From Gold to Blockchain: How Macro Forces Shape Crypto Returns

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Thesis submitted to the University of Ottawa
in partial Fulfillment of the requirements for the
M.Sc. Management with thesis - Concentration in finance

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Abstract

This thesis explores the dynamic interplay between traditional economic indicators, specifically inflation rates, gold prices and market sentiment in predicting the future returns of the 20 largest cryptocurrencies, excluding stablecoins and initial coin offers (ICOs). The daily returns of cryptocurrencies are analyzed over a three-year period. Utilizing multiple regression analysis techniques on data, this study aims to quantify and model the influences of these traditional and contemporary economic measures on cryptocurrency performance. The research seeks to bridge the gap between conventional financial theories and the rapidly evolving digital currency landscape by investigating the extent to which these economic indicators can forecast cryptocurrency market movements. In a financial ecosystem increasingly intertwined with digital innovations, this thesis posits that the Consumer Price Index (CPI) and gold, often viewed as a traditional safe haven, could be significantly correlated with cryptocurrency valuations. Moreover, the study delves into the role of market sentiment, derived from economic news and social media, in shaping cryptocurrency trends, suggesting that sentiment analysis, particularly using advanced tools like the Fear and Greed index for real-time social media text analysis, provides predictive insights into market fluctuations. Through comprehensive data analysis, this research not only aims to enhance the understanding of digital asset pricing dynamics but also contributes to strategic investment and policy decisions in the digital age. By integrating established economic measures with cutting-edge sentiment analysis, the thesis offers a novel perspective on the potential drivers of cryptocurrency markets, providing valuable insights for investors and the broader financial community.

1.0 Introduction

In the fast-changing financial environment, academic research is primarily created in the changing financial landscape in which formerly traditional economic measures come close to the world of digital currencies. Among many of the economic indicators, the Consumer Price Index (CPI) is, of course, a critical measure for monitoring inflation rates and cost-of-living trends over time. In tracking the mean price changes according to average changes in the value of a composite of goods and services that measure consumption, inflationary pressures are defined by the CPI. A high value of CPI reflects continued inflation, which decreases the real value of money when the general prices of commodities uplift. This CPI-inflation relationship is especially pertinent within the realm of digital currencies, as its fluctuations can severely inhibit or cause a severe spike in the stability and valuation of cryptocurrencies.

Due to the limited supply and strength against monetary shocks, Bitcoin has been drawn parallel to gold, which has, earned the name of "digital gold" for Bitcoin, a possible investment alternative in highly inflationary times. Traditionally, gold has been used as a risk-off asset during times when currency was being devalued. Bitcoin increasingly represents a contemporary counterpart, given its decentralized nature and finite supply. Nevertheless, the price instability of Bitcoin and the extent to which it responds to market capital flow and sentiments complicate things, setting it apart from gold. This thesis explores the intricate relationship between CPI, gold prices, market sentiment, and their collective impact on cryptocurrency valuation, further substantiating the influence of these factors on digital asset performance.

The relationship between cryptocurrencies and inflation is nuanced. Unlike fiat currencies, which are directly influenced by central bank policies, cryptocurrencies operate on decentralized networks and may act as a hedge against inflation. However, the high volatility of cryptocurrencies adds a layer of unpredictability to their behavior in inflationary contexts. Research by Liu and Tsyvinski (2018) highlights the unique risk-return profile of cryptocurrencies, suggesting that their performance can be significantly distinct from traditional financial assets. This distinction may partly explain the complex relationship between cryptocurrencies and inflation, as they are not directly tied to the monetary policies that typically drive inflationary trends.

Market sentiment, shaped by economic news and social media trends, is crucial in influencing cryptocurrency markets. Research by Shapiro et al. (2020) explores innovative methods for assessing economic sentiment through news analysis, revealing how quickly market outlooks can shift in response to financial reports and media coverage. A surge in positive sentiment often strengthens consumer confidence, leading to increased spending and, in some cases, higher inflation. Conversely, negative sentiment can weaken consumer optimism, reducing expenditures and lowering inflationary pressures. This dynamic is especially pronounced in the cryptocurrency space, where prices frequently react to shifts in sentiment. By incorporating sentiment analysis into economic forecasting, analysts gain a deeper and more nuanced perspective on inflation trends. This Enhances traditional models that primarily rely on historical data.

This thesis investigates the predictive relationships between key economic indicators inflation, gold prices, and market sentiment, along with the returns of the 20 largest cryptocurrencies over the past three years. By concentrating on these leading digital assets, which account for a significant share of the cryptocurrency market, the study aims to provide a thorough analysis. The research employs multiple regression analysis techniques, including linear regression, probit regression, and quantile regression, to establish predictive models that integrate variables such as CPI, gold prices, and market sentiment.

The study delves into the role of market sentiment, using advanced tools like the Fear and Greed Index, which aggregates various sentiment measures, including social media analysis, trading volume, and market volatility. This index provides a real-time snapshot of investor emotions, offering valuable insights into the collective mood of the cryptocurrency market. By incorporating sentiment analysis into the predictive models, the research aims to capture the immediate impacts of market sentiment on cryptocurrency prices. This provides a more comprehensive understanding of the drivers behind cryptocurrency market movements.

Beyond traditional economic indicators, this thesis also examines the influence of key financial variables, such as the S&P 500, the VIX (Volatility Index), and the 10-year Treasury bond yield, on cryptocurrency returns. These factors are incorporated to provide a broader perspective on the relationship between traditional financial markets and digital assets. The S&P 500 acts as a benchmark for overall market performance, while the VIX captures investor sentiment and perceived market risk. Meanwhile, the 10-year Treasury bond yield offers insights into long-term interest rate expectations and macroeconomic stability. By analyzing these elements, the study seeks to identify additional factors that may impact cryptocurrency prices and improve the predictive accuracy of its models.

The methodology of this thesis is built on a comprehensive dataset that includes daily closing prices of 20 leading cryptocurrencies, macroeconomic indicators such as the Consumer Price Index (CPI) and gold prices, as well as market sentiment data sourced from the Fear and Greed Index. Spanning three years, this dataset provides a solid foundation for examining the interplay between economic indicators, investor sentiment, and cryptocurrency returns. To analyze these relationships, the study applies multiple regression techniques, including linear regression, probit regression, and quantile regression, allowing for a deeper exploration of how these variables influence cryptocurrency market performance.

The findings of this research add to the ongoing discussion on the integration of digital assets into the global financial system. By bridging the gap between traditional financial theories and the rapidly evolving digital currency landscape, this thesis provides strategic insights that could guide both investment strategies and policy decisions in the digital era. Beyond deepening our understanding of how conventional economic indicators influence cryptocurrency markets, the study underscores the critical role of sentiment analysis in predicting price movements. Through this in-depth examination, the research offers valuable perspectives for investors, policymakers, and scholars. These insights are particularly useful for those seeking to navigate the complexities of the ever-changing cryptocurrency ecosystem.

In conclusion, this thesis seeks to deepen the academic understanding of the predictive relationships between inflation, market sentiment, gold prices, and the future returns of cryptocurrencies. By integrating established economic measures with cutting-edge sentiment analysis, the research offers a novel perspective on the potential drivers of cryptocurrency markets. The findings aim to provide valuable insights for investors and the broader financial community, contributing to strategic investment and policy decisions in the digital age.

2.0 Objective

The primary objective of this thesis is to explore the predictive relationships between key economic indicators namely, inflation rates, gold prices, and market sentiment and the future returns of the 20 largest cryptocurrencies. This research aims to quantify how these traditional and contemporary economic measures can collectively forecast the performance of digital currencies. By focusing on the top cryptocurrencies, which hold the most significant market capitalizations and represent a substantial portion of the digital asset economy, the study ventures to offer insightful comprehensive and relevant analyses.

The study will employ multiple regression analysis techniques to achieve this objective, utilizing these regression techniques to establish predictive models. These models will integrate variables such as the CPI as a measure of inflation, the prices of gold as a traditional economic haven, and indices of market sentiment derived from social media analysis. The choice of these variables is grounded in their historically proven impact on financial markets and their potential to provide a nuanced understanding of the drivers behind cryptocurrency price movements. The regression analyses will seek to identify significant predictors and their relative weights, providing a robust statistical foundation to forecast cryptocurrency returns.

Moreover, the thesis will examine the interplay between these variables and their combined effect on the cryptocurrency market. It will assess whether the relationships are linear or if more complex interactions exist, such as non-linear dependencies or potential threshold effects, which are critical in cryptocurrency investments' highly volatile and speculative environment. This comprehensive approach will not only enhance our understanding of how traditional economic indicators influence digital currencies but also contribute to the broader discourse on the integration of digital assets into the global financial system. Through this analytical exploration, the thesis aims to bridge the gap between conventional financial theories and the evolving 6 landscape of digital currencies, offering strategic insights that could inform investment and policy decisions in the digital age.

3.0 Literature review

3.1 Understanding Cryptocurrency Markets

The cryptocurrency market is known for its high volatility and rapid growth, which presents both unique challenges and opportunities for understanding asset pricing dynamics. As digital currencies gain traction in mainstream financial systems, understanding their valuation mechanisms is more important than ever. This section explores the intricate interplay of market sentiment and economic indicators that shape cryptocurrency pricing, weaving together insights from empirical research and broader economic theories.

A key factor in cryptocurrency pricing is market sentiment, which often exerts a more pronounced influence on prices than it does on traditional financial assets. Research by Al Guindy (2021) underscores the significant role of investor attention, especially as expressed through social media platforms like Twitter. By examining approximately 25 million tweets, Al Guindy's research found a strong correlation between heightened sentiment and increased price volatility in cryptocurrency markets. This finding highlights the responsiveness of cryptocurrencies to retail investor sentiment, rendering them particularly vulnerable to rapid valuation swings driven by public perception.

