Assessing the performance of safe haven assets during major crises

Sokhombela, Andiswa Luncedo Lwandile and Bonga-Bonga, Lumengo and Manguzvane, Mathias Mandla

22 December 2024

Assessing the performance of safe haven assets during major crises.

Abstract

This paper investigates the safe-haven characteristics of three assets, namely gold, crude oil and Bitcoin, and their ability to reduce downside risk of different portfolios during two severe financial crises: the 2008 global financial crisis (GFC) and the 2019 Coronavirus pandemic (COVID-2019). We examine the left-tail behaviour of portfolios consisting of 60/40 equity returns and bond yield from six G20 member nations by applying EVT, BMM in the context of portfolio optimisation and examine which selection of safe-haven assets between gold, crude oil and Bitcoin can be amalgamated to the stock/bond mix for an optimal portfolio during crises. The portfolios are from three developed countries: Canada, United States of America (USA) and United Kingdom (UK), while the three emerging countries are Russia, Brazil and South Korea. The sample data is from 2007 to 2009 for the GFC and 2019 to 2023 for COVID-19. The findings of the paper show that during the GFC, the addition of gold and crude oil and the combination of the two allowed the heavy Fréchet-type tails to transform into thin Weibull-type tails. This implies that the two assets acted as safe-haven assets during the crisis and gold being the best safe-haven option for all countries. Contrarily, COVID-19 yielded mixed results, all the assets including the digital cryptocurrency acted as a safe haven for only two emerging countries, namely Russia and Brazil, improving both tail behaviours to Weibull-type tails, with gold and Bitcoin serving safe-haven characteristics for both countries.

Keywords

Safe-haven assets, Global Financial Crisis (GFC), COVID-19, Extreme Value Theory (EVT), block maxima method/approach (BMM)

1.1 Introduction

Over the years, portfolio investors have sought to diversify their portfolios to shield their investments from risks arising from unforeseen circumstances. These arise mostly during financial turmoil rather than normal times, and often they induce a 'flight-to-quality'. This phenomenon sees investors rebalance their portfolios to move their investment to a safer asset (Akhtaruzzaman, Boubaker and Sensoy, 2021). As shown by Baur and McDermott (2010), investors who experience negative market shocks are likely to seek a safe haven.

Literature suggests that to be classified as a safe haven, an asset must hold its value in stormy or adverse market conditions and exhibit certain characteristics such as low correlation with other assets, high liquidity and a reputation for stability (Kang, McIver and Yoon, 2017; Liu, Wang and Lee, 2020; Liu and Lee, 2022). Traditionally, gold and government bonds have been considered safe-haven assets owing to their perceived stability and low risk. These assets were popularly considered safe havens during various crises such as the stock market crash in 1987, dot-com bubble crisis from 2000 to 2001, the GFC from 2007 to 2008 and the European debt crisis from 2010 to 2011 (Luther and Salter, 2017; Boubaker et al., 2020; Ji, Zhang and Zhao 2020; Ahmed et al.2022).

According to Ji et al., (2020), investors should incorporate safe-haven assets that are uncorrelated with other assets or portfolios during periods of market volatility, to reduce downside risk. It is in that context that gold has long been used as a store of value and natural currency. For instance, El Hedi Arour, Lahiani and Nguyen (2015) examined the relationship between global gold prices and stock returns in China. Their analysis of optimal weights and hedge ratios in dedicated gold-stock portfolios revealed that gold is a safe haven in the Chinese stock markets. This was particularly evident during the 2008 GFC, when gold prices surged while other asset classes experienced significant losses. As such, a gold-stock portfolio is considered an effective portfolio-hedging tool in both developed and emerging markets during periods of market volatility (Conover, Jensen, Johnson and Mercer, 2009; Wen and Cheng, 2018). Boubaker et al. (2020) tested the safe-haven characteristic of gold in the wake of various global crises by using the longest possible annual data available on gold prices over the period of 1258 to 2018. The author provided compelling evidence that gold acts as a safe haven and a strong hedge against risk during various crises.

Moreover, studies show that the role of crude oil as safe havens is controversial. For example, Mensi et al. (2021) investigated the safe haven and hedging qualities of crude oil in the Asian economy. They discovered that while oil could act as a safe haven for precious metals in a portfolio, its best use as a hedging tool was during COVID-19. However, Ciner, Gurdgiev and Lucey (2013) show that oil acted as a safe haven for bonds after the 1987 stock market crash and after 2000 which is allegedly connected to the collapse of telecommunications and technology stocks on the National Association of Securities Dealers Automated Quotations (NASDAQ) in the USA.

With the rise of digital assets, such as cryptocurrencies, investors have also begun to consider them as potential safe havens (Bouri, Lucey and Roubaud, 2020). According to previous studies one of the key advantages of digital assets, such as cryptocurrencies, as a safe haven is their decentralised nature. This means they are not tied to government or a central authority, which renders them resilient to economic and political shocks, which can be particularly important during crises (Luther and Salter, 2017; Corbet, Hou, Hu, Larkin and Oxley, 2020; and Meshcheryakov and Ivanov, 2020). Meshcheryakov and Ivanov (2020) find that cryptocurrencies can be used to hedge the downside risk of equity investments when performing an intraday analysis testing the hedging characteristics of Bitcoin and Ethereum, This way Bitcoin fits the idea of a safe-haven asset in booms and crises.

While they are a few studies that assess the role of commodities and digital assets as safe havens for optimal portfolio selection during crises times (Upper, 2000; Baur and McDermott, 2010; Conlon, Corbet and McGee, 2020), no paper has ever investigated how these assets may improve the downside risk of a traditional mix of stock/bond assets for portfolio optimisation during crisis time. In fact, it is often believed that the 60/40 stock-bond portfolio, a traditional strategy that involves dividing a portfolio between two assets, 60% stocks and 40% bonds, delivers a less volatile and reliable return for balanced investors because they lack a tolerance for the volatility and drawdowns of a pure equity allocation (Dbouk and Kryzanowski, 2009). However, studies show that a 60/40 stock-bond portfolio may not be a better combination for hedging during crises (Fidelity investments, 2023). Thus, it becomes important to assess the performance of the 60/40 stock-bond portfolio and which of the safe-haven assets may improve its efficiency, especially during crises.

The contribution of this paper is threefold. Firstly, the paper assess the performance of 60/40 stock-bond portfolio compare to other combinations of stock-bond portfolios, especially the equal weight stock-bond portfolio. Subsequently, the paper will assess which combination of safe-haven assets, between traditional and digital assets, can improve the different combinations stock/bond portfolio performance during crises. To this end, the paper applies tehe extreme value theory (EVT), especially the block maxima method (BMM) in the context of portfolio optimisation to examine which selection of safe-haven assets between gold, crude oil and Bitcoin can be amalgamated to the stock/bond mix for an optimal portfolio selection during crises. Lastly, the paper assesses the performance of these portfolios, distinguishing between developed and emerging economies portolios.

The paper will focus mainly on two main global crises, namely the GFC and COVID-19, given their negative global impacts. The choice of the crises is informed by the inclusion of periods of major financial turmoil and stocks market capitalisation, as the GFC was the largest financial crisis and COVID-19 being the largest health-induced crisis both resulting to severe global economic recessions.

The remainder of the paper is structured as follows: section two will discuss literature review of the paper. The following section, section three will illustrate the methodology of the paper. Section four will demonstrate the empirical results. The final section will be the conclusion and recommendations.

2. Literature Review

A number of studies have investigated different types of safe-haven assets and how they act as hedges in markets during crises. For example, one of the pioneering studies of Baur and Lucey (2010) investigates constant and time-varying relations between United States, UK and German stocks, bond returns and gold returns to investigate gold as a safe haven. The study revealed that gold is a safe haven in extreme stock market conditions. Another pioneer study was conducted by Baur and McDermott (2010), which examined a 30-year sample from 1979 to 2009 consisting of emerging and developed markets and found that, during certain crises, gold is a potent safe haven for most developed stock markets owing to the statistical properties of gold since they are negatively correlated with equities. This study accesses three popular safe-haven asset candidates: gold, crude oil and the currently prominent digital currency Bitcoin.

Although gold seems to be a safe-haven investment for stock markets, some studies give a different perspective, (Będowska-Sójka and Kliber, 2021; Lucey and Li, 2015; Manohar and Raju, 2021; Tuysuz, 2013; Yousaf et al., 2021). Tuysuz (2013) examined the importance of gold as a safe haven throughout various times of unrest. The study discovered that for the S&P's 500 gold does not act as a safe haven during crises in Asia or Russia, but that acted as a weak safe haven during the dot.com crisis, concluding that gold only functions as a strong safe haven during global financial crises. According to Yousaf et al. (2021), gold acted as an impressive safe haven for Singapore, Vietnam, Indonesia and China during COVID-19, but a weak safe haven for Thailand and Pakistan, this ability depended on the specific economic environment of the countries. Będowska-Sójka and Kliber (2021) investigated the reliance between the S&P 500 and prospective safe-haven instruments using a multivariate stochastic volatility model. They discovered that although gold might be seen as a safe haven, its potential is restricted to specific times, or even days, between 2015 and 2019. Nevertheless, it was unable to serve as a safe haven throughout COVID-19. Therefore, this paper also considers other safe-haven assets such as crude oil and Bitcoin, that will be examined together with gold in each of the portfolios.

The hedging potential of crude oil as a useful safe-haven asset for equity investors has been widely investigated (Assifuah-Nunoo et al. 2022, Creti, Joëts and Mignon 2013; Prabheesh, Padhan and Grag, 2020; Wu, Zhao, Ji and Zhang, 2020). Creti et al. (2013) explore the linkages between oil and other commodities together with gold against stocks between 2001 and 2011, and the study reveals the nonlinear relationship between oil-price volatility of the developed countries and emerging stock market returns.

Contrarily, according to Prabheesh et al. (2020), COVID-19 intensified the relationship between the stock market and the return on the price of crude oil in four significant Asian nations that are net importers of oil, resulting in an inappropriate safe-haven strategy. In another study, Assifuah-Nunoo et al. (2022) used daily crude oil prices and daily stock market indices for six main stock markets in Africa's oil-exporting economies: South Africa, Ghana, Nigeria, Tunisia and Egypt from January 2020 to May 2021. The findings indicate that crude oil cannot serve as a safe haven for stock markets in oil-exporting African nations. Notably, the oil-stock co-movement is persistent and more severe in the lower tails. According to a study conducted by Wu et al. (2020), the oil market does not act as a safe-haven asset for the stock markets in China during COVID-19. Nonetheless, there are times in China when it did act as a safe haven, among others is the first Gulf War of 1990 to1991 and the GFC in 2007.

Crude oil prices have fluctuated significantly throughout COVID-19, mostly due to two primary factors: COVID-19 and the pricing conflict between Russia and Saudi Arabia (CNBC, 2020). Following the closure of transportation and industry, the worldwide lockdown measures taken by the majority of nations to stop the coronavirus spread have had a significant negative impact on the price of oil. In light of the recent market collapse, it is debatable whether oil remains a solid safe haven.

Bitcoin is considered a digital safe-haven asset because of the detachment from financial regulation and has low correlation with conventional assets and its store of value characteristics (Conlon, Corbet and McGee, 2020; Corbet, Hou, Hu, Larkin and Oxley, 2020; Courtois, Grajek and Naik, 2014). Bouri, Gupta and Roubaud (2018) discovered that Bitcoin may serve as a safe haven from global financial stress. Other studies believe that cryptocurrencies might minimise risks when incorporated in asset portfolios (Guesmi et al., 2018; Symitsi and Chalvatzis, 2019). According to Symitsi and Chalvatzis (2019), the low correlation of Bitcoin with other assets reduces total portfolio risk, but this is not compensated for by its high volatility. Considering its resistance to banks and the European debt crisis, several research studies suggest that Bitcoin can be a substitute for gold as a safe-haven asset since it has many of its characteristics. In addition to certain parallels, Bitcoin offers distinct benefits over gold, like being built on precise algorithms and complex protocols and being independent of national politics and economies. Studies view cryptocurrencies as a safe haven in periods of turmoil (Bouri, Molnar, Azzi, Roubaud and Hagfors, 2017; Goodell and Goutte, 2020).

Bouri et al. (2017) discovered a reliable safe-haven ability of Bitcoin against volatile market situations when taking the first component of the VIXs of 14 emerging and developed equity markets. Goodell and Goutte (2020) demonstrate a direct correlation between the number of COVID fatalities and Bitcoin prices, indicating that Bitcoin may serve as a secure safe-haven investment option in the near future. According to Aysan, Khan, and Topuz (2021), cryptocurrencies like Bitcoin, give investors the chance to manage their portfolio risk throughout a pandemic. Bitcoin is often cited as a refuge from the potential dangers associated with sovereign risk and the vulnerability of the global financial system (Bouri, Molnár, et al., 2017).

By contrast, however, Shahzad et al. (2020) state that when looking at G7 market indices, Bitcoin only acts as a safe haven for the Canadian stock index concluding that Bitcoin may be regarded as a weak or strong safe haven in specific circumstances. Similarly, Mariana, Ekaputra, and Husodo (2020) discovered that Bitcoin and Ethereum can be temporary safe-haven investments in the midst of COVID-19, as seen by their inverse relationship to the S&P 500.

Further studies have looked empirically at different methods used to observe potential safe havens, for example researchers studied the possibility that gold may present as a safe-haven asset during different crises, but findings of different studies are conflicting (Akhtaruzzaman et al., 2021; Dimitriou, Kenourgios and Simo, 2020; Echaust and Just, 2022; Sharma and Karmakar, 2022; Wen and Cheng, 2018). For example, Wen and Cheng (2018) provided evidence that gold might be used by developing markets in China and Thailand as a safe-haven asset, using the Copula specification method developed by Sklar (1959). They discovered that a sub-sample of the GFCs had weakened extreme risk, indicating that gold acted as a safe haven during the crisis.

Dimitriou et al. (2020) investigated whether there were any potential safe-haven characteristics across a variety of asset classes during the GFC and Eurozone sovereign debt crisis. Using the Fractionally Cointegrated Vector Autoregressive model that was introduced by Johansen and Nielsen (2012), based on the Gaussian likelihood conditional on initial values that were developed by MacKinnon (2011) and discovered that gold only held true safe-haven properties at the start of the GFC and from mid-2011 until the end of the Eurozone sovereign debt crisis. The extraordinary function of gold is demonstrated by these results, showing that there is a negative correlation between gold and developed countries during those crises.

Akhtaruzzaman et al. (2021) studied the role of gold as a safe-haven asset during COVID-19, using a framework proposed by Baur and Lucey (2010) and Baur and McDermott (2010). The study found that hedging against stock market risk during phase one of COVID-19, which was between December 2019 and March 2020 of the pandemic, gold acted as a safe-haven asset therefore lending further support to findings of Dimitriou et al. (2020) and Wen and Cheng (2018). But in the second phase, when governments stepped in with monetary and fiscal impetus programmes, the status of gold as a safe-haven asset for market indices declined.

