Master

Applied Econometrics and Forecasting

Master's Final Work

Dissertation

THE ROLE OF CRYPTOCURRENCIES IN THE BRAZILIAN AND AMERICAN STOCK MARKETS

Rafael Ferreira Garcia

June - 2025

Master
Applied Econometrics and Forecasting

Master's Final Work
Dissertation

THE ROLE OF CRYPTOCURRENCIES IN THE BRAZILIAN AND AMERICAN STOCK MARKETS

Rafael Ferreira Garcia

Supervision:
Prof. Nuno Ricardo Martins Sobreira

June - 2025

GLOSSARY

ADF – Augmented Dickey-Fuller.

ARDL – Autoregressive Distributed Lag.

BG – Breusch-Godfrey test for Autocorrelation.

BP – Breusch-Pagan test for Heteroskedasticity.

BRA – Brazil.

BRICS – Brazil, Russia, India, China, and South Africa.

BTC – Bitcoin.

DF – Degrees of Freedom.

ETH – Ethereum

GDP – Gross Domestic Product.

GFC – Global Financial Crisis.

HAC – Newey-West Heteroskedasticity and Autocorrelation consistent standard errors.

NARDL – Non-linear Autoregressive Distributed Lag.

USA – United States of America.

VAR – Vector Autoregressive.

VIX – Chicago Board Options Exchange's Volatility Index

WTI – West Texas Intermediate Crude Oil

ABSTRACT

This dissertation investigates the relationship between major cryptocurrencies, Bitcoin and Ethereum, and the Brazilian and American stock markets, represented by the Ibovespa and S&P 500 indices, respectively, with the aim of assessing their potential roles as portfolio tools, specifically as diversifiers, hedges, or safe havens. The study employs Autoregressive Distributed Lag (ARDL) models and rolling regression techniques to explore the dynamic behavior of these digital assets over time, placing particular emphasis on periods of market stress. The findings reveal nuanced distinctions: Ethereum exhibits characteristics of a hedge against the Brazilian stock market, as evidenced by statistically non-significant coefficient in full-sample regression, whereas Bitcoin functions as a diversifier in that market. In contrast, both cryptocurrencies show statistically significant positive correlations with the S&P 500, suggesting a diversifying role in the American market. However, during high-stress episodes, correlations with both indices increase, signaling weak safe haven properties for both cryptocurrencies. These insights carry important implications for investors seeking to strategically incorporate digital assets into diversified portfolios, especially across varying economic environments.

KEYWORDS: Cryptocurrencies; Stock Markets; Diversification; ARDL; Rolling Regression.

Resumo

Esta dissertação investiga a relação entre as principais criptomoedas, Bitcoin e Ethereum, os mercados de ações brasileiro e americano, representados pelos seus principais índices Ibovespa e S&P 500, respetivamente; com o objetivo de avaliar seus potenciais como ferramentas potenciais para construção de portfolios de investimentos, especificamente como hedges, diversificadores ou *safe haven*. O estudo emprega modelos *Autoregressive Distributed Lag* (ARDL) e técnica de *rolling regression* para explorar o comportamento dinâmico destes ativos digitais ao longo do tempo, com particular ênfase em períodos de estresse nos mercados. Os resultados revelam distinções com nuances: Ethereum exibiu características de hedge contra o mercado brasileiro, evidenciado pelo coeficiente não estatisticamente significativo na regressão abordando a amostra completa, enquanto Bitcoin foi um ativo diversificador no mesmo mercado. Em contraste, ambas criptomoedas agiram como diversificadores para o S&P 500, evidenciado pelos coeficientes positivos e estatisticamente significativos. Durante os períodos de estresse mais alto as correlações com ambos índices se tornam mais relevantes, sinalizando capacidade fraca das criptomoedas serem *safe havens* para os mercados acionários. As inferências trazem importantes implicações para investidores que buscam incorporar ativos digitais estrategicamente em portfolios diversificados, especialmente em ambientes económicos distintos.

PALAVRAS-CHAVE: Criptomoedas; Mercado de Ações; Diversificação; ARDL; Rolling Regressions.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

To my family, whose support was always essential in the pursuit of my goals.

I would also like to thank my supervisor, Professor Nuno Sobreira, for his help and guidance along the way.

1. INTRODUCTION

The behavior of investment assets, particularly their risk and return profiles, has long been a focus of academic and private-sector research, since identifying the relationships between different asset classes is a key component in creating balanced portfolios tailored to particular investment objectives. In the last couple of decades, the creation of multiple digital assets, especially cryptocurrencies, has introduced new variables into portfolio theory. The dynamic world of cryptocurrencies continues to evolve and reshape global financial landscapes, with Bitcoin and Ethereum standing as two of the most influential digital assets. This study examines the performance and relationships of Bitcoin and Ethereum with the Brazilian and American stock markets, two economies with distinct financial infrastructures, adoption rates, and regulatory stances. Exploring these differences will contribute to a deeper understanding of cryptocurrency market behavior in diverse financial ecosystems, the possibilities to incorporate these assets into investment portfolios, and how that affects portfolio diversification in the evolving digital economy.

In light of the evolving financial landscape, expanding our knowledge of the roles played by cryptocurrencies holds significant value for investors seeking diversification and risk mitigation. This study aims to investigate the potential of Bitcoin and Ethereum, the two most prominent cryptocurrencies, to function as diversification tools and hedging instruments against the leading equity indices of two stock indices: Brazil's Ibovespa and the United States' S&P 500. By analyzing their performance and interactions with these indices, the research seeks to assess their practical utility in portfolio construction across distinct economic and regulatory environments.

The rapid increase in price of cryptocurrencies, especially Bitcoin, caught the attention of people, and through media coverage, communication through social media, and the Internet in general, numerous cases of "Bitcoin millionaires" were reported. The perceived possibility of enormous financial gains through digital assets was a big factor capturing the attention of the general public and attracting more investors into these types of markets. The increasing number of Brazilian investors negotiating cryptocurrencies is evidenced by the Special Department of Federal Revenue of Brazil (Receita Federal do Brasil) in its "Criptoativos – Dados Abertos" [Crypto assets – Open Data] report.

According to this document, the number of different individual Brazilian investors reporting crypto assets trading reached its highest number in November of 2023, when 9.2 million investors reported dealing with cryptocurrencies within that month. In comparison, the number of individual investors registered in the B3 (Brasil, Bolsa, Balcão) was 19.4 million, considering both stock market and/or fixed income investors.

With this in mind, it becomes important to differentiate between what is the atypical behavior of a new emerging market and the possible roles of cryptocurrencies in a balanced long-term investment portfolio. Since the launch of Bitcoin on January 3rd, 2009, several studies were published to explain its mechanism, explain and speculate the potential for alternative currencies not controlled by governments, and evaluate how cryptocurrencies behave in comparison and conjunction with other types of more traditional and understood assets.

Significant explorations within this domain have been conducted by Ghorbel, Frikha, and Manzli (2022), who examined the existence of asymmetries in the relationship between cryptocurrency returns and stock market indices. Additionally, Nzokem and Maposa (2024) analyzed the statistical properties of Bitcoin and the S&P 500 distributions, assessing their implications for risk and return. These studies provide valuable insights and are important sources to form the basis of this research. A more comprehensive discussion of these and other relevant contributions is presented in the subsequent literature review section.

Given the relatively short timeframe since Bitcoin's inception and the substantial fluctuations in its value, volatility, and regulatory landscape, understanding the evolving relationship between cryptocurrencies and other assets across different market conditions is of particular interest. Over the past eight years, the cryptocurrency market has experienced significant shifts, influenced by global events such as the COVID-19 pandemic, and the Russia-Ukraine war. These factors have contributed to new patterns of adoption, investment behavior, and regulatory responses, making the analysis of these dynamics crucial. This study aims to explore these evolving trends, offering an addition to the literature on the subject.

