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The Bitcoin Dilemma

An assessment of bitcoin as an inflation hedge, currency hedge, and a hedge or safe haven for stocks and bonds

En evaluering av bitcoin som en inflasjons-hedge, valuta-hedge, hedge og safe haven for aksjer og obligasjoner

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Abstract

This master thesis aims to clarify whether bitcoin acts as an inflation hedge, currency hedge, and a hedge or a safe haven for stocks and sovereign bonds in the United States, Europe, Japan, South Korea, and Norway. The data in this paper consists of the US. 10-Year Breakeven Inflation Rate, macro inflation indicators, foreign exchange rates denoted in US dollars, and stocks and sovereign bonds for each economy. We assess each property of interest separately through the Autoregressive Distributed Lag model and the Generalized Autoregressive Conditional Heteroskedasticity approach. The estimation procedure is performed in two stages, where we compute a linear model for the mean and employ the GARCH (1,1) in modeling the time-varying conditional error variance that each model residual exhibits. Our results show that bitcoin is an inflation hedge in the United States. The results also show that bitcoin behaves as a risk-on/risk-off against stocks and government bonds during normal and uncertain times.

Sammendrag

Denne masteroppgaven har som mål å avklare om bitcoin fungerer som en hedge mot inflasjon, valuta, samt hedge og safe haven for aksjer og statsobligasjoner i USA, Europa, Japan, Sør-Korea og Norge. Dataen som blir tatt i bruk gjennom denne oppgaven består av US. 10-Year Breakeven Inflation Rate, tradisjonelle makroindikatorer, forskjellige vekslingskurser mot den amerikanske dollaren, aksje indekser og obligasjonsindekser for hver økonomi. Vi vurderer hver egenskap for de nevnte argumentene separat gjennom en Autoregressiv Distribuert Lag modell og deretter gjennom en Generalisert Autroregressiv Betinget Heteroskedasitet (GARCH) tilnærming. Estimeringsprosedyren utføres i to trinn, hvor vi beregner en lineær modell for første del av ligningen og bruker GARCH (1,1) til å modellere variansen i hver modell. Vår empiriske analyse viser at bitcoin er en inflasjons hedge i USA. Resultatene viser også at bitcoin oppfører seg som en risk-on/risk-off aktiva mot aksjer og statsobligasjoner under normale og usikre tider.

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List of Abbreviations (or Symbols)

NBIM	Norges Bank Investment Management fund
NARDL	nonlinear autoregressive distributed lag
VAR	Vector autoregression
ADCC	asymmetric dynamic conditional correlation
OLS	Ordinary Least Squares
BLUE	Best Linear Unbiased Estimator
ARDL	Autoregressive Distributed Lag model
ARCH	Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
CPI	Consumer Price Index
PPI	Producer Price Index
M1	Circulating Money Supply
T5YIFR	US. 5-Year Forward Inflation Expectation Rate
T10YIE	US. 10-Year Breakeven Inflation Rate
TIPS	Treasury Inflation-Protection Securities
MSCI	Morgan Stanley Capital International
TMB	Tamilnad Mercantile Bank Limited
BTC	Bitcoin
USDT	Tether, a stable coin cryptocurrency and is pegged 1/1 with the US Dollar
BUSD	The Binance crypto exchanges stable coin pegged 1/1 with the US Dollar
BTC/USD	Bitcoin denoted in US Dollars
BTC/USDT	Bitcoin denoted in Tether
BTC/KRW	Bitcoin denoted in South Korean Won
EUR/USD	Euro denoted in US dollars
JPY/USD	Japanese Yen denoted in US dollars
WON/USD	South Korean Won denoted in US dollars
NOK/USD	Norwegian NOK denoted in US dollars
FX	Foreign Exchange
VIX	Chicago Board Options Exchange Volatility Index

1 Introduction

Following the global lockdown in March 2020, several companies have invested millions to billions of dollars of their cash holdings in bitcoin. These companies all show their sincere concerns about future economic uncertainty due to the post-pandemic of COVID-19, which led to unprecedented government stimulus and expansive quantitative easing worldwide. The fact that companies first now choose to invest portions of their cash holdings in bitcoin increases the curiosity to ask whether bitcoin is a hedge, a safe haven, a store of value. Although these arguments for bitcoin are nothing new to the crypto community, they have barely been tested in the literature. Therefore, we set out to demystify the role of bitcoin as an inflation hedge, currency hedge, hedge and safe haven for stocks and bonds in this thesis.

We analyze these arguments with traditional financial markets for five different economies, inspired by other literature studying gold and bitcoin. The first argument in this thesis investigates the inflation hedge capability of bitcoin. We evaluate this property through multiple inflation indicators. Where the primary approach uses the US. 10-Year Breakeven Inflation Rate. While the traditional macro indicators, CPI, PPI, and M1, are relegated to a robustness role for the main approach, given the limitations imposed by their frequency and bitcoins life span. The second argument assesses bitcoin's currency hedge characteristics against changes on foreign exchange rates denoted in US dollars. Finally, the last argument examines bitcoin's hedge and safe haven properties, consisting of weekly MSCI stocks and TMB 10-Year sovereign bond prices within five economies.

The econometric approach for the inflation argument is based on a regression model, where bitcoin returns are regressed on the inflation measures. Furthermore, we estimate a GARCH model for the regression residuals from the model with the US. 10-Year Breakeven Inflation Rate. The GARCH methodology is also applied for the following arguments, as each model displays evidence of time-varying conditional error variance. We entertain a variety of GARCH models in each argument, wherein the mean model of each argument differs between the assumption of a contemporaneous and a dynamic relationship between the returns of bitcoin and the financial series of interest. We apply these approaches to determine whether current and past changes in these indicators affect the price of bitcoin.

The five economies of interest in this thesis are the United States, Europe, Japan, South Korea, as the most traded national currencies for bitcoin,[1] and Norway. South Korea is of great interest due to periods of sizeable deviating bitcoin prices relative to other foreign exchanges.[2] We believe that the South Korean bitcoin price behaves differently and can potentially exhibit different results. We also include Norway as it is interesting to test how a small bitcoin market, such as Norway, behaves compared to the dominant bitcoin markets. More importantly, since the global financial crisis in 2008, the central bank of Norway has barely increased the money supply to stimulate the market. However, they have only used the key interest rate and shares of the operating profits from the Norges Bank Investment Management fund (NBIM) as their tools for monetary policy. With this in mind, this should lead to lower inflation in economic theory than for countries engaging expansive quantitative easing, as the Norwegian central bank would need to sell US dollars and buy back Norwegian kroner (NOK) when they withdraw funds from NBIM. This suggests a strengthening of NOK and thus reduces potential inflation through increased demand of the exchange rate.[3]

For centuries, gold has been notorious for being the dominant asset for an inflation hedge, safe haven, and a store of value for private investors, companies, and central banks worldwide. During the era of la Belle Époque, which lasted from mid-1800 until 1914, gold was even the global monetary standard which was a period of innovation and prosperity where most revolutionary inventions were developed, such as the automobile, the airplane, the telephone, and mass production (Ammous, 2018). The media, profiled investors, and people in the bitcoin community argue that bitcoin is more like a commodity than a currency and call it the "gold 2.0," given the similarities to gold. Gold and bitcoin are considered "hard money" due to their limited supply and hard to produce. The interpretation of a good's hardness is defined by its current supply (stock) and future increased supply (flow), which together is used as an indicator for measuring a good's hardness, called the stock-to-flow ratio. The higher the stock-to-flow, the more likely the good will maintain its value across time and assures the stakeholder's wealth. Today gold has a higher stock-to-flow ratio than bitcoin.

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[1] According to *Coinhills*.

[2] According to *Investopedia*, this phenomenon is called the Kimchi premium which in theory can be seen as an arbitrage opportunity for foreign and South Korean investors. However, due to capital controls and financial regulations in South Korea, it is virtually impossible to take advantage of this opportunity.

[3] *https://www.norges-bank.no/kunnskapsbanken/styringsrenten/hvordan-pavirker-renten-okonomien/*. and *https://www.norges-bank.no/tema/markeder-likviditet/Valutakjop-til-SPU/*.

However, as bitcoin block rewards are fixed and halved approximately every four years, bitcoin is estimated to overtake gold around 2022 and will continue to increase its stock-to-flow ratio further into the future. Another fundamental feature that bitcoin has in common with gold is that they both are considered sound money, implying that they cannot be exposed to sudden devaluation of their currency or long-term changes in the purchasing power. Gold and bitcoin are instead self-correcting mechanisms governed by a free market system. Until 1971, gold had been the world currency standard for many centuries, and throughout history, gold was always the fallback currency after a collapse of their former monetary systems. Given these similarities, but in a more digital society, is precisely why the crypto community believes that bitcoin can take over the role of gold. And as almost all western economies are working on developing a central bank digital currency (The Federal Reserve - Central Bank Digital Currency, 2021), this might be a run-up for a new la Belle Époque era, but with bitcoin as the global standard. However, such a thought is highly unlikely in the foreseeable future.

Considering the similarities between bitcoin and gold, we assume that the same hypothesis proposed for gold in previous literature can be applied to bitcoin. Following this assumption, we build a comprehensive study on bitcoin inspired by Erb & Harvey's (2013) work on gold. Erb and Harvey (2013, page 3) investigate six somewhat different arguments advanced for owning gold:

- gold provides an inflation hedge
- gold serves as a currency hedge
- gold is an attractive alternative to assets with low real returns
- gold a safe haven in times of stress
- gold should be held because we are returning to a de facto world gold standard
- gold is "under-owned."

Many of the same arguments have been made for bitcoin. We set out to analyze three of these claims where we swap the word gold with bitcoin:

- bitcoin is an inflation hedge
- bitcoin serves as a currency hedge
- bitcoin is a hedge, safe haven for stocks and bonds

Our empirical results suggest that bitcoin is an inflation hedge in the United States. On the other hand, we find no evidence of bitcoin as a currency hedge. However, our results imply that bitcoin is a risk-on/risk-off asset for stocks and government bonds during normal and adverse market conditions.

2 Bitcoin overview

Bitcoin was first introduced on October 31, 2008, to a small online cryptographic mailing list explaining the design from the pseudonymous creator Satoshi Nakamoto. Bitcoin is purely a peer-to-peer electronic cash system allowing online transactions between two individual parties without a financial institution serving as a trusted third party to process and evaluate the electronic payment (Nakamoto, 2008). Besides, the Bitcoin network[4] is not issued or controlled by any centralized authorities but rather by the market (Ammous, 2018). Furthermore, Bitcoin's underlying value is not based on any precious metals or economies but rather the security of a cryptographic proof protocol on a network that timestamps all historical transactions, namely the blockchain. Thus, making it a functional decentralized monetary system that has proven itself to work over a decade. Furthermore, by default, the network is set to issue a fixed rate of new bitcoins entering the market every eight to ten minutes, making bitcoin reliable and removing the risk of any monetary supply shock. Lastly, Bitcoin is also programmed to issue a fixed supply of 21 million coins, making it a finite asset, one of the leading arguments for comparing bitcoin to gold.

The main argument among bitcoin supporters as an inflation hedge follows the network's supply restrictions, namely the 21 million capsize. Bitcoin is also believed to be an inflation hedge as the short-run supply shock from the network is practically nonexistent, apart from the halving event, which occurs approximately every four years. Bitcoin halving is when miners receive 50 percent fewer bitcoins for verifying transactions while the cost for mining remains unchanged. This event occurs every 210 thousand new blocks, and since new blocks are constantly added every 8-10 minutes, this is equivalent to a halving occurring every four

[4] The word bitcoin is written in two ways:
Capital "B" denotes the Bitcoin network/protocol, while bitcoin with the lower case "b" defines bitcoin as the currency. The capital “B” and lower case “b” will be written consistent throughout the whole thesis.

years. These features define bitcoin as a scarce asset, and because of the fixed supply, the value can never be deliberately diluted through increased money supply, which is also a debated argument for gold as an inflation hedge.

