

A Work Project, presented as part of the requirements for the Award of a Master's degree in Finance  
from the Nova School of Business and Economics.

**REAL ESTATE AS INFLATION HEDGE AND THE EFFECT OF CENTRAL BANK  
MONETARY POLICIES ON REAL ESTATE INVESTMENT FINANCE INDEXES: A  
COMPARATIVE STUDY OF BRAZIL, THE EU, AND THE UK.**



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**Abstract**

This study examines the important role of real estate investments in protecting against inflation in a dynamic economic environment with changing monetary policies and the ongoing risk of rising prices. The research, supported by a comparative methodology that includes Brazil, the EU, and the UK, explores the complex relationship between central bank strategies, real estate sectors, and inflation dynamics. The study aims to identify indexes that can minimise expected deficits by utilising linear regression and advanced statistical models like Markov-Switching Vector Model, thus following the recent approach in the literature but within a new context, specifically in Brazil. Through examination of many structural characteristics in real estate investment funds and the efficacy of different investment indexes, the objective is to offer thorough perspectives that enable investors and policymakers to make well-informed choices in a difficult and unpredictable economic environment.

**Keywords:** Real Estate Finance, Inflation Hedging, Markov-Switching, VECM, Real Estate Indexes.

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## **1. Introduction**

During a time of fluctuating economic conditions, where the main focus is on controlling high double-digit inflation in European countries and the UK by increasing interest rates, investors and policymakers face the task of protecting and maximising their financial assets. In light of the current financial instability, there has been a noticeable increase in interest in real estate investing as a viable method to counteract the impact of inflation. Recognising the significant impact of central bank policies on real estate investment is essential, particularly in relation to contract revisions and changes in Real Estate Investment Trust (REIT) prices for both primary and secondary listed funds. The scope of our research encompasses multiple interrelated processes. The growing interest in real estate investing can be linked to the distinct ability of real estate assets to successfully counteract the negative effects of inflation. Real estate investments commonly consist of tangible assets that tend to increase in value over a period of time, such as residential properties, retail complexes, warehouses, and premium office spaces. These investments have continuously exhibited their capacity to maintain their worth throughout times of economic uncertainty, which is especially relevant to the present circumstances.

The ability to exceed the inflation rate is especially noticeable in economies such as South America, as demonstrated by the Brazilian situation. The consistent attractiveness of real estate as an investment has been emphasised by the country's history of economic instability. Moreover, the COVID-19 epidemic, geopolitical instability including worldwide conflicts, and subsequent disturbances in market demand and supply have triggered alterations in the real estate industry. The current increase in remote work has resulted in a rise of unoccupied premium office spaces. Despite firms' attempts to reintegrate personnel into the office during the peak of the COVID-19 pandemic, the demand for office space has continued to decrease as

more individuals choose to work remotely from home<sup>1</sup>. Shopping centres have significance in influencing consumer behaviour and impacting the real estate market. They present interesting concerns about how they are affected by inflation and changes in customer preferences. The integration of residential and business spaces in numerous major cities worldwide, driven by the logistics sector's increasing emphasis on last-mile operations in light of the growing significance of environmental, social, and governance (ESG) factors, adds extra complexity to the real estate industry.

The key objective of the research is to understand the function of different real estate indexes in relation to changing economic dynamics and their usefulness as elements of a diversified investment portfolio. Furthermore, the research is supported by a comparative technique, which centres on analysing three distinct geographical regions: Brazil, the EU, and the United Kingdom. These geographical regions offer unique viewpoints regarding the interplay among real estate investments, inflation trends, and central bank policies. The Brazil case study is notable for its adept handling of inflation and the robustness of its real estate industry, mainly present in São Paulo city. It is crucial to consider the varied regulatory landscapes and economic circumstances in the European Union (EU) and the United Kingdom (UK), especially in light of the initial occurrence of significant inflation after a long time and the need to prepare hedge strategies for investment portfolios.

In order to navigate this complex research landscape, this research employ a diverse range of data sources, such as Refinitiv and the European Public Real Estate Association (EPRA) databases. Regarding real estate, we will utilise indexes such as the FTSE 350 Real Estate Index in the UK, the Euronext Real Estate<sup>2</sup> in the EU, and the IFIX in Brazil<sup>3</sup>. To conduct

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<sup>1</sup> (CoStar via Financial Times – October 2023).

<sup>2</sup> Euronext RE (Stoxx Europe 600 Index) – Companies, and especially REITs being a RE indirect index.

<sup>3</sup> IFIX (Real Estate Investment Fund Index) – Monitors the financial health of REITs or Real Estate Funds being a Real Estate indirect index as all of the real estate indexes of this research.

more comprehensive market comparisons, this paper includes the following indexes: the FTSE 250 Index, the Euro Stoxx 50, and the Ibovespa Index from Brazil<sup>4</sup>. In terms of measuring inflation, it was used the UK CPI, the Harmonised Index of Consumer Prices (HICP) for European Union, and Brazil's IPCA<sup>5</sup>. In terms of measuring interest rates, it was used the historically UK interest rates through the Monetary Policy Committee (MPC), the European interest rates through the ECB and the Brazilian Interest Rates through the Brazilian Central Bank since 2012 to 2022. This will ensure that all the indexes compared are based on the same criteria, including the inclusion of dividends from stocks, REITs, or similar investments.

The research employs inflation decomposition following the literature, the linear regression, and an innovative statistical approach, as the Markov-Switching VECM model through a long run analysis, which has demonstrated its effectiveness in addressing non-linear relationships between variables and structural shifts in the context of rising interest rates and macroeconomic changes. This method is compatible with the present economic conditions, and it is one the best methods to verify an environment with changes as this paper will explain further through in the data-method sections. The investigation will primarily centre around the significance of diversification in the real estate industry and analyse the significance of real estate indexes as essential elements of investor portfolios, particularly in light of an imminent global recession. In addition, this thesis approaches the efficacy of various real estate investment indexes, including indirect indexes via REITs and Real Estate companies, as safeguards against inflation and interest rates.

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<sup>4</sup> These indexes provide an insight into the general patterns and condition of the equity markets of Britain, the European Union, and Brazil, respectively.

<sup>5</sup> These indexes have a crucial function in comprehending and monitoring inflationary patterns in their specific regions, directing governments, firms, and consumers in making well-informed choices about economic activity, investments, and personal finances.

## 2. Literature Review

Real Estate studies have a rich historical foundation, originating in the 1970s, when scholars like Fama and Schwert (1977) explored stable and linear relationships through statistical approaches. Subsequent research, such as that by Hoesli et al. (1997), and Hoesli and Macgregor (2008), delved into cointegration techniques. These studies aimed to understand the complex structure of real estate markets by examining the interplay of various variables. A prevailing theme in this body of literature has been the dissection of inflation into expected and unexpected components, coupled with an investigation of long-term balance and short-term fluctuations in the market. These early studies laid a strong foundation for comprehending the behaviour of real estate assets in inflationary environments. While these foundational studies offer valuable insights, it's imperative to acknowledge their potential limitations. Shifting monetary policies and business cycles, as highlighted by Muckenaupt et al. (2023), can disrupt the previously stable relationships between real estate variables. These contemporary challenges mirror the complex economic landscape we face today.

Considering the effect of Central Bank Monetary Policies, this study assumes that correlation among REITs results and inflation is subject to the influence of monetary policies, Glascock et al. (2002). In the context of unstable (non-linear) relationships, analysis suggests that real estate may serve as a partial safeguard regarding the office sector, particularly in response to deteriorating economic perspectives, such as rising inflation. This perspective aligns with the insights of Demary and Voigtlander (2009). Moreover, within the realm of volatility (non-linear) interactions, literature indicates that inflation hedging properties of assets fluctuates across distinct inflationary conditions, indicating an inflation hedge capability across the time (National and Low, 2000). The existing literature encompasses studies focusing on both expected and not expected inflation in the short run and studies exploring long-term

relationships utilizing cointegration techniques. However, the results remain mixed due to variations in the temporal dimensions of the analyses.

In the short run, the literature indicates that REITs may serve as a protective measure against inflation expectations, particularly in the context of equity REITs. However, it's worth noting that mortgage REITs exhibit sensitivity to real rates, as exemplified by the works of Chen and Tzang (1988). These studies explore both short-term and long-term dynamics, representing an initial strand of inflation hedge fundamentals in the realm of Real Estate studies. This line of research finds parallel work in scholars like Gyourko and Linneman (1998), Murphy and Kleiman (1989).

It is crucial to acknowledge that the traditional perspective, as discussed in Muckenaupt et al. (2023), supports with the results of prior research undertaken by Chatrath et al. (1998) and Bahrom et al. (2004). The authors uphold the prevailing the widely held belief that REITs are ineffective successful in reducing inflation effect, unlike direct investments. In their study, Lee et al. (2011) examined the efficacy of real estate shares in developing nations in eastern Asia to hedge against inflation over an extended period of time. As this research focuses on, the thesis explores this concept further by examining the Brazilian markets, offering a unique perspective beyond the Asian scenario.

Yokoyama, Neto, and Cunha (2017) observed that the growth of real estate assets in the Brazilian market has occurred only recently. Their study focused on a sample of Real Estate Investment Funds that went public on the São Paulo Stock Exchange during 2008-2014. In contrast, our study takes a more recent approach, examining the IFIX Brazil (Real Estate Fund Index) over the years from 2012 to 2022. This period coincides with the historical development of the index, providing us with a contemporary perspective on the topic. This research aims to

compare the hedging characteristics across different indexes, specifically within the realm of real estate, using an inflation-hedge portfolio.

Furthermore, this paper aims to expand upon the methodology proposed by Chiang et al. (2020) and Muckenhaupt (2023). Additionally, the study enhances the current corpus of research by incorporating a Markov-regime switching mechanism. Significantly, this analysis introduces the Brazilian market into this context, which has not been explored extensively in studies on non-Real Estate Investment Trust (REITs) countries<sup>6</sup>. The use of the MS-VECM analysis has been employed by these researchers to examine the interplay among property market returns and shares in the United States of America. Additionally, Muckenhaupt (2023) explored the hedging capabilities of LRE between 1990 and 2021 in the US, the UK, Australia, and Japan. In this paper, will be apply the same method to investigate listed real estate (LRE) funds from 2012 to 2022 in Brazil, the United Kingdom, and the European Union and using together the linear regression, well approached in the literature as evidenced above. This investigation will enhance the current body of research by widening the application to cover these specific regions and time frames and by using inflation decomposition, linear regression, and the very new recent approach, the MS-VECM – the methodological details will be discussed in the following section.

### **3. Data and Method**

The primary dataset was carefully compiled, utilising reliable sources such as Refinitiv DataStream, the Office for National Statistics (ONS) in the UK, and the ECB<sup>7</sup>. A complete collection of 12 indexes from the Real Estate industry, such as the FTSE 350 Real Estate Index in the UK, the Euronext Real Estate in the EU, and the IFIX in Brazil, covering the period from

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<sup>6</sup> Brazil's FII's, similar to UK REITs, operate as real estate investment vehicles allowing investors to pool resources into collective funds focused on real estate assets.

<sup>7</sup> European Central Bank.

2012 to 2022, was gathered. This study enhances its market analysis by incorporating supplementary benchmarks such as the FTSE 250 Index, the Euro Stoxx 50, and Brazil's Ibovespa. In order to evaluate the patterns of inflation, three significant indexes were employed: the UK CPI, HICP in the European Union, and Brazil's IPCA as mentioned earlier. In addition, the analysis of interest rates used historical data from the Monetary Policy Committee (MPC) of the UK, the European Central Bank (ECB), and the Central Bank of Brazil. The dataset, which covers the period from 2012 to 2022, was carefully processed in Microsoft Excel and further improved using Python (Appendix – [Python Codes & Table 1](#)).