In order to identify the ways cyptocurrencies and stock markets interact, time series of daily returns will be analysed. Moreover, we will estimate Auto Regressive Distibuted

Lag (ARDL) models, including significant explanatory variables to control other factors impacting stock market performance. This class of models includes the contemporanous and lagged values of the variables included, providing more information that might be relevant to estimate daily variation in the stock indices prices; to address the evolving relationship between the variables of interest, rolling regressions with windows of one year were performed in addition to regressions involving the whole sample available.

To categorize the ways cryptocurrencies are interacting with stock markets, the definitions presented in the Baur and Lucey (2007) study are utilized. In particular, we will consider three designations of assets: Hedge is an asset uncorrelated or negatively correlated with another asset on average; Diversifier are assets positively but not perfectly correlated with another asset on average; Safe Haven are assets negatively or uncorrelated with other assets or portfolio in times of market stress or turmoil.

Through the estimations performed, evidence was found for Bitcoin being a diversifier for the Brazilian Index while Ethereum being a hedge against the Ibovespa, but safe haven properties were not as clear, following the finding of positive and significant coefficients for the digital currencies during the Covid-19 pandemic and the start of the Russia-Ukraine conflict; gold was found to be a safe haven for the Brazilian stock market, having a negative effect in the higher volatility periods, while not being statistically significant. Bitcoin and Ethereum showed similar behaviors in relation to the S&P 500, acting as diversifiers against the American Index. Gold was found to be a hedge for the American stock index. However, in comparison to its role in the Brazilian market, the safe haven capability was not as strong.

2. Literature Review

Due to the nature of cryptocurrencies and their relatively recent creation and gain in popularity, the literature on the subject is still not as vast as for other topics and assets in the financial area. However, there are a number of important studies that lay the foundation and explore different aspects of this asset class, its market dynamics and relationships with stock and commodity markets, among others. This section will present brief reviews of such studies, their findings and methods, which are important for the procedure of the present work.

The nature and motivation of cryptocurrencies trading were explored by Delfabbro, King, and Williams (2021), presenting psychological mechanisms and associated particularities of this asset class in comparison to equities and other more commonly known assets in order to better understand the core motivations of people entering the cryptocurrencies trading and their behavior responding to movements in price, comparing to other addictive behaviors like gambling to ask for further research of the topic under the light of behavioral psychology.

Volatility dynamics was studied by Fakhfekh and Jeribi (2020), utilizing GARCH models to find the best specification to fit data of sixteen different cryptocurrencies; the authors identified an asymmetric effect to positive shocks, volatility tended to increase following positive shocks, unlike what is more often observed in the dynamics of other financial assets, in which volatility tends to be higher following negative shocks.

A non-linear approach was used by Ghorbel, Frikha, and Manzli (2022) to test asymmetries in the short- and long-run relationships between cryptocurrencies and stock markets. The authors estimated non-linear autoregressive distributed lag models (NARDL) for six cryptocurrencies and seven stock market indices (from the G7 countries), also controlling for the prices of Gold and WTI crude oil prices. Evidence was found for the existence of asymmetric correlations in the short- and long-run; for the long-run relationship, a positive asymmetry was noted, suggesting a weak safe-haven role for cryptocurrencies. In the short run, Bitcoin also had a mostly positive asymmetry. However, the relationships between the other digital currencies and stock markets were not as clear as the long-run ones.

The return and risk of Bitcoin and the S&P 500 index were studied by Nzokem & Maposa (2024). Observing the daily returns of the cryptocurrency and the stock market index, both were shown to be left-skewed and leptokurtic with the heavy tails being the main characteristic for the Bitcoin returns distribution; meanwhile, the more accentuated peaks were the main characteristic of the S&P 500 returns distribution.

Other researchers explored the capability of cryptocurrencies acting as hedge against stock markets, currencies and commodities; such a study was performed by Meshcheryakov and Ivanov (2020), analyzing intraday data for Ethereum, the S&P 500, Gold and USD, the study identified the hedging capability for the digital currency against the US stock market and Gold; with Ethereum also being a safe haven against Gold and acting as an intraday diversifier for the US Dollar. Similarly, Bouri , Gupta, Tiwari, and Roubaud (2017), Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017), and Dyhrberg (2016) found positive results for the capability of Bitcoin hedging against stock market indices and against the United States Dollar. Furthermore, Shahzad, Bouri, Roubaud, Kristoufek, and Lucey (2019) studied if Bitcoin, Gold and other commodities can be safe havens for different stock market indices using data from July 2010 to February 2018. They found that, for some cases, Bitcoin, Gold and the commodity index have weak safe haven properties for the stock market indices. Bitcoin, Ethereum and Litecoin were found to be hedges against Japanese and Asian Pacific equities in Bouri, Lucey, and Roubaud (2020), with evidence for time variability. Similar results were presented in Guesmi, Saadi, Abid, and Ftiti (2019), identifying returns and volatility spillovers between crypto, Gold and stock markets, indicating successful hedging strategies involving equities, crypto, Gold and oil.

The study by Gil-Alana, Abakah, and Rojo (2020) tested if six cryptocurrencies and six stock market indices were correlated, using data from May of 2015 until October of 2018. They identified a low level of connectedness between the cryptocurrencies and also between the cryptocurrencies and the stock indices, providing interesting possibilities for the use of crypto as diversification for stock portfolios. Similarly, Attarzadeh, Isayev, & Irani (2024) provide evidence for low connectedness of Bitcoin with Gold, renewable energies and stock markets in the period between November 2013 and August 2022 during non-crisis periods.

Furthermore, Chittineni (2025) explores the interdependence of cryptocurrencies with global uncertainties, finding evidence that the latter influences the former, with geopolitical risk having a positive effect on crypto returns, while economic policy uncertainty negatively affecting the crypto market. A study by Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) found that cryptocurrencies were relatively isolated from other financial assets, a conclusion supported by the low level of spillover between them. On the other hand, Toudas, Pafos, Boufounou, and Raptis (2024) provide evidence for time-varying correlations between Bitcoin, Gold, and the Dow Jones Index.

3. Dataset and Exploratory Analysis

The dataset begins on March 11th, 2016, and finishes on March 31st, 2025, corresponding to 2277 trading days. Due to calendar differences, some dates do not have data available for all the variables. To take this into account, days in which one or more variables are missing will be disregarded in the regressions, resulting in 2154 total observations to be used in the study.

3.1. Stock Indices

The stock indices analyzed in this study are the Ibovespa, representing the Brazilian stock market, and the S&P 500, representing the United States stock market. Daily closing price data, extracted from Bloomberg, was used for both indices, with values calculated in United States Dollar (USD). To assess stationarity, Augmented Dickey-Fuller (ADF) tests were conducted, revealing that the closing prices are non-stationary. Table I shows the stock indices and respective codes from the Bloomberg database.

However, daily returns — computed using the formula: Return of variable $R_t = (X_t - X_{t-1})/X_{t-1}$ — were found to be stationary based on the ADF tests. Given this fact, daily returns will serve as the primary data for the study. Table I presents the stock indices used as dependent variables.

