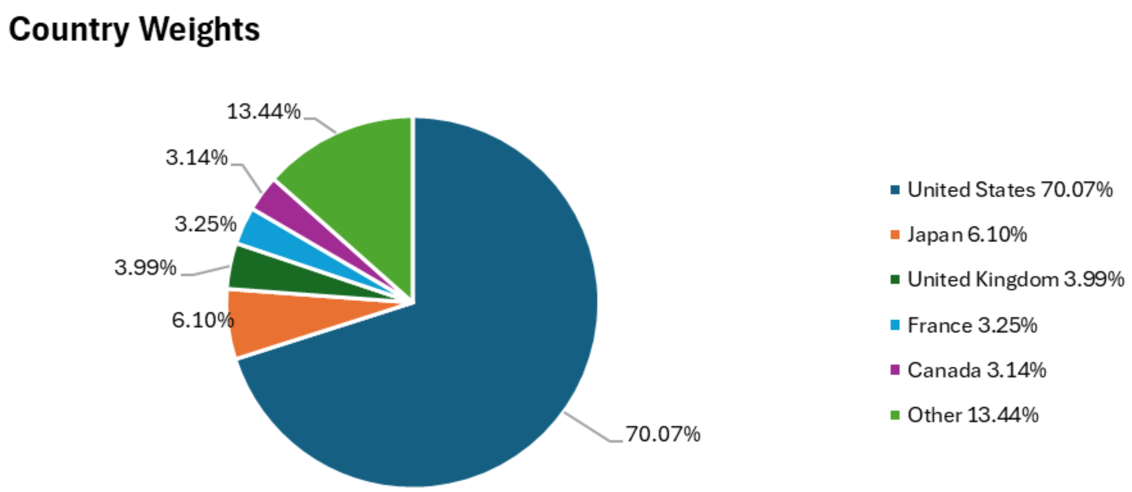

Figure 7 The weightings of the countries in the MSCI World index on 30th of November 2023. (MSCI Inc., 2023)

The Euro STOXX 50 is the derived index from the EURO STOXX index and represents the most significant 50 companies from the Eurozone. Compared to all other indices mentioned above, EURO STOXX has the most balanced sector weights across all industries.

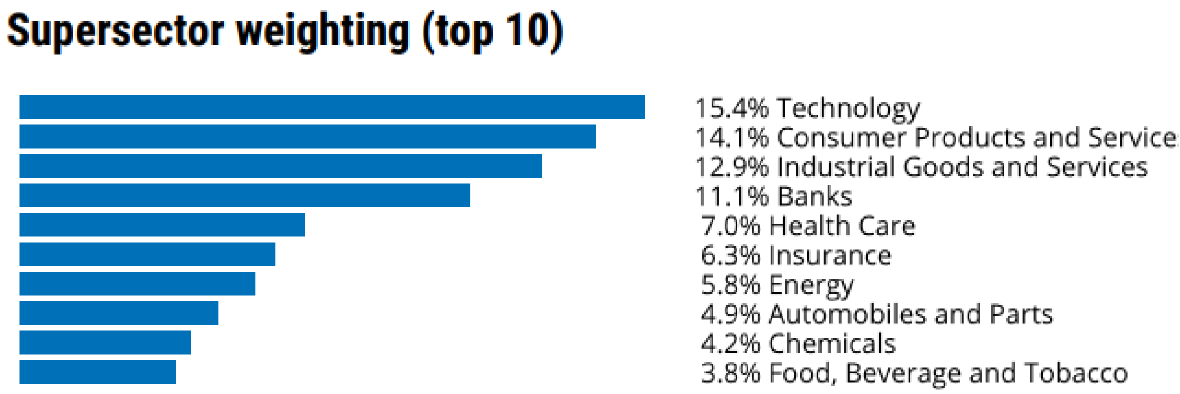

Figure 8 The weightings of the industries in the STOXX 50 index on 31th of August 2023. (Deutsche Börse AG., 2023)

Moreover, the country weights of the above sector are distributed with France's companies sharing the highest weighting, followed at a large distance by Germany and Netherlands' companies.

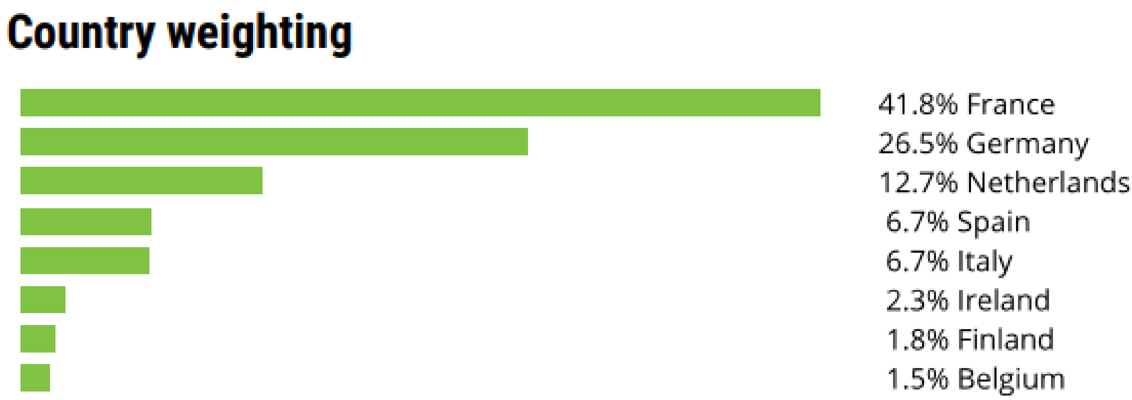

Figure 9 The weightings of the countries in the STOXX 50 index on 31th of August 2023. (Deutsche Börse AG., 2023)

In the analysis, I use the industrial production growth rate, the Three-Month Treasury Bill secondary market rate, the discount basis, and the CBOE Volatility Index as standard control variables. As Zhang(2011) emphasizes, these standard control variables are also widely used in the previous literature (Fama, 1981; Nai-Fu et al., 1986; Schmeling, 2009; Schmeling & Schrimpf, 2011). Nominal Long-Term Interests Rates will also be used as control variables in our later analysis. There is some useful information in information in interest rates and asset prices regarding future economic developments (Stock & Watson, 2003). The industrial production indicator measures the amount of production and the activity of the industry sector and is the primary meter of the real economic activity. The Three-Month T-Bill and CBOE volatility index will account for the macro conditions and factors – the first represents global liquidity, while the second represents financial market volatility. The US Industrial Production, EURO Industrial Production and OECD Industrial Production data were gathered using the OECD database. Both Nominal Long-Term Interests Rates were collected using the OECD database. The latest Three-Month T-Bill and CBOE Volatility Index were gathered using Federal Reserve Economic Data (FRED) St.Louis Fed. Again, all observations are monthly, from January 1999 to December 2020.

3.2. Methodology

The purpose and focus of this empirical research are to analyse and explore the relationship between inflation and stock market and commodity returns. The main part is to perform VAR analysis. Standard practice in VAR analysis is also to perform Granger-causality tests, impulse responses, and forecast error variance decompositions (Stock & Watson, 2001).

Inflation is decomposed into expected and unexpected inflation by using ARIMA models. The Vector Autoregressive model captures the relationship between changes in multiple variables over time. Granger causality tests will help determine if one variable's lagged values help predict another variable. Furthermore, the Forecast Error Variance Decomposition part of the impulse-response function will help to understand the relationship between inflation shocks and asset returns.

The analysis is conducted using Stata software.

3.2.1. ARIMA

Inflation is usually divided into two terms in economics: expected and unexpected inflation (Zhang, 2019). In my analysis, I will use ARIMA models to decompose inflation into unexpected and expected inflation. I have encountered significant challenges to obtain the necessary survey-based data for estimating expected and unexpected inflation, especially for OECD countries. Therefore, historical expected inflation data was calculated using the time series model estimation. Applying the ARIMA models in my estimation, allowed me to have a consistent approach to estimate expected and unexpected inflation for all three regions. According to Ang et al. (2007), ARMA (1,1) model is offering the best results for estimating the inflation. Moreover, they find that ARMA time series are offering better results comparing to the Phillips curve-based regressions or term structure models. Additionally, the inflation series are nonstationary similarly to Vassalou (2000) and to avoid the unbalanced regressions of equity returns on inflation levels, we apply similarly ARIMA models. This has facilitated the comparison and having a more uniform analysing approach. A similar method of inflation decomposition was used by Fama & Gibbons (1984), Vassalou (2000), and Zhang (2021). According to Vassalou (2000), ARIMA (0,0,1) model is commonly used in inflation forecasting. Although, in his research paper, Zhang (2021) chooses the AR (4) model. I will rely on Root Mean Square errors (RMSE) of the forecasted values, Mean of Absolute value of Errors (MAE) and a higher Direction of Change probability (DOC) to determine the most accurate ARIMA model. As Chai and Draxler (2014) mention, a single error indicator provides only one projection of the model errors and, therefore, determines the error only from one certain aspect. In order to have the most accurate assessment of the model performance, it is necessary to apply all error models. Moreover, since the decomposition of inflation implies forecasting an additional variable (expected inflation), I will also use the information criteria to determine which ARIMA model fits our forecast best.

Box et al. (2015) propose an ARIMA model that has the constant term θ_0, which results in a more general form:

$$(B)z_t = \phi(B)\nabla^d z_t = \theta_0 + \theta(B)a_t \tag{1}$$

where:

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \tag{2}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \tag{3}$$

and

$\phi(B)$ = is generalized autoregressive (AR) operator

$\theta(B)$ = is moving average (MA) operator

d = unit root; when d = 0, the model is stationary.

Box et al. (2015) suggest that the model selection uses information criteria such as the Akaike Information Criteria (AIC) proposed by Akaike (1974) or the Bayesian information criteria (BIC) of Schwarz (1978).

$$\text{AIC}_{p,q} = \frac{-2\ln(\text{maximized likelihood}) + 2r}{n} \approx \ln(\hat{\sigma}^2_a) + r\frac{2}{\text{n}} + \text{constant} \tag{4}$$

$$\text{BIC}_{p,q} = \ln(\hat{\sigma}^2_a) + r\frac{\ln(n)}{n} \tag{5}$$

The optimal lag length is chosen using the information criteria for an accurate model using the five variables. Kuha (2004) identifies the Akaike Information Criteria (AIC) and the Schwarz-Bayesian Information Criteria (SBIC) as the "most commonly used penalised model selection criteria". However, the Hannan-Quinn Information Criteria (HQC) will also be considered.

3.2.2. Unit test root

According to Box et al. (2015), stationarity is the process where the statistical equilibrium with probabilistic proprieties does not change over time. It means that the mean, variance and covariance are constant over time and do not change based on the time-varying.

In this thesis, I will perform both Augmented Dickey-Fuller (ADF), based on Said & Fuller (1984) testing proposal, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests. Applying both tests complements unit root tests (Kwiatkowski et al., 1992).

While the first one's H_0 hypothesis is that the trend is non-stationary and for performing estimations, we will have to reject the null hypothesis, for the later one, KPSS' H_0 is that our variable is stationary, and we need to accept the null hypothesis for us to be able to perform the estimation with the selected variable.

3.2.3. VAR analysis

Following the decomposition of the inflation using ARIMA, I will use Vector Autoregressive (VAR) analysis to estimate, forecast and analyse the relationship between USA, EURO19, and OECD Countries' real stock market returns of selected indices, expected and unexpected inflation, industrial production growth, U.S. Three-Month Treasury Bill, and volatility index CBOE VIX. Another part of the VAR analysis will use nominal long-term interest rates instead of the industrial production growth.

Vector Autoregression (VAR) is the stochastic model that is one of the most used models used in time series (Scott Hacker & Hatemi-J, 2008). Furthermore, as stated by Scott Hacker & Hatemi-J (2008), VAR allows for interaction between the variables, in this thesis – endogenous variables, and to analyse the long-term relationships between variables, combined with the short-term dynamic adjustments.

Compared to the ARIMA models or any other univariate and single equations models, VAR can have an unlimited number of variables, and all variables are endogenous.

The endogenous variables include the inflation decomposition of the expected and unexpected inflation, along with the returns from the specific industries and countries' most essential indices: S&P 500, Stoxx 50, MSCI World, and S&P GSCI Commodity Total Return. In the current statistical analysis, the total return indices have been used, which also have the reinvested returns included.

In this thesis, I have identified different lags that should be used for different areas. Nonetheless, the standard univariate VAR model can be expressed as follows:

$$y_t = A_0 + A_1 y_{t-1} + \varepsilon_t \tag{6}$$

Respectively a VAR(2) model:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \varepsilon_t \tag{7}$$

A Vector Autoregression of order 1 on a bivariate system is:

$$y_{1,t} = \varphi_1 + \varphi_{11} y_{1,t-1} + \varphi_{12} y_{2,t-1} + \varepsilon_{1t} \tag{8}$$

$$y_{2,t} = \varphi_2 + \varphi_{21} y_{1,t-1} + \varphi_{22} y_{2,t-1} + \varepsilon_{2t} \tag{9}$$

Where ε_{it} are the error terms and are supposed to be white noise processes.

3.2.4. Granger Causality tests

Causality tests are one of the most significant tests in my thesis. In the time series analysis, Granger causality tests help us examine whether one variable helps us predict another variable from our research model. The test examines whether one variable's lagged values help predict another variable (Stock & Watson, 2001).

As our main aim is to determine if unexpected and expected inflation impacts the stock market returns, the Causality test will help identify if one variable does cause changes in the second variable.

Granger (1969) has defined that a cause cannot come after the effect; in other words, a cause always occurs first, followed by an effect. Thus, if variable x affects a variable z, x should help improve the z predictions.

Therefore, as per Lütkepohl (2005), x_t causes z_t in Granger's sense if:

$$\Sigma_z (h \mid \Omega_t) < \Sigma_z (h \mid \Omega_t \setminus \{x_s \mid s \leq t\}) \tag{10}$$

$$for\ at\ least\ one\ h = 1,2, \ldots.$$

Where:

Ω_t, represents the set containing all the relevant information available at time t.

h is the step-predictor of the process z_t at origin t, based on the Ω_t

$\Sigma_z (h \mid \Omega_t)$ represents the corresponding forecast Minimum Squared Error (MSE)

$\Omega_t \setminus \{x_s \mid s \leq t\}$ represents the set containing all the relevant information available except for information in the past and present of process x_t.

The H_0 hypothesis in our analysis will be that variable x_t does not cause z_t.

3.2.5. Impulse-response and variance decomposition

Forecast Error Variance Decomposition (FEVD) is a further tool for interpreting VAR models (Lütkepohl, 2005). The Orthogonal Impulse response function allows us to identify and track how the variables in the VAR model respond to shocks to the error term. FEVD is the percentage of the variance of the error made in forecasting a variable due to a specific shock at a given horizon (Stock & Watson, 2001).

