**Modeling Volatility and Conditional Correlations between Financial Assets**

## Abstract

Massive price swings in crude oil were seen during the most recent COVID-19 outbreak. Numerous researchers argued that the oil market's volatility was exceptional and was readily ascribed to the pandemic because of its widespread devastation. The main issue we address in this work is whether or not this attribution is appropriate. We analyze the fluctuations in oil market volatility that occurred during the COVID-19 pandemic, the Global Financial Crisis of 2008 (GFC), and the SARS outbreak of 2002–2004 in a comparative manner (SARS). Two proxies for market sentiment oil price returns and oil price spread are used in preliminary analysis. We use the symmetric GJR-GARCH (1,1) and asymmetric GARCH (1,1) models for further research.According to our findings, which are based on both skewness and kurtosis, the COVID-19 crisis is a low likelihood but high severity event, also known as a "black swan event," with a very significant level of fat tail risk. Our findings further support the notion that COVID-19 experienced the highest level of asymmetries and volatility clustering (GARCH effect). Comparing the COVID-19 situation to the GFC and SARS, these facts make it more unclear and pessimistic overall.

## DECLARATION

I now certify that every content in this project report, with the exception of citations and quotations that have been properly recognized, is our own original work. Additionally, I certify that it has never been submitted simultaneously for any other degree or honor at ABC University.

.

Student Number: Name: Signature:

Date:

## SUPERVISOR

With this, I, the undersigned, certify that the report presented to ABC with my consent is true and pertains to the project carried out by the students previously indicated under my supervision.

Signature……………………………………………………. Date…………………………….

## DEDICATION

I dedicate this project to Mr. ABC, MY favorite educator, to all the stakeholders who helped make this project a reality, and to the ABC university as a whole.

Contents

[Abstract 1](#_Toc111676318)

[DECLARATION 2](#_Toc111676319)

[SUPERVISOR 3](#_Toc111676320)

[DEDICATION 4](#_Toc111676321)

[Introduction 6](#_Toc111676322)

[**Uses for volatility forecasts** 7](#_Toc111676323)

[Literature review 8](#_Toc111676324)

[Simple Moving Average 9](#_Toc111676325)

[Average Moving Weight 10](#_Toc111676326)

[Exponential Moving Averages 10](#_Toc111676327)

[An EMA is calculated in three steps. 10](#_Toc111676328)

[Methodology 11](#_Toc111676329)

[Data 11](#_Toc111676330)

[**Models** 12](#_Toc111676331)

[Sample size 14](#_Toc111676332)

[Sample methods 14](#_Toc111676333)

[**Results** 15](#_Toc111676334)

[**Risks** 16](#_Toc111676335)

[Conclusion 17](#_Toc111676336)

[Recommendations and Future work 18](#_Toc111676337)

[References 20](#_Toc111676338)

## Introduction

The worst worldwide economic downturn since the Great Depression has been brought on by the COVID-19 epidemic. Additionally, the amount of uncertainty on the financial markets, especially the oil market, has increased significantly and unprecedentedly, posing a number of problems for businesses, investors, and regulators. Despite the fact that there is a high level of volatility and uncertainty across almost all financial markets (Mirza et al., 2020b; Rizvi et al., 2020a) and all asset classes (Mirza et al., 2020a; Mirza et al., 2020c; Yarovaya et al., 2021), the oil market has distinguished itself by setting some new records.Since inventories all over the world piled up as a result of the lockdown and mobility restrictions, it attracted the attention of practitioners, investors, regulators, and policymakers during March 2020 when the price of oil literally entered into a negative domain, albeit for a very brief period of time.

Oil is a non-renewable source of fossil fuels and a necessary raw resource for industrial manufacturing. Production, unemployment, inflation, commerce, and the global economy are all impacted by oil prices. Additionally, it is impacted by the flow of global production levels, which can be altered by wars, uprisings, OPEC decisions, monetary considerations, and currency. The price of crude oil could fluctuate more than other energy prices. As it was in the 1970s, this volatility can be extremely pronounced at some times.