Bitcoin is seen as an alternative to traditional currency since it was initially designed as a decentralized monetary system. Bitcoin has a coded monetary policy, or as Elliott (2018) puts it, bitcoin is a self-regulating currency. Thus, the crypto community believes that bitcoin can act as an internal currency hedge if a debasement of a local currency occurs. For example, a debasement of a local currency might arise if a country has a struggling economic state and future uncertainty, where stimulus is needed for a full recovery. In the worst case, a loss of trust in the local financial system might also be a reason for a debasement in their local currency, which might be the case in certain economies. We have recently seen several examples of Venezuela, Argentina, Iran, and Zimbabwe struggling with high inflation resulting from devaluing their local currency by printing money to finance government spending and demolishing private wealth. However, this is less likely in developed economies.

On the other hand, such risk of a potential debasement on the price of bitcoin is theoretically nonexistent as no single entity or a group can decide the future of the Bitcoin network, making it reliable in terms of the set ground rule of continuous supply. Furthermore, Bitcoin is a system unlike anything we have ever witnessed, as the bitcoin community believes it to be the most equitable solution for global prosperity due to its potential of removing the control of the money supply from centralized authorities. The fundamental argument is based on Bitcoin as a global monetary system with its decentralized governance and programmatic supply, originated by an anonymous creator but is still maintained and further developed by the nodes,[5] developers, and miners worldwide. With all that being said, it is fair to argue that bitcoin might be a more reliable currency than for unstable governments with corrupt systems and leaders that are forced to devalue their currency due to, among else, sanctions from other countries.

[5] The general definition of a node is a computer that holds a complete copy of the blockchain ledger. This can be done by running the bitcoin software, where everyone can participate. The more nodes there are, the better it helps transmit information through the blockchain network, like network issues, and help validate previous transactions. Anyone can be a node, not just miners, but the miner's role is to add transactions to the blockchain, but since mining is costly, not all nodes desire to become a miner. The main benefit of being a node is that you have a voting right, on a par with miners, for further development and maintenance of the network. This means that the mining nodes do not authorize the network alone, making bitcoin decentralized by nature.

The crypto community has long argued that bitcoin is a safe haven for traditional assets due to its believed role as a store of value and decentralized nature, limited correlation with other financial assets, and no risk of being inflated or seized by any government. On the other hand, it has been counter-argued that the safe haven claim is a misassumption as safe haven assets are seen as protection for tail risk events where this claim has not been put to the test until now. However, due to the liquidity crisis in March 2020, it is now possible to test this argument. For this reason, it has been essential to include this in our analysis.

Our earliest recorded data point on bitcoin starts from September 13, 2010, potentially amounting to a total of 114 monthly observations. Although bitcoin launched in late 2008, it was not until Bitstamp started commercializing bitcoin trading in mid-2010 and has since then been one of the most known crypto exchanges. At first, bitcoin was only transacted among the cryptographic community, where they treated bitcoin as a playful collectible rather than a currency. However, as bitcoin experienced rapid attention, it did not take long before the first bitcoin exchange launched, and in October 2009, the first official purchase was registered for $0.00076 per bitcoin on an exchange site called New Liberty Standard.[6] However, since there were no established bitcoin markets in 2009, the bitcoin price was not determined on market value but instead priced on an estimated cost of electricity for mining bitcoin at the time of every purchase. On May 18, 2010, Laszlo Hanyecz was the first person to ever purchase a good with bitcoin, where he bought two pizzas for 10,000 bitcoins worth $25, which corresponded to a value of $0.0025 per bitcoin.[7] Ironically, nine months later, the price of one bitcoin reached a value of $1, meaning that those two pizzas suddenly became worth $10,000. After this historical event, more and more people started to show interest in Bitcoin, and the price has just continued to rise with an average increase of 200% annually.[8]

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[6] According to *Bullionstar*, New Liberty Standard is also known for having designed the famous bitcoin symbol, ฿, which is familiar for most people today. It is also unclear when it got shut down. The logical reasoning for such pricing was that the creator of the New Liberty Standard was a well-established bitcoin miner and used the crypto exchange as a platform to sell its minted bitcoins.

[7] To put it in even more *perspective*, ten years later, on May 18, 2021, the "Bitcoin pizzas" were worth $420 236 900.

[8] According to *Fiatmarketcap.com*.

3 Literature review

Although small, a growing number of papers have tried to determine the role of bitcoin as an inflation hedge, currency hedge, diversifier, a store of value, and a safe haven. However, there is still no consensus around the role of bitcoin in the financial market. Furthermore, as we are aware, there is no literature with such a comprehensive assessment of the arguments advanced in the crypto community.

Due to the shortage of literature surrounding the topics advanced in this thesis, we draw inspiration from previous literature conducted on gold. Hoang et al. (2016) study the role of gold on inflation in China, India, France, the UK, and the United States, using the CPI and local gold prices. The paper uses a nonlinear autoregressive distributed lag (NARDL) model to study the relationship between the short and long-term asymmetries. Their results indicate a significant short-run relationship in the US, UK, and India but fail to find evidence for long-run hedge capabilities for all countries in the model. Hoang et al. (2016) suggest that "*the difference in the sample period does not affect the results since they are country-specific."* Thus, implying that the hedge relation is affected by market characteristics, cultural attitude towards gold, and data time-frequency.

Lucey et al. (2017) study the relationship between gold and inflation and how stable the relationship is throughout their time series in the United States, the UK, and Japan, through CPI, PPI, and circulating money supply as a proxy for inflation. Instead of using local gold prices, they convert the dollar price of gold in local currency to model the relationship from a local investor's perspective. A cointegrating relationship is examined formally and visually through the Johansen test, using the trace test statistic approach. The authors expand upon the test to reflect the research question by adopting a time-varying vector error correction model, wherein the cointegrating relationship varies smoothly over time. The time-varying VECM is supplemented with a multiple breaks test, thereby deriving the structural breaks in cointegration for the time series models. Their result shows a break in the relationship between gold and US inflation from the mid-1990s. Gold did, however, offer protection against a rise in inflation and the growing money supply in the US and UK. On the other hand, only Japan shows a cointegrating relationship in the CPI. Most of their findings align with previous literature regarding the time-varying relationship in cointegration between gold, predicted, and realized inflation indicators. Furthermore, unlike several inflation measures, the result indicates the importance of money supply in the gold and inflation relationship. As motivation from this research article, we include these three inflation indicators in our analysis.

In contrast to the literature mentioned above, we can only find one reliable research paper that directly examines bitcoins properties of inflation hedging. Blau et al. (2021) examine the bitcoin price against the US. 5-Year Forward Inflation Expectation Rate (T5YIFR) as an inflation proxy. The authors refer to three research papers, Branch (1974), Fama & MacBeth (1974), and Outdet (1973), which state that "a security is an inflation hedge if its returns are independent of the rate of inflation." Their series consists of daily prices from January 1, 2019, to December 31, 2020, working with several multivariate time series tests to examine lead-lag relations and then estimate the series with a Vector autoregression (VAR) model. The VAR model captures multiple measures as they change over time. Their results indicate that bitcoin can hedge against expected inflation as movements in the price of bitcoin anticipate changes in the expected inflation, that is, in a granger sense. Furthermore, they suggest that bitcoin performs as a commodity and therefore can be used as a medium of exchange.

Capie et al.'s (2005) research on the currency hedge capability of gold inspires our empirical approach. They study to what extent gold acts as an exchange rate hedge, using weekly observations on the US price of gold with two exchange rates, namely the GBP/USD and YEN/USD. Since these indicators are volatile, they are interested in the response of the gold price to fluctuation in exchange rates, and therefore proceed with a dynamic regression model for the mean and a GARCH for the volatility since the error term exhibits conditional autoregressive heteroskedasticity. They find evidence of hedging capability in all the exchange rates, which shifts over time. Thus, indicating that the relationship between the dollar value of gold and the foreign exchange rates might be subject to external factors such as political attitude and other events. Focusing on bitcoin as a hedge or safe haven for foreign currencies, Urquhart & Zhang (2019) study the relationship between bitcoin in US dollars and other currencies. They use hourly intraday observations due to the significant volatility occurring throughout the day. They employ the asymmetric dynamic conditional correlation (ADCC) model to model the volatility dynamics, conditional correlations, and hedge properties between bitcoin and foreign exchange rates. Their results indicate that bitcoin can be a hedge for some currencies but acts as a diversifier for others. The authors suggest that further research contributions should consider the same methodology but with different financial assets.

In a more recent study, Palazzi, Júnior, and Klotzle (2020) examine the nonlinear relationship of bitcoin with six currencies: Euro, sterling, franc, renminbi, yen, and ruble, with each denominated in US dollars. They use the nonparametric causality test to estimate the nonlinear relationship and apply the multivariate filtering approach with a BEKK-GARCH for the residuals, controlling for conditional heteroskedasticity in the series. They also split the series into two samples, before and after a structural break. The results imply that the Euro and renminbi affect the price of bitcoin. Apart from their empirical contribution, the authors argue that the renminbi's significant effect on the bitcoin price is due to Chinas dominant role in the cryptocurrency market, quoted from an article in 2015. Their conclusion is quite odd because the Chinese government banned all cryptocurrency exchanges in September 2017. Nevertheless, we find it interesting that the Chinese currency still influences the price of bitcoin despite banning cryptocurrencies in 2017.

Baur and Lucey (2010) study a constant and a time-varying relationship between stock and bond returns with gold returns in the United States, UK, and Germany to investigate whether gold can be classified as a hedge, safe haven, or a diversifier for these two assets. The authors run a dynamic regression model and an asymmetric GARCH process to estimate the relationship between the assets dynamically while controlling for the conditional autoregressive heteroskedasticity. Baur and Lucey (2010) claim that "*it is important to analyze the link between the assets dynamically since lagged stock or bond returns can impact gold returns differently than contemporaneous stock or bond returns*." They find that gold is a hedge against stocks on average and a safe haven in extreme stock market conditions, but neither a hedge nor a safe haven for bonds. In our hedge and safe haven analysis, we follow Baur and Lucey's (2010) approach but exchange gold with bitcoin to assess the relationship between stocks and bonds.

On the other hand, Bouri et al. (2017) approach the hedging argument from another perspective. Using a dynamic conditional correlation model, they investigate hedge and safe haven properties against stock indices, government bonds, and commodity indices for several major economies. They also include the US dollar index in their analysis. Their empirical results show that bitcoin is an imperfect hedge against all stock indices but with the exception of Chinese stocks. While this might be the case, and as mentioned above, it is interesting to note that the Chinese government banned all crypto exchange platforms and other private crypto-related activities in September 2017, Xie, n.d. (2019, page 475).

This thesis follows the empirical framework set by the previous literature of Capie et al. (2005) and Baur & Lucey (2010). We also extract elements from the literature above, such as different macro variables, which will be elaborated in more detail in Section 5 of empirical analysis. Our contribution to the literature is to clarify the widely used claims about bitcoin as a financial asset, with various volatility analyses for five economies, unlike other literature, which primarily focuses on a single topic.

4 Data

The data in this thesis consists of weekly and monthly frequencies, ranging from September 13, 2011, to July 17, 2021. The data is modified to weekly to avoid potential serial correlation issues, while the monthly observations remain as observed. The weekly financial series consists of indicators such as the US. 10-Year Breakeven Inflation Rate, foreign exchange rates, stocks, and sovereign bond indices, covering the United States, Europe, Japan, South Korea, and Norway. The monthly observed data are the Consumer Price Index, Producer Price Index (PPI), and the circulating money supply (M1)[9], which are slow-moving indicators and consist of observations ranging from 79-113.