Table I – List of Stock Indices

Stock Index	Country	Currency	Bloomberg Code
S&P 500	USA	USD	SPX:IND
Ibovespa	BRA	USD	IBOV:IND

Figure 1 plots the time series, in levels, of the Ibovespa and the S&P 500. The initial value for the Ibovespa is 13727.51 and the last data point is 22759.12, representing a 65.79% increase in the period. The S&P 500 index initial observation is 2022.19 and its last observation is 5611.85, a 177.51% increase in the same period; the American index showed a clearer upward trend, while the Brazilian index had more erratic behavior and higher volatility. In addition, the two major stock market shocks that occurred in this period, namely the Covid-19 pandemic and the Russia-Ukraine conflict initiated on February 24th, 2022, presented more significant negative effects on the Ibovespa, regarding both the decline in prices and increase in volatility.

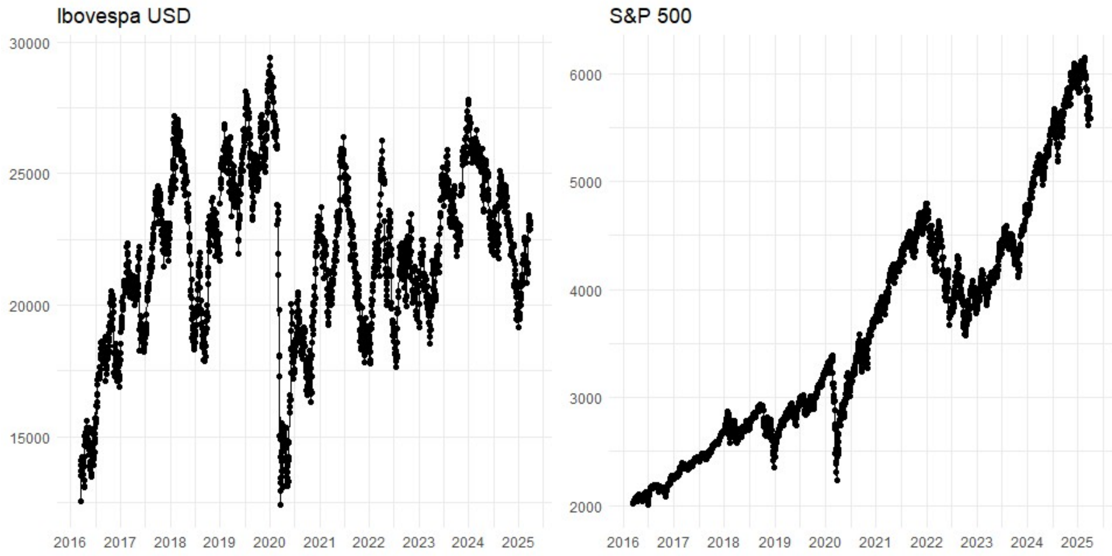

FIGURE 1 - Stock Indices Time Series

Figure 2 presents the volatilities of the stock market indices, Bitcoin and Ethereum, calculated as the standard deviation of daily returns, obtained using sample sizes of 252 consecutive observations. Similar behaviors can be seen in the two stock indices, having similar periods of increases and decreases in volatility, with the Ibovespa presenting higher values. The same can be said for the cryptocurrencies as similar patterns were observed and Ethereum had more significant volatilities.

The beginning of the Covid-19 pandemic caused a very clear spike in volatility for the stock markets. When addressing the start of the pandemic, this study uses as reference the date of January 20th, 2020, the date of the first confirmed Covid-19 case in the United States. For the cryptocurrencies, increases in volatility were also observed in this period, even though they were not in the same proportion, not being the highest levels observed in the dataset. While the start of the Russia-Ukraine conflict coincided with another period of increased volatilities in the stock markets, the same cannot be said for Bitcoin and

Ethereum, no increase in volatility was observed. In fact, the ending of 2021 and the beginning of 2022 represent the start of a clear downtrend for crypto volatility.

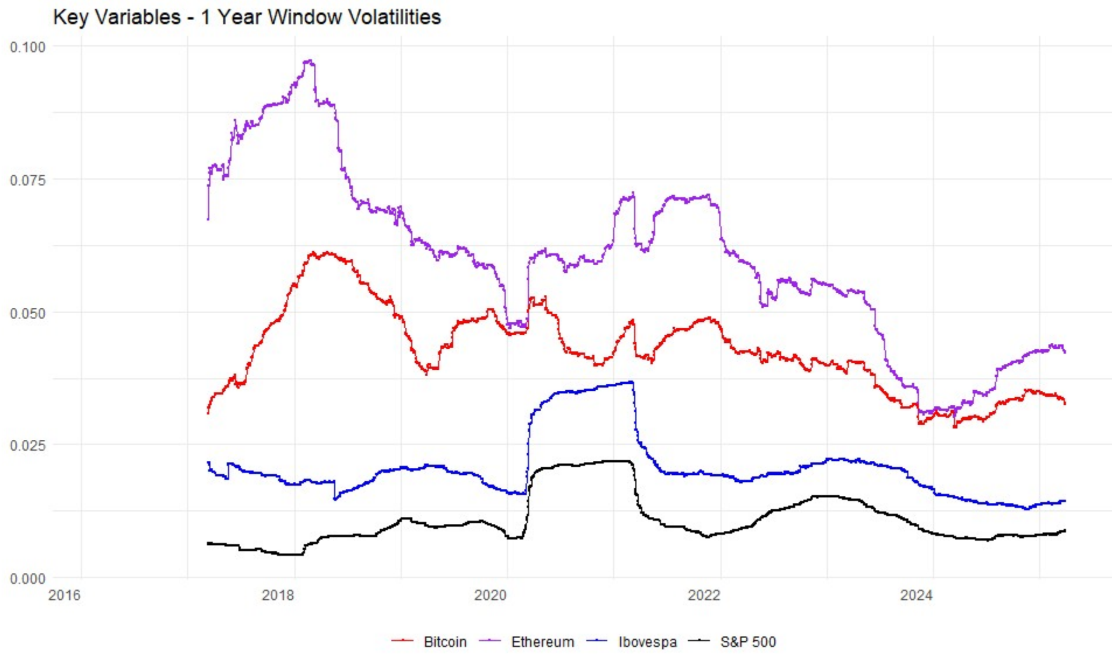

FIGURE 2 - Stock Markets and Crypto Volatilities (Standard Deviation)

3.2. Explanatory variables

The explanatory variables used were also extracted from Bloomberg daily closing prices in USD, except for Ethereum, which was extracted from the investing.com database for a larger sample size, and are the following: Gold, West Texas Intermediate (WTI) Oil, the Chicago Board Options Exchange Volatility Index (VIX), Bitcoin (BTC) and Ethereum (ETH). Additionally, the Bloomberg US Treasury Index (LUATTRUU) and the Bloomberg US Treasury Inflation-Linked Bond Index (LBUTTRUU) were used for the regressions involving the S&P500 index; meanwhile, for the Ibovespa regressions, the Bloomberg EM Local Currency Government Index (EMLCTRUU) and the Bloomberg EM Government Inflation-Linked All Maturities TRI (BEMG0Z) were used as explanatory variables.

ADF tests were performed to assess stationarity, and evidence was obtained for the stationarity of the daily returns of the explanatory variables, which will be used for the regressions and analyses in the present study. Table II presents the list of all the explanatory variables and their respective codes in the Bloomberg and investing.com databases.

TABLE II - LIST OF EXPLANATORY VARIABLES

Variable	Database Code
Bitcoin	XBTUSD BGN Curncy
Ethereum	ETH/USD
Gold	XAU BGN Curncy
WTI	CL1 COMB Comdty
VIX	VIX Index
US Treasury Bond Index	LUATTRUU Index
US Inflation-Linked Bond Index	LBUTTRUU Index
EM Local Currency Govt Bond Index	EMLCTRUU Index
EM Govt Inflation-Linked Index	BEMG0Z

Time series of the explanatory variables are shown in levels in Figure Figure 3. The same points of interest, mainly the starts of the Covid-19 pandemic and the Russia-Ukraine conflict, show declines in most assets under analysis, with the exceptions of Gold, the US Treasury Bond Index and the Volatility Index (VIX); Ethereum did not present a clear effect of the pandemic, which is a little surprising and will be further explored in the section dedicated to the empirical results, given this possible indication that the currency could possess hedging, or even safe haven qualities to the stock markets.