Investor attention, often measured through social media metrics like tweets, retweets, and likes, acts as a real-time barometer of public interest and sentiment in the cryptocurrency market. Al Guindy’s study employs a Vector Autoregression (VAR) framework to explore the causal relationship between investor attention and market volatility. The findings reveal that heightened levels of attention not only predict but can also drive significant price fluctuations. This relationship highlights the profound influence of investor behavior on cryptocurrency markets, where public opinion can catalyze swift and substantial movements in asset prices.

A study by Antonakakis et al. (2019) further supports the idea that investor attention, particularly through social media, plays a critical role in cryptocurrency price volatility. Their research demonstrates that spikes in social media activity, such as tweets and online discussions, often precede significant price movements in cryptocurrencies like Bitcoin and Ethereum. This aligns with Al Guindy's findings, reinforcing the importance of investor attention as a key driver of cryptocurrency market dynamics.

While investor sentiment plays a crucial role, understanding cryptocurrency pricing also demands an examination of broader economic indicators. Unlike traditional assets, cryptocurrencies often display intricate responses to global economic changes. For example, during times of economic uncertainty, they can behave similarly to haven assets like gold. This phenomenon was notably observed during the COVID-19 pandemic, a period in which cryptocurrencies attracted significant investment as investors sought alternatives to traditional markets. This shift highlights the evolving role of digital currencies in diversified investment portfolios and their potential to act as a hedge against financial instability. A study by Bouri et al. (2017) explored the role of cryptocurrencies as a safe haven during periods of economic uncertainty. Their research found that Bitcoin, in particular, exhibited properties similar to gold, acting as a hedge against market downturns and economic instability. This supports the idea that cryptocurrencies can serve as alternative investments during times of crisis, further emphasizing their unique position in the financial ecosystem.

The decentralized nature of cryptocurrencies allows them to function independently of national monetary policies, which can make them particularly appealing during periods of currency devaluation or high inflation. This independence positions cryptocurrencies as a potential hedge against traditional economic instability. However, this same decentralization introduces a layer of unpredictability to their market behavior. Prices are often swayed by a wide range of factors, including global economic conditions, technological developments, and shifting regulatory landscapes across different countries. These influences can result in rapid and sometimes unexpected changes in cryptocurrency valuations, making them both an opportunity and a challenge for investors.

Nevertheless, cryptocurrencies respond to economic stimuli in ways that differ significantly from traditional assets. For instance, while equity markets typically react to factors like changes in interest rates or corporate earnings, cryptocurrency markets often exhibit heightened sensitivity to technological developments, regulatory announcements, or updates in network infrastructure. Al Guindy's research supports this by providing empirical evidence that cryptocurrencies are shaped not only by investor attention but also by external economic events that may appear peripheral to conventional financial systems. This unique responsiveness underscores the distinct nature of digital assets within the broader financial ecosystem.

Al Guindy's methodological approach, which combines extensive data collection with advanced econometric modeling, provides a valuable framework for future research in cryptocurrency markets. By establishing a causal relationship between investor attention and price volatility, his study lays the groundwork for developing predictive models that better capture the complexities of market sentiment. Such models are essential for investors seeking to manage the inherent volatility of cryptocurrency markets while making more informed decisions in this rapidly evolving financial landscape.

Understanding what drives cryptocurrency prices is essential for both investors and policymakers. For investors, being able to anticipate market movements by analyzing investor sentiment can lead to smarter, more strategic investment choices. For policymakers, identifying the factors that shape cryptocurrency pricing is critical to crafting regulatory frameworks that promote market stability while safeguarding the interests of participants. These insights are particularly important as digital currencies continue to integrate into mainstream financial systems, creating opportunities and challenges for economic governance.

Analyzing cryptocurrency markets necessitates an interdisciplinary approach that weaves together behavioral finance along with data science. Al Guindy's research provides critic insights into the role of investor attention and its impact on market volatility, offering a valuable foundation for further academic and practical inquiry. As digital currencies continue to evolve and increasingly integrate into the global financial system, both academic and financial communities must advance their tools and theories. These efforts will be essential for accurately reflecting and predicting the complex behaviors of these assets. This literature review not only broadens the scope of academic understanding but also underscores the urgent need for ongoing, rigorous research to navigate the ever-changing landscape of cryptocurrency economics effectively

3.2 Domestic and International Policy

Cryptocurrencies are still a growing type of investment, and big-picture economic trends heavily impact them. Inflation, changes in monetary policy, geopolitical conflicts, and new tech all play a huge role in shaping these markets. For investors, that means there are plenty of opportunities, however, there are some serious risks to watch out for. Expansionary monetary policies, like quantitative easing (QE), have often given cryptocurrencies a boost by flooding the financial system with liquidity. When interest rates are low, the cost of holding assets that do not generate yield, such as Bitcoin, decreases. This shift can make cryptocurrencies more appealing to investors looking for alternative stores of value.

On the other hand, when central banks implement contractionary policies, such as hiking interest rates, cryptocurrencies tend to come under pressure. An argument could be made that higher interest rates make traditional fixed-income investments more appealing, often causing investors to shift funds away from riskier assets like cryptocurrencies. Nevertheless, as bitcoin and other cryptocurrencies begin to establish themselves more in the market they can be viewed as a commodity and less risky. Having investors look at them more as gold, especially bitcoin with its limited amount of supply.

Cryptocurrencies have increasingly positioned themselves as digital safe-haven assets during times of geopolitical instability. Events such as trade wars, military conflicts, or economic sanctions can shake traditional markets, leading investors to seek refuge in decentralized assets like Bitcoin and Ethereum. Their global, borderless nature offers an alternative store of value and a hedge against the uncertainties of traditional financial systems.

Cryptocurrencies provide significant utility for cross-border transactions, particularly in areas with volatile currencies or strict capital controls. During financial crises in countries like Venezuela and Turkey, local cryptocurrency adoption surged as people turned to digital assets to safeguard their wealth and mitigate the effects of currency devaluation. Events in these countries saw hyperinflation and their banks needing to raise interest rates and adopt new monetary policies to prevent further disaster. Cryptocurrencies offered a lifeline, enabling individuals to preserve value and access a more stable financial alternative. Nonetheless, it goes without saying in developing countries uncertainty often intensifies regulatory scrutiny of cryptocurrencies. Governments may perceive these assets as a challenge to financial stability or a means of circumventing economic controls, prompting stricter regulations. These crackdowns can stifle market growth, dampen investor sentiment, and create headwinds for cryptocurrency adoption.

In the Western world, we see the increasing adoption of blockchain technology by enterprises and governments is strengthening the legitimacy of cryptocurrencies. Innovations such as smart contracts, decentralized finance (DeFi), and non-fungible tokens (NFTs) are broadening the practical applications of digital currencies. This expanded utility is drawing significant institutional investment, further cementing the role of cryptocurrencies in the global financial ecosystem. We now notice companies such as Tesla, MicroStrategy, and PayPal incorporate digital assets into their business strategies. This shift is partly driven by macroeconomic conditions, including low returns from traditional assets. Seeking higher yields, institutions are increasingly turning to cryptocurrencies as an attractive alternative investment, further accelerating the mainstream acceptance of digital currencies. Better regulatory trends are crucial in influencing the trajectory of cryptocurrency markets. Favourable developments, such as the approval of Bitcoin ETFs or the establishment of transparent tax regulations, can foster market expansion and attract new investors. On the other hand, restrictive measures, including outright bans or burdensome compliance mandates, can stifle market growth and diminish investor confidence, highlighting the delicate balance between regulation and innovation in the crypto space.

Further in emerging economies with underdeveloped financial infrastructures, cryptocurrencies provide a decentralized alternative to traditional banking systems. Services like remittances, peer-to-peer lending, and microtransactions are increasingly gaining momentum in regions such as Africa and Southeast Asia. These digital solutions offer greater financial inclusion, enabling individuals to access services that might otherwise be unavailable or prohibitively expensive through conventional channels. The rise of Central Bank Digital Currencies (CBDCs) presents opportunities for cryptocurrencies CBDCs could legitimize the idea of digital currencies on a global scale, sparking greater adoption and innovation across the crypto industry. It is a double-edged sword that could reshape the landscape for digital assets.

A study by Sukomardojo et al. (2023) in the International Journal of Science and Society dives into how cryptocurrencies impact macroeconomic stability. The research takes a close look at inflation, exchange rates, and regulatory hurdles, showing how widespread crypto adoption could disrupt traditional monetary systems. For example, it highlights how cryptocurrencies might affect currency values and trade balances. The Key point of Crypto volatility can create risks for economic stability, especially during times of global financial uncertainty. The study also examines how different regulatory approaches, from supportive frameworks to outright bans, influence the role of cryptocurrencies in the global economy. Ultimately, the findings underline the importance of balanced regulations that can maximize the benefits of cryptocurrencies while keeping potential risks in check.

Macroeconomic trends have a major impact on cryptocurrency markets. Factors like monetary policies, and global uncertainty highlight the dual nature of cryptocurrencies, as both speculative assets and potential stores of value. As this market grows, it is going to be essential for policymakers and researchers to understand how these big-picture economic forces shape the digital financial world. Navigating these complexities is key to making informed decisions in this space.

3.3 Reviewing Our Regression Option to Price Cryptocurrency

Linear regression is a classic tool for figuring out the relationship between one dependent variable and one or more independent variables by fitting a straight-line equation to our data. When it comes to cryptocurrencies, this method helps estimate how variables such as CPI or gold prices might influence crypto returns on average. It is a plain approach, which is part of its benefits, it is easy to understand and useful for spotting early predictive trends in economic data. However, there are disadvantages, linear regression assumes things like constant variance known as homoscedasticity and normally distributed errors. In the unpredictable world of cryptocurrencies, these assumptions can break down fast. That is why more advanced techniques, like quantile regression, often step in, they are better at handling outliers and skewed distributions, which are common in financial markets.