We use the US. 10-Year Breakeven Inflation Rate (T10YIE) as an inflation proxy in the inflation hedge section of the argument. This rate reflects a measure of the average expected inflation in the next ten years derived from the 10-Year Treasury Constant Maturity Securities and the 10-Year Treasury Inflation-Indexed Constant Maturity Securities (Federal Reserve Bank of St. Louis, 2003). Following the estimation conducted with this proxy, the results are supplemented with additional inflation indicators, namely the CPI, PPI, and M1. We obtain the foreign exchange rates to capture the currency hedge characteristics of bitcoin (BTC) on

[9] (M1): Cash held by the people in the economy. Money in circulation outside all locked savings account which are not in direct control of by the central banks.

behalf of the US Dollar. We also use these exchange rates to convert the bitcoin price into local currencies for the hedge and safe haven argument. Finally, we employ the MSCI stock indices and the TMB sovereign bond indices to assess bitcoin's hedge and safe haven properties.

Table 1: All accumulated data

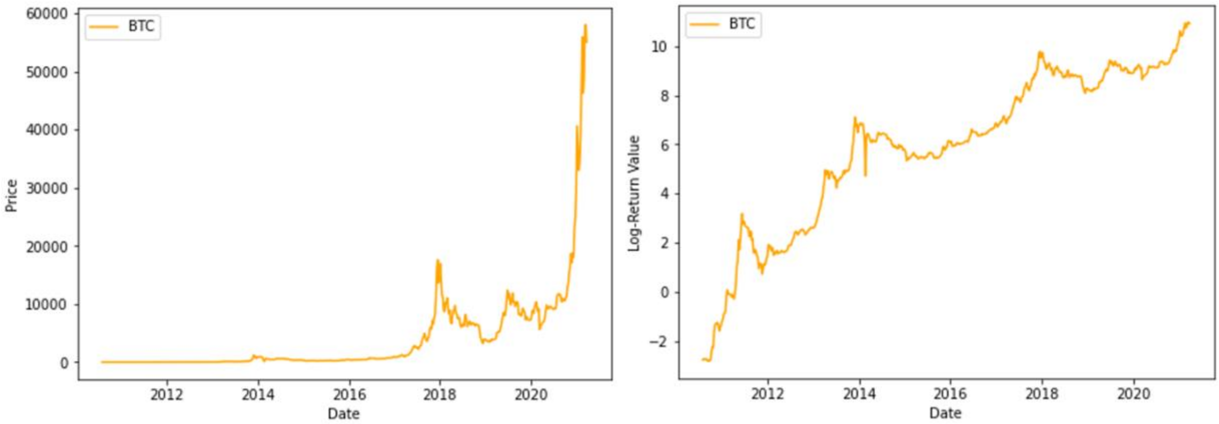
Name	Time Span	Frequency	Source
BTCUSD Bitstamp	Sep 13, 2011 - Jul 17, 2021	Monthly/weekly	BitcoinCharts.com
BTCKRW Korbit	Sep 3, 2013 - April 4, 2021	Monthly/weekly	BitcoinCharts.com
US. CPI, PPI, and M1	Jan 2010 - Jun 2021	Monthly	St. Louis FRED
European. CPI, PPI, and M1	Jan. 2010 - Jun. 2021	Monthly	ECB Statistical Data Warehouse
Japanese. CPI, PPI, and M1	Jan. 2010 - Jun. 2021	Monthly	e-Stat, Japanese Gov. Statistics / BOJ Time-Series Data Search
South Korean. CPI, PPI, and M1	Jan. 2010 - Jun. 2021	Monthly	Bank of Korea Economic Statistics System
Norwegian. CPI, PPI, and M1	Jan. 2010 - Jun. 2021	Monthly	Statistisk Sentralbyrå
US. 10-Year Breakeven Inflation Rate	Sep 13, 2011 - Jun 1, 2021	Weekly	St. Louis FRED
MSCI US Index	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
MSCI Europe Index	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
MSCI Japan Index	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
MSCI South Korea Index	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
MSCI Norway Index	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
TMB 10 Year US Sovereign Bonds	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
TMB 10 Year Europe Sovereign Bonds	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
TMB 10 Year Japan Sovereign Bonds	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
TMB 10 Year Korean Sovereign Bonds	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
TMB 10 Year Norwegian Sovereign Bonds	Sep 13, 2011 - Jun 1, 202	Weekly	Infront Professional Terminal
EUR/USD	Sep 13, 2011 - Jun 1, 202	Weekly	Refinitiv Eikon
JYP/USD	Sep 13, 2011 - Jun 1, 202	Weekly	Refinitiv Eikon
KRW/USD	Sep 13, 2011 - Jun 1, 202	Weekly	Refinitiv Eikon

Our bitcoin dataset is denoted in US Dollars and converted to local economies when necessary. Initially, we considered using local bitcoin prices for all the economies, thus yielding more realistic results instead of converting the bitcoin dollar price into local currency. However, as Hoang et al. (2016) propose in their research paper, the issue of converting the London gold price into other local currency may cause misleading results. They argue that it is essential to use local gold prices as the gold price quoted in London or Chicago does not reflect the economic state of the various economies. Although it is desirable to use local bitcoin prices, differing dataset lengths, missing observations, and multiple questionable data points following the initial data cleaning process made it difficult to implement this. We, therefore, proceed with the empirical estimations using the bitcoin US Dollar pair (BTC/USD) from Bitstamp. However, due to the interest of capital controls and trading constraints imposed on South Korean investors, we overlook the longevity restrictions and employ a local bitcoin price, namely Korbit, as a robustness check for the converted prices.

Further factor supporting our primary use of the Bitstamp dataset is that the general market primarily follows the BTC/USD pair. The majority of all bitcoin trading is done through foreign exchanges such as Bitstamp, Coinbase, and Binance, where the highest volume of BTC is somehow paired with the USD. While Bitstamp and Coinbase exchange the bitcoin pair in traditional currencies, Binance operates with BTC/USDT pair. Tether (USDT)[10] is an independent stable coin pegged 1/1 against the U.S. Dollar. USDT is among the largest stable coin in the crypto space with the highest volume and the third-largest crypto regarding market cap. The US dollar Tether is the stable coin of choice among the customers on Binance, even though Binance has established its stable coin called Binance USD (BUSD), which has far less trading volume.

[10] According to *Coinmarketcap* (The market cap is over 62 billion dollars at the time of writing).

Figure 1: Bitcoin price in levels (left panel) and log scale (right panel)



Financial time series are often exposed to exponential growth, and bitcoin is no exception, as displayed in the left panel of Figure 1. Thus, we log transform the series to better illustrate the historical trend movement of bitcoin. We can see that bitcoin experienced three significant price peaks starting from mid-2012, late 2013, and late 2017, marking the end of every official bitcoin bull run in the crypto community. Furthermore, the bitcoin series are differenced to stabilize the variance and display the returns, as people are more interested in returns than prices. This is also in line with the assumption of stationarity, as most econometric and statical methods are built on stationary series. We, therefore, proceed to convert our datasets to the first difference of the logarithm to obtain stationarity, except for the US. 10-Year Breakeven Inflation Rate:[11]

$$r_t = \left[ln * \frac{P_t}{P_1 - P_{t-1}} \right] * 100$$

Considering the rather sizeable number of financial series employed in this thesis and our preference for maintaining structure, only returns and moments of bitcoin are graphically explored in this section.

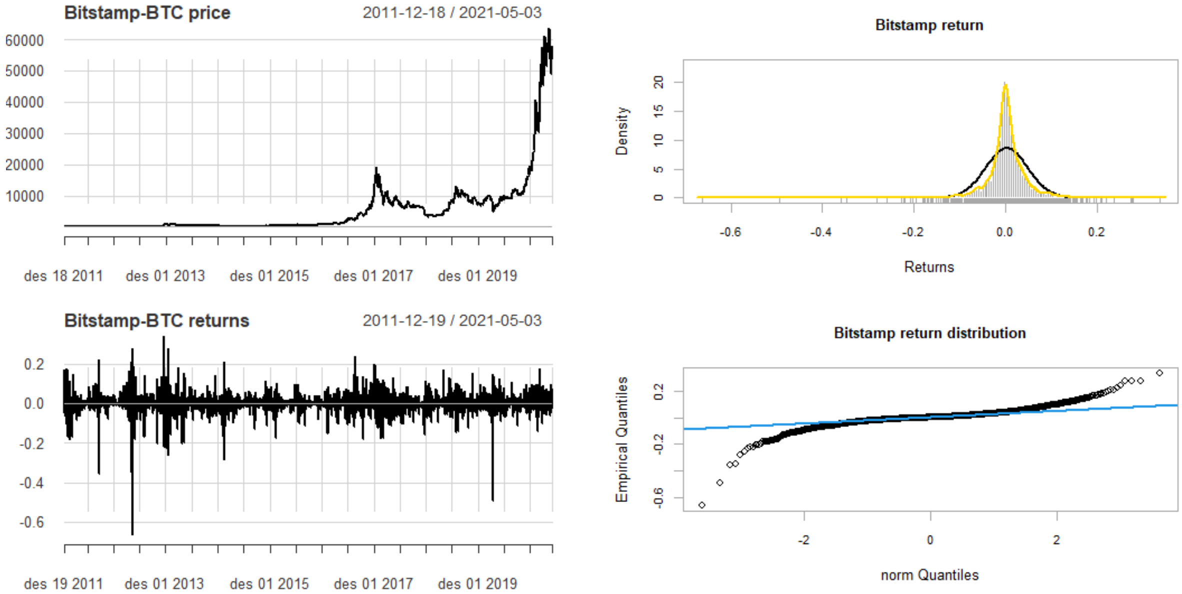
[11] As the unit for the US. 10-Year Breakeven Inflation Rate is given in percentages, the first difference was sufficient to attain stationarity.

Table 2: Sum statistics of bitcoin at different frequencies

Name	N. Valid	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
BTC-Bitstamp							
Daily	3424	0.002	0.05	-0.66	0.34	-1.38	23.15
Weekly	490	0.02	0.12	-0.59	0.54	-0.06	3.13
Monthly	114	0.09	0.28	-0.46	1.70	1.87	8.92
BTC-Korbit							
Daily	2755	0.002	0.04	-0.42	0.55	0.00	19.76
Weekly	391	0.02	0.12	-0.41	0.57	0.13	2.91
Monthly	92	0.07	0.31	-0.70	1.85	1.93	10.83

Table 2 displays multiple returns data for the price of bitcoin. These data are separated into two sections headlined by two bitcoin exchanges, Bitstamp and Korbit. The higher the mean and variance, the lower the frequency levels are. Therefore, the return distributions follow an intuitive progression for each frequency level. The lower the frequency, the higher the mean and the same goes for the variance. The results for both exchanges are also relatively similar, except for skewness for Korbit. Contrasting the values of Bitstamp, the third central moment suggests no skewness for the daily returns and positively skewed values for the other frequencies on Korbit returns. A closer investigation for the Bitstamp data follows in Figure 2, given that this series is our primary source of bitcoin data throughout the thesis.

Figure 2: Bitcoins distribution



A graphic overview of the daily log returns emphasizes what the tables indicate, as the series exhibit a rather volatile nature. The upper left panel of Figure 2 illustrates the price movements and is characterized by periods of price jumps. The bottom left panel illustrates this movement in a more statistical sound display, as the series is stationary. This graph indicates periods of volatility cluster, which is expected from such a financial series. The return distribution is compared to a normal distribution in both graphs to the right. The histogram in the upper right panel displays the density distribution for bitcoin returns in yellow and compares it to a fitted normal distribution. This histogram shows the leptokurtic distribution of the daily log returns. The fourth central moment of the distribution is more apparent than the third central moment, which is negative according to the values from Table 2. The heaviness of the tails is quite notable, given the frequency of outliers. The frequency of outliers is clearly depicted in the graph to the lower right. This graph displays a scatter plot from an empirical distribution and compares it to a normal distribution, in a blue line. The daily log return observations in black diverge from the line on either side. This significant deviation indicates a non-normal distribution for the daily returns. The normality test results also support this.[12] Interestingly, according to the results in Table 2, the distribution is closer to normal for the weekly series, given the values of excess kurtosis and skewness. This could also be attributed to the number of observations in the weekly series relative to the monthly. The combination of variance, min, max, and excess kurtosis of the daily series is indicative of

[12] Results for the normality test can be viewed in the appendix 2.

the leptokurtic nature of bitcoin returns. In conclusion, the returns seem more stable the lower the frequency, while the weekly series seems optimal in terms of the return distribution.

