Lisbon School of Economics & Management
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DISSERTATION

THE RELATIONSHIP BETWEEN INFLATION AND S&P 500 INDEX: EVIDENCE FROM THE PERIODS BEFORE AND AFTER THE PANDEMIC CRISIS

CATARINA FERREIRA NEVES

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SUPERVISION:

PAULO MIGUEL DIAS COSTA PARENTE

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"O que dá o verdadeiro sentido ao encontro é a busca, e é preciso andar muito para se alcançar o que está perto."

José Saramago

GLOSSARY

ADF Augmented Dickey-Fuller. ii, 21

AIC Akaike Information Criterion. ii, 10, 25

APT Arbitrage Pricing Theory. ii, 8, 23

ARDL Autoregressive Distributed Lag. ii, iii, 1, 2, 10, 18, 22, 25, 28, 32

BIC Bayesian Information Criterion. ii, 10, 25

CAPM Capital Asset Pricing Model. ii, 8, 9

CPI Consumer Price Index. ii, 12, 13, 16, 18, 20, 22, 23, 25, 26

ER Exchange Rate. ii, 12, 18, 20, 23

INF Expected Inflation. ii, 12, 16, 18, 23

IP Industrial Production. ii, 12, 16, 18, 23

KPSS Kwiatkowski-Phillips-Schmidt-Shin. ii, 21

LIR Long-term Interest Rate. ii, 12, 18, 20, 23

M2 Money Supply. ii, 12, 16, 18, 23, 25

SIR Short-term Interest Rate. ii, 12, 16, 18, 22, 23

VIF Variance Inflation Factor. ii, 11

ABSTRACT AND KEYWORDS

This study analyses the impact of inflation on S&P 500 returns, considering the periods before and after the pandemic crisis. To achieve this objective, an Autoregressive Distributed Lag (ARDL) model was employed, incorporating a breakpoint in March 2020. The Bai-Perron test was implemented using a wild fixed-regressor bootstrap method in order to ensure robustness. The results obtained indicate that the pandemic did not produce statistically significant changes in the structure of the series. Before the pandemic, inflation had a positive impact on the index's returns, although in a manner that diverged from what was theoretically expected. In contrast, in the post-pandemic period, inflation began to have the awaited effect on returns.

Furthermore, this research contributes to informing the influence of inflation on the S&P 500 during the pandemic period, since this event is relatively recent and the literature on the subject is scarce. Consequently, this constitutes an added value for investors or policymakers. However, the study period is short, in order not to cover other shocks that have caused fluctuations in the markets. Therefore, multicollinearity issues led to the elimination of three variables.

KEYWORDS: ARDL model; COVID-19; Structural breaks.

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RESUMO

Este estudo analisa o impacto da inflação nos retornos do S&P 500, considerando os períodos pré e pós crise pandémica. Para atingir esse objetivo, foi utilizado um modelo ARDL, incorporando um ponto de ruptura em Março de 2020. Para obter robustez no modelo, foi aplicado o teste de Bai-Perron em conjunto com o método bootstrap de regressor fixo selvagem. Os resultados obtidos indicam que a pandemia não produziu alterações estatisticamente significativas na estrutura da série. Antes da pandemia, a inflação teve um impacto positivo nos retornos do índice, embora de uma forma que divergiu do que era teoricamente esperado. Em contrapartida, no período pós-pandemia, a inflação começou a ter o efeito esperado nos retornos.

Além disso, esta pesquisa contribui para informar a influência da inflação no S&P 500 durante o período da pandemia, uma vez que este evento é relativamente recente e a literatura sobre o assunto é escassa. Consequentemente, isso constitui um valor agregado para investidores ou formuladores de políticas. No entanto, o período de estudo é curto, a fim de não abranger outros choques que causaram flutuações nos mercados. Portanto, questões de multicolinearidade levaram à eliminação de três variáveis.

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The Relationship between Inflation and S&P 500 Index: Evidence from the Periods Before and After the Pandemic Crisis

The current study employs an ARDL model with a breakpoint in March 2020 to examine the impact of inflation on S&P 500 returns, both before and after the pandemic. The Bai-Perron test included a wild fixed-regressor bootstrap method to achieve robustness. According to the results, there have not been any notable structural alterations. While the post-pandemic consequences were in line with expectations, the pre-pandemic inflation effects did not align with the predictions of the theory.

1 Introduction

The relationship between inflation and the stock market is a topic that has been extensively discussed in academic circles and remains a subject of controversy. The results obtained depend on the time horizon, economic context, and methodology used. Over the years, several events have caused economic shocks that have altered the behavior of macroeconomic variables, including industrial production, monetary mass, interest rates, exchange rate, and inflation. A recent example of this phenomenon is the global pandemic crisis caused by the SARS-CoV-2 virus. This crisis has had a profound impact on economic agents, resulting in a sudden and sharp decline in economic activity. Consequently, it is a relevant phenomenon for both investors and policymakers, so this study helps them offer insights into market behavior in times of crisis.

According to classical literature, such as (Fisher 1930) and (Fama 1981), there is a short-term negative and long-term positive relationship between inflation and stock prices. However, later studies present mixed evidence:(Chen et al. 1986), (Flannery & Protopapadakis 2001), and (Rapach et al. 2004) identify a negative relationship, while (Fama 1981), Gibbons, and (Panetta 2001) report a positive relationship. Other authors, such as (Floros 2004) and (Pilinkus 2009), do not find any significant relationship between these variables. However, the impact of the pandemic on this relationship remains under-researched.

It is important to note that inflation is not the only factor influencing stock returns. These are also affected by other macroeconomic variables, including industrial production, interest rates, monetary mass, and exchange rate, which are control factors in the analysis. To explore the relation between inflation and the S&P 500 before and after COVID-19, the period considered was from 2015 to 2021. The short time horizon is advantageous in that it enables us to circumvent the repercussions of the 2008 financial crisis and the ensuing geopolitical tensions between Russia and Ukraine. Additionally, the macroeconomic stabilizers include money supply, industrial production, short-term and long-term interest rates, and the exchange rate.

The impact of the pandemic will be measured by including a dummy variable in the model, which will divide the period into two segments: pre- and post-March 2020. The structural break is set at March 2020, corresponding to the month when the World Health Organization declared COVID-19 a global pandemic (March 11, 2020) and the Federal Reserve initiated emergency monetary policy responses, including reducing the federal funds rate to near-zero levels and announcing quantitative easing measures. These coordinated policy actions, combined with widespread lockdown announcements across major economies, represent a clear regime change in both market expectations and macroeconomic conditions. The utilisation of the Autoregressive Distributed Lag (ARDL) model in this analysis is instrumental in addressing variables of varying orders of integration, thereby facilitating the examination of both short-term and long-term dynamics. The objective was to study the descriptive statistics, stationarity tests, multicollinearity and model determination.

The objective of this study is to evaluate the impact of inflation on S&P 500 returns before and after the COVID-19 pandemic. To this end, the Autoregressive Distributed Lag (ARDL) model will be employed, with a pandemic dummy interacted with macroeconomic variables. This procedure will test structural changes in the relationship and provide recent evidence on the impact of the pandemic shock in the US, which will be helpful for portfolio management in times of crisis.

In Summary, this study aims to analyse the relationship between inflation and S&P 500 returns in the period between 2015 and 2021, before and after the pandemic crisis, considering the role of other macroeconomic variables as controls for this relationship. Additionally, it is necessary to test for the existence of structural breaks during the period under review, particularly in March 2020, to inform the analysis of the interaction between inflationary shocks and the stock market in crisis contexts. To this end, it will be necessary to estimate an ARDL model suitable for different integration orders and perform stationarity tests to consider structural breaks. Additionally, the model was tested for multicollinearity to ensure adherence to model assumptions (error autocorrelation, homoskedasticity, and stability). Finally, the Bai-Perron test with wild bootstrap is applied to strengthen the detection of structural breaks.

2 LITERATURE REVIEW

The S&P 500 index represents a combination of shares in US companies. As a result, it is often used as a benchmark to assess the behavior of the stock market in response to macroeconomic variations, such as monetary and fiscal policies. Consequently, the relationship between inflation and stock market performance has been an extensively debated topic in the economic and financial literature. In the short run, several studies have found a negative relationship between inflation and stock returns, implying the same relationship with stock prices (Fama 1981). However, in the long term, studies show a positive relationship between generalized price increases and stock returns, with stock prices reacting likewise Fisher (1930). Corroborating this view, Boudoukh & Richardson (1993) show that the negative relationship between the variables in question in the short term tends to weaken and even reverse over long time horizons, reflecting the adjustment of investor expectations to inflationary expectations.

2.1 Macroeconomic Factors Influencing Stock Prices

The stock market is recognized as highly sensitive to various factors, and macroeconomic variables are of particular significance. Consequently, inflation, industrial production, interest rate, money supply, and exchange rate exert substantial influence on this market and, by extension, the S&P 500 index. The economic landscape of a nation exerts a substantial influence on the valuation of shares (Keswani 2024). Despite the existence of other variables that have been shown to influence stock prices, the significance of these variables has not been consistently shown through statistical analysis over time.

