CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES
Institute of Economic Studies

Gold, oil, and stocks as safe havens for Bitcoin

Bachelor's thesis

Author: Martin Nedvěd

Study program: Economics and Finance

Supervisor: prof. PhDr. Ladislav Krištoufek, Ph.D.

Year of defense: 2022

Declaration of Authorship

The author hereby declares that he or she compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain any other academic title.

The author grants to Charles University permission to reproduce and to distribute copies of this thesis in whole or in part and agrees with the thesis being used for study and scientific purposes.

Prague, May 1, 2022

Martin Nedved

Abstract

Bitcoin is often compared to gold for its gold-like features such as a store of value, a limited supply, and a safe haven. However, due to Bitcoin's extreme price movements, investors might rather look for a safe haven against Bitcoin. In this thesis, we study such properties among traditional assets. Specifically, we analyze gold, oil, and stocks as safe havens for Bitcoin on a sample period from 2014 until March 2022. We find that gold acts as a strong safe haven suggesting gold's traditional role as a shelter during uncertainty holds also for this crypto asset.

JEL Classification	C22, C52, C58, G10
Keywords	Bitcoin, Safe haven, Gold, Cryptocurrency

Title	Gold, oil, and stocks as safe havens for Bitcoin

Abstrakt

Bitcoin je mnohdy pro jeho vlasnosti jako je uchovatel hodnoty, omezená nabídka a bezpečný přístav přirovnáván ke zlatu. Vzhledem k extrémním cenovým pohybům by však mohli investoři naopak hledat bezpečné útočistě proti Bitcoinu. V této práci studujeme, zda je tato vlastnost u některého tradičního aktiva. Konkrétně analyzujeme zlato, ropu a akcie jako bezpečné přístavy pro Bitcoin v období mezi rokem 2014 a březnem 2022. Závěr naší analýzy dokládá, že zlato se chová jako silný bezpečný přístav což naznačuje tradiční roli zlata jako úkryt během nejistoty i pro krypto aktiva.

Klasifikace JEL	C22, C52, C58, G10
Klíčová slova	Bitcoin, Bezpečný přístav, Zlato, Kryptoměny

Název práce	Zlato, ropa a akcie jako bezpečné přístavy pro Bitcoin

Acknowledgments

I would like to express my appreciation and gratitude to the supervisor prof. PhDr. Ladislav Krištoufek, Ph.D. for his valuable suggestions, guidance, and useful comments. I would like to thank my family and people close to me for the support during the process of writing and during my whole studies.

Typeset in FSV LaTeX template with great thanks to prof. Zuzana Havrankova and prof. Tomas Havranek of Institute of Economic Studies, Faculty of Social Sciences, Charles University.

Bibliographic Record
Nedvěd, Martin: *Gold, oil, and stocks as safe havens for Bitcoin.* Bachelor's thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies, Prague. 2022, pages 48. Advisor: prof. PhDr. Ladislav Krištoufek, Ph.D.

Contents

List of Tables

List of Figures

Acronyms

DCC Dynamic Conditional Correlation

ARCH Autoregressive Conditional Heteroscedasticity

GARCH Generalized Autoregressive Conditional Heteroscedasticity

ADF Augmented Dickey-Fuller

KPSS Kwiatkowski-Phillips-Schmidt-Shin

AIC Akaike information criterion

OLS Ordinary Least Squares

GJR Glosten, Jagannathan and Runkle

Bachelor's Thesis Proposal

Author	Martin Nedvěd
Supervisor	prof. PhDr. Ladislav Krištoufek, Ph.D.
Proposed topic	Gold, oil, and stocks as safe havens for Bitcoin

Research question and motivation Bitcoin was first introduced by Nakamoto, S. (2008) as a peer-to-peer electronic cash system. Since then many more cryptocurrencies were created such as Ethereum, Litecoin, or Dogecoin based on an internet meme. Although Bitcoin has many competitors it is still the most valuable cryptocurrency and as of July 2021 Bitcoin makes about half of the total cryptocurrency market cap according to https://coinmarketcap.com/.

Bitcoin is an attractive asset for investors for its decentralized nature, accessibility, and low trading fees but is also known for its significant price movements. Daily double-digit inclines and declines are not unusual. Investors with Bitcoin-oriented portfolios experience immense short-term losses during market turmoil.

The purpose of this thesis is to examine whether gold, oil, or stocks are safe havens for Bitcoin using Baur, D. G., & Lucey, B. M. (2010) definition of safe haven. In other words, whether these assets are uncorrelated or negatively correlated with Bitcoin in times of market stress or turmoil. The findings of this thesis might help Bitcoin-oriented investors decide what is the best strategy during market turmoil.

Contribution The thesis puts in the foreground Bitcoin as a base asset. There are many papers on Bitcoin as a safe haven for stocks for example Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019) or Bitcoin as a safe haven for oil price movements Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018), other papers inspecting safe haven properties of Bitcoin are for instance Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017) or a more recent one from Covid-19 pandemic by Conlon, T., & McGee, R. (2020).

But to the best of the author's knowledge, no paper concentrates solely on traditional assets as a safe haven for Bitcoin. Another extension to the existing literature is the use of data from the turbulent Covid-19 pandemic period when Bitcoin surpassed a \$1 trillion market cap for the first time. The results will then be compared with the findings of extensive existing literature on the topic of Bitcoin as safe haven for other assets.

Methodology We will analyze daily prices data for an ounce of gold, Crude Oil WTI, S&P500, and Bitcoin. For this purpose Dynamic Conditional Correlation estimators first proposed by Engle, R. (2002) will be used. This approach is also used by Ciner, C., Gurdgiev, C., & Lucey, B. M. (2013) for the advantage of providing time-varying correlations and dynamic relationships across pairs of return series. Another method that we will use is quantile regression.

As mentioned above we want to examine whether traditional assets are safe haven for Bitcoin that is analyzing correlations during market stress. Baur and Lucey (2010) solve this problem with the quantile regression approach using this method we can estimate correlations in the case when return is in the q%-th quantile, such as the 5% or 1% quantile.

Outline

1. Introduction
2. Literature review
3. Results
4. Conclusion

Bibliography

Ciner, C., Gurdgiev, C., & Lucey, B. M. (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. International Review of Financial Analysis, 29, 202-211.

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities?. International Review of Financial Analysis, 63, 322-330.

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review, 45(2), 217-229.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339-350.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. https://bitcoin.org/bitcoin.pdf

Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018). Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. Energy Economics, 74, 787-801.

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

Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. Finance Research Letters, 35, 101607.

Author

Supervisor

Chapter 1

Introduction

Bitcoin was first introduced by Nakamoto (2008) as a peer-to-peer electronic cash system. Although the original white paper describes Bitcoin as a cash system the literature suggests Bitcoin is rather a speculative asset (Yermack 2015; Baur *et al.* 2018b; White *et al.* 2020). But Bitcoin's price can be partially explained by traditional economic theory (Kristoufek 2015; Ciaian *et al.* 2016). Many more cryptocurrencies or crypto assets were soon created, among the most popular are Ethereum, Ripple, and Binance coin. Even though Bitcoin has many competitors and its market share is decreasing it is still the most valuable cryptocurrency and as of April 2022 Bitcoin makes about 40% of the total cryptocurrency market capitalization.[1] Bitcoin is an attractive asset for investors for its decentralized nature, accessibility, and low trading fees. Bitcoin survived the Coronavirus crisis which was the first major global financial crisis since Bitcoins's introduction. And is now traded at a much higher price level than before the Coronavirus. It even reached the 1$ trillion us dollar market capitalization in February 2021.[2]

Bitcoin is also known for its significant price movements. Daily double-digit inclines and declines are not unusual. Investors with Bitcoin-oriented portfolios experience immense short-term losses during market turmoil. The natural question that arises is how should investors protect themselves when the turmoil occurs. Bitcoin is sometimes referred to as digital gold and is studied as a safe haven for other assets.[3] But there are not many studies addressing the opposite question. This question will be the main objective of this thesis. We are studying whether traditional assets, specifically gold, oil, or

[1] according to https://coinmarketcap.com/
[2] according to https://coinmarketcap.com/
[3] Safe haven asset is defined later in Chapter 2

even stocks can serve as safe havens for Bitcoin. This is of particular interest to investors who consider selling their Bitcoins instead of holding them. Our research contributes to the poor literature regarding safe havens for Bitcoin and might help Bitcoin-oriented investors decide the best strategy during market turmoil. To the best of our knowledge, the existing literature only examines crypto assets as safe havens for Bitcoin, see Baumöhl (2019) or Baur & Hoang (2021) but we found no study that would analyze the role of traditional assets as a safe haven for Bitcoin. Our sample period is from 2014 until March 2022 and we utilize the daily returns of Bitcoin, gold, oil, and stocks.