4.1 Descriptive statistics for the data in our main models

Table 3: Summary statistics of all datasets in each argument

Name	N. Valid	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
Inflation Hedge							
US. 10-Year Breakeven Rate	479	0.00	0.06	-0.50	0.44	-0.46	13.70
Currency Hedge							
EURUSD	474	0.00	0.01	-0.04	0.03	-0.03	0.60
JPYUSD	474	0.00	0.01	-0.04	0.05	0.11	2.00
WONUSD	474	0.00	0.01	-0.04	0.04	-0.05	0.49
Hedge and Safe Haven							
Stock Indices							
MSCI USA	418	0.00	0.02	-0.14	0.11	-1.61	10.49
MSCI EU	418	0.02	0.03	-0.21	0.12	-1.75	14.87
MSCI Japan	418	0.00	0.02	-0.13	0.09	-0.64	3.67
MSCI Korea	419	0.00	0.03	-0.22	0.09	-0.99	6.59
MSCI Norway	418	0.00	0.03	-0.22	0.13	-1.09	7.87
Sovereign Bonds							
US10YT	418	0.00	0.01	-0.07	0.06	-1.06	9.62
EU10YT	418	0.00	0.03	-0.12	0.07	-3.32	22.37
JP10YT	419	0.00	0.00	-0.03	0.01	-1.86	11.37
KR10YT	419	0.00	0.01	-0.07	0.05	-1.85	15.55
NO10YT	418	0.00	0.01	-0.10	0.07	-1.40	30.70

Table 3 contains a summary statistic of the data series employed throughout this thesis. The table content is divided into multiple sections, grouping the data summary by argument relevance.

The first headline is of the inflation hedge argument data and contains a summary of the US. 10-Year Breakeven Inflation Rate. The US. 10-Year Breakeven Inflation Rate is the only data on display from the inflation hedge argument, as the macro indicators are reported in appendix 2. The moments from the US. 10-Year Breakeven Inflation Rate suggests a large number of data outliers, although the skewness of the Breakeven Rate indicates almost evenly distributed data.

The following headline is of the currency hedge and contains foreign exchange rate data. The data series are stationary as well, where each of the series summary statistics displays similar values, except for the Japanese yen skewness and kurtosis. The Japanese kurtosis seems to be platykurtic similar to the other exchange rate series. Higher kurtosis values may be attributed to higher outliers.

The last headline of the hedge and safe haven argument displays the data summary of stock and sovereign bond indices for all the five economies in this thesis. The summary statistics display several interesting values, especially the excess kurtosis for the sovereign bonds. To begin with, each of the sovereign bonds displays excess kurtosis. This is much more prevalent for the Norwegian and European bonds, implying significantly fatter tails than the other bond returns. The mean return values seem relatively similar for both stocks and bonds, which also applies to the variance. However, the stock returns section displays a slightly higher variance.

5 Methodology

The arguments advanced in this thesis are assessed through multiple econometric approaches. Thus, given how the empirical approach loosely differs with each section, only the main models and their estimation procedure will be explained here.

The Autoregressive Distributed Lag (ARDL) model and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are considered as our main models here, given their application in several of the arguments. The GARCH estimation is of particular interest in this section, given that we examine the volatility clustering in each argument. Such examination follows the assumption that the volatility process in our models is determined by its past values. However, a limitation occurs following the conclusion of Hwang & Pereira (2006), which suggest that at least 500 observations are required for the GARCH model to obtain sustainable estimates close to the parameters in the series, which might also be the main reason for the lack of research papers employing GARCH methodology on the argument about inflation hedge on bitcoin. Despite these limitations, we assume that our observations are sustainable enough to assess the relationship between bitcoin and inflation.

5.1 ARDL

Firstly, the ARDL model is applied to evaluate bitcoin's dynamic relationship with other financial assets by including lags for all the variables of interest. The ARDL is a general model that employs the OLS estimator, and if all assumptions are satisfied, the ARDL approach will generate consistent estimates. Further benefits of using the ARDL model lie in describing the short and long-run dynamics (Brooks, 3rd Edition). Therefore, we use an ARDL model throughout this thesis:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_0 X_t + \beta_1 X_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim IID(0, \sigma_\varepsilon^2),$$

where, α_0, is the model's constant, $\alpha_1 Y_{t-1}$, constitutes the autoregressive part of the model, β_0 and β_1 is known as the impact multipliers or short-run dynamics, and constitutes the distributed components. The long-run dynamics of the total multiplier given the ordered equation, $\frac{\beta_0\ \beta_1}{1-\alpha_1}$. β_0 generates the contemporaneous effect, while the β_1 yields the lagged effect, showing the immediate effects on the dependent variable for every unit change in the independent variables. Thus, the distributed coefficients show how it affects the following period as they depict the dynamics of interest for all our mentioned arguments in this thesis.

5.2 ARCH / GARCH

Since the OLS model requires that the error term has a constant variance, we must control for heteroscedasticity. Although in our case, the residuals in the regression do not show constant variance over time, the OLS estimators are therefore not BLUE. Nevertheless, the OLS estimators are still unbiased, but the issue lies in the precision of the estimated standard errors and the confidence intervals. However, it is common to see periods of varying volatility clustering for financial time series. Due to Autoregressive variance in our regression, we apply a volatility model that allows the conditional variance to change over time, such as an Autoregressive Conditional Heteroskedasticity (ARCH) model (Engle, 1982). The ARCH model can capture the volatility clustering effects, but the model requires long lag structures and, therefore, negatively impacting parsimony. For this reason, Bollerslev (1986) proposed the GARCH model to bypass the limitation of the ARCH model by imposing nonlinear restrictions, thus requiring fewer lags to predict the conditional variance. We consider two asymmetric GARCH extensions (Engle & Ng 1993),[13] but the standard GARCH (1,1) is found to be sufficient for this thesis due to violation of parameter constraints. The GARCH (1,1) is sufficient in describing the time-dependent autoregressive nature of the residuals in this thesis. The equation for the GARCH (1,1) volatility is as follows,

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where $\alpha_1 \mathrm{u}_{\mathrm{t}-1}^2$ denotes the ARCH component of the model and encompasses the volatility during the previous period as α_1 captures the short-term volatility clustering effects and $\mathrm{u}_{\mathrm{t}-1}^2$ are the lagged squares of the error term. Finally, $\beta\sigma_{t-1}^2$ denotes the GARCH term of the model, where σ_{t-1}^2 is the value of the conditional variance model in the previous period. The constraints for an unconditional variance to be constant is for, $\alpha_1 + \beta_1 < 1$, and violation of this implies that the model will not converge to the unconditional variance, and the unconditional variance is not defined, meaning the model is non-stationary in variance, $\alpha_1 > 0$, and $\alpha_0, \beta_1 \geq 0$, (Brooks page 428, 9.8 Generalised ARCH (GARCH)).

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[13] Both the Exponential GARCH & the Threshold are used in our thesis. These extensions offer advantages in capturing volatility responses to “good“ and “bad" news, which standard GARCH does not. However, the application of these extensions depends on the significance and the sign of the parameter gamma and the result from Engle & Ng test (1993).

6 Empirical analysis

Our three empirical analyses are divided into subsections where we introduce a general definition of each argument using traditional assets as an example. We then refer to statements from companies, highlighting their view on bitcoin as an asset class and the basis for their long-term investments in bitcoin. Finally, we introduce our methodology inspired by previous literature to test the three defined arguments and present the results generated from these models.

6.1 Bitcoin provides an inflation hedge

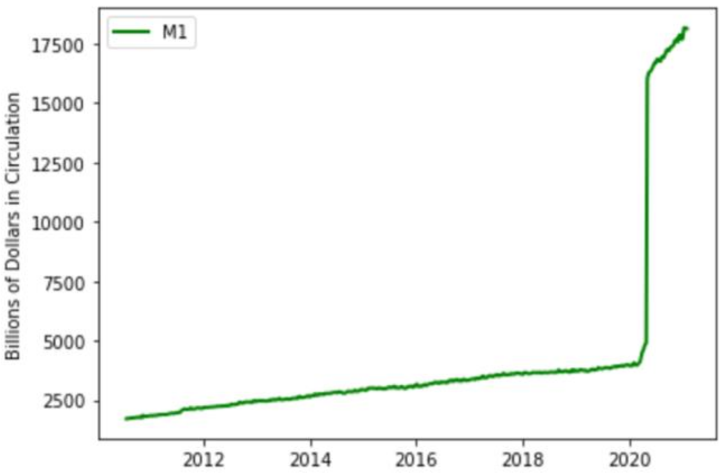
A direct side effect of inflation is reduced purchasing power, as prices for goods and services increase every year. Central banks, especially in developed economies, have an inflation target of around 2%. The central banks manage this primarily with two key instruments: the key interest rate and money supply. Increased inflation is a sign of a healthy growing economy, as consumption and investments rise, leading to increased activity in the local economy. However, if no institutions are controlling the activity level, as a central bank, the economy would spiral out of control with a potential for hyperinflation.

Since the global pandemic of Covid-19, there have been debates in the economic press concerning higher inflation rates due to increased stimulus, exceeding 6 trillion dollars, entering the markets in the United States, see Figure 3. The question is whether the ongoing expansionary monetary policy is too much for the economy to handle. If the recovery comes at a fast pace due to the Covid vaccine, it might overheat the economy as a shortage of capacity for goods and services might not meet the increased money supply, which can lead to increased prices. Another point we should not forget is the following of the financial crisis back in 2009, the start of the ongoing quantitative easing, that increased expansively until the beginning of 2020, in addition to a historically low interest rate that has been down-trending since the 1990s.

An interesting interpretation from Erb and Harvey (2013) mentions, "gold acts as a hedge of a local currency when the local government is printing an unprecedented amount of money." However, they refer to this statement as a currency debasement and argue that this can be interpreted as another inflation hedge argument. On the other hand, one could also argue that the extreme fear of inflation is exaggerated. As mentioned above, the interest rate has, after all, been declining in more than two decades, as the central banks have struggled to maintain their inflation targets while the demand for US Dollars has also increased for over a decade. Moreover, before the global pandemic, a falling unemployment rate showed signs of wealthy economic growth in the United States, suggesting that inflation would rise, which it did not.

Due to a combination of lower interest rates and a highly expanded money supply during the ongoing pandemic, and especially in the United States, it is understandable that the media and prominent economists are worried about periods of high inflation in the future, see Figure 3. Therefore, it is essential to consider an inflation-hedged position, such as TIPS, real estate, debt, precious metal, or perhaps even bitcoin.

Figure 3: US. M1 (Circulating money supply)



On August 11, 2020, MicroStrategy, Inc. announced its acquirement of 21 454 bitcoins[14] for 250 million dollars. Michael Saylor, CEO of MicroStrategy, comments that their predominant decision for investing in bitcoin is driven by an intersection of macro factors affecting their economic and business landscape, creating long-term risks for their corporate treasury program. They further express the basis of their belief in bitcoin as a store of value and state that bitcoin has a long-term appreciation potential than holding traditional cash. Furthermore, among several macro factors, they show their sincere concerns about the future economic uncertainty due to the post-pandemic of COVID-19, leading to unprecedented government stimulus and quantitative easing worldwide. Saylor comments further that they observer

[14] At the time of writing, MicroStrategy has, since August 11, 2020, accumulated a total of 50 000 bitcoins.

peculiar characteristics of bitcoin, which leads them to believe that it could provide a good hedge against inflation and, in addition, potentially gain higher returns than other assets.

The inflation hedge argument within the bitcoin community is largely dependent on certain fundamental characteristics shared with gold. These characteristics have to a certain degree, contributed to the inflation hedge argument that has been attributed to bitcoin, also known as "the digital gold." Erb & Harvey (2013) offer some guidelines related to reasoning around inflation hedge.