**Volatility,** as used in daily speech, refers to changes in a phenomenon over time. It is used a little more formally in economics to explain the variability of the random (unexpected) component of time without specifying any implied metrics. Concerns began to surface about the volatility that is primarily driven by the pandemic and its subsequent spillovers to the other financial markets because the oil market has established causal impact on other financial markets, which in turn are interrelated with each other. One of the earliest ones, (Bouri et al., 2020), looked at the ability of historical uncertainty connected to several infectious diseases (such as COVID-19, SARS, MERS, Ebola, H1N1, H5N1) to forecast future volatility in the price of oil. Volatility is frequently described in financial economics more specifically or narrowly.

as the instantaneous (or "sigma") standard deviation of the random Wiener-driven

component of a diffusion model with continuous time. Using phrases like the "implied

The term "volatility" from option prices is used. As used in this chapter, the phrase.In a more general descriptive sense, volatility is a defining feature of economics and econometrics.Instead of the precise idea that is frequently suggested in finance. However, a large portion of our discussion will be driven by the requirement to predict the volatility underlying financial return of assets.

Volatility models can be cast in discrete or continuous time, regarding the data accessibility and intended application of the case formulation and accompanying projections. However, it is evident that the pricing and trading of securities are changing in a mostly continuous manner throughout the trading day in many of today's liquid financial asset markets. Since this is the case, it makes sense to think of the cost and return series of financial assets as deriving from discrete observations of a core continuous-time process. However, it is frequently advantageous to formulate the underlying model directly in discrete domain, and this is indeed typical practice. We will discuss both strategies in this chapter.

Formally, the two approaches are not incompatible because it is always possible to infer the distributional implications for a price series observed only discretely from an underlying continuous-time model. At the same time, the construction and estimation of empirically plausible continuous-time models frequently poses significant difficulties. Because they are typically much simpler to deal with from an inferential standpoint, many popular discrete-time models currently in use—despite the fact that they are not formally consistent with underlying continuous-time price processes—remain the method of choice in the majority of practical applications.

The current thesis seeks to accomplish three goals and focuses on the topic of financial (stock) time series volatility forecasting. The first scope consists of a novel volatility forecasting method that is proposed in accordance with a recently established research line that indicated

utilizing both night volatility and intraday volatility metrics It begins with an

Hansen, Huang, and Shek (2010b) came up with the concept and proposed a partial version of a Bivariate

Realized Generalized Autoregressive Conditional Heteroskedastic (GARCH) model,

then uses it to create new bivariate versions of other realized GARCH-type models.

This study has two goals in mind. The first is to examine the Covid-19 pandemic's spread-related impact on the erratic nature of currency exchange rates, bitcoin, crude oil, and gold prices. Investigating the relationships between these volatilities is the second step. The "Literature Review" portion is divided into two sections. The first section provides theoretical context and empirical findings from research in the literature to explain the relationship between the volatility of the worldwide crude oil price, gold, exchange rate, and bitcoin. The second section investigates what occurred as a result of the Covid-19 pandemic through studies examining the association between the Covid-19 pandemic and the aforementioned characteristics.The models used to calculate the Covid-19 pandemic's effect on contagion and the correlation between the volatilities of those variables in Turkey are described in the following section. The chapter's conclusion and a summary of the chapter are included in the concluding part.

## **Uses for volatility forecasts**

This section examines the uses of volatility projections in both real-world settings and in academic literature. Although financial applications are the focus, the conversation is kept on a general scale. We therefore do not yet presumptively use a particular volatility forecasting algorithm. In the parts that follow, we'll talk about the problems with defining and estimating specific volatility forecasting models.

First, we'll go over a few general statistical forecasting scenarios where volatility dynamics are crucial. Then, we'll get more specific about some of the applications in finance. Finally, we'll describe a few applications in macroeconomics and other fields.

## Literature review

The studies examining the connections among bitcoin and some other investment options during the COVID-19 outbreak are briefly reviewed in this section. During the COVID-19 pandemic, Conlon and McGee (2020) examined the downside risk of bitcoin and discovered that it increased risk in comparison to solely holding the S&P 500. In contrast, Mariana et al. (2020) discovered that returns of bitcoin had a negative connection with S&P 500, showing that it possesses safe-haven characteristics.

According to Chen et al. (2020), coronaviruses generated unfavorable attitude as evidenced by the volume of searches for coronavirus-related terms. They demonstrated how the fear index was affected by this emotion by using it as a measure, and how it decreased bitcoin returns. According to Kristoufek (2020), gold offers greater risk diversification during the pandemic than bitcoin. In particular, during the epidemic, the correlation between bitcoin and S&P 500 returns significantly increased.