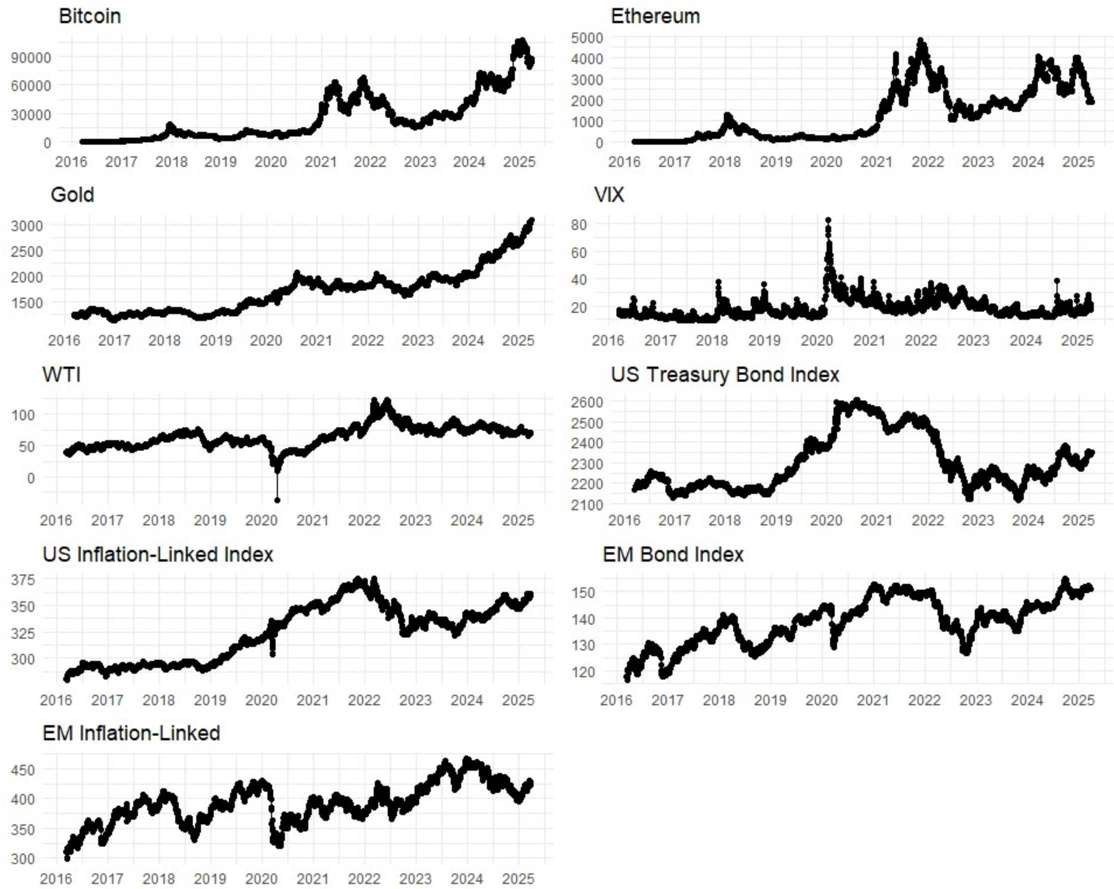

FIGURE 3 - Explanatory Variables Time Series

4. METHODOLOGY

In order to take into account the contemporaneous and one lag effects of the variables to the movement in the stock markets, the Autoregressive Distributed Lag (ARDL) model, as presented in Pesaran and Shin (1999) was used, with the specification (1,1,1,1,1,1,1), in a rolling regression setup, with sample sizes of 252 data points (approximately 1 year), in the format of equation (1) below. Different orders were tested for the model, this order was selected to keep a balance of simplicity and interpretability of results, given that the improvements perceived by more complex specifications in the selection criteria comparisons were minimal and different specification orders were found to minimize the Information Criteria for each different Stock Index-Cryptocurrency combination. Under this setup, we can estimate the dynamic relationships between the variables included in this study, having the advantage of making it possible to observe if trends exist, how they change and the variability of the occurring impacts. The ARDL approach is suited for examining the interactions among macroeconomic variables and financial indicators, allowing for the analysis of both the immediate and long-run effects.

The Rolling Regression technique is a dynamic method used to analyze the evolution of relationships between variables over time. Unlike static regression models, rolling regression applies moving windows, allowing for the estimation of time-varying coefficients. This method is particularly useful in situations where structural changes, regime shifts, or evolving economic conditions may influence the stability of parameter estimates, which are very relevant to the case analyzed. The rolling window approach will allow for the identification of temporal variations in coefficients, providing deeper insights into the stability and evolution of the examined relationships, contributing to a more comprehensive understanding of the dynamic interactions among key variables.

For each pair of dependent variable and cryptocurrency a different model was also estimated, with the complete sample available, generating one single set of results for the whole period, which will be used for comparison in the analysis. The model that is estimated is as follows:

$$\begin{gathered} Y_t = \alpha_{0,i} + \alpha_{1,i} Y_{t-1} + \beta_{0,i} Crypto_t + \beta_{1,i} Crypto_{t-1} + \beta_{2,i} Gold_t + \beta_{3,i} Gold_{t-1} + \\ \beta_{4,i} WTI_t + \beta_{5,i} WTI_{t-1} + \beta_{6,i} VIX_t + \beta_{7,i} VIX_{t-1} + \\ \beta_{8,i} Bond\ Index_t + \beta_{9,i} Bond\ Index_{t-1} + \\ \beta_{10,i} Inflation\ Bonds_t + \beta_{11,i} Inflation\ Bonds_{t-1} + u_{t,i}\ , \\ \\ t_j \in [j, j+1, \dots, j+251] \\ j = 1, 2, \dots, 1902 \end{gathered} \tag{1}$$

In this model, Y represents equity indices, specifically the Ibovespa and the S&P 500. The variable Crypto includes the cryptocurrencies Bitcoin and Ethereum. Bond Index refers to sovereign bond benchmarks, namely the Bloomberg US Treasury Bond Index and the Bloomberg EM Local Currency Government Bond Index. Finally, Inflation Bonds comprises inflation-protected securities, represented by the US Inflation-Linked Bond Index and the EM Government Inflation-Linked Bond Index, and u_t is the error term.

Impact multipliers are calculated according to Verbeek (2004). The immediate impact multiplier is given by equation (2).

(2) $$\frac{\partial Y_t}{\partial X_t} = \beta_0$$

Impact multiplier after one period is given by equation (3):

(3) $$\frac{\partial Y_{t+1}}{\partial X_t} = \alpha_1\beta_0 + \beta_1$$

Long-run multiplier is given by equation (4):

(4) $$\text{Long} - \text{run multiplier} = (\beta_0 + \beta_1) / (1 - \alpha_1)$$

4.1. Heteroskedasticity, Residual Autocorrelation, and ARCH Effects Tests

The Breusch-Godfrey (BG) test, presented by Breusch (1978) and Godfrey (1978), is a procedure used to detect the presence of autocorrelation in the residuals of a dynamic linear regression model. Autocorrelation occurs when the error terms in a regression equation are correlated across observations, violating the assumption of independence and potentially leading to biased and inconsistent parameter estimates. The Breusch-Godfrey test accommodates models with lagged dependent variables (dynamic models); in this study, the BG test will be applied to assess whether the residuals of the regression model exhibit autocorrelation and their results for the regressions involving the whole sample size period are presented in the section dedicated to the empirical results. The final outcome is that no evidence for first order serial autocorrelation was detected in the regressions.