Other studies measure the safe-haven properties of gold by identifying different geographic portfolios. For example, Echaust and Just (2022) carried out a study which focused on the level of extreme risk of an investment portfolio to access the safe-haven properties of gold rather than on the dependence between risky assets and gold. The study used the EVT developed by Gumbel (1958) to analyse the tail behaviour of the returns of 46 stock indices catalogued using geographical regions and economic development, where they allocated random gold weights (25%, 50% and 75%) to different portfolios that contain stock indices. The effect of a higher gold allocation to prevent infinite variance was studied by examining changes in the thickness of the tails of distribution of portfolio returns. Their results show that the lower tails of stock indices during COVID-19 were heavier than those over the GFC, with the heavy tails persisting even after hedging, whereas during the GFC gold enabled heavy Fréchet-type tails transform into svelte Gumbel-type tails indicating that gold acted as a safe-haven asset during the crisis.

Sharma and Karmakar (2022) examined the hedging and safe-haven characteristics of Bitcoin, gold and USD using data from August 2011 to June 2021, which includes COVID-19, using a combined GO-GARCH-EVT-copula technique. They used downside risk metrics derived from the suggested technique and other competing models during the crisis to investigate the attractiveness of these assets in lowering stock portfolio risk. The conclusion of the study showed that although Bitcoin functioned as a weak safe-haven asset, gold was the strongest safe-haven asset.

Bitcoin, introduced as the first cryptocurrency, has garnered significant interest from investors and scholars alike. It has provided investors with some level of stability during crises, such as the that of 2010 to 2013 in Europe and the banking crisis of 2012 to 2013 in Cyprus (Luther and Salter, 2017). Bouri, Molnár, Azzi, Roubaud and Hagfors (2017b) discovered that Bitcoin can only serve as a strong safe haven against weekly extreme down movements in Asian stocks, when using daily and weekly data within a DCC model (Engle, 2002). A separate study conducted by Bouri et al. (2017a) delved into the correlation between Bitcoin and commodities. The study centred on energy commodities, specifically electricity, since it played a crucial role in the production of Bitcoin. During the period from 2010 to 2015 and the pre-crash period, it was demonstrated that Bitcoin displayed hedge and safe-haven properties for both the general commodity index and the energy commodity index.

Despite the similarities between Bitcoin and gold as a hedge and safe-haven asset during economic uncertainty found in the above-mentioned studies, Klein, Hien and Walther (2018) discovered that Bitcoin exhibits a completely different behaviour compared to gold, despite their similarities as hedge and safe-haven assets in times of economic uncertainty. Through the application of the BEKK-GARCH model, the authors discovered that during periods of market decline, there is a notable shift towards positive conditional correlations between Bitcoin and other assets. In addition, the authors discovered that the ability of Bitcoin to hedge risks in a portfolio can change over time. Overall, the existing literature has presented conflicting findings regarding the effectiveness of Bitcoin as a safe haven.

Extant studies on the position of crude oil as a safe haven have yielded mixed findings even during COVID-19, due to a variety of factors, including sample heterogeneity, the net positions of oil-importing and oil-exporting economies, and methodology (Chang et al., 2020). When Mensi et al. (2021) employed the asymmetric-DCC (ADCC) model modified by Cappiello et al. (2006) to integrate the asymmetric influences on the correlations induced by good news and bad news, they were able to explore the safe-haven and hedging features of crude oil in the Asian economy. It was discovered that Brent oil's function as a safe haven for precious metals in a portfolio was inadequate; instead, it performed best as a hedge for precious metals in the Asian economy.

Bouoiyour et al. (2019) evaluated oil's safe-haven qualities in the context of political unpredictability in the US economy in comparison to Bitcoin and precious metals. Using the empirical mode decomposition technique introduced by Huang (1998), the authors discovered that, while it is time-dependent, oil acts as a potent safe haven during times of political risk. Additionally, Liu et al. (2020) used the asymmetric-DCC model in conjunction with quantile regression (QR) and the cross-quantilogram framework to evaluate the qualities of crude oil as a hedge, diversifier or safe-haven asset for conventional currencies. According to their research, there is a negative correlation between conventional currencies and crude oil during crises.

Another challenge faced by portfolio investors is that the classic 60/40 portfolio developed by Markowitz (1952) as an optimal portfolio, with literature showing that it was formerly used to generate real growth, but later to provide safety and income during the inevitable bear market where stocks fail to mitigate portfolio risk during crises (Doroghazi, 2021). According to Chaves, Hsu, Li and Shakernia (2012), many investors tend to opt for a 60/40 equity/bond strategic portfolio owing to the attractive 8 to 9% expected portfolio return associated with this mix. Nevertheless, the 60/40 portfolio is heavily influenced by equity risk owing to the substantial fluctuations in the stock market compared to the bond market.

According to Fidelity Investments Annual Report 2023, the year 2022 marked a rare year for the 60/40 stock versus bond blend in the United States, which suffered only its fifth double-digit decline of -25% since 1926. Reasons behind this poor showing included a volatile period marked by persistently high inflation, exacerbated by the Russia-Ukraine conflict on top of COVID-19, reduced consumer confidence and growing recessionary risks. Bonds historically have helped to protect against stock declines, driven by investors who sought relatively less-volatile assets in times of market distress. However, the traditional 60/40 portfolio seems to do less well during most major crises.

3. Methodology

3.1 ARMA-GJR-GARCH model

To simulate the extreme distribution of the different series used, it is crucial to first filter these series using an appropriate family of the GARCH model. To this end, our paper employs the ARMA-GJR-GARCH model based on various criteria selections to filter the return series. The conditional mean used is an autoregressive moving average (ARMA) model which is a combination of the Autoregressive model and the Moving Average model, following Box and Jenkins (1970). The general form $ARMA$ (p, q) is written as follows:

$$Y_t = w + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j} \qquad (1)$$

With $\varepsilon_t = \sigma_t . z_t$ $\quad$ $where$ $\quad$ $z_t \sim i.i.d\ N(0,1)$

For the variance equation, an asymmetric GARCH model proposed by Glosten, Jagannathan and Runkle, the GJR-GARCH model (Glosten, Jagannathan and Runkle, 1993) is used. The generalised form of the GJR-GARCH (p, q) model is given in the following form:

$$\sigma_t^2 = w + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-1}^2 + \sum_{i=1}^{p} \gamma \varphi_{t-1} \varepsilon_{t-1}^2 \qquad (2)$$

Where w, α and γ are parameters to be estimated. p and q are autoregressive orders. Equation 3is stationary if (α + β) < 1.

Once the return series are obtained from Equations 1 and 2, we proceed with the analysis by simulating their extreme value distributions based on the BMM. It is worth noting that the analysis will comprise of analysing the shape of these distributions representing the downside risks of stock/bond mix with the different combinations of safe-haven assets.

3.3 Extreme Value Theory

To analyse the shape of the tails of stocks/bonds-safe haven portfolios we fit extreme distribution using GEV distribution. The EVT is a useful method for quantifying market risk in the most severe circumstances. EVT has two substantial ways of modelling results: the Peak Over Threshold model (POT) and the BMM, which is used as the main model in this paper.

3.3.1 Block maxima method

The BMM in EVT involves breaking the observation period into non-overlapping intervals of equal length and focusing on the highest observation in each period (Gumbel, 1958). The model assumes that the distribution of returns follows a GEV distribution. The BMM algorithm partitions the sample into blocks and selects the maximum value (maxima) inside each block. These maxima are then used to fit the tail distribution. The BMM is less data-consuming, which is a crucial argument for considering an analysis of sub-periods, such as in crises. The average sample size that falls into the tail of a return distribution is less than 5% (Just and Echaust, 2021).

To apply the BMM, consider $[(x1, x2, xn)]$ are a sequence of random and independent variables with a common distribution function with $Mn = \max(x1, x2, xn)$ providing the block maximum of n values. If the random variables $Xt(t = 1 \ldots n)$are i.i.d. with cumulative distribution function $g(x)$ this can be expressed as:

$$\Pr(MN < x) = \Pr(\max(x1, x2, xn) < x) = \Pr(x1 < x, ., xn < x) = (fx(x))^n \qquad (4)$$

This statement shows that the return distribution may be used to quickly calculate the distribution of the maxima for a finite sample. For statistical reasons, the BMM makes use of the Fisher-Tippett theorem created by Fisher and Tippett (1928) as $fx(x)$ is based on the theorem. According to Gnedenko (1943) who later proved the theorem, the Fisher-Tippett theorem indicates that the GEV distribution is the limiting distribution of the maxima if a standardised maximum, for $n \rightarrow \infty$ converges to some non-degenerate distribution function. The general mathematical formula of GEV may be written as follows:

$$G_\xi(x) = \begin{cases} \exp(-\left(1 + \xi_x\right)^{\frac{-1}{\xi}}), & \xi \neq 0 \\ \exp(-e^{-x}), & \xi = 0 \end{cases} \qquad (5)$$

Where ξ denotes the shape parameter. The GEV distribution characterises three different tail tendencies. The critical parameter is the shape parameter, $\xi \in \mathbb{R}$, which determines the tail thickness of the distribution. When $\xi > 0$, the GEV corresponds to the Fréchet distribution, which is the domain of attraction for heavy-tailed distributions. The Weibull distribution, determined for $\xi < 0$, is the asymptotic distribution of finite endpoint distributions. Finally, if $\xi \rightarrow 0$, the GEV indicates the Gumbel distribution, which is the region of attraction for thin tailed.

This article then creates blocks, which are non-overlapping sub-samples of length n, and choose the maxima inside each of the M blocks. The time series of maxima $y1$, $y2$, yM are thus obtained. The maximum likelihood (ML) approach is used to estimate the parameters of the GEV distribution. We maximise the following log-likelihood function with regards to the shape parameter:

$$l = -Mlog\sigma - (1+\frac{1}{\xi})\sum_{i=1}^{M}\log[1+\xi(\frac{y_i-\mu}{\sigma})] - \sum_{i=1}^{M}[1+\xi(\frac{y_i-\mu}{\sigma})]^{-\frac{1}{\xi}} \tag{6}$$

Where $1+\xi\left(\frac{y_i-\mu}{\sigma}\right) > 0$ for $i = 1,..M$ and $\xi \neq 0$.

3.4 Mean-CVaR model

Finally, in order to obtain weight of the different constructed portfolios (the stock/bond mix ratio and gold, Bitcoin, oil or a combination of the safe-haven assets), we use the conditional value at risk (CVaR) developed by Rockafellar and Uryasev (2000) since it displays sub-additivity and convexity.

When choosing a financial portfolio, one of the most well-known methods is portfolio optimisation (Haugh, 2016). Markowitz (1952) created the mean-variance strategy, which is the oldest method for resolving the portfolio selection issue. A common risk measure is VaR. Nevertheless, there might be limitations and undesired characteristics of VaRs that restrict their use, such their lack of sub-additivity, which means that the VaRs of two distinct investment portfolios could be higher than the total of their individual VaRs (Letmark, 2010). Additionally, VaR contains numerous local minimums and is non-smooth and non-convex, whereas our goal is to find the global minimum.

Owing to its sub-additivity and convexity, CVaR is a coherent risk metric and is more consistent than VaR (Cui, Ding, Jin and Zhang, 2023; Pflug, 2000). CVaR gives the mean value of the losses that are larger than the VaR value. CVaR is the expected losses that exceed the VaR at some confidence level, which can be written as:

$$CVAR_\beta(y) = E\left[-y\middle|-y \geq VaR_\beta(y)\right] \tag{8}$$

where y is the returns of a portfolio, β is the confidence level, $VaR_\beta(y)$is the VaR at the β confidence level and $CVaR_\beta(y)$ represents the predicted losses of the portfolio at the β confidence level. The latter represents the total number of possible losses in the event that the losses above the threshold $VaR_\beta(y)$. Thus, $VaR_\beta(y) < CVaR_\beta(y)$. In risk management, VaR can be controlled simultaneously if we can manage to control CVaR (Rockafellar and Uryasev, 2002). Assuming a n assets in a portfolio, $X = (x_1 \dots, x_n)^T$ is the position for each asset $x_i \geq 0 (i = 1, \dots, n)$ and corresponding asset return is $= (y_1 \dots, y_n)^T$, the anticipated return of the portfolio is$\sum_{i=1}^{n} x_i y_i$, the expected loss is $-\sum_{i=1}^{n} x_i y_i$. The loss function of the portfolio is $(X, Y) = -\sum_{i=1}^{n} x_i y_i = -X^T Y$, assuming Y has density $P(Y)$. The task of minimising CVaR is transformed into the challenge of minimising a continuously differentiable and convex function by Rockafellar and Uryasev (2002), who combine CVaR with VaR via a special function $F_\beta(X, \alpha)$:

$$F_\beta(X, \alpha) = \alpha + \frac{1}{1-\beta} \int_{y \in R^m}^{\cdot} [f(X, Y) - \alpha]^+ P(Y) dY \tag{9}$$

$$VaR_\beta(X) \epsilon arg \min_{\alpha \epsilon R} F_\beta(X, \alpha) \tag{10}$$

$$CVaR_\beta(X) = \min_{\alpha \epsilon R} F_\beta(X, \alpha) = F_\beta(X, VaR_\beta(X)) \tag{11}$$

where $[U]^+ = \max(U, 0)$, $F_\beta(X, \alpha)$is convex and continuously differentiable with respect to α. Typically, the density of Y is not known in practice. However, we can use Monte Carlo simulations to generate a collection of Y under different scenarios of q, then the corresponding approximation to $F_\beta(X, \alpha)$:

$$F_\beta(X, \alpha) = \alpha + \frac{1}{q(1-\beta)} \sum_{k=1}^{q} [-X^T Y^k - \alpha]^+ \tag{12}$$

Next, we build a Mean-CVaR model by replacing variance with CVaR in the Mean-Variance model:

$$\min \alpha + \frac{1}{q(1-\beta)} \sum_{k=1}^{q} u^k$$

$$
s.t.\begin{cases} X^T Y^k + \alpha + u^k \geq 0 \\ u^k \geq 0 \\ \frac{1}{q} X^T \sum_{k=1}^{q} Y^k \geq \rho \\ \sum_{k=1}^{q} x_i = 1 \\ x \geq 0 \end{cases} \tag{13}
$$

where ρ is the investor’s expected return.

4. Data analysis and empirical results

4.1 Data

This paper investigates the tail behaviour and downside risk of a stock/bond mix and potential safe-haven assets (gold, Bitcoin and crude oil), by analysing the shape of the left side tail from a BMM distribution. The stock/bond mixes are composed of daily log returns of stock indices and bond yield to maturity from 6 different G20 countries, namely, Canada, the USA, the UK, Russia, Brazil and South Korea. The reasons for choosing these countries for the analysis are: firstly, G20 represents about 85% world's GDP making it a key forum for addressing international economic issues. The second reason is reliable data availability and finally the interconnected nature of the global economies. The data used in this paper was collected from www.investing.com online financial market service. Our sample comprises markets from several economic areas, such as Europe, Asia-Pacific and the Americas, which are classified as developing and developed markets by Morgan Stanley Capital International (MSCI) and are G20 countries. For Canada, we use (Toronto Stock Exchange (TSX) and the Canada 10-year yield bond), the USA (S&P 500 and TLT bond), the UK (Financial Times Stock Exchange 100 Index (FTSE 100) and UK 10-year yield bond), Russia (Moscow Exchange (MOEX) and Russian 10-year yield bond), Brazil (IBOVESPA stock index and Brazilian 10-year yield bond) and South Korea (Korean Composite Stock Price Index (KOSPI) and South Korean 10-year yield bond).