Firstly, will be applied the traditional linear regression<sup>8</sup> as a component of our investigation. Using a stable linear methodology, this regression analysis examines the long-term association between variables. Previous studies by Chatrath and Liang (1998) and Hoesli et al. (2008), have also employed this method. The results of the linear regression will assist the comprehension of relationship identification, since linear regression can demonstrate the analysis of how alterations in one variable affect another, consequently assisting in the comprehension of these connections. The ability to guess and forecast is a valuable skill that allows us to gain insights into probable future worth or patterns. The simplicity and accessibility of linear regression make it an attractive choice for researchers in numerous domains, as it is easy to use and allows for speedy data analysis. Additionally, the starting point acts as a standard for comparison, allowing for the evaluation of other models. It provides a fundamental comprehension of relationships before delving into more complex analysis. To enhance comprehension and expedite study, the initial analysis for this thesis was conducted using linear regression.

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<sup>8</sup> Linear Regression literature covered expected and unexpected inflation in the short and long-term relationship.

In relation to the second type of analysis, the MS-VECM<sup>9</sup> utilises the data series suggested in recent studies by Chiang et al. (2020) and Muckenhaupt (2023) to address regime shifts or alterations in relationships over time. This is particularly relevant given the current global scenario characterised by high market volatility caused by COVID-19 and geopolitical shocks affecting supply and demand. The incorporation of a dynamic adjustment mechanism that encompasses both short-term volatility and long-term balance is essential for comprehending the response of variables to short-term disturbances while maintaining a long-term equilibrium relationship. By employing both linear regression and MS-VECM, a comprehensive analysis may be conducted to reveal deep correlations within the dataset. This complete approach not only enhances the comprehension of long-term relationships but also showcases an effective and meticulous methodology in the research.

### **3.1 Inflation Decomposition**

The examination of inflation decomposition utilised the framework of Fama and Schwert (1977), similar to previous research conducted by Gürkaynak, Sack, and Swanson (2005), Faust and Leeper (1997), and Stock and Watson (1999). This methodology measures inflation by comparing the expected inflation rate with the actual inflation rate, considering differences between the expected and actual rates across consecutive periods. This study investigates the concepts of inflation (It), expected inflation (EIt), and unexpected inflation (UIt). The data analysis was performed in Python using the Box-Jenkins/ARIMA model. This model involves the complex task of determining the most suitable variables (p, d, q) correspond to the ARIMA equation. The variable p denotes the proportion of delay measurements that comprise the predictive equation, indicating the AR sequence. The variable d indicates the degree of differentiation applied to make time series data stationary (I order), and q represents

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<sup>9</sup> Examined in Chiang et al. (2020), observing the interplay among housing markets returns and shares (US).

the magnitude of the average shift frame window. (Appendix - Python Codes and [Graphs 1, 2 and 3](#)).

The ARIMA model is created by passing the series and order parameters to the ARIMA function. The code snippet fits the model and returns the expected inflation and unexpected inflation. The expected inflation is obtained applying the fitted values from model, while the unexpected inflation involves removing the expected inflation from the series. The complexities of unexpected changes in inflation are supported by a variety of factors. Disruptions in the fragile balance between supply and demand, as demonstrated during the COVID-19 pandemic and the geopolitical tensions since early 2021, are potential triggers within our dataset. According to Fisher (1930), sudden changes in a central bank's monetary policy, particularly adjustments in interest rates or money supply, might trigger unexpected inflationary forces. Blanchard & Quah (1989) emphasise the importance of supply and demand shocks, while Sargent & Wallace (1981) illuminate the wide-ranging consequences of fiscal policy adjustments. In addition, the complexities of changes in exchange rates and the consequences of economic predictions, as explained by Taylor (2000), contribute further levels of complexity to the concept of unexpected inflation. Fama & Schwert (1977) argue that unexpected inflation has a negative effect on the economy, as it increases uncertainty about future economic trends. This is likely to lead investors to demand greater premiums to compensate for the rising uncertainties.

Due to the health, social, and economic consequences of the 2020 crisis, there has been a substantial increase in volatility with regards to both predicted and unexpected inflation. The discrepancy between the average of predicted inflation and the mean of unexpected inflation is evident on Appendix in the [Graphs 1, 2 and 3](#) and has also been observed by Muckenaupt et al. (2023). Furthermore, it is intriguing to see that the Brazil IPCA curve exhibits a higher trajectory compared to the EU CPI and UK CPI curves. This disparity is not only evident from

2020 onwards, but also historically, indicating a more pronounced behaviour (more volatility) than that of the EU CPI and the UK CPI. It will be crucial to examine the  $R^2$  and coefficients in the next part of this work.

#### 4. Linear Regression and $R^2$

At first, a linear regression analysis was performed on the dataset covering the time period from 2012 to 2022. Using Python for data analysis, the data below was created to display individual results (Appendix – [Table 2](#)).

Prior to the mentioned index generation, it was collected and consolidated the dataset by calculating the  $R^2$  for the three regions. The inflation in each country was defined as an independent variable, specifically UK CPI, EU CPI, and Brazil IPCA. The  $R^2$ , as determined by a linear regression analysis, quantifies the sensitivity of the dataset to changes in inflation. This previous table displays the R-squared values obtained from regression models in which the UK CPI is used as the independent variable to predict changes in other indexes in the UK. The values closer to 0 (such as 0,09 for FTSE 250 index or 0,01 for FTSE 350 RE) suggest that the UK CPI has a limited capacity to respond for the variability in those particular indexes.

Regarding the R-squared values obtained from regression models in which the European Union Consumer Price Index (CPI) serves as independent variable to predict changes in other indexes within the European Union, the values of 0.06 for Euro Stoxx 50 and 0.00 for EU IR indicate that the EU CPI has a low level of effectiveness in predicting changes in these indexes. However, with regards to Euronext RE, our association is more robust with a value of 0.09. Lastly, regarding the R-squared values obtained from regression models in which the Brazil Inflation Rate (Brazil IPCA) is used as the independent variable to predict changes in other indexes within Brazil. Smaller R-squared values, such as 0.07 for Ibovespa or 0.03 for Brazil Interest Rates, suggest that the Brazil Inflation Rate has less ability to explain the variability in those particular indexes. Nevertheless, the analysis reveals a rather significant  $R^2$  value in this

case, indicating that [82%](#) of the fluctuations in IFIX movements can be accounted by the independent variable Brazil IPCA.

An additional linear regression analysis was performed on the dataset covering the time period from 2012 to 2022. By employing Python for data analysis, another table was created, each displaying distinct results. In this particular scenario, we considered the interest rates in each region as an independent variable (Appendix – [Table 3](#)). Through this process, was obtained the  $R^2$  values for the independent variables: UK IR (United Kingdom interest rates), EU IR (ECB - European Union interest rates), and Brazil IR (SELIC - Interest Rates from Brazil).

The R-squared value of 0.08 for the FTSE 250 index indicates that around 8% of the fluctuations in the index may be attributed to modified in the UK Interest Rate (UK IR). The link among the UK interest rate and the FTSE 250 index is quite modest. The FTSE 350 RE index has an R-squared value of 0.21, indicating that approximately 21% of the variability in the index can be attributed to fluctuations in the UK Interest Rate. This indicates a marginally more robust correlation in comparison to the FTSE 250 index.

Approximately 15% of the fluctuations in the Euro Stoxx 50 index can be explained for by fluctuations in the European Union Interest Rate (EU IR). There is a minor correlation between the EU IR and the Euro Stoxx 50 index. The R-squared value of 0.53 for the Euronext RE suggests that around [53%](#) of the fluctuations in the Euronext RE index can be attributed to changes in the EU Interest Rate. This indicates a reasonably robust correlation when compared to other indicators in this group.

Approximately 11% of the fluctuations in the Ibovespa index can be attributed to fluctuations in the Brazil Inflation Rate (Brazil IPCA). The data demonstrates a relatively low correlation between Brazil IPCA and the Ibovespa index. Additionally, the R-squared value of 0.26 for IFIX suggests that around 26% of the fluctuations in the IFIX index may be attributed

to changes in the Brazil Inflation Rate. The association exhibited is stronger than that of Ibovespa, while still moderate.

By utilising these linear comparisons, a ranking was produced based on the coefficient of determination ( $R^2$ ) – [Graph 4](#). The comparison encompassed 12 separate indexes, with inflation indicators - inflation and interest rates - in each location being considered as independent factors. It is important to mention that all the values were tested using the p-value, and the results were classified considering the significance levels as follows: [\\* \$p < 0.1\$](#) , [\\*\\* \$p < 0.05\$](#) , and [\\*\\*\\* \$p < 0.01\$](#) .

#### **4.1 Linear Regression and Coefficients**

Additionally, still in the same table presented ([Table 2](#) and [3](#) – Appendix) it was conducted a coefficients analysis to determine the positive or negative correlation between the sensitivity directions and the inflation statistics and interest rates of their respective regions. Furthermore, these findings are illustrated in graphics in the Appendix ([Graph 5](#)), which presents the correlation among inflation and interest rates across the indexes.

A negative correlation is indicated by negative coefficients between financial indexes and interest rates or inflation in specific places. For example, a negative coefficient of -0.01 between Euronext RE and EU CPI suggests that an increase in Euronext RE is linked to a decrease in the European Union's Consumer Price Index. Similarly, the rise of the Brazilian IPCA is associated with the increase of the IFIX Index (coefficient: [1.27](#)), which includes the hedge component in the rise of inflation. The coefficient of 1.27 between IFIX and Brazil IPCA suggests a relatively strong positive relationship between the financial index IFIX and the inflation rate in Brazil (IPCA).

The real estate indexes exhibited a poor correlation when the interest rates are considered as independent variable instead of the inflation component. The Euronext RE is the most representative index that exhibits a negative correlation with European Interest Rates.

Although not as substantial as the inflation described in [Table 3](#), it is nevertheless significant with a correlation coefficient of -0.16.

## 5. Empirical Results from the Linear Regression Analysis

Analysis of historical data has uncovered clear patterns in inflation rates among various regions, with Brazilian inflation consistently exhibiting higher indexes compared to those of Europe and Britain. The discrepancy in inflation indexes suggests the underlying composition of IFIX, the index for real estate investment funds in Brazil. It indicates that the funds in IFIX may be purposefully designed to either match or exceed current inflation rates, which is a significant component of their investing goals.

IFIX aims to function as a benchmark, reflecting the total efficacy of real estate funds traded in both Brazil's organised stock exchange and over-the-counter markets. The IFIX funds consist of shares from many RE Investment Funds listed at B3<sup>10</sup> organised stock and private markets. Based on data obtained from B3's website as of November 16th, 2023, the IFIX index was comprised of 109 individual real estate investment funds. The funds are classified into many categories, including credit funds, specifically real estate debt ('CRI'<sup>11</sup>), and equity funds that cover Shopping Centres, Logistics, Prime Offices (Residential and Corporate), and Commercial funds (Urban Income). These funds often conduct their Initial Public Offerings (IPOs) and tranches at their own discretion, generally basing their benchmarks on indexes such as the IPCA Index (representing inflation) or CDI (tracking the Brazilian interest rates SELIC).

Historically, South American countries, including Brazil, have seen larger inflation rates compared to their European and British counterparts. The European and UK economies have

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<sup>10</sup> B3 – Main Stock Exchange in Brazil.

<sup>11</sup> 'Certificados de Recebíveis Imobiliários' (CRIs) are financial instruments traded in the Brazilian market. They are a representation of receivables or credits related to real estate, usually originating from activities such as real estate financing, leasing, or real estate development.

faceted contractions due of recent events, including the COVID-19 pandemic and geopolitical tensions in early 2021<sup>12</sup>. This has resulted in a surge in interest rates to levels unprecedented since the 2008 financial crisis. Examination of the EU and the UK indexes indicates that alterations in interest rates, as a part of monetary policy adjustments, have a greater impact on the real estate market for investment funds in comparison to inflation than Brazil. The discrepancy emerges due to variations in the composition of real estate agreements in various areas. Contracts in the European Union (EU) and United Kingdom (UK) are often complex in order to include specific elements related to the project or collateral capacity. This helps to reduce the need for funds to consistently outperform or protect against inflation. The R<sup>2</sup> ranking presented in the Appendix ([Graph 4](#)) demonstrates a more logical association among interest rates and inflation in Europe and the UK. Additionally, the correlation presented in the Appendix [Graph 4](#) shows a negative relationship between inflation and the FTSE 350 RE and Euronext RE, but the negative correlation is stronger when it comes to changes in interest rates in both regions.