Health is essential for a wealthy and productive society, but illness and distress are likely to have an impact on the economy as a whole as well as on productivity, travel, recreation, and consumption of commodities. More money has been invested in ensuring the safety of the world's health as a result of several health catastrophes including the Ebola outbreak in West Africa, the "Middle East Respiratory Syndrome" (MERS) in Korea, and many other diseases. In order to stop the spread of illnesses throughout the world, the public health community is always working to support national systems. Given that it is obvious that such diseases or pandemics not only have an impact on global health but also cause a variety of socio-economic difficulties (UNGD, 2015).That such a communicable diseases could have some substantial and unexpected economic costs was proved by the Ebola outbreak in West Africa. This sickness caused Liberia's GDP growth to decrease from 8.7% to 0.7%. Additionally, Sierra Leone's GDP growth slowed from 5.3% to 0.8%. (World Bank, 2016).

The other discussion on Cost-Effectiveness in Health and Medicine stressed the importance of taking into account the economic impacts ofs an infectious disease from the perspective of the entire society rather than just the health sector in 2016. (Sanders et al., 2016).

For many years, volatility has been a hotly debated subject in time series econometrics. The myriad applications in real life, where volatility played a significant role, sparked attention.

Prominent position in a variety of tasks, from risk forecasting to portfolio allocation management. Numerous catastrophes and crises of varying sizes compelled the focus of practitioners, scholars, and regulators depart from conventional Financial Economics research

which suggested determining the average stock market returns, as well as the magnitude and stationarity of In order to create econometric tools that more accurately estimate price volatility.

With time, it became clear that volatility of returns was easy to estimate and that returns at high frequencies were harder to predict effectively. This explains why Financial Econometrics gave modeling financial volatility such a high priority because it became crucial to contemporary pricing and risk management theories. Financial economists discovered that any financial or economic time series' variation may be accurately described by the distributional pattern of returns. Conclusions about conditional distributions may reveal a lot about how to value a certain instrument, allocate money in accordance with a particular portfolio, assess risk and performance, and carry out the management decision-making process.The redistributive pattern is closely related to other portfolio characteristics, such as the conditioned return fractiles that predict the likelihood of large swings in value.

The COVID-19 pandemic has had a devastating impact on the world economy and increased market volatility. The actual economy and financial markets are both greatly impacted by COVID-19's high contagiousness and high level of uncertainty. Additionally, COVID-19 has a detrimental effect on demand overall by causing short-term instability in food prices1 and by obstructing worker and tourist migration. This outbreak's effects were so destructive and extensive that they simultaneously threatened the financial viability of businesses, financial instruments, and entire economies (Rizvi et al., 2020b; Yarovaya et al., 2020a, 2020b).

Volatility was defined differently depending on the situations in which it was used. The phrase "series of fluctuations" used to describe a phenomenon over a certain time period is a less strict definition of volatility. In a more formal sense, economics defines volatility as that of the fluctuation of a time series' random component without explicitly mentioning any particular underlying statistic.Depending on the data's availability or the model's use, volatility may be characterized in discrete or continuous time patterns. Given the highly liquid markets where transactions happen every second, the price of a security tends to follow a continuous rather than discrete pattern. Because of this, it makes sense to view the stock market time series as the result of discrete observations of an underlying continuous time process. To deduce the distributional implications of a time series that evolves under a continuous time pattern, for instance, models that explain continuous data may be built in discrete time. Both discrete and continuous formulations present difficult econometric problems, although they are not mutually exclusive.

## Simple Moving Average

Before the invention of computers, the simple moving average (SMA) was widely used since it is simple to calculate. Various moving averages and technical indicators are more accessible to measure because of current computing capacity. The average closing prices over a given period are used to calculate a moving average. Although it can be calculated for various timescales, a moving average is commonly computed using daily closing prices. You can also use other price information, like the starting or median prices. That data is added to the calculation after the next price period, while the series' oldest price data is dropped.

## Average Moving Weight

As more recent data points are more pertinent than those from the distant past, weighted moving averages give more weight to recent data items. The weights should total 1 (or 100%) when added together.

## Exponential Moving Averages

The more recent prices are likewise given more weight by exponential moving averages (EMAs), although the pace of decline between one price and its predecessor varies. The rate of reduction varies exponentially. There might be a difference between the first two period weights of 1.0, a difference of 1.2 for the two periods after those periods, and so on, rather than every preceding weight being 1.0 more diminutive than the weight in front of it.

## An EMA is calculated in three steps.

 Finding the SMA for the period, the initial input into the EMA algorithm comes first. After that, a multiplier is determined by dividing two by the number of periods plus one. The final step is the previous day's EMA multiplied by the multiplier plus the closing price.