Homoskedasticity is another assumption, and it will be tested with the Breusch-Pagan (BP) test. Developed by Breusch and Pagan (1979), is a test used to detect the presence of heteroskedasticity in a regression model. Heteroskedasticity occurs when the conditional variance of the error term is not constant across observations, violating the assumption of homoskedasticity in ordinary least squares (OLS) regressions. This violation can lead to inefficient parameter estimates and unreliable statistical inference. The Breusch-Pagan test was applied to assess whether the residuals exhibit heteroskedasticity, and the results are presented in the following section. If heteroskedasticity turns out to be significant, appropriate adjustments will be made to improve the robustness of the analysis, contributing to a more accurate interpretation of the estimated relationships.

Furthermore, a test for ARCH effects was performed. The ARCH-Lagrange Multiplier test, introduced by Engle (1982), is a diagnostic procedure used to detect Autoregressive Conditional Heteroskedasticity (ARCH) in the time series residuals. By regressing the squared residuals on their own lagged values, the test evaluates whether past variance influences current volatility, indicative of time-varying variance. Results of the tests performed on the whole sample regressions found evidence for the presence of ARCH effects in each model at 5% significance level.

4.2. Robust Standard Errors

Following the tests, the Newey-West estimator will be utilized. Introduced by Newey and West (1987), it is a widely used econometric technique for estimating robust standard errors in the presence of heteroskedasticity and autocorrelation. When the assumptions of homoskedasticity and/or residual autocorrelation are violated, conventional standard errors become unreliable, leading to inefficient and potentially biased inference. The Newey-West estimator corrects these issues by providing heteroskedasticity and autocorrelation consistent (HAC) standard errors. In this study, the Newey-West HAC estimator will be employed to ensure that standard errors remain robust in the presence of heteroskedasticity and autocorrelation. This methodological choice enhances the reliability of the empirical findings and ensures that statistical inference is not compromised by violations of standard OLS assumptions.

5. Empirical Results

This section is dedicated to bringing and analyzing the results of the performed regressions, including the complete time frame of available observations as well as the rolling regressions, which sum to a total of 1902 estimated models for each pair of stock index and cryptocurrency.

5.1. Ibovespa-Bitcoin Results

Table III presents the results of the Ibovespa-Bitcoin regression encompassing the complete data sample. In this regression, Bitcoin return has a positive coefficient, being statistically significant at the 5% level, its lagged variable has a negative coefficient and is not statistically significant. This indicates that adding Bitcoin to a Brazilian stock portfolio has potential for diversification. The long run multiplier in this regression is positive.

WTI oil also has a positive coefficient and is not statistically significant in this regression. VIX and Gold have negative coefficients, with the latter not being statistically significant, showing a greater potential for it to be a safe haven for the Brazilian market.

Now the results for the rolling regressions for the Ibovespa-BTC are shown in Figure 4 . The 252 days rolling volatility of the Ibovespa had a big spike in the covid-19 period and decreased since; the Bitcoin volatility has consistently decreased throughout the years, showing more stability for the crypto market.

The coefficients for the contemporaneous Bitcoin returns were, almost always, positive and had statistical significance at 5% in the period following the first cases of Covid, in which both assets lost value and had an increase in volatility. From the total 1902 regressions, the coefficients for the cryptocurrency were statistically significant at the 5% level in 363, representing 19.08% of total cases. These results indicate the potential benefits for diversification when adding Bitcoin to a Brazilian stock portfolio, including a weaker possibility of it being used as a hedge against the Ibovespa.

TABLE III – IBOV-BTC REGRESSION FOR THE WHOLE PERIOD

Term	Coefficients	Std. Error	t_Value	p_Value
(Intercept)	0,0003	0,0003	1,184	0,2370
lag(returns_ibovespa)	-0,186***	0,049	-3,842	0,0001
returns_bitcoin	0,019**	0,008	2,466	0,0138
lag(returns_bitcoin)	-0,013	0,009	-1,403	0,1601
returns_gold	-0,035	0,043	-0,812	0,4166
lag(returns_gold)	-0,027	0,057	-0,473	0,6360
returns_wti	0,010	0,009	1,166	0,2438
lag(returns_wti)	-0,0007	0,004	-0,190	0,8490
returns_vix	-0,048***	0,006	-8,130	7,18E-16
lag(returns_vix)	0,009**	0,004	2,122	0,0339
returns_em	-0,491***	0,156	-3,149	0,0017
lag(returns_em)	0,288**	0,130	2,204	0,0276
returns_inflation_em	1,929***	0,113	17,077	2,13E-61
lag(returns_inflation_em)	0,142	0,090	1,568	0,117

R^2 = 0.5536 | F-statistic = 204, p-value = 2.2E-16 | BG-statistic = 0.0164, p-value BG-statistic = 0.9

BP-statistic = 51.213, p-value BP-statistic = 1.844E-6

*, ** and *** indicates significance level at 10%, 5% and 1%, respectively

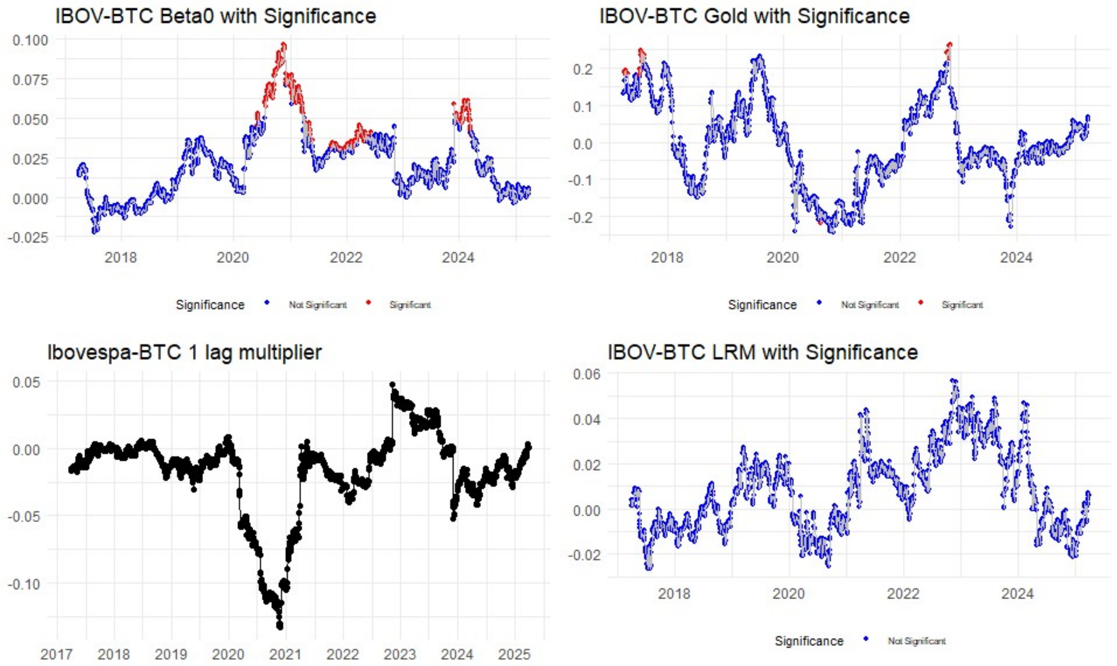

FIGURE 4 - Ibovespa-BTC Regression Results

5.2. Ibovespa-Ethereum Results

The estimated Ethereum returns coefficient was found to be positive and not statistically significant at 5% level in the regression for the Ibovespa index involving the whole sample space available; the lagged variable, however, was shown to be significant and have a negative coefficient. This indicates diversification and hedging potential for this cryptocurrency. VIX, WTI Oil, and Gold followed the same pattern as in the regression using Bitcoin as the cryptocurrency.

