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A Statistical Analysis to Evaluate whether Gold Is Still the Safe Haven of Old

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Abstract: Gold is revered for its tangible nature, historical usage as a currency, and its role as a store of value, particularly during times of economic turmoil. This research delves into the enduring allure of gold as a valuable asset in financial markets and examines whether the attributes that have sustained its prominence throughout history are still applicable. We have elected to focus on the log returns of gold, three stock indices (namely, the MSCI World Index, S&P 500, FTSE 100) and a cryptocurrency (i.e. Bitcoin) in the 21st century, for a period spanning from 1/1/2000 to 31/5/2023 (which has not been studied so far in the literature). This analysis serves a dual purpose: studying the relationships between gold and the other variables; and assessing its ability to be a hedge or safe haven for them. For the first part, we use a generalized autoregressive conditional heteroskedasticity (GARCH) model to study the conditional volatility, rolling window correlation and a vector autoregressive (VAR) model; for the second part, we use the classical linear regression method. Our analysis employs a mixture of methodologies found to be prominent in existing literature so that our results may remain comparable. We ultimately find that gold retains the attributes under study, although they seem to be deteriorating in strength compared to what has been observed previously.

Keywords: Conditional volatility, cryptocurrencies, GARCH, gold, hedging, safe haven, VAR model.

1 Introduction

Investors are often driven by loss aversion, a psychological phenomenon that prioritizes the avoidance of losses over the pursuit of gains. This idea is what motivates the concept of an investment safe haven. Investors seek out safe haven assets to protect their capital during periods of market uncertainty, driven by their fear of potential losses [1]. Gold has long held the mantle as a premier safe haven asset, as it provides protection against inflation and is easily liquidated. However, some research suggests that its effectiveness as a hedging tool may only be evident over the long-term and may not provide the same benefits in the short- and medium-term [2]. Despite the general expectation that gold would exhibit its hedging properties during the COVID-19 pandemic, recent findings by [3] suggest that gold may not be the most efficient safe haven asset compared to crypto-assets. Additionally, gold prices have dropped and have shown positive correlations with several other assets [3]. The review of various studies on gold investments reveals several key findings. For instance, the results of [4] suggested that gold is a zero-beta asset (i.e., indicating it bears minimal market risk and can serve as a hedge against inflation). Furthermore, [5] showed that gold was a safe haven during crises and could diversify portfolios away from stocks, especially in bear markets. Additionally, [6] showed that gold's effectiveness as a hedge may vary during different bear market periods. [7] and [8] differentiated between gold's roles as a short-term safe haven and long-term hedge and they observed that gold can act as a safe haven briefly during extreme stock market downturns but may not provide consistent protection in the longer term, especially in emerging markets. [9] suggested that gold's hedging and safe haven functions depend on the specific market under observation. [9] extended on the work done by [7] by using a smooth transition regression model using an exponential transition function which splits the regression model into two extreme regimes. The augmented approach presented by [9] enabled a smooth discrete switching from one scenario to the other, thus allowing for a more flexible and realistic approach in testing the properties of gold in stock markets. [9]'s study covered the period from 1970 to 2012, and one would say it tried to account for the entire market, as it covered 18 individual markets and five regional indices, which comprised of the largest developed countries, the largest emerging markets, as well as major gold consumers and producers.

Bekiros et al. [10] highlighted the low correlation of commodity futures, including gold with stocks, and their varying impact on different markets. [11] concluded that gold serves as a safe haven and a hedge in countries like the US and India, but its effectiveness varies in other regions. In the US, gold plays a significant role in economic health, while in the UK, it is more profitable during stock market collapses. [12] conducted a study during the Global Financial Crisis (GFC) to examine the relationship between gold returns, stock market returns, and stock market volatility in the UK, US, and Japan. Moreover, [12]

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considered mutual dependence among different asset classes and used Granger causality to assess gold's hedging and safe haven properties and their findings surprisingly revealed that during the crisis gold lost its safe haven status in these countries, contrary to previous research. Furthermore, [12] attributed this difference to their bidirectional and multi-directional approach, nonlinear causality methods, and the complex outlook of investors in turbulent financial conditions. Additionally, [10] contributed to the literature by analyzing gold's diversification, hedging, and safe haven properties in BRICS (Brazil, Russia, India, China and South Africa) stock markets during significant events like the GFC. Bekiros et al. [10] also considered the impact of the financialization of commodity markets and used Morgan Stanley Capital International (MSCI) stock market indices along with three-month gold futures prices to assess gold's performance as an investment.