The thesis is further divided into the following chapters. Chapter 2 reviews the existing literature related to our study. It briefly explores the technicalities behind Bitcoin. Then we present the key definition of a safe haven first introduced by Baur & Lucey (2010). Additionally, we take a look at the literature regarding traditional safe havens which helps us understand the concepts and methods used for the analysis of safe havens. Finally, the safe haven topic in the context of Bitcoin is examined. Chapter 3 introduces the data used in this thesis along with descriptive statistics. Chapter 4 specifies the used methodology, Chapter 5 presents the empirical results. Finally, Chapter 6 concludes our findings and the whole thesis.

Chapter 2

Literature Review

The amount of available literature on safe havens assets in the context of traditional assets such as gold and stocks is extensive. Unsurprisingly many authors replicate these studies and they consider Bitcoin to act as a safe haven for traditional assets. In this chapter, we present the relevant literature regarding Bitcoin in general, then explore the safe haven literature along with the definitions. Finally, we cover the recent literature related to the Coronavirus pandemic and very limited literature about safe havens for Bitcoin.

2.1 Background of Bitcoin

Bitcoin is a digital peer-to-peer payment electronic cash system first introduced by Nakamoto (2008). Bitcoin relies on the peer-to-peer network and open-source software which guarantees that no central authority is in charge. Nakamoto (2008) defines Bitcoin as a chain of digital signatures, every user has a private key used for signing the transaction and a public key used for verification. All the transactions are recorded on a public ledger, known as a blockchain, available to anyone. Instead of verifying the transactions by a trusted financial institution, the network solves a computationally demanding problem. Whoever solves this problem first creates a new block with verified transactions that is added to the blockchain, in return he, usually called a miner, receives a block reward and transaction fees paid by users. A more detailed explanation can be found in the original Nakamoto (2008) paper or Dwyer (2015).

As the initial paper suggests Bitcoin is an alternative currency to the traditional banking system. However, the existing literature does not provide a straightforward classification of Bitcoin. Yermack (2015) examines whether Bitcoin satisfies the classical properties of a currency, that is a medium of exchange, a unit of account, and a store of value. The author challenges these properties and due to excessive volatility likens the behavior of Bitcoin to speculative investment rather than a currency. Baur *et al.* (2018b) present similar results, they analyze the user types together with their behavior and find that only a small fraction of users use Bitcoin as a medium of exchange, and about a third is held by users that only receive Bitcoin and never make transactions to other users. More recent literature also questions Bitcoin as a currency. White *et al.* (2020) show that Bitcoin fails as a unit of account and thus does not serve as a currency, the authors further suggest that Bitcoin's behavior is more comparable to a technology-based product, an emerging asset, or a bubble event. Hazlett & Luther (2020) on the other hand argue that Bitcoin's use as a medium of exchange among some people makes it worthy of the label money for this relatively small domain.

Ciaian *et al.* (2016) analyze Bitcoin price using both the traditional determinants of a currency price and digital currency-specific factors, such as attractiveness for investors. The article studies the price formation of Bitcoin with Barro's (1979) augmented version of the model for the gold standard and demonstrates the importance of market forces for the Bitcoin price. They argue that the price can be to a large extent explained by a standard economic currency price model and also suggest that due to the large price movements Bitcoin is not an ideal medium of exchange which corresponds with Yermack's (2015) findings. Kristoufek (2015) shows similar results, that over the long term standard fundamental factors affect Bitcoin price. The author also investigates the impact of investors' interest in Bitcoin on its price among other drivers of the price.

The existing literature delivers different approaches for studying Bitcoin classification and its price formation, Bitcoin is more of a speculative asset rather than a currency (Yermack 2015; Baur *et al.* 2018b; White *et al.* 2020). And its price can be examined using both the traditional economic theory and the crypto-currency specific factors (Kristoufek 2015; Ciaian *et al.* 2016).

2.2 Safe Haven

Kristoufek (2015) raises the question of whether Bitcoin can serve as a safe haven by examing the relationship of Bitcoin prices with the Financial Stress

Index and the gold price, the author finds no evidence that Bitcoin can be considered a safe haven. In this section, we will explore relatively rich literature regarding the topic of safe havens both in general and Bitcoin-related.

2.2.1 Definitions

Baur & Lucey (2010) clarify the difference between a diversifier, a hedge, and a safe haven asset. They define a hedge as an asset that is on average uncorrelated or negatively correlated with another asset, a diversifier is by their definition a positively correlated but not perfectly correlated asset with another asset on average and finally, a safe haven is an asset that is uncorrelated or negatively correlated with another asset during the times of market turmoil. This definition was further extended by Baur & McDermott (2010), who differentiate between a strong safe haven and a weak safe haven, and a strong hedge and a weak hedge. The authors define a strong safe haven as an asset that is negatively correlated with another asset and a weak safe haven as an asset that is uncorrelated with another asset again during a time of market stress. The definition of a strong (weak) hedge is analogous.

2.2.2 Traditional safe havens

Numerous studies examine the safe haven properties of various assets. Gold is arguably the most profound one. Baur & Lucey (2010) use quantile regression which was later employed by many other studies and portfolio analyses to show that gold serves as a safe haven for stocks for a limited time around 15 trading days. Baur & McDermott (2010) present similar results, that gold acts as a safe haven asset for most developed country stock markets, they also emphasize that the effect is strongest for extreme shocks and short periods of time. The authors also utilize quantile regression. The same approach is likewise used by Ciner *et al.* (2013) but they furthermore study the general relations between assets with Dynamic Conditional Correlation (DCC). They primarily focus on the role of oil and gold as safe haven assets and find that gold does not act as a safe haven for stocks which is against Baur & Lucey's (2010), Baur & McDermott (2010) results, the authors argue that this difference is due to a more recent period when the gold price increased significantly. But they report that gold serves as a monetary asset since it functions as a safe haven for extreme exchange rate drops. Finally, they suggest that oil's role is less significant than the role of gold. Beckmann *et al.* (2015) augment the empirical testing procedure of Baur & Lucey (2010) and Baur & McDermott (2010), they extend the model to a smooth transition regression and claim that gold can provide a safe haven function for stocks, the authors comment that this function is likely market-specific. The DCC approach is also used by Baruník *et al.* (2016), although the authors use it mainly for comparison and their primary method is the wavelet approach. The purpose of their study is to analyze the pairwise dynamic correlations between gold, oil, and stock. They present different findings than Baur & Lucey (2010) and dispute the role of gold as a hedge and a safe haven asset for stocks.

2.2.3 Bitcoin as a safe haven

The first comparison of Bitcoin to gold is as old as Bitcoin itself. Nakamoto (2008) analogizes the addition of new coins to gold mining. Other similarities to gold are for example no central authority controls either of them and both assets have limited supply. For these reasons, many papers address the question of whether Bitcoin exhibits similar hedging and safe haven properties as gold. Dyhrberg (2016b) compares Bitcoin and gold, the author shows that Bitcoin shares many similarities to gold. But Baur *et al.* (2018a) replicate and extend Dyhrberg's (2016b) study and argue that Bitcoin is very different from gold which is in stark contrast with Dyhrberg's (2016b) findings. Kristoufek (2015) also studies the relationship between gold and Bitcoin and finds practically no relationship. Smales (2019) takes a different approach and focuses on Bitcoin characteristics such as correlation with other assets, pricing variation across different exchanges, volatility, and finally liquidity. The author concludes that due to higher volatility, less liquidity, and higher transaction costs in terms of fees and time, especially during periods of higher volatility, Bitcoin should not be considered a safe haven asset.