Regarding the rolling regressions using Ethereum as the cryptocurrency explanatory variable, the significance was similar when compared to Bitcoin, having greatly increased in the period right after the first Covid-19 cases, and falling in the subsequent periods, being not significant at 5% in most of the regressions as only 9.04% of the estimated coefficients were found to be statistically significant at 5% level, being concentrated in the end of 2019 and beginning of 2020, correlating with the higher stock markets volatility. Observing that the coefficients are also positive in these periods, it can be concluded that the digital currency did not present strong safe-haven properties.

TABLE IV – IBOV-ETH REGRESSION FOR THE WHOLE PERIOD

Term	Coefficients	Std. Error	t_Value	p_Value
(Intercept)	0,0004	0,0003	1,401	0,161
lag(returns_ibovespa)	-0,186***	0,047	-3,977	7,2E-05
returns_ethereum	0,007	0,007	0,963	0,335
lag(returns_ethereum)	-0,016**	0,007	-2,250	0,025
returns_gold	-0,027	0,042	-0,638	0,523
lag(returns_gold)	-0,025	0,058	-0,430	0,667
returns_wti	0,011	0,009	1,198	0,231
lag(returns_wti)	-0,0009	0,004	-0,241	0,810
returns_vix	-0,048***	0,006	-8,579	1,8E-17
lag(returns_vix)	0,007*	0,004	1,860	0,063
returns_em	-0,487***	0,154	-3,168	0,002
lag(returns_em)	0,296**	0,131	2,261	0,024
returns_inflation_em	1,924***	0,108	17,768	5,5E-66
lag(returns_inflation_em)	0,142	0,091	1,557	0,120

R^2 = 0.5542 | F-statistic = 204.5, p-value = 2.2E-16 | BG-statistic = 0.007, p-value BG-statistic = 0.93

BP-statistic = 52.372, p-value BP-statistic = 1.162E-6

*, ** and *** indicates significance level at 10%, 5% and 1%, respectively.

The instant and long-run multipliers for ETH were mostly negative throughout the regressions, showing a greater hedging potential of this cryptocurrency against the

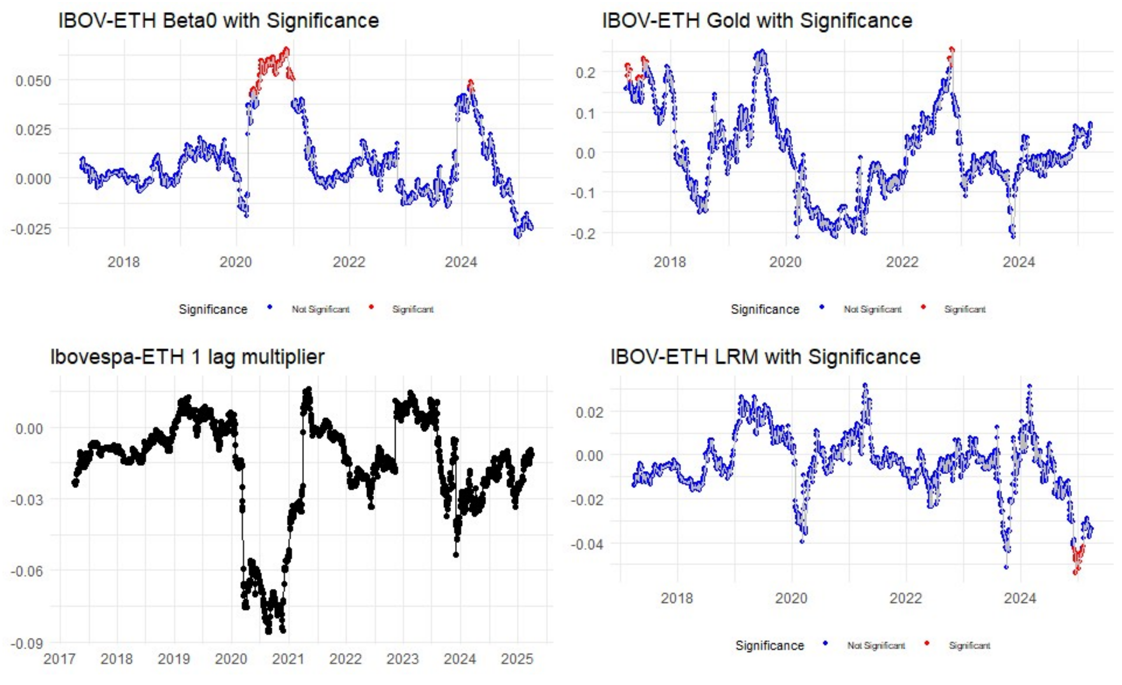

FIGURE 5 - Ibovespa-ETH Regressions

Brazilian stock market when compared to BTC; however, the greater volatility must be considered. Results are found in Figure 5.

5.3. S&P 500-Bitcoin Results

In the regression where the S&P 500 daily returns were used as the dependent variable and Bitcoin returns were introduced as the cryptocurrency in the explanatory variables, the results are presented in Table V. In this case, Bitcoin also had positive immediate and long-run impact multipliers. The contemporaneous variable was significant at 1%, while the lagged variable was not significant. Here, we also observe potential for Bitcoin being used for portfolio diversification.

Gold returns had a positive, albeit not statistically significant coefficient in the S&P regression for the whole period, having less potential for being used as a safe haven in comparison to the Brazilian market. WTI was not statistically significant with a positive coefficient, while the VIX index had a negative coefficient and was significant at 1%.

The coefficients associated with contemporaneous Bitcoin (BTC) returns are predominantly positive, while those related to the lagged BTC variable tend to be negative. Both sets of coefficients exhibit extreme values following the emergence of the first COVID-19 cases. The estimated long-run multipliers are mostly positive, as illustrated in Figure 6. Regarding statistical significance, after the onset of the COVID-19 pandemic, 764 coefficients—representing 40.17% of the total estimations—were found to be significant at the 5% level. These findings indicate a weaker hedging potential for BTC against the S&P 500, while still being useful as a diversifier for the American stock market portfolio.

The behavior of Gold is more similar to BTC in the S&P 500 regressions, when compared to the Ibovespa regressions, with gold returns coefficients having more points of statistical significance when compared to the Brazilian market regressions, and mostly positive coefficients.