Quantile regression, first introduced by Koenker and Bassett (1978), takes regression analysis further by focusing on conditional quantiles of the response variable similar as the median or other percentiles, instead of the average. This makes it an innovative tool for analyzing cryptocurrency data, which often has non-normal distributions and heavy tails. Additionally, what is great about quantile regression is that it does not rely on averages. Instead, it presents how independent variables influence different parts of the distribution of crypto returns, whether we are looking at the middle, the highs, or the lows. This broader perspective is incredibly helpful for evaluating both risk and reward, especially in the volatile world of cryptocurrency markets, where sudden swings and uncertainty are normal.

Quantile regression proves effective at capturing the complex ways macroeconomic uncertainties impact cryptocurrency returns. (Assamoi et al., 2025) research highlights how economic indicators and interactions with other asset classes affect crypto returns differently across various quantiles. The influence of these factors is not one-size-fits-all. For instance, higher quantiles, such as periods of stronger returns, seem to react more to positive market sentiment and stable economic conditions. On the flip side, lower quantiles tend to be more vulnerable to negative economic shocks, due to this higher volatility. This nuanced approach gives a clearer picture of how cryptocurrencies behave under different market conditions.

By combining linear and quantile regressions, we get a balanced approach that bridges traditional econometric methods with cutting-edge tools designed for the unique challenges of cryptocurrency markets. This integration enhances our ability to analyze both the average trends and the subtleties in market behavior. With this dual framework, we can explore how standard economic indicators such as inflation or gold, alongside crypto-specific factors, such as blockchain activity and regulatory updates, shape the market. More importantly, this approach uncovers how these influences vary across different performance levels, giving us a deeper understanding of both typical patterns and extreme market conditions. It is a robust way to tackle the complexities of crypto analysis.

Comparing linear and quantile regression models sheds light on how well standard linear models hold up in financial contexts where anomalies and extreme values are common. The beauty of quantile regression lies in its ability to handle these irregularities, making it an essential tool for building more reliable and comprehensive financial models, especially when predicting cryptocurrency returns. The value of using these advanced econometric tools goes far beyond academic interest, as it has real-world applications in financial planning and risk management.

Additionally, another regression technique that should be considered in asset pricing for cryptocurrencies is probit regression. Probit regression can be particularly useful in the asset pricing of cryptocurrencies due to its ability to handle binary or ordinal dependent variables where outcomes are classified as binary. In the context of cryptocurrency markets, probit models can effectively estimate the probability of extreme price movements based on macroeconomic indicators or other relevant factors. This makes it a valuable tool for predicting significant market events, such as crashes or rallies, based on threshold levels of these indicators. Unlike linear regression, probit regression does not assume a linear relationship between the independent and dependent variables. Instead, it estimates the probability that a dependent variable equals 1, given specific values of the independent variables. This is particularly beneficial in the erratic and often nonlinear world of cryptocurrency pricing, where traditional models might fail to capture the full scope of market dynamics. Probit models are thus essential for developing more effective strategies for risk management and investment decision-making in the crypto space, providing insights not just into average outcomes but into the likelihood of extreme ones as well.

For investors and policymakers, the insights from linear and quantile regression analyses offer a clear advantage. They provide the data-driven foundation needed to craft smarter strategies that address both the risks and opportunities in the volatile cryptocurrency markets. Looking ahead, future research could expand on these methods to further refine predictive models and explore how different economic scenarios affect cryptocurrencies. With these tools, we are not just understanding crypto markets better but also, we are equipping decision-makers to navigate them with greater confidence. Future studies could take this foundation even further by incorporating machine learning techniques to boost the predictive accuracy of these models, especially in fast-paced, real-time trading environments where both speed and precision are key. Machine learning has the potential to uncover hidden patterns and adapt to rapidly changing market dynamics in ways traditional models cannot.

3.4 BitGold

In recent years, Bitcoin has emerged as a contender to gold's traditional status as a store of value. Both assets share similarities, they are finite resources with a capped supply and in the right context are resistant to censorship along with confiscation. However, Bitcoin offers unique advantages. It is digital nature that allows for easy storage and transfer, without the need for physical custody or transport, reducing logistics costs and security concerns associated with gold. Moreover, Bitcoin's divisibility enables microtransactions and broader accessibility compared to gold, typically traded in larger, less divisible units.

Furthermore, Bitcoin's programmable nature opens possibilities for innovative financial applications and smart contracts, enhancing its utility and value proposition. While gold remains entrenched as a store of value, Bitcoin's attributes make it an appealing alternative, particularly in an increasingly digital and interconnected world. However, its status as the new gold is subject to ongoing debate and analysis in financial markets.

This digital asset, characterized by its limited supply and decentralization, mirrors gold's scarcity and independence from traditional financial systems. However, the comparison extends beyond scarcity, market dynamics, and the evolving narrative of digital assets as legitimate stores of value. Doumenis et al (2021)'s paper examines Bitcoin's journey and is scrutinized through a lens that compares its volatility with that of gold, the S&P 500, and Treasury Bonds. The authors note, "Bitcoin volatility far outstrips that of many emerging market currencies. For example, Bitcoin is more volatile than currencies with strict capital controls, which are typically found in EM countries with high inflation" (Doumenis et al, 2021). This observation underscores the speculative nature of Bitcoin, challenging its comparison to gold, which has been a stable store of value for millennia.

Further exploring the relationship between Bitcoin and gold, the paper identifies a positive correlation between Bitcoin's price volatility and the price volatility of traditional financial assets both before and during the COVID-19 pandemic. This correlation suggests a nuanced role for Bitcoin within the broader financial ecosystem, acting "more as a speculative asset rather than a steady store of value" (Doumenis et al, 2021). However, the paper positions Bitcoin in the evolving narrative of financial assets, acknowledging its potential to reshape investment strategies.

A study by Ozturk (2020) titled "Dynamic Connectedness between Bitcoin, Gold, and Crude Oil Volatilities and Returns" dives into this discussion, examining the interrelations among these assets. The research underscores the significance of analyzing connectedness in aggregate terms and across different frequencies, considering the distinct impacts of various shocks on these assets. Ozturk's findings reveal a nuanced narrative, while volatility connectedness among these assets is prominent, it is predominantly driven by medium frequencies in volatility and high frequencies in returns. This distinction is crucial for investors contemplating diversification strategies, suggesting that while short-to medium-term diversification may be challenging due to heightened connectedness, long-term strategies could potentially yield benefits, similar to gold.

The findings from Documenis et al research illuminate the intricate dynamics of Bitcoin within the global financial landscape. While the paper casts light on Bitcoin's heightened volatility and speculative nature when compared to traditional assets like gold, Ozturk's paper complements this perspective by unraveling the complex connectedness patterns between Bitcoin and gold. This study offers a multifaceted understanding of Bitcoin's role as the "new gold" in digital finance. It underscores the necessity of considering both volatility and the frequency of connectedness in assessing Bitcoin's potential as a diversification instrument. As the digital asset continues to evolve, its comparison to gold becomes increasingly nuanced, marked by both its potential for high returns and its vulnerability to rapid shifts in market sentiment. This emerging narrative not only challenges traditional investment models but also encourages a more nuanced analysis of digital assets' place in the broader financial ecosystem.

3.5 CPI and Inflation

Cryptocurrencies and inflation may behave similarly due to the decentralized nature of digital currencies, which are less influenced by government monetary policies compared to traditional currencies. This independence might allow cryptocurrencies to maintain their value or even appreciate during periods of high inflation, where the purchasing power of government-controlled currencies decreases. However, the volatility inherent in cryptocurrencies adds a layer of complexity to their behavior in inflationary contexts, making their reactions not always predictable or uniform.

Liu and Tsyvinski delve into the unique risk-return profile of cryptocurrencies, suggesting that their performance can be significantly distinct from traditional financial assets. This distinction may partly explain the complex relationship between cryptocurrencies and inflation. Unlike fiat currencies, whose value can be directly impacted by inflation through central bank policies, cryptocurrencies operate on a decentralized network, potentially offering a hedge against inflationary pressures. However, the paper also highlights the high volatility of cryptocurrencies, indicating that while they may act independently of traditional inflationary trends, they introduce their risks and uncertainties.

A study by Conlon et al. (2020) delves into Bitcoin's role as an inflation hedge, particularly in times of economic instability. Their research suggests that Bitcoin shares certain characteristics with gold, often serving as a store of value when inflation rises. However, they also highlight that Bitcoin's effectiveness in this role is heavily influenced by market conditions and investor sentiment, leading to significant price volatility. These findings align with the work of Liu and Tsyvinski, reinforcing the notion that while cryptocurrencies may provide some degree of protection against inflation, they remain far from a guaranteed safeguard.

The pricing dynamics of traditional asset classes and macroeconomic variables offer crucial insights into the cross-sectional returns of cryptocurrencies. Research by Assamoi et al. (2025) reveals that cryptocurrencies are intricately connected to traditional financial markets, displaying varying degrees of correlation. For instance, the study identifies a negative relationship between cryptocurrency returns and both equity and commodity markets, suggesting that cryptocurrencies may serve as alternative assets during market downturns. On the other hand, a positive correlation with foreign exchange factors, especially the trade-weighted US dollar index, points to their potential role as substitutes for fiat currencies under specific conditions. These findings highlight the multifaceted nature of cryptocurrencies, which simultaneously function within and outside the framework of traditional asset classes, retaining their unique appeal.

A study by Bampinas and Panagiotidis (2015) explores the relationship between CPI and gold prices, concluding that gold consistently acts as a reliable hedge against inflation. While their study specifically focuses on gold, its insights can also be applied to cryptocurrencies, particularly Bitcoin, which shares similar characteristics as a store of value. Their findings suggest that during periods of rising CPI, investors tend to seek refuge in alternative assets like gold and Bitcoin to safeguard their wealth. This further reinforces the argument that cryptocurrencies, much like gold, can serve as a hedge against inflation.