Several studies have explored the safe haven and hedging properties of traditional assets like gold and emerging assets like cryptocurrencies, particularly during significant financial events such as the GFC and the COVID-19 pandemic. Some of the studies, for instance [8] and [13] emphasized that emerging markets may not experience international investor movement towards traditional safe haven assets during crises, necessitating the search for alternative safe havens. [14] revealed that the relationship between gold, cryptocurrencies, and stock markets is more complex than previously thought, with the COVID-19 pandemic leading to higher uncertainty and stronger returns in the gold market. [15] observed that gold effectively hedges against market uncertainty induced by health risks such as pandemics and epidemics. At the same time [16] suggested that Bitcoin's emergence may have diminished gold's hedging role in certain markets. [17] compared the roles of gold and Bitcoin as safe havens, hedges, and diversification assets in the Group of Seven (G7) developed countries, with gold generally outperforming Bitcoin in terms of safety and hedging. [18] examined Bitcoin's potential as a safe haven and concluded that it functions better as a diversifier but requires maturation and investor trust to qualify as a safe haven. [19] discussed gold, cryptocurrencies (Bitcoin and Tether), and other stocks during COVID-19 and observed that Tether serves as a strong safe haven, while Bitcoin's safe haven role is weak, possibly due to systematic pandemic risk. Lastly, [20] investigated gold-backed cryptocurrencies like PAX gold during the COVID-19 crisis and the 2020 bear market, and their results indicated that gold-backed cryptocurrencies can act as safe haven assets during extreme financial crises, with time-varying characteristics.

Some literature emphasizes that understanding the interactions between gold and stocks requires considering additional factors, such as economic uncertainty and behavioral finance. [21] contributed to this area by examining the relationship between gold price movements and measures of economic and political uncertainty. Previous research by [22], [23] and [21] has shown that news-based uncertainty can impact various financial variables, including stock prices. Instead of isolating the effects of individual variables on gold price movements, it is more informative to directly investigate how gold returns and volatility respond to economic and political uncertainty. In addition to that, [24] proposed incorporating behavioral finance into financial system dynamics as a response to this situation; they developed a model of gold price trends that combines the 1980 Grossman-Stiglitz model with behavioral factors to better reflect market realities.

The abovementioned studies collectively underscore the evolving landscape of safe haven assets, with gold retaining its value in certain scenarios (particularly in the US and India), while cryptocurrencies offer an emerging alternative. The effectiveness of these assets as hedges and safe havens may vary depending on economic conditions and specific markets. The objective of this research work is to comprehensively examine gold's role as a valuable asset, particularly as a historical safe haven, and to assess the impact of significant events such as pandemics and market crashes on gold's safe haven status. Additionally, the study aims to evaluate the emergence of cryptocurrencies, with focus on Bitcoin, as a potential contender to gold's traditional safe haven position. The research questions encompass categorizing gold as a safe haven asset; understanding its behaviour during pandemics like the COVID-19 crisis; exploring its performance during severe market crashes; and assessing whether cryptocurrencies have replaced or complemented gold as safe haven assets, considering their security and resilience during market turbulence. Methodologically, we used a combination of various methods with the traditional linear regression by [8] being used to assess the safe haven and hedging properties. Next, the popular methods such as Vector Autoregression (VAR) and rolling window correlation being used to study the dynamics between gold and the other variables of interest.

The rest of the paper is structured as follows: In Section 2, the different datasets to be used are described and the corresponding theoretical methods mentioned in the latter paragraph are discussed. Next, in Section 3, a detailed data analysis is provided using the methods described in Section 2. Finally, Section 4 provides concluding remarks.

2 Data and Methodology

2.1 Data description

The dataset includes the daily closing prices as well as the log returns of gold, 3 stock indices (the MSCI World Index, S&P500, FTSE100) and Bitcoin. The MSCI World Index is made up of approximately 1950 constituents, from 23 developed countries [25]. The S&P500 is a composite index comprising 500 prominent publicly traded US companies, and its weights are determined based on market capitalization. On the other hand, the FTSE100 index represents a share index of the 100 companies listed on the London Stock Exchange, with their rankings determined by the highest market capitalization. We selected these stock indices based on their worldwide prominence, making them representative indicators of global stock market performance. The data spans nearly 23 years, starting from the 1st of January 2000 and extending until the 31st of May 2023, except for Bitcoin which spans from the 1st of January 2014 to the 31st of May 2023 due to the fact that it only gained prominence in 2014, due to the collapse of Mt. Gox (which was the largest Bitcoin exchange at the time) and financial platforms started to track it closely.