TABLE V – S&P 500-BTC WHOLE PERIOD

Term	Coefficients	Std_Error	t_Value	p_Value
(Intercept)	0,0009***	0,0001	5,313	1,2E-07
lag(returns_sp)	-0,186**	0,072	-2,563	0,010
returns_bitcoin	0,027***	0,006	4,506	7E-06
lag(returns_bitcoin)	-0,006	0,005	-1,126	0,260
returns_gold	0,055	0,035	1,552	0,121
lag(returns_gold)	0,0001	0,028	0,005	0,996
returns_wti	0,003	0,003	0,765	0,445
lag(returns_wti)	-0,003***	0,001	-3,495	0,0004
returns_vix	-0,083***	0,007	-12,42	3E-34
lag(returns_vix)	-0,014***	0,005	-2,831	0,005
returns_us_treasury	-0,676***	0,196	-3,446	0,0005
lag(returns_us_treasury)	-0,143	0,136	-1,052	0,293
returns_us_inflation	0,508**	0,232	2,188	0,029
lag(returns_us_inflation)	0,323**	0,155	2,086	0,037

$R^2 = 0.5261$ | F-statistic = 182.6, p-value = 2.2E-16 | BG-statistic = 2.10, p-value BG-statistic = 0.15
BP-statistic = 184.71, p-value BP-statistic = 2.2E-16
*, ** and *** indicates significance level at 10%, 5% and 1%, respectively

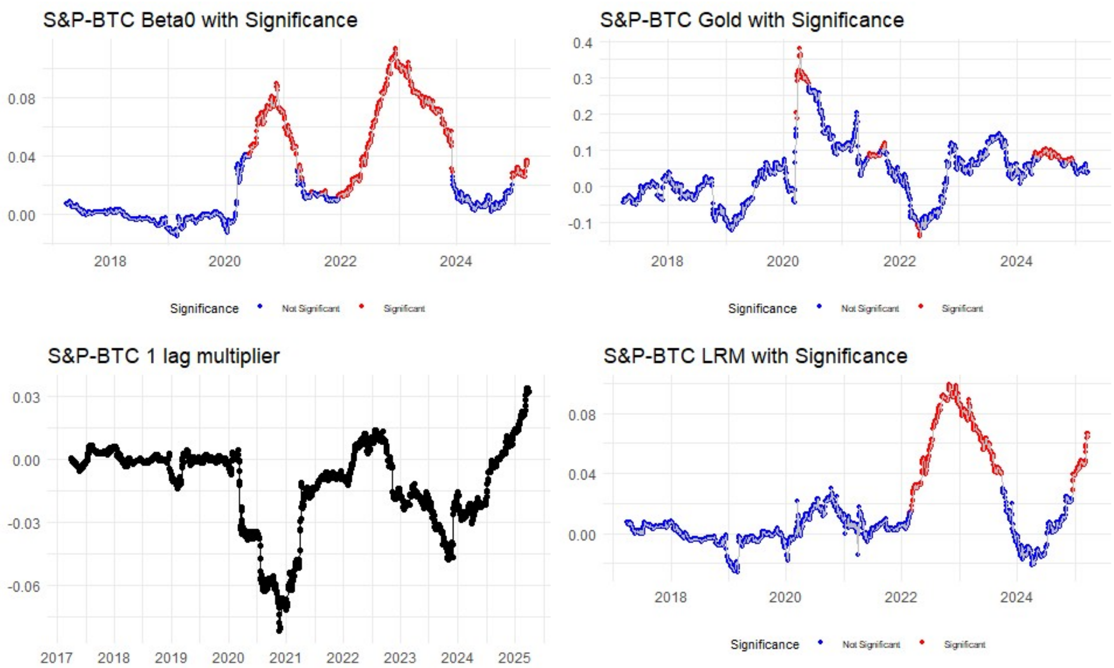

FIGURE 6 - S&P 500-BTC Results

5.4. S&P 500-Ethereum Results

Table VI reports the results for the regression involving the complete dataset for the S&P 500 and Ethereum. The cryptocurrency returns have a positive and statistically significant coefficient, at the 1% level; Gold returns as well presented a positive but not statistically significant coefficient at 1%. This indicates that both assets were diversifiers, with gold also being a hedge against the American stock index.

To evaluate the possibility of these being safe havens, an analysis of the rolling regressions will be performed, checking the behavior during the important negative shocks that occurred in this period.

Very similar behavior to BTC in the ETH regressions, but here the long-run multiplier has more alternation between positive and negative values. During the COVID-19 pandemic—marked by the most significant negative shocks— Ethereum displayed positive and statistically significant coefficients. This pattern provides evidence against its role as a safe haven for the U.S. stock market, suggesting instead that it functioned solely as a diversifier. The corresponding results are shown in Figure 7. Out of the 1902 regressions, Ethereum had 764 statistically significant coefficients (40.17%), these being concentrated in the periods following the negative shocks.

Gold returns also have very similar patterns here in relation to the BTC regressions, with positive and statistically significant coefficients following the beginning of the pandemic in 2020; after the negative shock in 2022, the estimated coefficients were negative, presenting mixed signals for the possibility of the precious metal being a safe haven.

TABLE VI – S&P 500 – ETH WHOLE PERIOD REGRESSION

Term	Coefficients	Std. Error	t_Value	p_Value
(Intercept)	0,0008***	0,0002	5,735	1,1E-08
lag(returns_sp)	-0,186***	0,069	-2,703	0,007
returns_ethereum	0,017***	0,006	3,074	0,002
lag(returns_ethereum)	-0,004	0,005	-0,928	0,353
returns_gold	0,058	0,036	1,586	0,113
lag(returns_gold)	-0,0007	0,027	-0,028	0,978
returns_wti	0,003	0,003	0,883	0,377
lag(returns_wti)	-0,003***	0,001	-3,559	0,0003
returns_vix	-0,083***	0,007	-12,605	3,4E-35
lag(returns_vix)	-0,014***	0,005	-2,904	0,004
returns_us_treasury	-0,665***	0,197	-3,370	0,0008
lag(returns_us_treasury)	-0,146	0,141	-1,037	0,300
returns_us_inflation	0,504**	0,234	2,158	0,031
lag(returns_us_inflation)	0,327**	0,155	2,106	0,035

R^2 = 0.5253 | F-statistic = 182.1, p-value = 2.2E-16 | BG-statistic = 2.99, p-value BG-statistic = 0.084 | BP-statistic = 181.2, p-value BP-statistic = 2.2E-16

*, ** and *** indicates significance level at 10%, 5% and 1%, respectively

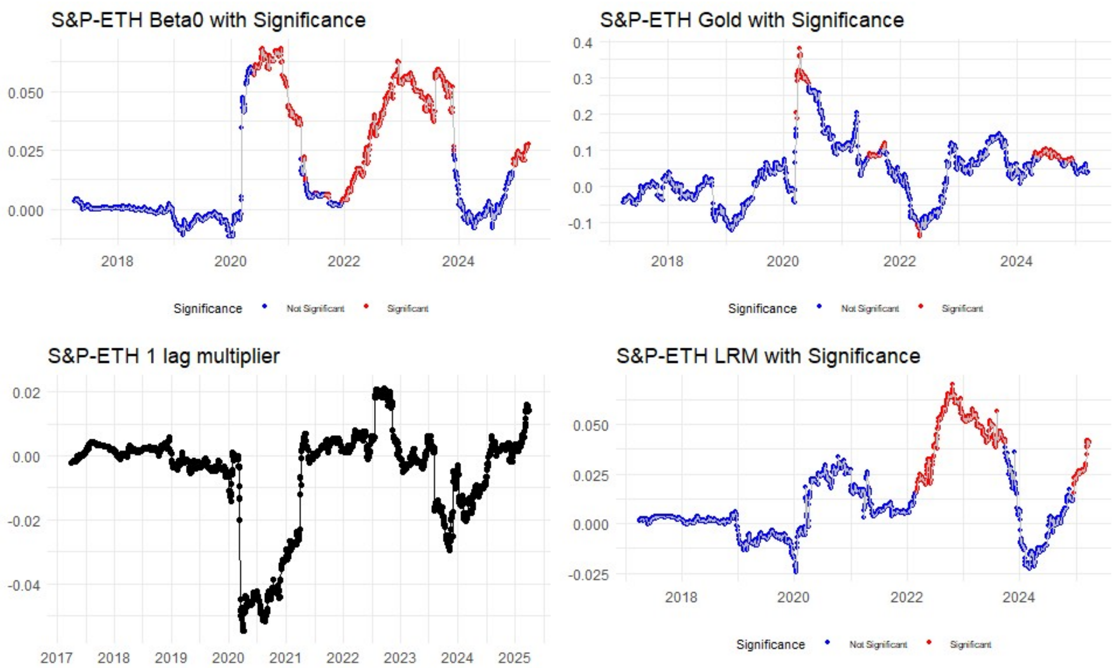

FIGURE 7 - S&P 500-ETH Regressions

6. CONCLUSION

This work studies the relationships between the daily returns of stock markets and cryptocurrencies, namely the Ibovespa, main stock index for the Brazilian market, and the S&P 500, main American index; the two cryptocurrencies used were the Bitcoin and Ethereum, the two most well-known and traded digital currencies at this moment. To control for other factors involved in the pricing of stock indices, government bond indices, the volatility index VIX, gold, and oil were also introduced as explanatory variables. The most important aspect of the present analysis is whether cryptocurrencies showed evidence of being suitable diversifiers, hedges, or safe havens for the stock markets.