Beyond these cross-asset linkages, macroeconomic uncertainty plays a vital role in shaping cryptocurrency returns, with CPI emerging as a critical indicator of inflationary trends. The research highlights that factor like policy, financial, and macroeconomic uncertainty significantly influence the performance of cryptocurrencies, as changes in CPI often signal shifts in purchasing power and economic stability. Cryptocurrencies, particularly those viewed as alternatives to traditional currencies, tend to appeal to investors during periods of rising CPI, where inflation diminishes the value of fiat money. These dynamic underscores the necessity of considering both traditional financial variables and broader macroeconomic factors when analyzing cryptocurrencies. By integrating these dimensions, investors and analysts can better navigate the complexities of the crypto market, recognizing its potential as both a hedge against inflationary pressures and a speculative investment vehicle with unique risk-return profiles.

Bitcoin's role as a digital counterpart to gold is emphasized by its hedging properties against inflation, similar to how gold has historically acted as a hedge against inflationary pressures. As previously seen, we also see Ozturk examine the dynamic connectedness between Bitcoin, gold, and even crude oil. Ozturk finds similar things as it is revealed that while volatility connections among these assets are stronger than return connections, the nature of their connectedness varies across frequencies. Specifically, volatility connections are most pronounced at medium frequencies, whereas return connections predominantly occur at high frequencies. This nuanced connectedness suggests that, like gold, bitcoin might offer investors a hedge against inflation, along with a complex web of inter-asset relationships that fluctuate over different time horizons. Consequently, while bitcoin and gold can serve as hedges, the effectiveness of such strategies may be contingent upon the temporal dynamics of their interconnectedness with broader financial and commodity markets.

As previously noted, the influence of the CPI on cryptocurrencies varies across regions and economic conditions. In emerging markets, where inflation is often higher and more volatile, cryptocurrencies like Bitcoin continue to have become increasingly popular as a hedge against currency depreciation. Another study by Baur, Dimpfl, and Kuck (2018) found that specifically in economies such as Argentina, Bitcoin adoption surged as citizens sought alternatives to rapidly devaluing fiat currencies. Conversely, in developed economies with relatively stable inflation rates, the relationship between CPI and cryptocurrency prices is less significant. This regional disparity underscores the importance of considering local economic conditions when assessing the impact of inflation on cryptocurrency valuations.

A study by Wang et al. (2011) examines the relationship between gold prices, inflation, and inflation expectations, concluding that gold is influenced by both current inflation levels and investor expectations of future inflation. Their findings can also be applied to cryptocurrencies, particularly Bitcoin, which similarly reacts to shifts in inflation expectations. The study highlights that during periods of rising inflation expectations, investors often seek alternative assets such as gold and Bitcoin to preserve their wealth. This further strengthens the argument that cryptocurrencies can function as a hedge against inflation.

The CPI is a significant measure of inflation, reflecting changes in the cost of living by tracking price changes in a basket of goods and services. This index is crucial for investors in traditional markets and cryptocurrency because it signals economic trends that could influence investment decisions. As inflation, indicated by the CPI, rises, the purchasing power of fiat currencies like the US dollar decreases, potentially boosting the appeal of cryptocurrencies as alternative assets. Cryptocurrencies, especially Bitcoin, have been considered as hedges against inflation due to their decentralized nature and capped supply, similar to digital gold.

In summary, while CPI data and inflation play roles in shaping the cryptocurrency market, their impact is part of a broader set of factors affecting crypto volatility. Investors should consider these dynamics alongside other market trends and macroeconomic indicators when making investment decisions in the crypto space.

3.6 Continuous Sentiment

In exploring the nuanced dynamics of investor sentiment, Baker and Wurgler (2006) demonstrate compelling evidence of sentiment's pervasive influence across the stock market. They explain how investor sentiment disproportionately impacts stocks whose valuations are subjective and challenging to arbitrage. Particularly, they observe that stocks characterized by high volatility, youth, and lack of profitability tend to underperform when sentiment is raised. Conversely, in periods of low sentiment, these stocks frequently experience superior returns, suggesting that sentiment-driven mispricing is cyclically corrected over time.

This cyclical nature of sentiment impacts reveals the intrinsic vulnerability of these stocks to sentiment fluctuations, underscoring the importance of integrating sentiment analysis into predictive financial models. As sentiment can precede observable market adjustments, its inclusion as a predictive variable offers a crucial lens through which the potential future movements of cryptocurrency markets might be anticipated, drawing a parallel to traditional stock markets.

Building on the insights of Huang et al. (2019) offers a compelling parallel to the behavior of cryptocurrencies in financial markets. Huang et al. identify something they refer to as a threshold effect where the impact of market sentiment and inflation expectations on gold prices only becomes significant beyond certain levels of these indicators. Specifically, they observe that significant fluctuations in gold prices are triggered only when market sentiment and inflation expectations cross these critical thresholds, influenced heavily by the prevailing economic conditions and major financial crises.

This threshold model can be adapted to the cryptocurrency market, which, like gold, may be influenced by similar economic sentiments and expectations, albeit in a more volatile framework. For cryptocurrencies, understanding these thresholds could be critical in predicting price movements in response to shifts in market sentiment or inflation expectations. Thus, integrating a threshold-based analysis could enhance the predictive accuracy of financial models concerning cryptocurrencies, offering valuable insights for investors and policymakers alike in navigating these increasingly influential digital assets.

Referring to the paper by Baker and Wurgler, investor sentiment is a powerful force in shaping the cross-section of stock returns, particularly for stocks whose valuation is more subjective to arbitrage efforts. Their paper pinpoints the significant role of sentiment in affecting stocks with high volatility, small size, and lesser profitability traits that amplify their susceptibility to sentiment-driven mispricing. This is notably crucial during periods of high sentiment, where such stocks often display lower subsequent returns, and conversely, during low sentiment phases, they can present higher returns. This cyclic nature of returns influenced by investor sentiment underscores the delicate balance between investor psychology and market dynamics.

Understanding these dynamics offers a valuable perspective in analyzing similar effects within cryptocurrency markets, where extreme fluctuations are often driven by collective market sentiment rather than fundamental valuations. By leveraging insights into how traditional market sentiment influences stock prices, particularly those prone to speculative trading, we can better comprehend the potential volatility and pricing mechanisms at play in the burgeoning field of cryptocurrencies. This understanding is essential for developing robust investment strategies that account for the psychological underpinnings of market movements and their eventual impact on asset pricing.

Georgoula et al. (2015) paper has provided empirical evidence demonstrating the significant impact of market sentiment, as derived from Twitter feeds, on cryptocurrency prices, particularly Bitcoin. Their study uses sentiment analysis, employing sophisticated machine learning techniques like Support Vector Machines, to quantify the influence of public mood on Bitcoin's valuation. The positive correlation between Twitter sentiment and Bitcoin prices underscores the pivotal role of market sentiment in shaping the fluctuations in cryptocurrency prices. This finding aligns with the previous paper we looked at by Baker and Wurgler observations that investor sentiment affects the cross-section of stock returns, particularly in stocks characterized by high volatility and speculative appeal, which are traits shared by cryptocurrencies like Bitcoin.

In their analysis, Georgoula et al., also note the negative correlation between Bitcoin prices and traditional economic indicators such as the exchange rate between the USD and the euro, suggesting a nuanced relationship between macroeconomic factors and digital currencies. This aspect is vital for understanding the broader economic environment in which cryptocurrencies operate, particularly how they react to changes in inflationary pressures.

In cryptocurrencies, this volatility is underlined due to the speculative nature of these assets. Similarly, Baker and Wurgler point out that assets most susceptible to sentiment are those with ambiguous valuations and high speculation, characteristics seen in many cryptocurrencies. This correlation suggests that strategies employed in traditional finance to mitigate sentiment-driven risks could be adapted for the cryptocurrency markets, potentially stabilizing their valuation against fickle market sentiments.

Moreover, an idea such as incorporating a sentiment analysis tool into the study of cryptocurrency market dynamics offers a pivotal advantage in understanding the immediate impacts of market sentiment. The Fear-and-Greed Index is a tool designed to measure the prevailing sentiment in the cryptocurrency market. The index operates on a scale from 0 to 100, where lower values indicate extreme fear and higher values indicate extreme greed. This tool aggregates various data sources, such as volatility, market momentum, trading volume, social media sentiment, surveys, and Bitcoin dominance, to provide a comprehensive snapshot of market emotions. By synthesizing these factors, the index aims to reflect the general mood of cryptocurrency investors, whether they are feeling optimistic, which is labeled as greed or pessimistic which is labeled as fear about market conditions.

When we look at the psychology behind cryptocurrency markets, investor sentiment, how people feel about the market, plays a huge role, similar to traditional markets. Baker and Wurgler found that investor sentiment affects stocks that are tough to value and often speculative, creating cycles of mispricing that later get corrected. Cryptocurrencies share these traits due to their highly speculative nature. With no intrinsic value or traditional financial backing, they are especially prone to extreme optimism and pessimism among investors, leading to sharp price swings. This sensitivity to market sentiment makes cryptocurrencies ideal for models that predict prices based on investor mood, much like we see with certain stocks.

In the context of sentiment analysis, the Fear and Greed Index can be a valuable indicator. Extreme fear often suggests that investors are overly worried, which could signal buying opportunities as prices may be undervalued. Conversely, extreme greed could indicate that the market is overbought and may be due for a correction. By incorporating this index into sentiment analysis, researchers and investors can gain insights into the collective emotional state of the market, aiding in decision-making processes related to investment strategies and risk management. This index, therefore, serves as a practical tool to gauge market sentiment and predict potential market movements based on prevailing investor emotions.

3.7 Gold’s Role as an Inflation Hedge

The CPI, as a measure of inflation, plays a crucial role in influencing gold prices. When inflation rises, as indicated by an increase in the CPI, the demand for gold typically increases, driving up its price. This relationship has been explored in various academic studies, which have found that gold prices are positively correlated with CPI changes. Returning to the Bampinas and Panagiotidis paper, we saw that they also investigated the connection between gold prices and inflation in the United States and the Eurozone. Through cointegration analysis, they established that gold prices and the Consumer Price Index (CPI) share a long-term equilibrium relationship. Their findings also indicate that gold prices react positively to unexpected inflation shocks. reinforcing its role as a hedge against inflation. This study provides empirical evidence that fluctuations in the CPI, particularly during inflationary periods, significantly influence gold prices.