In context of the representation:

$$\omega_{jk,h} = \sum_{i=0}^{h-1} \left(e_j' \Theta_i e_k\right)^2 / \text{MSE}[y_{j,t}(h)] \tag{11}$$

where:

$\omega_{jk,h}$ - represents the proportion of the h-step forecast error variance accounted for by innovations in variable k, if ω_{kt}can be associated with k

Θ_i represents the impulse responses. It consists of elements interpreted as responses of the system to an innovation of size one standard deviation.

Thus, the forecast error variance is decomposed into components accounted for by innovations in the different variables of the system (Lütkepohl, 2005).

h – step forecast error variance in the MSE matrix can be represented as:

$$\Sigma_y(h) = \text{MSE}[y_t(h)] = \sum_{i=0}^{h-1} \Theta_i \Theta_i' = \sum_{i=0}^{h-1} \Phi_i \Sigma_u \Phi_i' \tag{12}$$

3.2.6. Engle & Granger's Cointegration Test

Engle & Granger (1987) propose the definition of cointegration as "the components of the vector x_t are said to be co-integrated of order d, b, denoted $x_t \sim CI\ (d, b)$, if (i) all components of x_t are $I(d)$; (ii) there exists a ($\neq 0$) so that $z_t = a'x_t \sim I(d - b)$, $b > 0$. The vector a is called the co-integrating vector.

In case the variables are cointegrated, there is a linear combination of integrated variables, which are stationary. I have been using the Engle & Granger test method to identify if the variables are cointegrated.

Engle & Granger's (1987) cointegration test is based on the error correction model. While testing the null and alternative hypotheses for a test on the residuals of potentially cointegrating regression:

$$\Delta y_t = \beta_1 \Delta x_t + \beta_2(\hat{u}_{t-1}) + u_t \tag{13}$$

where:

$$\hat{u}_{t-1} = y_{t-1} - \hat{y} x_{t-1} \tag{14}$$

H_0: unit root in cointegrating regression's residuals.
H_1: residuals from cointegrating regression are stationary.

4. EMPIRICAL ANALYSIS

4.1. Descriptive statistics

This section discusses the descriptive properties of all the variables of interest from this thesis. In the beginning, inflation and real returns are studied and compared between areas of interest. Later, the remaining control variables are explained. The data consists of observations from January 1999 to December 2020, except for the Euro Stoxx 50, which started in February 2001. I am investigating how unexpected and expected inflation influences real stock and commodities returns in this paper. During this period, we have experienced several events that have caused spikes in the time series, such as the Dot-Com Bubble burst, the Global Financial Crisis, and the European Debt Crisis. The results obtained based on this time series sample would provide better results that can be comparable with other results from this area.

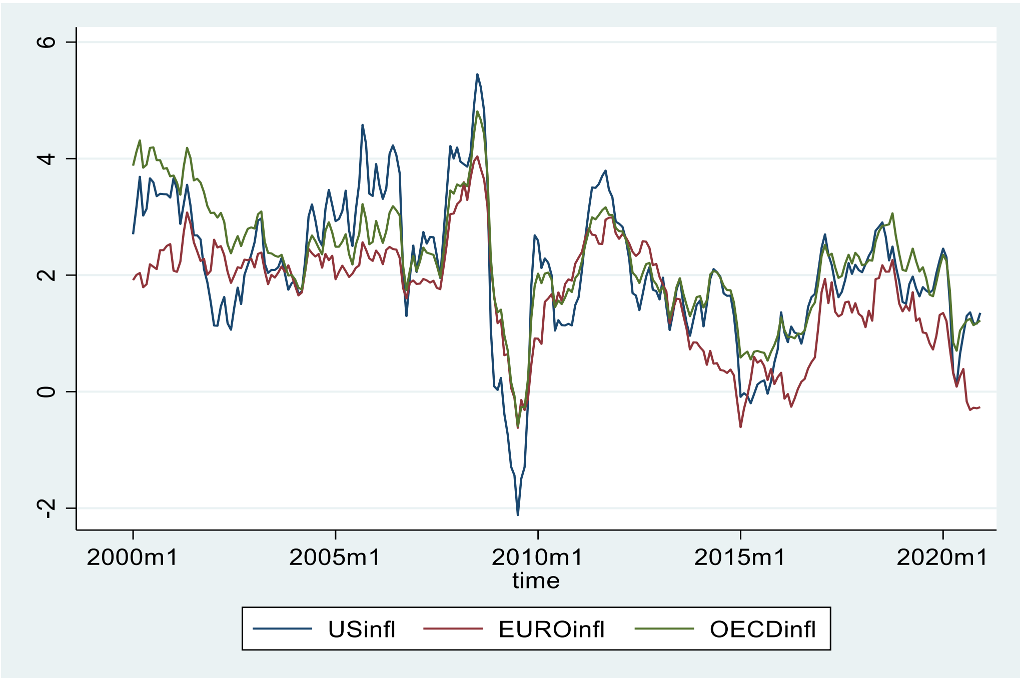

Figure 10 Comparison of inflation trends: US inflation (USinfl), Euro19 inflation (EUROinfl), and OECD countries inflation (OECDinfl).

From Figure 10, it can be inferred that inflation rates change in the United States, Euro Area19, and OECD World Countries simultaneously, and the changes are similar between these three. Nonetheless, Figure 10 shows that more significant changes in the inflation rate can be observed during a crisis period, in particular, during 2008 financial crisis. For example, a more significant drop in US inflation corresponds to the post-Financial Crisis period. Furthermore, Europe was seriously affected by the COVID-19 pandemic, and we can observe a decline in inflation during COVID-19 when businesses were reluctant to invest and make financial contributions or even the population spending due to the uncertainty of the pandemic. As shown in Figure 10, inflation tends to be more volatile during 2010s, but approaching 2020, inflation begins to stabilize and be less volatile.

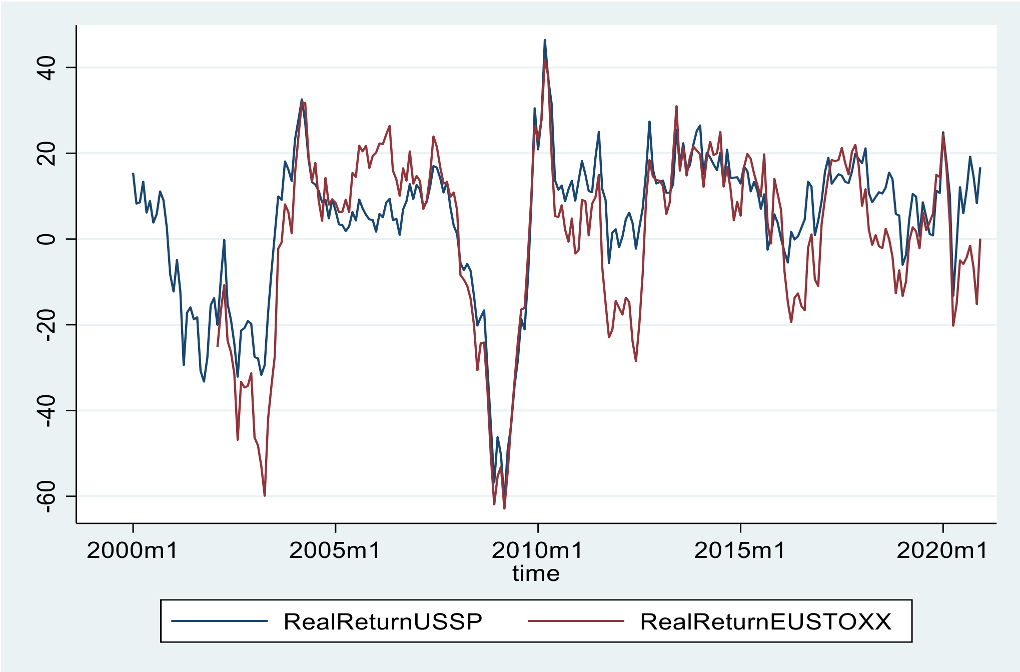

Figure 11 Comparison of indices trends: S&P 500 index real stock return (RealReturnUSSP) and Euro Stoxx 50 index real stock return (RealReturnEUSTOXX).

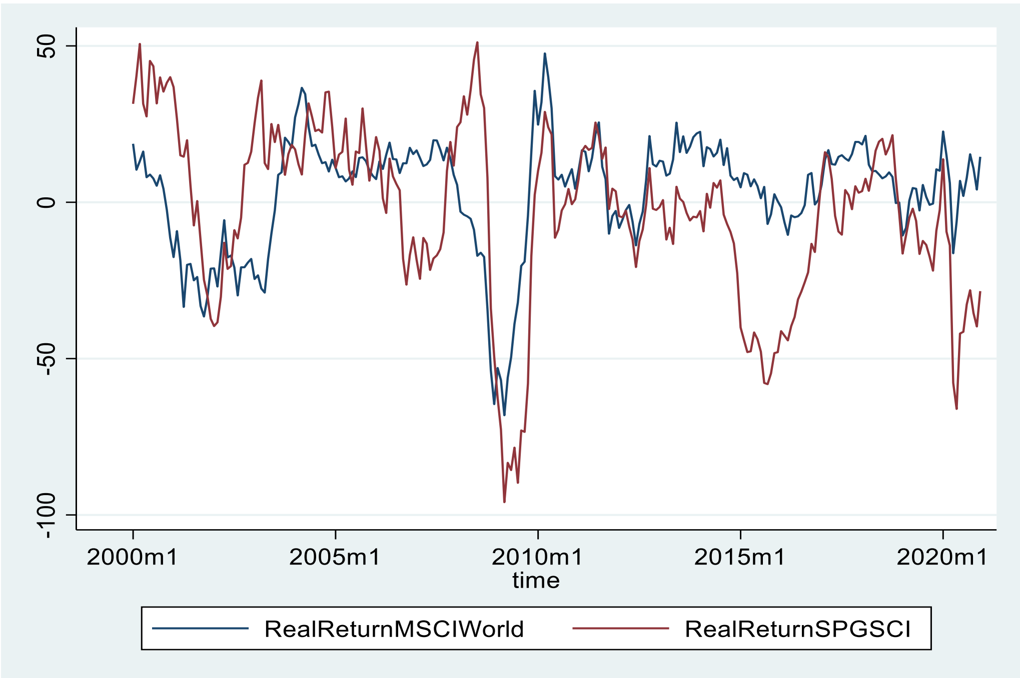

Figure 12 Comparison of indices trends: MSCI World index real stock return (RealReturnMSCIWorld) and S&P GSCI index real commodity return (RealReturnSPGSCI).

Figure 11 plots the S&P 500, and Euro Stoxx 50 indices' real stock returns, and Figure 12 plots the MSCI World real stock return and S&P GSCI real commodity return. For better granularity, it was decided to keep the graphs separately.

Figure 11 shows that there is a correlation between indices S&P 500 and Euro Stoxx 50. However, it can be inferred from the same figure that there are periods where the returns behave in different way. For example, the European Debt crisis is impacting the Euro Stoxx 50 returns between 2012-2014. Moreover, based on the negative spikes in early 2000s and later during 2010-2020, it can be inferred that Euro Stoxx 50 are more likely to be affected from the market turmoil comparing to the S&P 500.

Figure 12 presents MSCI World index, which represents global equity market, and the S&P GSCI, which reflect commodity markets. Similar to above stock indices, these show substantial negative returns during 2008 crisis, with S&P GSCI showing almost 100 per cent drop.

On another hand, US indices, S&P 500 and S&P GSCI exhibit a more pronounced volatility's peak, which therefore is suggesting higher volatility overall.

Based on the plots presented above, the real returns decline after significant adverse shocks or events that occurred during a certain period. A significant negative spike happened during and after the Global Economic Crisis, or for the EURO Stoxx 50 during and after the European Crisis. The GSCI real return spike, which is not correlated to other stock market indices returns, occurred between 2014 – 2016 and 2020. These can be linked to the oil crisis between (2014 -2016) when the oil price declined sharply and was followed by significant price volatility, or during COVID-19. Upon reviewing the figures, it is reasonable to deduce that stock market returns and commodities returns are not always correlated and do not always move in tandem.

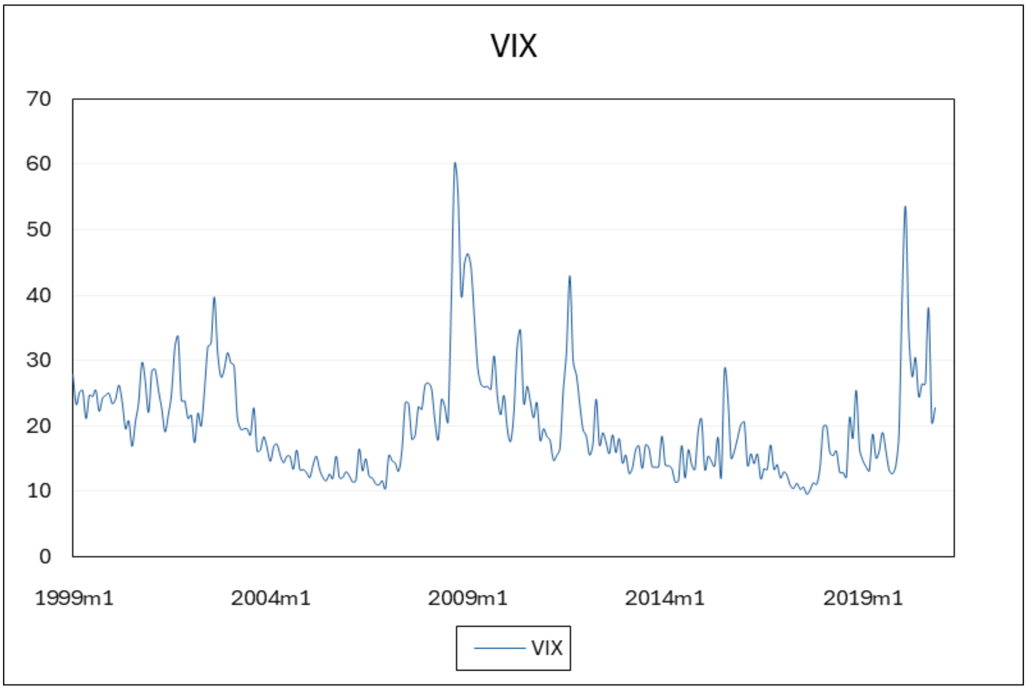

Figure 13 Monthly observations of CBOE Volatility index (VIX)

Figure 13 present the CBOE Volatility index (VIX), or also called the "fear gauge" amongst investors. This index measures the market expectations for near-term volatility. It reached the peak during the crisis 2008-2009, and also during Covid-19 times. It presents additional spikes during earlies 2000s and 2012, periods characterised by market uncertainties. The graph above illustrates that volatility reacts actively during more significant financial events.