**The most effective moving average is which one?**

Some people think an exponential moving average (EMA) is a superior trend indicator to a WMA or SMA since it uses an exponentially weighted multiplier to give greater weight to recent prices. Some people think that the EMA reacts to trend changes more quickly. On the other hand, the SMA's more superficial smoothing may make it more helpful in identifying specific regions of support and resistance on a chart. Moving averages typically smooth price data that may otherwise be visibly erratic.

## Methodology

We use the wavelet coherence method of Torrence and Compo in order to characterize the relationship between bitcoin and other asset classes in terms of time and frequency (i.e., the short-, medium-, and long-term) (1998). Using distinct time horizons, this methodology enables us to evaluate the relationship at each point in our sample period. The ability to capture linkages across different time scales distinguishes the wavelet technique from more traditional time series models (such as the vector autoregression model, BEKK or DCC GARCH approach), allowing investors with different holding periods to examine the risk spillover between bitcoin and financial assets (Reboredo and Rivera-Castro, 2013).

The two models developed by Engle and Bollerslev in 1982 and 1986, GARCH and ARCH, respectively, are commonly employed to estimate the various variances of economic variables. It is possible to model the change in the variable variances since GARCH models take time-dependent variability into account. This trait helps the model to account for the fluctuation in economic situations throughout time. Today, GARCH-based models take on several forms, which is especially prevalent in financial time series. It made it possible to assess asymmetric effects within the parameters of the model.

Depending on their degrees of risk tolerance, how well they assimilate and absorb information, and the limitations imposed by institutions, investors typically have varying preferences for investment horizons (Chakrabarty et al. 2015). Additionally, the approach can be used even if the two time series include seasonal or cyclical patterns, structural discontinuities, or are nonlinear or non-stationary (Crowley, 2005; Roueff and Sachs, 2011).

## Data

There are numerous sources of financial data, some of which are freely accessible while others require a subscription. When available, we will use publicly accessible data in this book; in all other cases, we will use commercial datasets. Here is a list of a few data sources:

http://finance.yahoo.com/:

You can download daily, weekly, and monthly data for specific stocks, indexes, mutual funds, and ETFs from the Yahoo Finance website. The starting and closing daily prices, the maximum and minimum intraday prices, and the volume are all included in the data. The website also offers the adjusted closing price, which is modified to account for dividend payouts and stock splits.

Several R tools provide instant data download without the need to first save a file. It is essential to know the asset's ticker.

**http://finance.yahoo.com/:**

Data for specific stocks, indexes, mutual funds, and ETFs can be downloaded daily, weekly, or monthly from the Yahoo Finance website. The data is broken down into the volume, top and lowest intraday prices, and opening and closing daily prices. Also available on the website is the adjusted closing price, which takes dividends and stock splits into account. This website's data was used to create Figure 1.2 above.

[**http://www.truefx.com**](http://www.truefx.com)**:**

A fintech business called TrueFX offers traders financial information and services. It is available to get quotations data for numerous currency pairings in monthly files commencing in 2009 by registering on their website.

Under the historical prices page, you may download the data as a csv file.

R has a number of programs that enable direct data download without the need to first save a file. The asset's ticker has to be known.

[**https://fred.stlouisfed.org/**](https://fred.stlouisfed.org/)**:**

The Reserve Bank Economic Database (FRED) is a sizable database of economic and financial statistics both for United States and other countries, and can be found at https://fred.stlouisfed.org.

Similar to Yahoo Finance, users have the option of downloading data in csv format or directly using R.

We obtain statistics on gold, bitcoin, and crude oil from the St. Louis FRED database. The beginning point of the sample period is limited by the availability of Bitcoin data; it spans from December 2014 to March 2020. The descriptive statistics values are presented in Table 1 in Panel A for the entire sample and Panel B for the epidemic period. We discuss the performance of various financial markets from January 2020 to March 2020 in Panel B. 1 Although these indices weren't so volatile when the entire sample was taken into account, the results imply that all the crude oil markets exhibit considerable volatility throughout the COVID-19 period.

[**http://www.quandl.com**](http://www.quandl.com)**:**

An aggregator of financial and economic datasets is called QUANDL.

We obtain statistics on gold, bitcoin, and crude oil from the St. Louis FRED database. The beginning point of the sample period is limited by the availability of Bitcoin data; it spans from December 2014 to March 2020. The descriptive statistics values are presented in Table 1 in Panel A for the entire sample and Panel B for the epidemic period. We discuss the performance of various financial markets from January 2020 to March 2020 in Panel B. 1 Although these indices weren't so volatile when the entire sample was taken into account, the results imply that all the crude oil markets exhibit considerable volatility throughout the COVID-19 period.