Regarding inflation, many opinions are distinct about its relation to stock prices. Chen et al. (1986), Flannery & Protopapadakis (2001), Rapach et al. (2004), Menike (2006), and Singh et al. (2010) verify a significantly negative relation — when inflation increases, it is expected that stock prices tend to decrease. On the other hand, Fama and Gibbons (1980), Panetta (2001), Maysami et al. (2004), and Hachicha & Chaabane (2007) verify a signifi- cantly positive relation. Thus, if a rise in inflation is observed, stock prices also increase. Maysami et al. (2004) describe that the primary rationale for this phenomenon is the state's proactive involvement, as observed during the 1997 crisis. In addition, Floros (2004), Shanken & Weinstein (2006), and Pilinkus (2009) observe that there is no relation between these variables.

Theoretically, inflation exerts a direct influence on consumer prices, thereby impacting the purchasing power of society and influencing corporate revenues. Thus, stock prices reflect the capital held and performance of companies. These elements change with the behavior of consumers. Therefore, there is a negative relation between inflation and stock prices.

Regarding industrial production, the majority of studies conclude that there exists a positive relationship between this variable and stock prices, such as Fama (1981), Chen et al. (1986), Panetta (2001),Maysami et al. (2004), Shanken & Weinstein (2006), and Mahmood & Dinniah (2009). However, Günsel & Çukur (2007) and Büyükşalvarcı (2010) conclude that the relation is significantly negative, and Flannery & Protopapadakis (2001) did not observed a statistically significant relation.

In economic terms, an increase in industrial production reflects an increase in the real economy, a rise in revenues, and consequently in profits. Accordingly, as stock prices reflect investors' expectations about future corporate earnings, it is possible to assume a positive relation between industrial production and stock prices. An increase in industrial production raises market expectations and, consequently, stock values.

The interest rate has a significant impact on stock values according to Chen et al. (1986), Panetta (2001), Shanken & Weinstein (2006), and Günsel & Çukur (2007). These authors found that this effect can be assessed using two key indicators: the term spread and the risk premium.

The term spread is the difference between the long-term interest rate and short-term interest rate of the title, generally issued by the same issuer, like treasury bonds. If the term spread is positive, it indicates investors' inclination to lend over a longer period, reflecting associated uncertainties and risks. On the other hand, a negative term spread indicates that the short-term interest rate is greater than the long-term one, which signals economic deceleration. Then, investors prefer secured options like bonds.

The risk premium represents the compensation investors request to accept additional risk, which is influenced by monetary conditions, volatility, trust in the market, and monetary policy.

Rapach et al. (2004), Menike (2006), and Büyükşalvarcı (2010) observe a significant negative relationship between interest rate and share value. On the other hand,Günsel & Çukur (2007) identify a statistically significant positive relation. From another perspective, Chen et al. (1986) find a negative relation between the term structure of interest rates and stock returns, and a positive relation between risk premium and stock value. Panetta (2001), in his study based on the Italian market, noticed a positive relation between stock returns and term spread and a negative relation with the risk premium.

Rapach et al. (2004) conclude that short-term and long-term interest rates exhibit a negative relation with stock returns, while risk premium and term spread show a positive relation. A summary of relevant studies on the impact of inflation on returns is provided in Table I.

Theoretically, the relation between interest rate and stock value is negative. It should be noted that an increase in interest rates tends to generate a rise in the cost of equity for companies; consequently, investments decrease, negatively influencing expected profits. In addition, a rise in interest rates increases the discount rate used to calculate future cash flows, resulting in a lower intrinsic valuation of shares. Therefore, a variation of this type generates a reallocation of capital — investors prefer secured assets (Fama 1981). Then, with a rise in interest rates, a decrease in stock prices is expected. This relation is predominantly related to short-term interest rates, which are impacted by monetary policy determined by central banks. Fama (1981) posited that restrictive monetary policy results in diminished expected profits for companies, thereby exacerbating the prevailing negative correlation between short-term interest rates and stock value.

The long-term interest rate reflects investors' expectations of future inflation, economic growth, and risk across time. Instead of representing immediate policy decisions, long-term rates signal expected economic outcomes. Consequently, increases in long-term interest rates could indicate expectations of robust economic expansion or higher inflation. Thus, they generate ambiguous effects in the market because they can indicate a resilient economy or imply an increase in discount rates that negatively affect stock valuation.

Sharpe (2000) studied the relationship between stock prices and inflation, emphasizing the impact of expected inflation on long-term stock returns. He identified two channels through which expected affects stock prices: the expected real growth of corporate earnings and the required returns demanded by investors. Regarding the first channel, a negative relationship is observed: an increase in expected inflation leads to lower projected growth in corporate earnings, implying a decline in stock prices. As Sharpe (2000) states, "expected inflation is negatively correlated with expected real earnings growth." Regarding the second channel, a positive relationship is observed: higher expected inflation leads investors to demand greater real returns, which in turn puts downward pressure on stock prices. As Sharpe (2000) notes, "an increase in expected inflation may boost the real rate of return required by investors," thereby contributing to stock devaluation.

According to the antecedents, monetary policy affects short-term interest rates, where the principal instrument is the management of the money supply. Thus, the money supply exhibits a direct relationship with stock value, considering the available liquidity in the economy, investment levels, and, consequently, the expected profits of companies. According to Maysami et al. (2004), the augmentation of the money supply is predicated on genuine economic growth, which engenders an escalation in stock value. Another perspective, offered by Hachicha & Chaabane (2007), suggests that a decrease in the money supply leads to lower inflation, which, in turn, drives variations in stock prices similarly. In addition, Hamburger & Kochin (1972),Kraft & Kraft (1977), Flannery & Protopapadakis (2001), Günsel & Çukur (2007), Pilinkus (2009), Büyükşalvarcı (2010), and **?** observe a strong positive relation between money supply and stock returns. Despite the majority of studies presenting this result, Cooper (1974), Hashemzadeh & Taylor (1988), Panetta (2001), and Menike (2006) do not observe a relation, and Singh et al. (2010) find a negative relation.

Consequently, several empirical studies found that the exchange rate was related to stock prices. Menike (2006), Singh et al. (2010), Büyükşalvarcı (2010), and **?** found a significant negative relationship, while Owusu-Nantwi & Kuwornu (2011), Pilinkus (2009), Günsel & Çukur (2007) found no relationship. In addition, Mahmood & Dinniah (2009) and Panetta (2001) observed a positive relationship. The relationship between the exchange rate and share prices is complex, since currency appreciation benefits importing companies and attracts foreign investors, leading to an increase in shares. On the other hand, currency devaluation can favor exporting companies but harm companies with costs or debts in foreign currency, resulting in mixed effects. The S&P 500 is essentially made up of companies with significant international exposure, so when the dollar rises, profits converted from abroad into USD fall, putting pressure on the share price of these companies, while when the dollar falls, profits increase, benefiting the market. Therefore, a negative relationship is expected between the exchange rate and stock returns.

TABLE I: Summary of Empirical Studies on Inflation and Stock Returns

Study	Methodology	Relationship	Key Findings
Negative Relationship			
Chen et al. (1986)	APT Model	Negative	Inflation negatively affects stock returns through discount rate channel
Flannery & Protopapadakis (2001)	Factor Model	Negative	Inflation announcements lead to negative market reactions
Rapach et al. (2004)	Predictive Regression	Negative	Short-term and long-term interest rates negatively impact returns
Menike (2006)	Cointegration	Negative	CPI growth reduces stock market performance
Singh et al. (2010)	VAR Model	Negative	Inflation expectations depress equity valuations
Positive Relationship			
Fama & Gibbons (1980)	Regression	Positive	Real activity proxy hypothesis explains positive correlation
Panetta (2001)	VAR	Positive	Term spread positively related to stock returns
Maysami et al. (2004)	Cointegration	Positive	Government intervention during crises creates positive link
Hachicha & Chaabane (2007)	Panel Data	Positive	Controlled inflation supports market growth
No Significant Relationship			
Floros (2004)	GARCH	Insignificant	No robust evidence of inflation impact
Shanken & Weinstein (2006)	Factor Analysis	Insignificant	Industrial production dominates inflation effects
Pilinkus (2009)	Correlation	Insignificant	Transition economy shows weak linkages

Note: This table synthesizes key empirical studies examining the relationship between inflation and stock returns.

2.2 *Theoretical Models of Asset Pricing*

In order to analyze the relationship between macroeconomic variables and stock prices, theoretical models have been developed to assess expected returns considering various risk factors, such as the Arbitrage Pricing Theory (APT) and the Capital Asset Pricing Model (CAPM).

Markowitz (1952) developed modern portfolio theory, which contributed to the expansion of models for determining the expected rate of return on assets. By this theoretical framework, all investments are characterized by two fundamental components: a return, which is the profit or loss incurred by an investment, and a variance, which is the statistical discrepancy between the actual returns and the expected returns. Consequently, the author anticipates a favorable return and perceives its variability as unfavorable. The objective of that study was to ascertain an instrument that would enable investors to identify the most advantageous investment alternative, i.e. the alternative with the highest return, within the context of a given risk level, considering their individual preferences. Tobin (1958) later extended Markowitz's study by adding a risk-free asset to modern portfolio theory.

Therefore, the set of efficient portfolios results from combining the optimal portfolio with granting or obtaining loans at a risk-free interest rate.