Our sample period covers daily data from 1 August 2007 to 30 April 2023 periods. These periods are divided into the GFC, from 2007 to 2009 and COVID-19, from 2019 to 2023.

4.2 Descriptive Statistics

Table 1 and 2 present the descriptive statistics of the returns of stock indices and also the yield to maturity of bonds. Considering the mean of the analysis, the paper found that all developed countries reported a negative mean value in the stock indices during the GFC while during COVID-19, they were positive. The bonds are slightly positive except for the Canadian bond for the GFC and are negative for COVID-19except for the Canadian bond. In the emerging markets, only KOSPI reported a negative mean; the rest reported a positive mean, with IBOVESPA reporting the highest mean for the GFC, and all reported a positive mean for the stock indices during COVID-19. The bonds presented positive means for both crises.

The skewness varies when looking at each stock index and bond. The UK index (FTSE 100), the Russian 10-year yield bond and the USA bond (TLT) displays skewness that have positive distribution during GFC, this indicates that the positive side of the distribution curve has a longer tail, which is not a desirable quality when looking at the distribution of the data because it indicates poor expected returns. The remaining equities and bonds under the GFC table have skewness values that are close to zero, indicating a moderately skewed distribution. Looking at COVID-19, the skewness of the Canadian bond, Russian bond, South Korean bond and Brazilian bond illustrate a positive distribution, while the Canadian stock index (TSX), Russian stock index (MOEX) and UK bond show a negative distribution in terms of skewness, this indicates that the negative side of the distribution curve has a longer tail, indicating there is risk of loss. The rest of the COVID-19 skewness results illustrate moderately skewed distributions.

Moreover, the kurtosis of the stock markets and bonds was found to be greater than three except for FTSE 100 and TLT during the GFC, and kurtosis of the markets and bonds are all greater than three during COVID-19 for all developed countries, signalling the presence of leptokurtic distribution, and implying that in times of financial crises price drop occurs resulting in extreme losses. The emerging countries have a kurtosis greater than three for stocks and bonds, except for IBOVESPA during the GFC.

Table 1: Descriptive Statistics (GFC)

	Mean	**Standard Deviation**	**Skewness**	**Kurtosis**
Equities				
Canada	-0.016	2.01	-0.31	3.77
USA	-0.03	2.12	0.29	4.7
UK	-0.02	1.93	0.23	0.2
Russia	0.007	3.63	0.75	1.94
South Korea	-0.007	2.066	-0.22	4.74
Brazil	0.066	2.59	0.27	2.71
Bonds				
Canada	-0.03	1.7	-0.11	2.38
USA	0.01	1.08	0.56	1.21
UK	0.01	0.49	0.35	3.91
Russia	0.18	5.04	0.66	5.92
South Korea	0.013	1.45	-0.22	4.74
Brazil	0.05	2.86	0.19	3

(Source: Own calculations)

Table 2: Descriptive Statistics (COVID-19)

	Mean	Standard Deviation	Skewness	Kurtosis
Equities				
Canada	0.03	1.32	-0.86	8.77
USA	0.04	1.53	-0.46	6.71
UK	0.01	1.26	-0.87	2.06
Russia	0.011	2.09	-0.16	6.11
South Korea	0.02	1.32	0.49	7.65
Brazil	0.029	1.79	-0.96	7.54
Bonds				
Canada	0.16	4.44	0.25	3.44
USA	-0.02	1.18	0.3	5.06
UK	-0.013	0.46	0.36	1.38
Russia	0.08	2.33	0.35	1.68
South Korea	0.09	1.75	0.75	4.65
Brazil	0.07	1.97	0.37	4.19

(Source: Own calculations)

4.3 Risk-reward analysis for stock returns and bonds

Figure 1 displays the risk-reward plot during the GFC. The graph demonstrates that during the GFC, the emerging countries' indices and bonds had the highest return and largest risk; because emerging countries have less stable economies in terms of economic growth, therefore, investing in these countries can yield higher returns because of the growing economies but amplifies risk as there are weaker currencies present, meaning foreign exchange rate risk, lack of corporate governance and lack of liquidity (Kapalu and Kodongo, 2022). According to Chiang and Zhang (2018), high anticipated variances are correlated with greater projected stock returns. Developed countries report moderate risk with low returns. Compared to established market indices and bonds, emerging market indices are riskier and provide better returns during the GFC. Figure 2 below displays the risk-reward plot for COVID-19. It demonstrates that during COVID-19, outcomes are different. The Canada bond has the highest risk and return, although most emerging bonds are still high in risk and return compared to the other two developed countries, the US and the UK. Looking at stock indices, it is a mix of emerging and developed countries with almost a similar range in risk and return, unlike the GFC. During COVID-19, the world came to a stop, and all countries experienced similar backlashes since all trade decreased and all economies suffered huge downfalls.

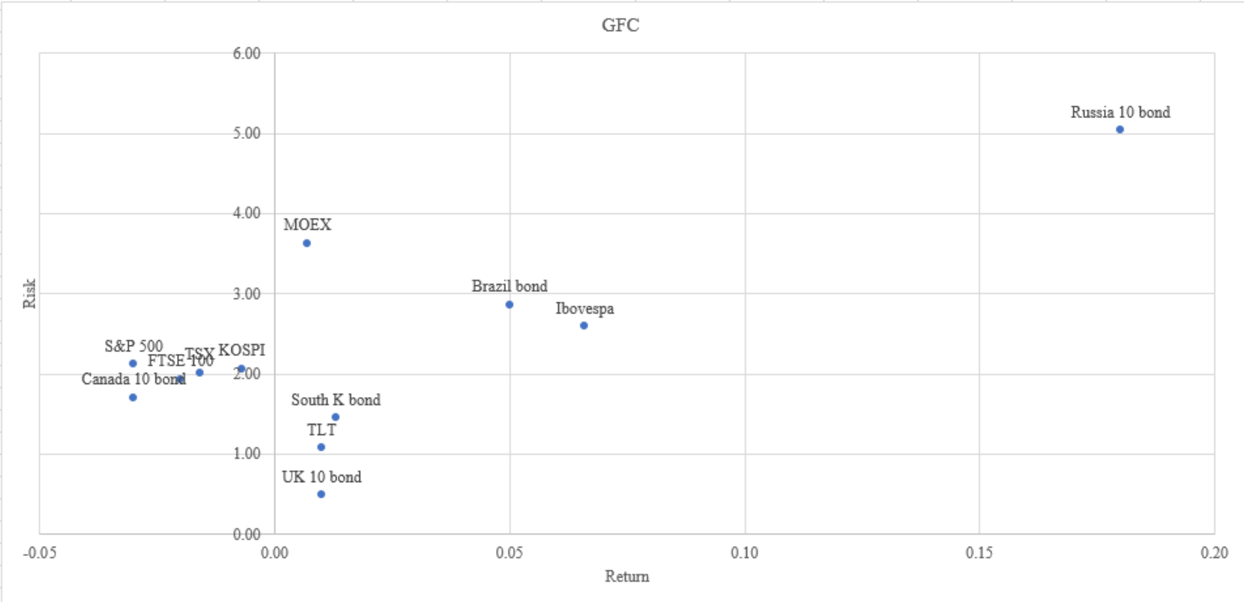

Figure 1: Risk Reward Plot (GFC)

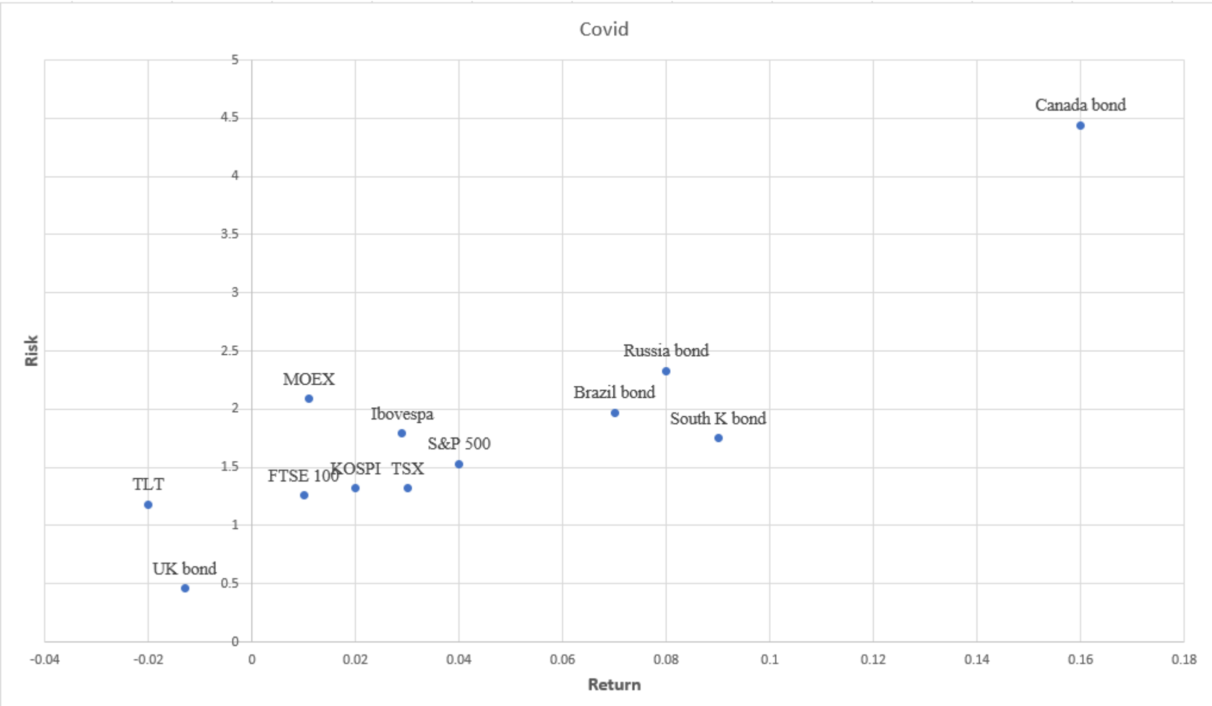

Figure 2: Risk Reward Plot (COVID-19)

4.4 ARMA-GJR-GARCH (1,1) conditional volatility estimations

As the first step to obtain the downside risk, shape, for the BMM distribution, we filter the series based on 60/40 stock/bond portfolios in each country based on ARMA-GJR-GARCH (1,1) model. The order for the GARCH model was selected for the Akaike Information Criteria. Tables 3 and 4 show the estimation of the ARMA-GJR-GARCH (1,1) 60/40 stock/bond portfolio returns. It is important to note that filtered portfolio return series obtained from the estimation of this model eliminates possible serial correlation. The conditional mean and conditional variance of each portfolio return are shown in the tables. The ACF graphs in figures 3 and 4 show that there is no serial correlation. The statistical significance of all β coefficients indicates that the volatility of the past has an effect on the volatility of the present. Looking at the tables, alpha α of all the developed and emerging countries portfolios are significant, therefore indicating that prior shocks have little effect on volatility for these bonds and indices. Additionally, because there is no consistency in volatility, the $\alpha + \beta < 1$ condition is upheld, thereby eliminating heteroscedasticity. Negative shocks enhance volatility for all markets and bonds where the γ parameter is statistically different from zero.

Table 3: Sixty-forty portfolio Conditional volatility estimation using ARMA-GJR-GARCH (1,1) with student-t distribution (GFC)

Portfolio	**Canada**	**USA**	**UK**	**Russia**	**South Korea**	**Brazil**
mu1	-0.0518	-0.0090	-0.0125	0.0123	-0.0141	0.0605
	(0.012)	(0.045)	(0.034)	(0.028)	(0.021)	(0.033)
ar1	-0.8064	0.4501	-0.4831	0.8675	-0.5317	-0.8634
	(0.011)	(0.031)	(0.043)	(0.030)	(0.024)	(0.042)
ma1	0.8352	-0.5693	0.3946	-0.9107	0.53501	0.8161
	(0.044)	(0.029)	(0.038)	(0.045)	(0.041)	(0.043)
Ω	0.0185	0.0110	0.030	0.0405	0.04561	0.0362
	(0.041)	(0.021)	(0.032)	(0.025)	(0.025)	(0.023)
α	0.0293	0.0296	0.0233	0.0566	0.011	0.0348
	(0.032)	(0.01)	(0.01)	(0.022)	(0.01)	(0.034)
β	0.9112	0.9265	0.8779	0.8786	0.87853	0.9131
	(0.032)	(0.011)	(0.038)	(0.033)	(0.033)	(0.037)
γ	0.1015	0.1186	0.1829	0.1282	0.17868	0.0813
	(0.023)	(0.032)	(0.037)	(0.024)	(0.023)	(0.043)
Ψ	29.0746	20.2955	25.8752	5.9315	11.4391	7.9703
	(0.045)	(0.033)	(0.045)	(0.013)	(0.022)	(0.023)

(Source: Own calculations, p-values reported in brackets)

Table 4: Sixty-forty portfolio Conditional volatility estimation using ARMA-GJR-GARCH (1,1) with student-t distribution (COVID-19)

Portfolio	**Canada**	**USA**	**UK**	**Russia**	**South Korea**	**Brazil**
mu1	0.0431	0.0427	-0.0082	0.0592	0.0402	0.0241
	(0.023)	(0.031)	(0.046)	(0.013)	(0.031)	(0.047)
ar1	-0.5252	-0.2634	-0.6683	0.7810	-0.9427	-0.1312
	(0.042)	(0.033)	(0.038)	(0.031)	(0.012)	(0.019)
ma1	0.5052	0.2158	0.6234	-0.8040	0.9568	0.0780
	(0.05)	(0.0271)	(0.042)	(0.036)	(0.046)	(0.012)
Ω	0.0964	0.0172	0.0156	0.0411	0.0367	0.0727
	(0.034)	(0.035)	(0.012)	(0.040)	(0.017)	(0.018)
α	0.0753	0.0577	0.0165	0.1458	0.0360	0.0423
	(0.021)	(0.024)	(0.049)	(0.031)	(0.031)	(0.045)
β	0.8478	0.8410	0.8510	0.8024	0.8941	0.8565
	(0.028)	(0.031)	(0.042)	(0.019)	(0.037)	(0.017)
γ	0.0949	0.1590	0.2069	0.0526	0.0682	0.1120
	(0.044)	(0.033)	(0.025)	(0.011)	(0.041)	(0.025)
Ψ	14.0537	8.6015	5.6944	4.6598	6.5603	5.6671
	(0.033)	(0.038)	(0.041)	(0.015)	(0.041)	(0.032)

(Source: Own calculations, p-values reported in brackets)

Note: ARMA-GJR-GARCH results for the stock/bond optimised and safe-haven inclusive portfolios are in the appendix (table 13-21).