## **Models**

Regression Model: The regression analysis has many uses in finance, particularly in investment research. We'll go over the model's fundamental components and presumptions before using it to assess the risk of asset portfolios.

Time series models are particularly practical tools when working with greater data since predictor variables may not be observable, difficult to measure, or just too noisy to be effective. Time series models solely rely on the past values of the variable to predict its future.

Volatility Models: These time series models for forecasting the variance or standard deviation of market return are known as volatility models. The essential premise of these models is that risk changes over time, and that measures of risk like the standard deviation of returns should take this into account. These models have found extensive use since risk is a crucial component of financial choices, particularly with the development of risk management practices in financial institutions.

**DCC GARCH**

It is possible to think of the Dynamic Conditional Correlation GARCH model (DCC-GARCH) as an expansion of the CCC-GARCH model proposed by Bollerslev. Engle and Sheppard initially introduced it in 2001. (1990). The DCC-GARCH permits the correlation structure to be dynamic and change over time, in contrast to the CCC-GARCH, which does not. The most notable advantage of the DCC-GARCH model is that the number of parameters that are estimated in the correlation process is independent of the number of series that are to be estimated, which results in a significant computational advantage when estimating large covariance matrices. This makes the DCC-GARCH model easier to compute than many other complex MGARCH models (Engle 2002).

**Computer program used for analysis**

**PACKT library**

In empirical finance, it is a well-known and widely acknowledged stylized truth that the volatility of series data changes over time. But measuring and forecasting volatility is a difficult task because it is non-observable. Variable volatility models are typically driven by three empirical findings:

Volatility clustering: This is the empirical finding that in the financial markets, tranquil periods are set backs by calm periods and tumultuous times by turbulent periods.

Asset returns' non-normality: According to empirical data, asset returns typically exhibit fat tails when compared to the normal distribution.

Leverage effect: This results in the finding that volatility tends to respond differently to positively or negatively price changes; a decrease in prices raises the volatility more significantly than an increase of comparable magnitude.

**Quantmod package**

We compute log returns from the daily closing since the daily return series is what we are interested in. Although it is a basic computation, the Quantmod package provides an even more clear method:

**Moments package**

Instead of excess kurtosis, R reports the base rate of kurtosis, which is as follows:

> kurtosis(ret)

daily.returns

     12.64959

For GARCH modeling, R has a number of packages. **Rugarch**, rmgarch (for multivariate models), and **fGarch** are the most well-known; however, some **GARCH** functions are also included in the fundamental **tseries** package. We will show off the modeling features of rugarch package in this chapter. The notes in this chapter are consistent with the output and documentation of the rugarch package.

**GetQuandlData**

The well-known and extensive portal Quandl gives users access to a variety of both free and paid data. On this platform, a number of central banks and research organizations offer free economic and financial data. I strongly advise perusing the Quandl website's accessible tables43. You will probably discover datasets that you are already familiar with.

Standard GARCH models can account for fat tails and volatility clustering, but more complex models are required to account for asymmetries brought on by the leverage effect. We will now discuss the idea of news impact curves in order to approach the asymmetry problem visually.

Pagan, Schwert, and Engle and Ng (1991) presented news impact curves, which are valuable tools for illustrating how much volatility varies in reaction to shocks. The word is derived from the typical understanding of shocks as news that moves markets.

## Sample size

We can examine the effects of spillover across the global stock, gold, and energy markets before and during the COVID-19 period because we use daily data from January 13, 2015 to May 15, 2020. The closing prices for the S&P Global Broad Market Stock Index, the CSCI gold index, and the GSCI energy index serve as our primary variables. Four control variables that have been extensively researched in the literature as the primary drivers of the returns on the three markets are used to account for the confounding factors of the three markets. S&P Dynamic Volatility Futures (VIX), US trade-weighted exchange rate index (EXR), China Volatility Index (VXFXI), and Bitcoin in the US dollar index are the factors under management.

## Sample methods

The standard deviation is typically the method used to measure volatility, as most investors are aware. The square root of the average variance of the data out of its mean serves as the simple definition of standard deviation. Although it is very simple to calculate, the assumptions that underlie its interpretation are more intricate, which raises questions regarding the correctness of the statistic. As a result, its effectiveness as a reliable risk indicator is viewed with some degree of doubt.

It is necessary to make the assumption that investment performance data has a normal distribution for standard deviation to be a reliable indicator of risk. In terms of graphics, a bell-shaped curve will appear on a chart if the data are distributed normally. If this benchmark is accurate, then roughly 68% of projected outcomes should fall within a standard deviation of the investment's expected return, 95% should fall within a standard deviation of two standard deviations, and 99.7% should fall within a standard deviation of three standard deviations.