Subsequently, Sharpe (1964) with the collaboration of Mossin (1966) and Lintner (1965) perfected the existing model, giving rise to a model that related risk and return on assets, the Capital Asset Pricing Model (CAPM). In this new model, developed by Sharpe (1964), the return on any asset depends on the return on the risk-free asset and the market premium adjusted by the beta factor, where this factor measures the sensitivity of the returns on this asset to the returns on the market portfolio. Extensively, Steven Ross (1977) developed a model with the same form as the CAPM model, but in which he did not establish assumptions regarding the utility function of investors, the empirical distribution of asset returns, or the perfection of financial asset markets in terms of taxation, transaction costs and information, so the author developed a valuation model by Arbitrage Pricing Theory (APT) (Pinho & Soares 2006).

According to Brealey et al. (2011), the APT model is not based on the construction of efficient portfolios but assumes that the return on each share depends partly on macroeconomic influences or event factors unique to each company. Therefore, according to this model, investments have two types of risk - systematic and specific. The latter risk can be eliminated through diversification, as it is unique to each company. Thus, the expected risk premium depends only on macroeconomic factors. Therefore, a sufficiently diversified portfolio, constructed to be neutral to macroeconomic factors, is considered risk-free and offers a return equal to the risk-free rate. If it has a return above this, an arbitrage opportunity arises.

In 1993, Fama and French realized that the CAPM model did not capture certain factors, which had an anomalous influence on returns As a response, Fama and French developed a three-factor model that significantly explains the variation of asset returns. The model includes the market risk factor, according to Sharpe (1970) and the CAPM model, the firm size, and the B/M ratio (book-to-market), where B/M reflects the ratio between the book value and market value of ordinary company shares. However, empirical tests of the model concluded that the beta did not explain significant variations in returns and the variable's size and Index B/M explain the differences in asset returns.

Over the years, researchers have realized that various statistical and macroeconomic factors influence asset returns. To build more efficient portfolios in line with investors' objectives, Rosenberg (1987) developed the multiple-factor model. This model is based on historical data and is, therefore, a helpful tool for studying uncertainties such as changes in inflation or interest rates.

In contrast, Connor & Korajczyk (1988) considers that asset returns are mainly influenced by a sin- gle risk factor, such as general market performance, thus simplifying the analysis. This approach gives rise to the Single Factor Model of systematic risk, which explains fluctu- ations in asset returns based on a single common factor. This model assumes that fluctua- tions in the returns of different assets can be caused by the risk factor, disregarding other factors that can affect returns. Overall, understanding the relationship between macroe- conomic variables and asset returns is something complex that has presented a significant evolution in recent decades that has gradually led to complex and realistic models. From the modern portfolio theory of Markowitz to multi-factor models, the objective remains unchanged: to provide investors with tools that allow them to better estimate risk and select the most efficient asset.

To summarise, the relationship between inflation and stock market performance is unclear, with different studies indicating positive, negative, or no correlations depending on time horizons, countries, and methodologies. However, there is a paucity of studies that have explicitly compared this relationship before and after a major global disruption such as the present pandemic. The present research aims to address this literature gap by investigating how the inflation-stock price nexus in the US, as captured by the S&P 500, may have shifted in the wake of the pandemic.

3 METHODOLOGY

The present study has been to analyze the impact of inflation — both expected and actual — on the S&P 500 index price, comparing the periods before and after the advent of the pandemic caused by the severe acute respiratory syndrome coronavirus 2 virus. To accomplish this objective, it is imperative to develop an econometric model in which the dependent variable is the value of the S&P 500. The explanatory variables to be included in the model, based on both theoretical and empirical literature reviewed (Chen et al. (1986); Floros (2004); Büyükşalvarcı (2010); Singh et al. (2010)), are consumer price index (CPI), expected inflation (INF) and other relevant macroeconomic indicators, namely money supply (M2), industrial production index (IP), short-term interest rate (SIR), long-term interest rate (LIR), and exchange rate index (ER). The hypothesized functional relationship can be expressed as:

$$S\&P500 = f(\mathrm{CPI}, \mathrm{INF}, M2, \mathrm{IP}, \mathrm{SIR}, \mathrm{LIR}, \mathrm{ER})$$

To capture changes in the index's behavior caused by the pandemic, a dummy variable will be introduced that takes the value zero before March 2020 and one after that date, reflecting the onset of the economic effects of the SARS-CoV-2 crisis. In addition to controlling for abrupt changes in the average level of the S&P 500, this dummy is multiplied by the explanatory variables. This allows for an assessment of whether the impact of these variables on the index changed after the onset of the pandemic.

The variables are transformed, taking first differences when necessary, to ensure stationarity. An ARDL model is then considered, which allows for the analysis of dynamic relationships between the variables. The ARDL model can be represented in general by the following Equation 1:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=0}^{q} \beta_j x_{t-j} + \varepsilon_t \tag{1}$$

where y_t is the dependent variable (S&P 500), x_t represents the set of explanatory variables, p and q are the lag orders chosen based on information criteria, such as Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC), and ε_t is the error term.

The ARDL method was used to estimate the parameters of the regression model specified in Equation 1, and all estimations were performed using Python packages.

Methodological framework:

1. Descriptive statistics: number of observations, mean, median, maximum, minimum, standard deviation, skewness, kurtosis and its corresponding p-value;

2. Stationarity of the variables was tested using the Perron and Zivot-Andrews tests. At this stage, since the Perron test requires a preliminary analysis to identify the timing of the structural break will be applied a graphical analysis of each variable;

3. Multicollinearity was assessed to evaluate correlations among the variables included in the model, using the correlation matrix and the Variance Inflation Factor (VIF);

4. Estimation of the multiple linear regression model;

5. Model assumptions tests:

   (a) Autocorrelation of the error term (**Breusch-Godfrey test**);

   (b) Homoskedasticity of the error term (**Breusch-Pagan and White tests**);

   (c) Parameter stability (**CUSUM test**);

6. To identify statistical significance at the break-point adopted during the study, the Bai-Perron test with wild fixed-regressor bootstrap was employed - **Structural Break Analysis**

4 EMPIRICAL STUDY

4.1 Data

This section describes the variables used in the empirical analysis according to the relevant literature. In addition to inflation, other macroeconomic variables are used to explain the variation in the S&P 500 index price. Therefore, seven macroeconomic variables were selected to establish a relationship with the S&P 500 index: the consumer price index (Consumer Price Index (CPI)), expected inflation (Expected Inflation (INF)), money supply (Money Supply (M2)), industrial production index (Industrial Production (IP)), short-term interest rate (Short-term Interest Rate (SIR)), long-term interest rate (Long-term Interest Rate (LIR)), and exchange rate (Exchange Rate (ER)).

The values of the explanatory variables were obtained from the Federal Reserve Bank of St. Louis (FRED) website. In the case of the dependent variable, the values were obtained using Yahoo!Finance. In this study, monthly observations were used, with all variables studied between January 1, 2015, and December 31, 2021. This study aims to understand the impact of inflation before and after COVID-19. It would not be prudent to extend the observation period, since before 2015, the variables would be significantly affected by monetary and economic policies related to the 2008 crisis (sub-prime crisis), and after 2021, the conflict between Ukraine and Russia emerged, which substantially affected exchange rates and production. In addition, the period in question marks a phase of economic stability, except for the interference caused by the pandemic. In the case of the dependent variable, the values used will be the monthly closing price, that is, the last closing price of each month.

Additionally, the logarithm was applied to the original data. The non-stationary variables were transformed into monthly rates, based on the empirical results, by taking the first differences of the logarithmic series:

$$DL(V_{j,t}) = \ln(V_{j,t}) - \ln(V_{j,t-1}) \tag{2}$$

where $DL(V_j)$ is the first difference of the logarithm (continuous growth rate) of variable j in month t. As well as, $V_{j,t}$ and $V_{j,t-1}$ are the levels of variable j for month t and $t-1$, respectively.

Dependent Variable

The S&P 500 index, one of the most important in the US financial market, comprises 500 companies from various sectors, giving it a highly diversified character. Consequently, it is considered a benchmark indicator of investor sentiment regarding the stock market and the US economy. Thus, the index reflects the aggregate expectations of investors about future corporate earnings, economic growth, and macroeconomic conditions. Thus, an analysis of the S&P 500 provides a better understanding of how macroeconomic variables, such as inflation, influence stock market performance.

Based on financial theory (Fama 1981, Chen et al. 1986) and previous results, this study investigates how the relationship between inflation and the index developed before and after the COVID-19 crisis.

Explanatory Variables

Consumer Price Index (CPI

The consumer price index (CPI) in this study was measured using the CPIAUSCL index, which evaluates the CPI for all urban consumers in the United States. This is one of the main references to inflation in the country. This index reflects the average variation in prices paid for a wide range of goods and services, including food, housing, clothing, and health.

Inflation directly influences the economy, reflecting the value of nominal interest rates. Consequently, an increase in inflation tends to raise nominal interest rates, consequently increasing the discount rate applied to companies' future cash flows. Consequently, the present value of these flows decreases, theoretically resulting in a fall in share prices.

Empirical studies (Chen et al. 1986, Rapach et al. 2004, Menike 2006, Singh et al. 2010) have shown that rising inflation negatively impacts the stock market, confirming the relevance of this index in macroeconomic and financial analyses.