Other studies analyze Bitcoin's safe haven properties in a similar means as we presented in the previous section about traditional safe havens such as gold. Bouri *et al.* (2017) use DCC to find that Bitcoin can act as a safe haven for Chinese stocks and Asia Pacific stocks. However, this ability only holds for weekly data. Guesmi *et al.* (2019) extend the literature using various model specifications from the DCC models and although they do not directly answer the question of Bitcoin's safe haven properties, their results show that Bitcoin offers diversification and hedging benefits for investors against all different financial assets. The hedging capabilities of Bitcoin also documents Dyhrberg

(2016a) who shows that Bitcoin can be used as a hedge against the Financial Times Stock Exchange Index. Shahzad *et al.* (2019) employ a very different approach using the cross-quantilogram for the comparison of safe-haven properties of commodities, gold, and Bitcoin. Their findings suggest that Bitcoin shares weak safe haven properties with commodities for the Chinese market. It is noteworthy mentioning that their definition of a weak (strong) safe haven is not the same as we presented previously.

Bitcoin's safe haven properties could not have been fully tested because there was no extreme situation in the financial markets since Bitcoin's introduction. This changed in 2020 when the Covid-19 pandemic hit the economy. Conlon & McGee (2020) examine whether an equity portfolio diversified with Bitcoin can reduce the exposure to downside risk in order to quantify this hypothesis they measure the relative change in portfolio value at risk. The study shows that Bitcoin did not act as a safe haven for stocks since diversifying a stock portfolio with Bitcoin increased the downside risk. Kristoufek (2020) studies the interconnection between the Standard & Poor's 500 index and the CBOE Volatility Index. The author does not find Bitcoin to be a safe haven, at least not in comparison with gold.

The existing literature shows that Bitcoin can act as a safe haven and hedge on some markets and for limited time periods. The most extreme market turmoil since the introduction of Bitcoin did not prove its safe haven properties.

2.2.4 Safe havens for Bitcoin

In the previous section, we examined the literature concerning the safe haven properties of Bitcoin, now we will look at relatively poor literature concerning safe havens for Bitcoin. To the best author's knowledge, the first study that deals with this question is Baumöhl (2019) who presents Ripple to exhibit the safe haven properties for Bitcoin. This observation is only a byproduct since the main topic of the study is the connectedness between various cryptocurrencies and forex. Baur & Hoang (2021) take a more direct approach to address the matter of a safe haven against Bitcoin. They analyze whether stablecoins provide a crypto safe haven for Bitcoin. The authors employ Baur & Lucey's (2010) quantile regression method and show that there exist stablecoins that provide a safe haven for Bitcoin, but at the same time, these stablecoins violate their initial purpose, i.e. being stable.

We found no literature that would address our question. The abovementioned studies only examine crypto assets as safe havens for Bitcoin but to the best of our knowledge, the topic of traditional assets as safe havens for Bitcoin remains undiscovered. Hence we believe that our thesis will enrich the existing literature and will help better understand the interactions between traditional assets and cryptocurrencies, specifically Bitcoin.

In this section, we examined the literature about Bitcoin in general, and then we moved to the safe haven topic, we accepted Baur & Lucey's (2010) definition of a safe haven with the extension proposed by Baur & McDermott (2010). Finally, we reviewed traditional safe havens, Bitcoin as a safe haven, and safe havens for Bitcoin.

Chapter 3

Data

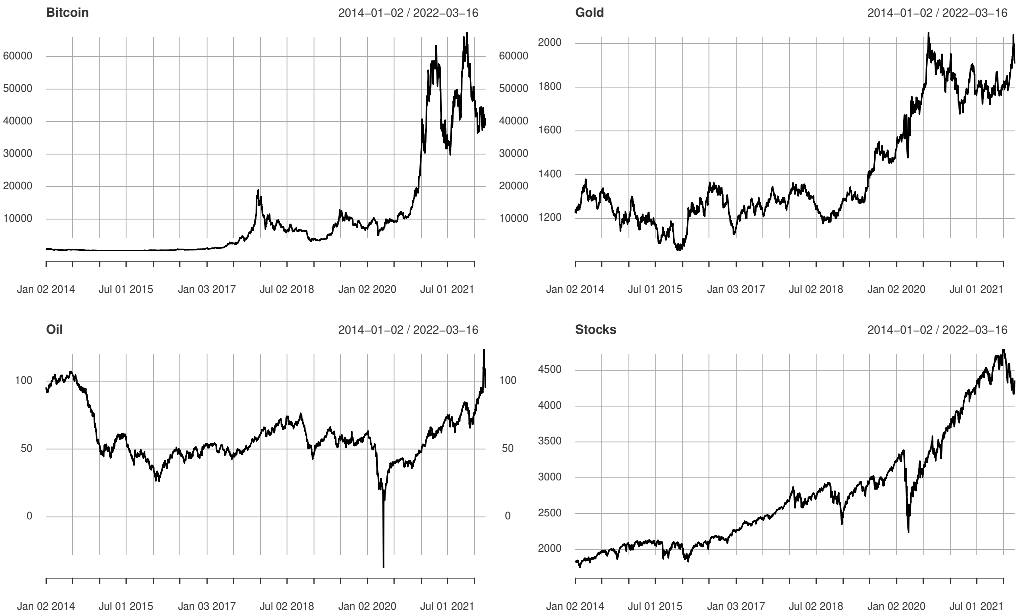
In this chapter, we present, describe and transform our data. The transformation is briefly described later in this chapter. For our analysis, we use the daily prices of Bitcoin, gold, oil, and stocks denoted in the United States dollar. The choice of these assets is not arbitrary. In Chapter 2 we examined the literature regarding safe havens and found that both gold and oil are studied as safe haven assets. The addition of stocks to our analysis might seem odd as this asset is not traditionally regarded as a safe haven, but we reason that Bitcoin is such a specific asset that even stocks can be considered a safe haven for Bitcoin.

Daily prices for Bitcoin are obtained from Coinmetrics.[1] We choose this data source for two reasons. The first one is that it provides data back to 2009, and the second reason is that it meets Alexander & Dakos's (2020) guidance for relevant cryptocurrency prices as Conlon & McGee (2020) argue. Although the data are dated back to January 2009 and the first record containing the Bitcoin price is 18/7/2010, we restrict our analysis to start from 2014. Data for other assets are obtained from Yahoo Finance[2]. More specifically Yahoo Finance provides gold data from the Commodity Exchange, Inc., oil is represented by West Texas Intermediate crude oil, also known as "light" oil, which is traded on the New York Mercantile Exchange. Finally, stocks are proxied by the Standard & Poor's 500 index. There is no restriction on starting date for the traditional assets, in conclusion, our sample is from 2/1/2014 to 16/3/2022. Since Bitcoin is traded on a 24/7 basis and other assets are not, we omit the weekends and holidays, this leaves us with 2063 observations. All the data were

[1] https://coinmetrics.io/community-network-data/
[2] https://finance.yahoo.com/

obtained from publicly available sources therefore this thesis can be effortlessly reproduced by other studies.