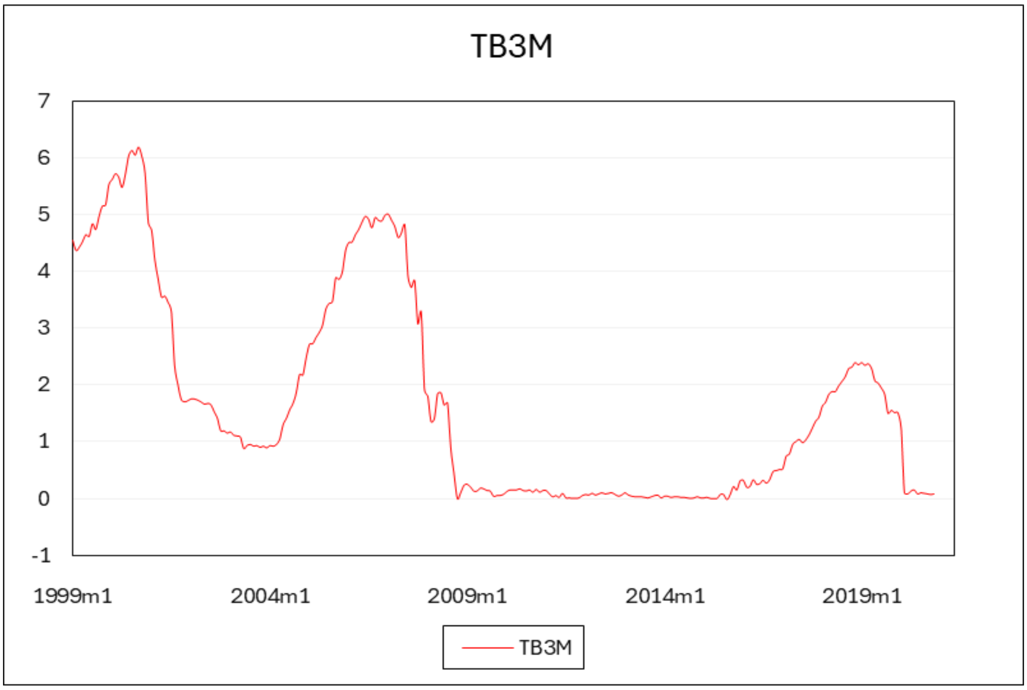

Figure 14 Monthly observations of Three-Month Treasury Bill (TB3M)

Figure 14 presents the Three-Month U.S. Treasury Bill, an index that usually is used as a common control variable in research papers, being a common indicator of short-term interest rates and monetary policy situation. Between 2000-2008, the TB3M was relatively high, reflecting the Federal Reserve's tighter monetary policy position. During 2008-2009, TB3M had a decline in its activity, especially post-crisis. In this period Federal Reserve was opting for a monetary easing programme to support the economy.

Analysing both Figure 13 and Figure 14, these provide important insights regarding the market behaviour. The 2008 financial crisis is characterised by increased volatility and also by aggressive interest rate cuts by Federal Reserve, attempting to lower the financial pressure and collapse of the banking and financial systems. There is an obvious inverse relationship between these two. When the TB3M falls indicating a looser monetary policy, VIX is increasing characterised by the market uncertainty.

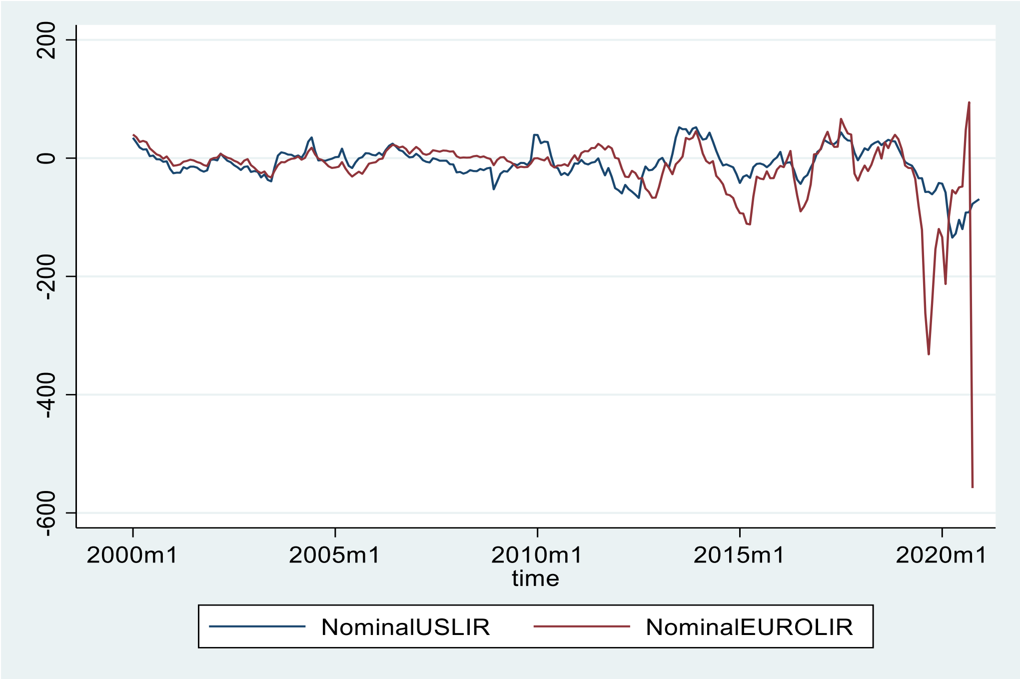

Figure 15 Nominal US Long-Term Interest Rate (NominalUSLIR), Nominal EURO19 Long-Term Interest Rate (NominalEUROLIR)

Figure 15 displays both United States Nominal Long-Term Interest Rate and Euro Area 19 Nominal Long-Term Interest Rate are behaving relatively similarly over the research period. However, there is a sharp drop to negative figures for the Euro Area 19 Nominal Long-Term Interest Rate at the end of 2019. These patterns reflect general economic conditions and therefore how central banks react to such situations by doing things like providing liquidity as well as stimulating investment. During some periods, the Eurozone faced significant changes in prices and negative interest rates. This shows that the economy was experiencing series of uncertainties, especially during Covid-19.

Table 2 Detailed descriptive statistics and unit root tests.

Subset 1: USA Variables

	Obs	Mean	Std. dev.	Min	Max	Variance	Skew	Kurt	ADF	KPSS
USinfl	252	2.10	1.22	-2.12	5.45	1.49	-0.32	3.72	-2.47	0.06
USunexp	251	-0.01	0.21	-1.12	0.98	0.04	-0.47	7.97	-7.60***	0.04
USexp	251	-0.01	0.39	-1.94	1.55	0.15	-0.51	6.66	-7.73***	0.02
RealReturnUSSP	252	4.02	16.74	-61.22	46.43	280.29	-1.27	5.01	-2.91	0.05
RealReturnSPGSCI	252	-3.27	27.95	-95.91	51.18	781.10	-0.79	3.60	-3.28	0.05
NominalUSLIR	251	-0.41	10.63	-50.28	43.19	112.89	-0.05	6.23	-2.29	0.08
USIPgrowth	252	0.31	4.61	-18.95	8.17	21.26	-1.94	7.28	-3.21	0.06

Subset 2: EURO 19 Variables

	Obs	Mean	Std. dev.	Min	Max	Variance	Skew	Kurt	ADF	KPSS
EUROinfl	252	1.66	0.96	-0.62	4.04	0.92	-0.37	2.63	-2.89	0.07
EUROunexp	251	-0.01	0.06	-0.20	0.17	0.00	0.04	3.51	-5.44***	0.03
EUROexp	251	0.00	0.25	-0.94	0.76	0.06	-0.02	3.87	-5.51***	0.03
RealReturnEUSTOXX	227	0.88	20.54	-62.88	41.80	421.85	-1.02	3.69	-3.33	0.07
NominalEURPOLIR	249	-2.40	46.54	-652.49	113.85	2165.67	-10.97	154.95	3.99	0.11
EUROIPgrowth	252	0.31	5.66	-33.50	8.93	31.99	-2.55	11.80	-3.73**	0.05

Subset 3: OECD countries Variables

	Obs	Mean	Std. dev.	Min	Max	Variance	Skew	Kurt	ADF	KPSS
OECDinfl	252	2.26	0.96	-0.59	4.81	0.92	-0.01	3.14	-2.54	0.10
OECDunexp	251	-0.01	0.13	-0.68	0.58	0.02	-0.30	6.67	-6.78***	0.02
OECDexp	251	0.00	0.24	-1.10	0.88	0.06	-0.37	5.47	-7.01***	0.02
RealReturnMSCIWorld	252	3.05	18.17	-68.12	47.61	330.27	-1.23	5.14	-2.68	0.05
WorldIPgrowth	252	0.77	4.86	-22.13	9.34	23.62	-2.33	9.78	-3.34	0.05

Subset 4 : Control Variables

	Obs	Mean	Std. dev.	Min	Max	Variance	Skew	Kurt	ADF	KPSS
TB3M	264	1.71	1.83	-0.01	6.19	3.36	0.91	2.51	-3.88**	0.181**
VIX	264	20.21	8.17	9.51	59.89	66.77	1.66	7.00	-2.33	0.09

Notes: The data from Table 2 illustrates the detailed descriptive statistics for all variables of interest for United States of America, Euro19 countries and OECD countries, amongst with the control variables – Three-Month Treasury Bill and Volatility index. In the analysis, I have performed the Augmented Dickey-Fuller tests (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin tests (KPSS) to identify unit root in the time series. The *** represents the statistically significance at 1% level, and ** indicates statistically significance at 5% level.

Table 2 provides an essential summary of statistics from the dataset that can allow a swift understanding of the data. The US and OECD countries inflations show an average of 2.10 per cent and respectively 2.26 per cent, comparing to 1.66 per cent for Euro Area 19. In all three cases, standard deviation is around 1, which signify a moderate variability. The negative skewness across there inflations suggests a slight tendency towards lower inflation rates.

The variance observations from the table are that the variance is relatively high for all indices real returns: RealReturnUSSP, RealReturnEUSTOXX, RealReturnMSCIWorld, and, in particular, RealReturnSPGSCI. A high variance is relatively common for the indices since most have a higher volatile nature. The prices can be highly sensitive to economic, financial and geopolitical shocks. The diversified basket of companies or sectors causes a second reason. The mean of the indices' real return is 4.02 RealReturnUSSP and -3.27 for RealReturnSPGSCI, whichs signifies a high volatility in US markets. In contrast EURO Stoxx 50's mean is only 0.88. MSCI World' real return mean is 3.05; however, this can be characterized by the global equity markets and not only a specific region.

In the majority of variables' time series, the ADF test statistics suggests a non-stationarity time series, therefore I could not prove the stationarity of those. I have identified non-stationarity time series for the US inflation (ADF -2.47), EURO19 inflation (ADF -2.89), and OECD countries inflation variables (ADF -2.54). After performing the first-order differencing method for these variables, I have controlled for possible spikes, trends, or seasonality. Having the series stationary was a mandatory exercise to estimate and calculate the expected and unexpected inflation. Therefore, it has resulted in expected and unexpected inflation in all three subsets being statistically significant at a 1 per cent level. Only the EURO19 Industrial Production growth unit root results are statistically significant. Therefore, it can be inferred that the series is stationary.

An interesting statistical observation can be observed in the Three-Month Treasury Bill series. Performing the ADF unit root test, I identified a stationary series at a 5 per cent level; however, the KPPS test indicated that the series were non-stationary. Performing additional unit root tests and analysing the graphs of the TB3M series, it can be concluded that time series are non-stationary, and the first-order differencing method should be applied. The Three-Month U.S. Treasury Bill Rate mean rate is 1.71 per cent with a standard deviation of 1.83 per cent, indicating a slight volatility in short-term interest rates. The volatility index VIX has a mean of 20.21 and high skewness of 1.66 and kurtosis of 7.00. This indicates frequent occasions of extreme high volatility, especially during economic crises.

Table 3 Correlation analysis

Subset 1: US S&P 500 Variables

	dRealReturnUSSP	USunexp	USexp	dUSIPgrowth	dTB3M	dVIX
dRealReturnUSSP	1					
USunexp	0.16***	1				
USexp	0.21***	-0.03	1			
dUSIPgrowth	0.25***	0.22***	0.12*	1		
dTB3M	0.16**	0.12*	0.09	0.13**	1	
dVIX	0.07	0.17***	-0.05	0.17***	-0.18***	1

Subset 2: EURO 19 Variables

	dRealReturnEUSTOXX	EUROunexp	EUROexp	EUROIPgrowth	dTB3M	dVIX
dRealReturnEUSTOXX	1					
EUROunexp	-0.07	1				
EUROexp	0.18***	0.00	1			
EUROIPgrowth	-0.06	0.29***	0.23***	1		
dTB3M	0.14**	0.01	0.06	0.08	1	
dVIX	0.05	0.01	-0.04	0.15**	-0.18***	1

Subset 3: OECD countries Variables

	dRealReturnMSCIWorld	OECDunexp	OECDexp	dWorldIPgrowth	dTB3M	dVIX
dRealReturnMSCIWorld	1					
OECDunexp	0.16***	1				
OECDexp	0.26***	-0.03	1			
dWorldIPgrowth	0.35***	0.22***	0.25***	1		
dTB3M	0.18***	0.10*	0.08	0.15**	1	
dVIX	0.06	0.17***	-0.05	0.13**	-0.18***	1

Subset 4: US S&P GSCI Variables

	dRealReturnSPGSCI	USunexp	USexp	dUSIPgrowth	dTB3M	dVIX
dRealReturnSPGSCI	1					
USunexp	0.33***	1				
USexp	0.68***	-0.03	1			
dUSIPgrowth	0.31***	0.22***	0.12*	1		
dTB3M	0.08	0.12*	0.09	0.13**	1	
dVIX	0.07	0.17***	-0.05	0.17***	-0.18***	1

Subset 5: US S&P 500 Variables (IR)

	dRealReturnUSSP	USunexp	USexp	dNominalUSLIR	dTB3M	dVIX
dRealReturnUSSP	1					
USunexp	0.16***	1				
USexp	0.21***	-0.03	1			
dNominalUSLIR	0.33***	0.22***	0.24***	1		
dTB3M	0.16**	0.12*	0.09	0.21***	1	
dVIX	0.07	0.17***	-0.05	-0.06	-0.18***	1

Subset 6: EURO 19 Variables (IR)

	dRealReturnEUSTOXX	EUROunexp	EUROexp	dNominalEUROLIR	dTB3M	dVIX
dRealReturnEUSTOXX	1					
EUROunexp	-0.07	1				
EUROexp	0.18***	0.00	1			
dNominalEUROLIR	0.03	0.08	-0.04	1		
dTB3M	0.14**	0.01	0.06	-0.03	1	
dVIX	0.05	0.01	-0.04	-0.15**	-0.18***	1

Subset 7: US S&P GSCI Variables (IR)

	dRealReturnSPGSCI	USunexp	USexp	dNominalUSLIR	dTB3M	dVIX
dRealReturnSPGSCI	1					
USunexp	0.33***	1				
USexp	0.68***	-0.03	1			
dNominalUSLIR	0.21***	0.22***	0.24***	1		
dTB3M	0.08	0.12*	0.09	0.21***	1	
dVIX	0.07	0.17***	-0.05	-0.06	-0.18***	1

Notes: The *** represents the statistically significance at 1% level, ** indicates statistically significance at 5% level, and *** indicates statistically significance at 10% level.