Expected Inflation (INF)

Expected inflation (INF) is quantified using the T5YIEM index, which reflects the projected inflation rate for the US over a five-year time horizon. This index is a benchmark for long-term inflation expectations and is used by investors and policymakers. It effectively captures the average inflation expected over a five-year period. Thus, the information refers to market expectations regarding inflation trends.

This indicator influences financial markets because it affects the required returns on investments. In a scenario of rising inflation, nominal interest rates are projected to increase, resulting in an increase in the discount rate applied to companies' future cash flows. As a result, the present value of cash flows decreases, exerting downward pressure on prices.

As demonstrated by several empirical studies (Sharpe 2000), an increase in expected inflation reduces the projected real growth of corporate profits while increasing the returns demanded by investors. This double effect reinforces the negative impact of expected inflation on stock valuations, underscoring the importance of expected inflation in macroeconomic and financial market analyses.

Money Supply (M2)

The M2SL index is used as an indicator of the money supply (M2), as it encompasses coins, banknotes, demand deposits (including current and NOW accounts), time deposits, savings deposits, and non-institutional money market funds. According to economic theory, the term 'money supply' refers to the total amount of money in circulation held by economic agents, including businesses, individuals, and local governments.

An increase in the money supply causes an increase in liquidity in the economy, which tends to raise nominal stock prices and facilitates investment and consumption. This relationship is corroborated by empirical studies, notably those by (Flannery & Protopapadakis 2001), (Bilson et al. 2000), (Maysami et al. 2004), which find a positive impact of money supply growth on stock market performance.

Industrial Production (IP)

Industrial production, as indicated by the INDOPROD index, is a relevant indicator for measuring growth in the real sector, as it represents the total production of a country's factories, public services, and mines.

This economic indicator reflects the overall strength of the economy and the robustness of the currency. Thus, industrial production provides a measure of economic activity that influences stock prices through its effect on expected cash flows.

Empirical studies conducted by (Chen et al. 1986), (Panetta 2001), (Maysami et al. 2004) and (Bilal Savasa 2010) consistently identified a positive relationship between stock prices and industrial production. Therefore, it is plausible to predict that an increase in the industrial production index will increase stock prices.

Interest Rate (SIR and LIR)

The 10-year Treasury bond yield (GS10) and the federal funds rate (FEDFUNDS) serve as indicators of long- and short-term interest rates, respectively. As shown in the literature, there is a distinct connection between economic variables and stock prices in the short-run. Historically, a decline in interest rates leads to increased investment and consumption, which subsequently benefits publicly traded companies and the S&P 500 Index. Therefore, changes in interest rates result in opposite movements in asset values. Several studies, such as those by (Maysami et al. 2004), (Rapach et al. 2004), (Menike 2006) and (Büyükşalvarcı 2010) have demonstrated a negative correlation between these factors.

Exchange Rate (ER)

The proxy used to capture the effect of unexpected changes in exchange rates on stock returns is the trade-weighted US dollar index, which measures the value of the US dollar against a basket of the currencies of the major trading partners.

Exchange rate (ER) fluctuations are a key factor influencing the international competitiveness of US companies, especially during the COVID-19 pandemic, which affected global trade and financial markets. As many US companies rely on imports for production inputs or sell products internationally, changes in the value of the dollar affect their costs and revenues. A stronger US dollar makes imports cheaper, but can reduce the competitiveness of US exports.

Consequently, exchange rate movements influence the cash flows, profits, and stock prices of US companies. Empirical studies by (Panetta 2001), (Maysami et al. 2004) and (Mahmood & Dinniah 2009) found a positive relationship between exchange rates and stock returns. Therefore, a positive relationship is expected between the exchange rate and S&P 500 returns.

In summary, the anticipated signs for the coefficients of each macroeconomic variable in relation to the S&P 500 index, serving as a standard point of reference for comparison with the results of this study, are as follows in Table II.

TABLE II: Expected Signals for the Independent Variables

This table summarizes the expected signals for each macroeconomic variable coefficient in relation to the S&P 500. These expected signals will be the standard signals for comparison with those found in our study. The acronyms columns include the normal series and its logarithmic transformation.

Macroeconomic Variable	Acronym	Logarithmic Series	Expected Signal
Consumer Price Index	CPI	LCPI	−
Expected Inflation	INF	LINF	−
Money Supply	M2	LM2	+
Industrial Production	IP	LIP	+
Short-term Interest Rate	SIR	LSIR	−
Long-term Interest Rate	LIR	LLIR	−
Exchange Rate	ER	LER	+

4.2 Descriptive Statistics

Descriptive statistics for the dependent variable are presented in Table III, suggesting generally positive performance over the period, as shown by the positive mean. Although the standard deviation is higher than the average return, indicating notable volatility, we need to check the skewness to confirm whether negative asymmetry is present. The kurtosis is less than three, indicating a platykurtic distribution, which suggests that the series is flatter and possesses thinner tails than the normal distribution. Moreover, the frequency of extreme returns (outliers) was less pronounced than what a standard model would predict.

The tables IV and V present a statistical description of the data, both with and without first differences. The series exhibits a mean with a high value at the level, indicative of a long-term tendency. Upon application of the transformation, the indicator approaches zero, suggesting that the first differences remove the drift. Moreover, the standard deviation of the CPI and M2 in levels demonstrates that the variance in the series is attributable to a tendency, with the first differences exhibiting a higher degree of precision, as shown in Table V. The variables IP, SIR, and INF exhibit negative skewness, which is indicative of shocks. Conversely, M2 demonstrates positive skewness, suggesting high growth potential. Most of the variables display a kurtosis greater than three, with the first differences confirming the presence of fat tails. This is indicative of infrequent events, such as the global pandemic of Coronavirus.

TABLE III: Summary Statistics for the Dependent Variable

This table presents the main descriptive statistics estimated for the returns of S&P 500.

Variable	Obs.	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
RS&P 500	84	0.010493	0.017035	0.119421	-0.133668	0.041824	-0.624162	1.574432

TABLE IV: Summary Statistics of the Independent Variables without First Differences

This table presents the main descriptive statistics estimated for each explanatory variable in levels (log-transformed), without first differences.

Variable	Obs.	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
LCPI	84	5.5254	5.5259	5.6377	5.4585	0.0444	0.4724	-0.4490
LINF	84	0.5016	0.4916	1.0919	-0.4005	0.2765	-0.5640	1.2845
LM2	84	9.6060	9.5558	9.9745	9.3749	0.1766	0.7629	-0.6503
LIP	84	4.6040	4.6076	4.6454	4.4389	0.0340	-2.5254	9.2586
LSIR	84	-0.8647	-0.9163	0.8838	-2.9957	1.3321	-0.0975	-1.5885
LLIR	84	0.6006	0.7178	1.1474	-0.4780	0.4086	-1.1370	0.6687
LER	84	4.7289	4.7312	4.8145	4.6421	0.0332	-0.1759	0.2937

TABLE V: Summary Statistics of the Independent Variables with First Differences

This table presents the main descriptive statistics estimated for each explanatory variable with first differences.

Variable	Obs.	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
LCPI	83	0.0022	0.0023	0.0094	-0.0080	0.0026	-0.2644	2.6090
LINF	83	0.0100	0.0147	0.2713	-0.8579	0.1264	-3.6990	25.3022
LM2	83	0.0072	0.0047	0.0614	-0.0002	0.0089	4.3321	20.9775
LIP	83	-0.0002	0.0007	0.0638	-0.1420	0.0197	-4.2124	32.248
LSIR	83	-0.0038	0.0042	0.6931	-2.5649	0.3277	-5.9037	44.0575
LLIR	83	-0.0030	0.0000	0.2451	-0.5447	0.1072	-1.6237	6.9488
LER	83	0.0013	0.0010	0.0363	-0.0243	0.0122	0.2292	-0.1842

4.3 Stationarity Test

To create a reliable model of the returns on the S&P 500 index and the factors that influence them, it is essential first to examine the stationarity of the variables. In the context of potential structural breaks caused by the global pandemic crisis, this aspect assumes particular importance. The subsequent section presents the results of unit root tests that account for these breaks, ensuring the suitability of the ARDL approach. Consequently, we elected to undertake evaluations that expressly encompass the potential for structural breaks, namely the Perron (1989) and Zivot & Andrews (1992) tests.

The Perron test operates under the assumption that the break date is known in advance and permits the testing of the presence of a unit root whilst considering this break.

To investigate the structural break caused by the COVID-19 pandemic, a graphical analysis of each variable will be conducted to determine the most appropriate break date for each variable and to study stationarity. The dependent variable, illustrated in Figure 1, shows the most substantial structural variation in April 2020. Following, when analyzing the graph, it was possible to verify that the IP, M2, CPI, and SIR showed a structural break in April 2020, as observed in Figure 2. Concerning the INF, ER, and LIR indicators, a break is visible in March 2020, as showed in Figure 3.