It can be inferred that the real estate investment funds in the EU and the UK are experiencing greater negative effects from the current crisis compared to the assets included in the IFIX Index in Brazil. The hedge scenario in the Brazilian real estate market seems to provide greater protection to investors against inflation movements. This is due to its positive correlation with inflation and its significant R<sup>2</sup> value, which cannot be ignored. Despite recent hawkish (early 2023) interest rate movements in the three regions, the IFIX index appears to have experienced less impact compared to the Euronext RE index and a similar impact to the UK 350 Index (Appendixes – [Graph 6](#) and [7](#)) illustrate this information.

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<sup>12</sup> The geopolitical tensions arising from the conflict between Ukraine and Russia in early 2021 resulted in disruptions to global supply networks, affecting the supply and demand dynamics in various industries across Europe and the UK.

The investing landscape in Brazil has increased inflationary volatility, leading investors to explore options beyond government securities in order to achieve significant returns. Investors in Brazil have the opportunity to utilise credit options, which allows them to take advantage of spreads of 500 basis points (bps) higher than inflation or 200 bps higher than the CDI/SELIC<sup>13</sup> rates for some high-grade bonds per example. This strategy is in line with changes in monetary policy. The wide range of investment choices in Brazil gives it a favourable advantage compared to the more limited investment opportunities in Europe and the UK. When comparing the coefficients, it is evident that IFIX exhibits a positive correlation with inflation, and it is perceptible a more significant negative correlation among EU and EU CPI coefficient.

Finally, the linear regression analysis reveals that the structure and behaviour of real estate indexes are influenced by both the economic conditions specific to each region and the strategic investment goals within the real estate investment sector. This makes IFIX a potential safeguard against inflation. Brazil's distinctive investment landscape in real estate investment funds can provide investors with a wider array of choices compared to its European equivalents, highlighting the intricate influence of inflation and interest rate dynamics on RE investment funds. The Brazilian case demonstrated greater dynamism and resilience compared to the UK and the EU real estate markets due to the presence of a "protected" contractual agreement against inflation.

## **6. The Markov Switching Vector Error Correction Model (MS-VECM)**

Regarding the MS-VECM, the analytical tool is used to analyse the long-term and immediate fluctuations among numerous non-stationary variables in a multivariate time series. The method is an altered version of the Vector Autoregression (VAR) method that incorporates

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<sup>13</sup> The CDI (Certificado de Depósito Interbancário) denotes the interest rates at which financial institutions lend to each other, commonly utilised as a financial benchmark. The SELIC (Sistema Especial de Liquidação e Custódia) is the benchmark interest rate set by Brazil's central bank, which has a significant impact on other interest rates and monetary policy choices.

for the existence of interaction among variables, indicating that they have a shared stochastic trend. It includes both short-term deviations from equilibrium, represented by error correction terms, and long-term correlations between variables.

Markov switching (MS) models are probabilistic models that enable the transition of parameters or states across distinct regimes over time. The MS models are employed in the analysis of economic data to detect changes in economic regimes, such as the global expansions observed in 2019 and the inflation scenario anticipated from 2021 onwards. These models are designed to capture the distinct statistical characteristics associated with each regime. Simulations are crucial instruments for examining shifts among different phases in an analysis, particularly with historical data that display unpredictable attributes (Hamilton, 1989). In accordance with the study conducted by Beckman and Czudaj in 2013, a Multivariate Structural Vector Error Correction Model is utilised to analyse the correlation among asset prices and both expected and unexpected inflation. Variables in the system are intended to maintain a uniform value within settings and transition abruptly from a single scenario to a different one with fluctuating shifting possibilities. It is assumed that the switches between states are governed by an external random mechanism. An M-regime pth order MS-VECM is a model that can accommodate changes in multiple aspects, including the baseline conditions, autoregressive part, long-term structure, and variance-covariance array of mistakes.

$$\Delta Y_t = v(s_t) + \Gamma(L)(s_t)\Delta Y_{t-1} + \Pi(s_t)Y_{t-1} + \varepsilon_t,$$

The  $\Delta$  sign indicates the distinct function.  $Y_t$  corresponds to a K-dimensional matrix of time sequence, specifically expressed as  $Y_t = [R, EI, UI, X]$ . R is a function that denotes the financial gains or losses from various assets, such as shares and real estate funds. X are economy's influences such the Consumer Price Index (CPI), real interest rates, and value of the currency value. The symbol  $v(st)$  denotes a K-dimensional array of capture components that

vary depending on the regime. The vector  $et$  represents the error terms and has a variance-covariance matrix  $\Sigma(st)$  that depends on the regime. The error terms  $et$  follow a normal independent and identically distributed (NIID) distribution has a mean of 0 and variance-covariance matrix  $\Sigma(st)$ . The matrix  $\Gamma(L)$  represents the short-term dynamics that depend on the state, and it has dimensions  $K \times K$ . The reference is from Beckmann and Czudaj's work published in 2013.

The analysis was performed using the Python programming language, where programmes were created to compare the smoothed probability for State 0 and State 1 using the MS-VECM approach. Initially, it was collected the dataset from a CSV file that includes financial indexes data. Later, it was created columns containing numerical values that necessitate preprocessing, such as transforming comma-separated values into floating-point numbers. Subsequently, the data was transformed into a Pandas DataFrame format to facilitate the application of a Markov regime-switching model, commonly referred to as 'Markov regression', to every column of the dataset. The visualisation component produces a line chart that exhibits the [smoothed probability for state 0 and state 1](#). The list of dictionaries was transformed into a Pandas DataFrame called 'ms\_vecm\_results\_df'. The X-Axis indicates the names of the indexes, while the Y-Axis indicates values of likelihood. The charts provide a comparison view of the distribution of each index between the two states using the Markov regime-switching model.

## **7. Results of Markov Switching Vector Error Correction Model (MS-VECM)**

Through the experimental investigation conducted using the Markov Switching Vector Error Correction Model produced results that were categorised into [State 0 and State 1](#). State 0 might symbolise a phase in which the market is steady, displaying consistent and predictable behaviour. This may suggest a period of economic growth or stability. In contrast, State 1 may

suggest another market state, maybe characterised by volatility, downturns, or less predictable behaviour.

In the UK, the initial state has a chance of  $2.07 \times 10^{-5}$ , while the likelihood for state 1 is 0.99. Based on the algorithm, the likelihood of the interest rate in the UK being in state 0 is very low, while the likelihood of it being in state 1 is considerable. The UK CPI has a probability of  $2.95 \times 10^{-21}$  for state 0 and a probability of 1.0 for state 1. According to the model, there is an extremely low likelihood of being in state 0 and a full possibility of being in state 1.

The FTSE 250 index has a probability of around 1.0 (or 100%) for state 1 and an extremely small likelihood of  $1.26 \times 10^{-14}$  for state 0. The FTSE 350 RE has a probability of 0.99 for state 0 and a probability of  $3.30 \times 10^{-6}$  for state 1. It is [the only UK index](#) among the indexes analysed in this study that has a significantly high probability of being in state 0 and an exceptionally low probability of being in state 1. It implies that the FTSE 350 RE exhibits greater consistency during periods when the markets are relatively steady and display a more predictable pattern of action.

The likelihood of the EU IR (European Union's Interest Rate) being in state 0 is  $9.24 \times 10^{-25}$ , whereas the probability of it being in state 1 is 1.0. Based on the model, the likelihood of the interest rate in the European Union being in state 0 is very small, whereas the probability of it being in state 1 is 1.0. In relation to the EU CPI, State 0 has a probability of  $3.73 \times 10^{-21}$ , while State 1 has a probability of 1.0. Based to the model, the probability of the EU CPI being in state 0 is extremely small, whereas the probability of it being in state 1 is 1.0. The Euro Stoxx 50 has a probability of  $1.15 \times 10^{-9}$  in state 0 and a probability of 1.0 in state 1. According to the model, the Euro Stoxx 50 index has an extremely low probability of being in state 0 and a 100% probability of being in state 1. Regarding the European indexes, the [Euronext RE is the only](#)

[european index](#) that has a very high probability of 0.99 in State 0 and a very low probability of  $6.1e-06$  in State 1.

The likelihood of the Brazil IR being in state 0 is  $9.47e-06$ , whereas the probability of it being in state 1 is 0.99. In light of the model, the likelihood of the Brazilian interest rate being in state 0 is very low, while the likelihood of it being in state 1 is considerable. The likelihood of Brazil's Consumer Price Index (IPCA) being 0 in state 0 is 0.00, whereas in state 1 it is 0.99. According to the model, the likelihood of the Brazil IPCA being in state 0 is low, while the likelihood of it being in state 1 is higher. The Ibovespa, has a probability of 0.015 for State 0 and a probability of 0.98 for State 1, the index has a moderate likelihood of being in state 0 and a greater likelihood of being in state 1. The IFIX, exhibits a distinct characteristic compared to other real estate indexes in Europe. Specifically, it has a probability of  $5.79e-08$  for being in state 0, and a probability of 0.99 for being in state 1. According to the model, the likelihood of the IFIX index being in state 0 is extremely low, whereas the probability of it being in state 1 is quite high.

Regarding the analysis, it was possible to observe two indexes, FTSE 350 RE and Euronext RE, which are tracked after the state 0 at the end of 2022. Both indexes are considered advantageous investments in times of decreased market volatility and reduced occurrences of slumps. However, during times of high volatility, there is a tendency for a negative correlation among inflation and interest rates, which differs from the situation observed in the IFIX index in Brazil. The IFIX index, on the other hand, exhibits higher volatility and more downturns, making it occasionally difficult to predict using the MS-VECM data-series model. Finally, was proceeded with the analysis by examining the fluctuations of the MS-VECM data as the smoothed probabilities evolve over time. It is worth mentioning that these probabilities can also change, as demonstrated in the Appendix ([graphs 9, 10 and 11](#)), where both FTSE 350 RE and

Euronext RE transition to state 0 status. This shift is primarily attributed to geopolitical shocks and global inflationary pressures.

## 8. Consolidating Results & Conclusion

It is curious to watch the fluctuations of indexes over time and how items might be tested during periods of significant market volatility. Over a range of 10 years, it was observed a bull market followed by the European crises in 2011 and 2012. From 2016 to 2019, we experienced a global bull market, accompanied by negative interest rates in certain regions. Additionally, in 2020, the world faced the COVID-19 pandemic, which led to an inflation stress scenario starting in 2021 and an intensification of geopolitical stress scenario from 2022 onwards. Prior to reaching a conclusion, it was further categorised the data into distinct tables (Appendix) statistics scenario ([Table 1](#)), the linear regression ([Table 2](#) and [Table 3](#)), and the MS-VECM data series analysis ([Table 4](#)). This division aims to improve comprehension.

Regarding the statistics, it was calculated the mean and standard deviation separately. The deviation, variation, maximum, and minimum of each index were calculated. In addition, we obtained the following information by conducting a linear regression analysis with one independent variable. Initially, it was considered the Consumer Price Index (CPI), and later, it was evaluated the Interest Rates in the study region. The  $R^2$  and the coefficient offer insights into the impact of variables on the indexes and the level of correlation between them as the p-value generated the significance level for each index (\* $p < 0.1$ , \*\* $p < 0.05$ , and \*\*\* $p < 0.01$ ).

Following the linear regression analysis, it was selected the MS-VECM model based on the VECM and Markov model from current literature. This model allowed to observe how the indexes behave in different macroeconomic scenarios. The MS-VECM is applicable in specific scenarios involving fluctuations in inflation or interest rates, among other factors. The paper approached models as Box-Jenkins/ARIMA, to analyse market behaviours and inflation

dynamics. It reveals complex relationships between economic indicators and financial instruments.

The empirical findings obtained via linear regression provide detailed insights into the relationships between financial indexes and regional economic indicators, particularly inflation and interest rates. As previously mentioned, the existing literature demonstrates that the effectiveness of assets to protect against inflation varies depending on the inflationary environment classification. This suggests that the effectiveness of inflation hedging changes over time. Additionally, negative coefficients between certain indexes and inflation or interest rates indicate specific correlations, revealing how changes in these indexes can affect related economic indicators. For instance, the negative correlation between Euronext RE and EU CPI indicates a possible decline in Euronext RE as a result of variations in the European Union's Consumer Price Index. In contrast, the strong positive correlation between IFIX and Brazil IPCA suggests a simultaneous increase in IFIX and Brazil's inflation levels.