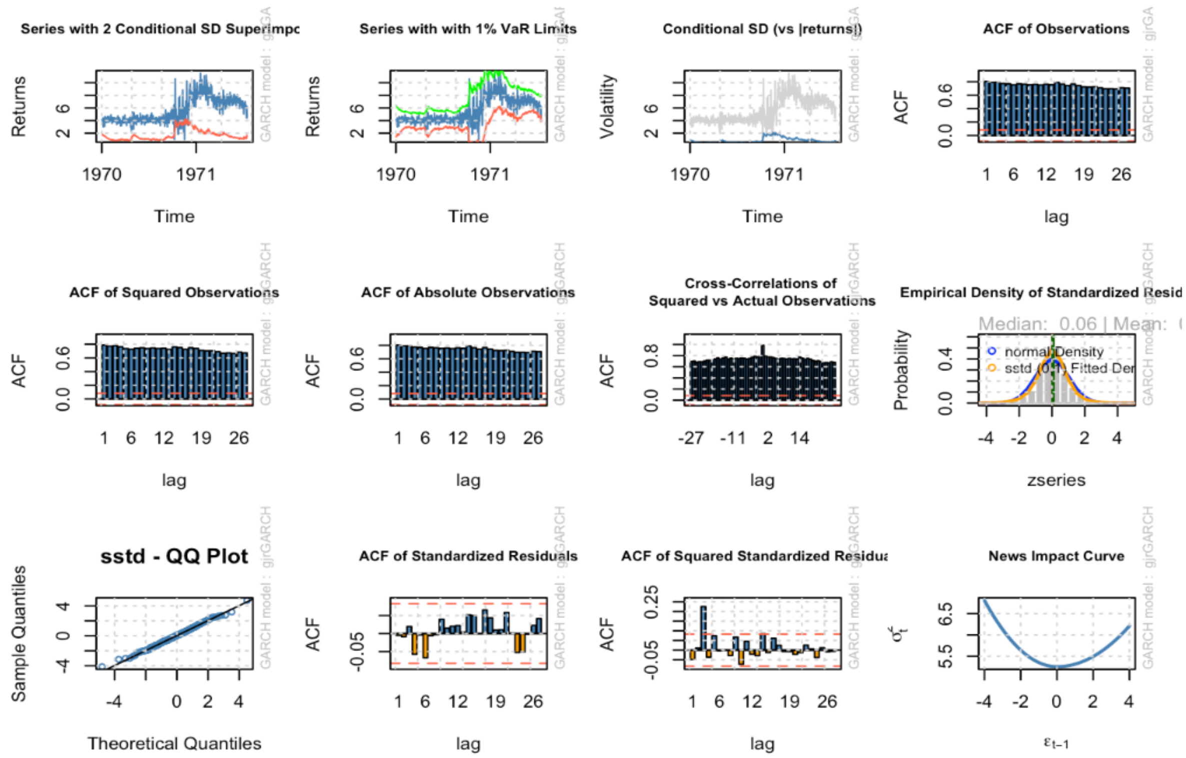

Figure 3: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for sixty-forty portfolio (GFC)

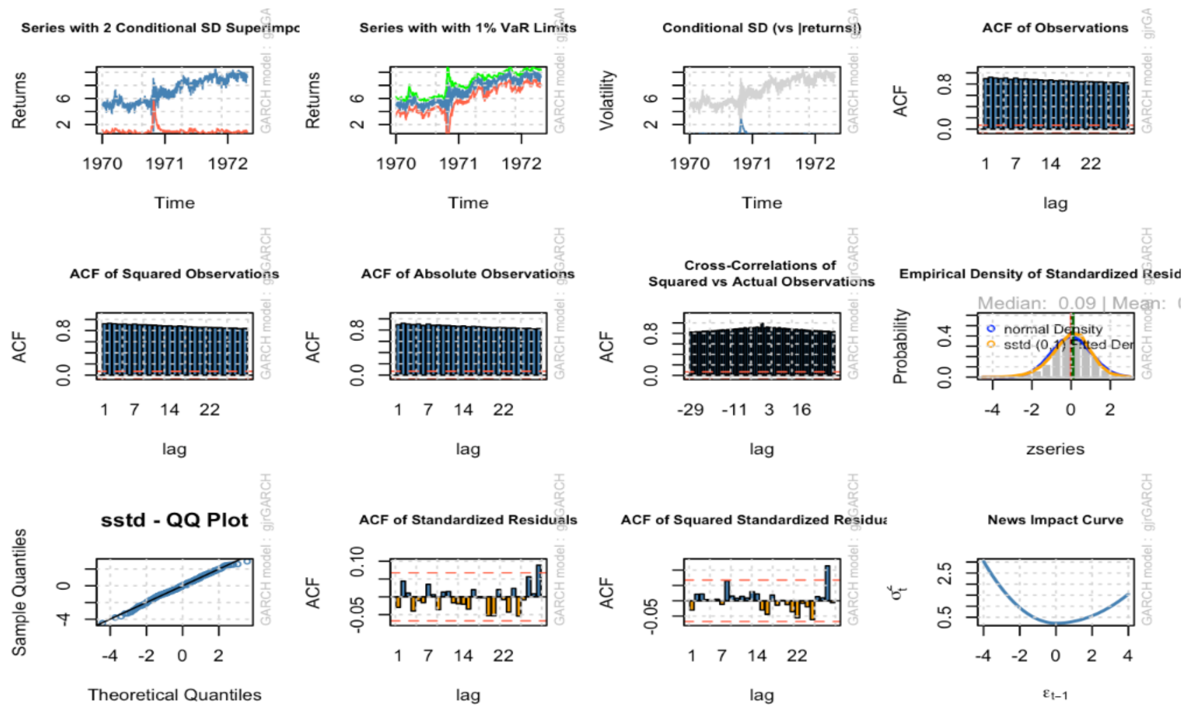

Figure 4: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for sixty-forty portfolio (COVID-19)

Note: Plot results for the stock/bond optimised and safe-haven inclusive portfolios are in the appendix (Figures 5-13).

4.5 Sixty-forty portfolio analysis and Generalised Extreme Value (GEV) Distribution Estimations

We then fit the above portfolio return series with a BMM distribution to obtain their shape, a measure of downside risk. The paper uses bi-weekly blocks, which are 10 returns of the 60/40 portfolio returns. All the BMM fitted 60/40 portfolio returns in both emerging and developed countries show heavy tails (Fréchet type tails) during both crises which indicates that there is underperformance displayed by all the portfolios. A number of reasons may explain the high downside of the 60/40 stock/bond portfolio returns in developed economies compared to emerging economies, such as, the GFC started in the United States and first had an impact on developed economies and international financial institutions. According to Abuzayed et al. (2021) the developed markets of Europe and North America had the primary responsibility for transferring and receiving marginal severe risk to and from the global market during COVID-19.

During COVID-19, we also observe Fréchet type shape parameters from all the countries which indicates downside risk. These outcomes are similar to the results displayed by Malander and Pepo (2023) as they observed that 60/40 portfolios underperform during major crises when looking at the United States stock/bond portfolios. Compared to emerging economies, developed markets are more susceptible to market downturns. This result supported the conclusions of (Choi and Jung, 2021; Yong and Laing, 2021; Yousfi et al., 2021). Developed countries are the biggest net risk senders, have a big influence on stock markets around the world and are connected closely.

Table 5: Sixty-Forty stock/bond mix for international portfolios.

Portfolio	Weights		Shape ξ
	Bonds	**Equities**	
GFC			
Canada	0.4	0.6	1.5726
USA	0.4	0.6	1.7150
UK	0.4	0.6	2.3093
Russia	0.4	0.6	0.0057
South Korea	0.4	0.6	0.2078
Brazil	0.4	0.6	0.0676
Covid – 19			
Canada	0.4	0.6	0.2948
USA	0.4	0.6	0.2411
UK	0.4	0.6	0.1618
Russia	0.4	0.6	0.0761
South Korea	0.4	0.6	0.3470
Brazil	0.4	0.6	0.1499

(Source: Own calculations)

4.6 Stock/bond optimised mean-CVaR portfolio analysis Generalised Extreme Value (GEV) Distribution Estimations

Given that the 60/40 stock/bond combination did not manage to reduce downside risks during the GFC and COVID-19, the article assesses whether a combination of these assets, whereby the weight of each asset is determined based on C-VaR portfolio selection may do better than the 60/40 weights in reducing downside risk. the results presented in Table 6 show the different weights obtained from the C-VaR portfolio selection and the corresponding shape from the BMM (GEV) distribution. It can be observed that the optimised portfolio allocated more weight to bonds compare to stocks. Studies show the importance of bonds in term of reducing risks during normal and turmoil time, for example Thapar and Maloney (2021) highlight that the correlation with respect to growth sensitivity is inverse for bonds and equities, leading to the combination of these two assets being highly advantageous during both economic booms and recessions, which has made them widely popular and acknowledged. It also been observed that during the GFC, the Canadian optimised portfolio is the only positive shape parameter indicating a greater downside risk, while other combinations managed to reduce the downside risk considerably compared to the 60/40 cases.

However, in observing COVID-19, heavy lower tails can be seen in every country with the exception of Brazil, indicating a higher risk than return rate. The fact that extraordinarily high losses occur more frequently during crises than what a normal distribution would anticipate is confirmed as a simple investing reality. The p-values of the results show that the difference in tail thickness between the two crises is statistically significant. This discovery explains why the COVID-19 epidemic had heavier left tails than the GFC did with the exception of Brazil in this case. This outcome is consistent with research by Gunay and Can (2022), who found that COVID-19 caused stock markets to experience more severe contagion and risk transmission than they did during the GFC. These findings are consistent with those of Cheema et al. (2020), who discovered broad indications of a decline in the safe-haven characteristics of a number of conventional safe-haven assets, including gold, treasury bonds, oil and sliver during COVID-19 compared to the GFC. The more erratic path of market movements during the last crisis was motivated by this outcome.

Table 6: Stock/bond optimised international portfolios.

Portfolio	**Weights**		**Shape** ξ
	Bonds	**Equities**	
GFC			
Canada	0.8338	0.1662	3.1795
USA	0.8059	0.1941	-3.2496
UK	0.7455	0.2545	-3.3030
Russia	0.7653	0.2347	-3.1622
South Korea	0.7310	0.2690	-3.2144
Brazil	0.5028	0.4972	-2.9440
Covid – 19			
Canada	1	0	4.9610
USA	1	0	4.9610
UK	1	0	4.9610
Russia	0.8258	0.1742	3.3030
South Korea	0.941	0.0590	4.9610
Brazil	0.7275	0.2725	-3.2556

(Source: Own calculations)

4.7 Safe-haven assets and 60/40 stock/bond

Tables 7-12 report the mean-CVaR hedged portfolios under the GEV distribution. The portfolios allocate lesser weightings to market indices and bonds as they are more prone to risk, and the rest of the portfolio includes one of the safe-haven assets or all of them at once. The GFC only has two safe-haven assets that are investigated: gold and crude oil; the Bitcoin cryptocurrency is not considered in this article for the GFC because it was not yet in the market during the GFC. COVID-19 considers all the safe-haven assets that are under investigation (gold, crude oil and Bitcoin).

Table 7 reports the Canadian portfolio with gold as a safe haven, as the best portfolio to invest in during GFC exhibiting a Weibull type tail, showing a decrease in downside risk. Looking at the COVID-19 results in the table, none of the assets reduced the downside risk of the portfolios. Table 8 shows the USA portfolios, with the best performing portfolio during GFC having gold as a safe haven resulting in a Weibull type (showing a decrease in downside risk), this in line with Cheema et al (2020) when their outcome presented gold as a strong safe-haven asset during GFC. The COVID-19 results show that only the stock/bond with crude oil managed to reduce downside risk.

The last developed country, the portfolios of the UK are presented in table 9 in the appendix. The portfolios with gold and crude presented a reduction of downside risk. COVID-19 presents no reduction in downside risk, further attesting to the findings of Manohar and Raju (2021) illustrating that assets are losing their safe-haven qualities owing to the increment of volatility during COVID-19.

Emerging countries produced similar results to those of the developed countries. Table 10 in the appendix reports the Russian portfolios, the best portfolio in the GFC is composed gold as a safe-haven asset. During COVID-19, only crude oil reduced downside risk in a portfolio resulting in a Weibull type tail. Table 11 shows the South Korean portfolios, with both gold and crude oil acting as strong safe-haven assets in GFC. The COVID-19 results show a reduction in downside risk in the portfolio allocated with crude oil, resulting to a Weibull type tail. In line with findings of Disli et al. (2021), showing that gold and Bitcoin did not act as safe haven during COVID-19 for four major Asian markets. The last table in the appendix shows results from the Brazilian portfolios, gold and crude oil acting as the best safe havens for the GFC and COVID-19, resulting to a Weibull type tail.

During the GFC, the shape parameters of all portfolios indicate a decrease in tail thickness with the inclusion of gold and crude oil when added to the portfolios separately; these indicate similar results when compared to Echaust and Just (2022) as the downside risk of the portfolios decreases with the inclusion of gold as a safe haven when examining their portfolio return distributions. During the crisis the safe-haven assets were less volatile compared to stocks and bonds (Ankudinov et al., 2017). In general, these results should significantly show that investors utilised safe-haven assets to keep their investments safe during GFC. With Canada being the best country to invest in by observing its shape parameter outcomes in comparison to the other five countries and Brazil portfolios being the least favourable to invest in during the crisis. We may draw to the conclusion that during the GFC, oil and gold served as reliable safe havens against market declines in all portfolios.

However, the tail behaviour of portfolios during COVID-19 is very different from the tail behaviour during the GFC. The results indicate a mixed conclusion on the potential of the assets acting as safe havens and reducing extreme risk. All the assets including the digital currency (Bitcoin) acted as a safe haven for only two emerging countries which are Russia and Brazil improving both tail behaviour to Weibull type tails, with gold and the Bitcoin cryptocurrency serving the best safe-haven characteristics for both countries, in the USA, crude oil did serve as a weak safe-haven asset. The rest of the portfolios return distributions are in the Fréchet region of attraction, severe losses may occur considerably more frequently than thin-tailed distributions indicate. The global financial markets and system were pushed to their most severe limitations by COVID-19.During COVID-19, developed markets in Europe and North America mostly transmitted and received marginal severe risk, affecting the global market (Abuzayed et al., 2021).

Table 7: Mean-CVaR weights and shape of the GEV distribution for the Canadian-portfolio.

GFC	**Optimal Weights**	**Shape**
TSX-Canada 10-year	0.8025	
Gold	0.1975	-3.2851
TSX-Canada 10-year	-	-
Bitcoin	-	-
TSX-Canada 10-year	0.9054	
Crude Oil	0.0946	-3.1107
TSX-Canada 10-year	0.7873	
G+CO	0.2127	-3.2320
COVID-19		
TSX-Canada 10-year	1	
Gold	0	4.9610
TSX-Canada 10-year	1	
Bitcoin	0	4.9610
TSX-Canada 10-year	0.9995	
Crude Oil	0.0005	0.8086
TSX-Canada 10-year	0.3188	
G+B+CO	0.6812	3.7354

(Source: Own calculations)

Table 8: Mean-CVaR weights and shape of the GEV distribution for the USA-portfolio.