Evidence was found for Ethereum having greater hedging potential against the Ibovespa, while Bitcoin did not present desirable characteristics in this sense, being classified as a diversifier for the Ibovespa. The results for the American market were not so significant, with the cryptocurrencies showing behavior of diversifiers, none of the digital currencies presented the characteristics of safe haven assets following the negative shocks in the period studied.

In the same period, the results regarding gold provided evidence for it being a safe haven for the Brazilian market, being negatively correlated in high stress moments for the Ibovespa in both regressions. Comparatively, the results for the S&P 500 were not as clear in regard to the role of gold, where the metal was found to have positive and statistically significant coefficients in some cases following the higher stress periods, however it could still be qualified as a safe haven for the S&P 500 in this period.

These findings offer interesting insight into how incorporating cryptocurrencies to stock portfolios can be beneficial, especially for Brazilian investors. Further useful knowledge could be gained by the continuous study of this area, with possible expansions involving other developed and emerging markets, as well as more digital assets. This area can gain renewed interest following the last American federal elections of 2024, with the Trump administration indicating possible important changes in regulations for cryptocurrencies that, if confirmed, could amplify the incorporation of crypto in investment portfolios, as well as a more common reserve of value in daily life. This would provide new possibilities and demand new studies accommodating these new characteristics and expanding the time horizon of further analyses. Further research possibilities also include different model specifications within the ARDL framework, different models with ARCH/GARCH effects, and other formats to incorporate possible structure breaks in the relationship between these variables.

References

Attarzadeh, A., Isayev, M., & Irani, F. (2024). *Dynamic interconnectedness and portfolio implications among cryptocurrency, gold, energy, and stock markets: A TVP-VAR approach. Sustainable Futures, 8*, 100375. doi:https://doi.org/10.1016/j.sftr.2024.100375

Baur, D., & Lucey, B. (2007, February). *Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. Financial Review, 45*. doi:10.1111/j.1540-6288.2010.00244.x

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). *Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters, 23*, 87-95. doi:https://doi.org/10.1016/j.frl.2017.02.009

Bouri, E., Lucey, B., & Roubaud, D. (2020). *Cryptocurrencies and the downside risk in equity investments. Finance Research Letters, 33*, 101211. doi:https://doi.org/10.1016/j.frl.2019.06.009

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). *On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Finance Research Letters, 20*, 192-198. doi:https://doi.org/10.1016/j.frl.2016.09.025

Breusch, T. S. (1978). *Testing for Autocorrelation in Dynamic Linear Models*. Australian Economic Papers, 17*, 334-355. doi:https://doi.org/10.1111/j.1467-8454.1978.tb00635.x

Breusch, T. S., & Pagan, A. R. (1979). *A Simple Test for Heteroscedasticity and Random Coefficient Variation. Econometrica, 47*, 1287–1294. Retrieved May 9, 2025, from http://www.jstor.org/stable/1911963

Caporin, M., Chang, C.-L., & McAleer, M. (2019). *Are the S&P 500 index and crude oil, natural gas and ethanol futures related for intra-day data? International Review of Economics & Finance, 59*, 50-70. doi:https://doi.org/10.1016/j.iref.2018.08.003

Chittineni, J. (2025, February). *Cryptocurrency Market Dynamics: Interconnectedness and Interdependence with Global Uncertainties. Journal of Applied Economic Sciences (JAES)*, 123. doi:10.57017/jaes.v20.1(87).08

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). *Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economics Letters, 165*, 28-34. doi:https://doi.org/10.1016/j.econlet.2018.01.004

Delfabbro, P., King, D. L., & Williams, J. (2021, July). *The psychology of cryptocurrency trading: Risk and protective factors. Journal of behavioral addictions, 10*(2), 201-207.

Dyhrberg, A. H. (2016). *Hedging capabilities of bitcoin. Is it the virtual gold? Finance Research Letters, 16*, 139-144. doi:https://doi.org/10.1016/j.frl.2015.10.025

Engle, R. F. (1982). *Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation.* Econometrica, 50(4), 987–1007. https://doi.org/10.2307/1912773

Fakhfekh, M., & Jeribi, A. (2020). *Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. Research in International Business and Finance, 51*, 101075. doi:https://doi.org/10.1016/j.ribaf.2019.101075

Ghorbel, A., Frikha, W., & Manzli, Y. S. (2022). *Testing for asymmetric non-linear short- and long-run relationships between crypto-currencies and stock markets. Eurasian Economic Review, 12*, 387–425. doi:10.1007/s40822-022-00206-8

Gil-Alana, L. A., Abakah, E. J., & Rojo, M. F. (2020). *Cryptocurrencies and stock market indices. Are they related? Research in International Business and Finance, 51*, 101063. doi:https://doi.org/10.1016/j.ribaf.2019.101063

Godfrey, L. G. (1978). *Testing for Higher Order Serial Correlation in Regression Equations when the Regressors Include Lagged Dependent Variables. Econometrica, 46*, 1303-1310. Retrieved from https://onlinelibrary.wiley.com/doi/abs/0012-9682(197811)46:6<1303:TFHOSC>2.0.CO;2-U

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). *Portfolio diversification with virtual currency: Evidence from bitcoin. International Review of Financial Analysis, 63*, 431-437. doi:https://doi.org/10.1016/j.irfa.2018.03.004

Meshcheryakov, A., & Ivanov, S. (2020). *Ethereum as a Hedge: The intraday analysis. Economics Bulletin, 40*, 101-108. Retrieved from https://ideas.repec.org/a/ebl/ecbull/eb-19-01010.html

Newey, W. K., & West, K. D. (1987). *A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica, 55*, 703–708. Retrieved May 9, 2025, from http://www.jstor.org/stable/1913610

Nzokem, A., & Maposa, D. (2024). *Bitcoin versus S&P 500 Index: Return and Risk Analysis. Mathematical and Computational Applications, 29*. doi:10.3390/mca29030044

Pesaran, M. H., & Shin, Y. (1999). *An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. In S. Strøm (Ed.)*, *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium* (pp. 371–413). Cambridge University Press.

Shahzad, S. J., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). *Is Bitcoin a better safe-haven investment than gold and commodities? International Review of Financial Analysis, 63*, 322-330. doi:https://doi.org/10.1016/j.irfa.2019.01.002

Toudas, K., Pafos, D., Boufounou, P., & Raptis, A. (2024). *Cryptocurrency, Gold, and Stock Exchange Market Performance Correlation: Empirical Evidence. FinTech, 3*, 324–336. doi:10.3390/fintech3020018

Verbeek, M. (2004). *A Guide to Modern Econometrics* (2 ed.). John Wiley and Sons.