This analysis explores the intricacies of Brazil's real estate investment environment, emphasising its distinct reactions to changes in inflation and interest rates. This highlights the fact that this particular environment, which is characterised by more significant fluctuations in inflation, provides a wider range of investment opportunities compared to the relatively more limited markets in Europe and the UK regarding the inflation scenario. The durability of Brazil's real estate sector makes it an attractive option for investors seeking to safeguard their investments from inflation fluctuations.

The analysis of inflation dynamics, utilising methodologies such as Fama and Schwert's model and Box-Jenkins/ARIMA, reveals the fundamental factors that contribute to unexpected inflation. The COVID-19 pandemic and geopolitical tensions have a disruptive effect on the equilibrium between supply and demand, providing support for economic theories proposed by

Fisher, Blanchard & Quah, Sargent & Wallace, and other scholars. These crises significantly contribute to unexpected inflationary pressures. Moreover, the analysis of Brazil's IPCA in relation to the EU's CPI and the UK's CPI reveals past trends in behaviour, suggesting possible differences in economic paths. This comprehensive analysis highlights the crucial influence of unexpected economic factors in creating market circumstances and investor reactions.

This synthesis, based on a comprehensive survey of existing literature, showcases the progression of real estate studies from the works of Fama and Schwert (1977) to current research that investigates both the anticipated and unforeseen aspects of inflation. Although initial research offers significant perspectives, current obstacles stemming from fluctuating monetary policies and business cycles, as emphasised by Muckenaupt et al. (2023), introduce fresh intricacies in comprehending real estate dynamics.

The application of MS-VECM in analysing listed real estate funds in various locations such as Brazil, the UK, and the EU between 2012 and 2022 is a significant contribution to the current body of research. This study expands on the methodologies proposed by Chiang et al. (2020) and Muckenaupt (2023) by incorporating specific regions and time periods into the analysis. It utilises inflation decomposition, linear regression, and MS-VECM as not just innovative approaches but, through these methods, is possible to explore the complexities of financial markets and the patterns of inflation in the markets since 2020. It not only interprets market behaviours but also highlights the subtle reactions of various locations to economic stimuli, including the Brazilian markets capability, through the IFIX, to serve as a hedge against inflation or even the negative correlation between inflation and the real estate indirect indexes in Europe and UK (Euronext RE and FTSE 350 RE). These findings also facilitate a more profound comprehension of future economic environments, increasing the ability to make predictions and providing a strong basis for additional investigation in the realm of real estate and inflation dynamics.

## 10. Appendix

### Python Codes, Graphs and Tables

#### 1. Statistics Models & Output

```

# Display dataset preview
The code snippet utilizes Python's Pandas library to work with data and Scikit-learn's LinearRegression model
for machine learning.

# Initialize an empty DataFrame for output
output_table = pd.DataFrame()
# List of numerical columns for preprocessing
numerical_columns = ['FTSE 250 index', 'FTSE 350 RE', 'UK CPI','UK IR','Euro Stoxx 50', 'Euronext RE',
'EU CPI','EU IR', 'Ibovespa', 'IFIX', 'Brazil IPCA','Brazil IR']

# Preprocess numerical columns
for col in numerical_columns:
dataset[col] = dataset[col].str.replace(',', '.').astype(float)
# Independent variable (UK CPI)
independent_variable = 'UK CPI'

#From here the code goes to a linear regression model using Scikit-learn, where the dataset contains information
for modeling.

#It prepares the independent variable(s) by extracting values from the dataset based on specified columns,
reshaping them if needed.

#The dependent variable is similarly extracted. The model trained (fit) using the fit() method, which fits the
linear regression to the provided independent and dependent variables.

#Finally, it retrieves and stores the estimated value of the variable calculated by the equation, which signify
their impact on predicting the dependent variable.

r2_score = model.score(X, y)
# Create a DataFrame with the statistical results
index_stats = pd.DataFrame({
'Index': [independent_variable],
'Number of Observations': [len(dataset)],
'Mean Value': [dataset[independent_variable].mean()],
'Standard Deviation': [dataset[independent_variable].std()],
'Variance': [dataset[independent_variable].var()],
'Maximum Value': [dataset[independent_variable].max()],
'Minimum Value': [dataset[independent_variable].min()],
'R2 Score': [r2_score],
'Coefficient': [coefficients]
})
# Concatenate results to the output table
output_table = pd.concat([output_table, index_stats])
# From here the code output_table resets the DataFrame output_table, removing the old index and reassigning
a new sequential index starting from 0.
# This operation modifies the DataFrame in place without creating a new one, providing a reindexed
representation of the data for further analysis or processing.

# Display the output table
print(output_table)

```

**Aggregate**

**Monthly Statistics (from Jan. 2012 to Dec. 2022)**

<b>Index</b>	<b>Obs.</b>	<b>Mean (USD)</b>	<b>Std. Dev.</b>	<b>Var.</b>	<b>Max. (USD)</b>	<b>Min. (USD)</b>
FTSE 250	132	9.493,45	912,22	8,32	11.534,21	7.043,46
FTSE 350	132	2.318,74	325,51	1,05	2.984,19	1.430,21
UK CPI	132	110,78	7,48	5,59	134,24	100
UK IR	132	0,6	0,46	2,11	3,5	0,1
Eur. St. 50	132	3.853,12	477,09	2,27	4.954,67	2.618,17
Eur. RE	132	188,77	24.480.529,00	5,99	233,54	108,53
EU CPI	132	102,28	4,2	1,76	118,6	97,5
EU IR	132	0,55	0,53	2,86	2,75	0,25
Ibovespa	132	21.789,93	4.994,54	2,49	38.395,83	10.072,62
IFIX	132	2.068,64	607,41	3,68	3.197,58	1.200,43
IPCA	132	4.803,08	855,3	7,31	6.474,09	3.422,79
Brazil IR	132	8.961,97	3,58	1,27	14,15	1,9

Python Codes and Table 1: Python Codes and Output (Monthly Statistics).

**2.Inflation Decomposition & Outputs (Graphs 1, 2 and 3)**

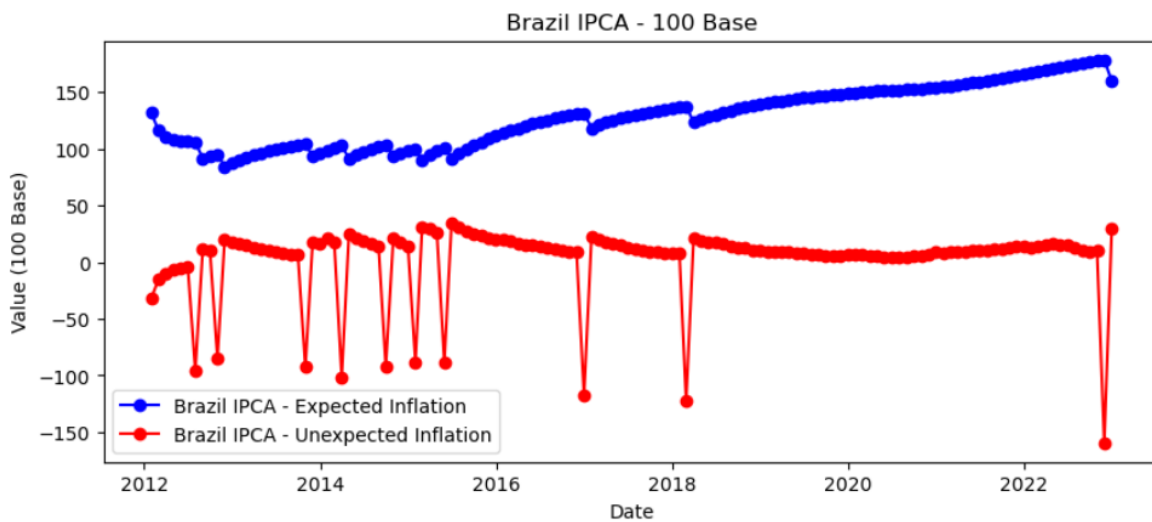
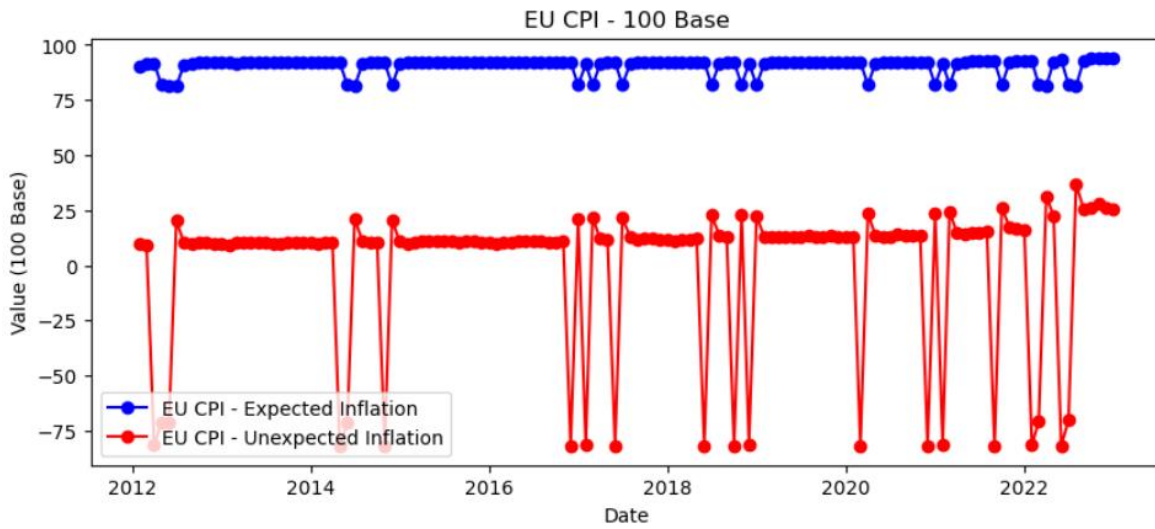
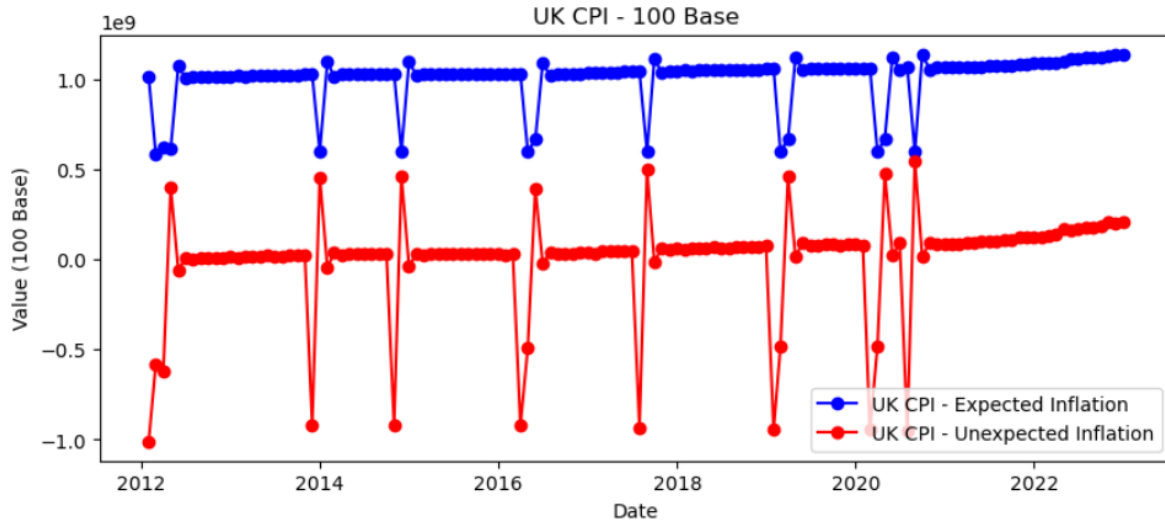
```
# The code imports the ARIMA model from statsmodels.tsa.arima.model and initializes an ARIMA model
named model using series data and a specified order.

#This sets up an ARIMA model for time series analysis based on the provided parameters.

# Fit the model
results = model.fit()

#From here the code calculates expected inflation by obtaining fitted values from results and computes
unexpected inflation by subtracting the expected values from the original series data, helping to distinguish
anticipated trends from the actual observed data.

# Return values
return expected_inflation, unexpected_inflation
```



Codes and Graph 1, 2 and 3: Python Code and Output Inflation Decomposition.