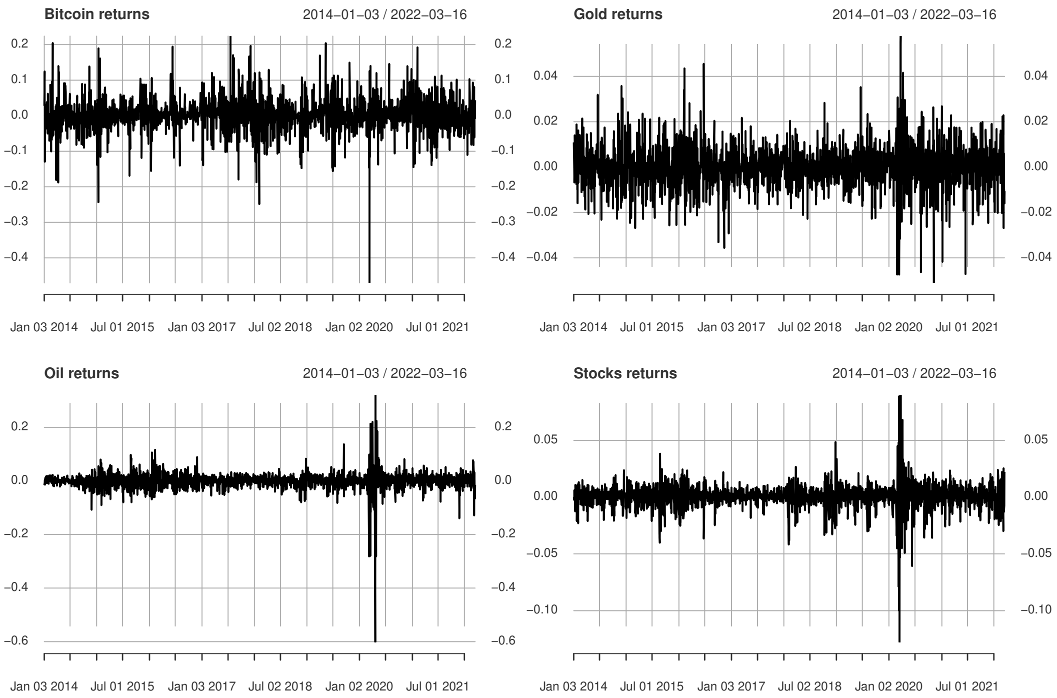
Figure 3.1: Time series plots



The daily prices of the assets are graphically visualized in Figure 3.1. We can see that Bitcoin experienced the most significant price spike of all the other assets. Gold and stocks also shared a notable increase in value in the sample period. Bitcoin, stocks, and oil were all hit hard by the Covid-19 pandemic. The uncertainty even led to the negative price of oil. But they quickly recovered the losses and are now traded at much higher price levels than before the pandemic. We can explain this by loose monetary policies and support packages for businesses and citizens to stimulate the demand. The second interesting event in our sample period is the Russian invasion of Ukraine in February 2022 which led to increased demand for oil and gold.

For each series, we calculate daily return as the first difference of the logarithm of closing prices, that is $r_t = log(p_t) - log(p_{t-1})$, where r_t is the return, p_t is the closing price at time t, and p_{t-1} is the price at time $t-1$. This also deals with the problem that we omitted weekends data for Bitcoin because weekend price change is calculated as $log(Monday\ closing\ price) - log(Friday\ closing\ price)$ and thus projected in Monday return. We also have to account for the date 20/4/2020 when the closing oil price was -37.6USD, since our method for calculating daily log return does not work with negative prices, we omit this date, then the daily log return on Tuesday 21/4/2020 for all the assets is calculated as $log(Tuesday\ closing\ price) - log(Friday\ closing\ price)$. In total, we have 2061 daily return observations.

Figure 3.2: Log returns



We plot the returns in Figure 3.2. At first glance, we can see periods of lower and higher volatility among all the assets. For example, oil shows quite a calm period between 2017 and 2019. But then there is the beginning of 2020 when oil exhibits extreme returns in both directions. This behavior is sometimes called volatility clustering which we address in Chapter 4.

Table 3.1 reports the descriptive statistics of the daily returns for Bitcoin, gold, oil, and stocks. The table contains the number of observations, the minimum value, the maximum value, the mean, the standard deviation, the skewness, and the excess kurtosis. We also report the results of the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. These tests are briefly explained in Chapter 4. We observe that oil exhibits the most extreme negative return (-60.168) and also the most extreme positive return (31.963). This is due to the pandemic period as we explained earlier. Bitcoin has the greatest average daily return (0.192) and correspondingly the largest standard deviation (4.644). Which is over five times the standard devi-

Table 3.1: Descriptive statistics for daily returns

	Gold	*Oil*	*Stocks*	*Bitcoin*
Observations	2061	2061	2061	2061
Min (%)	-5.107	-60.168	-12.765	-47.056
Max (%)	5.778	31.963	8.968	22.405
Mean (%)	0.021	-0.0002	0.042	0.192
Standard deviation (%)	0.927	3.262	1.106	4.644
Skewness	-0.049	-2.919	-1.01	-0.549
Excess Kurtosis	4.349	72.517	20.322	8.287
ADF	-12.377***	-12.694***	-12.578***	-11.161***
KPSS	0.117	0.192	0.045	0.210

Note: The sample period is from 3 January 2014 till 16 March 2022.
*** Indicates significance at 1% level or better.

ation of gold and four times the standard deviation of stocks. Oil also suffers from great deviation (3.262) and extreme daily returns, but its average daily return (-0.0002) is the smallest among the assets under our study. Unsurprisingly gold has the lowest standard deviation and the smallest range between the minimum and maximum daily return. The negative skewness across all assets implies the distribution to be skewed to the left. Thus the returns are primarily positive and small. In contrast, the negative returns tend to be more extreme. The reported positive excess kurtosis indicates heavy tails and more outliers in our time series than we would observe in a normal distribution. For these reasons, the returns do not appear to be normally distributed. We acknowledge that gold's skewness and excess kurtosis is much smaller in comparison with the skewness and kurtosis of other assets thus these effects are less notable. Finally, the ADF test suggests we reject the null hypothesis of a unit root process, and for the KPSS test, we do not have enough evidence to reject the null hypothesis of stationarity thus we are quite confident that our log returns meet the stationary assumption.

Chapter 4

Econometric Methodology

In this chapter, we present the econometric models for testing the safe haven properties of gold, oil, and stocks. We will follow Baur & Lucey's (2010) model which is now well-established in the safe haven literature. For better clarity, we use Baur & McDermott's (2010) notation of the model. We acknowledge other methods such as Beckmann *et al.*'s (2015) smooth transition augmentation of Baur & Lucey's (2010) model. But we stick to the most basic one as this was in the original paper that presented the safe haven definition and thus should be appropriate for our case.

We will also cover the theoretical background for the financial time series analysis and explain conditional heteroscedastic models that are popular for dealing with volatility clustering. Brooks (2008) and Tsay (2005) provide the necessary theory for this chapter.

4.1 Econometric model

Baur & Lucey's (2010) introduced the following model to test whether gold is a hedge, a diversifier, or a safe haven for stocks and bonds, with minor modifications we get:

$$\begin{aligned} r_{i,t} &= a + b_t r_{btc,t} + u_t \\ b_t &= c_0 + c_1 D(r_{btc} q_{0.05}) + c_2 D(r_{btc} q_{0.025}) + c_3 D(r_{btc} q_{0.01}) \end{aligned} \tag{4.1}$$

Where $r_{i,t}$ is the return of asset i at period t, $D(r_{btc} q_j)$ is a dummy variable that is equal to one if the Bitcoin's return is in the j-th% lower quantile, that is in our case 5%, 2.5%, or 1%. The error term is denoted as u_t. When estimating this model we plot b_t from the second equation into the first equation. If any of the parameters c_1, c_2, or c_3 is significantly different from zero then there is an evidence of a non-linear relationship between the two assets. Baur & Lucey (2010) furhter employ Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and asymmetric GARCH process to account for possible heteroskedasticity in the model. We extend our baseline model (4.1) with either standard GARCH(1,1) (4.7) or asymmetric GJR-GARCH(1,1) (4.8). These equations are then jointly estimated with Maximum Likelihood. The methodological steps are described in the following sections.

The overall effect

To decide whether the asset acts as a safe haven at the $j-th\%$ quantile, we have to calculate the sum of the coefficients

$$\sum_{i=0}^{j} c_i$$

we define this sum as the overall effect. For example, the overall effect for the 1% quantile is the sum of all the coefficients $(c_0 + c_1 + c_2 + c_3)$. To distinguish between weak and strong safe haven we have to calculate the significance of the overall effect, that is, the joint significance of the summed coefficients. Then we classify the asset in the following way. If the overall effect is positive and significant an asset is not a safe haven at that quantile. If the overall effect is positive or negative and not significant then the asset acts as a weak safe haven. Finally, if the overall effect is negative and significant we found a strong safe haven. We test the joint significance with either the F-test or the Likelihood-ratio test. We briefly explain these tests in the following subsections.

F-test

Under this test, two regressions are required. Unrestricted regression is in our case (4.1) and we get restricted regression if we impose restrictions on some c's from (4.1). For example, when calculating the significance for the 5% quantile, the null hypothesis is $H_0 : c_0 = 0, c_1 = 0$, our restricted regression is

$$\begin{aligned} r_{i,t} &= a + b_t r_{btc,t} + u_t \\ b_t &= c_2 D(r_{btc} q_{0.025}) + c_3 D(r_{btc} q_{0.01}) \end{aligned} \tag{4.2}$$

Then we obtain the residual sums of squares from each regression (RSS_u from unrestricted, RSS_r from restricted) and calculate the F-test statistic which is distributed as an F random variable in the following way

$$Fstatistic = \frac{(RSS_r - RSS_u)/q}{RSS_u/(n-k-1)} \sim F(q, n-k-1) \tag{4.3}$$

where q is the number of restrictions, n number of observations, and k number of independent variables in the unrestricted model.