Table 3 presents the correlation analysis between the economic variables chosen in this thesis.

The S&P 500 real return is statistically significant and positively correlated with the unexpected inflation at 0.16 Pearson correlation coefficient and with expected inflation at 0.21 correlation coefficient. This indicates that changes in decomposed inflation contribute to higher S&P 500 real returns. Similarly, industrial production growth is also statistically significant at 0.25, and its improvements also leads to higher real returns.

On another hand, there is a weaker correlation between EURO Stoxx 50 real return and unexpected inflation. The non statistically significance at -0.07, indicates little to no relationship between these two variables. However, there is a statistically significance at 0.18 between expected inflation and EURO Stoxx 50.

The MSCI World real return is positively correlated with almost all variables, except the Volatility index. The statistically significant values for OECD unexpected inflation at 0.16, OECD expected inflation at 0.26, World Industrial Production growth at 0.35 and Three-Month Treasury Bill at 0.18 reflect a strong correlation between MSCI World return and the economic indicators.

It can be observed that TB3M is correlated very differently with different indices' real return, from a not statistically significant correlation with the US S&P GSCI to a statistical correlation at 18 per cent with the Real Return MSCI World.

Nominal US long-term interest rate has a statistically significant correlation with S&P 500 and S&P GSCI of 33 and respectively 21 per cent and a not statistically significant correlation with EURO Stoxx 50.

Similarly, to the S&P 500, S&P GSCI real return is also strongly correlated with unexpected and expected inflation. This indicates that commodities tend to perform well during the periods of that level of inflation. Moreover, the correlation coefficient of 0.31 being statistically significant indicates a higher sensitivity of commodity returns to economic activity.

Upon replacing the industrial production growth variable with the long-term interest rate, it can be identified almost the same pattern and behaviour in terms of the remaining economic indicators. Therefore, it can be inferred that real returns have the same correlation behaviour with the long-term interest rate as with industrial production growth.

Nonetheless, the table presents that in Subsets 1 – 7, there is a positive correlation between expected inflation and real returns of 18 per cent to 68 per cent, which are statistically significant at a 1 per cent level. There is also a positive correlation between unexpected inflation and real returns of 16 per cent to 33 per cent; except for the EURO 19 Variables subsets, where unexpected inflation has a negative correlation with Real Returns EURO Stoxx 50.

4.2. Empirical Results

In my analysis, I am using ARIMA models to decompose inflation into unexpected and expected inflation. A similar method of inflation decomposition was used by Fama & Gibbons (1984), Vassalou (2000), and Zhang (2021).

Vassalou (2000) emphasizes that the ARIMA (0,0,1) model is widely used for inflation forecasting in research analyses. Zhang (2021) is using an AR (4) model to generate the expected inflation. Unexpected inflation is the difference between actual inflation minus the generated AR (4) model's expected inflation. Equally comparable to this approach, I am using the same approach as Zhang (2021). As per previous literature and empirical methods approach, to have a good ARIMA model for estimating our required variables, it is required to have statistically significant coefficients at selected lags.

Additionally, when performing the Portmanteau test for white noise, the white noise test results should not be statistically significant. The Null hypothesis H_0 of the Portmanteau test is that the residuals are not correlated. Due to this, we should not be able to reject the H_0 and accept it. This indicates that the model adequately captures the information, making it robust for forecasting future values. Besides the Portmanteau tests, I have selected the correct ARIMA model based on RMSE's dynamic forecasts for ARIMA models.

Since the inflation variable is non-stationary for all areas (US, EURO19 and OECD countries), I have applied the differencing method at level 1 – *I (1)* before forecasting ARIMA models.

Table 4 ARIMA models selections

		Subset 1: US Inflation		
	AIC	**BIC**	**Portmanteau test**	**RMSE Dynamic forecast**
ARIMA (0,0,1)	251.71	262.29	0.37	0.2780
ARIMA (1,0,2)	251.00	268.62	0.53	0.2770
		Subset 2: EURO19 Inflation		
	AIC	**BIC**	**Portmanteau test**	**RMSE Dynamic forecast**
ARIMA (0,0,2)	15.83	29.93	0.47	0.2649
ARIMA (1,0,2)	15.74	33.37	0.84	0.2607
		Subset 3: OECD Inflation		
	AIC	**BIC**	**Portmanteau test**	**RMSE Dynamic forecast**
ARIMA (2,0,0)	-1.04	13.07	0.20	0.2086
ARIMA (1,0,2)	-2.08	15.55	0.43	0.2677

Notes: ARIMA models highlighted in bold are selected for forecasting. For all inflations, ARIMA(1,0,2) has been selected as forecasting model.

Table 4 represents the best two ARIMA models for each inflation variable. Surprisingly, applying the selection criteria, ARIMA (1,0,2) was the best model for all inflation variables. Considering the EURO Area consists of 19 countries and the OECD

World list consists of 37 countries, internal economic or industrial shocks in each country can have a significant impact on the overall area.

4.2.1. VAR analysis

I am using the Vector Autoregressive (VAR) model to analyse the relationship between inflation and stock market returns. Moreover, for the comparison, I am using the percentage values of the logarithmic base of annual change of indices real stock/commodity return, industrial production values; unexpected and expected inflation calculated using ARIMA models, and monthly Three-Month Treasury Bill and CBOE Volatility Index. As mentioned earlier in this paper, I am using industrial production growth as the control variable, similarly as Zhang (2021). In other several studies (Humpe & Macmillan, 2009; Boudoukh et al., 1994; Geetha et al. 2011) long-term interest rate is used as the control variable.

Transitioning to the VAR estimation itself, in order to be able to run the VAR models, I ensured that our variables were in the same order of integration and were stationary. The order of the VAR model variables is essential because of the impulse response specification and Cholesky decomposition. When performing the Cholesky decomposition, we also need to select the variables based on the exogenous criteria.

Prior to running the VAR analysis, I obtained the lag-order selection statistics for VAR. The empirical preestimation command is used for determining the appropriate VAR lag length. Specifically, highlighting this crucial point, in case of using an incorrect VAR lag length, the model can be mis-specified. Conversely, if it is too big, we can lose the degrees of freedom, making our VAR analysis ineffective. As Lutkepohl (2005) demonstrates, choosing the p (VAR lag) minimizing BIC (Bayesian information criterion) or the HQIC (Hannan-Quin information criterion) would provide more robust and consistent estimates of the correct lag order, p. On the contrary, aiming for a lower AIC (Akaike information criterion) or the FPE (Akaike's Final Prediction Error) will overestimate the true lag order with the positive probability that will generate an infinite sample size.

Table 5 VAR Lag-order selection criteria

Subset 1: US S&P 500 VAR Lag-order

Lag *(Obs = 247)*	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-2006.81				0.48229	16.298	16.3324	16.3833
1	-1481.71	1050.2	36	0.000	0.009191	12.3377	12.5779	12.9344
2	-254.904	2453.6	36	0.000	6.0e-07*	2.69558*	3.14176*	3.80381*
3	-226.555	56.699*	36	0.015	6.0e-07	2.75753	3.40964	4.37725
4	-204.571	43.967	36	0.170	7.1e-07	2.87102	3.72906	5.00223

Subset 2: EURO19 VAR Lag-order

Lag *(Obs = 222)*	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-1735.27				0.261812	15.6871	15.7243	15.7791
1	-1393.18	684.18	36	0.000	0.016613	12.9296	13.1895	13.5733
2	2072.28	6930.9	36	0.000	6.3e-16	-17.9665	-17.4838	-16.7709*
3	2128.74	112.93*	36	0.000	5.0e-16*	-18.2049*	-17.5365*	-16.5495
4	2152.47	47.464	36	0.096	5.3e-16	-18.1484	-17.2944	-16.0332

Subset 3: OECD countries VAR Lag-order								
Lag *(Obs = 247)*	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-1783.85				0.079295	14.4927	14.5270	14.5779
1	-1286.25	995.2	36	0.000	0.001888	10.755	10.9953	11.3518
2	-99.6531	2373.2*	36	0.000	1.7e-07*	1.43849*	1.88467*	2.54671*
3	-77.6153	44.076	36	0.167	1.9e-07	1.55154	2.20365	3.17126
4	-60.4055	34.42	36	0.544	2.2e-07	1.70369	2.56173	3.8349
Subset 4: US S&P GSCI VAR Lag-order								
Lag *(Obs = 247)*	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-2012.23				0.503935	16.3420	16.3763	16.4272
1	-1517.1	990.26	36	0.000	0.012242	12.6243	12.8645	13.221
2	-284.533	2465.1	36	0.000	7.6e-07*	2.93549*	3.38167*	4.04371*
3	-253.39	62.285	36	0.004	7.9e-07	2.97482	3.62693	4.59454
4	-223.337	60.106*	36	0.007	8.3e-07	3.02297	3.88101	5.15418
Subset 5: US S&P 500 VAR Lag-order (IR)								
Lag *(Obs = 247)*	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-2494.45				25.01080	20.247	20.2809	20.3318
1	-1983.78	1021.3	36	0.000	0.535733	16.4031	16.6433	16.9998
2	-764.867	2437.8*	36	0.000	.000037*	6.82483*	7.27101*	7.93306*
3	-743.737	42.26	36	0.219	0.00	6.94524	7.59735	8.56496
4	-719.594	48.287	36	0.083	0.00	7.04124	7.89929	9.17245
Subset 6: EURO19 VAR Lag-order (IR)								
Lag *(Obs = 220)*	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-2203.96				21.397300	20.0905	20.1279	20.1831
1	-2071.68	264.55	36	0.000	8.918710	19.2153	19.4769	19.8632
2	1380.28	6903.9	36	0.000	0.0000	-11.8389	-11.3531	-10.6357*
3	1433.84	107.11	36	0.000	2.4e-13*	-12.0531*	-11.3803*	-10.3871
4	1462.83	57.975*	36	0.012	0.00	-12.0439	-11.1842	-9.9152

Subset 7: US S&P GSCI VAR Lag-order (IR)								
Lag *(Obs = 247)*	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-2510.71				28.529900	20.3782	20.4125	20.4635
1	-2027.5	966.47	36	0.000	0.763165	16.7569	16.9971	17.354
2	-802.044	2450.9	36	0.000	.00005*	7.12586*	7.57204*	8.23409*
3	-772.55	58.985	36	0.009	0.000	7.17855	7.83066	8.79827
4	-745.454	54.195*	36	0.026	0.00	7.25064	8.10868	9.38184

Notes: The asterisk * indicates the optimal lag for the VAR analysis.

Table 5 displays the optimal lags that have been suggested by Stata software.

I have identified that when using the industrial production (IP) growth as the control variable, the VAR (2) model is the best fit for the US S&P 500 for EURO19 - VAR (3) model, for OECD countries – VAR (2) model, and for US S&P GSCI – VAR (2) model were found to be optimal, by comparison, the information criterion. The same results in VAR length selection have been obtained when using the Interest-Rate as a control variable, just like when IP growth is used.

Following the above-mentioned considerations, these VAR models satisfy the Eigenvalue stability condition. Emphasizing this factor, all eigenvalue values are required to lie inside the unit circle. Otherwise, it implies that our VAR model does display explosive behaviour over time. It suggests that the shocks and disturbances do not have an increasing effect on the forecast results, and the VAR model is reliable and suitable for our analysis.

To extend the VAR model stability analysis, the Lagrange Multiplier test shows that our residuals are not statistically significant at the selected lag order. This would define no autocorrelation in the VAR models, making them fit for our purposes.

Table 6 VAR Analysis with Industrial Production growth as a control variable

Subset 1: US S&P 500 VAR

Dependent Variable	Lag: 2	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dRealReturnUSSP	***dRealReturnUSSP***	-0.0686	0.067	-1.030	0.303	-0.199	0.062
	USunexp	-0.8383	2.068	-0.41	0.685	-4.891	3.215
	USexp	-0.8522	1.096	-0.78	0.437	-3.001	1.296
	dUSIPgrowth	0.3471	0.317	1.1	0.273	-0.274	0.968
	dTB3M	-1.9367	2.103	-0.92	0.357	-6.059	2.186
	dVIX	-0.1871	0.091	-2.06	0.040**	-0.366	-0.009
	_cons	0.0089	0.420	0.02	0.983	-0.813	0.831

Subset 2: EURO19 VAR

Dependent Variable	Lag: 3	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dRealReturnEUSTOXX	***dRealReturnEUSTOXX***	-0.0375	0.067	-0.560	0.576	-0.169	0.094
	EUROunexp	-13.2326	9.353	-1.41	0.157	-31.563	5.098
	EUROexp	2.9726	2.124	1.4	0.162	-1.190	7.135
	EUROIPgrowth	-0.3413	0.095	-3.61	0.000***	-0.527	-0.156
	dTB3M	2.8603	2.709	1.06	0.291	-2.450	8.171
	dVIX	0.2025	0.106	1.9	0.057*	-0.006	0.411
	_cons	0.0391	0.500	0.08	0.938	-0.941	1.019

Subset 3: OECD countries VAR

Dependent Variable	Lag: 2	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dRealReturnMSCIWorld	***dRealReturnMSCIWorld***	-0.0533	0.068	-0.780	0.434	-0.187	0.080
	OECDunexp	-1.5973	3.320	-0.48	0.630	-8.104	4.910
	OECDexp	-3.7978	1.880	-2.02	0.043**	-7.482	-0.114
	dWorldIPgrowth	0.6318	0.299	2.12	0.034**	0.047	1.217
	dTB3M	-2.3876	2.121	-1.13	0.260	-6.544	1.769
	dVIX	-0.2393	0.091	-2.62	0.009***	-0.418	-0.061
	_cons	-0.0368	0.423	-0.09	0.931	-0.866	0.793

Subset 4: US S&P GSCI VAR

Dependent Variable	Lag: 2	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dRealReturnSPGSCI	***dRealReturnSPGSCI***	0.0385	0.097	0.400	0.693	-0.152	0.230
	USunexp	-1.8855	3.399	-0.55	0.579	-8.547	4.776
	USexp	-1.5026	2.343	-0.64	0.521	-6.095	3.090
	dUSIPgrowth	1.1959	0.477	2.5	0.012**	0.260	2.132
	dTB3M	0.5490	3.119	0.18	0.860	-5.563	6.661
	dVIX	-0.4828	0.136	-3.56	0.000***	-0.749	-0.217
	_cons	-0.2333	0.625	-0.37	0.709	-1.459	0.992

Notes: The *** represents the statistically significance at 1% level, ** indicates statistically significance at 5% level, and * indicates statistically significance at 10% level.