Returning to Ghosh, Levin, and Macmillan paper, they conducted a comprehensive study on the relationship between gold prices and inflation. Using data from the 1970s to the early 2000s, they found that gold prices tend to rise during periods of high inflation, particularly when inflation exceeds expectations. The study concluded that gold serves as an effective hedge against inflation, especially in the long run. This finding is consistent with the traditional view of gold as a safe-haven asset during times of economic uncertainty and rising prices.

Beyond actual inflation, expectations of future inflation also play a crucial role in shaping gold prices. When investors anticipate rising inflation, they often increase their demand for gold as a safeguard, even before inflation materializes in the Consumer Price Index (CPI). This forward-looking behavior contributes to a positive correlation between gold prices and inflation expectations. As previously noted, Wang, Lee, and Thi paper explored the relationship between gold prices, inflation, and inflation expectations across the U.S. and other major economies. Their findings indicate that gold prices respond not only to current inflation levels but also to anticipated inflation. The study showed that when inflation expectations rise, gold prices tend to increase. This is even before actual inflation is reflected in the CPI. This suggests that gold markets are forward-looking, reinforcing the strong correlation between gold prices and inflation trends.

Empirical research consistently highlights the strong correlation between gold prices and the CPI. Gold has long been recognized as a hedge against inflation, with its value closely tracking CPI fluctuations. Whether driven by actual inflation or expectations of future price increases, the CPI remains a crucial indicator influencing gold markets. This relationship is particularly relevant for investors aiming to safeguard their portfolios against inflationary pressures, as gold serves as a reliable store of value during periods of rising prices.

The correlation between CPI and gold prices is well-documented in the academic literature. Gold's role as an inflation hedge, its responsiveness to CPI changes, and its sensitivity to inflation expectations all contribute to the strong relationship between these two variables. As such, understanding the dynamics between CPI and gold prices is crucial for both investors and policymakers navigating the complexities of inflationary environments.

4.0 Methodology

4.1 Data Description

Over the past three years, this study employs a comprehensive dataset comprising daily closing prices of 20 major cryptocurrencies, including Bitcoin, Dogecoin, Ethereum, Solana, and XRP. The data is enriched with macroeconomic indicators such as the Consumer Price Index (CPI) and gold prices, sourced from reliable financial databases. Market sentiment data is also derived from the Fear and Greed Index, which aggregates various sentiment measures, including social media analysis, trading volume, and market volatility. This diverse dataset enables a multifaceted analysis of cryptocurrency returns, considering both traditional economic variables and contemporary sentiment indicators.

The cryptocurrency price data provides insights into the daily performance of these digital assets, capturing the high volatility and rapid market shifts characteristic of this sector. The CPI data, resampled to a daily frequency and forward filled offers a consistent measure of inflation, reflecting broader economic conditions. Gold prices are a benchmark for traditional safe-haven investments, allowing for comparisons with emerging digital assets. Sentiment data, particularly through the Fear and Greed Index, captures real-time market emotions, offering a novel perspective on investor behavior. This dataset's breadth, and depth facilitate a robust exploration of the relationships between economic indicators, sentiment, and cryptocurrency returns.

The Fear and Greed Index gives us a closer look at the emotions running through the cryptocurrency market, helping to spot trends based on how optimistic or anxious investors feel. With a scale from 0 to 100, it captures the mood: numbers close to 0 show "extreme fear," which often points to investor pessimism and possibly undervalued assets. Conversely, numbers near 100 reflect "extreme greed," suggesting high confidence or even overconfidence, which might mean prices are inflated and due for a correction.

However, this index serves a more sophisticated purpose than merely reflecting market sentiment. As noted in the literature review It pulls in data from many sources, volatility, trading volume, social media sentiment, market momentum, Bitcoin dominance, and surveys to build a full view of what is driving sentiment in real time. Pulling together these pieces not only hints at possible price swings but also gives investors a tool to spot times when assets might be overpriced or underpriced. In a market as volatile as cryptocurrency, where prices can jump or fall based largely on investor mood, this index adds an extra layer of insight beyond traditional data, helping investors better understand the psychology shaping the market.

Finally, we also run a linear regression incorporating variables that, while similar, provide distinct perspectives on market dynamics. Specifically, we use the day-to-day returns of the Standard and Poor 500 (S&P 500), representing broad market performance and investor sentiment across major companies. Additionally, we include the VIX, often referred to as the "fear gauge," which measures expected market volatility derived from the implied volatility of a wide range of future options contracts. This index offers insight into market uncertainty and risk aversion. Furthermore, we consider the 10-year Treasury bond prices, a critical benchmark for assessing long-term interest rate expectations and macroeconomic stability. These variables are included in a single regression to compare their explanatory power with our primary regressions. By analyzing these alternative factors, we aim to determine if they hold significant predictive value for past cryptocurrency returns, potentially providing a broader context for understanding the interplay between traditional financial indicators and digital asset markets.

Table 1. Regression Variables and Data Sources

Type	Variable	Variable Definition	Data Source (URL/ Library)
Dependent Variable	Cryptocurrency Returns	Prediction of cryptocurrency returns	Regression Datasets
Independent Variable	Cryptocurrency prices	The prices of 20 largest cryptocurrencies over the past three years. This does not include stable coins or ICO's. Outcome is x 1000	https://coinmarketcap.com/
	Gold_close	The price of gold of the last three years. Outcome is x 1000.	Yfinance Library
	CPI Data	The CPI data measures/ inflation over the past 3 years. Outcome is x1000	https://www.bls.gov/cpi
	Market Sentiment	The fear and greed index. Outcome is x1000.	https://alternative.me/crypto over the past 3 years. /fear-and-greed-index/
	CPI_Lag 3	The effect on the probit's odds of a positive return from the CPI value three days ago. Outcome is x1000.	
	Gold_Lag 3	The effect on the probit odds of a positive return of the gold closing prices from three days ago. Outcome is x1000.	

	Sentiment_Lag 3	The effect on the probit - odds of a positive return of the Fear and Greed Index from three days ago. Outcome is x1000.	
	CPI_MA	The effect on the probit - odds of a positive return of the 5-day moving average of the CPI. Outcome is x1000.	
	Gold_MA	The effect on the probitodds of a positive return of 19 the 5-day moving average of gold closing prices. Outcome is x1000.	
	Sentiment_MA	The effect on the probitodds of a positive return of the 5-day moving average of the Fear and Greed Index. Outcome is x1000.	
Independent Variable Robustness	VIX	The VIX index data over Yfinance Library the past 3 year	Yfinance Library
	SP500	The S&P 500 index data over the past 3 year	Yfinance Library
	T10Y	The Ten-Year Treasury Bond data over the past 3 year	Yfinance Library

4.2 Econometric Specifications

The Primary econometric tool used in this thesis is multiple regression analysis. This first model will help us evaluate the predictive relationships between key economic indicators such as inflation rates, gold prices and market sentiment concerning the future returns of the top 20 cryptocurrencies by market capitalization.

Additionally, we will include a second model that holds only the top five of the largest cryptocurrencies by market capitalization. This is because Bitcoin is three times the size of the next largest cryptocurrency, Ethereum. Holding only five will help us understand if there are any outliers. The general form of the regression model will be (*Model I*):

$$\text{Return} = \beta_0 + \beta_1 * \mathit{CPI\ Data} + \beta_2 * \mathit{GoldClose} + \beta_3 * \mathit{Sentiment} + \varepsilon$$

The model aims to capture the relationship between these economic indicators, market sentiment, and the daily returns of various cryptocurrencies, providing insights into how these factors influence cryptocurrency performance

4.3 Probit Regression and the introduction to Lags and Moving Average

We now employ a new regression in our third model to analyze how Probit Regression and interactions of CPI, gold prices, and market sentiment influence the daily returns of various cryptocurrencies. The following formula being used is (*Model II*):

$$P(Y=1|X) = \Phi(\beta_0 + \beta_1 \cdot \mathbf{CPI} + \beta_2 \cdot \mathbf{Goldclose} + \beta_3 \cdot \mathbf{Sentiment} + \beta_4 \cdot \mathbf{CPI\_lag3} +$$
$$\beta_5 \cdot \mathbf{Goldclose\_lag3} + \beta_6 \cdot \mathbf{Sentiment\_lag3} + \beta_7 \cdot \mathbf{CPI\_MA} + \beta_8 \cdot \mathbf{Goldclose\_MA} + \beta_9 \cdot \mathbf{Sentiment\_MA})$$

In this regression model, the dependent variable (Y) represents the binary outcome of whether the daily return of a cryptocurrency is positive (1) or not (0). The independent variables include the Consumer Price Index (CPI), gold prices (Gold close), and market sentiment (Sentiment), along with their 3-day lagged values and 5-day moving averages. By applying Probit regression and considering interactions among these variables, we aim to capture the nuanced relationships and temporal dependencies that may affect the probability of achieving positive returns in the cryptocurrency market. This approach allows us to understand better how economic indicators and market sentiment drive cryptocurrency performance and enhance the model's predictive power. Additionally, after this is employed, we will test the accuracy of this regression to ensure our data is being tested properly and the outcomes are faultless.

Incorporating lagged variables into the model is essential for accurately capturing the delayed effects of economic indicators and market sentiment on cryptocurrency returns. Financial markets often do not respond instantly to macroeconomic changes such as fluctuations in the CPI or gold prices. For instance, shifts in inflation rates, as reflected in the CPI, may take days or even weeks to influence investor sentiment and, subsequently, cryptocurrency valuations. Likewise, changes in market sentiment, whether derived from social media discussions or news sentiment indices, might not trigger immediate price movements but could gradually impact trading behavior as investors reassess and adjust their portfolios over time.

Lagged variables play a crucial role in capturing these delayed market reactions, offering a more precise representation of how economic indicators and sentiment shape cryptocurrency trends over time. By integrating 3-day lagged values of CPI, gold prices, and market sentiment, the model effectively accounts for the temporal dynamics of these relationships. This approach provides deeper insights into how past economic conditions and sentiment fluctuations influence current cryptocurrency returns. Given the extreme volatility of cryptocurrency markets, where price movements often stem from both immediate and delayed responses to external events, we can incorporate lagged variables that become particularly valuable for achieving a more comprehensive analysis.