### 3.Linear Regression Python Code | $R^2$ and Coefficients (Local Inflation & Local Interest Rates as Independents Variables) & Outputs - Table 1 and Table 2

```

# Code starts importing necessary libraries (pandas & LinearRegression from sklearn.linear_model) and then
load a dataset.

# List of numerical columns for preprocessing
numerical_columns = ['IFIX', 'Brazil IPCA', 'Euronext RE', 'EU CPI', 'EU IR', 'FTSE 350 RE', 'UK CPI',
                    'FTSE 250 index', 'UK IR', 'Euro Stoxx 50', 'Ibovespa', 'Brazil IR']

# Preprocess numerical columns
for col in numerical_columns:
    dataset[col] = dataset[col].str.replace(',', '.').astype(float)

# Initialize an empty DataFrame for output
output_table = pd.DataFrame()
# Define pairs for linear regression
pairs = [('FTSE 350 RE', 'UK CPI'), ('FTSE 250 index', 'UK CPI'), ('UK IR', 'UK CPI'),
        ('UK CPI', 'UK CPI'), ('Euro Stoxx 50', 'UK CPI'), ('Euronext RE', 'UK CPI'),
        ('EU CPI', 'UK CPI'), ('EU IR', 'UK CPI'), ('Ibovespa', 'UK CPI'), ('Brazil IPCA', 'UK CPI'),
        ('Brazil IR', 'UK CPI'), ('IFIX', 'UK CPI')]

# Iterate over pairs and perform linear regression.

# The code then iterates through pairs of columns in the dataset, fitting a linear regression model for each
pair.

#It calculates coefficients for the relationship between the columns and their corresponding R-squared scores.

# Create a DataFrame
index_stats = pd.DataFrame({
    'Index X': [pair[0]],
    'Index Y': [pair[1]],
    'Number of Observations': [len(dataset)],
    'Mean Y': [dataset[pair[1]].mean()],
    'Standard Deviation Y': [dataset[pair[1]].std()],
    'Variance Y': [dataset[pair[1]].var()],
    'Maximum Y': [dataset[pair[1]].max()],
    'Minimum Y': [dataset[pair[1]].min()],
    'R2 Score': [r2_score],
    'Coefficient': [coefficients[0]]
})

# Concatenate results to the output table
output_table = pd.concat([output_table, index_stats])

# Lastly the code reset the index of the output_table DataFrame, dropping the old index and reassigning a new
sequential index starting from 0, and then prints the modified output_table with the reset index.

```

<i>Linear Regression</i>	<i>Variables</i>	<i>Index</i>	<i>FTSE 250 index</i>		<i>UK IR</i>	<i>UK CPI</i>	<i>Euro Stoxx 50</i>	<i>Euron-ext RE</i>	<i>EU IR</i>	<i>EU CPI</i>	<i>Ibovespa</i>	<i>IFIX</i>	<i>Brazil IR</i>	<i>Brazil IPCA</i>
<i>Independent Variable</i>	<i>Brazil IPCA</i>	<i>Coefficients</i>	0,90	-0,34	720,1	107,31	0,76	3,51	-629,89	169,28	-0,04	1,27	-42,58	-
	<i>Brazil IPCA</i>	<i>R<sup>2</sup> Score</i>	0,14	0,12	0,15	0,88	0,18	0,01	0,16	0,70	<b>0,07</b>	<b>0,82</b>	<b>0,03</b>	-
	<i>Brazil IPCA</i>	<i>p-value</i>	0,00***	0,00***	0,00***	0,00***	0,00***	0,25	0,00***	0,00***	<b>0,00***</b>	<b>0,00***</b>	<b>0,04**</b>	-
	<i>EU CPI</i>	<i>Coefficients</i>	0,00	0,00	6,33	0,53	0,00	<b>-0,05</b>	0,53	-	0,00	0,00	0,06	0,00
	<i>EU CPI</i>	<i>R<sup>2</sup> Score</i>	0,07	0,01	0,48	0,91	<b>0,06</b>	<b>0,09</b>	<b>0,00</b>	-	0,01	0,49	0,00	0,70
	<i>EU CPI</i>	<i>p-value</i>	0,00***	0,24	0,00***	0,00***	<b>0,00***</b>	<b>0,00***</b>	<b>0,43</b>	-	0,33	0,00***	0,51	0,00***
	<i>UK CPI</i>	<i>Coefficients</i>	0,00	<b>0,00</b>	9,85	-	0,00	-0,03	-1,92	1,70	0,00	0,01	-0,27	0,01
	<i>UK CPI</i>	<i>R<sup>2</sup> Score</i>	<b>0,09</b>	<b>0,01</b>	<b>0,37</b>	-	0,15	0,01	0,02	0,91***	0,01	0,72***	0,02	0,88***
	<i>UK CPI</i>	<i>p-value</i>	<b>0,00***</b>	<b>0,19</b>	<b>0,00***</b>	-	0,00***	0,20	0,12	0,00***	0,14	0,00***	0,00***	0,00***

**Consolidated (Table 2):** Linear Regression - Coefficients, R<sup>2</sup> (Local Inflation as Independent Variable) and p-value. Linear Regression, monthly data 2012-2022. The deviations are enclosed by brackets, denoting their resilience. The significance levels are as follows: \*p < 0,1, \*\*p < 0,05, and \*\*\*p < 0,01.

<i>Linear Regression</i>	<i>Variables</i>	<i>Index</i>	FTSE 250 index	TSE 350 RE	UK IR	UK CPI	Euro Stoxx 50	Euronext RE	EU IR	EU CPI	Ibovespa	IFIX	Brazil IR	Brazil IPCA
	<i>Brazil IR</i>	<i>Coefficients</i>	0,00	0,00	0,81	-0,06	0,00	-0,02	0,78	0,00	0,00	<b>0,00</b>	1,00	0,00
	<i>Brazil IR</i>	<i>R<sup>2</sup> Score</i>	0,05	0,06	0,01	0,02	0,06	0,02	0,01	0,00	<b>0,11</b>	<b>0,26</b>	<b>1,00</b>	0,03
	<i>Brazil IR</i>	<i>p-value</i>	0,013**	0,00***	0,23	0,12	0,00***	0,11	0,18	0,51	<b>0,00***</b>	<b>0,00***</b>	<b>0,00***</b>	0,04**
<i>Independent Variable</i>	<i>EU IR</i>	<i>Coefficients</i>	0,00	0,00	0,50	0,00	0,00	<b>-0,01</b>	1,00	0,00	0,00	0,00	0,01	0,00
	<i>EU IR</i>	<i>R<sup>2</sup> Score</i>	0,00	0,63	0,19	0,02	<b>0,15</b>	<b>0,53</b>	<b>1,00</b>	0,00	0,25	0,10	0,01	0,16
	<i>EU IR</i>	<i>p-value</i>	0,83	0,00***	0,00***	0,12	<b>0,00***</b>	<b>0,00***</b>	<b>0,00***</b>	0,43	0,00***	0,00***	0,18	0,00***
	<i>UK IR</i>	<i>Coefficients</i>	0,00	<b>0,00</b>	1,00	0,03	0,00	-0,01	0,37	0,08	0,00	0,00	0,01	0,00
	<i>UK IR</i>	<i>R<sup>2</sup> Score</i>	<b>0,08</b>	<b>0,21</b>	<b>1,00</b>	0,36	0,02	0,33	0,19	0,48	0,00	0,12	0,01	0,15
	<i>UK IR</i>	<i>p-value</i>	<b>0,00***</b>	<b>0,00***</b>	<b>0,00***</b>	0,00***	0,08*	0,00***	0,00***	0,00***	0,99	0,00***	0,23	0,00***

**Consolidated (Table 3):** Linear Regression – Coefficients, R<sup>2</sup> (Local Inflation as Independent Variable) and p-value. Linear Regression, monthly data 2012-2022. The deviations are enclosed by brackets, denoting their resilience. The significance levels are as follows: \*p < 0.1, \*\*p < 0.05, and \*\*\*p < 0.01.

## 4. Ranking R<sup>2</sup> Score | Local Inflation vs Local Interest Rates & Output

```
# The code starts obtaining the necessary libraries: pandas as pd, np for arithmetic calculations, plt for
visualization, and LinearRegression from sklearn.linear_model for performing linear regression analysis.

# Loading Dataset
dataset = pd.read_csv("")

# Preprocess numerical columns
numerical_columns = ['FTSE 250 index', 'FTSE 350 RE', 'UK CPI', 'Euro Stoxx 50', 'Euronext RE', 'EU CPI',
'Ibovespa', 'IFIX', 'Brazil IPCA', 'Brazil IR']
for col in numerical_columns:
    dataset[col] = dataset[col].str.replace(',', '.').astype(float)
# Additional preprocessing for 'UK IR' column
dataset['UK IR'] = dataset['UK IR'].str.replace(',', '.').astype(float)
# Additional preprocessing for 'EU IR' column
dataset['EU IR'] = dataset['EU IR'].str.replace(',', '.').astype(float)

# Initialize DataFrames for the ranking
ranking_df_brazil_ipca = pd.DataFrame(columns=['Index', 'R2 Score', 'Independent Variable'])
ranking_df_brazil_ir = pd.DataFrame(columns=['Index', 'R2 Score', 'Independent Variable'])
ranking_df_uk_cpi = pd.DataFrame(columns=['Index', 'R2 Score', 'Independent Variable'])
ranking_df_uk_ir = pd.DataFrame(columns=['Index', 'R2 Score', 'Independent Variable'])
ranking_df_eu_cpi = pd.DataFrame(columns=['Index', 'R2 Score', 'Independent Variable'])
ranking_df_eu_ir = pd.DataFrame(columns=['Index', 'R2 Score', 'Independent Variable'])

# List of indices to analyze
indices_to_analyze = ['IFIX', 'Ibovespa', 'FTSE 250 index', 'FTSE 350 RE', 'Euro Stoxx 50', 'Euronext RE']

# From here the code iterates through each index specified in indices_to_analyze. For each index does not
present in the exclusion list (['Euro Stoxx 50', 'Euronext RE', 'FTSE 250 index', 'FTSE 350 RE']), it prepares
the data for regression analysis using 'Brazil IPCA'.

# It then fits a linear regression model, calculates the R-squared, and independent variable to a DataFrame
named ranking_df_brazil_ipca

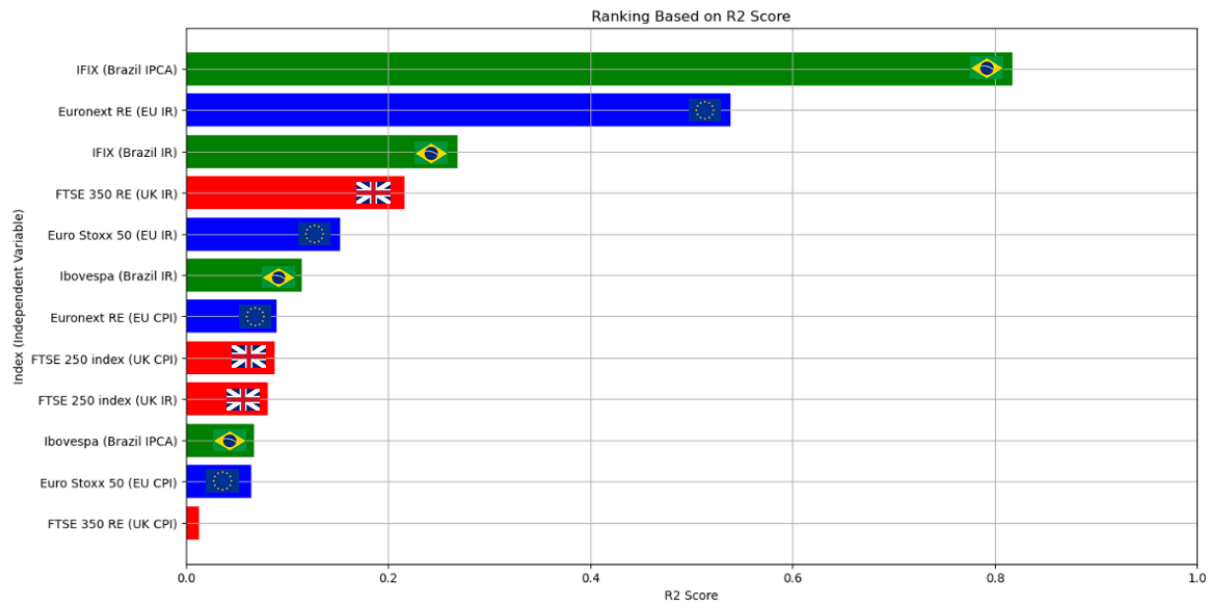
# From here the lines prepare data for regression analysis, setting 'Brazil IR, and then fit a linear regression
model to the prepared data for further analysis of their relationship.

    r2_score_brazil_ir = model_brazil_ir.score(X_brazil_ir, y_brazil_ir)
    ranking_df_brazil_ir = ranking_df_brazil_ir.append({'Index': index_column, 'R2 Score':
r2_score_brazil_ir, 'Independent Variable': 'Brazil IR'}, ignore_index=True)

# Exclude Ibovespa and IFIX from the analysis for 'EU CPI' and 'EU IR'
if index_column not in ['Ibovespa', 'IFIX', 'FTSE 250 index', 'FTSE 350 RE']:

# The code segments prepare data for regression analysis with different independent variables ('UK CPI', 'UK
IR', 'EU CPI', 'EU IR') against each index in the loop, fit linear regression models, calculate R-squared scores,
and store the results in respective DataFrames (ranking_df).

# Finally, it concatenates all ranking DataFrames, sorts them based on R-squared scores, and generates a plot
to visualize the R-squared scores across the different independent variables for each index.
```