Table 7 VAR Analysis with Long-Term Interest Rate as a control variable

Subset 5: US S&P 500 VAR (IR)

Dependent Variable	Lag: 2	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
	dRealReturnUSSP	-0.0396	0.068	-0.580	0.560	-0.173	0.093
	USunexp	-0.0879	2.084	-0.04	0.966	-4.173	3.997
	USexp	-0.5439	1.112	-0.49	0.625	-2.723	1.635
dRealReturnUSSP	*dNominalUSLIR*	-0.0413	0.044	-0.94	0.345	-0.127	0.044
	dTB3M	-1.4301	2.111	-0.68	0.498	-5.567	2.707
	dVIX	-0.1767	0.090	-1.96	0.050**	-0.353	0.000
	_cons	-0.0087	0.420	-0.02	0.984	-0.832	0.814

Subset 6: EURO19 VAR (IR)

Dependent Variable		Lags:	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dRealReturnEUSTOXX	*dRealReturnEUSTOXX*	2	0.0207	0.077	0.270	0.787	-0.130	0.171
		3	0.0190	0.068	0.280	0.780	-0.114	0.152
	EUROunexp	2	-8.8996	12.426	-0.72	0.474	-33.254	15.455
		3	-17.6608	9.062	-1.95	0.051*	-35.422	0.100
	EUROexp	2	-2.3204	2.077	-1.12	0.264	-6.392	1.751
		3	2.2919	2.832	0.81	0.418	-3.259	7.843
	dNominalEUROLIR	2	0.0294	0.024	1.25	0.212	-0.017	0.076
		3	-0.0124	0.025	-0.49	0.624	-0.062	0.037
	dTB3M	2	-1.7462	2.848	-0.61	0.540	-7.328	3.836
		3	3.1175	2.763	1.13	0.259	-2.297	8.532
	dVIX	2	-0.3263	0.107	-3.04	0.002***	-0.537	-0.116
		3	0.1098	0.124	0.88	0.377	-0.134	0.353
	_cons		-0.1536	0.509	-0.3	0.763	-1.150	0.843

Subset 7: US S&P GSCI VAR (IR)

Dependent Variable	Lag: 2	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
	dRealReturnSPGSCI	0.0951	0.096	0.990	0.323	-0.093	0.284
	USunexp	-1.5175	3.523	-0.43	0.667	-8.422	5.387
	USexp	-2.0620	2.410	-0.86	0.392	-6.786	2.662
dRealReturnSPGSCI	*dNominalUSLIR*	0.0125	0.064	0.2	0.845	-0.113	0.138
	dTB3M	1.5266	3.168	0.48	0.630	-4.683	7.736
	dVIX	-0.4246	0.135	-3.13	0.002***	-0.690	-0.159
	_cons	-0.2406	0.633	-0.38	0.704	-1.482	1.000

Notes: The *** represents the statistically significance at 1% level, ** indicates statistically significance at 5% level, and * indicates statistically significance at 10% level.

VAR models presented in the Table 6 and Table 7 give valuable insights into the dynamics between different economic variables and the indices returns, especially in relation to US economy. Each result in this model represents the stock or commodity indices real return as the variable of interest and explanatory factors of other variables.

The coefficient estimates generated by this VAR model, give insights into the connections between these variables and how they affect each other over time.

In the above subsets we analyse the impact of unexpected, expected inflation, growth in industrial production, the Three-Month Treasury Bill rate and the volatility index on stock and commodity returns. On the second part of the subsets, I have substituted industrial production growth with long-term interest rates.

In the subset 1, the US S&P 500 Real Return is the dependent variable. According to coefficient estimates, these variables vary significantly, meaning that they have a potential effect on the S&P 500 index. Analysing the coefficient estimates, it can be observed that all coefficients except US industrial production growth show a negative relationship with S&P 500 Real Return: US unexpected inflation -0.8383, US expected inflation -0.8522. However, since these are not statistically significant, it implies that the coefficients do not highly affect its dependent value. Similarly, the constant term is not statistically significant with p-value of 0.983, meaning the intercept term does not explain the real return variability of S&P 500 index either. Only the CBOE Volatility Index (dVIX) with a p-value of 0.040 is statistically significant. This suggests that VIX has a negative impact and high volatility affects the current index's real return.

When analysing subset 2, it can be noticed a different pattern of coefficient estimates. Firstly, it can be noticed that the Euro Stoxx 50 Real Return itself (-0.0375), unexpected inflation (-13.2326), and industrial production growth (-0.3413) are negatively correlated with the Euro Stoxx 50 Real Return, and the remaining are positively correlated with the dependent variable. Moreover, industrial production growth at 1 per cent significancy and volatility index at 10 per cent are statistically significant, indicating that changes in these variables significantly impact the real return of the Euro Stoxx 50 index. This emphasises the importance of considering regional economic dynamics and market-specific factors.

Compared to all other subsets in our analysis, in subset 3, expected inflation is statistically significant at 5 per cent with a p-value of 0.043, and suggests that it has a significant negative impact on the real return of the MSCI World Index. Furthermore, it was found the world industrial production growth rate coefficient is positively correlated with MSCI World real return and is statistically significant at 5 per cent, too, with a p-value of 0.034.

Similarly, a higher level of market volatility has a substantial negative impact on the index's real return. These results show that global industrial production growth and market instability all have important roles to play in determining actual returns made from investment on the MSCI world index for OECD countries.

Compared to Subset 1, which focuses on the S&P 500, subset 4 uses the same control variables, but its focus is the S&P GSCI index. After an initial overview, it can be noticed that the index itself has a positive but not statistically significant relationship with the dependent variable. Moreover, the US IP growth is now statistically significant at 5 per cent with a p-value of 0.012. Moving to the remaining economic variables, there is a negative correlation between the control variables, such as unexpected and expected inflation, volatility index, and the intercept constant and the dependent variables. In contrast, the remaining control variables have a positive relationship: US IP growth and Three-Month Treasury Bill.

Analysing the subsets 5 to 7, we see that the picture has not changed significantly overall. The main difference is that Long-Term Interest Rate (LTIR) is not statistically significant in any subsets. We observe a negative relationship between LTIR and indices real return in subset 5, where the dependent variable is S&P 500 and in subset 7 where we analyse the relationship with S&P GSCI. An important change occurred in subset 6, where after replacing IP growth with LTIR, the unexpected inflation became statistically significant at 10 per cent at lag 3. We can infer that unexpected inflation can significantly impact the Euro Stoxx 50 Real Return for a more extended period.

4.2.2. Granger Causality

In continuation, I ran the Granger causality Wald tests to test if our variables of interest can help predict other variables. To reiterate, the test's null hypothesis for our scope is that "excluded" variables do not Granger-cause the variable of interest.

Table 8 Granger causality Wald test

Subset 1: US S&P 500 Granger causality

		Variable of interest					
		dRealReturnUSSP	**USunexp**	**USexp**	**dUSIPgrowth**	**dTB3M**	**dVIX**
Excluded	*dRealReturnUSSP*		0.404	0.480	0.001***	0.809	0.065*
	USunexp	0.685		0.322	0.586	0.07*	0.563
	USexp	0.437	0.104		0.455	0.083*	0.416
	dUSIPgrowth	0.273	0.217	0.006***		0.248	0.297
	dTB3M	0.357	0.150	0.402	0.512		0.501
	dVIX	0.04**	0.000***	0.177	0.000***	0.258	
	ALL	0.335	0.000***	0.057*	0.000***	0.141	0.258

Subset 2: EURO19 Granger causality

		Variable of interest					
		dRealReturnEUSTOXX	**EUROunexp**	**EUROexp**	**EUROIPgrowth**	**dTB3M**	**dVIX**
Excluded	*dRealReturnEUSTOXX*		0.133	0.551	0.316	0.505	0.635
	EUROunexp	0.157		0.830	0.257	0.352	0.908
	EUROexp	0.162	0.000***		0.049**	0.527	0.129
	EUROIPgrowth	0.000***	0.000***	0.174		0.684	0.250
	dTB3M	0.291	0.434	0.452	0.184		0.374
	dVIX	0.057*	0.01**	0.280	0.000***	0.489	
	ALL	0.001***	0.000***	0.693	0.000***	0.801	0.323

Subset 3: OECD countries Granger causality

		Variable of interest					
		dRealReturnMSCIWorld	**OECDunexp**	**OECDexp**	**dWorldIPgrowth**	**dTB3M**	**dVIX**
Excluded	*dRealReturnMSCIWorld*		0.487	0.966	0.011**	0.740	0.150
	OECDunexp	0.630		0.753	0.786	0.115	0.239
	OECDexp	0.043**	0.037**		0.842	0.07*	0.735
	dWorldIPgrowth	0.034**	0.242	0.229		0.173	0.879
	dTB3M	0.260	0.292	0.728	0.658		0.610
	dVIX	0.009***	0.000***	0.131	0.000***	0.239	
	ALL	0.024**	0.000***	0.529	0.000***	0.165	0.355

Subset 4: US S&P GSCI Granger causality

		Variable of interest					
		dRealReturnSPGSCI	USunexp	USexp	dUSIPgrowth	dTB3M	dVIX
Excluded	*dRealReturnSPGSCI*		0.768	0.712	0.001***	0.835	0.07*
	USunexp	0.579		0.259	0.577	0.079*	0.940
	USexp	0.521	0.305		0.169	0.164	0.609
	dUSIPgrowth	0.012**	0.195	0.012**		0.292	0.261
	dTB3M	0.860	0.119	0.436	0.223		0.326
	dVIX	0.000***	0.000***	0.167	0.000***	0.252	
	ALL	0.002***	0.000***	0.066*	0.000***	0.142	0.268

Subset 5: US S&P 500 Granger causality (IR)

		Variable of interest					
		dRealReturnUSSP	USunexp	USexp	dNominalUSLIR	dTB3M	dVIX
Excluded	*dRealReturnUSSP*		0.458	0.779	0.521	0.956	0.133
	USunexp	0.966		0.878	0.046**	0.104	0.758
	USexp	0.625	0.133		0.811	0.107	0.541
	dNominalUSLIR	0.345	0.250	0.05**		0.946	0.611
	dTB3M	0.498	0.157	0.168	0.959		0.623
	dVIX	0.05**	0.000***	0.300	0.04**	0.346	
	ALL	0.369	0.000***	0.231	0.059*	0.227	0.337

Subset 6: EURO19 Granger causality (IR)

		Variable of interest					
		dRealReturnEUSTOXX	EUROunexp	EUROexp	dNominalEUROLIR	dTB3M	dVIX
Excluded	*dRealReturnEUSTOXX*		0.209	0.441	0.891	0.876	0.319
	EUROunexp	0.103		0.464	0.189	0.393	0.715
	EUROexp	0.378	0.000***		0.019**	0.483	0.647
	dNominalEUROLIR	0.455	0.504	0.364		0.023**	0.026**
	dTB3M	0.475	0.412	0.905	0.898		0.991
	dVIX	0.006***	0.225	0.086	0.147	0.222	
	ALL	0.039**	0.000***	0.592	0.282	0.038**	0.178

Subset 7: US S&P GSCI Granger causality (IR)

		Variable of interest					
		dRealReturnSPGSCI	USunexp	USexp	dNominalUSLIR	dTB3M	dVIX
Excluded	*dRealReturnSPGSCI*		0.504	0.377	0.996	0.643	0.102
	USunexp	0.667		0.603	0.084*	0.095*	0.719
	USexp	0.392	0.525		0.818	0.143	0.544
	dNominalUSLIR	0.845	0.159	0.056*		0.940	0.322
	dTB3M	0.630	0.132	0.154	0.910		0.507
	dVIX	0.002***	0.000***	0.286	0.045**	0.330	
	ALL	0.035**	0.000***	0.180	0.07*	0.211	0.295

Notes: The table should be read from left to right, where "Excluded" variables do Granger-cause the "variable of interest". E.g. US unexpected inflation (USunexp) does not cause Granger-cause on S&P500 real return (dRealReturnUSSP) (0.685 > 0.05). The *** represents the statistically significance at 1% level, and ** indicates statistically significance at 5% level.

The Granger causality Wald test helps us examine if the past values of the "excluded" variables from Table 7 can help us estimate the "variable of interest" from our model. My analysis mainly focuses on how "excluded" variables and past information influence the real returns of market indices.

The above table presents that the Volatility index does Granger-cause real returns of US S&P 500, MSCI World, and S&P GSCI, and it Granger-causes on EURO

Stoxx 50 at 10 per cent significance. Moreover, industrial production growth is the following variable that does Granger-cause indices real returns. An interesting finding is that United States industrial production growth past information does Granger-cause real returns of S&P GSCI; however, it does not Granger-cause real returns of S&P 500.

On the other hand, the other control variable – long-term interest rate does not Granger-cause real returns for any of the indices of interest. There is no statistical significance, and the coefficients are relatively high compared to Industrial Production growth. The nominal US long-term interest rate does Granger-cause US expected inflation, at 5 per cent and 10 per cent; however, the nominal EURO long-term interest rate does not Granger-cause Euro expected inflation.

Above all, emphasizing the crucial consideration, only OECD expected inflation Granger-cause MSCI World real return. In all other areas, expected inflation does not Granger-cause the real returns. Moreover, similar to expected inflation, unexpected inflation is also not statistically significant enough to reject the Null hypothesis.

In conclusion, unexpected does not Granger-cause the real returns of any indices in our research scope. Similar behaviour is presenting the expected inflation, too. However, as mentioned above, OECD's expected inflation is statistically significant and does Granger-cause MSCI World real returns. Overall, there needs to be more evidence that variables in my research scope do Granger cause the indices' real returns. However, due to their limitations Granger causality tests are not always a strong predictor. Granger causality tests are typically the most common way of assessing a useful predictor; however, the method does not confirm that predictive relation is stable (Stock & Watson, 2003). Moreover, they mention that a statistically significant Granger causality does not necessarily contain accurate or reliable information that the indicator can be used as a predictor.

4.2.3. Impulse Response Function (IRF) and Variance Decomposition

The impulse response function allows us to estimate the effect and development of one variable in the other after the shock. To explain in other terms, I analyse how indices' real return responds to the shocks or impulses in unexpected and expected inflation separately after the VAR analysis.