The return on the t^{th} day, when compounded continuously, is defined as follows,

$$r_t = \log\left(\frac{p_{t+1}}{p_t}\right), \tag{1}$$

where p_t represents the price on the t^{th} day [26]. The 5 number summary of the returns' descriptives computed with Equation (1) are illustrated in Figure 1 for the prices of gold, S&P500, FTSE100 and World index; these descriptives are further discussed in Section 3.1.

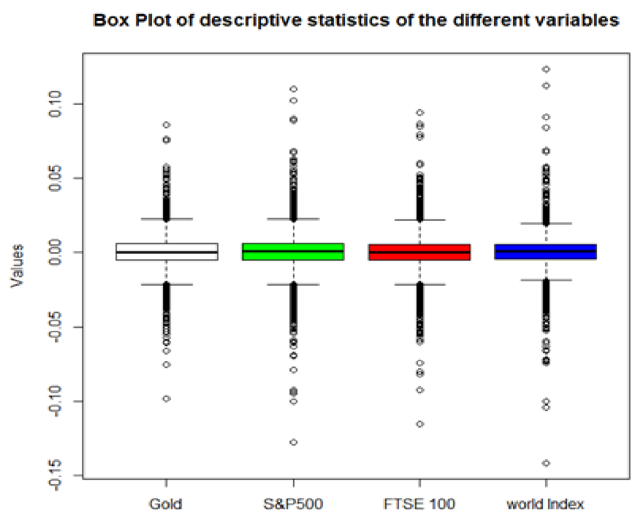


Fig. 1: Summary of the log returns of the stock indices and gold

2.2 GARCH model (volatility)

An inherent challenge in the modelling of financial time series is the presence of heteroskedastic effects, indicating that the volatility of the underlying process is typically not constant. In this context, volatility refers to the square root of the conditional variance of the log return process given its past values. Specifically, if p_t represents the time series value at time t, the log returns are defined as per Equation (1), and the volatility σ_t, where,

$$\sigma_t^2 = Var[r_t^2|F_{t-1}], \tag{2}$$

where, F_{t-1} represents the σ-field generated by the log returns from time 0 to $t-1$. Intuitively, it is reasonable to expect that the volatility of such processes would change over time due to various economic and political factors, and this phenomenon is a well-known stylized fact in mathematical finance.

To address this issue, [27] introduced the autoregressive conditional heteroskedasticity (ARCH) models. These models incorporate an autoregressive structure for the conditional variance process and model log returns as white noise multiplied by the volatility:

$$r_t = e_t\sigma_t \tag{3}$$

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \cdots + \alpha_p r_{t-p}^2, \tag{4}$$

where, the e_t are independent and identically distributed (iid) with a mean of 0 and a variance of 1. They are assumed to be independent of σ_k for all $k \leq t$. The lag length, $p\ (p \geq 0)$, is a part of the model specification and can be determined using tests for autocorrelation significance like the Box-Pierce test. To ensure that σ_t^2 remains positive, it is required that ω and α_i are non-negative for all i. Within the ARCH framework, a substantial disturbance often leads to subsequent substantial disturbances, resembling the pattern of volatility clustering seen in asset returns [28].

While the ARCH model is straightforward, it frequently demands a significant number of parameters to describe the volatility dynamics of an asset's return. [29] extended the ARCH model to allow σ_t^2 to have an additional autoregressive structure within itself, resulting in the GARCH(p, q) (generalized ARCH) model:

$$r_t = e_t \sigma_t \quad (5)$$

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \cdots + \alpha_p r_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2. \quad (6)$$

In particular, the simpler GARCH($1,1$) model has gained widespread popularity in financial time series modeling and is implemented in most statistics and econometric software packages. GARCH($1,1$) models are preferred over other stochastic volatility models due to their relatively straightforward implementation. These models are defined by stochastic difference equations in discrete time, making the likelihood function more manageable compared to continuous-time models. This is advantageous given that financial data is generally collected at discrete intervals. We estimated the conditional volatility using a GARCH($1,1$) model, because it has been found to outperform various GARCH (p, q) models for various stock returns; see [8], [30] and [31].