Likelihood ratio test

We again estimate restricted and unrestricted regressions in the same manner as we did for the F-test. We obtain the log-likelihood from each regression (LLF_u from unrestricted, LLF_r from restricted). The Likelihood ratio test statistic asymptotically follows a Chi-squared distribution and is given by

$$LR = -2(LLF_u - LLF_r) \sim \chi^2(m) \tag{4.4}$$

where m is the number of restrictions. The null hypothesis is the same as for the F-test.

4.2 Testing of Assumptions

Heteroskedasticity

The model can be estimated using Ordinary Least Squares (OLS) but one of the Classical Linear Regression Model assumptions is the constant variance of the error known as homoskedasticity. The violation of this assumption leads to the wrong estimation of standard errors. In Chapter 3 we mentioned volatility clustering which can be explained as a tendency of large price changes to be followed by large changes and on the other hand small changes to be followed by small changes. For example, in Figure 3.2 we can see that there is a relatively calm period on the stock market from 2014 to the beginning of 2020. Then the stock market experienced much larger volatility caused by the fear of the Covid 19 pandemic. For this reason, it is doubtful that in the context of financial time series the variance of the errors is constant over time. There are several ways to account for heteroskedasticity, such as estimating robust standard errors or using the Feasible Generalized least squares method. However, we will focus on

Conditional heteroscedastic models which are popular in financial time series modeling and also used by Baur & Lucey (2010).

ARCH

Engle (1982) introduced a new class of stochastic processes called Autoregressive Conditional Heteroscedasticity (ARCH) processes. This model allows conditional variance to be dependent on the past variances. The general ARCH model with q lags known as ARCH(q) is then

$$\begin{aligned} y_t &= X_t\beta + u_t, u_t \sim N(0, \sigma_t^2) \\ \sigma_t^2 &= \alpha_0 + \alpha_1 u_{t-1}^2 + ... + \alpha_q u_{t-q}^2 \end{aligned} \tag{4.5}$$

Where σ_t^2 is the conditional variance of the error term u_t, X_t is the vector of random variables, and β is the vector of unknown parameters, σ_t^2 then depends on previous values of the squared error term. Since σ_t^2 is a conditional variance it must be always strictly positive, this puts constraints on α coefficients to be non-negative.

For testing whether ARCH effects are present in the residuals, we employ the test presented by Engle (1982). He proposed the Lagrange multiplier test procedure, where we first run the linear regression and save the residuals $\hat{u}_t$,

$$y_t = X_t\beta + u_t$$

Then we square the residuals and regress them on q own lags,

$$\hat{u}_t^2 = \gamma_0 + \gamma_1\hat{u}_{t-1}^2 + ... + \gamma_q\hat{u}_{t-q}^2 + v_t \tag{4.6}$$

Finally we test joint significance of those paramters, under the null hypothesis $\gamma_1 = \gamma_2 = ...\gamma_q = 0$ there is no ARCH process present in the residuals. Other tests were also proposed for example Ljung-Box test, but we will follow Engle's (1982) method.

ARCH models suffer several weaknesses, such as the number of lags in the model, also this number might be very large, and with a large number of lags, the probability of violation of the non-negativity constraints is higher. Another problem is that the model assumes that positive and negative shocks have the same effect on volatility. For these reasons, the ARCH model is rarely used in the context of the financial markets.

GARCH

Bollerslev (1986), who was Engle's Ph.D. student, proposed a GARCH model which is an extension of Engle's (1982) ARCH model. This model extends ARCH by allowing conditional variance to be dependent on both the squared errors and on its previous lags. The GARCH(p,q) is a process with q lags of the squared error and p lags of the conditional variance, that is

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2$$

In financial time series modeling GARCH with higher-order lags is rarely used, for this reason, we will only consider GARCH(1,1) given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4.7}$$

where $\alpha_0 > 0, \alpha_1 >= 0, \beta_1 >= 0$, and $\alpha_1 + \beta_1 < 1$ implies the unconditional variance of u_t to be constant.

As standard OLS cannot be used for the estimation of ARCH/GARCH models maximum likelihood estimation is employed.

Asymmetric GARCH models

In the limitations of ARCH models, we mentioned the symmetric response of volatility to positive and negative shocks. Standard GARCH models do not solve this issue either. That is why asymmetric GARCH models were introduced. Among the most popular asymmetric GARCH are the Glosten, Jagannathan and Runkle (GJR) model named after its authors (Glosten *et al.* (1993)) and the exponential GARCH proposed by Nelson (1991). We will focus solely on the GJR model as this is the one used in the original Baur & Lucey (2010) model. This model extends GARCH with an additional term that accounts for possible asymmetries, the model is then in the following format

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{4.8}$$

where $I_{t-1} = 1$ if $u_{t-1} < 0$ and zero otherwise. If there is some levarege effect than $\gamma > 0$. The condition for non-negativity is now $\alpha_0 > 0, \alpha_1 > 0, \beta >= 0$, and $\alpha_1 + \gamma >= 0$, this lets γ to be also $\gamma < 0$ as long as the condition $\alpha_1 + \gamma >= 0$.

Testing for asymmetries

To test whether we need to use the asymmetric GARCH model we present Engle & Ng's (1993) test for asymmetry in volatility. The authors proposed the following regression

$$\hat{u}_t^2 = \theta_0 + \theta_1 S_{t-1}^- + \theta_2 S_{t-1}^- u_{t-1} + \theta_3 S_{t-1}^+ u_{t-1} + v_t \tag{4.9}$$

where $\hat{u}_t$ are residuals of a GARCH fit to the returns data, S_{t-1}^- is a dummy variable, that equals 1 if $\hat{u}_{t-1} < 0$ and zero otherwise, $S_{t-1}^+ = 1 - S_{t-1}^-$, and v_t is an error term. Further θ_1 captures the presence of sign bias, that is positive and negative shocks have a different effect on future volatility. Coefficients θ_2, θ_3 indicate the presence of size bias, this means that the size of shock is also determining factor volatility. To test asymmetry in volatility, we jointly test the significance of these 3 estimators under the null hypothesis of no asymmetric effects.

Information criteria

To compare which model better fits the data we will use the well-known Akaike information criterion (AIC), which is defined as

$$AIC = \frac{-2}{T} \ln \hat{L} + \frac{2k}{T}$$

where $\hat{L}$ is the likelihood function evaluated at the maximum likelihood estimates, k is the number of estimated parameters and T is the sample size. The advantage of AIC over a simple comparison of likelihoods is that AIC penalizes for overfitting. The lower the information criteria the better the model.

Normality

In (4.5) we assumed conditional normality for u_t which is essential in specifying the likelihood function. If this assumption does not hold the parameter estimates will still be consistent given correctly specified equations for the mean and variance. But the usual standard errors estimates will be inappropriate. This issue can be overcome by assuming non-normal distribution, in this thesis we will consider student's t-distribution which is popular in financial time series analysis.

To test for normality we will first standardize the error term

$$v_t = \frac{u_t}{\sigma_t}$$

v_t is now assumed to be normally distributed $v_t \sim N(0,1)$. The sample counterpart is then

$$\hat{v}_t = \frac{\hat{u}_t}{\hat{\sigma}_t}$$

Whether $\hat{v}_t$ follow normal distribution can be tested for example with the Bera-Jarque normality test. Consider the following equation

$$JB = \frac{\hat{S}^2(\hat{v}_t)}{6/T} + \frac{(\hat{K}(\hat{v}_t) - 3)^2}{24/T} \tag{4.10}$$

Where T is the number of observations (in our case number of residuals), $\hat{S}$ is the sample skewness, and $\hat{K}$ is the sample kurtosis. Then JB is asymptotically distributed as a chi-squared random variable with 2 degrees of freedom with the null hypothesis of normality. Thus rejecting the null hypothesis suggests using other than the normal distribution assumption in (4.5).