An important point deducted from the IRF analysis is that the order of the variables in the VAR analysis can offer different results. Therefore, when using the industrial production growth variable in my analysis, I used the same variable orders as (Zhang, 2021), and I would replace the industrial production growth variable with the long-term interest rate in the same position.

Figure 15 illustrates how shocks in different variables influence the response of the "targeted" variable.

Analyzing the Orthogonalized IRF, the shock in the United States' expected and unexpected inflation created a slight negative response in the S&P 500 real return. It can be observed that the percentage of variation for all shocks on the S&P 500 real return is around -2 and 1 for all the variables with a standard error confidence. A slightly more negative percentage variation for the S&P 500 real return occurred from the Three-Month Treasury Bill shock. As the Granger causality, Wald test has indicated, US industrial production growth is the only variable that has a minor positive impact on the index's real return.

Compared to the S&P 500 impulse response, behaviour is significantly different with the EURO19 variables. From the graph, it can be inferred that the positive percentage variation is around two within standard error confidence. Conversely, we see a significant negative variation for the Euro19 unexpected inflation shock on the EURO Stoxx 50 real return. The confidence interval's width might reflect the uncertainty level around the estimated response. Compared to S&P 500 analysis, here we find that the results are more ambiguous and harder to interpret. One of the reasons that can explain these differences is the size of the EURO economy. The area and the economy itself are formed from different countries, causing different impacts on the economy itself. Moreover, the Stoxx 50 weighting is not directly proportional to the industrial production growth weighting by the country.

In addition, intensifying the exploration into this topic, there are no impulses and respective responses from EURO Stoxx 50 on itself. Furthermore, the volatility index does not have any impulses either; however, the Three-Month Treasury Bill has a positive impact on period two and a very insignificant negative impact on the sixth period.

Inferring from the OECD countries' IFR graph, it can be noted that the impulse-reaction activity is almost the opposite of the real return on the S&P 500 and EURO Stoxx 50. MSCI world real return does not have such a strong response after the unexpected inflation shock, in comparison to the EURO Stoxx 50. Nonetheless, it has a stronger reaction than the S&P 500 real return. On the other hand, the shock in OECD's expected inflation has a more negative significant impact on the MSCI World index, and its response is stronger than any of the above areas. Moreover, the Three-Month Treasury Bill shock is causing a significant negative response to the MSCI World Index.

In addition, when compared to the previously mentioned variables' IRF analysis, unexpected and expected inflations have adverse shocks that last only one step. It can be deduced that one to two standard deviation shocks in the decomposed inflations have a negative effect on the S&P 500 GSCI real return. Positive shocks can be noticed in the Three-Month Treasury Bill and the United States Industrial Production Index.

Using the nominal long-term interest rates results in slightly different results. The shock in the United States' expected inflation has a minimal negative response in the S&P 500 real return. However, comparatively, the shock of unexpected inflation has created a slight positive response in the S&P 500 real return. It can be observed that the same percentage variation for the S&P 500 real return occurred from the Three-Month Treasury Bill shock. However, there is no impulse-response effect from the real return, long-term interest rate or volatility index.

In Figure 20, it can be noticed a minimal shock in EURO unexpected inflation has created an impulse for Stoxx 50 real return; however, there is almost a non-significant shock in expected inflation that has created a minimal response. Similarly to the S&P 500 graph, there is no impulse-response effect from the real return, long-term interest rate or volatility index, and the shock in the Three-Month Treasury Bill is minimal to create a significant response in Stoxx 50 real return.

The same pattern can be observed in the last Impulse-response function, Figure 21. There are more negative shocks in unexpected and expected inflation, and the percentage of variation for all shocks on the S&P GSCI real return is around -2 for all the variables with standard error confidence. Now, it can be noticed a positive shock in the Three-Month Treasury Bill that has a response of around 2 per cent of the variation. Moreover, there is no impulse-response effect from the real return, long-term interest rate or volatility index.

For all indices analyses, the standard error confidence intervals and confidence bands can be observed to be moderately sizable. Therefore, I cannot affirm that the results are strongly reliable. As mentioned earlier, both unexpected and expected inflation variables are calculated based on the ARIMA models, which are only forecasted values. In addition, aside from the stated facts, for clarification, it is noteworthy to highlight that the confidence bands extends typically for a duration not more than one to three periods.

We will use the variance decomposition analysis to address the percentage of the error made forecasting a variable over time due to a specific shock. Variance decomposition is a method used in the VAR post estimations that also applies the Cholesky Decomposition, like the impulse-response function. Variance decomposition complements the IRF as it will analyse and explain how much their own shocks explain the change in the variable versus the shocks or changes in other variables from our VAR model.

Table 9 VAR postestimation: Variance Decomposition

Subset 1: US S&P 500 Cholesky VD

		Response at lag (8)					
		dRealReturnUSSP	**USunexp**	**USexp**	**dUSIPgrowth**	**dTB3M**	**dVIX**
Impulse	***dRealReturnUSSP***	0.9765	0.0263	0.0393	0.0989	0.0237	0.0189
	USunexp	0.0010	0.8829	0.0128	0.0091	0.0082	0.0115
	USexp	0.0012	0.0149	0.9094	0.0108	0.0090	0.0061
	dUSIPgrowth	0.0029	0.0042	0.0258	0.7826	0.0081	0.0111
	dTB3M	0.0012	0.0202	0.0055	0.0132	0.9464	0.0667
	dVIX	0.0172	0.0515	0.0073	0.0853	0.0046	0.8857

Subset 2: EURO19 Cholesky VD

		Response at lag (8)					
		dRealReturnEUSTOXX	**EUROunexp**	**EUROexp**	**EUROIPgrowth**	**dTB3M**	**dVIX**
Impulse	***dRealReturnEUSTOXX***	0.9262	0.0013	0.0476	0.0488	0.0207	0.0087
	EUROunexp	0.0220	0.8048	0.0015	0.1170	0.0051	0.0039
	EUROexp	0.0022	0.1238	0.9407	0.0836	0.0028	0.0210
	EUROIPgrowth	0.0296	0.0336	0.0034	0.6795	0.0171	0.0092
	dTB3M	0.0025	0.0110	0.0011	0.0212	0.9521	0.0515
	dVIX	0.0175	0.0255	0.0056	0.0499	0.0022	0.9057

Subset 3: OECD countries Cholesky VD

		Response at lag (8)					
		dRealReturnMSCIWorld	OECDunexp	OECDexp	dWorldIPgrowth	dTB3M	dVIX
Impulse	*dRealReturnMSCIWorld*	0.9492	0.0283	0.0606	0.1303	0.0277	0.0136
	OECDunexp	0.0009	0.8761	0.0096	0.0050	0.0065	0.0166
	OECDexp	0.0087	0.0257	0.9139	0.0236	0.0088	0.0069
	dWorldIPgrowth	0.0134	0.0040	0.0048	0.7073	0.0102	0.0018
	dTB3M	0.0014	0.0144	0.0021	0.0138	0.9419	0.0656
	dVIX	0.0264	0.0516	0.0090	0.1200	0.0049	0.8956

Subset 4: US S&P GSCI Cholesky VD

		Response at lag (8)					
		dRealReturnSPGSCI	USunexp	USexp	dUSIPgrowth	dTB3M	dVIX
Impulse	*dRealReturnSPGSCI*	0.9284	0.0741	0.4299	0.0958	0.0061	0.0159
	USunexp	0.0012	0.8415	0.0749	0.0060	0.0064	0.0128
	USexp	0.0010	0.0067	0.4603	0.0066	0.0068	0.0059
	dUSIPgrowth	0.0173	0.0050	0.0224	0.7882	0.0127	0.0117
	dTB3M	0.0044	0.0217	0.0049	0.0205	0.9632	0.0664
	dVIX	0.0477	0.0510	0.0077	0.0829	0.0047	0.8873

Subset 5: US S&P 500 Cholesky VD (IR)

		Response at lag (8)					
		dRealReturnUSSP	USunexp	USexp	dNominalUSLIR	dTB3M	dVIX
Impulse	*dRealReturnUSSP*	0.9780	0.0297	0.0403	0.0954	0.0253	0.0177
	USunexp	0.0008	0.8786	0.0082	0.0400	0.0077	0.0099
	USexp	0.0013	0.0160	0.9265	0.0338	0.0090	0.0075
	dNominalUSLIR	0.0026	0.0132	0.0102	0.8103	0.0263	0.0173
	dTB3M	0.0009	0.0174	0.0098	0.0019	0.9281	0.0572
	dVIX	0.0166	0.0451	0.0049	0.0187	0.0035	0.8905

Subset 6: EURO19 Cholesky VD (IR)

		Response at lag (8)					
		dRealReturnEUSTOXX	EUROunexp	EUROexp	dNominalEUROLIR	dTB3M	dVIX
Impulse	*dRealReturnEUSTOXX*	0.8070	0.0369	0.0307	0.0047	0.0091	0.0114
	EUROunexp	0.0132	0.3617	0.0064	0.0221	0.0112	0.0089
	EUROexp	0.0090	0.5199	0.8312	0.0557	0.0184	0.0256
	dNominalEUROLIR	0.1285	0.0606	0.1056	0.8880	0.2373	0.2296
	dTB3M	0.0038	0.0080	0.0016	0.0010	0.7087	0.0567
	dVIX	0.0385	0.0129	0.0244	0.0285	0.0152	0.6679

Subset 7: US S&P GSCI Cholesky VD (IR)

		Response at lag (8)					
		dRealReturnSPGSCI	USunexp	USexp	dNominalUSLIR	dTB3M	dVIX
Impulse	*dRealReturnSPGSCI*	0.9533	0.0803	0.4536	0.0388	0.0069	0.0150
	USunexp	0.0007	0.8342	0.0680	0.0392	0.0062	0.0113
	USexp	0.0011	0.0063	0.4538	0.0381	0.0070	0.0058

dNominalUSLIR	0.0014	0.0162	0.0094	0.8638	0.0379	0.0157
dTB3M	0.0057	0.0182	0.0103	0.0019	0.9384	0.0552
dVIX	0.0378	0.0447	0.0049	0.0181	0.0036	0.8970

Notes: The table should be read from left to right: how the dependent variables respond to the impulse generated by left side variables. e.g. US unexpected inflation can explain 0.1% of the S&P500 real return (dRealReturnUSSP) variation.

In the table 9, variance decomposition analysis provides further insight into how dependent variables respond to the impulses. Across all the subsets, the strongest impulses are coming from their own shocks. For example, when using industrial production growth as the control variable, S&P 500 real return is explained by its own shock – 97.65 per cent. Similarly, EURO Stoxx 50 real return is explained by its own shock at 92.62 per cent. Moreover, when industrial production growth is replaced by long-term interest rates, the variance in EURO Stoxx 50 real return is explained by its own shocks in proportion of 80.70 per cent. Here, the next highest impact has the long-term interest rate itself, with 12.85 per cent.

We can observe that, overall, no significant impulses are coming from the unexpected or expected inflations for any of the indices.

The impulses vary between 0.1 and 2.2 per cent across all four indices. The highest impulse occurs from the EURO19's unexpected inflation that affects 2.2 per cent EURO Stoxx 50 real return. Moreover, most of the variables' responses change from their own impulses. Using the nominal interest rate, we observe that we have similar results: there is a slightly higher impact from expected inflation rather than unexpected inflation on the S&P 500 and S&P GSCI, and a higher impact from unexpected inflation on the Euro Stoxx 50.

Based on the table 9 results, the most significant impulses that come from other than indices' impulses are industrial production growth and volatility index; hence, it aligns with the Granger causality tests that have provided the same results. The majority of the variances in real returns and inflation is explained by their own past values.

5. CONCLUSION

The main objective of this thesis was to explore and analyse the impact of the inflation on the stock and commodities markets. Furthermore, I was interested in analysing particularly unexpected and expected inflation relationship with stock and commodities markets performance, and various macroeconomic indicators. For this purpose I used Vector Autoregressive (VAR) method, Granger Causality test, Cholesky decomposition and Impulse Response Function (IRF). By applying these analyses, the thesis aimed to test the validity of several established theories and research papers.

As a first step in my analysis, decomposition of the inflation was the first step. Similarly to Fama and Gibbons (1984), Vassalou (2000), and Zhang (2021), I have used ARIMA models to estimate the unexpected inflation and calculate the expected inflation as a difference between the actual inflation and estimated unexpected inflation.

The VAR models analyse of the different subsets, consistently indicate that the stock market returns are not influenced by their own past values. The lagged values of stock market returns are not statistically significant; therefore, based on this, it can be concluded that the variable own historical performance cannot be a significant predictor of future returns. Moreover, the decomposed inflation variables – unexpected and expected inflation showed a minimal direct impact on the stock and commodities markets returns. These findings contradict with Zhang's (2021) findings.

However, it could be noted that the VAR results highlight significant influence of market volatility and economic growth on market returns. This supports Zhang's (2021) emphasis on monetary policies for economic stability.

Moreover, even though there is a negative relationship between inflation and market returns as per Lintner (1975), Fama & Schwert (1977), Fama (1981), VAR analysis indicates other factors (like volatility or industrial production growth) may be more critical in influencing stock returns. This also aligns with Baker et al. (2003) and Pastor & Veronesi's (2003) findings that direct impact of inflation on market returns is less pronounced and that central banks should focus on price stability.

On another hand, the findings in the thesis aligns with Wei's (2009) and Laopodis' (2006) findings who mentions a negative reaction of equity returns to unexpected inflation. Similar observations were made by Blanchard & Gali (2007) and De Gregorio et al. (2007), that currently there is a diminished relationship between oil prices and inflation in advanced economies and a opposite, a reduced impact of the oil prices shocks on inflation and economic activity.

However, the thesis findings align with majority of the authors, like Peersman & Van Robays (2012), Furlong & Ingenito (1996), Katz et al. (2017), Madsen (2004) and Ciner (2011), that there is a significant decline in effectiveness of inflation impact on the commodities, and that macroeconomic variables and economic activity variables, in our cases industrial production growth, long-term interest rates and volatility, play a more crucial role in analysis the thesis topic.

Furthermore, there is a complex relationship between inflation and market returns with more variables to be included in the analysis.

Answering to the first thesis question: "What is the behaviour of the stock market and commodity indices in relation to expected or unexpected inflation rate changes over time? "it can be noted that historical responses indicate that stock and commodities market returns are more vulnerable to their own past values as well as economic growth indices and market volatility rather than to the inflation changes themselves. Both expected and unexpected inflation generally do not have a statistically significant impact on the market returns.

Answering to the second question: "Which indices benefit and which loose due to changes in the inflation rates?" S&P GSCI might benefit from the inflation changes, and therefore, actings as hedging solutions against inflation. However, the potential is limited. In the contrast the remaining indices, US S&P 500, EURO Stoxx, MSCI World, are more likely to be adversely impacted by changes in the inflation rate, particularly due to their sensitivity to economic growth and market volatility.