In accordance with the graphics, the World Health Organisation declared a pandemic on 11 March 2020. As a result, the US Federal Reserve cut interest rates on two occasions, the first before the declaration and the second a few days after it. In March, unlimited quantitative easing resulted in a structural change in monetary policy, impacting interest rates, inflation, and asset prices. The sensitivity of financial markets became evident with the rapid entry into the S&P 500, which entered bear market territory with unprecedented speed, falling more than 20% from its peak in just 16 trading days—the fastest decline in market history. This reaction underscores the forward-looking nature of financial markets, which respond to policy regime changes and expectation shifts rather than to realized macroeconomic data. Thus, even before the complete effects materialized in April 2020, March already reflected the transition of the regime.

In Perron's test, the null hypothesis corresponds to the absence of stationarity in the series, which has a unit root and a structural break. In contrast, the alternative hypothesis is that the series is stationary around a trend with a break. Thus, this test is advantageous when there is robust theoretical or empirical evidence to corroborate the date of the break, as is the case in the study in question. Observation of the graphs enables us to identify a structural break in the series, resulting from the pandemic crisis's impact.

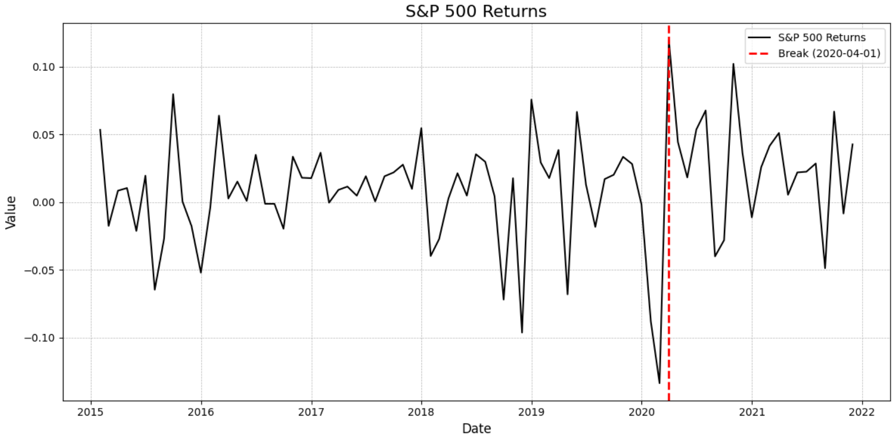

FIGURE 1: Break of S&P 500

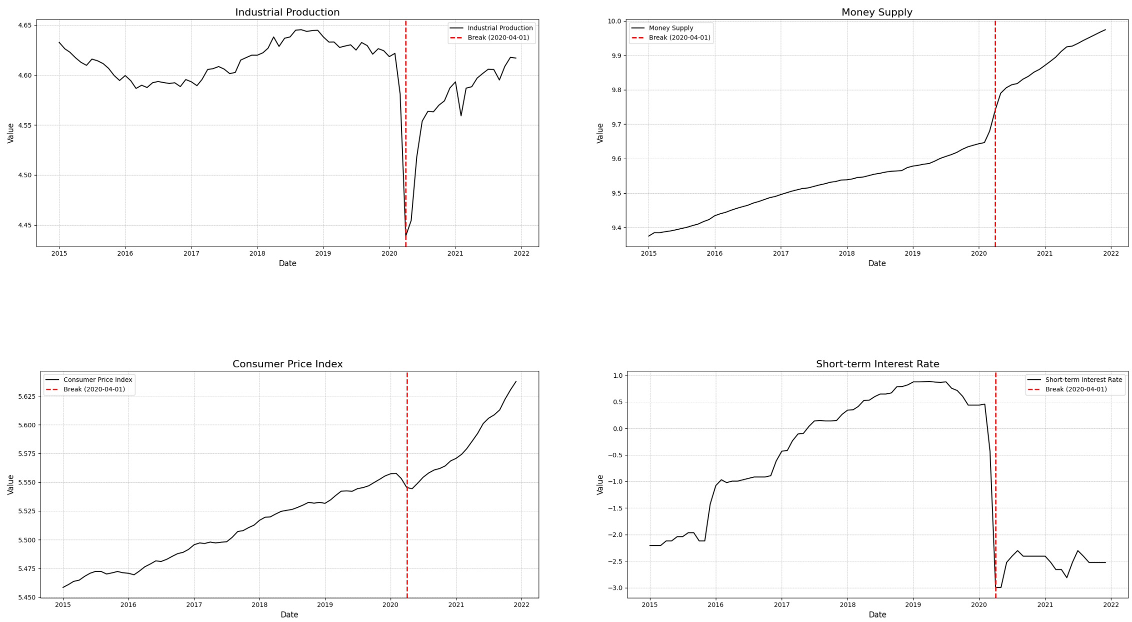

FIGURE 2: Structural breaks in macroeconomic variables in April 2020

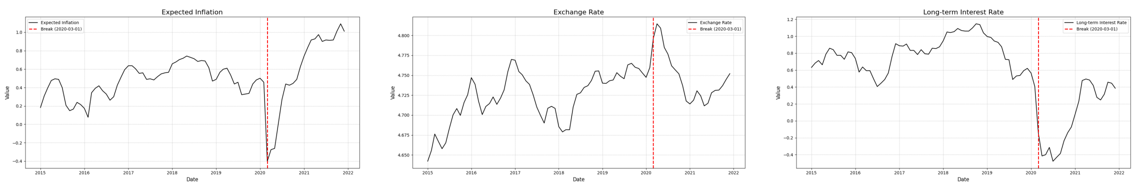

FIGURE 3: Structural breaks in macroeconomic variables in March 2020

In contrast, the Zivot-Andrews test treats the break date as an endogenous variable. In this way, the test itself allows the most likely date of the structural change to be detected based on the data, avoiding the error caused by an arbitrary choice. To this end, the test performs multiple regressions throughout the series, estimating the coefficients and the t-value associated with the presence of a unit root for each possible structural break point. Thus, the date with the lowest t-value is determined as the date of the structural analysis. The procedure involves comparing the obtained values with the critical thresholds to determine whether the null hypothesis is rejected. As demonstrated in the Zivot-Andrews test, the null hypothesis corresponds to the presence of a unit root without a break. In contrast, the alternative hypothesis implies the existence of stationarity with a structural break.

In summary, applying the Zivot-Andrews and Perron tests to the S&P 500 returns and explanatory variables, taking into account the prior identification of the structural break date for the Perron test, allows conclude the following. As illustrated in Table VI, the variables Exchange Rate (ER), Long-term Interest Rate (LIR), and Consumer Price Index (CPI) show higher test statistics and p-values greater than 0.05, indicating the non-rejection of the null hypothesis of unit root, i.e., the non-stationarity of these series. On the other hand, the remaining variables tested reject the null hypothesis, demonstrating evidence of stationarity, even in the presence of structural breaks.

TABLE VI: Stationarity Test Results (ZA and P with structural break)

Variable	ZA Statistic	P-value	ZA Conclusion	P Statistic	P Conclusion
$RS\&P500_t$	-8.4302	0.000010	Stationary	-10.6285	Stationary
$LCPI_t$	-4.1924	0.378592	Non-stationary	-3.7067	Non-stationary
$LINF_t$	-5.1516	0.041254	Stationary	-4.6028	Stationary
$LM2_t$	-7.1113	0.000979	Stationary	-7.2701	Stationary
LIP_t	-6.9743	0.000983	Stationary	-5.8082	Stationary
$LSIR_t$	-5.4290	0.017890	Stationary	-4.1840	Stationary
$LLIR_t$	-4.5590	0.187552	Non-stationary	-3.7054	Non-stationary
LER_t	-2.9544	0.970624	Non-stationary	-2.5796	Non-stationary

The employment of the ARDL econometric methodology necessitates the stationarity of all variables. Thus, it will apply the first differences to the three variables that did not verify this characteristic: ER (Exchange Rate), LIR (Long-term Interest Rate), and CPI (Consumer Price Index). After applying the procedure described above, the results obtained are presented in Table VII, where all variables have test statistics below -5.07 regarding the Zivot-Andrews test and below -4.11 in the case of the Perron test. In addition, the p-values are less than 0.05, allowing us to not reject the hypothesis of stationarity for all series analyzed.

TABLE VII: Stationarity Test Results After First Differencing (ZA and P with structural break)

Variable	ZA Statistic	ZA P-value	ZA Conclusion	P Statistic	P Conclusion
$RS\&P500_t$	-8.4302	0.000010	Stationary	-10.6285	Stationary
$LCPI_{t-1}$	-6.3351	0.000477	Stationary	-4.8260	Stationary
$LINF_t$	-5.1516	0.041254	Stationary	-4.6028	Stationary
$LM2_t$	-7.1113	0.000979	Stationary	-7.2701	Stationary
LIP_t	-6.9743	0.000983	Stationary	-5.8082	Stationary
$LSIR_t$	-5.4290	0.017890	Stationary	-4.1840	Stationary
$LLIR_{t-1}$	-6.3808	0.000430	Stationary	-5.6055	Stationary
LER_{t-1}	-6.9227	0.000010	Stationary	-5.8572	Stationary

Note: LCPI, LLIR and LER are stationary only after first differencing.