GFC	Optimal Weights	Shape
S&P 500-TLT	0.7901	
Gold	0.2099	-3.2673
S&P 500-TLT	-	-
Bitcoin	-	-
S&P 500-TLT	0.8252	
Crude Oil	0.1748	-2.9603
S&P 500-TLT	0.8098	
G+CO	0.1902	-3.0098
COVID-19		
S&P 500-TLT	1	
Gold	0	4.9610
S&P 500-TLT	0.9546	
Bitcoin	0.0454	4.9610
S&P 500-TLT	0.9289	
Crude Oil	0.0711	-3.2792
S&P 500-TLT	0.6090	
G+B+CO	0.3910	2.4826

(Source: Own calculations)

5.Conclusion and recommendations

This article investigated the safe-haven properties of three assets, namely gold, crude oil and Bitcoin during two major financial crises: the GFC and COVID-19. The paper delved into those safe-haven properties by assessing which selection of assets among gold, crude oil and Bitcoin can be added to a mix of a stock/bond portfolio for an optimal portfolio and also lower heavy-tails (Fréchet-type tails) that occurred during the two crises.

The data used comprised stock returns indices and bond yields from three developed countries and three emerging countries classified by Morgan Stanley Capital International (MSCI) and are part of the G20 group of nations. For Canada, we use TSX and the Canada 10-year yield bond), the USA (S&P 500) and TLT bond); the UK (FTSE 100 and UK 10-year yield bond); Russia (MOEX and Russian 10-year yield bond); Brazil (IBOVESPA stock index and Brazilian 10-year yield bond) and South Korea (Korean Composite Stock Price Index (KOSPI) and South Korean 10-year yield bond). The returns of the potential safe-haven assets (gold, crude oil and Bitcoin).

The EVT was used in context of portfolio optimisation through usage of the mean-CvaR as a benchmark for portfolio selection and to reflect the extent of portfolio allocation during turmoil periods. Based on a mean-CVaR portfolio selection, the GEV distribution shape parameter was employed as a performance metric. We then removed autocorrelation and heteroscedasticity from the returns by filtering them using an ARMA-GJR-GARCH procedure before applying the EVT. The preliminary research and empirical results showed that performance of all 60/40 portfolios declined sharply during the GFC and COVID-19, as the portfolios exhibited heavy Fréchet-type tails during both crises.

We proceeded and optimised the stock and bond combination, and results show that the optimalisation reduced the GEV shape parameters of all countries displaying Weibull-type tails except for Canada, therefore indicating the lowering of the downside risk of the portfolios. For COVID-19, the optimised stock/bond portfolios showed heavy tails indicating high risk exposure for all portfolios excluding the Brazilian portfolio.

Finally, the paper employs the mean-CVaR for portfolio weight allocation and to optimise the portfolio by adding a potential safe-haven asset or a combination of safe-haven assets. The results show that during the GFC, the addition of gold, crude oil and the combination of the two allowed the heavy Fréchet-type tails to transform into thin Weibull-type tails. This implies that the two assets acted as safe-haven assets during the crisis with gold being the best safe-haven option for all countries (developed and emerging). Contrarily, COVID-19 yielded mixed results, all the assets including the digital cryptocurrency Bitcoin acted as a safe haven for only two emerging countries which are Russia and Brazil improving both tail behaviour to Weibull type tails with gold and the Bitcoin cryptocurrency serving the best safe-haven characteristics for both countries. Findings are similar to those found by Echaust and Just (2022) who found that gold acted as an excellent safe-haven asset during the GFC but weakened during COVID-

19, and crude oil did serve as a weak safe-haven asset for the US portfolio. The rest of the portfolios return distributions are in the Fréchet region of attraction, indicating high potential downside risk for investors and portfolio managers. The results are also similar to Enilov, Mensi and Stankov (2023) who found that oil did not act as a safe-haven asset during COVID-19 as it did not lower the downside risk of most portfolios made up of indices.

Moreover, this article clarifies the role of gold, crude oil and Bitcoin as safe-haven assets for mitigating stock market risk and bond market for investors, regulators and policymakers. The results support how investors perceive risk in their portfolio allocation where the stock market and bond market are concerned. Investors should get information and tactics for optimising their portfolios. Furthermore, the findings show that investors and portfolio managers should consider economic conditions of the countries when assessing the merits of a safe-haven asset.

Further research may be conducted to expand on the insights offered in this paper. Firstly, the research may expand the number of countries used in the data set for the portfolios so that readers may get more accurate results. Secondly, other different types of potential safe-haven assets may be examined to assist portfolio managers to have a variety of commodities to choose from. Finally, a different EVT method may be used to assess the safe-haven characteristics of the asset, for example, a Peak Over Threshold model (POT).

APPENDIX

Table 9: Stock/bond optimised portfolio conditional volatility estimation using ARMA-GJR-GARCH (1,1) with student-t distribution (GFC)

Portfolio	Canada	USA	UK	Russia	South Korea	Brazil
mu1	-0.0701	-0.0018	0.0138	0.01768	0.0200	0.0678
	(0.049)	(0.040)	(0.035)	(0.048)	(0.048)	(0.043)
ar1	-0.7630	-0.6263	0.4866	0.8978	-0.9437	0.2997
	(0.015)	(0.034)	(0.035)	(0.023)	(0.034)	(0.018)
ma1	0.8257	0.6772	-0.6686	-0.9610	0.9324	-0.4286
	(0.034)	(0.023)	(0.05)	(0.029)	(0.044)	(0.045)
Ω	0.0138	0.0039	0.0154	0.0458	0.0154	0.0277
	(0.033)	(0.034)	(0.023)	(0.011)	(0.044)	(0.041)
α	0.0021	0.0331	0.0765	0.0933	0.0483	0.0480
	(0.043)	(0.021)	(0.021)	(0.031)	(0.023)	(0.048)
β	0.9495	0.9334	0.7651	0.8377	0.9382	0.9055
	(0.049)	(0.049)	(0.012)	(0.044)	(0.037)	(0.022)
γ	0.0561	0.1186	0.1500	0.1370	0.0068	0.0770
	(0.015)	(0.039)	(0.047)	(0.025)	(0.018)	(0.009)
Ψ	12.7340	20.2955	7.3827	4.6982	4.2122	6.8581
	(0.010)	(0.044)	(0.041)	(0.024)	(0.028)	(0.030)

(Source: Own calculations, p-values reported in brackets)

Table 10: Stock/bond optimised portfolio conditional volatility estimation using ARMA-GJR-GARCH (1,1) with student-t distribution (COVID-19)

Portfolio	**Canada**	**USA**	**UK**	**Russia**	**South Korea**	**Brazil**
mu1	0.0271	0.0208	-0.0057	0.0802	0.0405	0.01746
	(0.031)	(0.031)	(0.023)	(0.040)	(0.038)	(0.045)
ar1	-0.8678	-0.9578	0.5131	-0.2202	0.7477	-0.8334
	(0.034)	(0.045)	(0.034)	(0.034)	(0.023)	(0.033)
ma1	0.8920	0.9694	-0.5450	0.3470	-0.7657	0.8405
	(0.034)	(0.034)	(0.021)	(0.036)	(0.044)	(0.038)
Ω	0.0239	0.01842	0.0023	0.0596	0.0378	0.0859
	(0.015)	(0.022)	(0.042)	(0.018)	(0.042)	(0.036)
α	0.021	0.0560	0.0861	0.0632	0.0382	0.0728
	(0.01)	(0.025)	(0.041)	(0.033)	(0.012)	(0.036)
β	0.8310	0.8490	0.8437	0.7295	0.8884	0.8422
	(0.027)	(0.045)	(0.034)	(0.046)	(0.026)	(0.023)
γ	0.3027	0.1311	0.1115	-0.1861	0.0711	0.0769
	(0.038)	(0.039)	(0.021)	(0.043)	(0.040)	(0.039)
Ψ	9.2287	11.5148	7.8324	3.2155	7.1836	4.9219
	(0.023)	(0.044)	(0.036)	(0.009)	(0.012)	(0.012)

(Source: Own calculations, p-values reported in brackets)

Table 11: Stock/bond optimised portfolio with Gold conditional volatility estimation ARMA-GJR-GARCH (1,1) with student-t distribution (GFC)

Portfolio	**Canada**	**USA**	**UK**	**Russia**	**South Korea**	**Brazil**
mu1	0.0102	0.0190	0.01675	0.0642	0.02935	0.08276
	(0.034)	(0.033)	(0.037)	(0.018)	(0.019)	(0.039)
ar1	0.74722	-0.5828	0.4872	0.7333	-0.0010	-0.6305
	(0.031)	(0.029)	(0.025)	(0.039)	(0.020)	(0.040)
ma1	-0.7993	0.6513	-0.6602	-0.7887	0.0318	0.5832
	(0.044)	(0.033)	(0.024)	(0.023)	(0.049)	(0.029)
Ω	0.0099	0.0052	0.0138	0.0229	0.0070	0.0152
	(0.033)	(0.024)	(0.023)	(0.042)	(0.012)	(0.034)
α	0.024	0.04821	0.0785	0.0404	0.022	0.0366
	(0.01)	(0.039)	(0.030)	(0.029)	(0.01)	(0.029)
β	0.9508	0.9291	0.7882	0.9287	0.9422	0.9233
	(0.023)	(0.043)	(0.023)	(0.017)	(0.018)	(0.033)
γ	0.0742	0.0253	0.10591	0.03464	0.0936	0.0537
	(0.044)	(0.048)	(0.039)	(0.020)	(0.034)	(0.032)
Ψ	13.8903	18.0352	7.0383	12.0658	30.4776	59.9995
	(0.036)	(0.019)	(0.037)	(0.034)	(0.024)	(0.027)

(Source: Own calculations, p-values reported in brackets)

Table 12: Stock/bond optimised portfolio with Gold conditional volatility estimation ARMA-GJR-GARCH (1,1) with student-t distribution (COVID-19)

Portfolio	**Canada**	**USA**	**UK**	**Russia**	**South Korea**	**Brazil**
mu1	0.0307	0.01841	-0.0039	0.0291	0.0273	0.0397
	(0.034)	(0.022)	(0.022)	(0.033)	(0.023)	(0.032)
ar1	-0.8472	-0.9708	-0.2482	0.7498	0.7371	0.3691
	(0.023)	(0.034)	(0.029)	(0.023)	(0.044)	(0.022)
ma1	0.8645	0.9841	0.2618	-0.7694	-0.7397	-0.4588
	(0.034)	(0.034)	(0.020)	(0.011)	(0.023)	(0.042)
Ω	0.0605	0.0232	0.0033	0.0527	0.01350	0.0531
	(0.0057)	(0.003)	(0.004)	(0.010)	(0.023)	(0.003)
α	0.1722	0.0408	0.0846	0.1585	0.0313	0.1685
	(0.023)	(0.043)	(0.011)	(0.029)	(0.034)	(0.044)
β	0.7307	0.8416	0.8560	0.7970	0.9225	0.7722
	(0.043)	(0.036)	(0.012)	(0.017)	(0.020)	(0.05)
γ	-0.0303	0.1103	0.0656	-0.0503	0.0323	-0.0485
	(0.022)	(0.034)	(0.033)	(0.031)	(0.033)	(0.028)
Ψ	6.3595		6.6983	3.9854	9.7045	7.0065
	(0.035)	13.8984 (0.030)	(0.009)	(0.029)	(0.045)	(0.009)

(Source: Own calculations, p-values reported in brackets)

Table 13: Stock/bond optimised portfolio with Crude oil conditional volatility estimation ARMA-GJR-GARCH (1,1) with student-t distribution (GFC)

Portfolio	**Canada**	**USA**	**UK**	**Russia**	**South Korea**	**Brazil**
mu1	-0.0409	0.0014	0.0152	0.0422	0.0446	0.07825
	(0.040)	(0.05)	(0.033)	(0.003)	(0.040)	(0.034)
ar1	-0.6600	-0.6616	0.5263	0.5283	-0.4517	0.2601
	(0.045)	(0.032)	(0.034)	(0.010)	(0.031)	(0.029)
ma1	0.73100	0.7041	-0.7082	-0.6036	0.4737	-0.4213
	(0.034)	(0.023)	(0.011)	(0.023)	(0.018)	(0.039)
Ω	0.0207	0.0032	0.01595	0.0449	0.0085	0.0294
	(0.012)	(0.022)	(0.035)	(0.027)	(0.043)	(0.021)
α	0.0376	0.0251	0.0792	0.0866	0.0654	0.0236
	(0.013)	(0.029)	(0.035)	(0.023)	(0.013)	(0.011)
β	0.9159	0.9421	0.7565	0.8652	0.9352	0.9154
	(0.032)	(0.012)	(0.025)	(0.017)	(0.042)	(0.029)
γ	0.0682	0.0550	0.1501	0.0951	-0.0115	0.0942
	(0.012)	(0.022)	(0.035)	(0.027)	(0.043)	(0.021)
Ψ	10.0643	11.810	8.2724	6.7001	4.8916	6.9609
	(0.041)	(0.042)	(0.032)	(0.022)	(0.023)	(0.033)

(Source: Own calculations, p-values reported in brackets)

Table 14: Stock/bond optimised portfolio with Crude oil conditional volatility estimation ARMA-GJR-GARCH (1,1) with student-t distribution (COVID-19)

Portfolio	Canada	USA	UK	Russia	South Korea	Brazil
mu1	0.0416	0.0219	-0.0042	0.0733	0.0433	0.0337
	(0.012)	(0.034)	(0.041)	(0.013	(0.041	(0.041)
ar1	0.3245	-0.9707	0.4837	-0.1742	-0.3604	0.3329
	(0.034)	(0.032)	(0.015)	(0.017)	(0.023)	(0.020)
ma1	-0.3023	0.9807	-0.5112	0.2584	0.3976	-0.3725
	(0.019)	(0.012)	(0.039)	(0.037)	(0.023)	(0.041)
Ω	0.0203	0.0164	0.0024	0.0495	0.0276	0.0957
	(0.022)	(0.032)	(0.034)	(0.047)	(0.023)	(0.011)
α	0.0473	0.0504	0.0856	0.3145	0.0362	0.07916
	(0.019)	(0.012)	(0.025)	(0.017)	(0.05)	(0.022)
β	0.8381	0.8639	0.8439	0.7409	0.81364	0.444
	(0.014)	(0.042)	(0.015)	(0.027)	(0.043)	(0.021)
γ	0.2000	0.1132	0.1120	-0.1139	0.0921	0.031
	(0.032)	(0.024)	(0.031)	(0.047)	(0.033)	(0.021)
Ψ	8.8385 (0.023)	11.0704 (0.034)	7.8068 (0.003)	3.2763 (0.050)	5.3259 (0.034)	4.569 (0.023)

(Source: Own calculations, p-values reported in brackets)

Table 15: Stock/bond optimised portfolio with Bitcoin conditional volatility estimation ARMA-GJR-GARCH (1,1) with student-t distribution (COVID-19)