Stationarity

In Chapter 3, we transformed our data to log returns, we explained how these returns are calculated. With this transformation, we expect to remove the unit root process often present in the financial time series and consequently have stationary variables. The stationarity assumption is critical for working with time series data. We will employ the ADF test (Dickey & Fuller (1979)) and the KPSS test (Kwiatkowski *et al.* (1992)) for testing the stationarity assumption. The reason for using two tests is that each of them has a different null hypothesis thus our results should be more powerful.

ADF test

Suppose we have the following model:

$$\Delta r_t = \beta r_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta r_{t-i} + u_t$$

Where r_t is the return series, u_t is an error term, Δr_{t-i} are the lags of Δr_t, β and α_i are estimated coefficients. In the ADF test, we are testing for the presence of a unit root process, hence the null hypothesis assumes $\beta = 0$, meaning that the series contains a unit root.

KPSS test

Consider the following model:

$$r_t = d_t + \epsilon_t$$
$$d_t = d_{t-1} + u_t$$

Where r_t is the return series, ϵ_t is a stationary error, d_t is a random walk and u_t are independent and identically distributed $(0, \sigma_u^2)$. Then the null hypothesis is $\sigma_u^2 = 0$ stating that the series is stationary.

To assume our returns to be stationary we should reject the ADF's null hypothesis and not reject the KPSS's null hypothesis.

Chapter 5

Empirical results

In this chapter, we report our empirical results. We first estimate our baseline model with the OLS, then we test for ARCH effects in residuals from the OLS regression. Further, we employ the test for the asymmetric GARCH process and test for normality in residuals. Finally, we run asymmetric GJR-GARCH(1,1) for the whole period as well as sub-periods to find whether traditional assets serve as a safe haven for Bitcoin.

5.1 Baseline regression

In Chapter 4, we presented conditional heteroscedastic models that are popular in the context of financial time series. In order to test whether we need to employ this model we first have to run standard OLS and save residuals. In Table 5.1 we report the OLS estimates with standard errors in parentheses. The coefficient estimate for the average effect of Bitcoin on gold is 0.0161, on oil, the effect is 0.025 and on stocks, we can see the average effect of 0.0178. The effect is significant only for gold and stocks. Gold and stocks estimates for the average effect are positive and significant thus these two assets do not act as a hedge for Bitcoin. Oil's average effect is also positive but insignificant, thus oil could be regarded as a weak hedge for Bitcoin. We will not further examine the assets hedge role as this is not the purpose of this thesis, we only wanted to show the definition of weak and strong hedge since it corresponds to the safe haven definition.

For extreme negative Bitcoin returns, the coefficient estimates are positive for the 2.5% and 1% quantile for all the assets. For the 5% quantile, the coefficient is negative only for gold. The overall effect for any quantile is then

Table 5.1: Estimation results of OLS

Dependent variable			
	Gold	*Oil*	*Stocks*
c_0	0.0161***	0.0250	0.0178***
	(0.0056)	(0.0196)	(0.0065)
c_1	-0.0223	0.0008	0.0158
	(0.0169)	(0.0594)	(0.0197)
c_2	0.0147	0.0230	0.0378
	(0.0214)	(0.0752)	(0.0250)
c_3	0.0014	0.0347	0.0338
	(0.0180)	(0.0633)	(0.0210)
a	0.0001	0.0001	0.0007***
	(0.0002)	(0.0008)	(0.0003)
R^2	0.005	0.004	0.048
$Adjusted R^2$	0.003	0.002	0.046

Note:*p <0.1; **p<0.05; ***p<0.01, coefficient estimates (standard errors)
Model: (4.1)

the sum of all coefficient estimates up to that quantile. Specifically, the overall effect for the 1% quantile is the sum of all the coefficients. For example, the overall effect for gold equals 0.0099. The number itself is not of interest to us as we are only interested in the sign. To decide whether the overall effect is significant we calculate the joint significance of the estimates using the F-test. Table 5.2 presents the overall effects and the corresponding significance. We can see that the only negative overall effect is for gold for the 5% quantile. The effect is also statistically significant, thus suggesting that gold can serve as a strong safe haven for Bitcoin. Oil's overall effects for the 5% and 2.5% quantiles are positive but insignificant hence oil fits the definition of a weak safe haven for these quantiles.

5.2 Extended model

We perform the test for ARCH effects explained in the Chapter 4 with 5 lags. We find that the ARCH effect is present in all the models. Hence suggesting the use of the GARCH process is adequate. The results of this test are reported in Table 5.3.

Now we will estimate our model extended with GARCH(1,1) to account

Table 5.2: Estimation results of OLS - the overall effect

Dependent variable	*Gold*	*Oil*	*Stocks*
Hedge	0.0161***	0.0250	0.0178***
5%	-0.0062**	0.0258	0.0335***
2.5%	0.0085**	0.0488	0.0714***
1%	0.0099**	0.0836*	0.1052***

Note:*p <0.1; **p<0.05; ***p<0.01

Table 5.3: Test for the ARCH effects

	Gold	*Oil*	*Stocks*
F-statistic	13.34	58.22	186.3
p-value	<0.001	<0.001	<0.001

Note: Model: (4.6), with 5 lags ($q = 5$)
F-statistic is the joint significance of all the parameters in the model.

for the ARCH effect in the residuals. Table 5.4 presents the overall effects. We calculate the overall effect along with the joint significance using the Likelihood ratio test. The outcome is similar to the one of the OLS, but in addition, we now have evidence that gold also serves as a weak safe haven for shocks exceeding the 1% quantile. Oil is now also a weak safe haven at the 1%.

Testing for normality and asymmetry

To estimate the GARCH model we assumed the error term u_t to follow the normal distribution. We test this assumption using the Bera-Jarque normality test on standardized residuals $\hat{v}_t = \frac{\hat{u}_t}{\hat{\sigma}_t}$ obtained from the estimation results. We reject normality in standardized residuals for all the assets hence student distribution might be more appropriate. The results of the Bera-Jarque test are reported in Table 5.5. Estimating our model with the student distribution assumption delivers similar results but the gold's role as a safe haven at the 1% quantile becomes more significant. A second observation is that oil is no longer a weak safe haven for the 5% quantile. Other findings from normal GARCH hold for GARCH under the student distribution assumption. Table 5.4 reports the overall effects.

We perform the test for asymmetry in volatility and report the outcome in Table 5.6. The test for gold does not show any evidence of asymmetry. This is unlike for oil and stocks where the joint effect is significant thus we reject the null hypothesis of symmetry. For these assets the use of GJR-GARCH is reasonable.

Table 5.4: Estimation results GARCH - the overall effect

Normal GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.0122**	0.0092	-0.0002
5%	-0.0077**	0.0198	0.0278*
2.5%	0.0023*	0.0002	0.0204*
1%	-0.0001	0.0114	0.0314***
AIC	-6.6051	-4.7223	-6.7869
Normal GJR-GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.0127**	0.0094	-0.0003
5%	-0.0074**	0.0209	0.0283**
2.5%	0.0019*	0.0048	0.0245**
1%	-0.0016	0.0144	0.0309***
AIC	-6.6058	-4.7431	-6.8035
Student GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.0118***	-0.0044	-0.0008
5%	-0.0077**	0.0311***	0.0274**
2.5%	0.0048*	0.0016	0.0118**
1%	-0.0051	0.0032	0.0254***
AIC	-6.7164	-4.8361	-6.8737
Student GJR-GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.0112**	-0.0022	-0.0013
5%	-0.0073**	0.0302	0.027**
2.5%	0.0055*	0.001	0.0098**
1%	-0.0048	0.0058	0.0267***
AIC	-6.7170	-4.8406	-6.9118

Note:*p <0.1; **p<0.05; ***p<0.01

Table 5.5: Bera-Jarque test for normality

	Gold	*Oil*	*Stocks*
statistic	888	2266	795
p-value	<0.001	<0.001	<0.001

Notes: Model: (4.10)
Statistic is the value of JB. Degrees of freedom = 2

Table 5.6: Test for the symmetry

	Gold	*Oil*	*Stocks*
F-statistic	1.70	12.50	14.48
p-value	0.638	0.006	0.002

Notes: Model: (4.9)
F-statistic is the joint significance of all the parameters in the model.