2.3 Rolling window correlation

In real-world scenarios, there might be constraints on the amount of available data for accurately estimating the stationary distribution of market parameters. To tackle this issue, a method called rolling analysis can be applied. Rolling analysis entails the generation of 'fresh' observations by using consecutive data sets, see [32]. For example, if you have a series of returns represented as $\{r_t\}$ and aim to calculate an aggregated return over a duration ΔT, you can take the $\{r_t\}$ dataset and divide it into non-overlapping sub-samples of equal size, each containing $T/\Delta T$ observations. Subsequently, you can compute summary statistics of the stationary distribution, such as the mean and variance, based on these sub-samples. However, this approach may encounter difficulties when the dataset size, denoted as T, is not sufficiently large, leading to potential inaccuracies due to the limited number of aggregated observations for ΔT. The latter is not a problem for this study as we gathered many observations, with the lowest sample size being above 2300 observations. A preferred alternative is to implement rolling analysis. Instead of dividing the sample into non-overlapping sub-samples, rolling analysis involves moving a data window forward one observation at a time. Assuming that $\{r_t\}$ is a stationary time series with a mean μ_r and autocovariance function $\gamma_r(.)$, according to [32] the rolling-returns, denoted as $\{\tilde{r}_t\}$, can be defined as follows:

$$\tilde{r}^{(\Delta T)}(k) = \sum_{t=k}^{k+\Delta T-1} r_t \quad (7)$$

with $k = 1, \ldots, T - \Delta T + 1$. By rewriting this process as

$$\tilde{r}^{\Delta T}(k) = \mu_{\tilde{r}} + \sum_{t=k}^{k+\Delta T-1} (r_t - \mu_r) \quad (8)$$

where $\mu_{\tilde{r}} = \Delta T \mu_r$, it is evident that $\tilde{r}^{(\Delta T)}$ represents a moving average process of order ΔT with mean and variance given by:

$$E\left(\tilde{r}^{(\Delta T)}(k)\right) = \mu_{\tilde{r}} \quad (9)$$

$$Var\left(\tilde{r}^{(\Delta T)}(k)\right) = \Delta T \sigma_r^2 = \sigma_{\tilde{r}}^2. \quad (10)$$

In this context, the innovations are represented by $\{r_t - \mu_r\}$. Assuming that $\{r_t - \mu_r\}$ follows an independent and identically distributed distribution with a mean of 0 and variance σ_r^2, it can be concluded that $\{\tilde{r}(t)\}$ is indeed stationary with a mean of $\mu_{\tilde{r}}$ and a variance of $\Delta T\sigma_r^2$, and an autocovariance function $\gamma_r(.)$, with no lags beyond ΔT. Rolling analysis offers benefits such as additional observations and maintained stationarity of the return distribution.

2.4 Vector autoregressive (VAR) model

Vector autoregressive (VAR) models have been pivotal in macroeconomic analysis since the work of Sims in 1980, see the review by [33]. VAR modeling is a statistical technique used to analyze the relationships between multiple time series variables. In a VAR model, you work with a system of multiple time series variables, often denoted as $y_1, y_2, \dots, y_p$, where p is the number of variables in the system. The key idea is that each variable in the system is modelled as a linear combination of its past values and the past values of the other variables in the system. This allows you to capture the interdependencies and feedback loops between the variables.

The general form of a VAR(p) model is [34]:

$$r_t = c + \Phi_1 r_{t-1} + \Phi_2 r_{t-2} + \cdots + \Phi_p r_{t-p} + \varepsilon_t \tag{11}$$

where, r_t is a $p \times 1$ vector of returns at time t, c is a $p \times 1$ vector of constants, Φ_t are $p \times p$ matrices of coefficient parameters and ε_t vector of error terms at time t.

VAR models are often estimated using methods like least squares, maximum likelihood, or Bayesian techniques. Once estimated, VAR models can be used for various purposes. We estimated our VAR model using maximum likelihood and we employed it to help us further understand the interactions between the daily log returns of gold and the other variables. We also ran an ordinary least squares (OLS) regression to identify non-stationarity in the time series data. Stationarity is an essential assumption for VAR modeling. VAR modelling and analysis is undertaken according to the steps outlined in Table 1 and these steps were compiled using the diagram in [35].

Table 1: A breakdown of the VAR model analysis process

Step 1	Specifying and estimating a reduced form of a VAR model
Step 2	Checking the model for reasonableness, if the model is found not to be reasonable it is rejected, and Step 1 is repeated.
Step 3	If the model is not rejected, the VAR model can then be used for 3 purposes: forecasting, Granger causality analysis or structural analysis.
Step 4	Structural analysis can be broken down into: • Analysis of forecast scenarios. • Historical decomposition. • Impulse response analysis. • Forecast error variance decomposition (FEVD).