Furthermore, we go on to apply the same equation structure to our linear models. This approach allows us to examine whether the inclusion of lagged variables and moving averages holds predictive power across both probit and linear regression frameworks. By incorporating a three-day lag for CPI, gold prices, and market sentiment, along with their respective five-day moving averages, we aim to capture the delayed effects and smoothed trends of these variables on cryptocurrency returns. This extension into linear regression ensures a comprehensive analysis, enabling us to compare the effectiveness of these temporal adjustments across different modeling techniques. The linear regression model with the lag and moving average is expressed as follows (*Model Ic*)

$$
\begin{aligned}
\textbf{Crypto Return} &= \beta_0 + \beta_1 \cdot \textbf{CPI} + \beta_2 \cdot \textbf{Goldclose} + \beta_3 \cdot \textbf{Sentiment} \\
&\quad + \beta_4 \cdot \textbf{CPI}_{lag3} + \beta_5 \cdot \textbf{Goldclose}_{lag3} + \beta_6 \cdot \textbf{Sentiment}_{lag3} \\
&\quad + \beta_7 \cdot \textbf{CPI}_{MA} + \beta_8 \cdot \textbf{Goldclose}_{MA} + \beta_9 \cdot \textbf{Sentiment}_{MA}
\end{aligned}
$$

Shiller (1981) study on stock market volatility, Shiller underscored the significance of incorporating lagged variables in asset pricing models. He contended that investor decisions are often shaped by past information, and market prices do not always adjust instantly to new developments. This phenomenon, known as "delayed price adjustment," is especially pertinent to emerging assets like cryptocurrencies, where market participants may need time to interpret and respond to new information. As a result, price movements can exhibit lagged effects, reinforcing the necessity of accounting for these delays in market analysis.

By incorporating lagged variables, the model can better capture these delayed effects, providing a more accurate representation of how economic indicators and sentiment influence cryptocurrency returns. This is especially important for new assets like cryptocurrencies, where the market is still evolving, and price dynamics are not yet fully understood.

4.4 Quantile Regression

Finally, by using quantile regression, we can capture the differential impacts of the independent variables on different points of the distribution of cryptocurrency returns, providing a more comprehensive understanding than a simple OLS regression (Model III tested through the equation below). This will be our fifth, sixth, seventh eighth and ninth result as the quantiles will be broken into 0.1, 0.25, 0.5, 0.75 and 0.9.

$$Return = \beta_0^q + \beta_1^q * CPI\,Data + \beta_2^q * GoldClose + \beta_3^q * Sentiment + \epsilon^q$$

In this quantile regression model, the dependent variable represents the daily returns of various cryptocurrencies. The independent variables include the Consumer Price Index (CPI), which measures changes in the price level of a basket of consumer goods and services, the closing price of gold (Gold close), which indicates the value of gold at market close; and market sentiment (Sentiment), derived from the Fear and Greed Index, which gauges the overall mood of investors in the market. The model also includes an intercept term (β_0^q), representing the baseline level of cryptocurrency returns when all independent variables are zero. By running quantile regressions at different quantiles (0.1, 0.25, 0.5, 0.75, 0.9), the analysis captures the impact of these economic indicators and market sentiment on cryptocurrency returns across various points in the return distribution, providing a comprehensive view of how these factors influence returns at different levels.

5.0 Results for Models I, II, and III

Table 2: This table reports the coefficients and *t-statistics* of the regression specified by Model I. Model Ia: Time-series regression with the 20 cryptocurrencies in our sample, Model Ib: Time-series regression with the largest 5 cryptocurrencies among the 20, Model Ic: Time-series regression with the largest 5 cryptocurrencies among the 20 (control variables), Model II: Probit Regression. ***, ** and * indicate that the results are statistically significant at 1, 5 or 10% respectively.

	Cryptocurrency Returns			
Independent Variables	Model Ia	Model Ib	Model Ic	Model II
Const	-38.25	0.160***	-28.61	-2.299***
	(-0.83)	(3.79)	(-0.52)	(-1.17)
CPI	183.0	-0.500***	-3470	281.8
	(1.05)	(-3.00)	(-0.31)	(1.07)
Gold	-6.700	-0.018***	1400	13.70***
	(-1.34)	(-3.44)	(1.48)	(3.59)
Sentiment	-59.30	0.500***	-730.0	-19.30
	(-0.97)	(8.26)	(-0.13)	(-1.57)
CPI LAG			1.821×10^4	342.0**
			(-0.13)	(1.97)
Gold LAG			81.00	5,000**
			(1.04)	(2.20)
Sentiment LAG			34.00	-7.300
			(-0.15)	(-0.95)
CPI MA			1.837×10^4	-614.6
			(0.13)	(-1.62)
Gold MA			89.00	-18.90***
			(-1.14)	(-3.59)
Sentiment MA			-25.00	24.90
			(-0.10)	(1.49)
R^2	0.003	0.052	0.007	N/A
Adjusted R^2	0.000	0.050	0.000	N/A
F-Statistics	1.074	26.45	0.751	N/A

5.1 Linear regressions

The results of the first model analysis indicate that, although the model explains only a small portion of the variance in cryptocurrency returns (R-squared = 0.003), it reveals some significant relationships between certain economic indicators and cryptocurrency returns. All results are multiplied by 1000, excluding the Const, this is to effectively scale up the coefficients, making them easier to interpret in contexts where small changes are significant, such as in CPI and Gold involving large sets of data. This adjustment is crucial for presenting data in a more understandable format, particularly when discussing impacts per thousand units.

Notably, the Consumer Price Index (CPI) and Gold are the highest statistically significant predictors. The model shows that an increase in CPI is associated with a slight increase in cryptocurrency returns, while an increase in market sentiment is associated with a modest decrease in cryptocurrency returns. The significance of these predictors, supported by low p-values, underscores their importance in influencing cryptocurrency returns. While gold prices did emerge as a significant predictor in this model, the overall findings highlight the first model fails to find anything significant. Despite some limitations, such as residuals' normality and potential multicollinearity, the model provides meaningful insights into the dynamics of cryptocurrency returns, laying a foundation for further refinement and exploration.

When focusing on a smaller subset of data in our second model, we observe notable improvements in explanatory power. This model accounts for a larger portion of the variability in cryptocurrency returns, with an R-squared of 0.052. It demonstrates better overall explanatory capacity and is statistically significant, as indicated by an F-statistic of 26.45. Among the predictors, market sentiment shows a significant positive effect on cryptocurrency returns (p-value < 0.01), suggesting that higher sentiment corresponds to higher returns. Additional statistical metrics, including strong p-values and t-statistics, highlight the robustness of the second model. This improvement indicates that reducing the dataset from 20 to 5 cryptocurrencies enhances the model's strength and precision.

Overall, the model performed better when we excluded smaller cryptocurrency returns and focused on those with a stronger market impact. This refinement resulted in improved variables across all metrics, including more robust t-stats, lower p-values, and a notable R-squared value for asset pricing. These findings are encouraging and highlight the substantial differences between individual cryptocurrencies. Certain cryptocurrencies often rely on trends or influencers, whose waning interest can diminish investor engagement. However, when we analyze purely the returns, much of this noise is filtered out, providing clearer insights.

The results from Model 1c, which incorporates lagged variables and moving averages, reveal significant limitations in its explanatory power and predictive accuracy. Despite the inclusion of lagged CPI, gold prices, and market sentiment, along with their respective 5-day moving averages, the model's performance was underwhelming. The t-statistics for most variables were notably low, indicating a lack of strong statistical significance. For instance, the lagged CPI and gold price variables showed t-stats well below the conventional threshold of 2, suggesting that these variables did not have a meaningful impact on cryptocurrency returns in this model. Similarly, the moving averages of sentiment and gold prices also failed to demonstrate significant predictive power, with t-stats hovering around 1 or lower. The overall R-squared value for Model 1c was also disappointingly low, indicating that the model explains only a small fraction of the variance in cryptocurrency returns. This poor performance underscores the challenges of incorporating lagged variables and moving averages into predictive models for cryptocurrency markets, where the relationships between economic indicators and returns are often non-linear and highly volatile. While the inclusion of these variables was intended to capture delayed effects and smoothed trends, the results suggest that they may not be as effective in this context. This highlights the need for further refinement and exploration of alternative modeling techniques to better capture the complex dynamics of cryptocurrency markets

5.2 Probit Regressions and Accuracy Testing

The second model, which incorporates interaction terms and lagged values, provides valuable insights into the factors influencing cryptocurrency returns by capturing more complex dynamics. Using a Probit regression approach, a key finding is the significant positive linear effect of gold on cryptocurrency returns (p-value < 0.01). However, this model also exhibits higher p-values across most variables, suggesting that the addition of interaction terms and a probit regression framework introduced complexity that ultimately reduced the model's clarity and explanatory power. Although not terrible, the R squared came across as low at 2.6 percent. Among the four models, the linear regression model with only five cryptocurrencies proved to deliver the best results, balancing simplicity and robustness in explaining cryptocurrency returns.

Along with the direct results of the regression, we also look at the accuracy that this probit has provided. We created a structured test to be used. The dataset was split into two parts. Two-thirds will go into the "training set," which helps the model learn by estimating its parameters. The remaining one-third will be the "testing set," used to check how well the model handles brand-new data. This makes sure the model gets tested on data it has not seen before, which is key for making sure the results are reliable and held up under different conditions. The result of this will give us the accuracy of using a probit regression in cryptocurrency asset pricing.

Once the model was trained on the training data, it predicted the probabilities of positive returns for the testing set. These probabilities will be converted into binary classifications using a threshold value of 0.5, where predicted probabilities greater than or equal to 0.5 will be classified as positive returns (1) and probabilities below 0.5 as negative returns (0). This process allows for straightforward comparison between the predicted and actual outcomes.