Firstly, a question arises from such an argument. For whom might bitcoin be an inflation hedge? For instance, the accessibility of bitcoin differs based on location and regulations. One such case is in South Korea, where only South Korean investors have exclusive access to one of the largest bitcoin markets due to strict trading laws caused by the legal and capital limitations imposed by the Korean government. Constraints of accessibility on some investors imply that not all can observe the real price, which causes further limitation on the inflation hedge argument investigation. Therefore, the South Korean results are estimated twice with the converted price of the Bitstamp exchange rate and one with a local crypto exchange in South Korea called Korbit.

Secondly, the argument can be deconstructed to an internal hedge, implying that it is a perfect hedge if the nominal price of bitcoin rises at an equal rate to changes in the inflation rate. This essentially relates the argument to bitcoin's co-movement with inflation indicators. Thus, a perfect co-movement suggests that the purchasing power of bitcoin is maintained in case of unit increases for inflation indicators. Ideally, the inflation hedge relationship is assessed using CPI, M1, and PPI. However, the lifespan of bitcoin and the frequency of these macro indicators limits the number of data points, which affects the optimality of the results acquired from such an approach. Following these limitations, the indicators are instead included as a robustness check. We, therefore, perform our primary analysis on the inflation hedge argument with the US. 10-Year Breakeven Rate. Which is an indicator for expected inflation, and unlike the three macro indicators above, it is a forward-looking inflation proxy.

The following methodology models the expected inflation as a price driver of bitcoin. The hedge argument here can be thought of in terms of purchasing power. Thus, we outline the following definitions for an inflation hedge,

- Bitcoin is an inflation hedge if the nominal price of bitcoin rises positively with a unit increase of inflation. Thus, it is an inflation hedge if bitcoin is positively correlated with an inflation indicator.
- Bitcoin is a perfect inflation hedge when it maintains its purchasing power. Thus, Bitcoin is a perfect inflation hedge when the nominal price rises at the same rate of a unit increase of the inflation indicator.

The structure of the model is predicated on the assumption of the dynamic relation between bitcoin and expected inflation. Hence an ARCH model is considered, where the variable of interest is the response of bitcoin to changes in expected inflation.

$$\Delta lnBTC_t = \alpha_0 + \alpha_1 \Delta lnBTC_{t-1} + \beta_0 \Delta INF_t + \beta_1 \Delta INF_{t-1} + \varepsilon_t ,$$

where the coefficient denoted, INF is the expected inflation measured in percentages, while BTC denotes the logarithm of bitcoin. We assume a linear dependence between bitcoin, the contemporaneous and lagged changes in expected inflation, and past prices of bitcoin. The model residuals from the OLS estimation exhibit evidence of time-varying conditional error variance,[15] hereby negatively impacting any statistical inferencing. We proceed to model this conditional variance by entertaining a variety of GARCH processes, such as the standard GARCH, the exponential GARCH, and the threshold GARCH. The estimation also assumes either a Gaussian, Student-t, Skewed Student-t, Generalized error and the Skewed General error distribution for the innovations, ε_t. According to the information criterion, we find the GARCH (1,1) with the Skewed Generalized Error Distribution (SGED) to be the best fit.

[15] Diagnostics for this model can be found in appendix 2.

Table 4: Estimation results for the US. 10-Year Breakeven Rate

	Weekly Observation	
US. 10-Year Breakeven	With Lagged variables (**1**)	No lagged variables (**2**)
$\Delta T10YIFR$	**0.311***** (0.085)	**0.317***** (0.085)
$\Delta T10YIFR_{t-1}$	0.033 (0.108)	
$\Delta lnBTC_{t-1}$	0.079 (0.085)	
Constant	**0.018**** (0.006)	**0.019***** (0.006)
α	0.257 (0.000)	0.237 (0.000)
β	0.655 (0.000)	0.682 (0.000)

*, **, *** suggest statistical significance at the 0.10, 0.05, and 0.01 level.
Under the coefficient estimators, the values in brackets are the standard robust standard errors of the coefficients.

Table 4 displays two models. The first model is dynamic with the lagged values of bitcoin and the current and past values of expected inflation as explanatory variables. The second model is a reduced version that includes only the significant variable from the dynamic model. The expected inflation is significant on both models and displays similar values as well. Although the coefficient only marginally increases when removing the insignificant values. Interestingly the lagged value of bitcoin is not significant in determining its current price variations, and the same applies to the lagged values of expected inflation. The ARCH and GARCH effects are both highly significant and indicate a similar effect on volatility regardless of the model. The sum for these effects is close to one, indicating high volatility persistence while still maintaining stationarity in variance. Our findings are quite interesting, as they indicate a highly significant hedge relationship and a conditional variance equation that suggests the presence of extremely persistent shocks.

We proceed to test the robustness of these findings by using the following macro indicators CPI, PPI, and M1. However, only the mean equation is tested here, given the number of observations and lack of ARCH effects for the three indicators. We devise this assessment within the framework of the internal hedge definition above. Thus, evaluating the co-movement of macro indicators and bitcoin. We examine the co-movement first through a correlation matrix, following up with a contemporaneous regression model for the economies of interest. Furthermore, bitcoin prices are converted in local currencies to consider the argument from the local investor's perspective.

Table 5: Correlation between macro indicators and bitcoin

Bitcoin	United States	Europe	Japan	Korea (Bitstamp)	Korea (Korbit)	Norway
CPI	0.134	-0.145	-0.146	-0.008	-0.027	-0.065
PPI	0.062	-0.062	0.222	0.201	-0.050	-0.082
M1	0.191	0.130	0.016	0.002	0.213	0.135

Table 5 depicts the co-movement argument through correlation. This approach is an initial overview of which direction the relationship moves. Nevertheless, none of the indicators suggests a clear relationship across all economies. In fact, most values are closer to suggesting an independent relationship. The CPI is the indicator that comes closest to a consistent relationship across all economies. A surprisingly negative relationship is observed for the CPI in all the economies, except for the United States. The PPI for both Japan and South Korea and the South Korean M1 indicates a relatively high correlation. However, as correlation does not imply causation, we employ the following multiple regression model for the robustness check.

$$y_i = \alpha + \beta \mathbf{X}_{\boldsymbol{i}} + u_i \quad u_i \sim IID(0, \sigma^2)$$

Where y_i denotes the changes in bitcoin returns, while the constant α is the intercept, and X represents the explanatory variables, CPI, PPI, and M1 for each economy. We proceed with the inclusion of CPI and PPI in the same model, as we find low evidence of multicollinearity.

The interpretation for the hedge is in line with the explanation presented above for the expected inflation. Thus,

- Bitcoin is an inflation hedge if the associated beta coefficient is positive on average, all else equal.

- Bitcoin offers a perfect hedge when the associated beta coefficient is one, which implies a constant purchasing power, all else equal.

Although given that each of the three macro indicators is a measure of inflation, any significant coefficient is an indication of a hedge. Ideally, the results should be fairly similar across all indicators, and any deviation should be interpreted with care.

Table 6: Estimation results for the macro indicators

	United States	**Europe**	**Japan**	**Korea (Bitstamp)**	**Korea (Korbit)**	**Norway**
Bitcoin	Coeff. est.	Coeff. est.	Coeff. est.	Coeff. est.	Coeff. est.	Coeff. est.
CPI	-3.415 (18.107)	-8.160 (6.290)	-19.300 (11.200)	-12.600 (10.000)	-16.500 (10.300)	-3.210 (8.310)
PPI	8.612 (4.951)	6.280 (5.130)	**11.800**** (5.130)	**14.900**** (6.790)	**19.800**** (7.620)	1.320 (1.090)
M1	0.028 (0.112)	0.936 (5.220)	1.770 (6.590)	0.329 (2.350)	-2.500 (3.250)	-0.351 (0.518)
Constant		**0.115*** (0.064)	**0.123**** (0.062)	**0.130**** (0.050)	**0.103**** (0.047)	**0.135***** (0.041)
Obs	112	78	78	78	90	78
Adj. R^2	0.011	0.004	0.05	0.02	0.044	0.028

*, **, *** suggest statistical significance at the 0.10, 0.05, and 0.01 level.
Under the coefficient estimators, the values in brackets are the standard robust standard errors of the coefficients.

The results from the model are relatively similar to the correlation table, as several indicators display no statistical significance. However, the PPI indicator for both Japan and South Korea are the exceptions for these results, also similar to the correlation table results. Both indicators suggest a positive significant relationship. According to the results, a one percent increase for the PPI in these countries is associated with an average increase of 11.8, 14.9, and 19.8 percent increase in BTC price returns. The lack of predictive power could be attributed to model selection or the low number of observations that occur due to the low frequency associated with such economic indicators and the lifespan of bitcoin.

We fail to reject the hypothesis of bitcoin as an inflation hedge with the US. 10-Year Breakeven Inflation Rate. Our results strongly suggest that bitcoin acts as an inflation hedge in the United States. This is in line with Blau et al.'s (2021) findings, where they test bitcoin for hedging properties with the US. 5-Year Forward Inflation Expectation Rate. On the other hand, our robustness check suggests otherwise for the United States, Europe, and Norway, thereby rejecting the inflation hedge hypothesis for these economies. However, we fail to reject the hypothesis for the PPI in Japan and South Korea, suggesting that bitcoin can act as an inflation hedge for these two economies.

In conclusion, our main model suggests a statically significant relationship. Thus, indicating that bitcoin has hedging capabilities and thereby a role as a financial asset in mitigating inflation risk. Although, the slow-moving macro indicators contradict these findings, which occur in the form of insignificance. These contradictions are based on estimations conducted with a limited number of observations, thereby clouding the statistical validity of the results. Thus, bitcoin can be included on the list of instruments that can reduce inflation risk, though these findings are only statistically sound for the US. 10-Year Breakeven Inflation Rate.

6.2 Bitcoin serves as a currency hedge

Currency hedging is a way of insuring against expected, unwanted, or unpredicted exchange rate fluctuations related to foreign investments or different currency positions. Investors and multinational businesses use hedging strategies to limit or eliminate the impact of foreign exchange (FX) risk when encountering international transactions or having shares of their revenue and operations abroad. FX risk, in general, is due to appreciation or depreciation of either the base or denominated currency, which can affect the company's operating cash flows as denominated profits or losses will at one point be converted to the base currency and hence result in potentially lower expected earnings.

For many centuries until the end of the Bretton Woods system in 1971, gold was a currency hedge by nature as it was the underlying value of the monetary system. Even though silver was the basis in some areas, gold was still the standard for all currencies, which is a reason to believe why gold is a currency hedge. Like gold, we want to see if bitcoin can also serve its role as a currency hedge which can potentially substitute or replace gold as a better alternative. Suppose there is significant evidence for bitcoin as a currency hedge. In that case, there is room for further arguing whether bitcoin is a better alternative to gold, based on the structure of Bitcoin as a coded global monetary system. Briefly explained, it is a global money system for all interested participants without restrictions on who holds bitcoin. Bitcoin is programmed, by default, so that no individual stakeholder can depreciate the value via the network, reducing the risk for any economic conditions being a key factor for its values. Parts of the bitcoin community believe that the value of bitcoin is neither based on certain economies or tangible assets but rather on the security of the Bitcoin network, driven by the difficulty rate of an algorithm[16] tracking all historical transactions where the difficulty level varies depending on the number of participants in the mining process. In theory, it makes sense to believe that bitcoin could potentially be a better currency hedge due to its democratic global monetary system.

In January 2021, Tesla invested 1.5 billion dollars in bitcoin and contemplates the possible acceptance of bitcoin as a payment for their products in the future. As Tesla is a multinational corporation, they have to transact their business globally in several currencies, facing several challenges. Tesla, Inc. (2021, page 23) states:

> "*foreign currency risks related to our revenue, costs of revenue, operating expenses and localized subsidiary debt denominated in currencies other than the US dollar, currently primarily the Chinese yuan, euro, Canadian dollar, and British pound (Tesla, Inc., 2021).*"

Tesla does not directly mention their beliefs about bitcoin acting as possible protection for currency risk, although they added the above citation in the same section on their reasoning for adding bitcoin to their balance sheet. However, Tesla may be trying to act cautiously and avoid claiming facts that are difficult to prove about bitcoin. Nevertheless, the argument is still of interest as it is still prevalent in the bitcoin community.