While the VAR estimates provide insights into the temporal relationships between the modelled variables, further diagnostic tests are needed to assess the VAR model's validity and reliability comprehensively. Additional tests will be conducted to offer a comprehensive evaluation of the model's performance. After estimating the VAR and understanding the interactions that gold has with our other variables, we will be able to then look at the Granger causality tests, the impulse response functions, CUSUM test and variance decomposition for each of the variables in order to diagnose the model (to read up more on VAR analysis, see [35]). The diagnostic analysis was broken down as follows:

- *Granger causality analysis*: Granger causality is a crucial concept in VAR models, helping us understand how changes in one variable may influence another. It enables us to assess the existence of a causal relationship by statistically evaluating whether including lagged values of certain variables, such as FTSE100, S&P500, World Index, and Bitcoin, enhances the predictive accuracy for the target variable, gold. If using past values of one variable improves the prediction of another, it provides evidence supporting Granger causality.

- *Structural analysis*:

  - The CUSUM chart is a valuable tool for monitoring process stability over time, particularly in identifying shifts, structural breaks, and changes in the mean of a time series. In the context of our VAR model, the CUSUM chart becomes even more important as it helps evaluate the effectiveness of the estimated coefficients in capturing the dynamics of the underlying model for each variable concerning gold.

  - The Impulse Response Function (IRF) is a valuable tool for understanding how variables in a model react to temporary changes or shocks in one or more variables. It considers potential feedback effects among these variables, see [36]. In essence, the IRF helps us measure and comprehend the changes in a VAR model by showing how other variables in the system are influenced over time when there's a shock to a particular variable. It reveals the magnitude and direction of the response in both the short and long term and whether the variables take a while to react to the shock.

- Forecast error variance decomposition (FEVD) is a crucial analytical technique that goes beyond the insights gained from the VAR model. Instead of just examining how past variables affect each other immediately, it delves into understanding the factors that contribute to the overall variability in each variable, providing insights into their relationships. Variance decomposition breaks down the overall variability into an endogenous component and an exogenous component.

2.5 Hedging and safe haven properties

The econometric methodologies for examining the protective attribute of gold are introduced. We posit that fluctuations in the stock market impact the value of gold and consider the connection to be variable, i.e., influenced by distinct and exceptional market circumstances.

$$r_{Gold,t} = a + b_t r_{stock,t} + e_t \tag{12a}$$

$$b_t = c_0 + c_1 D(r_{stock} q_{10}) + c_2 D(r_{stock} q_5) + c_3 D(r_{stock} q_1) \tag{12b}$$

$$h_t = \pi + \alpha e_{t-1}^2 + \beta h_{t-1} \tag{12c}$$

Equations (12a), (12b), and (12c) outline the main regression model used to assess the safe haven characteristic of gold, in accordance with [8]. Equation (12a) maps out the portrayal of the connection between gold and stock returns. The parameters necessitating estimation encompass a and b_t, while the error is indicated by the e_t error term. The b_t parameter is formulated as a dynamic process as outlined by Equation (12b). The parameters up for estimation within Equation (12b) are c_0, c_1, c_2 and c_3. The binary variables, $D(\cdot)$, encapsulate pronounced movements in the stock market and hold a value of one if the stock market surpasses a specific threshold from the 10%, 5% or 1% quantiles of the return distribution.

The presence of a non-zero value in any of the parameters c_1, c_2 and c_3 signifies the existence of a non-linear interrelation between gold and the stock market. In the event that the parameters within Equation (12b) are negative (inclusive of c_0), gold performs as a weak safe haven for the studied market. Should these parameters hold a negative value while being statistically distinct from zero, gold functions as a strong safe haven. Also, note that gold operates as a hedging mechanism for the examined market when c_0 assumes a zero value (indicative of a weak hedge) or a negative value (indicative of a strong hedge), and the cumulative value of c_1 through c_3 collectively fails to be positively inclined beyond the magnitude of c_0. Lastly, Equation (12c) reintroduces a GARCH(1,1) model to model the variance (defined as h_t) in the residuals of the regression, constructed in a similar way to Equation (6), effectively addressing heteroskedasticity within the data. Equations (12a), (12b), and (12c) are concurrently appraised through the lens of maximum likelihood estimation. Equation (12b) is tailored to focus on instances of notably adverse returns, thus modeling the potential non-linear aspects of the gold-stock index return relationship. The existence of non-linearity in this context implies differential investor behavior in moments of extreme market circumstances as opposed to more typical conditions.