Graph 4 - R<sup>2</sup> ranking: Local Inflation and Local Interest Rates – IFIX movements can be explained by the local Brazilian Inflation in more than 80% of the cases.

### 5.Coefficients/Correlations Graphs & Output

```
# This script defines a function named compare_indices that takes in a dataset and a list of pairs as inputs.

# Within the function, it iterates through each pair, where each pair consists of two indices. It performs linear
# regression analysis for each pair, calculates coefficients and R-squared scores, and compiles statistics about
# the relationship between the paired indices, such as mean, standard deviation, variance, maximum, and
# minimum values of the second index in each pair.

# The function creates an output table storing these statistics for each index pair and resets the table's index
# before returning the table.

return output_table

# Loading datasets
file_path = "your_file_path.csv" # Replace with the correct file path
dataset1 = pd.read_csv(file_path, delimiter=',')
dataset2 = pd.read_csv(file_path, delimiter=',')

# Preprocessing numerical columns for each dataset
numerical_columns1 = ['IFIX', 'Brazil IPCA', 'Euronext RE', 'EU CPI', 'FTSE 350 RE', 'UK CPI']
for col in numerical_columns1:
    dataset1[col] = dataset1[col].str.replace(',', '.').astype(float)

numerical_columns2 = ['IFIX', 'Brazil IR', 'Euronext RE', 'EU IR', 'FTSE 350 RE', 'UK IR']
for col in numerical_columns2:
    dataset2[col] = dataset2[col].str.replace(',', '.').astype(float)

# Define pairs for comparison
pairs1 = [('IFIX', 'Brazil IPCA'), ('Euronext RE', 'EU CPI'), ('FTSE 350 RE', 'UK CPI')]
pairs2 = [('IFIX', 'Brazil IR'), ('Euronext RE', 'EU IR'), ('FTSE 350 RE', 'UK IR')]

# Generate output tables for both comparisons
output_table1 = compare_indices(dataset1, pairs1)
output_table2 = compare_indices(dataset2, pairs2)
```

```
# Chart output_table1
colors1 = ['red' if c < 0 else 'green' for c in output_table1['Coefficient']]
axes[0].barh(output_table1['Index X'] + ' - ' + output_table1['Index Y'], output_table1['Coefficient'],
color=colors1)
axes[0].set_xlabel('Coefficient')
axes[0].set_title("The Inflation Effect")

# Chart for output_table2
colors2 = ['red' if c < 0 else 'green' for c in output_table2['Coefficient']]
axes[1].barh(output_table2['Index X'] + ' - ' + output_table2['Index Y'], output_table2['Coefficient'],
color=colors2)
axes[1].set_xlabel('Coefficient')
axes[1].set_title("The Interest Rates Effect")

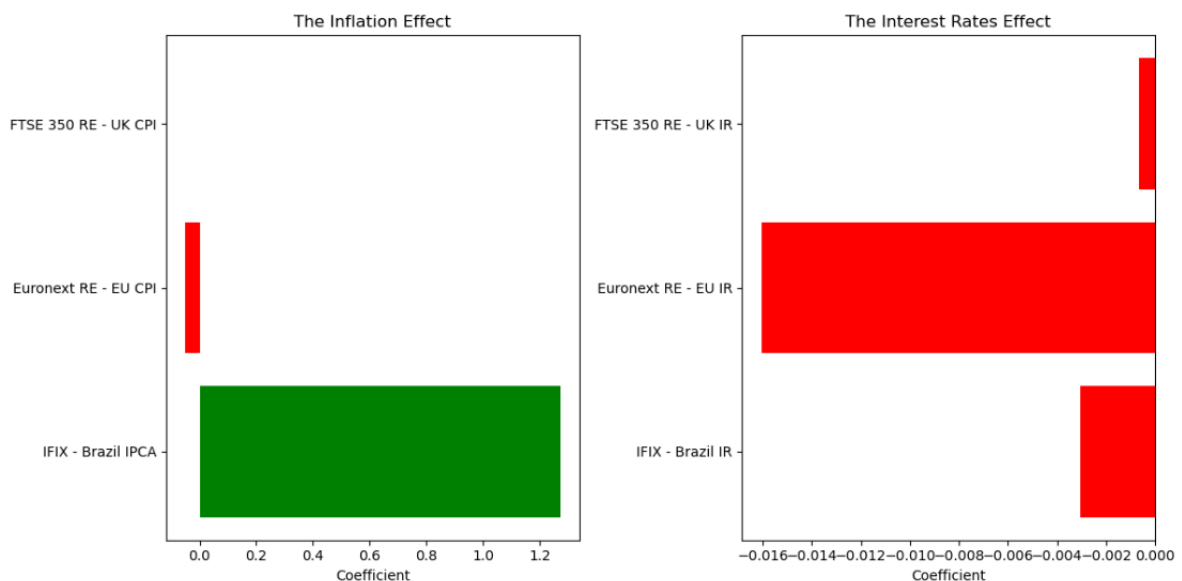
plt.tight_layout()
plt.show()

# This script defines and executes a comparison between two datasets (dataset1 and dataset2) by applying the
compare_indices function to pairs of indices specified for each dataset (pairs1 and pairs2).

# It preprocesses numerical columns in both datasets by replacing commas with periods and converting these
columns to floating-point numbers for analysis. The comparison generates output tables for both datasets,
presenting statistics.

# Additionally, it creates column charts using Matplotlib to visualize the coefficients obtained from the
comparisons.

# The first chart (axes[0]) displays the coefficients related to the inflation effect, distinguishing positive and
negative coefficients with red and green colors, respectively, for the pairs in output_table1.
```



Graph 5 - Correlation Between Real Estate Indexes.

## 6.Index Movements from Jan. 2012 to Dec. 2022

```

# The code uses Pandas to read a CSV file named "your_dataset.csv" and stores its contents in a DataFrame
named dataset, facilitating data manipulation and analysis in Python using Pandas functionalities.

# Preprocess numerical columns.

numerical_columns = ['FTSE 350 RE', 'Euronext RE', 'IFIX']
for col in numerical_columns:
    dataset[col] = dataset[col].str.replace(',', '.').astype(float)

# This code snippet utilizes Pandas' to_datetime() function to convert the 'Data' column within the dataset
DataFrame into a datetime format.

# The format='%d/%m/%Y' parameter specifies the existing date format in the 'Data' column, allowing Pandas
to accurately interpret the date string and convert it into a datetime object.

# Filter data for January 2012 and December 2022
jan_2012 = dataset[dataset['Data'].dt.year == 2012]
jan_2012 = jan_2012[jan_2012['Data'].dt.month == 1]
dec_2022 = dataset[dataset['Data'].dt.year == 2022]
dec_2022 = dec_2022[dec_2022['Data'].dt.month == 12]

# Calculate variation for each index in percentage.
variations = {}
for index in numerical_columns:
    jan_value = jan_2012[index].values[0]
    dec_value = dec_2022[index].values[0]
    variation = ((dec_value - jan_value) / jan_value) * 100
    variations[index] = variation

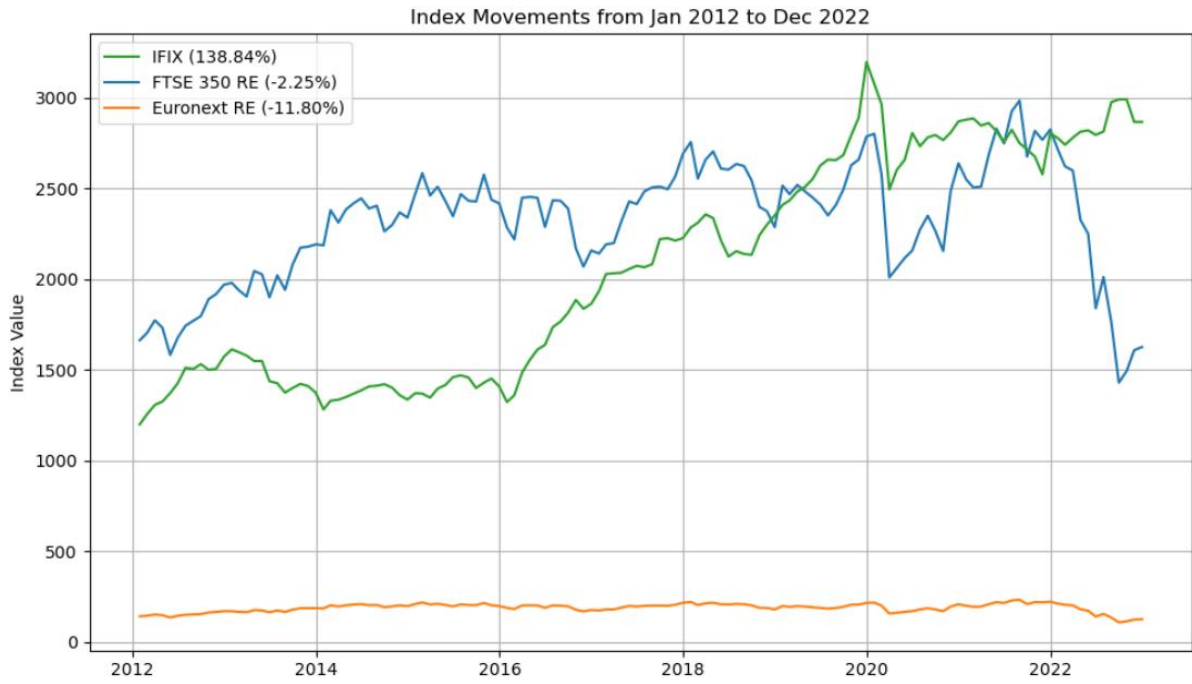
# This line of code initializes a new Matplotlib figure with a size of 10x6 inches, preparing a canvas for plotting
a line chart or any other visual representation using Matplotlib's plotting functions.

# Set legend labels and lines:
legend_labels = [f"{index} ({{variations[index]:.2f}}%)" for index in numerical_columns]
lines = [] for index in numerical_columns: line, = plt.plot(dataset['Data'], dataset[index], label=index)
    lines.append(line).

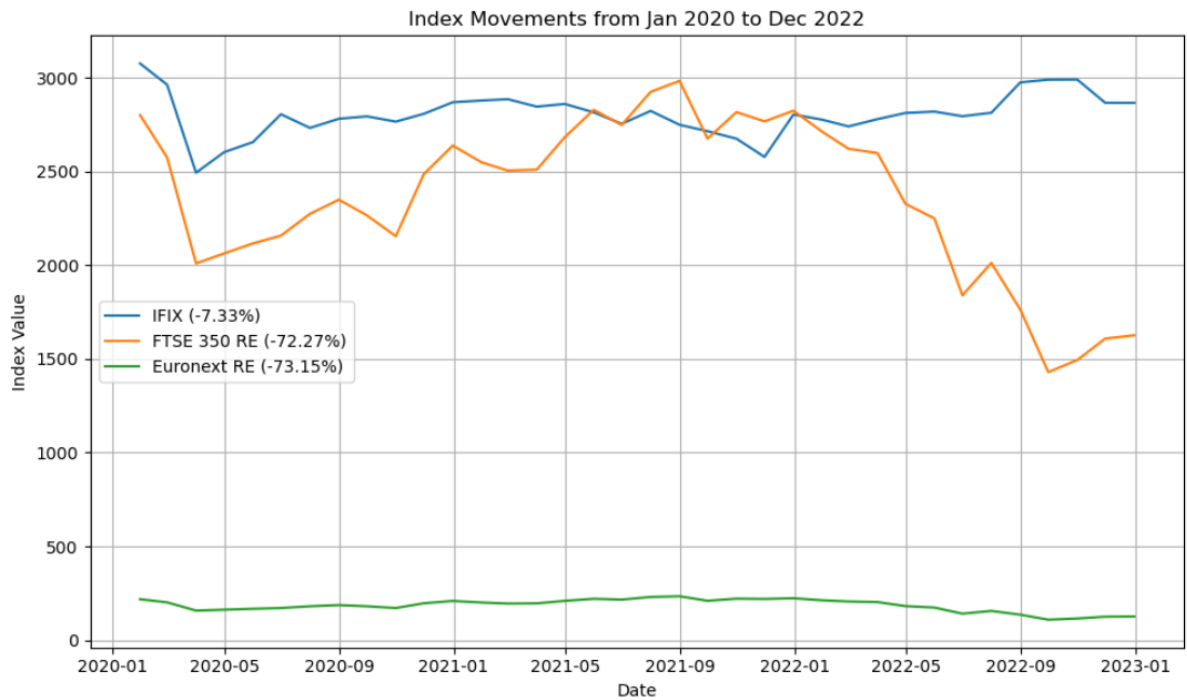
#This code segment generates a legend for the plotted lines, arranging the legend entries based on
numerical_columns and their corresponding legend_labels in reverse order.

#It then labels the x-axis as 'Date', the y-axis as 'Index Value', sets the plot title as 'Index Movements from Jan
2012 to Dec 2022', enables gridlines, ensures a tight layout, and displays the plot.