Tesla has historically experienced that any strengthening of the US dollar results in lower revenues within foreign operations, measured in US Dollars. Therefore, if we are to consider their statement implying that bitcoin is a currency hedge, then bitcoin must at least increase at the same rate as the US exchange rate on foreign currencies for Tesla to gap the possible revenue losses. Tesla also invested a large proportion of its cash reserves in bitcoin in early 2021. In their 10-k report (2021, page 23), Tesla expressed their concerns about potential significant depreciation of the US Dollar against other currencies they operate in, leading to increased costs measured in US dollars and drastically reducing their margins. Their statement might be Tesla's way of saying that they fear a dramatic increase in inflation in the United States for the potential future and, therefore, a depreciation in the dollar.

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[16] Every node has the opportunity of being a mining node and add new transactions (new blocks) to the blockchain. By doing so, miners then receive bitcoin in reward and the cost of transaction fees to process this work. To add blocks to the network, the miner must retrieve a mathematical puzzle, mainly the algorithm provided by the blockchain software. The algorithm is based on a set of present transactions, the primary identifier of previous blocks, and a random nonce which is an integer between 0 and 4,294,967,296. This shows how highly complex the mining process really is.

The methodology in this section examines bitcoins hedging capability against one unit of interest, namely the dollar. This approach is for many reasons, but primarily due to the dollar’s dominance in global trade relative to other economies where bitcoin is prevalent. Furthermore, currency hedge examination for other economies where bitcoin is widespread is also limited by data availability. The empirical approach for this argument is motivated by Capie et al. (2005), who interpret the currency hedge argument in terms of changes in the dollar's internal and external purchasing power. The former suggests bitcoin is a currency hedge against changes in the domestic purchasing price of the dollar. The latter considers an outwards perspective where the objective is changes in the dollar's purchasing power regarding foreign currencies. Thus, a perfect hedge following the external argument implies an exact inverse relationship between the nominal dollar price of bitcoin and the number of units of foreign currency per dollar. For instance, bitcoin is a perfect external hedge if the nominal dollar price rises at a precise rate and time, as the number of units of foreign currency per dollar decreases, and vice versa.

As mentioned above, this section of the thesis uses a similar methodology for bitcoin as Capie et al. (2005) apply to gold. Capie et al. (2005) assess the presence of a dynamic relationship between gold and the dollar, more specifically, the possibility of any significant external hedging capabilities. The authors define this relationship in terms of an autoregressive distributed lag model. Furthermore, they also use an asymmetric GARCH model after detecting a time-varying conditional error variance. We consider a slight deviation in our research design regarding the data frequency. The consideration is due to the assumption that daily data are more likely to exhibit the dynamic relationship of interest.

Our model is set up to capture the response of bitcoin returns to changes in the exchange rate. The dynamic structure of the model assumes that the magnitude of these responses may differ relative to a contemporaneous model. Essentially the model assumes a linearly dependent causal relationship, wherein the right-hand side of the equation measures the impact of both the contemporaneous and lagged effects of the dependent and independent variables. The model estimate exhibits an autoregressive time-varying variance[17], and thus we model the

[17] Diagnostic test of ARCH-test in the appendix 2.

volatility through a standard GARCH model. The following equation depicts the mean and variance of our model:

$$\Delta lnBTC\$_t = \alpha_0 + \alpha_1 lnBTC\$_{t-1} + \beta_0 \Delta lnExchange_t + \Delta lnExchange_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

The coefficients, β_0 and β_1, are of particular interest, given that these values and their significance determine the relationship of, namely, the hedging capability.

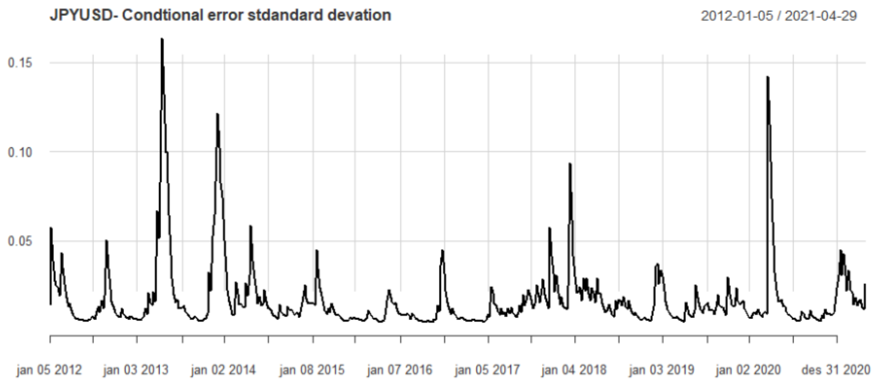
Table 7: Estimation results for currency hedge

	EUR (€)	Yen (¥)	Won (₩)	NOK (kr.)
Bitcoin	Coeff. est.	Coeff. est.	Coeff. est.	Coeff. est.
$\Delta lnExchange_t$	-0.250 (0.531)	0.493 (0.523)	0.155 (0.598)	-0.617 (0.483)
$\Delta lnExchange_{t-1}$	-0.635 (0.610)	0.459 (0.556)	-0.231 (0.549)	0.334 (0.402)
$\Delta lnBTC_{t-1}$	0.102 (0.074)	0.098 (0.046)	0.065 (0.086)	0.084 (0.084)
Constant	**0.018***** (0.006)	**0.017***** (0.005)	**0.019***** (0.006)	**0.019***** (0.006)
Conditional Volatility				
ω	0.0016 (0.104)	0.0017 (0.001)	0.0015 (0.000)	0.0013 (0.000)
α	0.3417 (0.076)	0.3423 (0.104)	0.3495 (0.100)	0.3495 (0.065)
β	0.6245 (0.055)	0.6216 (0.065)	0.6044 (0.069)	0.6044 (0.052)
Distribution	Skewed-std	Skewed-std	Skewed-ged	Skewed-ged

*, **, *** suggest statistical significance at the 0.10, 0.05, and 0.01 level.
Under the coefficient estimators, the values in brackets are the standard robust standard errors of the coefficients.

The output from the estimated models indicates no significant relationship between bitcoin's nominal value in dollars and the foreign exchanges. We, therefore, reject the hypothesis of bitcoin as a currency hedge for the external purchasing power of the dollar. The results are similar across all exchange rates as we detect no significance for either the lagged or the contemporaneous effects for the variables of interest in each model. Unsurprisingly the lagged value of bitcoin returns displays significant effects on explaining the variation of current bitcoin returns.

Figure 4: Conditional error standard deviation from the Japanese Yen equation



We find the GARCH (1,1) process sufficient in capturing the volatility clustering within each model, and the results suggest a fairly similar effect on volatility for each exchange. The ARCH and GARCH effects are all positive and significant at the 5% level, with each indicating approximately 30% volatility impact on the following week for the ARCH term and 60 % for the GARCH term. Although stationary in variance, the sum of both the ARCH and GARCH effects signifies highly persistent shocks, but nevertheless still mean reverting. Figure 4 depicts this shock persistence for the Japanese yen exchange equation, while we omit the rest of the plots given their similarities. The figure displays periods of volatility clustering, where some of these bursts are visually traceable to bitcoins price surges.

Our empirical findings reject the hypothesis of bitcoin as a currency hedge on all exchange rates, which raises the question of Tesla's argument for adding bitcoin to their balance sheet. However, Tesla may have attributed such property to bitcoin based on its fundamental characteristics and not on bitcoin's historical price movements. If this is the case, then our findings collide with Teala’s conclusion, as we presumably do not follow the same methodology and interpretation of a currency hedge. However, there are far better financial instruments for reducing FX risks, such as forward contracts and options. By using forward contracts as a hedging instrument, a company can lock the current denominated exchange rate to the given transaction date, regardless of the closing rate of the exchange rate. On the other hand, a denominated exchange rate at execution is fixed when using options. A company can then decide whether they want to exercise the option or not, depending on whether the current market exchange rate on the expiration date is in favor of the company or not.

6.3 Bitcoin is a hedge or a safe haven for stocks and bonds

Safe haven properties tend to be negatively correlated or uncorrelated with other assets defining an asset as a place of safety during market turmoil. As Baur and McDermott (2010) put it, the terminology comes from the shipping industry, where ships seek a harbor for safety during stormy weather. So, with that in mind, the general envision of a safe haven asset is that it holds its value during extreme market conditions. These assets offer investors an opportunity to protect their wealth in adverse market conditions such as the Dot com bubble in 2002, the global financial crisis in 2008, and the liquidity crisis in March 2020. As Baur and Lucey (2010) put it, a safe haven asset is nonpositive or uncorrelated with a well-diversified portfolio during tail risk events. These assets should somehow compensate for potential losses during extreme market conditions.

Traditional safe haven assets are typically sovereign bonds, like the US and Norwegian Treasury Bills. In times of economic uncertainty, investors tend to hold these securities. Local cash is also considered a safe haven during times of market uncertainty. Some even proclaim that cash is the only safe haven during these periods. On the other hand, certain currencies provide even more safe haven guarantees than other global currencies, such as the US dollar, the Japanese Yen, and the Swiss franc. The former financial downturn in March 2020 was called "the dollar liquidity crisis" due to the shortage of American dollars, contributing to further decline in the stock markets. However, there is no clear explanation for this event. Investors and companies were likely searching for a safe haven asset during these turbulent times, which might be one reason for the so-called dollar liquidity crisis. The Swiss franc is also considered a safe haven currency due to its stable government, financial system, and independence from the European Union, resulting in solid foreign demand for the Swiss franc under times of financial distress.

The safe haven characteristic of bitcoin is a less disputed property that has gained ground in recent times. However, the advancement of this argument can also be traced back to what the bitcoin community considers a comparable asset, namely gold. Thus, to shed light and gain further insight into the statistical validity of this argument, we resort to previous methodology, contributed to the field of gold.

Baur and Lucey (2010) study the hedge and safe haven properties for gold within three countries by estimating a dynamic relationship between the gold price, MSCI stocks, and total sovereign bond returns. They added three different quantiles in their dynamic model, representing the safe haven components. These quantiles capture the lower 5%, 2.5%, and 1% returns, defining the most extreme adverse market conditions in their time series. Furthermore, they employ an asymmetric GARCH model after detecting evidence of time-varying conditional error variance. Since our hedge and safe haven analysis proceeds with a similar approach to Baur and Lucey (2010), it is reasonable to follow their empirical interpretation on hedge and safe haven properties. A weak (strong) hedge defines an asset that, on average, is uncorrelated (negative correlated) with another asset. A weak (strong) safe haven asset is uncorrelated (negatively correlated) with another asset/market during extreme market conditions.

For our empirical framework, we proceed with a similar approach to Baur and Lucey (2010) and introduce the same regression model as displayed below. A standard GARCH model is sufficient for modeling the time-varying conditional error variance. We are interested in finding the relationship between bitcoin and the selected financial assets from a local investor's perspective. Therefore, we convert the bitcoin dollar price into local currency. We also perform the same analysis with the Korbit data series. However, since the results are equivalent, we, therefore, choose to omit the Korbit model output. Baur and Lucey (2010) augment lagged gold, stock, and bond returns in their equation if the terms are statistically significant. However, we choose to diverge from their approach and employ the information criterion as a basis for our model selection. Therefore, our equation is set up as follows,

$$r_{bitcoin} = a + b_1 r_{stocks,t} + b_2 r_{stock,t(q)} + c_1 r_{bonds,t} + c_2 r_{bonds,t(q)} + e_t$$

where b_1 denotes the MSCI stock markets, c_1 denotes sovereign bonds for each economy. b_2 and c_2 represent the different quantile levels. The empirical results, displayed in Table 8, show the coefficient estimates for average effects and the three quantiles on weekly frequencies. The coefficient estimates for average effects measure the hedge properties, and the quantile estimates measure the extreme negative returns, hence a measurement of safe haven properties. The basis for the three selected quantiles is motivated by Baur and Lucey's specification, where we only include the lower 1%, 2.5%, and 5% observed returns in the dataset. The three quantiles are deemed as dummy variables in our equation, as returns exceeding the 5% level are set to zero.