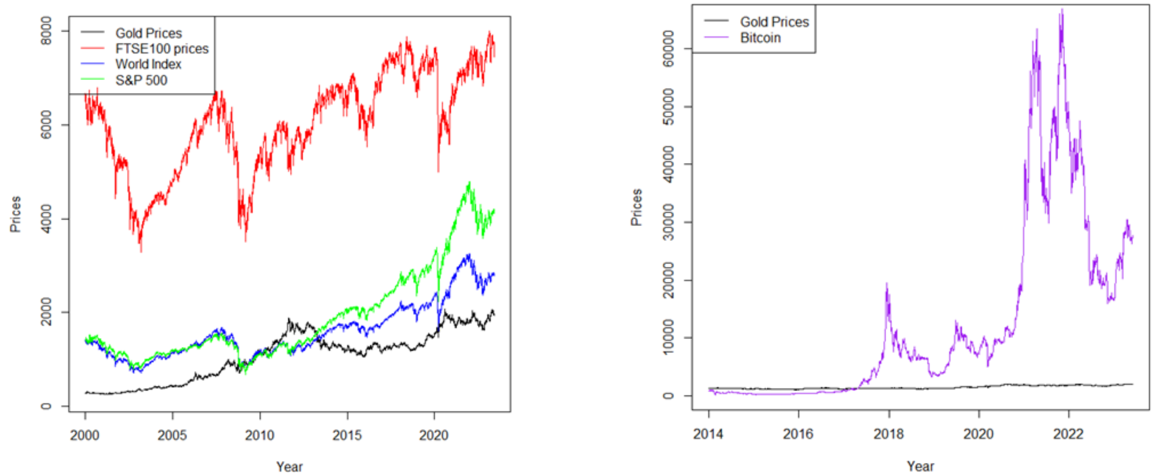
3 Analysis

3.1 Descriptive statistics

The empirical summary of the indexes outlined in Figure 1 are provided in Table 2. The gold market appeared to be the most stable, having the lowest standard deviation, the smallest range and the highest average daily return. Bitcoin on the other hand exhibits the most volatility with the largest standard deviation as well as the widest range.

Table 2: The descriptive statistics of all the variables based on the daily log returns

	Observations	Mean	Standard Deviation	Minimum	Maximum
World Index	5 836	0.000118	0.011170	-0.141466	0.123182
Gold	5 836	0.000335	0.011045	-0.098105	0.085890
S&P500	5 836	0.000189	0.012523	-0.127652	0.109572
FTSE100	5 836	0.000001	0.011768	-0.115124	0.093843
Bitcoin	2 351	0.001464	0.059919	-0.848829	1.474180



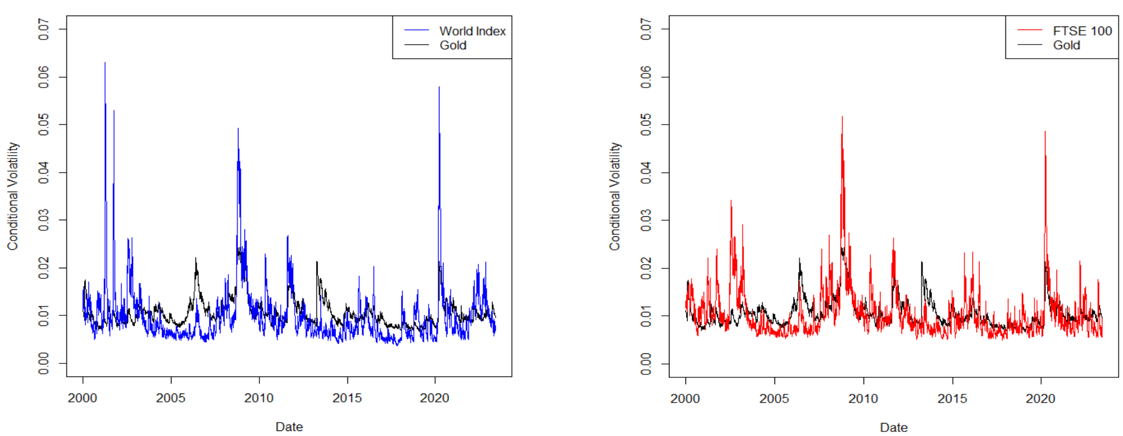
(a) (b)

Fig. 2: The evolution of the different markets' price over the 23-year period (2000 to 2023). (a) contains the prices of all the stock indices and gold. (b) contains the prices of Bitcoin and gold from 2014 to 2023.