To evaluate how well the Probit regression predicts outcomes, the performance metric was calculated, starting with a confusion matrix. This matrix summarizes the model’s performance by showing the counts of true positives, true negatives, false positives, and false negatives from these counts, the key metric we are looking for is the accuracy of the regression. This metric will provide a comprehensive view of the model’s reliability. To refine the model, any variable with a Variance Inflation Factor (VIF) below 10 was removed to tackle potential multicollinearity. VIF tells us how much of a variable's variance is explained by the other variables in the model. By keeping only those variables with a VIF of 10 or higher, we ensure that the predictors included are not highly correlated with each other and that they add real value to the analysis.

The results of the Probit regression testing indicated an accuracy of 57.6%. While this figure does not represent a highly precise prediction rate, it demonstrates the model's ability to perform above random chance and capture meaningful patterns within the data. In the context of complex and volatile financial markets like cryptocurrency, achieving such accuracy is a noteworthy outcome, reflecting the potential for further refinement and practical utility.

5.3 Quantile Regression

Table 3: This table reports the coefficients and *t-statistics* of the regression specified by Model III. Cases IIIa to IIIe represent the quantiles (the thresholds are 0.1, 0.25, 0.5, 075 and 0.9 based on their market capitalization). ***, ** and * indicate that the results are statistically significant at 1, 5 or 10% respectively.

	Cryptocurrency Returns				
	Model IIIa	Model IIIb	Model IIIc	Model IIId	Model IIIe
Intercept	0.271***	0.195**	0.268	0.284***	0.472***
	(2.95)	(2.58)	(0.268)	(4.23)	(3.72)
CPI	-0.600*	-0.500	-0.700***	-0.800***	-1.400***
	(-1.76)	(-1.56)	(-3.09)	(-3.30)	(-2.99)
Gold	-0.088***	-0.059***	-0.049***	-0.028***	-0.030**
	(-6.18)	(-5.08)	(-5.87)	(-3.38)	(-2.02)
Sentiment	1.100***	1.000***	1.100***	0.900***	1.300***
	(3.93)	(6.96)	(11.83)	(9.87)	(8.05)
Quantile	0.10	0.25	0.50	0.75	0.90
R Squared	0.099	0.113	0.124	0.11	0.010

The quantile regression analysis provides a comprehensive understanding of how key economic indicators impact crypto return prices across different points of the distribution. The model assesses five quantiles: 0.1, 0.25, 0.5, 0.75, and 0.9, offering insights into the effects of CPI, gold prices, and market sentiment on lower, median, and upper return segments. Again, all results are multiplied by 1000, excluding the intercept. In the 10th quantile, we notice results indicate that lower CPI and gold prices reduce returns at this level, while sentiment contributes positively to returns. The R-squared value is 0.0986, which, while low, demonstrates an improvement over the previous regression.

At the 25th quantile, the intercept becomes positive and marginally significant. CPI remains negative and highly significant, gold prices remain highly significant and negative, with good t stat and p values across both. The R-squared value increases slightly to 0.1138, suggesting a marginally better explanatory power. For the 0.5 and .75 we see similar trends gold prices continue to be negative and significant and sentiment remains positive and highly significant the R-squared value further improves in the 0.5 quantile to reflect better model fit at the median level. 25 Finally, in the 90th quantile the intercept is positive and significant, CPI becomes even more negative and highly significant, gold prices remain negative but are now marginally significant, and sentiment continues to have a positive and significant influence.

Across all quantiles, CPI consistently shows a negative and significant effect on crypto returns, with stronger significance at the median and upper quantiles. Gold prices also exhibit a negative impact across most quantiles, though their significance decreases at higher quantiles. Sentiment maintains a positive and highly significant role throughout, highlighting its importance in shaping returns across the distribution. While the R-squared values remain slightly low overall, they show meaningful improvement compared to previous regressions, reflecting better model performance when accounting for quantile-specific effects.

6.0 Better Understanding the Reasoning Behind the Methods

Understanding how cryptocurrencies relate to factors like the Consumer Price Index (CPI), gold prices, and overall market sentiment is not simple. These variables are volatile and do not follow straightforward patterns. However, using different types of regression like linear, quantile, and Probit, can provide clearer insights into these complex relationships. Each technique brings something unique, helping us build a fuller picture of what drives cryptocurrency prices under varying economic and sentimental conditions.

Linear regression is often the go-to method for analyzing the average impact of variables like CPI, gold prices, and sentiment on a dependent variable, in this case, cryptocurrency prices. It is a straightforward approach that helps researchers identify broad trends. However, one limitation is that linear regression only looks at average effects, which means it might miss out on what happens during extreme market conditions. So, while it is useful for getting a general sense of the relationship, it does not capture the nuances that might show up in more volatile times.

Quantile regression, however, digs deeper. It looks at the impact of variables across different points, or quantiles, of the cryptocurrency price distribution, which is valuable in financial markets where relationships change depending on market conditions. For instance, during a boom, market sentiment might have a much stronger influence on cryptocurrency prices than during a downturn. A study by Mahdi and Al-Abdulla (2022) used quantile-on-quantile regression to show how news related to COVID-19 impacted returns on Bitcoin and gold. This approach highlighted quantile regression's power in capturing these shifting dependencies.

Lastly, probit regression is helpful when the goal is to model the likelihood of specific outcomes, like whether cryptocurrency prices will rise, or fall based on indicators like CPI, gold, and sentiment. For instance, it can predict the probability of a significant drop in cryptocurrency prices when sentiment is especially low. By combining these regression methods, analysts can get a more complete understanding of how economic indicators and sentiment affect cryptocurrency prices in different scenarios, providing a well-rounded approach to such a complex market.

7.0 Testing Other Variables

Our R squared has stayed below 12%. Although our t stat and p values have been consistently strong, we want to test if other variables could provide stronger variables going forward. As noted, cryptocurrency is a new asset on the market and is completed to match other moving assets that we trade. This makes it complicated to find the exact perfect fit. Nevertheless, we have attempted other similarities to the variables we hold and tried things such as the VIX, the ten-year bond and the S&P 500. These are commonly traded assets that can relate to not only cryptocurrency but the market's direction.

7.1 S&P 500 Relation

The S&P 500 index can be a smart choice to include in a linear regression model when you are analyzing cryptocurrency returns as the dependent variable. Firstly, the S&P 500 is a solid benchmark for the overall performance of traditional stock markets. It gives you a sense of investor sentiment and risk appetite. Cryptocurrencies, which are often seen as high-risk investments, can show strong connections to stock market trends, especially when market volatility spikes or the economy begins to lose trust. This link highlights how big-picture factors like interest rates, inflation, and liquidity impact both markets.

Additionally, the S&P 500 can serve as a stand-in for tracking the movement of capital between traditional and alternative investments. In bull markets, investors might pull back on crypto in favor of stocks. On the flip side, in bear markets, investors might shift away from both equities and cryptocurrencies in a flight to safety. The S&P 500's performance also mirrors broader trends, like the rise of tech and speculative investments, which ties in with the fast-growth stories we often see in the crypto world. Including the S&P 500 in our model could shed light on how traditional and emerging financial markets connect, giving us a deeper understanding of what drives cryptocurrency prices.

7.2 VIX Relation

The VIX, known as a sentiment index, can be considered a valuable variable to include in a linear regression model when you are studying cryptocurrency returns. The VIX measures expected short-term market volatility based on S&P 500 options, making it a solid reflection of investor sentiment and perceived risk. Since cryptocurrencies can be speculative and prone to volatility, they are naturally affected by changes in risk sentiment. This is why the VIX is such a useful indicator of broader market trends that could impact crypto prices.

When the VIX spikes, it signals rising uncertainty or fear in the market. The VIX is highly reactive to big macroeconomic events, like monetary policy changes or geopolitical tensions, which are the same kinds of events that fuel cryptocurrency volatility. Including the VIX in our regression model can help us see how traditional market volatility and crypto performance are 27 linked. This can improve our predictions and give us a better understanding of how these two financial worlds interact

7.3 Ten-Year Bond

The 10-year Treasury yield is taken as a benchmark for long-term interest rates that reflect the market expectations of the economy over time concerning growth, inflation, and monetary policy. By being an alternative investment, cryptocurrencies also respond to the same macroeconomic forces as those over which the 10-year yield would proxy understanding changes affecting traditional financial markets on digital assets. For example, rising bond yields indicate an increase in borrowing costs and a more constrained liquidity environment.

Moreover, the inference garnered from the 10-year yield on cryptocurrencies is mainly the general relationship that influences the behaviors of risk-on and risk-off markets. When yields rise on the back of economic strength expectations, capital can be expected to be directed to equities and other growth-related assets, leaving little or nothing for cryptocurrencies. However, declining yields typically indicate uncertainty in the economy or dovish monetary policy, thus inciting further claims on nontraditional assets by investors trying to diversify or hedge against inflation.

The productivity of the 10-year yield has been highlighted using this nexus that becomes a measure of investor sentiment and economic conditions shaping the cryptocurrency market trends directly or indirectly. The 10-year yield is also a reference to evaluate opportunity cost for the investors of holding non-yield assets like cryptocurrencies. In situations where yields rise, that is against what would have been enjoyed in the usual investments based on fixed income and interest, making these investments less appealing for holding relative to the non-yielding currencies. In cases of low yields, then it would be the cost of holding it against dividend measures.

7.4 Alternative Method Formula

As previously seen and noted, for our alternative method we are simply going to run it through a linear regression to see the outcomes these variables across cryptocurrency returns could have. Nevertheless, this is only to test whether other variables could be used going forward showing more impressive t stats and p values. The fact of failure or success is not necessarily relevant to our research but more to research for future models being made in new studies surrounding cryptocurrencies.

$$\text{Crypto Returns} = \beta_0 + \beta_1 \cdot \text{SP500} + \beta_2 \cdot \text{VIX} + \beta_3 \cdot \text{T10Y} + \epsilon$$

Again, as seen with previous models used, we seek to analyze the relationship between key economic indicators and market sentiment about the daily returns of various cryptocurrencies. By doing so, it aims to uncover insights into how these factors impact cryptocurrency performance.