Additionally, the pandemic disrupted the series, resulting in sudden fluctuations that affected the series' underlying structure. This situation affects the application of conventional stationarity tests, such as the Augmented Dickey-Fuller (Augmented Dickey-Fuller (ADF)) and Kwiatkowski-Phillips-Schmidt-Shin (Kwiatkowski-Phillips-Schmidt-Shin (KPSS)) tests, which were not included in the present study. Instead, tests that address this issue were preferred, namely the Perron (1989) and Zivot & Andrews (1992) tests.

4.4 Multicollinearity

The ARDL model, utilised in this study to address the research objective, does not necessitate the absence of multicollinearity as a formal assumption. However, given the limited time frame and number of observations, it is suitable to test for multicollinearity among the independent variables to enhance the accuracy and consistency of the model's estimates.

The existence of multicollinearity can be ascertained through the utilisation of various indicators. For instance, if the individual t-tests for the slope coefficients are not statistically significant ($p > 0.05$) while the overall F-test is significant ($p < 0.05$) and the R-squared is high, it may indicate that the explanatory variables, although collectively effective, do not individually contribute to the model due to potential overlap in the information they convey.

In this context, the correlation matrix is a pertinent diagnostic tool, as high correlation coefficients between explanatory variables suggest multicollinearity. This phenomenon has been shown to increase the variance of the estimates and hinder the interpretation of coefficients. The correlation matrix for this study reveals strong correlations between the Consumer Price Index (CPI) and Expected Inflation (0.68), and between the Short-term Interest Rate (SIR) and Industrial Production (0.62), as observed in Table XII.

Furthermore, the Variance Inflation Factor (VIF) is utilised to quantify the inflation of the variance of estimated coefficients resulting from correlations among explanatory variables. This metric, calculated according to equation (3), has been shown to indicate multicollinearity problems when values exceed 10.

$$\mathrm{VIF}_j = \frac{1}{\mathrm{Tolerance}_j} = \frac{1}{1 - R_j^2} \tag{3}$$

where R_j^2 is the R^2 value obtained by regressing the jth variable on the remaining explanatory variables.

As demonstrated in Table XIII, three variables — Industrial Production, Money Supply, and Expected Inflation — have VIF values that exceed this threshold. Following a comprehensive analysis of the correlation matrix and the VIF criterion, it was determined that the variables Industrial Production and Expected Inflation should be excluded from the regression equation.

In accordance with statistical inference, it was decided to exclude expected inflation rather than the Consumer Price Index in this case, for three main reasons. First, the

CPI indicator directly captures realized inflation, which affects corporate costs, consumer purchasing power, and central bank policy responses. During the pandemic period, observed inflation dynamics drove policy shifts more than expectations did. Second, the INF exhibited extreme volatility and unprecedented measurement problems in terms of uncertainty, reflected in high kurtosis, as shown in Table V. In contrast, the CPI, despite its volatility, remained more stable. Third, the high correlation between INF and the CPI indicates that expected inflation closely follows realized inflation. In summary, the CPI captures both dimensions, especially in the post-pandemic period, when inflation reached persistent levels and expectations adjusted accordingly.

In the context of industrial production, despite the proven theoretical relevance of APT models, the strong correlation with SIR reflects the well-documented cyclical relationship between the two variables. According to economic theory, industrial activity increases when interest rates are reduced and decreases when they rise. During the pandemic, this relationship became more pronounced, as the Federal Reserve implemented a monetary policy to support industrial production, which had been impacted by measures taken during the pandemic crisis, such as lockdowns. Thus, by preserving the SIR, the model obtains indirect information on the financial cycle, which is incorporated into the IP through this relationship. In addition, the Federal Reserve directly manipulates interest rates, giving them a key role in understanding structural changes during the coronavirus crisis, compared to the impact of the IP. However, it does not negate its potential economic contribution. Instead, it implies that its impact was already evident in other correlated variables (interest rates and effective inflation, respectively) during the period under study. This decision resulted in the retention of M2, SIR, LIR, ER, and CPI as the primary explanatory variables.

Following the elimination of these variables, the correlation matrix and VIF were updated. This process did not reveal significant correlations (Table VIII) and all VIF values were below 3 (Table IX). Consequently, the impact of inflation on the S&P 500 will be assessed solely through the CPI, with M2, SIR, LIR, and ER serving as macroeconomic stabilisers in the model.

TABLE VIII: Correlation Matrix of Independent Variables Post-Exclusion

Variable	$LCPI_{t-1}$	$LM2_t$	$LSIR_t$	$LLIR_{t-1}$	LER_{t-1}
$LCPI_{t-1}$	1.00	0.47	-0.26	0.42	-0.28
$LM2_t$		1.00	-0.44	0.05	-0.13
$LSIR_t$			1.00	-0.17	0.02
$LLIR_{t-1}$				1.00	-0.24
LER_{t-1}					1.00

TABLE IX: Variance Inflation Factor (VIF) Post-Exclusion

Variable	VIF
LCPI_{t-1}	2.275
LM2_t	2.209
LSIR_t	1.534
LLIR_{t-1}	1.254
LER_{t-1}	1.126

4.5 Autocorrelation of the Error Term

Following the conclusions presented above, the linear regression process became simpler, resulting in the following representation of the ADRL model:

$$\begin{aligned}
\Delta \log(\text{S\&P500}_t) = \alpha_0 &+ \sum_{i=1}^{p} \alpha_i \Delta \log(\text{S\&P500}_{t-i}) + \sum_{j=0}^{q_1} \beta_j \Delta \log(CPI_{t-j}) \\
&+ \sum_{j=0}^{q_2} \gamma_j \log(M2_{t-j}) + \sum_{j=0}^{q_3} \delta_j \log(SIR_{t-j}) + \sum_{j=0}^{q_4} \eta_j \Delta \log(LIR_{t-j}) \\
&+ \sum_{j=0}^{q_5} \theta_j \Delta \log(ER_{t-j}) + \phi\, D_{COVID,t} \\
&+ \psi_1(D_{COVID,t} \cdot \Delta \log(CPI_t)) \\
&+ \psi_2(D_{COVID,t} \cdot \log(M2_t)) + \psi_3(D_{COVID,t} \cdot \log(SIR_t)) \\
&+ \psi_4(D_{COVID,t} \cdot \Delta \log(LIR_t)) + \psi_5(D_{COVID,t} \cdot \Delta \log(ER_t)) + \widehat{\varepsilon}_t
\end{aligned} \tag{4}$$

where $SP500_t$ is the dependent variable, $D_{COVID,t}$ is the COVID-19 dummy, and $CPI_t, M2_t, SIR_t, LIR_t, ER_t$ are the explanatory variables, which may have lags. The interaction terms between the dummy and each explanatory variable are contemporaneous. The parameters $\alpha_i, \beta_j, \gamma_j, \delta_j, \eta_j, \theta_j, \phi, \psi_k$ represent the coefficients to be estimated, and $\widehat{\varepsilon}_t$ is the error term.

Having established the stationarity assumption, all variables involved in the model are stationary at the level or in the first difference. It is essential to verify the existence of autocorrelation in the model error. According to the Breusch-Godfrey test, there is autocorrelation of the error when the p-value of the test is less than 0.05, indicating that we reject the null hypothesis of no autocorrelation in the residuals.

Initially, it was assumed that both the dependent and explanatory variables were free of lags. To begin the model selection process, the lagged values of the dependent variable were progressively incorporated until a model was found that showed no autocorrelation in the residuals. This occurs for the model with six lags, as indicated by the p-value greater than 0.05, as shown in Table XIV.

The first model, without autocorrelation, shows statistical significance for almost all explanatory variables, as demonstrated in Table XVII. The exception is the M2 variable, which is not significant at the level and in interaction with the COVID-19 dummy. Furthermore, considering the correlation matrix, M2 demonstrates a relatively high correlation with the CPI variable (0.47), which is the highest value among the correlations of the explanatory variables. Given the low contribution of M2 to the model and the high correlation with CPI, the M2 variable will be removed from the final model specification.

The process of adding lags of the dependent variable to the model was repeated, now excluding the explanatory variable M2. The initial model, with no autocorrelation of errors, includes a lag of the dependent variable. In this case, the p-value of the Breusch-Godfrey test is less than 0.05, as shown in Table X.

The incorporation of lags in the ARDL model is essential for accurately capturing both short-term and long-term dynamics. Following a thorough evaluation of the lagged dependent variable, it is necessary to understand if the lags in explanatory variables are statistically significant. The findings suggest that the model does not exhibit autocorrelation in the residuals (p = 0.1495), as illustrated in Table XVI.

To select the most appropriate model, considering the presence or absence of lags in the explanatory variables, it is possible to use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). BIC (Black-Litterman-Hirschman) is an approach that favours simplicity, whereas AIC (Akaike Information Criterion) is a model that tends to favour more complex structures. Then, due to the limited sample size and number of variables, the BIC was the best option.

As demonstrated in Table XVIII, the model that does not incorporate lags in the explanatory variables has a BIC of -282.447. Conversely, Table XIX shows that the BIC for the model with lags is -268.161. Consequently, the model without lags is the most suitable.