Table 8: Estimation results on Hedge and Safe Haven

	United States	**Europe**	**Japan**	**South Korea**	**Norway**
Bitcoin	Coeff. est.	Coeff. est.	Coeff. est.	Coeff. est.	Coeff. est.
b_1	**0.735**** (0.343)	**0.612**** (0.0.294)	0.173 (0.336)	-0.327 (0.233)	-0.049 (0.203)
b_2 (5%)	0.089 (0.797)	-0.457 (0.677)	0.853 (0.990)	0.715 (0.8513)	**-1.360*** (0.775)
b_2 (2.5%)	-0.039 (1.191)	1.093 (1.021)	-0.885 (0.994)	-1.310 (0.937)	**1.920**** (0.976)
b_2 (1%)	0.508 (1.049)	-0.073 (0.941)	**1.340**** (0.065)	**2.218**** (0.949)	-0.169 (0.402)
c_1	0.302 (0.712)	-0.329 (0.630)	**-4.091**** (1.992)	**-3.007***** (0.965)	-0.180 (0.634)
c_2 (5%)	0.779 (1.359)	-0.645 (1.638)	**8.005**** (4.010)	**6.164**** (2.985)	0.802 (1.925)
c_2 (2.5%)	1.723 (1.681)	1.567 (1.162)	-1.773 (4.386)	-5.389 (3.620)	0.692 (2.241)
c_2 (1%)	-2.384 (1.462)	-0.193 (0.815)	1.067 (6.077)	1.895 (2.024)	-0.005 (1.473)
Conditional Volatility					
α	0.248 (0.095)	0.292 (0.890)	0.420 (0.180)	0.287 (0.141)	0.249 (0.096)
β	0.647 (0.118)	0.499 (0.130)	0.381 (0.248)	0.480 (0.312)	0.643 (0.126)

*, **, *** suggest statistical significance at the 0.10, 0.05, and 0.01 level.
Under the coefficient estimators, the values in brackets are the standard robust standard errors of the coefficients.
b_1 denotes the MSCI stock markets for each economy, and b_2 represents the different quantile levels. c_1 denotes sovereign bonds.

The average effects of stocks on bitcoin are 0.735 for the United States, 0.612 for Europe, 0.173 for Japan, -0.327 in South Korea, and -0.049 for the Norwegian stock indices, ceteris paribus. However, the estimates are only significant for the US and European stock markets, at the 0.05 level. These results indicate that bitcoin is not a hedge for stocks in either the United States or the European area. In fact, bitcoin covaries with the stock markets, implying that bitcoin is a risk-on/risk-off asset, which is the opposite of our hypothesis of bitcoin being a hedge for stocks. However, the three remaining economies fail to display statistical significance, thereby rejecting the hypothesis of bitcoin as a hedge for stocks in Japan, South

Korea, and Norway. Nevertheless, considering the coefficient estimates for average effects on US and European stock markets, investors could consider bitcoin as an alternative investment when searching for higher yields than traditional stocks during stable markets and showing low volatility in the VIX index (McCauley, 2013).

For sovereign bonds, only Japan and South Korea show statistical significance at the 0.05 and 0.01 levels with an average effect of -4.091 and -3.007, showing strong evidence of hedging properties for bitcoin on Japanese and South Korean government bonds.

Table 9: The overall effect for the three quantiles for stocks

	United States	**Europe**	**Japan**	**South Korea**	**Norway**
Bitcoin	Overall effect	Overall effect	Overall effect	Overall effect	Overall effect
b_2 (5%)	0.824	0.155	1.026	0.388	**-1.409***
b_2 (2.5%)	0.785	1.248	1.141	-0.922	**0.511****
b_2 (1%)	1.293	1.175	**1.481****	**1.296****	0.342

*, **, *** suggest statistical significance at the 0.10, 0.05, and 0.01 level.

As for Safe Haven properties, we measure these effects by summarizing all the coefficient estimates up to the selected quantile (Baur & Lucey, 2010). For example, the overall effect on the lower 1% quantile on stock returns in South Korea is the sum of all the coefficient estimates, equaling 1.296 (-0.327 + 0.715 - 1.31 + 2.218). As the 1% quantile is statistically significant at the 0.05 level, suggesting that the price of bitcoin declines way beyond the Korean stock markets, during the most extreme market conditions. Our findings also suggest similar effects in the Japanese market, with corresponding values on the overall effects and significance level. This also seems to be the case for the Norwegian stock markets at the 5% quantile with an overall effect of -1.409, but not at the lower 2.5% quantile, with an overall effect of 0.511. These results are quite peculiar, as they suggest that bitcoin is a safe haven for Norwegian stocks at the 5% lower returns but a risk-off asset at the 2.5% lower returns. However, given the small size of the bitcoin market in Norway, we assume that these overall estimate values, indicating safe haven characteristics, to be a spurious relationship. Given the lack of statistical significance for stocks in the United States, Europe, and Japan, our findings do not support the safe haven asset hypothesis for these economies under extreme adverse market conditions. Our concluding assessment on the safe haven argument for stocks roughly reflects the same interpretation from our results on the hedging argument, that bitcoin behaves as a risk-off asset during periods of turbulent stock markets. We, therefore, conclude that bitcoin is not a hedge nor a safe haven for stocks and is at least as risky, if not riskier, than stocks.

Table 10: The overall effect for the three quantiles for bonds

	United States	**Europe**	**Japan**	**South Korea**	**Norway**
Bitcoin	Overall effect	Overall effect	Overall effect	Overall effect	Overall effect
b_2 (5%)	1.081	-0.974	**3.914****	**3.157****	0.622
b_2 (2.5%)	2.804	0.593	2,141	-2.232	1.314
b_2 (1%)	0.42	0.4	3.208	-0.337	1.309

*, **, *** suggest statistical significance at the 0.10, 0.05, and 0.01 level.

The quantile estimates for extreme negative bond returns were only statistically significant for Japanese and South Korean bonds at the 5% lowest returns with an overall effect of 3.914 and 3.157. These findings suggest that bitcoin is a risk-off asset for bonds during adverse market conditions in Japan and South Korea which is the opposite of our hypothesis.

Based on these results we find it reasonable to assume that bitcoin is a risk-off asset for all economies during tail risk events, as it does not make sense that investors use bitcoin as protection for government bonds during market turmoil. This is in line with our findings on bitcoin as a risk-on asset for stocks and bonds. Our findings make sense as investors tend to downsize future potential losses during turbulent stock markets, whereas the VIX index shows a rising trend. As a result, they liquidate high-risk positions and move their values into cash holdings or low-risk government bonds, such as US Treasury bonds or even the Japanese Yen, as it tends to rise under such circumstances (McCauley, 2013).

In conclusion, our empirical findings display statistical evidence of bitcoin behaving opposingly to our initial hypothesis for hedge and safe haven properties. The results imply that bitcoin acts more as a risk-on/risk-off asset for stocks and bonds. However, our results only suggest risk-on characteristics for the United States and European stock markets, implying that investors might receive higher bitcoin returns against positive stock returns on average. Only the Japanese, South Korean, and Norwegian stock markets display significant results for the safe haven hypothesis. Bitcoin acts as a risk-off asset at the 1% quantile for both Japanese and South Korean stocks, during extreme market turbulence. On the other hand, Norwegian stocks suggest mixed signals with weak support for safe haven properties at the 5% quantile while showing slightly stronger significance on risk-off characteristics at 2.5%. We do not see the economic mechanism behind these relationships as they exhibit opposing interpretations. Thus, we cannot dismiss the possibility of a spurious relationship for both quantiles. We can, therefore, not attribute any hedge or safe haven properties for stocks and bonds for all the economies of interest in this section.

Further on, we find strong statistical evidence of bitcoin acting as a hedge for Japanese and South Korean sovereign bonds, but strong significance results for risk-off properties for both the Japanese and South Korean bonds. However, we find these results quite counterintuitive as there was strong evidence suggesting hedge properties for Japanese and South Korean government bonds but risk-off characteristics during turbulent markets. It does not make any sense that bitcoin acts as a risk-off asset for bonds during turbulent markets but a hedge for low-risk securities. All in all, we conclude that bitcoin is not a hedge for government bonds and believe these estimates are a result of yet a spurious relationship.

Based on our empirical findings, bitcoin is not a good investment for risk averse investors that seeks safe assets with guaranteed returns. There are far better hedge and safe haven alternatives for stocks and bonds, such as options. On the other hand, Bitcoin can be a good bet during healthy and more stable markets, potentially yielding higher returns than stocks and bonds. However, we are not suggesting that bitcoin is less volatile during normal market conditions. On the contrary, Bitcoin has repeatedly shown periods of significant price declines over longer intervals, regardless of the economic state. After all, bitcoin is a risk-on/risk-off asset. This assumption makes sense as the higher the risk, the higher the potential returns.

7 Conclusion

Our master thesis contributes to a small but a growing field of academic literature on the role of bitcoin as a financial asset, where we aim to analyze whether bitcoin is an inflation hedge, currency hedge, and, lastly, hedge and safe haven within five economies.

Our empirical results show strong statistical evidence of bitcoin acting as an inflation hedge for the US. 10-Year Breakeven Inflation Rate. However, we reject the hypothesis of bitcoin as a currency hedge throughout all the exchange rates. Finally, we struggle to find consistent evidence for bitcoin as a hedge and a safe haven for stocks and bonds in all five economies. Nevertheless, our results suggest that bitcoin acts as a risk-on/risk-off asset, showing the opposite of our hypothesis. Even though bitcoin is a risky asset within the financial markets, it is interesting to see that bitcoin offers protection from expected inflation. In conclusion, our findings suggest that bitcoin has a role in a portfolio as a financial asset, since it can be used in portfolio analysis and risk management, due to its hedging capability against expected inflation.

The main limitation following the composition of this paper is related to data observations, which are even more restrictive for the three macro inflation indicators. Thus, leading to undesirable combinations when assessing the slow-moving macro indicators, contributing to the relegation of the CPI, PPI, and M1 to a robustness check position in the assessment of the inflation hedge argument property. The limitations are also prevalent for the hedge and safe haven argument. The argument outlines somewhat arbitrary percentiles of what the model considers a tail risk. Values outside these percentiles are set to zero. Thus, the limitation is caused by the lack of tail risk events or outliers within the defined parameters.

Bitcoin is relatively young compared to the other financial assets in this paper, and thus the data limitation persists for each argument. Thus, prompting the question of whether the observed data variations are sufficient in assessing the arguments advanced in this thesis. However, such limitations are easily mitigated with time. Future research in the field should therefore revisit these arguments, as there is no current indication for them being less compelling in the bitcoin community with time.