```



Graph 6 - Contracts Indexed in Inflation and Interest Rates in Brazil produced a better hedge against inflation than Europe and United Kingdom.



Graph 7 - Contracts Indexed in Inflation and Interest Rates in Brazil produced a better hedge against inflation than Europe and United Kingdom more evident after the global crises from Jan 2020 onwards.

## 7. MS-VECM Part 1

#The code starts imports the pandas library for data manipulation and utilizes the MarkovRegression class from statsmodels to implement regime-switching models in time series analysis.

# Loading Dataset

```
dataset = pd.read_csv("your_dataset.csv") # Replace with the correct file path
print(dataset.head()) # Display dataset preview
```

# Columns with numerical values that need preprocessing

```
numerical_columns = ['FTSE 250 index', 'FTSE 350 RE', 'UK CPI', 'UK IR', 'Euro Stoxx 50', 'Euronext RE', 'EU CPI', 'EU IR', 'Ibovespa', 'IFIX', 'Brazil IPCA', 'Brazil IR']
```

# Preprocess numerical columns

```
for col in numerical_columns:
    dataset[col] = dataset[col].str.replace(',', '.').astype(float)
```

# Initialize an empty DataFrame to store results

```
ms_vecm_results = []
```

# Loop through each index column

```
for index_column in dataset.columns[1:]: # Exclude the first column ('Data')
```

```
    # Prepare the data for MS-VECM (using a single endogenous variable at a time)
```

```
    data = dataset[index_column]
```

#From here the code sets up a Markov regime-switching model for each endogenous variable in the dataset, specifying two states.

# It employs the MarkovRegression class from statsmodels, defining two regimes and enabling switching trends within the model.

```
    # Get smoothed probabilities (you may want other results as well)
```

```
    smoothed_probabilities = regime_results.smoothed_marginal_probabilities
```

```
    # Store results for the current variable in a dictionary
```

```
    result = {'Index': index_column, 'Smoothed Probabilities': smoothed_probabilities}
    ms_vecm_results.append(result)
```

# Convert the list of dictionaries to a DataFrame

```
ms_vecm_results_df = pd.DataFrame(ms_vecm_results)
```

# Print or use the ms\_vecm\_results\_df DataFrame with smoothed probabilities for each variable

```
print(ms_vecm_results_df)
```

## 8. MS-VECM Part 2 & Outputs

```
import matplotlib.pyplot as plt

# Data for FTSE 250 index
ftse_250_state_0_probs = 1.260699e-14
ftse_250_state_1_probs = 1.0

# Data for other indexes
indexes = ['FTSE 250', 'FTSE 350 RE', 'UK CPI', 'UK IR', 'Euro Stoxx 50', 'Euronext RE', 'EU CPI', 'EU IR',
'Ibovespa', 'IFIX', 'Brazil IPCA', 'Brazil IR']
state_0_probs = [ftse_250_state_0_probs, 0.999997, 2.951948e-21, 2.078970e-05, 1.159027e-09, 0.999999,
3.739459e-21, 9.247683e-25, 0.01542273, 5.794467e-08, 1.6e-05, 9.472855e-06]
state_1_probs = [ftse_250_state_1_probs, 3.3e-06, 1.0, 0.99997921, 1.0, 6.1e-06, 1.0, 1.0, 0.98457727,
0.9999999, 0.999984, 0.99999]

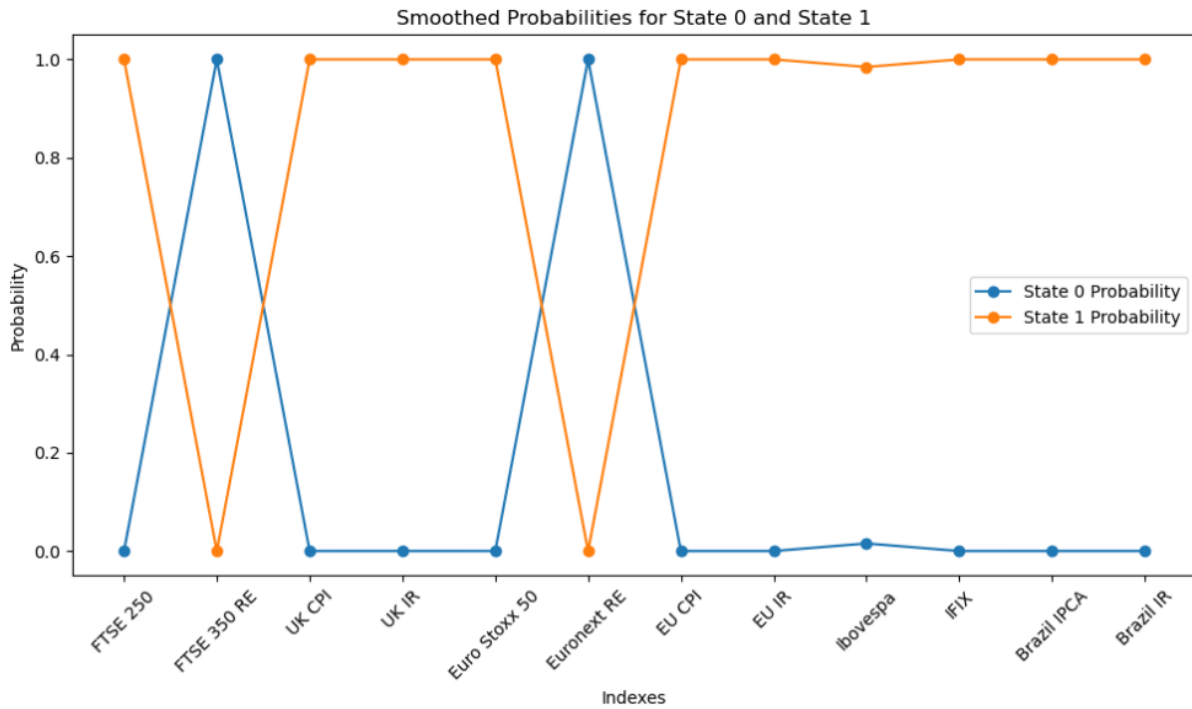
# From here the code generates a line chart with the smoothed probabilities for State 0 and State 1, using
indexes as the x-axis data.

# It sets labels, a title, and legend for clarity, displaying the probabilities of each state's occurrence over the
given indexes. Finally, it plots and displays the chart using Matplotlib in Python.
```

### MS-VECM (Markov Switching Vector Error Correction Model) & Smoothed Probabilities Output

	Index	Smoothed Probabilities	
		0	1
0	FTSE 250 index	0	1
0	1.260699e-14 1.0		
...			
1	FTSE 350 RE	0	1
0	0.999997 3.3...		
2	UK CPI	0	1
0	2.951948e-21 1.0		
...			
3	UK IR	0	1
0	2.078970e...		
4	Euro Stoxx 50	0	1
0	1.159027e-09 1.0		
...			
5	Euronext RE	0	1
0	0.999999 6.1...		
6	EU CPI	0	1
0	3.739459e-21 1.0		
...			
7	EU IR	0	1
0	9.247683e-25 ...		
8	Ibovespa	0	1
0	1.542273e-02 ...		
9	IFIX	0	1
0	5.794467e...		
10	Brazil IPCA	0	1
0	0.000016 0.99998...		
11	Brazil IR	0	1
0	9.472855e-06 ...		

**Graph 8: MS-VECM & Smoothed Probabilities**



**Table 4: Aggregate – MS-VECM Data Series**

<u>Consolidate</u> Index	MS-VECM Data Series			Real Estate Indexes   Return	
	Smoothed Probabilities			Jan./2012 to Dec.2022	Jan./2020 to Dec.2022
	State 0	State 1	State (2022)		
FTSE 250	0,00	1,00	1	-	-
FTSE 350	0,99	0,00	0	-2,25%	-7,33%
UK CPI	0,00	1,00	1	-	-
UK IR	0,00	0,99	1	-	-
Eur. St. 50	0,00	1,00	1	-	-
Eur. RE	0,99	0,00	0	-11,80%	-72,27%
EU CPI	0,00	1,00	1	-	-
EU IR	0,00	1,00	1	-	-
Ibovespa	0,01	0,98	1	-	-
IFIX	0,00	0,99	1	138,84%	-73,15%
IPCA	0,00	0,99	1	-	-
Brazil IR	0,00	0,99	1	-	-