TABLE X: Breusch-Godfrey Test for Autocorrelation of the Errors

Number of lags explanatory variables	0
Number of lags S&P500	1
LM Statistic	20.5736
LM p-value	0.0570
F Statistic	0.1030
F p-value	0.1030
Are there Autocorrelation?	No

To summarise, the most suitable model to explain the impact of inflation on S&P 500 returns prior to and following the advent of the pandemic is demonstrated in Equation 5.

$$\begin{aligned}
\Delta \log(\text{S\&P500}_t) = &\underset{(0.007)}{0.0026} - \underset{(0.111)}{0.3743}\,\Delta \log(\text{S\&P500}_{t-1}) \\
&- \underset{(0.393)}{0.9529}\,\Delta \log(ER_{t-1}) + \underset{(0.064)}{0.1076}\,\Delta \log(LIR_{t-1}) \\
&+ \underset{(0.004)}{0.0012}\,\log(SIR_t) + \underset{(2.555)}{5.2594}\,\Delta \log(CPI_{t-1}) \\
&- \underset{(0.837)}{0.2812}\,\big(D_{COVID,t} \cdot \Delta \log(ER_{t-1})\big) \\
&- \underset{(0.090)}{0.1712}\,\big(D_{COVID,t} \cdot \Delta \log(LIR_{t-1})\big) \\
&- \underset{(0.020)}{0.0859}\,\big(D_{COVID,t} \cdot \log(SIR_t)\big) \\
&- \underset{(2.247)}{4.5698}\,\big(D_{COVID,t} \cdot \Delta \log(CPI_{t-1})\big) - \underset{(0.049)}{0.1846}\,D_{COVID,t} + \widehat{\varepsilon}_t
\end{aligned} \tag{5}$$

where $\widehat{\varepsilon}_t$ is the error term.

Based on the model's constant in the equation 5, it is possible to conclude that the returns are, on average, positive. Following the COVID-19 pandemic, this behavior change, as demonstrated by the dummy, indicates a decrease in the fixed effect of the pandemic on returns, reflecting the average decline observed during the pandemic period.

Subsequently, the preceding variation in returns exerts a reversal effect, as evidenced by the observation that when the previous return variation is 1%, the subsequent actual return is observed to decrease by 0.37%.

Observation of equation 5 shows that the Exchange Rate (ER) negatively influences S&P 500 returns, both before and after the COVID-19 pandemic. A 1% increase in the exchange rate results in a reduction of approximately 0.95% in returns before the pandemic and 0.28% after the crisis. The change in the behavior of the impact of the exchange rate on returns is justified by a reduction in international activity, which suggests the sensitivity of S&P 500 returns to the exchange rate decreases after COVID-19.

The relationship between interest rates and returns was positive before the pandemic crisis and became negative afterward, reflecting the monetary policies adopted during this period. The Federal Reserve drastically reduced benchmark interest rates to stimulate credit and consumption, such as making financing cheaper for businesses and households.

Finally, the Consumer Price Index (CPI) demonstrated a positive relationship with returns in the period preceding the pandemic, with a 1% increase in the CPI being associated with a growth of around 5.25% in returns. However, during the pandemic period, returns decreased by 4.57% in response to a 1% change in the CPI. This decline coincided with a broader economic slowdown, resulting in a prolonged period of deflationary pressures.

These dynamics can largely be attributed to the sharp decrease in energy prices.

4.6 Homoskedasticity of the Error Term

The residuals must be homoscedastic, meaning that the variance of the errors is required to be constant over time, in addition to all of the ARDL model's previously mentioned requirements. As of right now, this presumption has been validated. Formally, we evaluate it using the Breusch-Pagan and White (1980) tests, where the null hypothesis is homoscedasticity. As a result, the null hypothesis is accepted when the p-value is greater than 0.05, suggesting that the variance of the errors is constant.

Table XX shows that both the White and Breusch-Pagan tests have p-values higher than 0.05 for our model (equation 5). Thus, the null hypothesis is not rejected. Consequently, the model errors are homoscedastic.

4.7 Parameter Stability

Moreover, the model parameters must remain stable over time, consistent with the preceding assumptions. The CUSUM test is the most widely used method for evaluating stability. Equation 6 illustrates how this test is the cumulative sum of the model's recursive residuals.

$$CUSUM_t = \sum_{i=1}^{t} \widehat{\epsilon}_i, \quad t = 1, 2, \dots, T \tag{6}$$

If the null hypothesis of parameter stability and absence of structural change is true, then the cumulative sum should randomly fluctuate around zero. Any systematic deviation suggests either structural flaws or model misspecification. At the 5% significance level, the test involves plotting the cumulative sum of standardized recursive residuals against time, with stability confirmed if the path remains within the critical bounds. Conversely, if the plot crosses these bounds, it indicates that the model may have structural instability or parameter breakdowns. In the model of this study (equation 5), Figure 4 illustrates that the sum remains inside the bounds. Consequently, parameters are stable.

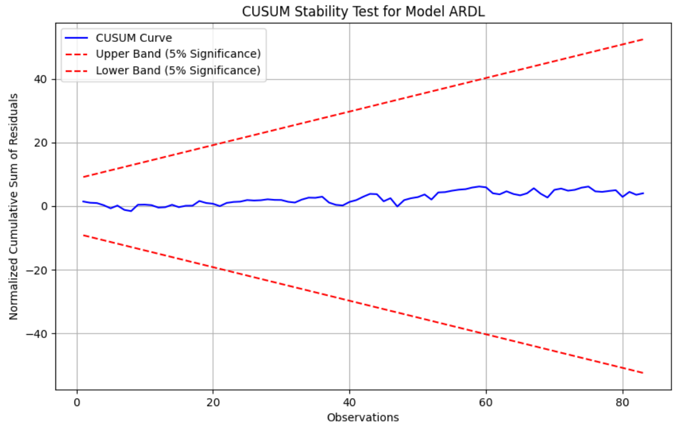

FIGURE 4: CUSUM Test

4.8 Structural Break Analysis

The final model, shown in equation 5 and estimated under verified assumptions, is consistent with ARDL model. However, to ensure the statistical robustness and credibility of the study, the Bai & Perron (1998) test will be applied using a wild fixed-regressor bootstrap method. Boldea et al. (2019) proposed a methodology that consists of the ADRL model coefficients ($\hat{\beta}$) and the residuals given by the equation 7.

$$\hat{u}_t = y_t - X_t\hat{\beta} \tag{7}$$

The sample was divided into two segments at each possible breakpoint $\tau \in [\pi T, (1 - \pi)T]$, with trimming ($\pi$) representing 15%, 20% or 25% of the sample. The Wald statistic is calculated by:

$$W(\tau) = T \cdot (\hat{\beta}_1 - \hat{\beta}_2)' R' \left[R \cdot \hat{V}(\tau) \cdot R' \right]^{-1} R \cdot (\hat{\beta}_1 - \hat{\beta}_2) \tag{8}$$

where:

- $\hat{\beta}_1, \hat{\beta}_2$ are the vectors of coefficients estimated by OLS for the two segments;
- $\hat{V}(\tau)$ is the heteroskedasticity-robust covariance matrix;
- $R = [I_k, -I_k]$ is the restriction matrix that tests the equality of coefficients across regimes;
- T is the sample size;

- $W(\tau)$ is the Wald statistic for the break at point τ.

And the statistic sup Wald is given by:

$$\text{sup Wald} = \max_{\tau \in [\pi T, (1-\pi)T]} W(\tau) \tag{9}$$

The estimated break point ($\hat{\tau}$) corresponds to the value that maximizes $W(\tau)$.

In the context of finite samples and heteroscedasticity, the sup Wald distribution can be subject to imprecision, as indicated by its theoretical properties. To address this challenge, Boldea and colleagues have proposed a bootstrapping procedure. This approach generates a random variable (J_t) adhering to the Rademacher distribution ($P(J_t = 1) = P(J_t = -1) = 0.5$), followed by the introduction of fixed regression terms to perturb the residuals, having a new series of residues given by:

$$u_t^* = J_t \cdot \hat{u}_t \tag{10}$$

The sequence of values constituting the bootstrap series is as follows:

$$y_t^* = X_t \hat{\beta} + u_t^* \tag{11}$$

Subsequently, the sup Wald distribution is recalculated (sup Wald*). The bootstrap p-value is calculated as:

$$\text{p-value} = \frac{1}{B} \sum_{b=1}^{B} 1\{\text{sup Wald}_b^* > \text{sup Wald}\} \tag{12}$$

where $1\{\cdot\}$ is the indicator function.

The critical values for significance levels $\alpha \in \{10\%, 5\%, 1\%\}$ correspond to the $(1 - \alpha)$ quantiles of the sorted bootstrap distribution. The null hypothesis of no structural break is rejected if:

$$\text{sup Wald} \geq \text{Critical Value}_\alpha \quad \text{or} \quad \text{p-value} < \alpha \tag{13}$$

Within the scope of this study, a test using a bootstrap of 1500 replications and trimming the data by 15%, 20%, and 25% to understand whether the bootstrap p-values and the conclusion drawn from the Wald statistic would be affected. As shown in Table XI, the bootstrap p-values range from 0.297 to 0.397, depending on the trimming. However, all critical values for significance levels of 10%, 5% and 1% were higher than the SUP Wald statistic, and the null hypothesis was not rejected, as demonstrated in Tabel XXI. Consequently, since the Wald value does not exceed the critical values and the p-value is high, there is no substantial statistical evidence of a structural break. However, the test results consistently indicate a break in observation 60, in March 2020, corresponding to the period of the pandemic crisis referred to during the study.