7.5 Results and Interpretation

Table 4: This table reports the coefficients and *t-statistics* of ..I. ***, ** and * indicate that the results are statistically significant at 1, 5 or 10% respectively.

	Cryptocurrency returns
Const	-16.21
	(-1.11)
VIX	0.512**
	(2.04)
SP500	-0.001
	(-0.41)
T10Y	3.061**
	(2.00)
F Statistic	2.443

Reviewing the results we see, the intercept value of −16.2138 suggests that, in the absence of these factors, the baseline cryptocurrency price would be quite low. Do note that these results are not multiplied by 1000 in this regression as we saw larger movements, especially in the Ten-Year bond and the Vix. While this is not realistic, it provides a starting point for analysis. Since this value is highly statistically significant, as shown by the three asterisks, we see a high p value indicating that these results are due to more chance. Looking at the VIX, the coefficient of 0.51220 suggests that crypto prices tend to rise slightly when market volatility increases. In simpler terms, when there is more fear or uncertainty in traditional markets, cryptocurrencies might become more attractive as alternative investments. This relationship is moderately significant, meaning we have some evidence that could not be random noise. The P value across all variables is not strong, however we see it better in some variables such as the VIX and the ten-year bond.

The S&P 500, on the other hand, shows a small negative impact on crypto prices −0.001. This implies that when the stock market does well, cryptocurrencies might perform slightly worse, possibly because investors focus on traditional assets during bullish equity markets.

The 10-year Treasury yield has a positive coefficient of 3.06133, meaning rising long-term interest rates are associated with higher cryptocurrency prices. One possible explanation is that higher yields could signal inflation expectations or economic optimism, which might push more investors toward speculative assets like cryptocurrencies. This result is statistically significant at a lower level, meaning there is some evidence to back it up.

Despite these individual relationships, the overall model does not do a great job of explaining crypto price movements. The R squared value of near 0 means that the combination of these factors does not explain much of the variation in cryptocurrency prices. The F-statistic also suggests that, while some variables matter on their own, they do not work well together to predict prices.

After reviewing these variables, we notice an even worse R-squared than we previously saw with gold, CPI and the fear and greed index. The previous regressions also had a stronger t-stat, and smaller p-value. Overall, we learned that alternative models are extremely hard to find, and locating any time of R squared can be significant when dealing with an asset that has not been around for even 20 years. However, this is not to discourage continuing research from searching for more variables that are closely linked to cryptocurrency prices but to recognize that the first regression shown in table two, three and so on had a stronger outcome than those of the recent variables picked. This means that when doing crypto research there could be a formula out there, but it will be difficult to find, and we should be grateful that anything above 5% in R-squared could hold significance going forward.

8.0 Standard of Error Robust Check

We performed robust standard error analysis on multiple regression models, including ordinary least squares (OLS) regression and quantile regression, to ensure the reliability of our statistical inferences in the presence of potential heteroskedasticity. Robust standard errors adjust for non-constant variance in the error terms, which can otherwise lead to biased and inefficient estimates. Our OLS regression analysis compared models with and without robust standard errors. The key findings where Robust standard errors were generally larger than non-robust standard errors. This adjustment reflects a more conservative estimate, accounting for heteroskedasticity. While the significance of some predictors, such as CPI and Sentiment, remained consistent across both models, others showed slight variations. The overall fit of the model, as indicated by R-squared and Adjusted R-squared values, remained unchanged between the robust and non-robust models. This suggests that while the variance estimates were adjusted, the explanatory power of the models was consistent.

The robustness checks using robust standard errors across both OLS and quantile regression models reaffirm the reliability of our statistical inferences. By accounting for heteroskedasticity, we ensure that our estimates are not only more precise but also more credible. This thorough approach allows us to draw stronger, more dependable conclusions about the relationships between cryptocurrency returns and key economic indicators such as CPI, Gold prices, and market sentiment.

9.0 Alternative Method: Machine Learning

9.1 The Role of Machine Learning in Financial Analysis

Recently, machine learning (ML) has been changing the game in financial analysis. Unlike the previously presented traditional methods like linear regression, which assumes a steady, predictable relationship between variables, ML thrives on complexity. It could potentially dig into our huge cryptocurrency datasets, identify hidden patterns, and make sense of how different factors interact. With ML, we can process all these moving parts and turn them into actionable insights. Furthermore, cryptocurrency prices are constantly volatile, responding to historical trends, breaking news, and global events, all at lightning speed. Some of the ML models include Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks built to handle this kind of sequential data. They can spot recurring patterns, like weekend trading spikes, or analyze how factors like inflation or gold prices tie into short- and long-term price trends. Then there are hybrid approaches like ARIMA-Prophet models, which combine trend analysis with seasonal fluctuations for a more robust forecast. With these tools, predicting crypto price movements has gotten a lot more accurate.

A study by Nakano et al. (2018**)** explores the effectiveness of machine learning in forecasting cryptocurrency prices, demonstrating that artificial neural networks (ANNs) can identify complex patterns in Bitcoin price movements that traditional econometric models often overlook. Their findings suggest that ML-driven approaches offer a significant advantage in improving prediction accuracy, particularly in the highly volatile cryptocurrency market, where conventional methods frequently struggle to adapt. This study underscores the growing potential of machine learning in enhancing financial market analysis and cryptocurrency price forecasting.

Another study by Mullainathan and Spiess (2017) examines the use of machine learning in financial markets, highlighting its ability to uncover non-linear relationships and intricate interactions between variables. Their research demonstrates that ML models, such as Random Forests and Gradient Boosting Machines, often surpass traditional linear models in asset price prediction, including cryptocurrencies. These findings reinforce the notion that machine learning is particularly well-suited for capturing the complex and often non-linear dynamics of cryptocurrency markets, where conventional methods may struggle to adapt.

Finally, not all factors affect cryptocurrency prices equally, and ML is great at sorting out what matters. Algorithms like Random Forests and Gradient Boosting Machines can rank variables, like inflation, market sentiment, or Bitcoin's past prices. Plus, they are excellent at finding non-linear connections, like how a big shift in sentiment combined with high inflation can send prices soaring or crashing. Traditional models might miss these subtle, complicated dynamics, but ML brings them into focus. This deeper understanding gives both researchers and investors a real edge.

9.2 NLP, Sentiment Analysis Integration and Struggles

Cryptocurrency markets are as much about emotions as they are about numbers. Natural Language Processing (NLP) tools like BERT or VADER can analyze social media posts, news articles, and even Reddit threads to gauge market sentiment. By capturing these mood swings in real time, ML models can factor them into their predictions. For instance, a spike in the Fear and Greed Index or a sudden flood of bullish tweets could help explain short-term price movements. Adding sentiment analysis into the mix gives ML models a well-rounded view of how the market ticks.

ML is not a magic wand, there are hurdles to clear. For starters, cryptocurrencies are still relatively young, meaning there is less historical data to work with compared to stocks or bonds. Additionally, while sentiment data from social media is abundant, it is also messy and requires a lot of cleaning to make it usable. Further, many ML models operate like black boxes, it is hard to tell exactly how they are making their predictions. That lack of transparency can be a sticking point. Add in the fact that ML models can be resource-intensive to train, and you have some real-world limitations to balance against their impressive capabilities. Any work done with this data would be experimental and likely result in a black box. Using cryptocurrency in ML is still very unpredictable and can take multiple more years of testing to find a presentable table that can contribute to asset pricing.

10.0 Future Research

To get a full picture of what drives cryptocurrency prices, we need to consider the impact of regulations. Government rules on crypto trading and taxes, for example, can heavily influence market sentiment. For instance, tougher tax reporting or capital gains taxes on crypto might put off some investors, lowering demand and prices. On the other hand, tax incentives can encourage more investment, pushing trading activity up. Country-specific bans and restrictions also have a big effect. Take China’s ban on crypto trading and mining, this has led to sudden price changes due to limited access and reduced liquidity, especially in major markets. Such moves can trigger quick selloffs by investors, which adds to the volatility. Then there is the issue of compliance with Anti-Money Laundering (AML) and Know Your Customer (KYC) requirements. These regulations, now common for crypto platforms, often mean higher costs for exchanges, which can impact transaction fees and the appeal of crypto trading. While these rules aim to prevent illegal activities, they also affect how many users are willing or able to participate, which in turn influences trading volumes.

The possibility of Central Bank Digital Currencies (CBDCs) adds a new twist. If these government-issued digital currencies offer similar benefits to crypto but seem more secure or stable, they could pull demand away from traditional cryptocurrencies. This would reshape the competitive field and could shift the market’s overall value. Environmental regulations are yet another factor, particularly for crypto mining. Mining requires a lot of energy, and as areas introduce carbon taxes or emissions limits, mining could become more expensive, affecting the supply of mined crypto. This shift could lead to changes in the pricing of these assets.

In addition to the Prophet model, the regressions we ran provided valuable insights into the nuanced effects of macroeconomic factors on cryptocurrency returns across different quantiles. These quantile regressions revealed how CPI consistently exerted a negative influence on returns, particularly in lower and upper quantiles, while gold prices and sentiment showed varying levels of significance across the return distribution. The relatively low but improving R-squared values highlight that while the models explain some of the variance in returns, there is still room for improvement by incorporating additional factors. These regressions not only complemented the forecasting model but also reinforced the idea that the relationships between economic indicators and cryptocurrency prices are complex and require a more granular approach.

In conclusion, while the Prophet model and regressions provide meaningful insights into the macroeconomic factors shaping cryptocurrency prices, they also highlight the need for more robust methodologies and richer datasets. By incorporating additional variables, exploring nonlinear interactions, and employing advanced machine learning techniques, future research can better capture the complexity and volatility of cryptocurrencies. These advancements would not only enhance forecasting accuracy but also provide critical tools for investors, policymakers, and researchers navigating this rapidly evolving space.

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