Portfolio	Canada	USA	UK	Russia	South Korea	Brazil
mu1	0.0469	0.0322	-0.0053	0.0819	0.0624	0.0549
	(0.044)	(0.039)	(0.035)	(0.033)	(0.033)	(0.021)
ar1	0.7289	0.3784	-0.4991	-0.1318	0.7313	-0.4912
	(0.033)	(0.045)	(0.025)	(0.017)	(0.013)	(0.011)
ma1	-0.7015	-0.3936	0.4932	0.2041	-0.7474	0.4604
	(0.012)	(0.032)	(0.005)	(0.007)	(0.003)	(0.021)
Ω	0.0440	0.0241	0.0023	0.0957	0.0457	0.0818
	(0.023)	(0.032)	(0.031)	(0.021)	(0.042)	(0.023)
α	0.0184	0.0522	0.0819	0.2708	0.0367	0.0971
	(0.022)	(0.032)	(0.025)	(0.031)	(0.043)	(0.012)
β	0.7836	0.8462	0.8432	0.7410	0.8791	0.8270
	(0.012)	(0.022)	(0.015)	(0.027)	(0.043)	(0.021)
γ	0.3020	0.1203	0.1214	-0.1212	0.0678	0.0563
	(0.042)	(0.012)	(0.025)	(0.029)	(0.021)	(0.013)
Ψ	12.2685 (0.013)	10.6594 (0.003)	7.821 (0.05)	3.2713 (0.032)	9.0267 (0.022)	5.5439 (0.002)

(Source: Own calculations, p-values reported in brackets)

Table 16: Stock/bond optimised portfolio with all assets conditional volatility estimation ARMA-GJR-GARCH (1,1) with student-t distribution (GFC)

Portfolio	Canada	USA	UK	Russia	South Korea	Brazil
mu1	-0.0518	-0.0090	-0.0125	0.0123	-0.0141	0.0605
	(0.015)	(0.012)	(0.033)	(0.027)	(0.040)	(0.031)
ar1	-0.8064	0.4501	-0.4831	0.8675	-0.5317	-0.8634
	(0.012)	(0.022)	(0.035)	(0.017)	(0.023)	(0.027)
ma1	0.8352	-0.5693	0.3946	-0.9107	0.53501	0.8161
	(0.032)	(0.010)	(0.030)	(0.028)	(0.033)	(0.041)
Ω	0.0185	0.0110	0.030	0.0405	0.04561	0.0362
	(0.025)	(0.042)	(0.035)	(0.023)	(0.023)	(0.018)
α	0.0293	0.022	0.021	0.0566	0.013	0.0348
	(0.002)	(0.032)	(0.025)	(0.024)	(0.043)	(0.023)
β	0.9112	0.9265	0.8779	0.8786	0.87853	0.9131
	(0.022)	(0.024)	(0.025)	(0.024)	(0.041)	(0.028)
γ	0.1015	0.1186	0.1829	0.1282	0.17868	0.0813
	(0.042)	(0.022)	(0.035)	(0.027)	(0.033)	(0.021)
Ψ	29.0746	20.2955	25.8752	5.9315	11.4391	7.9703
	(0.044)	(0.042)	(0.044)	(0.033)	(0.023)	(0.033)

(Source: Own calculations, p-values reported in brackets)

Table 17: Stock/bond optimised portfolio with all assets conditional volatility estimation ARMA-GJR-GARCH (1,1) with student-t distribution (COVID-19)

Portfolio	Canada	USA	UK	Russia	South Korea	Brazil
mu1	0.0062	0.0190	0.0184	0.0664	0.0450	0.0861
	(0.012)	(0.022)	(0.015)	(0.017)	(0.023)	(0.024)
ar1	-0.5084	-0.5911	0.5207	0.7067	-0.1129	0.6246
	(0.044)	(0.033)	(0.035)	(0.027)	(0.003)	(0.011)
ma1	0.5534	0.6547	-0.6877	-0.7543	0.1584	-0.7009
	(0.019)	(0.020)	(0.035)	(0.020)	(0.043)	(0.028)
Ω	0.0087	0.0047	0.01357	0.0198	0.0069	0.01515
	(0.032)	(0.042)	(0.015)	(0.023)	(0.043)	(0.023)
α	0.012	0.0441	0.0841	0.0352	0.0191	0.0227
	(0.022)	(0.024)	(0.035)	(0.017)	(0.042)	(0.025)
β	0.9515	0.9329	0.7942	0.9346	0.9346	0.9295
	(0.032)	(0.021)	(0.045)	(0.022)	(0.050)	(0.031)
γ	0.0750	0.0264	0.0875	0.0337	0.0700	0.0644
	(0.032)	(0.029)	(0.035)	(0.037)	(0.033)	(0.046)
Ψ	11.7091	17.0232	7.5058	15.4133	18.4990	59.999
	(0.033)	(0.033)	(0.032)	(0.022)	(0.023)	(0.039)

(Source: Own calculations, p-values reported in brackets)

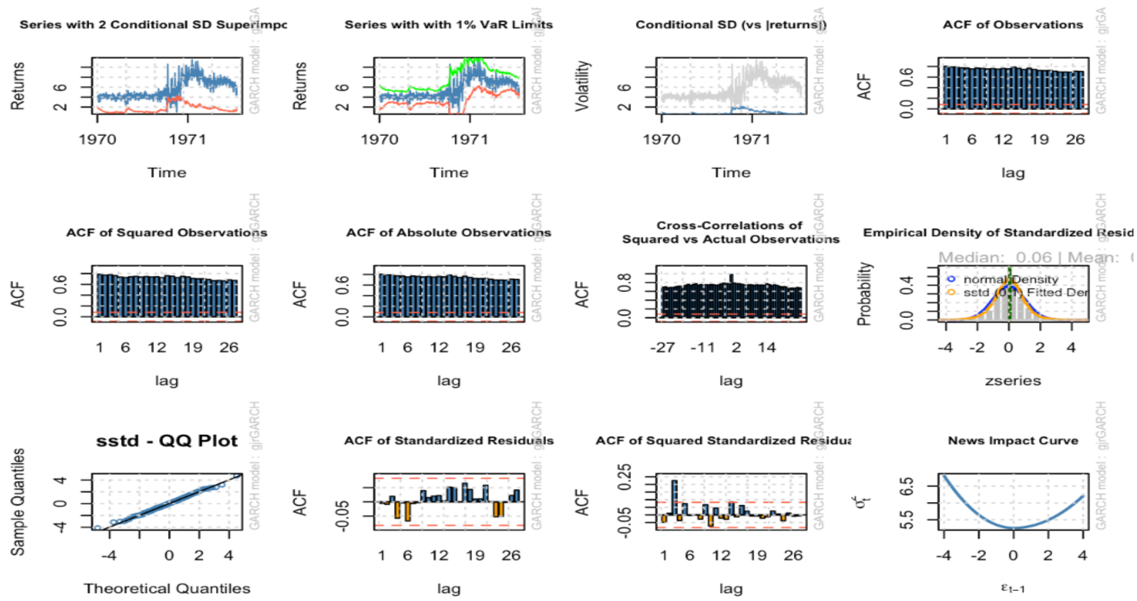

Figure 5: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised portfolio (GFC)

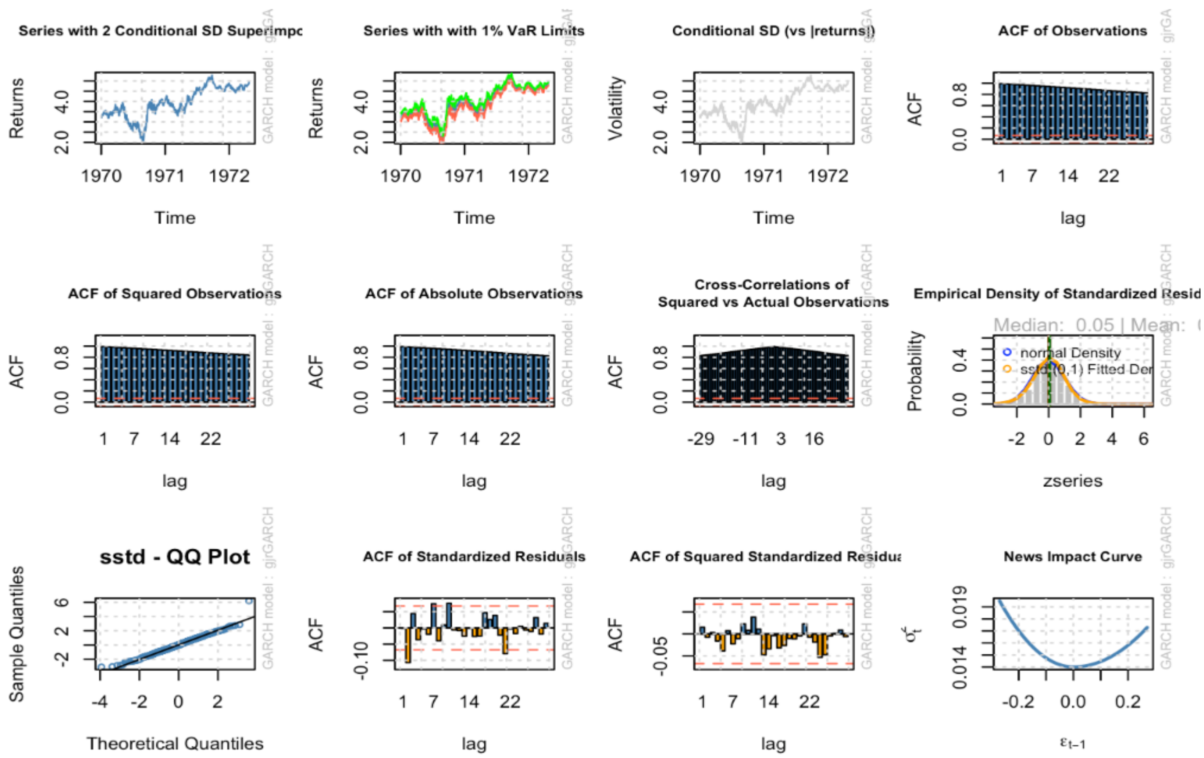

Figure 6: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised portfolio (COVID-19)

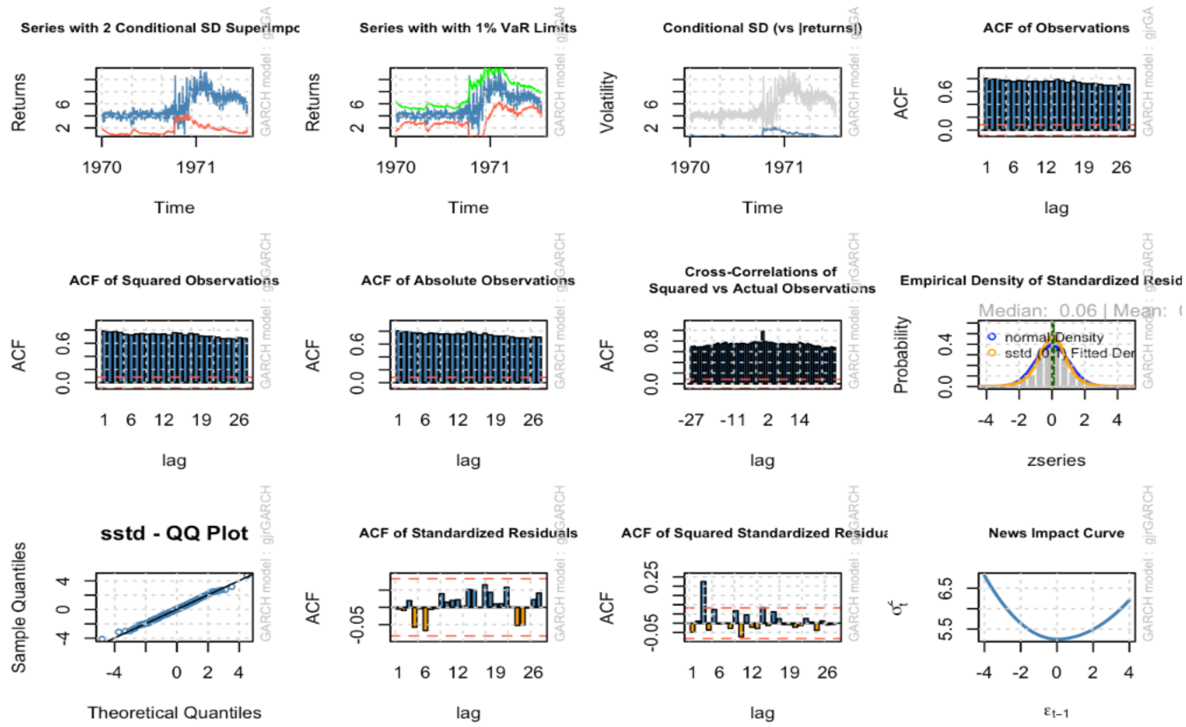

Figure 7: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised with gold portfolio (GFC)

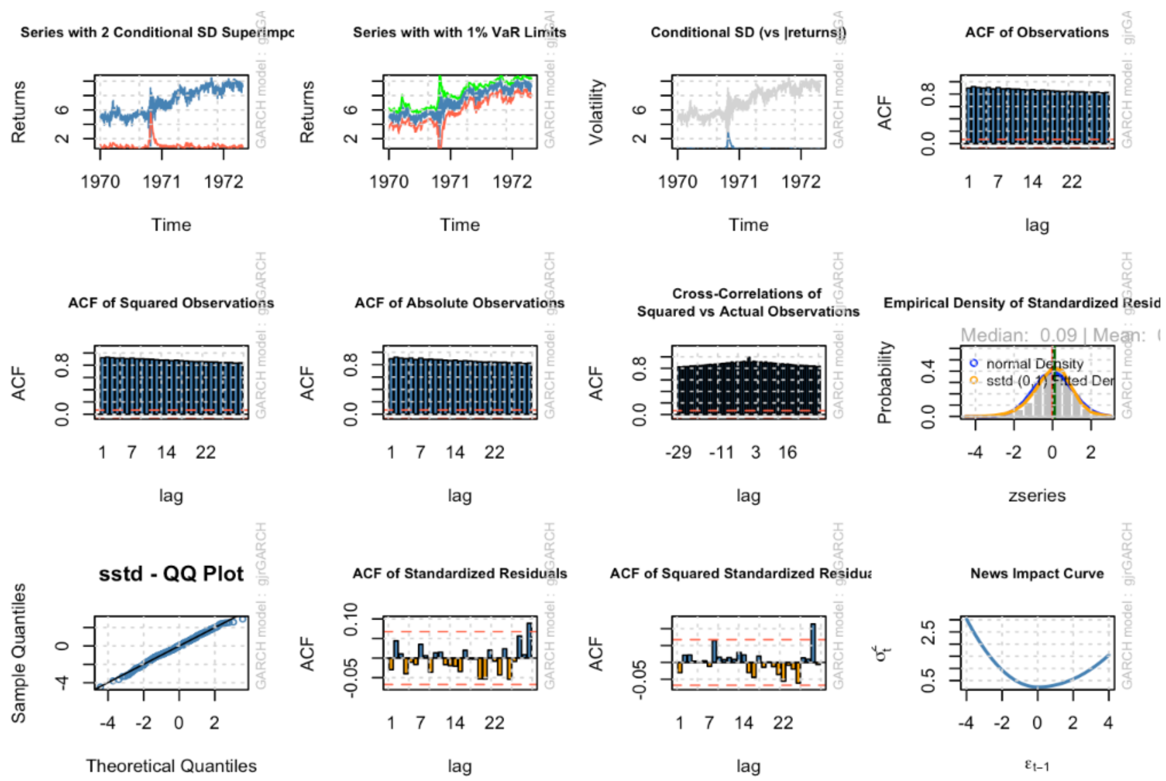

Figure 8: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised with gold portfolio (GFC)