The effects of heteroskedasticity will render standard deviation an inaccurate indicator of risk, similar to skewness and kurtosis. When considered as a whole, these three issues may lead investors to underestimate the volatility of their investments and possibly take on a lot more risk than they had originally intended.

Performance data of investments may unfortunately not be regularly distributed for three basic reasons. First, since return distributions are often asymmetrical due to the usual skewedness of investment performance. Investors frequently endure phases of performance that are extraordinarily high and low. Second, the performance of investments frequently displays a characteristic known as kurtosis, which denotes an abnormally high number of both positive and negative performance periods.

Fortunately, there is a method known as that of the historical method that makes measuring and analyzing risk considerably simpler and more accurate. Investors can use this strategy by creating a histogram, which is a graph that shows the historical performance of their investments.

A histogram is a graph that shows how many observations fall inside each of a number of category ranges. For instance, the performances of the S&P 500 Index over a three-year rolling annual average from June 1, 1979, to June 1, 2009, has been constructed in the chart below.

## **Results**

The study's sample period, which spans fromDecember 2019 to December 20, 2022, is included in this. The data has been chosen to cover the Covid-19 timeframe and is daily data. Therefore, it was intended to research Covid-19's impact on the financial markets. The proper ARMA model was chosen first, and then the EGARCH model was built, all within the scope of EGARCH modeling as indicated in the methodology. Time series with an upward or downward trend are extensively employed, especially in finance. As a result, based on the analysis used, the results could not be accurate. Measures and the construction of accurate models are crucial for obtaining accurate findings.

First, the proper ARMA models will be chosen to check the stationarity of the variables utilized in the investigation. The stage of choosing the best EGARCH model is started if the ARCH effect desired is discovered in the residues acquired from the model in the next stage.

The Augmented Dickey-Fuller (ADF) test was used to examine the stationary variables. The first differential procedure was used to stabilize the non-stationary variables, according to the test results. At a 1% significance level, the hypothesis of a unit root in a series has been disproved. The structure of the ARMA model estimating process was then initiated. First, the correlograms of the variables have been evaluated in order to ascertain the correlation pattern of each variable in the construction of the ARMA model. By developing the most appropriate ARMA models in following the criteria, the parameters of the models, and by testing the significance of the models for latency values that exceed the limitations, its significance has been tested.

## **Risks**

Evidence on the diversification or hedging capabilities of ESG assets in the context of the ongoing pandemic crisis is much more scarce than that for gold and cryptocurrencies. Studies already published conclude the possible function of ESG assets as diversifiers, hedges, or safe havens from correlation and dependence analysis using various econometric techniques. The findings of Arif et al. (2021), focusing on clean energy equity investments, show limited dynamic connectivity between green and conventional stock indices over the long term, suggesting chances for diversification for investors with long investment horizons.

First, from a risk standpoint, the pandemic's persistence shows significant individual risk and dependence between various asset classes, which supports the enlarged concept of higher interconnection between financial markets during periods of severe market volatility. However, over the entire 2020–2021 decade, renewable energy equities might be able to offer a meaningful level of diversification in the broader equity market.

Furthermore, due to their low connection with commodities, cryptocurrencies, and Treasury securities, clean energy stocks can be utilized as a hedge for such assets and a diversifier (roughly 0.20). According to the minimum variance portfolio analysis, SRI can be used as a strategy to reduce risk exposure across all asset combinations and for every frequency of rebalancing, allowing it to be employed for diversification throughout the pandemic crisis and the period that follows.

The findings of the diverse advantages of clean energy assets could be used to create the best possible policies to hasten the shift to a more sustainable economy. Policy actions are crucial to meeting global environmental and climate targets in supporting capital mobilization for sustainable investments and promoting renewable energy systems. To emphasize the importance of supportive policies in sustainable financing, policymakers must comprehend the effects external shocks, such as the current sanitary crisis, may have on the demand for green financial instruments. Beyond environmental considerations, the findings of this study indicate that investors are likely to want renewable energy assets in times of economic unrest for diversification or hedging purposes.

Additionally, the correlation and portfolio performance analysis we use consider the presence of highly adverse movements in the chosen assets, which is particularly appropriate in a time of financial instability like the COVID-19 crisis, increasing the relevance of our results to investors and policymakers.