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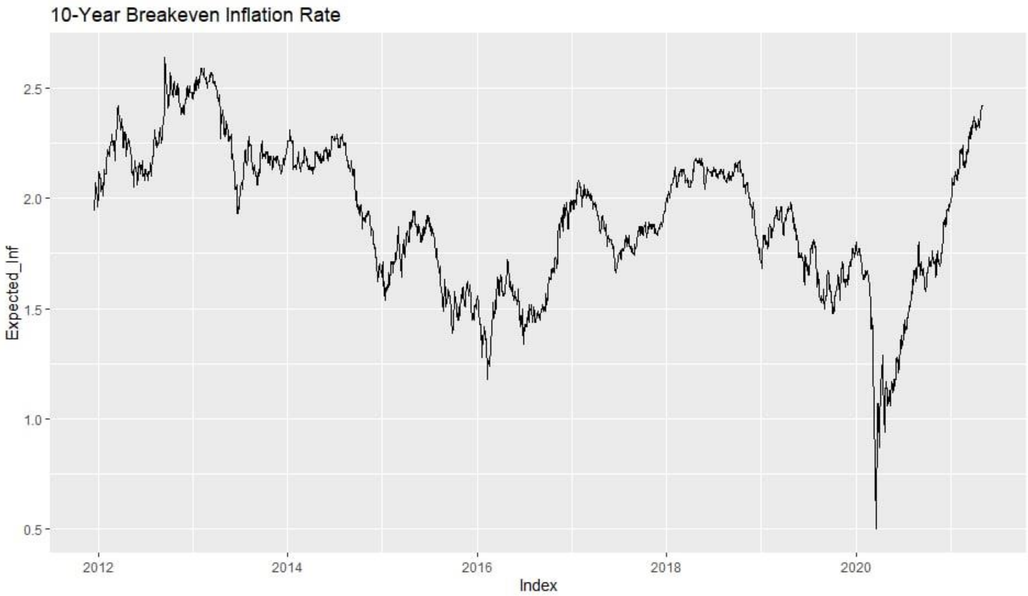
11Appendices

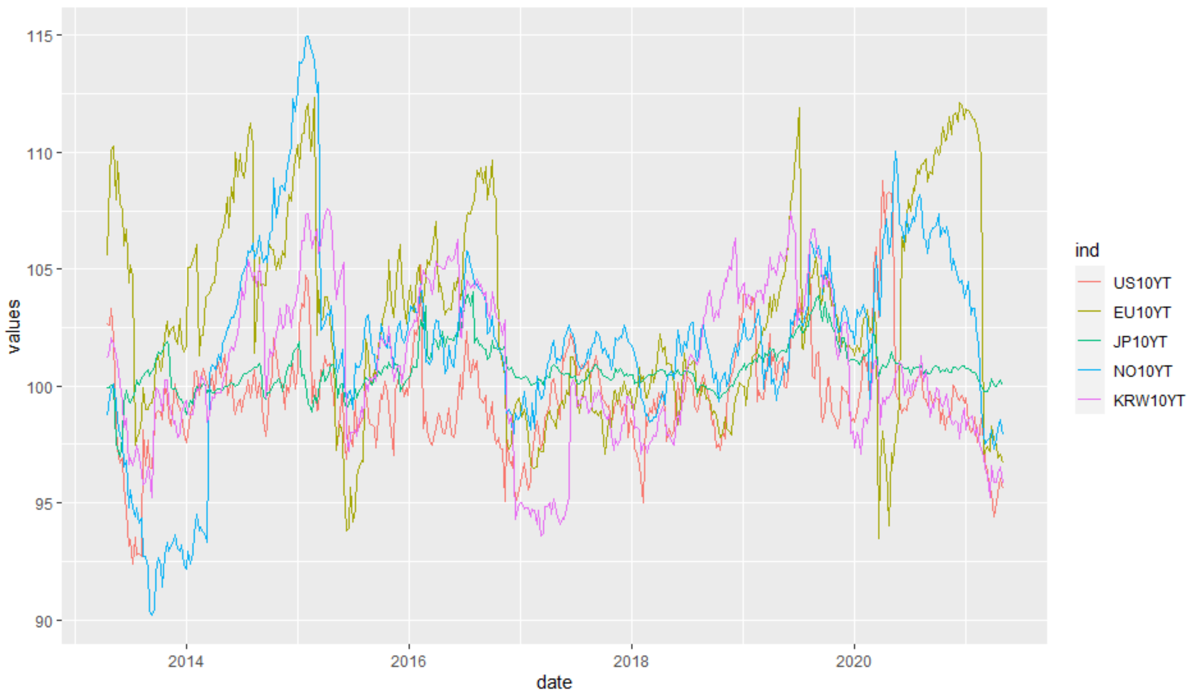
Appendix 1: Figures

US. 10-Year Breakeven levels in percentage



Graph distribution of MSCI stock Indices

Graph distribution of TMB Sovereign bond Indices



Appendix 2: Tables

Data

All bitcoin datasets from different exchanges

Name	Time Span	Frequency	Source
Bitstamp USD	Sep 13, 2011 - Jul 7, 2021	Daily	BitcoinCharts.com
Kraken USD	Jan 7, 2014 - Jul 7, 2021	Daily	BitcoinCharts.com
Kraken EUR	Jan 8, 2014 - Jul 7, 2021	Daily	BitcoinCharts.com
CEX EUR	Sep 26, 2014 - Jul 7, 2021	Daily	BitcoinCharts.com
BTCBOX JPY	Apr 04, 2014 - Jul 7, 2021	Daily	BitcoinCharts.com
Korbit KRW	Sep 03, 2013 - Jul 7, 2021	Daily	BitcoinCharts.com

Results from the Unit Root tests on Bitstamp and Korbit dataset

Indicators	**ADF**	**PP**	**KPSS**
BTC			
(Bitstamp)	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
Korbit	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm

Inflation Hedge

Diagnostic test on the Inflation Hedge

US. 10-Year Breakeven	Model (1)	Model (1)
Observation	478	479
ARDL		
Adj.R^2	0.027	0.026
AIC	-618.43	-624.17
Breusch-G test, P-value	0.84	0.63
Durbin Watson	0.52	0.042
ARCH-LM, P-value	0.000	0.000
Ramsey Reset test, P-value	0.47	0.84
GARCH		
Distribution	**SGED**	**SGED**
AIC	-1.6532	-1.6595
BIC	-1.6096	-1.6159
Ljung-Box Q-stat, P-Value	0.54	0.14
ARCH-LM, P-value	0.95	0.95

Ljung-box and ARCH-LM (standardized residuals)
Lags set to 15 for Breusch-G, Ljung-box, and ARCH-LM.

Results from the Unit Root tests on Inflation Hedge

Indicators	ADF	PP	KPSS
United States			
CPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
PPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
M1	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
Europe			
CPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Non- Stationary at first difference of log
PPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
M1	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Non- Stationary at first difference of log
Japan			
CPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
PPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Non- Stationary at first difference
M1	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Non- Stationary at first difference
South Korea			
CPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
PPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
M1	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
Norway			
CPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
PPI	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
M1	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm

Summary statistics of data for the robustness check

Name	N. Valid	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
United States							
CPI.US	112	0.00	0.00	-0.01	0.01	-0.52	1.73
PPI.US	112	0.00	0.01	-0.03	0.02	-0.98	3.52
M1.US	112	0.02	0.12	-0.01	1.23	10.11	102.34
Europe							
CPI.EU	78	0.00	0.01	-0.02	0.02	0.18	0.94
PPI.EU	78	0.00	0.01	-0.04	0.02	-1.85	9.65
M1.EU	78	0.01	0.01	0.00	0.06	3.39	15.39
Japan							
CPI.JP	78	0.00	0.00	-0.01	0.02	2.36	14.66
PPI.JP	78	0.00	0.01	-0.03	0.01	-1.02	2.46
M1.JP	78	0.01	0.01	0.00	0.03	1.84	4.51
South Korea							
CPI.KR	78	0.00	0.00	-0.01	0.01	0.25	0.45
PPI.KR	78	0.00	0.01	-0.2	0.02	-0.27	1.20
M1.KR	78	0.01	0.01	-0.01	0.08	1.79	5.38
Norway							
CPI.NO	78	0.00	0.00	-0.01	0.01	-0.08	0.14
PPI.NO	78	0.00	0.03	-0.15	0.06	-0.93	3.31
M1.NO	78	0.01	0.07	-0.05	0.61	7.53	60.19

All the displayed data series are monthly observations.

Currency Hedge

Diagnostic test on the Currency Hedge

	EUR (€)	Yen (¥)	Won (₩)	NOK (kr.)
Observation	473	473	476	487
ARDL				
Adj.R^2	0.007	0.008	-0.001	0.009
AIC	-658	-658.73	-620	-658.77
Breusch-G test, P-value	0.062	0.25	0.32	0.76
Durbin Watson	2	2.01	2	2.01
ARCH-LM, P-value	0.000	0.000	0.000	0.000
Ramsey Reset test, P-value	0.001	0.000	0.000	0.14
GARCH				
AIC	-1.673	1.683	-1.661	-1.693
Ljung-Box Q-stat, P-Value	0.37	0.41	0.096	0.26
ARCH-LM, P-value	1	1	0.67	0.9
GARCH Distribution	**Skewed-std**	**Skewed-std**	**Skewed-ged**	**Skewed-ged**
Skew	1.09	1.103	1.077	1.090
Shape	3.913	3.830	1.046	1.071

Ljung-box and ARCH-LM conducted on standardized residuals.
Lags set to 15 for Breusch-G, Ljung-box, and ARCH-LM.
Shape depicts the additional degrees of freedom parameter compared to normal distribution.
Skew depicts skewness parameter compared to normal distribution.

Results from the Unit Root tests on Currency Hedge

Indicators	ADF	PP	KPSS
Exchange Rates			
EUR/USD	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
JPY/USD	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
WON/USD	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
NOK//USD	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm

Ljung-box and ARCH-LM (standardized residuals)
Lags set to 15 for Breusch-G, Ljung-box, and ARCH-LM.

Hedge and Safe Haven for stocks and bonds

Diagnostic test on the Hedge and Safe Haven for stocks and bonds

	United States	Europe	Japan	South Korea	Norway
Observation	417	417	417	417	417
ARDL					
Adj.R^2	0.025	0.025	0.028	0.056	0.008
AIC	-602.44	-598.08	-602.88	-621.07	-599.00
Breusch-G test, P-value	0.14	0.15	0.18	0.33	0.29
Durbin Watson	0.25	1.95	1.98	1.96	1.95
ARCH-LM, P-value	0.000	0.000	0.000	0.000	0.000
Ramsey Reset test, P-value	0.046	0.081	0.031	0.019	0.000
GARCH					
AIC	-1.710	-1.694	-1.715	-1.732	-1.703
Ljung-Box Q-stat, P-Value	0.18	0.2	0.32	0.36	0.47
ARCH-LM, P-value	0.97	0.98	0.91	0.99	0.99
GARCH Distribution	**GED**	**Sked-GED**	**Student-t**	**GED**	**GED**
Skew		1.077			
Shape	1.154	1.119	4.407	1.206	1.119

Ljung-box and ARCH-LM conducted on standardized residuals.
Lags set to 15 for Breusch-G, Ljung-box, and ARCH-LM.
Shape depicts the additional degrees of freedom parameter compared to normal distribution.
Skew depicts skewness parameter compared to normal distribution.

Continuation of Hedge and Safe Haven estimation results

	United States	**Europe**	**Japan**	**South Korea**	**Norway**
Bitcoin	Coeff. est.	Coeff. est.	Coeff. est.	Coeff. est.	Coeff. est.
Intercept	**0.013**** (0.006)	**0.014**** (0.006)	**0.019***** (0.006)	**0.019***** (0.006)	**0.014**** (0.006)
BTC_1	0.082 (0.081)	0.827 (0.078)	0.093 (0.080)	0.101 (0.076)	-0.098 (0.082)
BTC_2			0.051 (0.058)	0.041 (0.058)	

*, **, *** suggest statistical significance at the 0.10, 0.05, and 0.01 level.
Robust standard error in brackets ()

Results from the Unit Root tests on Hedge and Safe Haven

Indicators	**ADF**	**PP**	**KPSS**
Stocks			
MSCI US Index	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
MSCI Europe Index	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
MSCI Japan Index	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
MSCI South Korea Index	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
MSCI Norway Index	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
Bonds			
TMB 10 Year US Sovereign Bonds	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
TMB 10 Year Europe Sovereign Bonds	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
TMB 10 Year Japan Sovereign Bonds	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
TMB 10 Year Korean Sovereign Bonds	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm
TMB 10 Year Norwegian Sovereign Bonds	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm	Stationary at first difference of the logarithm