Estimating our model with GJR-GARCH(1,1) leads to the same findings as standard GARCH(1,1). We also reestimate GJR-GARCH(1,1) with the student distribution assumption. These results are similar to the standard GARCH(1,1) with the student distribution assumption. But oil now acts as a weak safe haven at the 5% quantile.

5.3 Comparison of models

In Table 5.4 we show the AIC of the models, since we found the presence of ARCH effects in all models we prefer GARCH over OLS. GJR-GARCH specification has a lower AIC for all assets. We would like to emphasize the size of AIC for gold's models. Note that the difference between normal GARCH, where AIC equals -6.6051, and normal GJR-GARCH's AIC which is equal to -6.6058, thus they differ only by 0.0007 which is much smaller than for the identical oil's models, where the difference is about 0.0208 and for stocks 0.0166. This confirms the results of the asymmetry test on standardized residuals from gold's GARCH(1,1). Thus we will prefer standard GARCH over GJR-GARCH for gold. For oil and stocks, we pick GJR-GARCH as the most fitting model. Further, we rejected normality for all models, hence we assume standard errors to follow student distribution. To conclude, we find gold to act as a strong safe haven for Bitcoin at the 5% quantile and as a weak safe haven at the 1% quantile. Suggesting gold's traditional role as an asset that investors seek during times of market stress holds even for Bitcoin. Oil serves as a weak safe haven for all quantiles under our study. Thus oil's price should not change when Bitcoin is experiencing extreme negative returns. We found no evidence of stocks acting as a weak or strong safe haven for Bitcoin. When Bitcoin exhibits its worst returns stocks returns are also negative.

5.4 Subsample analysis and Discussion

In this section, we examine whether the full sample period results are also valid in subsamples. We will analyze three subsamples. First, we consider Bitcoin's Large-cap ($10 billion to $200 billion) period that spans between 2014 and December 2017 and Mega-cap (> $200 billion) period from December 2017.[1] This allows us to study whether Bitcoin's characteristics changed as Bitcoin's market cap rose. The third subsample is the covid period, we define this period from February 2020 until December 2021. We base this decision on the increase of the Total Monetary Base in the US.[2] We follow the same approach as for the whole sample analysis but now we only assume the student distribution.

Subsample results

We find the presence of the ARCH effects in squared residuals in all regressions. We should acknowledge that the p-value of the ARCH test for gold in the Large-cap period is quite high (about 0.07) but we still prefer GARCH over OLS. Asymmetry tests suggest that GJR-GARCH is reasonable for some assets during some periods. We only comment on the model choice for periods when the outcome of GARCH and GJR-GARCH differs. First for gold, in the Mega-cap period, we choose GARCH over GJR-GARCH because we did not reject symmetry. And second, we prefer GJR-GARCH over GARCH during the Large-cap period for gold since we rejected symmetry. We report the results of these tests in Table A.1 and Table A.2.

The most interesting outcome of the subsample analysis is that gold did not

[1] We use Investopedia's definition of market caps from https://www.investopedia.com/investing/market-capitalization-defined/

[2] The increase of the Total Monetary Base in the US was provided by: Board of Governors of the Federal Reserve System (US), Monetary Base; Total [BOGMBASE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/BOGMBASE

serve as a strong safe haven in any period. The second finding is that stocks did act as a weak safe haven for Bitcoin at the 2.5% and 5% quantiles in the Large-cap period. This suggests that before Bitcoin matured and became so valuable it did not share the price movement with stocks when its returns were in the lowest quantiles. This is further strengthened by the outcome of the Mega-cap period when stocks returns were positive and very statistically significant. The overall effects are reported in Table A.3, Table A.4, and Table A.5.

The subsample analysis confirms the results we found when analyzing the whole sample. That is, both gold and oil act as safe havens for Bitcoin, although subsamples show that these assets serve only as weak safe-havens. The most important finding of the subsample analysis is the change in the relationship between stocks and Bitcoin as Bitcoin matured and became more valuable.

Discussion

As we do not know about any study that considers traditional assets as safe havens for Bitcoin we cannot directly compare our findings with other authors. Baur & Hoang (2021) find Tether and some other major stablecoins to react positively to extreme negative Bitcoin returns. They use the same method as we do and thus the relevance of our results should be comparable. We extend the knowledge of Bitcoin with our discovery of gold and oil as safe haven assets for Bitcoin. But we should emphasize that the effect of these assets is not the same. Gold had positive returns when Bitcoin experienced the most extreme negative returns whereas oil only offered nonnegative returns. Subsample analysis confirmed that both these assets are still at least uncorrelated with Bitcoin during market stress. Also, our results do not answer how long this property holds after the collapse. Still, our findings might be of interest to Bitcoin-oriented investors who decide not to HODL[3] when the price plummets as they offer suggestions on which traditional assets can act as a safe haven.

[3]Originaly a typo for "hold", now a slang in the crypto community for holding the cryptocurrency instead of selling it.

Chapter 6

Conclusion

This paper analyzes the role of gold, oil, and stocks as safe havens for Bitcoin. Offering protection to Bitcoin investors during the times of extreme market downturns. Our sample period runs from the beginning of 2014 until March 16, 2022, we further analyze three subsample periods based on Bitcoin's market capitalization and the Covid pandemic which we defined as a period between February 2020 and December 2021. We employ GARCH and asymmetric GARCH models to account for volatility clustering present in financial time series.

Analyzing daily returns we find the evidence of gold's safe haven properties in the whole sample as well as in the subsample periods. The finding strengthens gold's role as a traditional shelter for investors during times of market turmoil. Oil did also serve as a weak safe haven for Bitcoin both in the whole period and in subsamples. Hence Bitcoin investors might find our thesis helpful when deciding what to do when the price of this cryptocurrency rapidly falls. Finally, we found that stocks acted as a weak safe haven for Bitcoin between 2014 and December 2017, after this period stocks do not protect investors against the most extreme Bitcoin returns. This finding suggests that as Bitcoin matured and become more valuable the relationship between these assets changed.

Although there exist many papers studying Bitcoin's safe haven properties, the literature examining safe haven assets for Bitcoin is very poor. Our paper enriches the existing literature on this topic. We showed gold's role as a traditional safe haven holds even for Bitcoin and examined the relationship change over the years between stocks and Bitcoin. As we restrict our analysis only to finding a safe haven for Bitcoin future research could study safe haven assets also for other cryptocurrencies. Augmentation of our model with a smooth transition approach as presented in the Chapter 4 or methods examing the tail dependence or asymmetric connectedness between assets could also bring a new viewpoint to our study. For the next research, it might be interesting to see whether the frequency of data, such as high-frequency data or weekly returns, leads to different results. These extensions might further help us better understand the behavior of both cryptocurrencies and traditional safe haven assets.

Bibliography

Alexander, C. & M. Dakos (2020): "A critical investigation of cryptocurrency data and analysis." *Quantitative Finance* **20(2)**: pp. 173–188.

Barro, R. J. (1979): "Money and the Price Level Under the Gold Standard." *The Economic Journal* **89(353)**: pp. 13–33.

Baruník, J., E. Kočenda, & L. Vácha (2016): "Gold, oil, and stocks: Dynamic correlations." *International Review of Economics & Finance* **42**: pp. 186–201.

Baumöhl, E. (2019): "Are cryptocurrencies connected to forex? A quantile cross-spectral approach." *Finance Research Letters* **29**: pp. 363–372.

Baur, D. G., T. Dimpfl, & K. Kuck (2018a): "Bitcoin, gold and the US dollar - A replication and extension." *Finance Research Letters* **25**: pp. 103–110.

Baur, D. G. & L. T. Hoang (2021): "A crypto safe haven against Bitcoin." *Finance Research Letters* **38**. 101431.

Baur, D. G., K. Hong, & A. D. Lee (2018b): "Bitcoin: Medium of exchange or speculative assets?" *Journal of International Financial Markets, Institutions and Money* **54**: pp. 177–189.

Baur, D. G. & B. M. Lucey (2010): "Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold." *Financial Review* **45(2)**: pp. 217–229.

Baur, D. G. & T. K. McDermott (2010): "Is gold a safe haven? International evidence." *Journal of Banking & Finance* **34(8)**: pp. 1886–1898.