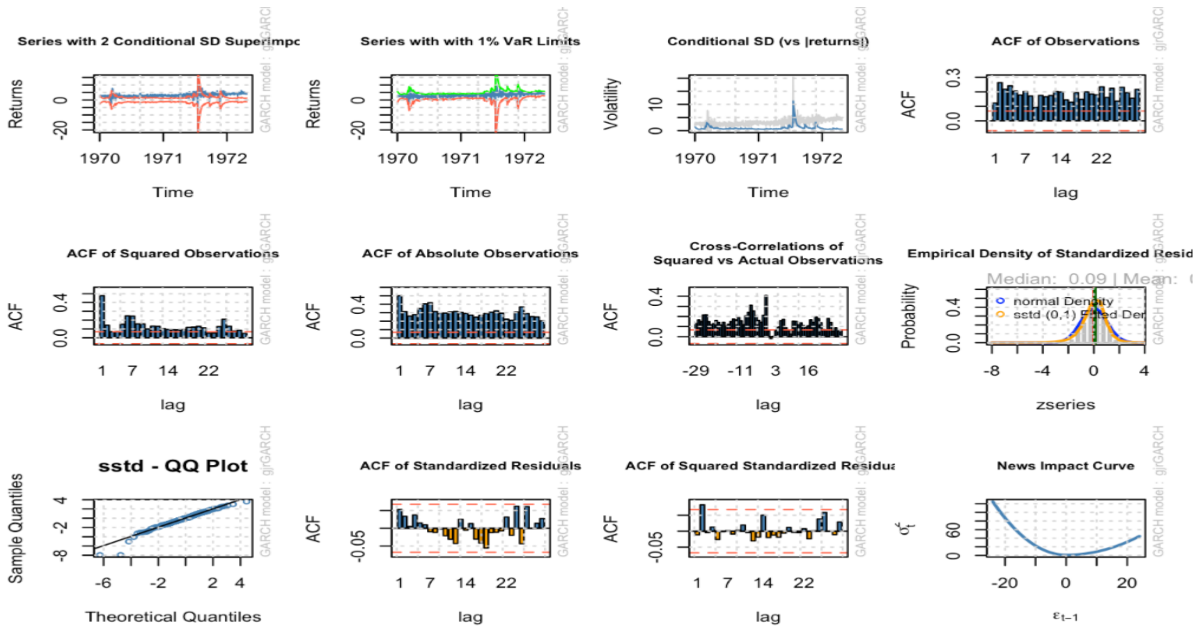

Figure 9: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised with Crude Oil portfolio (GFC)

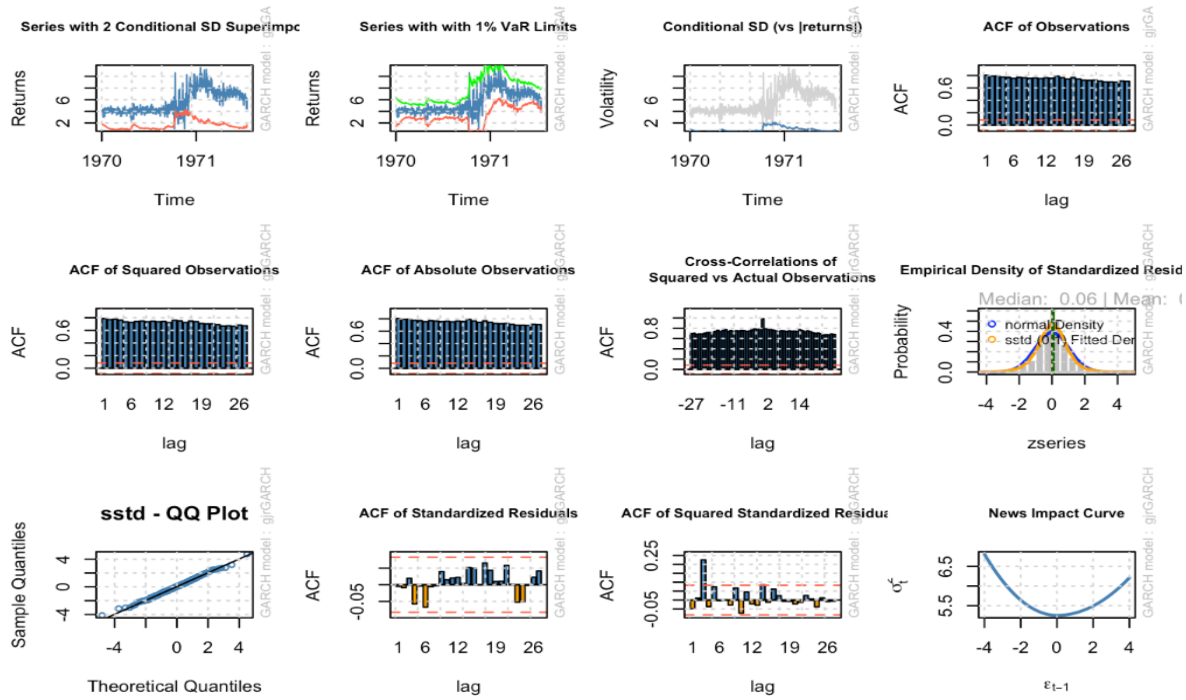

Figure 10: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised with Crude Oil portfolio (COVID-19)

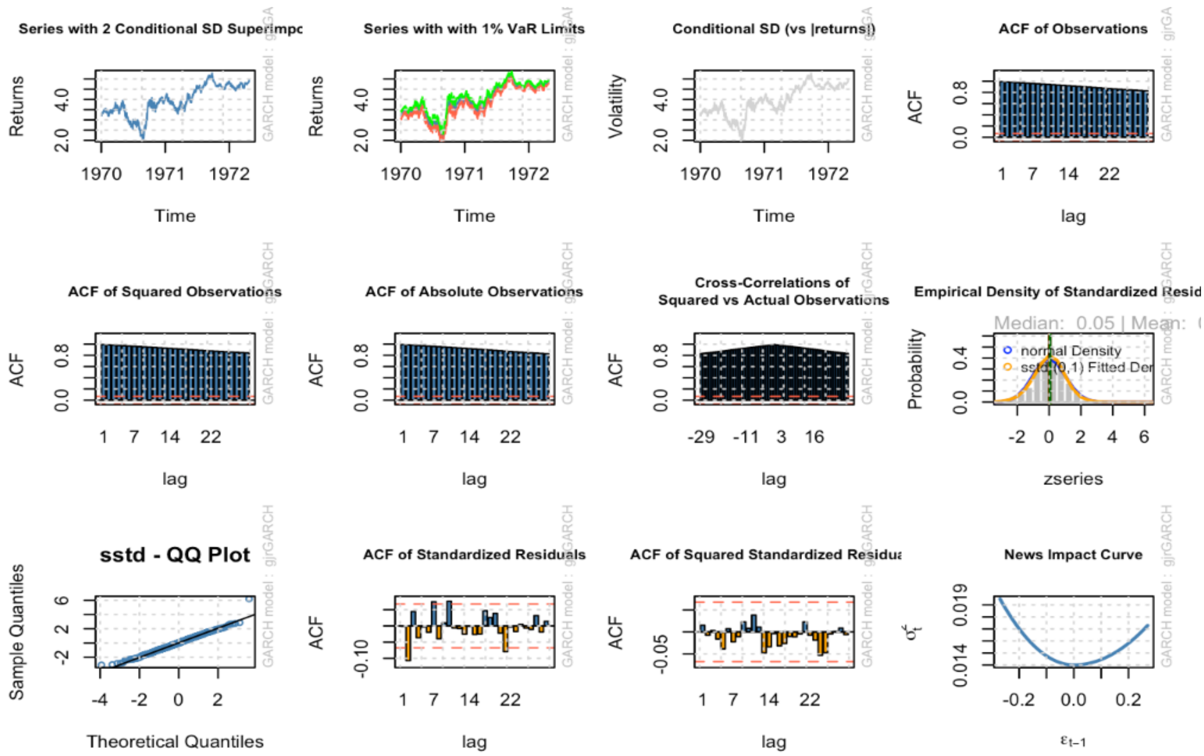

Figure 11: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised with Bitcoin portfolio (COVID-19)

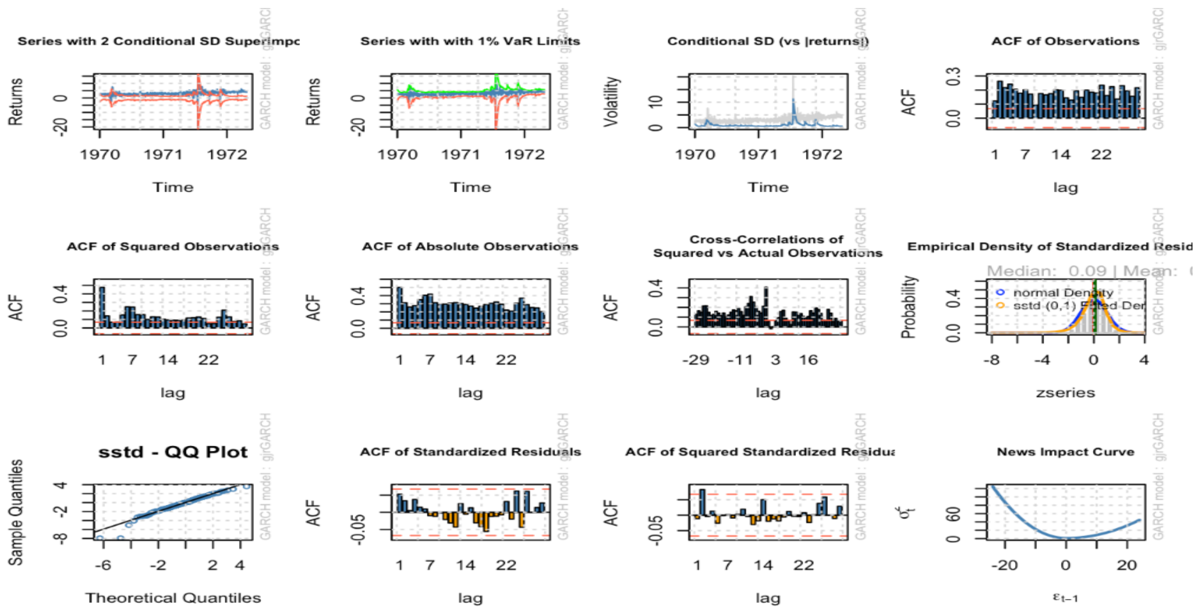

Figure 12: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised with all assets portfolio (GFC)

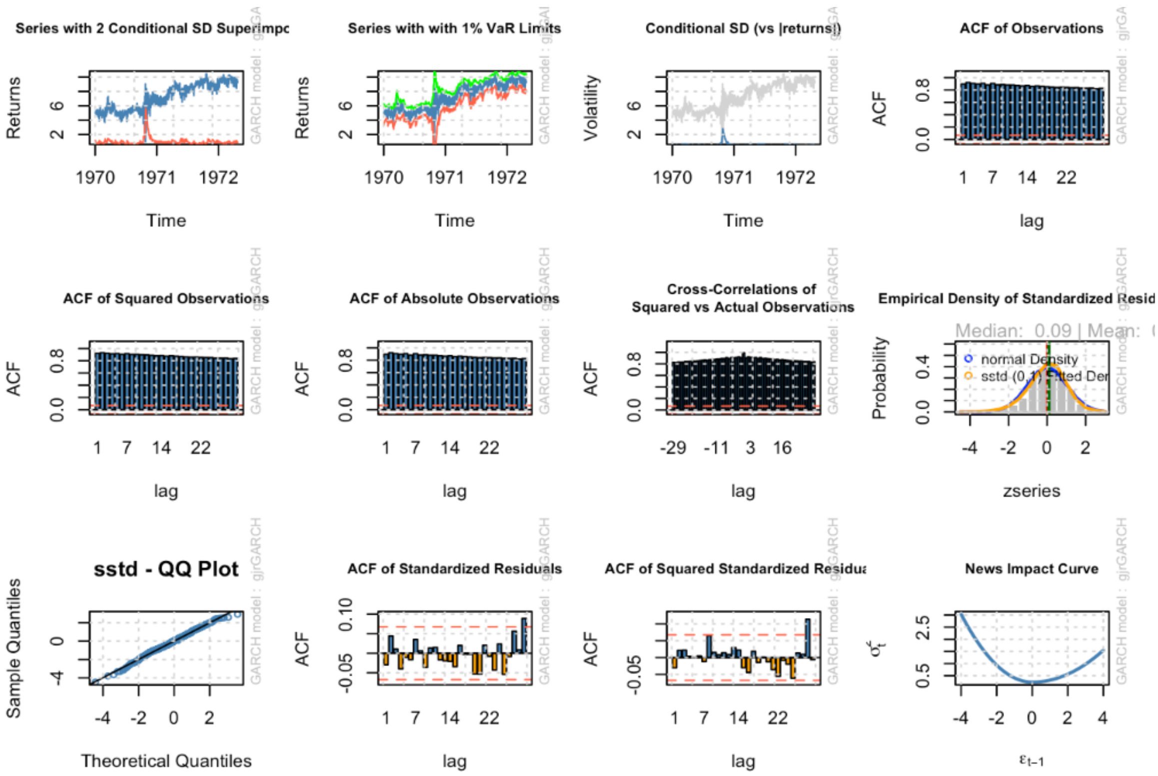

Figure 13: Autocorrelation function (ACF), Q-Q Plot and News Impact Curve for Stock/bond optimised with all assets portfolio (COVID-19)

Table 18: Mean-CVaR weights and shape of the GEV distribution for the UK-portfolio.

GFC	Optimal Weights	Shape
FTSE 100-UK 10 year	0.8082	
Gold	0.1918	-3.1795
FTSE 100-UK 10 year	-	-
Bitcoin	-	-
FTSE 100-UK 10 year	0.8402	
Crude Oil	0.1598	-3.1450
FTSE 100-UK 10 year	0.6964	
G+CO	0.3036	-3.2320
COVID-19		
FTSE 100-UK 10 year	1	
Gold	0	4.9610
FTSE 100-UK 10 year	1	
Bitcoin	0	4.9610
FTSE 100-UK 10 year	1	
Crude Oil	0	0.8086
FTSE 100-UK 10 year	0.8306	
G+B+CO	0.1694	1.8831

(Source: Own calculations)

Table 19: Mean-CVaR weights and shape of the GEV distribution for the Russian-portfolio.