Finally, this finding opens up several directions for further investigation. It encourages explicitly taking into account other green assets to gain further understanding of the performance of ESG portfolios. For instance, green bonds that take into account the performance of the ESG fixed income market, clean energy stocks that offer broader exposure to the renewable energy sector, or even the newest green cryptocurrencies that provide exposure to the speculative market of digital currencies with a focus on lowering energy consumption in the mining process.

Investigating how recent events have affected the diversifier qualities of renewable energy stocks is encouraged because they have made it clear that the green energy transition needs to be accelerated.

## Conclusion

Global pandemic COVID-19's introduction has caused a decline in crude oil prices due to decreased demand for imports globally. Impending downside risks in the oil markets have been brought on by the possibility of a global economic downturn. Investors that own assets produced from oil are so vulnerable to adverse changes in the price of oil. It is crucial to understand an alternate tool to hedging such risks associated with oil exposure. In light of the COVID-19 outbreak, this study compares the safe haven quality of gold to crude oil.The DCC-GARCH model is used, and the results confirm the conclusions of the earlier studies by showing that gold serves as a safe haven for both WTI and Brent crude oil markets during the COVID-19 epidemic (Baur and McDermott, 2010; Ciner et al., 2013; Reboredo, 2013). However, at this period, Bitcoin simply serves as a diversifier, which is consistent with the overall conclusions of Bouri et al. (2017a) and Das et al (2019). Therefore, the results of this study may help investors in these areas create successful portfolio strategies. Future research may compare gold's effectiveness in hedging against crude oil to that of other precious metals. 3 Similar to this, Bitcoin's performance can be compared to cryptocurrencies backed by US dollars and gold.

## Recommendations and Future work

The literature contests the ability of bitcoin to diversify. Numerous studies show that compared to other assets like gold, currencies, and bonds, bitcoin is more prone to volatility (e.g., Smales 2019). The greatest crisis after the active trading of bitcoin futures in December 2017 was the COVID-19 epidemic. In light of this, we look into how the volatility of key asset classes and bitcoin is linked together by the pandemic effect (oil, foreign exchange, gold, stocks, and bonds).

We provide evidence of the significant volatility of bitcoin, which rises during the pandemic and supports its speculative tendency (Gandal et al. 2018; Corbet et al. 2018). More importantly, there is almost no correlation between the volatility of bitcoin and the price of bonds. Additionally, the volatility relationship between bitcoin, gold, and foreign exchange is only relevant in the short- and medium-term.

In order to reduce portfolio variance over a range of time horizons, we propose risk management techniques such as hedging ratios and optimal weights after determining the level of volatility shock spillover between Bitcoin and financial assets. Our findings have ramifications for actual investments. For instance, investors may think about buying oil together with bitcoin to diversify the pandemic risk given the possible losses from possessing volatile assets during the pandemic. In the short, medium, and long terms, oil is the least expensive hedge for bitcoin. We also discover that while utilizing gold, foreign currencies, and the S&P 500 was more expensive during the pandemic, it was also more successful.

Since 2019, the coronavirus has been on the rise and has caused major issues with healthcare as well as with the economy, psychology, and society. People have altered their living arrangements and decisions as a result of rising death rates and contagion due to fear and panic. All economic activities and indicators were impacted and interacted with one another throughout the epidemic as decisions regarding consumption and investment changed. The risk of such an epidemic was in no way anticipated by the financial sector. It was also impossible to be ready. because existing risk understanding is restricted to modeling just the hazards that have been addressed in the past.

The value of bitcoin and other cryptocurrencies dropped, particularly in March 2020 when the pandemic was observed in numerous nations. All markets are believed to be impacted by the same process' effect.

We wanted to look into these consequences in this study, specifically for Covid-19. Using ARMA-EGARCH modeling, we looked at the volatility of bitcoin, crude oil prices, exchange rates, and gold prices over the period from February 2nd, 2019, through December 20th, 2020. The mutual transmission of shocks in the variables for bitcoin, crude oil prices, exchange rate, and gold prices was also examined. The findings showed that Covid-19 had statistically significant effects on the conditional variability of the variables, with effects on gold, exchange rates, oil prices, and bitcoin being more volatile throughout the epidemic. Our findings thus demonstrate that the Covid-19 epidemic has a contagious influence on the bitcoin, oil, gold, exchange markets, and market shocks.

Finally, this finding opens up several directions for further investigation. It encourages explicitly taking into account other green assets to gain further understanding of the performance of ESG portfolios. For instance, green bonds that take into account the performance of the ESG fixed income market, clean energy stocks that offer broader exposure to the renewable energy sector, or even the newest green cryptocurrencies that provide exposure to the speculative market of digital currencies with a focus on lowering energy consumption in the mining process.