Table 4: Aggregate – MS-VECM Data Series

## **9. MS-VECM & Smoothed Probabilities– Real Estate Indexes from 2012 to 2022.**

```

# The code imports pandas for data handling, matplotlib for plotting, and the MarkovRegression class from
statsmodels for implementing regime-switching models in time series analysis.

# Loading Dataset
dataset = pd.read_csv()

# Later the code will convert the 'Data' column in the dataset to a datetime format, explicitly defining the
format as day/month/year.

# Then, it sorts the dataset based on the 'Data' column and sets the 'Data' column as the index for the dataset,
facilitating time-based analysis.

# Columns with numerical values that need preprocessing
numerical_columns = ['FTSE 250 index', 'FTSE 350 RE', 'UK CPI', 'UK IR', 'Euro Stoxx 50', 'Euronext RE',
'EU CPI', 'EU IR', 'Ibovespa', 'IFIX', 'Brazil IPCA', 'Brazil IR']

# Preprocess numerical columns
for col in numerical_columns:
    dataset[col] = dataset[col].str.replace(',', '.').astype(float)

# Extract FTSE 350 RE data
ftse_350_re = dataset['FTSE 350 RE']

# Fit Markov regime-switching model for FTSE 350 RE
num_states = 2 # Specify the number of states
regime_model = MarkovRegression(ftse_350_re, k_regimes=num_states, trend='c', switching_trend=True)
regime_results = regime_model.fit()

# Get smoothed probabilities
smoothed_probabilities = regime_results.smoothed_marginal_probabilities

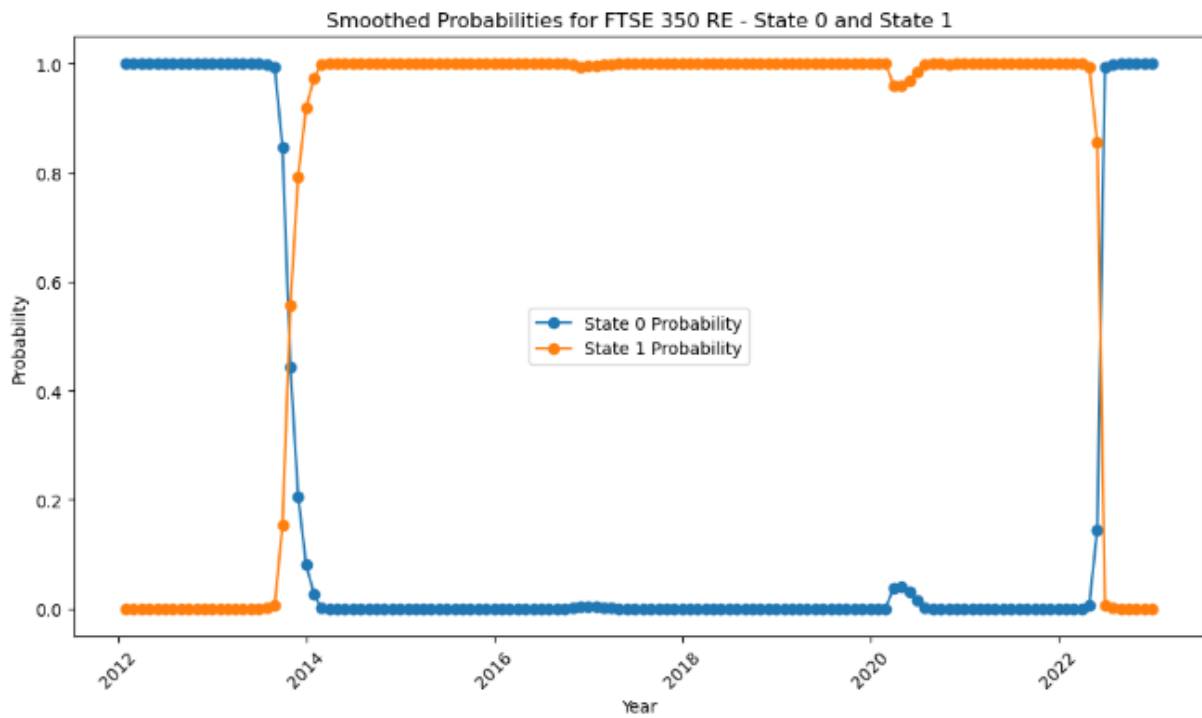
# Data
indexes = dataset.index # Assuming the index is the date
state_0_probs = smoothed_probabilities.iloc[:, 0].values
state_1_probs = smoothed_probabilities.iloc[:, 1].values
plt.plot(indexes, state_1_probs, marker='o', label='State 1 Probability')

# The code will use Matplotlib to create a line chart with two lines (state_0_probs and state_1_probs) plotted
against indexes, visualizing the probabilities of two states, each marked with 'o' markers and labeled
accordingly. It also configures a Matplotlib plot, setting the x-axis label as 'Year', y-axis label as 'Probability',
and the title as 'Smoothed Probabilities for FTSE 350 RE - State 0 and State 1'.

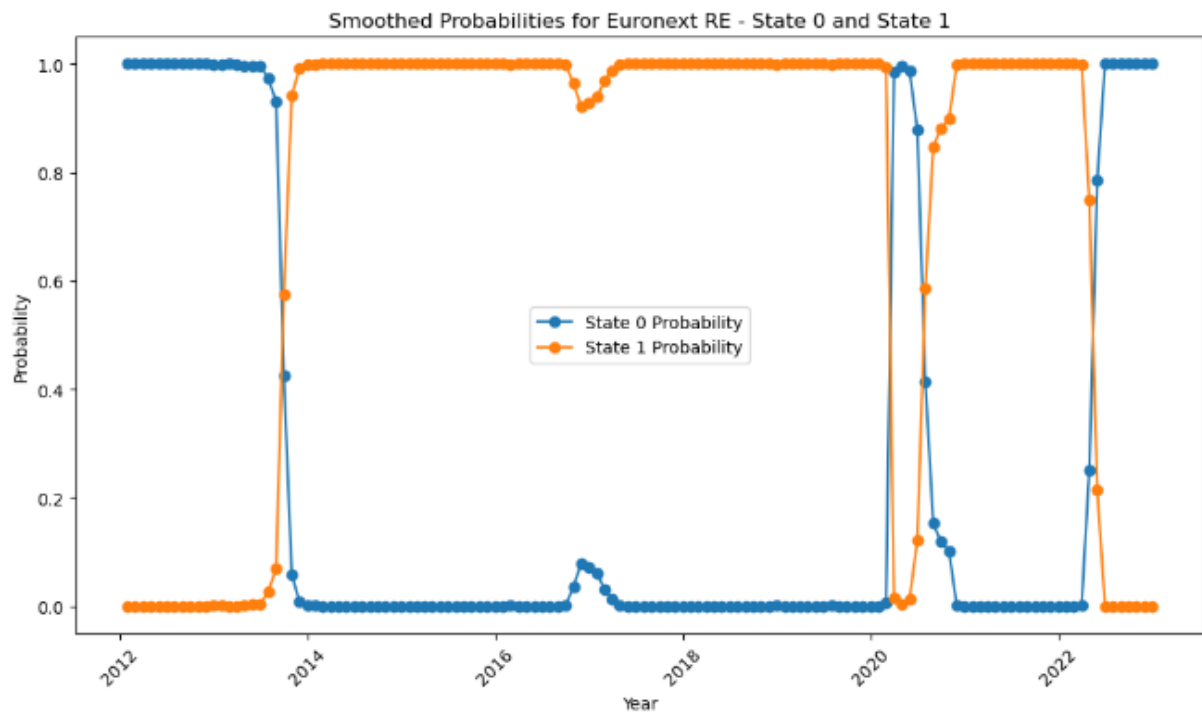
# Lastly, the code includes x-axis label rotation for better readability and calls the necessary functions to
display the plot with the specified labels and title.

```

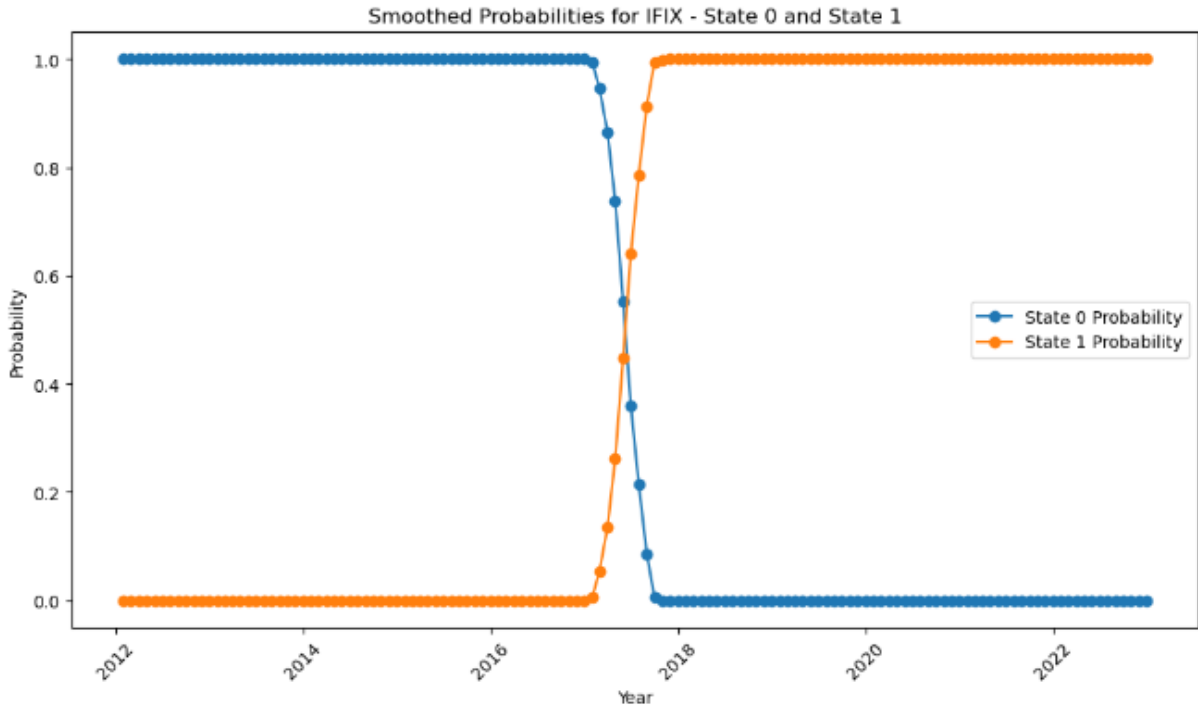
**Graph 9 – MS-VECM & Smoothed Probabilities Evolution – FTSE 350 RE from 2012 to 2022.**



**Graph 10 - MS-VECM & Smoothed Probabilities Evolution – Euronext RE from 2012 to 2022.**

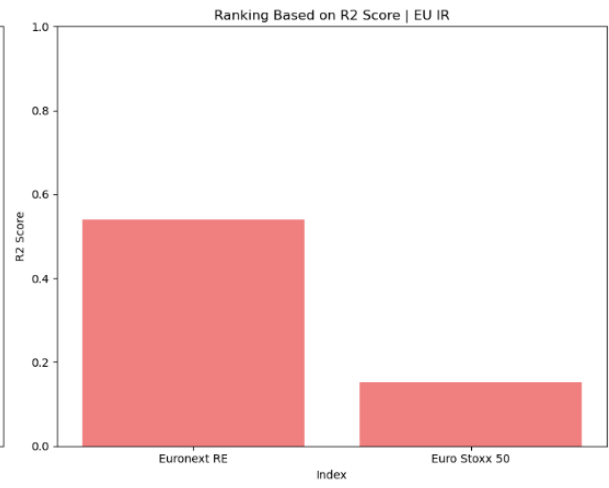
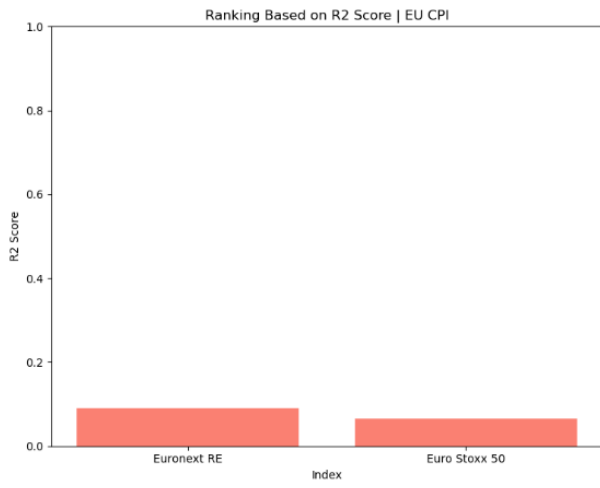


**Graph 11 - MS-VECM & Smoothed Probabilities Evolution – IFIX from 2012 to 2022.**



**Graphs 12 - Correlation Between Interest Rates and Inflation between the Indexes**





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