This thesis contributes to the academic literature by providing evidence that challenges the traditional inflation – market returns relationship analysis. Based on the analyses evidences, further recommendations are to include in future research analysis more macroeconomic and economic activity variables to incorporate all macroeconomic shocks and global economic events.

Future research should also explore nonlinear models to better predict and understand the responses of the market returns to macroeconomic changes. Another key point is to expand the analyses to the emerging markets and other regional economies. As we observed there is quite significant results analysing OECD countries. Further research can include ASEAN-5, Asian Tigers, Sub-Saharan and others.

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Annex

List of variables:

dRealReturnEUSTOXX	*Differenced Real Return of Euro Stoxx 50*
dRealReturnMSCIWorld	*Differenced Real Return of MSCI World*
dRealReturnSPGSCI	*Differenced Real Return of S&P GSCI*
dRealReturnUSSP	*Differenced Real Return of S&P 500 Composite*
dTB3M	*Differenced 3-Month Treasury Bill Secondary Market Rate*
dUSIPgrowth	*Differenced United States Industrial Production growth*
dVIX	*Differenced CBOE Volatility Index*
dWorldIPgrowth	*Differenced OECD 37 Industrial Production growth*
EUROCPI	*Harmonised Index of Consumer P7rices (Euro Area 19)*
EUROexp	*Euro Area 19 expected inflation*
EUROIP	*Harmonised EURO Area 19 Industrial Production*
EUROIPgrowth	*Differenced Euro Area 19 Industrial Production growth*
EUROunexp	*Euro Area 19 unexpected inflation*
EUSTOXX	*Euro Stoxx 50 Index - Total Return*
MSCIWorld	*MSCI World Index - Total Return*
OECDCPI	*Harmonised Index of Consumer Prices (OECD 37)*
OECDexp	*OECD expcted inflation*
OECDunexp	*OECD unexpected inflation*
SPGSCI	*S&P GSCI Commodity - Total Return*
TB3M	*3-Month Treasury Bill Secondary Market Rate, Discount Basis*
USCPI	*United States Consumer Index Price*
USexp	*United States expected inflation*
USIP	*United States Industrial Production*
USSP	*S&P 500 Composite Index - Total Return*
USunexp	*United States unexpected inflation*
VIX	*CBOE Volatility Index: VIX, Index, Monthly, Not Seasonally Adjusted*
WorldIP	*Harmonised OECD 37 Industrial Production*

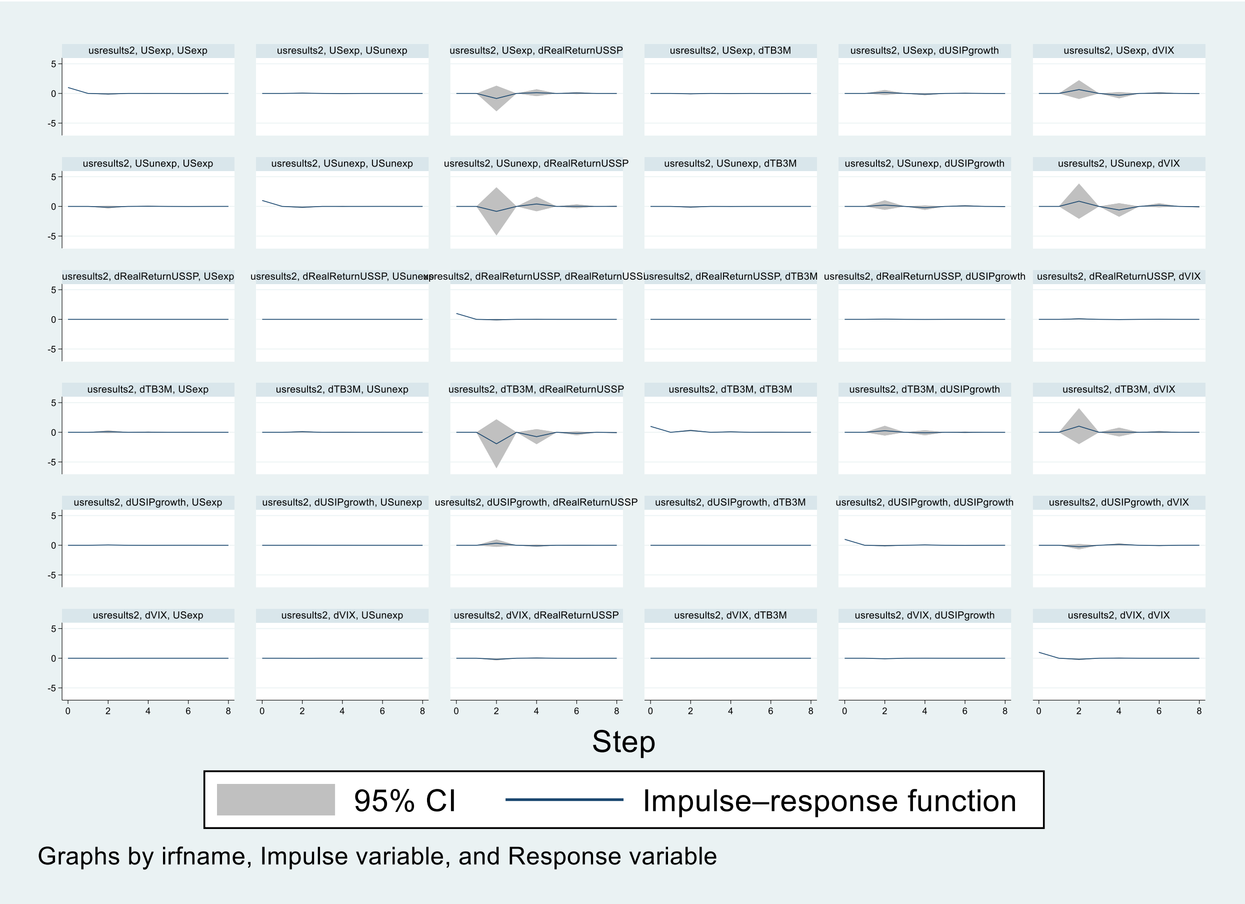

Figure 16 Impulse-Response functions. US unexpected inflation (USunexp), US expected inflation (USexp) and S&P 500 real return (dRealReturnUSSP), with Industrial Production growth (dUSIPgrowth).

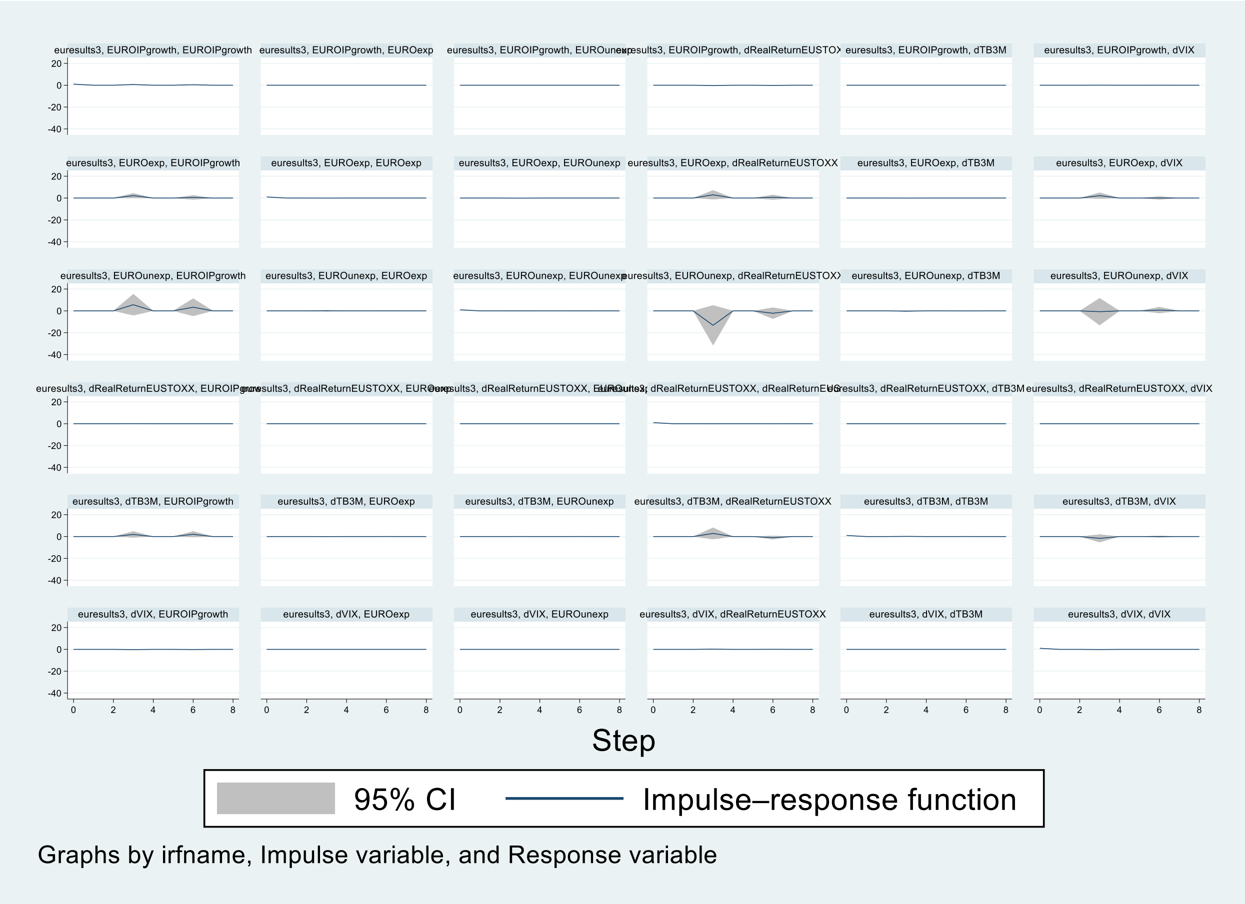

Figure 17 Impulse-Response functions. EURO19 unexpected inflation (EUROunexp), EURO19 expected inflation (EUROexp) and EURO Stoxx50 real return (dRealReturnEUSTOXX), with Industrial Production growth (EUROIPgrowth).

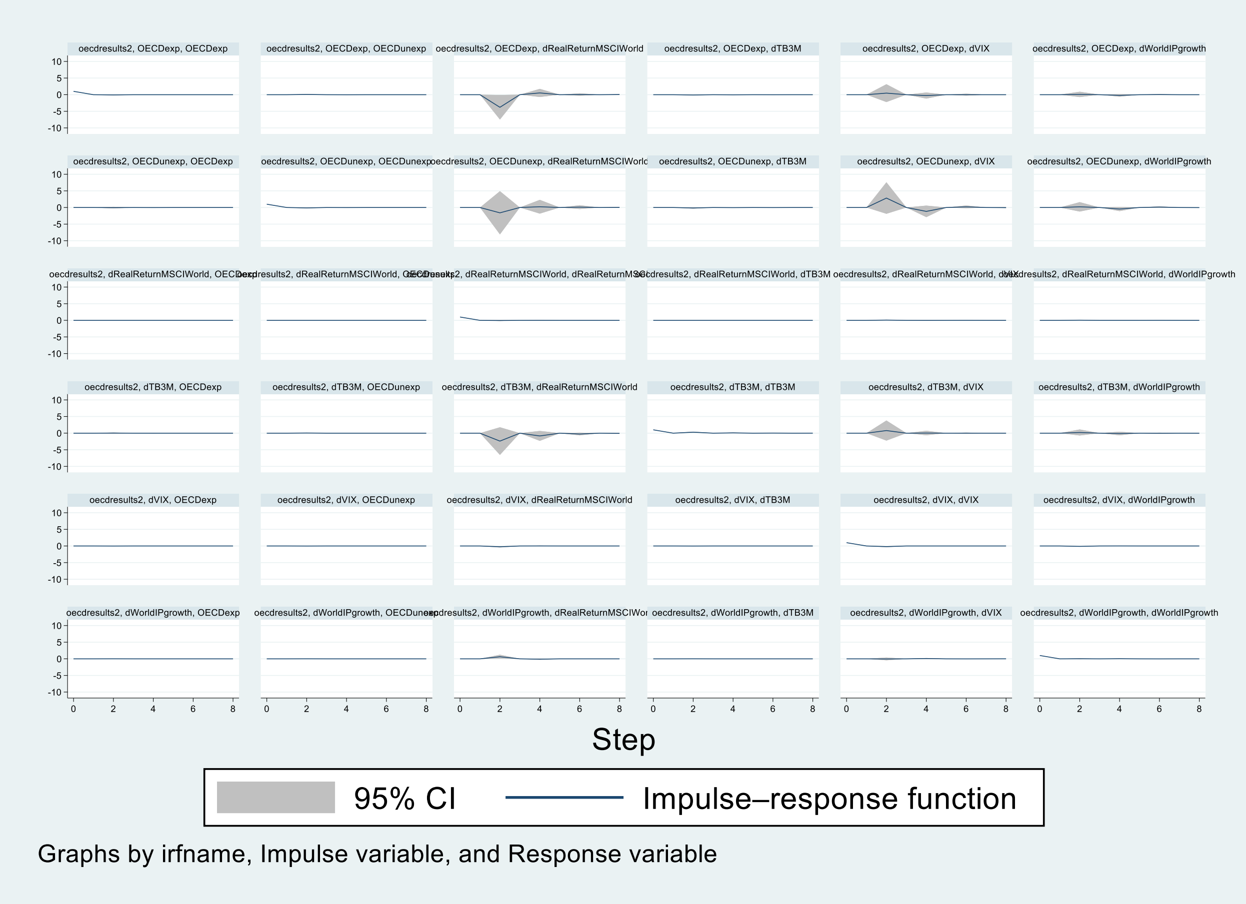

Figure 18 Impulse-Response functions. OECD countries unexpected inflation (OECDunexp), OECD countries expected inflation (OECDexp) and MSCI World real return (dRealReturnMSCIWorld), with Industrial Production growth (dWorldIPgrowth).