Investigating how recent events have affected the diversifier qualities of renewable energy stocks is encouraged because they have made it clear that the green energy transition needs to be accelerated.

## References

Aguiar‐Conraria, L. and Soares, M.J., 2014. The continuous wavelet transform: Moving beyond uni‐and bivariate analysis. *Journal of economic surveys*, *28*(2), pp.344-375.

Billio, M., Caporin, M. and Gobbo, M. 2005. Flexible Dynamic Conditional Correlation Multivariate GARCH models for Asset Allocation. Ca´Foscari University of Venice, Department of Economics. Bollerslev, T. Engle, R.F. and Woolridge, J.M. 1988. A Capital Asset Pricing

Model with Time-Varying Covariances. Journal of Political Economy. vol. 96. no. 11. pp. 116-131. Bollerslev, T. 1986. Generalized autoregressive conditional heteroscedasticity, Journal of Econometrics, vol. 31, no. 3, pp. 307-327.

Chia-Ju Lee, Tuan-Nam Lai, Chang-Chou Chiang and Hai-Chin Yu (2019). Dynamic conditional correlation and volatility distributions in Tokyo, London, and New York gold markets. Investment Management and Financial Innovations, 16(4), 146-155. doi:10.21511/imfi.16(4).2019.13

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

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

Bouri, E., Gupta, R., Tiwari, A.K. and Roubaud, D., 2017. Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, pp.87-95.

Das, D., Le Roux, C.L., Jana, R.K. and Dutta, A., 2020. Does Bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US Dollar. *Finance Research Letters*, *36*, p.101335.

Adekoya, O. B., Oliyide, J. A., & Oduyemi, G. O. (2020). How COVID-19 upturns the hedging potentials of gold against oil and stock markets risks: Nonlinear evidences through threshold regression and markov-regime switching models. Resources Policy, 101926. <https://doi.org/10.1016/j.resourpol.2020.101926>

Aslam, F., Aziz, S., Nguyen, D. K., Mughal, K. S., & Khan, M. (2020). On the efficiency of foreign exchange markets in times of the COVID-19 pandemic. Technological Forecasting and Social Change, 161, 120261. <https://doi.org/10.1016/j.techfore.2020.120261>

Bedoui, R., Braiek, S., Guesmi, K., & Chevallier, J. (2019). RETRACTED: On the conditional dependence structure between oil, gold and USD exchange rates: Nested copula based GJR-GARCH model. Energy Economics, 80, 876-889. <https://doi.org/10.1016/j.eneco.2019.02.002>

Bhattacharjee, S. (2016.) A statistical analysis of Bitcoin transactions during 2012 to 2013 in terms of premier currencies: Dollar, Euro and Rubles, Vidwat. The Indian Journal of Management 9(1), 8-16.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity, Journal of Econometrics, 31(3), 307-327. <https://doi.org/10.1016/0304-4076(86)90063-1>

Cheah ET, Fry J (2015) Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Econ Lett 130:32–36

Chen, C., Liu, L. and Zhao, N., 2020. Fear sentiment, uncertainty, and bitcoin price dynamics: The case of COVID-19. *Emerging Markets Finance and Trade*, *56*(10), pp.2298-2309.

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

Billio, M., Getmansky, M., Lo, A.W. and Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of financial economics, 104(3), pp.535-559.

Cheah, E.T. and Fry, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Economics letters, 130, pp.32-36.

 Agyei-Ampomah, S., Gounopoulos, D. and Mazouz, K., 2014. Does gold offer a better protection against losses in sovereign debt bonds than other metals?. Journal of Banking & Finance, 40, pp.507-521.

Akhtaruzzaman, M., Boubaker, S., Lucey, B.M. and Sensoy, A., 2021. Is gold a hedge or a safe-haven asset in the COVID–19 crisis?. Economic Modelling, 102, p.105588.

Arif, M., Hasan, M., Alawi, S.M. and Naeem, M.A., 2021. COVID-19 and time-frequency connectedness between green and conventional financial markets. Global Finance Journal, 49, p.100650.

Becchetti, L., Ciciretti, R., Dalò, A. and Herzel, S., 2015. Socially responsible and conventional investment funds: performance comparison and the global financial crisis. Applied Economics, 47(25), pp.2541-2562.

Çelik, İ., Sak, A.F., Höl, A.Ö. and Vergili, G., 2022. The dynamic connectedness and hedging opportunities of implied and realized volatility: Evidence from clean energy ETFs. The North American Journal of Economics and Finance, 60, p.101670.