TABLE XI: Results of Bai-Perron Test with Wild Fixed-Regressor Bootstrap

Trimming (%)	**Sup Wald**	**Bootstrap P-value**	**Break Obs.**	**Conclusion**
25	611.8364	0.2967	60	Break not significant
20	611.8364	0.3060	60	Break not significant
15	611.8364	0.3967	60	Break not significant

5 CONCLUSION

This study aims to analyse the relationship between inflation and S&P 500 returns before and after the COVID-19 pandemic. To this end, an ARDL model was employed, which incorporates a dummy variable to account for the structural break induced by the pandemic in March 2020. However, although the Bai-Perron structural break test identified March 2020 as the break point, in line with theoretical expectations, it does not confirm statistical significance, reflecting the limitations imposed by the sample size.

The results suggest a reversal of the relationship under analysis, with inflation exhibiting a positive coefficient before the pandemic and an adverse effect thereafter. As demonstrated in theory, the impact caused by the macroeconomic variable on S&P 500 returns depends on the inflationary regime in which we find ourselves.

Consequently, sensitivity to inflation depends on the regime. In circumstances of economic instability, statistical protection strategies may prove ineffective. In conclusion, the results highlight that asset prices act as monetary transmission channels and constitute potential trade-offs between inflation control and wealth effects. As demonstrated, analyzing structural changes with short samples presents considerable challenges. In this context, it is imperative to develop methods that can simultaneously handle parametric instability, mixed integration orders, and multicollinearity.

Lastly, the study focuses on short-term dynamics, analysing the impact of macroeconomic shocks on S&P 500 returns, as opposed to the stock prices. The investigation of long-term relations is not applicable within the remit of this study because the dependent variable is stationary at a given level by virtue of its construction. This choice is consistent with the efficient market hypothesis and helps to understand the immediate response to macroeconomic shocks. Thus, it is convenient for the status of the portfolio and for decisions regarding short-term investments. The future research can focus on analysing the long-term relationship between macroeconomic variables and stock prices. Therefore, this will facilitate the analysis of long-term dynamics that cannot be captured in models based on returns.

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A Appendices

TABLE XII: Correlation Matrix of Independent Variables

Variable	$LCPI_{t-1}$	$LINF_t$	$LM2_t$	LIP_t	$LSIR_t$	$LLIR_{t-1}$	LER_{t-1}
$LCPI_{t-1}$	1.00	0.68	0.47	0.18	-0.26	0.42	-0.28
$LINF_t$		1.00	0.43	0.47	0.02	0.43	-0.09
$LM2_t$			1.00	-0.31	-0.44	0.05	-0.13
LIP_t				1.00	0.62	0.05	0.12
$LSIR_t$					1.00	-0.17	0.02
$LLIR_{t-1}$						1.00	-0.24
LER_{t-1}							1.00

TABLE XIII: Variance Inflation Factor (VIF)

Variable	**VIF**
$LCPI_{t-1}$	4.10
$LINF_t$	10.69
$LM2_t$	38.27
LIP_t	37.20
$LSIR_t$	2.65
$LLIR_{t-1}$	1.48
LER_{t-1}	1.23

TABLE XIV: Breusch-Godfrey Test for Autocorrelation of the Errors

Number of lags S&P500	0	1	2	3	4	5	6
LM Statistic	23.2139	23.6647	25.2277	23.7907	22.8790	24.5155	14.2368
LM p-value	0.0260	0.0226	0.0138	0.0217	0.0288	0.0173	0.2858
F Statistic	1.9027	1.9399	2.1190	1.9031	1.8180	1.9910	0.9006
F p-value	0.0579	0.0533	0.0342	0.0598	0.0747	0.0493	0.5538
Are there Autocorrelation?	Yes	Yes	Yes	Yes	Yes	Yes	No

TABLE XV: Breusch-Godfrey Test for Autocorrelation of the Errors (Model without M2)

Number of lags S&P500	0	1
LM Statistic	23.5311	20.5736
LM p-value	0.0235	0.0570
F Statistic	2.0421	1.6712
F p-value	0.0395	0.1030
Are there Autocorrelation?	Yes	No

TABLE XVI: Breusch-Godfrey Test for Autocorrelation of the Errors with Lagged Dependent Variable

Number of lags explanatory variables	1
Number of lags S&P500	1
LM Statistic	19.3452
LM p-value	0.0805
F Statistic	1.5189
F p-value	0.1495
Are there Autocorrelation?	No

TABLE XVII: ARDL Model with 6 lags of the S&P500

Variable	**Coefficient**	**P-value**	**Significance**
const	-1.2174	0.4353	
$\Delta\log(\text{S\&P500})$.L1	-0.5645	0.0000	***
$\Delta\log(\text{S\&P500})$.L2	-0.3250	0.0046	***
$\Delta\log(\text{S\&P500})$.L3	-0.2433	0.0200	**
$\Delta\log(\text{S\&P500})$.L4	-0.1462	0.1844	
$\Delta\log(\text{S\&P500})$.L5	-0.2638	0.0166	**
$\Delta\log(\text{S\&P500})$.L6	-0.2796	0.0069	***
$\Delta\log(\text{CPI})$.L0	6.4349	0.0615	*
$\log(\text{M2})$.L0	0.1291	0.4308	
$\Delta\log(\text{LIR})$.L0	0.1601	0.0159	**
$\log(\text{SIR})$.L0	-0.0054	0.6600	
$\Delta\log(\text{ER})$.L0	-1.1486	0.0069	***
D_{COVID}.L0	-0.9187	0.7361	
$D_{COVID}\cdot\Delta\log(\text{CPI})$.L0	-6.7791	0.1964	
$D_{COVID}\cdot\log(\text{M2})$.L0	0.0793	0.7793	
$D_{COVID}\cdot\Delta\log(\text{LIR})$.L0	-0.1674	0.0712	*
$D_{COVID}\cdot\log(\text{SIR})$.L0	-0.0486	0.0752	*
$D_{COVID}\cdot\Delta\log(\text{ER})$.L0	-0.5917	0.5494	
Model Statistics:			
Log Likelihood		166.306	
S.D. of Innovations		0.028	
AIC		-294.611	
BIC		-250.079	
HQIC		-276.798	

TABLE XVIII: ARDL Model with 1 lag of the S&P500

Variable	Coefficient	P-value	Significance
const	0.0026	0.7151	
Δ log(S&P500).L1	-0.3743	0.0012	***
Δ log(CPI).L0	5.2594	0.0394	**
Δ log(LIR).L0	0.1076	0.0974	*
log(SIR).L0	0.0012	0.7837	
Δ log(ER).L0	-0.9529	0.0179	**
$D_{COVID} \cdot \Delta$ log(CPI).L0	-4.5698	0.0421	**
$D_{COVID} \cdot \Delta$ log(LIR).L0	-0.1712	0.0625	*
$D_{COVID} \cdot$ log(SIR).L0	-0.0859	0.0000	***
$D_{COVID} \cdot \Delta$ log(ER).L0	-0.2812	0.7380	
D_{COVID}.L0	-0.1846	0.0003	***
Model Statistics:			
Log Likelihood		167.664	
S.D. of Innovations		0.031	
AIC		-311.328	
BIC		-282.447	
HQIC		-299.733	

TABLE XIX: ARDL Model with one lag in the S&P500 and Explanatory Variables

Variable	Coefficient	P-value	Significance
const	0.0035	0.6825	
Δ log(S&P500).L1	-0.3257	0.0093	***
Δ log(CPI).L0	5.5353	0.1133	
Δ log(CPI).L1	-0.7894	0.7396	
Δ log(LIR).L0	0.1211	0.0676	*
Δ log(LIR).L1	-0.0433	0.4122	
log(SIR).L0	-0.0219	0.3776	
log(SIR).L1	0.0231	0.3413	
Δ log(ER).L0	-0.9466	0.0353	**
Δ log(ER).L1	0.3467	0.3850	
$D_{COVID} \cdot \Delta$ log(CPI).L0	-0.7874	0.1465	
$D_{COVID} \cdot \Delta$ log(LIR).L0	-0.1379	0.1571	
$D_{COVID} \cdot$ log(SIR).L0	-0.0591	0.0270	**
$D_{COVID} \cdot \Delta$ log(ER).L0	-0.7417	0.4157	
D_{COVID}.L0	-0.1366	0.0201	**
Model Statistics:			
Log Likelihood		169.334	
S.D. of Innovations		0.031	
AIC		-306.668	
BIC		-268.161	
HQIC		-291.208	

TABLE XX: Homoskedasticity Tests

Test	**F-Statistic**	**p-value**	**Conclusion**
Breusch-Pagan	1.1317	0.3522	Homoskedasticity not rejected
White	0.7302	0.8176	Homoskedasticity not rejected

TABLE XXI: Sup Wald and Critical Values for Different Trimmings

Trimming (%)	**Sup Wald**	**Critical 10%**	**Critical 5%**	**Critical 1%**	**Decision**
25	611.8364	930.8863	1172.6950	1991.3399	No Reject H0
20	611.8364	1040.2039	1287.0667	2044.9484	No Reject H0
15	611.8364	1076.1171	1345.5042	1940.7951	No Reject H0