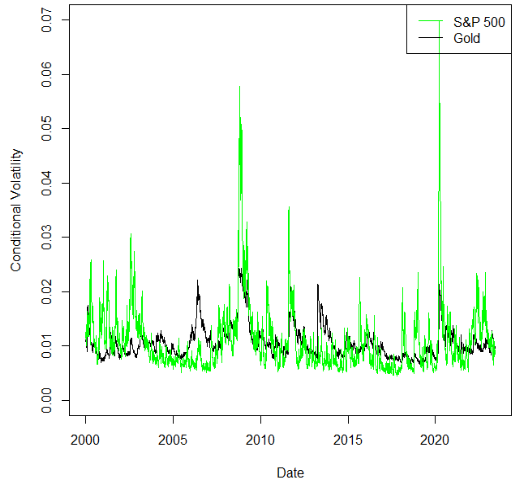
Figure 2 is a good visualization of observed daily price movements. In Figure 2(a) we can see that the World Index started the century at a price of approximately \$1400 and is up to approximately \$2700 in 2023, with the highest peak at approximately \$3300 in 2021. Gold started the century at a price of approximately \$200 and is up to approximately \$1900 in 2023, reaching its highest peak of approximately \$2000 in 2020. S&P500 started at approximately \$1500 and has risen to approximately \$4000, with its highest peak at approximately \$4500 in 2022. FTSE100 started at approximately \$6500 and is up to approximately \$7800 in 2023, reaching its highest peak of approximately \$8000 in 2023. Bitcoin started at approximately \$900 in 2014 and rises to approximately \$30000 in 2023, reaching its highest peak of approximately \$75000 in 2021. The prices on the World Index and S&P500 exhibit very similar trends, which may be an indication of the US having the largest coverage in the World Index. There is a distinct dip in the returns of all the indices in 2002, 2008 and 2020, and gold does not appear to sustain any decreases in the two periods with the exception of 2008.

3.2 Conditional Volatility

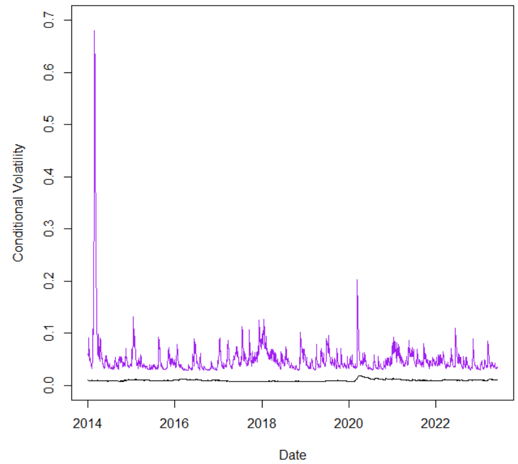
Figure 3 illustrates the changing volatility over time in various return series analyzed using a GARCH(1,1) model, fitted by using $p = 1$ and $q = 1$ in Equation (6). In the 23-year analysis of daily log-returns in different markets, distinct patterns in conditional volatility emerge. In Figure 3(a) the World Index's conditional volatility starts relatively low but experiences spikes around 2001-2002, 2007, and 2020. Gold's conditional volatility begins high and gradually declines until a period of elevated volatility from 2007 to 2014, coinciding with the GFC. This can be contrasted with the observations in Figure 3(b), S&P500 initially settles into stable conditional volatility but sees noticeable rises from 2007 to 2012 and a massive spike in 2020. Additionally, in Figure 3(c), FTSE100 experiences a steady rise in conditional volatility with spikes in 2001-2002, 2007, and 2020, and Bitcoin's volatility, as seen in Figure 3(d), remains low until a small spike in 2020.



(a) (b)



(c)



(d)

Fig. 3: The evolution of the daily conditional volatility (i.e. GARCH(1,1) estimates) of the different markets over the 23-year period: (a) Gold vs MSCI World Index, (b) Gold vs FTSE100, (c) Gold vs S&P500 and (d) Gold vs Bitcoin.