Beckmann, J., T. Berger, & R. Czudaj (2015): "Does gold act as a hedge or a safe haven for stocks? A smooth transition approach." *Economic Modelling* **48**: pp. 16–24.

Bollerslev, T. (1986): "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics* **31(3)**: pp. 307–327.

Bouri, E., P. Molnár, G. Azzi, D. Roubaud, & L. I. Hagfors (2017): "On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?" *Finance Research Letters* **20**: pp. 192–198.

Brooks, C. (2008): *Introductory Econometrics for Finance*. Cambridge: Cambridge University Press, 2 edition.

Ciaian, P., M. Rajcaniova, & d. Kancs (2016): "The economics of BitCoin price formation." *Applied Economics* **48(19)**: pp. 1799–1815.

Ciner, C., C. Gurdgiev, & B. M. Lucey (2013): "Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates." *International Review of Financial Analysis* **29**: pp. 202–211.

Conlon, T. & R. McGee (2020): "Safe haven or risky hazard? bitcoin during the covid-19 bear market." *Finance Research Letters* **35**: p. 101607.

Dickey, D. A. & W. A. Fuller (1979): "Distribution of the estimators for autoregressive time series with a unit root." *Journal of the American statistical association* **74(366a)**: pp. 427–431.

Dwyer, G. P. (2015): "The economics of Bitcoin and similar private digital currencies." *Journal of Financial Stability* **17**: pp. 81–91.

Dyhrberg, A. H. (2016a): "Bitcoin, gold and the dollar - A GARCH volatility analysis." *Finance Research Letters* **16**: pp. 85–92.

Dyhrberg, A. H. (2016b): "Hedging capabilities of bitcoin. Is it the virtual gold?" *Finance Research Letters* **16**: pp. 139–144.

Engle, R. F. (1982): "Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation." *Econometrica* **50(4)**: pp. 987–1007.

Engle, R. F. & V. K. Ng (1993): "Measuring and Testing the Impact of News on Volatility." *The Journal of Finance* **48(5)**: pp. 1749–1778.

Glosten, L. R., R. Jagannathan, & D. E. Runkle (1993): "On the relation between the expected value and the volatility of the nominal excess return on stocks." *The journal of finance* **48(5)**: pp. 1779–1801.

Guesmi, K., S. Saadi, I. Abid, & Z. Ftiti (2019): "Portfolio diversification with virtual currency: Evidence from bitcoin." *International Review of Financial Analysis* **63**: pp. 431–437.

Hazlett, P. K. & W. J. Luther (2020): "Is bitcoin money? and what that means." *The Quarterly Review of Economics and Finance* **77**: pp. 144–149.

Kristoufek, L. (2015): "What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis." *PLOS ONE* **10(4)**: p. e0123923. Publisher: Public Library of Science.

Kristoufek, L. (2020): "Grandpa, grandpa, tell me the one about bitcoin being a safe haven: New evidence from the covid-19 pandemic." *Frontiers in Physics* **8**: p. 296.

Kwiatkowski, D., P. C. Phillips, P. Schmidt, & Y. Shin (1992): "Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?" *Journal of econometrics* **54(1-3)**: pp. 159–178.

Nakamoto, S. (2008): "Bitcoin: A peer-to-peer electronic cash system." Available at: `https://bitcoin.org/bitcoin.pdf`.

Nelson, D. B. (1991): "Conditional heteroskedasticity in asset returns: A new approach." *Econometrica: Journal of the Econometric Society* pp. 347–370.

Shahzad, S. J. H., E. Bouri, D. Roubaud, L. Kristoufek, & B. Lucey (2019): "Is Bitcoin a better safe-haven investment than gold and commodities?" *International Review of Financial Analysis* **63**: pp. 322–330.

Smales, L. A. (2019): "Bitcoin as a safe haven: Is it even worth considering?" *Finance Research Letters* **30**: pp. 385–393.

Tsay, R. S. (2005): *Analysis of financial time series.* John wiley & sons.

White, R., Y. Marinakis, N. Islam, & S. Walsh (2020): "Is bitcoin a currency, a technology-based product, or something else?" *Technological Forecasting and Social Change* **151**: p. 119877.

Yermack, D. (2015): "Chapter 2 - Is Bitcoin a Real Currency? An Economic Appraisal." In D. Lee Kuo Chuen (editor), "Handbook of Digital Currency," pp. 31–43. San Diego: Academic Press.

Appendix A

Appendix A - tables

Table A.1: Test for the ARCH effects - subsamples

Large cap	*Gold*	*Oil*	*Stocks*
F-statistic	2.05	28.05	41.34
p-value	0.07	<0.001	<0.001
Mega cap	*Gold*	*Oil*	*Stocks*
F-statistic	10.42	30.01	84.24
p-value	<0.001	<0.001	<0.001
Covid	*Gold*	*Oil*	*Stocks*
F-statistic	2.781	12.26	36.11
p-value	0.017	<0.001	<0.001

Notes: Model: (4.6), with 5 lags ($q = 5$)
F-statistic is the joint significance of all the parameters in the model.

Table A.2: Test for the symmetry - subsamples

Large cap	*Gold*	*Oil*	*Stocks*
F-statistic	7.527	0.413	11.091
p-value	0.057	0.938	0.011
Mega cap	*Gold*	*Oil*	*Stocks*
F-statistic	1.237	12.478	7.659
p-value	0.744	0.006	0.054
Covid	*Gold*	*Oil*	*Stocks*
F-statistic	0.856	7.171	1.887
p-value	0.836	0.067	0.596

Notes: Model: (4.9)
F-statistic is the joint significance of all the parameters in the model.

Table A.3: Estimation results for Large cap period - the overall effect

OLS	*Gold*	*Oil*	*Stocks*
Hedge	0.0074	-0.0267	-0.0112
5%	0.0119	0.0720	-0.0059
2.5%	0.0035	0.0185	0.0212
1%	-0.0278	-0.0170	0.0471***
GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.0091	-0.024*	-0.0081*
5%	0.0076	0.0554	0.0169*
2.5%	0.0064	-0.0063	0.0038
1%	-0.0237	-0.0338	0.0277**
AIC	-6.6997	-4.9308	-7.2148
GJR-GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.0093	-0.0229	-0.0068*
5%	0.0087	0.0602	0.0147
2.5%	0.0055	-0.0136	0.0002
1%	-0.0243	-0.0323	0.0279**
AIC	-6.6989	-4.9441	-7.2628

Note:*p <0.1; **p<0.05; ***p<0.01

Table A.4: Estimation results for Mega cap period - the overall effect

OLS	*Gold*	*Oil*	*Stocks*
Hedge	0.0217***	0.0631**	0.0404***
5%	0.0029**	0.0273	0.0602***
2.5%	0.0004**	0.0557	0.1054***
1%	0.0336***	0.1469**	0.1415***
GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.0129**	0.0105	0.0101*
5%	0.0094*	0.0516	0.0425***
2.5%	-0.0073	0.0043	0.0160***
1%	0.0101	0.0622	0.0128***
AIC	-6.7268	-4.7744	-6.5644
GJR-GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.012**	0.0128	0.0076
5%	0.0084	0.0507	0.0424***
2.5%	-0.0064	0.0064	0.0143***
1%	0.01	0.0582	0.0172***
AIC	-6.7275	-4.7807	-6.5939

Note:*p <0.1; **p<0.05; ***p<0.01

Table A.5: Estimation results for Covid period - the overall effect

OLS	*Gold*	*Oil*	*Stocks*
Hedge	0.0377**	0.1919***	0.0901***
5%	0.0176**	0.0091**	0.0957***
2.5%	0.0187*	0.1154**	0.2103***
1%	0.0417**	0.211***	0.2012***
GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.0148	0.0187	0.0236**
5%	0.0222	0.0308	0.0525***
2.5%	0.0061	-0.0216	0.0292***
1%	-0.032	0.0411	0.0695***
AIC	-6.2296	-4.4056	-6.3012
GJR-GARCH(1,1)	*Gold*	*Oil*	*Stocks*
Hedge	0.014	0.0285	0.0184**
5%	0.0206	0.0404	0.0485**
2.5%	0.0042	-0.0154	0.0397**
1%	-0.028	0.0383	0.0672***
AIC	-6.2261	-4.4433	-6.3235

Note:*p <0.1; **p<0.05; ***p<0.01