GFC	Optimal Weights	Shape
MOEX-Russian 10 year	0.8437	
Gold	0.1563	-3.1107
MOEX-Russian 10 year	-	-
Bitcoin	-	-
MOEX-Russian 10 year	0.7946	
Crude Oil	0.2054	-3.0937
MOEX-Russian 10 year	0.6016	
G+CO	0.3984	-3.0599
COVID-19		
MOEX-Russian 10 year	1	
Gold	0	-3.3030
MOEX-Russian 10 year	1	
Bitcoin	0	-3.3030
MOEX-Russian 10 year	0.8517	
Crude Oil	0.1483	-3.2673
MOEX-Russian 10 year	0.2745	
G+B+CO	0.7255	2.1092

(Source: Own calculations)

Table 20: Mean-CVaR weights and shape of the GEV distribution for the South Korean-portfolio.

GFC	Optimal Weights	Shape
KOSPI-South Korean 10-year	1	
Gold	0	-3.2144
KOSPI-South Korean 10-year	-	-
Bitcoin	-	-
KOSPI-South Korean 10-year	0.7813	
Crude Oil	0.2187	-2.8634
KOSPI-South Korean 10-year	0.7667	
G+CO	0.2333	-2.8159
COVID-19		
KOSPI-South Korean 10-year	0.9576	
Gold	0.0424	4.9610
KOSPI-South Korean 10-year	0.9929	
Bitcoin	0.0071	4.9610
KOSPI-South Korean 10-year	0.9939	
Crude Oil	0.0061	0.8086
KOSPI-South Korean 10-year	0.4760	1.1077
G+B+CO	0.5240	

(Source: Own calculations)

Table 21: Mean-CVaR weights and shape of the GEV distribution for the Brazilian-portfolio.

GFC	**Optimal Weights**	**Shape**
IBOVESPA-Brazil 10-year	1	
Gold	0	-0.1025
IBOVESPA-Brazil 10-year	-	-
Bitcoin	-	-
IBOVESPA-Brazil 10-year	0.7893	
Crude Oil	0.2107	-2.7535
IBOVESPA-Brazil 10-year	0.7893	
G+CO	0.2107	-2.7535
COVID-19		
IBOVESPA-Brazil 10-year	0.6194	
Gold	0.3806	-3.2792
IBOVESPA-Brazil 10-year	0.9213	
Bitcoin	0.0787	-3.2438
IBOVESPA-Brazil 10-year	0.8753	
Crude Oil	0.1247	-3.1968
IBOVESPA-Brazil 10-year	0.2704	
G+B+CO	0.7296	1.1593

(Source: Own calculations)

6. Reference List

Ahmed R., Chaudhry S., Kumpamool C., Benjasak.,2022. Tail risk, systemic risk of crude oil and precious metals. *Energy Economics v.112*, 106063 https://doi.org/10.1016/j.eneco.2022.106063.

Akhtaruzzaman, M., Boubaker, S., Lucey, B.M., Sensoy, A., 2021. Is gold a hedge or a safe-haven asset in the COVID–19 crisis. *Economic Modelling v.102, 105588* https://doi. org/10.1016/j.econmod.2021.105588.

Ali, F., Jiang, Y., Sensoy, A., 2021. Downside risk in Dow Jones Islamic equity indices: precious metals and portfolio diversification before and after the COVID-19 bear market. *Research in International Business and Finance*V.58, 101502 https://doi.org/10.1016/j.ribaf.2021.101502.

Assifuah-Nunoo E., Junior P.O., Adam A.M and Bossman A., 2022. Assessing the safe haven properties of oil in African stock markets amid COVID-19: a quantile regression analysis. *Quantitative Finance and Economics. Volume 6, Issue 2, pp244–269*.

Aysan, A.F., Khan, A.U.I., Topuz, H., (2021). Bitcoin and altcoins price dependency: resilience and portfolio allocation in COVID-19 outbreak. *Risks 9 (4), pp74*.

Baur, D.G., McDermott, T.K., 2010. Is gold a safe haven? International evidence. *Journal of Bank of Finance 34 (8), 1886–1898*. https://doi.org/10.1016/j.jbankfin.2009.12.008.

Baur, D.G., Lucey, B.M., 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review V.45 (2), pp217–229*.

Będowska-Sójka, B., Kliber, A., 2021. Is there one safe-haven for various turbulences? The evidence from gold, bitcoin and ether. *The North American Journal Of Economics And Finance* . V.56, 101390 https://doi.org/10.1016/j.najef.2021.101390.

Bollerslev. T. (1987) Generalised Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31: 307-327*.

Boubaker H., Cunado J., Gil-Alana L., Rangan R., 2020. Gold crises and gold as a safe haven: Evidence from over seven and half centuries of data. *Physica A: Statistical Mechanics and its Applications v.540* https://doiorg/10.1016/j.physa.2019.123093

Bouri, E., Gupta, R., and Roubaud, D. (2018). Herding behaviour in cryptocurrencies.

Finance Research Letters. https://doi.org/10.1016/j.frl.2018.07.008.

Bouri, E., Lucey, B., and Roubaud, D. 2019. Cryptocurrencies and the downside risk in equity investments. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2019.06.009.

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, 192–198.

Box, G.E.P. and Jenkins, G.M, 1976. Time Series Analysis: Forecasting and Control, Revised Edition, San Francisco: Holden Day. Journal of Mathematical Finance.

Bredin, D., Conlon, T., Potì, V., 2017. The price of shelter – downside risk reduction with precious metals. *International Review of Financial Analysis*. *49, 48–58*. https://doi.org/10.1016/ j.irfa.2016.12.005.

Chaves, D.B., Hsu, J.C., Li, F., Shakernia O. 2012. Efficient Algorithms for Computing Risk Parity Portfolio. *Weights Review of Financial Studies*: http://ssrn.com/abstract=2117303.

Cheema, M.A., Faff, R.W., Szulczuk, K., 2020. The 2008 global financial crisis and COVID-19 pandemic: how safe are the safe haven assets. *SSRN Electron. J*. https:// doi.org/10.2139/ssrn.3642945.

Chiang, T. and Zhang, Y., 2018. An empirical investigation of risk-return relations in Chinese equity markets: Evidence from aggregate and sectoral data. International *Journal of Financial Studies, 6(2): 35*.

Choi C, Jung H (2021) COVID-19's impacts on the Korean stock market. *Applied Economics Letters, 1–5*

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*. http://dx.doi.org/10.1016/j.irfa.2012.12.001.

CNBC, 2020. The Saudi-Russia oil price war was a very big mistake. Qatar Energy Minister Says. Website. Accessed on June 9, 2020. Available at: https://www.cnbc. com/2020/06/09/saudi-russia-oil-price-war-was-very-big-mistake-qatar-energy-minister.html.

Conlon, T., Corbet, S., McGee, R.J., 2020. Are cryptocurrencies a safe haven for equity markets? An international perspective from COVID-19. *Research in International Business and Finance*

Conover, C. M., Jensen, G. R., Johnson, R. R., and Mercer, J. M. (2009). Can precious metals make your portfolio shine? *The Journal of Investing, 18(1), pp 75-86*. http://dx.doi.org/10.3905/JOI.

Corbet, S., Hou, G., Hu, Y., Larkin, C. J., and Oxley, L., 2020. Any port in a storm: Cryptocurrency safe-havens during COVID-19. *Economics Letters, 194, Article 109377*.

Corbet, S., Larkin, C., Lucey, B., 2020. The contagion effects of the COVID-19 pandemic: evidence from gold and cryptocurrencies. *Financial Research Letters 35, 101554*.

Courtois, N.T., Grajek, M., Naik, R., 2014. Cryptography and security systems. Optimizing SHA256 in Bitcoin Mining. *Springer, pp. 131–144*.

Creti, A., Joëts, M., and Mignon, V. 2013. On the links between stock and commodity markets' volatility. *Energy Economics, 37, pp16–28*.

Danielsson, J., 2011. Financial Risk Forecasting: The Theory and Practice of Forecasting Market Risk with Implementation in R and MATLAB. *Wiley-Blackwell*.

Dbouk, W., Kryzanowski, L., 2009. Diversification benefits for bond portfolios. *European Journal of Finance. 15 (5–6), pp533–553*.

Dimitriou, D., Kenourgios, D., Simos, T., (2020). Are there any other safe haven assets? Evidence for "exotic" and alternative assets. *International Review of Economics & Finance*69, pp614–628. https://doi.org/10.1016/j.iref.2020.07.002.

DiTraglia, F.J. and Gerlach, J.R. (2012). Portfolio Selection: An Extreme Value Approach. *Journal of Banking and Finance, 37(2): 305-323*.

Dong, X., Li, C., Yoon, S.M., 2021. How can investors build a better portfolio in small open economies? Evidence from Asia's Four Little Dragons. The North American Journal of Economics and Finance58, 101500 https://doi.org/10.1016/j.najef.2021.101500.

Echaust, K., Just, M., 2022. Is gold still a safe haven for stock markets? New insights through the tail thickness of portfolio return distributions. *Research in International Business and Finance, 63 (101788)*. https://10.1016/j.ribaf.2022.101788

El Hedi Arouri, M., Lahiani, A., Nguyen, D.K., 2015. World gold prices and stock returns in China: insights for hedging and diversification strategies. *Economic Modelling 44, 273–282*. https://doi.org/10.1016/j.econmod.2014.10.030.

Fidelity Investments. 2023. Three Key Catalysts for the 60/40 Strategy. *Fidelity Investments, 1.9909468.100*.

Fisher, R.A., Tippett, L.H.C., 1928. Limiting forms of the frequency distribution of the largest or smallest member of a sample. *Mathematical Proceedings of the Cambridge Philosophical Society. 1928;24(2):180-190.* https://doi.org/10.1017/S0305004100015681.

Goodell, J. W., and Goutte, S. 2020. Co-movement of COVID-19 and bitcoin: Evidence from wavelet coherence analysis. *Finance Research Letters, Article 101625*.

Glosten, L., Jagannathan, R., and Runkle, D. (1993). Relationship between the expected value and the volatility of the nominal excess return on stocks. *Journal of finance 48, pp1779-1801*.

Gunay, S., Can, G., 2022. The source of financial contagion and spillovers: an evaluation of the COVID-19 pandemic and the global financial crisis. *PLOS ONE 17 (1), e0261835*. https://doi.org/10.1371/journal.pone.0261835.

Guesmi, K., Saadi, S., Abid, I., and Ftiti, Z. (2018). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*. https:// doi.org/10.1016/j.irfa.2018.03.004.

Haugh, M., 2016. Mean-Variance Optimisation and the CAPM. *Foundations of Financial Engineering Course, Columbia University*.

Ji, Q., Zhang, D., Zhao, Y., 2020. Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis 71:101526*https://doi.org/10.1016/j.irfa.2020.101526.

Klein T, Hien P and Walther T,2018. Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance, *International Review of Financial Analysis, 59, pp 105-116*.
https://econpapers.repec.org/article/eeefinana/v_3a59_3ay_3a2018_3ai_3ac_3ap_3a105-116.htm

Liu C, Naeem MA, Rehman MU, Farid S, Shahzad S, 2020. Oil as hedge, safe-haven, and diversifier for conventional currencies. *Energies 13: 1–19.* https://doi.org/10.3390/en13174354.

Lucey, B.M., and Li, S. 2015. What precious metals act as safe havens and when? Some US evidence. *Applied Economics Letters, 22, pp35-45*.

Luther W.J., Salter A.W., 2017 Bitcoin and the bailout. *The Quarterly Review of Economics and Finance. 2017;66:50–56*. doi: 10.1016/j.qref.2017.01.009.

Malander, L., and Papo L, 2023. 50/30/20. The New 60/40 Portfolio. *HAVYN research. AC HoldingLimitedarticle*.https://static1.squarespace.com/static/6305a9572a27de7b7044ca8f/t/63edde838da7e75ca0b65376/1676533400549/HAYVN.

Manohar, J.M., Raju, G.A., 2021. Does gold retain its hedge and safe haven role for energy sector indices during COVID-19 pandemic? A cross-quantilogram approach. *International Journal of Energy Economics and Policy*. https://doi.org/10.32479/ijeep.10294.

Mensi W, Nekhili R, Vo XV, et al. 2021 Oil and precious metals: Volatility transmission, hedging, and safe haven analysis from the Asian crisis to the COVID-19 crisis. *Economic Analysis and-Policy 71: pp73– 96* https://doi.org/10.1016/j.eap.2021.04.009.

Meshcheryakov, A., Ivanov, S., 2020. Ethereum as a hedge: The intraday analysis. *Economics Bulletin, 40(1), 101–108*.

Nakamoto, S. 2008. Bitcoin: A peer-to-peer electronic cash system[J]. *Decentralized Business Review, 21260*.

Prabheesh, K. P., Padhan, R., and Garg, B, 2020. COVID-19 and the Oil Price–Stock Market Nexus: Evidence from Net Oil-Importing Countries. *Energy Research Letters, 1, 13745*.

Pflug, G. 2000. Some Remarks on the Value-at-Risk and the Conditional Value-at-Risk. In: S. Uryasev (Ed) Probabilistic Constrained Optimization: Methodology and Applications. *Kluwer Academic Publishers*

Ritchie, J., and Dowlatabadi, H. 2014. Understanding the shadow impacts of investment and divestment decisions: Adapting economic input–output models to calculate biophysical factors of financial returns. *Ecological Economics, 106, 132–140.* http://doi.org/10.1016/j.ecolecon.2014.07.005

Rockafellar R.T, Uryasev S, 2000. Optimization of Conditional Value-at-Risk, *Journal of Risk, 2, 21-41*.

Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., 2020. Safe haven, hedge and diversification for G7 stock markets: gold versus bitcoin. *Economic Modelling, Elsevier, vol. 87(C).pp212–224*.

Sharma, U., and Karmakar, M. 2023. Are gold, USD, and Bitcoin hedge or safe haven against stock? The implication for risk management. *Review of Financial Economics, 41, 43–64*. https://doi. org/10.1002/rfe.116.

Tiwari A.K., Abakah E.K.A., Rehman M.Z and Lee C., 2020. Quantile dependence of Bitcoin with clean and renewable energy stocks: new global evidence. *Applied Economics* https://doi.org/10.1080/00036846.2023.2167921.

Tuysuz, S. 2013. Conditional correlations between stock index, investment grade yield, high yield and commodities (gold and oil) during stable and crisis periods. *International Journal of Economics and Finance, 5(9), 28–44*. https://doi.org/10.5539/ijef.v5n9p28.

Wen, X., Cheng, H., 2018. Which is the safe haven for emerging stock markets, gold or the US dollar. *Emerging Markets Review, Elsevier, vol. 35(C), pages 69-90.*. https://doi.org/10.1016/j. ememar.2017.12.006.

Wu, F., Zhao, W., Ji, Q., and Zhang, D. 2020. Dependency, centrality and dynamic networks for international commodity futures prices. *International Review of Economics and Finance, 67,pp 118–132*.

Yousfi M, Zaied YB, Cheikh NB, Lahouel BB, Bouzgarrou H .2021. Effects of the COVID-19 pandemic on the US stock market and uncertainty: a comparative assessment between the first and second waves. Technological Forecasting and Social Change 167:120710.

Yousaf, I., Bouri, E., Ali, S., and Azoury, N. 2021. Gold against Asian stock markets during the COVID-19 outbreak. *Journal of Risk and Financial Management, 14(4), 186. https://doi.org/10.3390/jrfm14040186*

Author's Acknowledgment

I acknowledge that I edited my paper by using Grammarly.