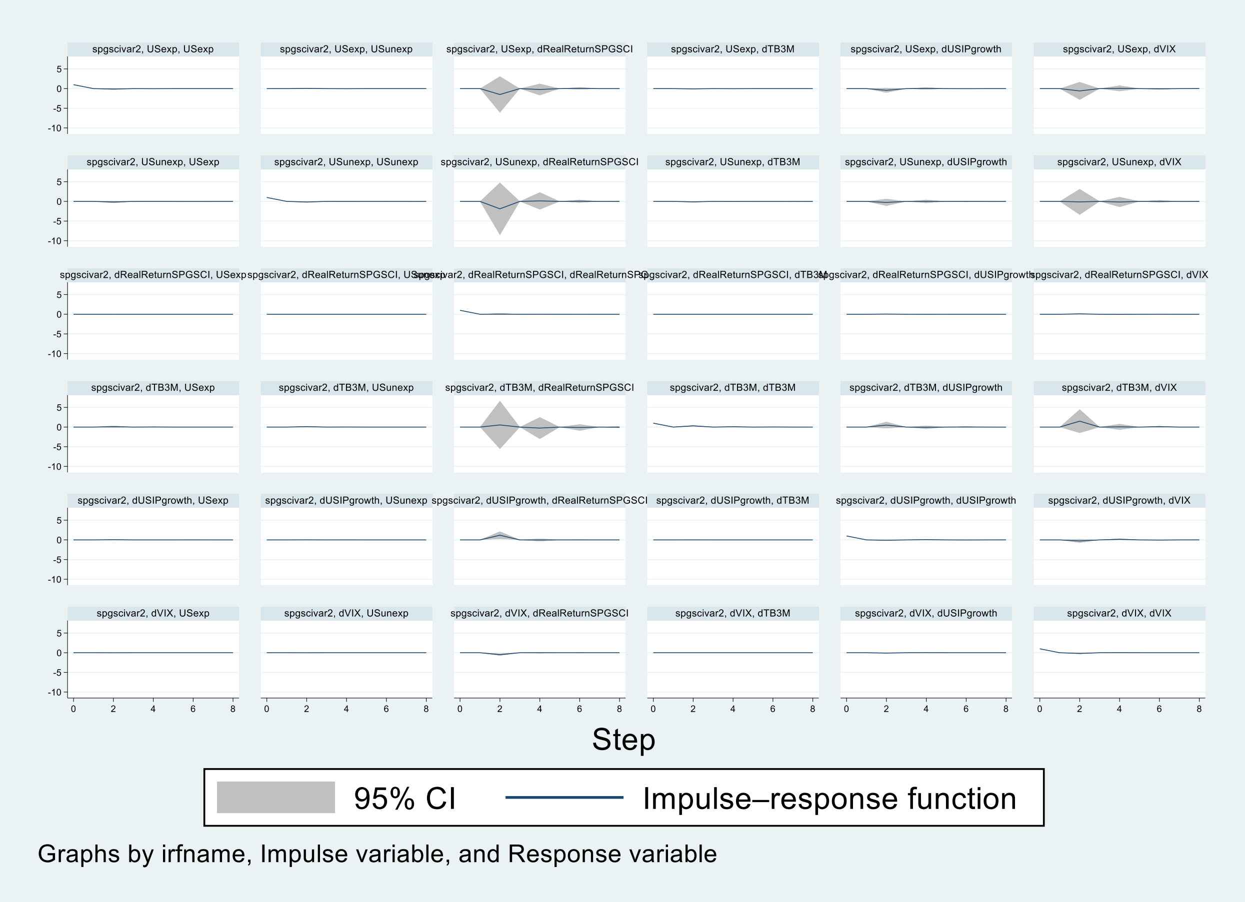

Figure 19 Impulse-Response functions. US unexpected inflation (USunexp), US expected inflation (USexp) and S&P GSCI (dRealReturnSPGSCI), with Industrial Production growth (dUSIPgrowth).

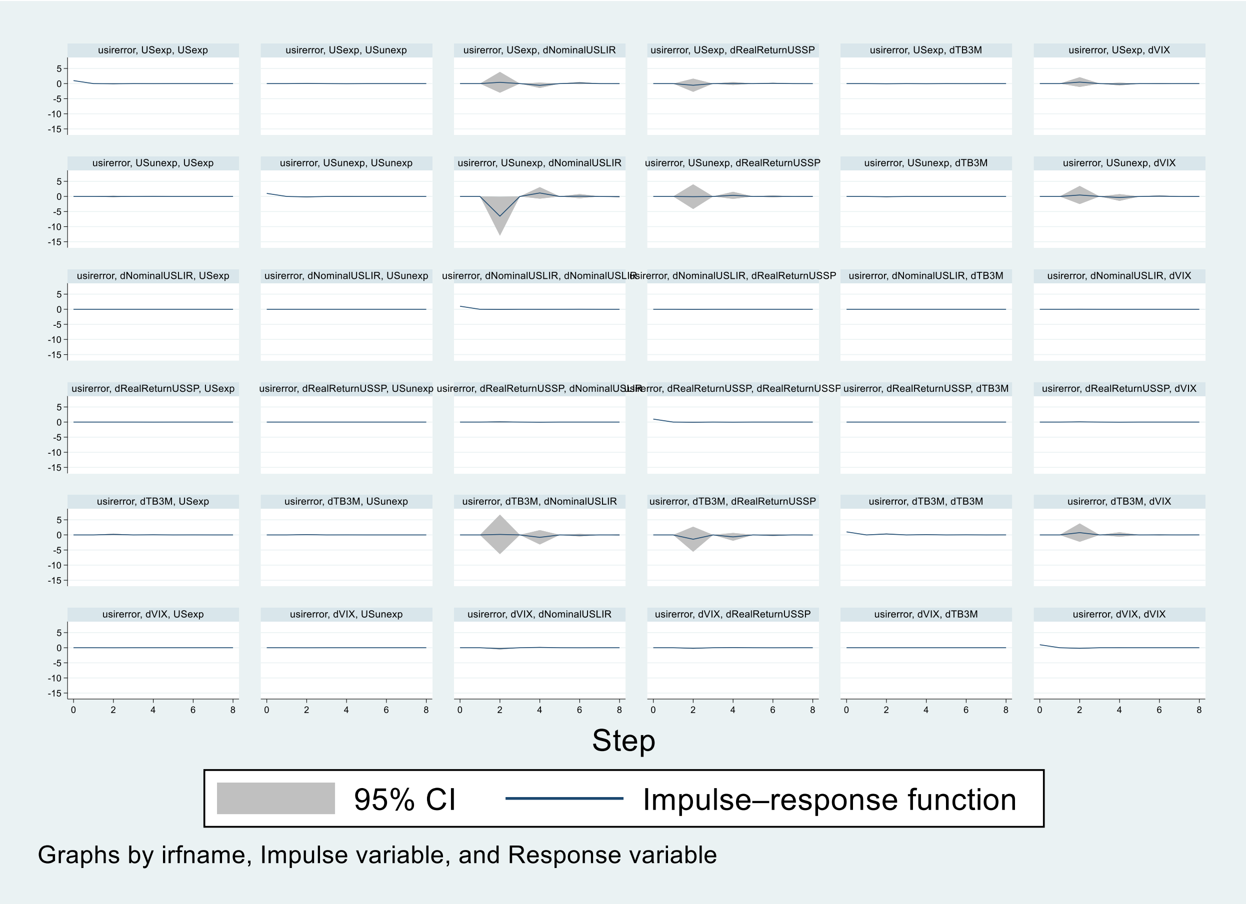

Figure 20 Impulse-Response functions. US unexpected inflation (USunexp), US expected inflation (USexp) and S&P 500 real return (dRealReturnUSSP), with Nominal US Long-Term Interest Rate (dNominalUSLIR).

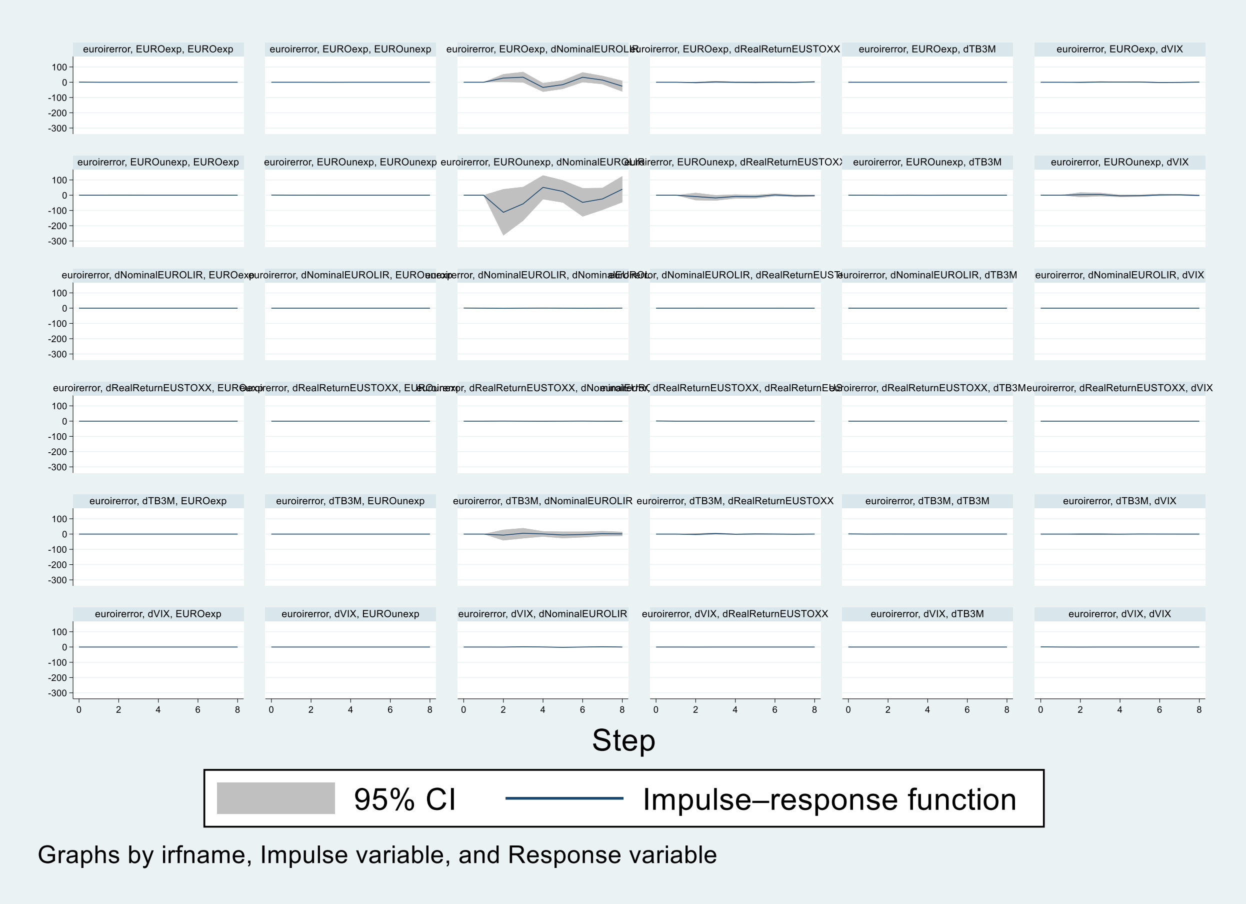

Figure 21 Impulse-Response functions. EURO19 unexpected inflation (EUROunexp), EURO19 expected inflation (EUROexp) and EURO Stoxx50 real return (dRealReturnEUSTOXX), with Nominal EURO Long-Term Interest Rate (dNominalEUROLIR).

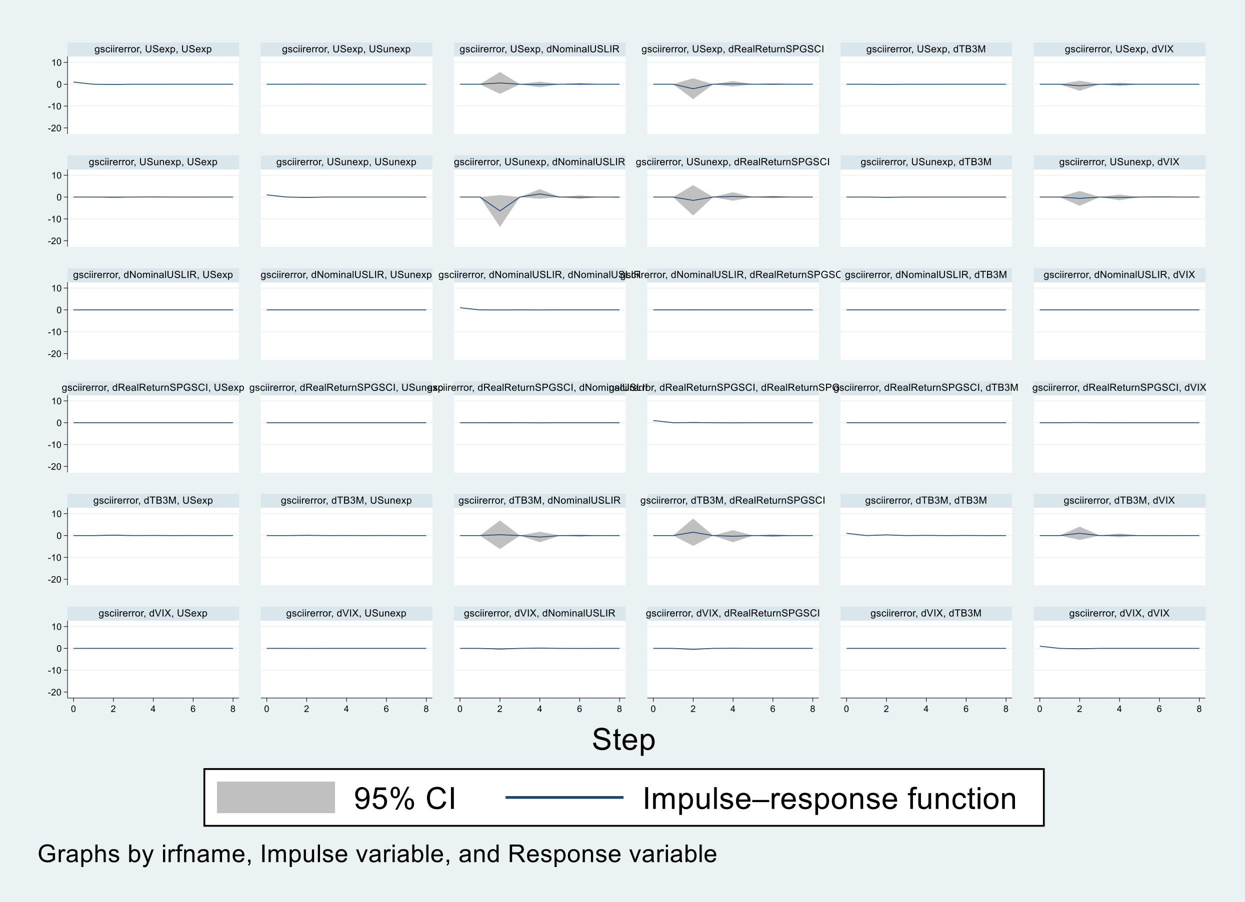

Figure 22 Impulse-Response functions. US unexpected inflation (USunexp), US expected inflation (USexp) and S&P GSCI (dRealReturnSPGSCI), with Nominal US Long-Term Interest Rate (dNominalUSLIR).