The observed volatility patterns correlate with significant events and market sentiment shifts, including the Dot.com Bubble burst and the 9/11 attacks in 2001-2002, the 2007-2009 GFC, and the COVID-19 pandemic in 2020-2022. The World Index was affected the most by the Dot.com bubble and 9/11 attack, while S&P500 was particularly impacted by the 2008 GFC and the COVID-19 pandemic. Throughout these crises, gold's volatility remains relatively stable when compared to the indices considered here and Bitcoin.

3.3 Rolling window correlation

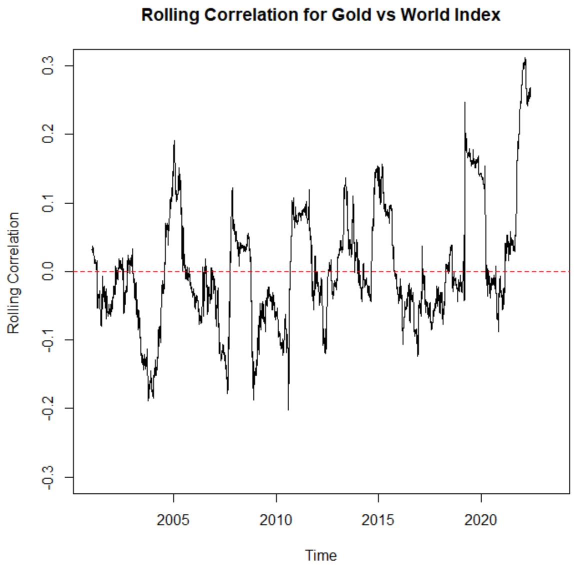
Figure 4 displays the rolling correlation between different indices and gold with the ΔT, the moving window, in Equation (8) equal to 250. This approach provides insights into changing relationships over time. Gold does not maintain a long-term stable correlation with any of the indices, but short periods of moderate stability are observed, this lack of stability is an indication of gold's inability to be a diversifier or a long-term hedge for any of the indices, according to the commonly used [7] definition of a hedge.

The World Index, see Figure 4(a), has a predominantly negative relationship with gold from 2000 to 2002, followed by more extreme negatives in 2004, this may be an indication of the extended effects of 9/11 and the Dot.com bubble burst. Post-2004, the relationship becomes highly volatile, with distinct troughs in 2007, 2009, and late 2010, coinciding with the advancement of the GFC. After 2010, it gradually moves toward zero, with minor dips in 2012 and a positive correlation period until 2015. From 2015, the relationship approached zero again, with a surge in 2017 and sustained positivity until 2018/19. It became negative in 2019/20, coinciding with the COVID-19 pandemic and has its highest surge into positivity in 2022.

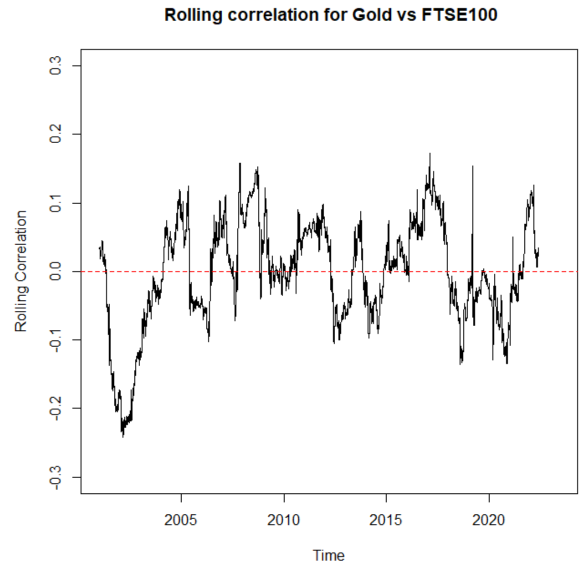
In Figure 4(b), S&P500 has a consistently negative relationship with gold in the early 2000s, persisting until 2004/05. From 2005, the relationship becomes volatile, settling into negatives from 2007 to 2009. After 2009, another volatile period begins (this could be as a result of the long-term effects of the GFC), with notable troughs in 2011/12 and 2013/14. The relationship remains positive until 2016, turns volatile again, briefly positive in 2017, and then becomes strongly negative from 2018 to 2020. Post-2020/21, the correlation becomes fairly positive.

In Figure 4(c), FTSE100 exhibits a strictly negative relationship with gold from 2000 to 2004, with the most extreme trough in 2001. After 2001, the relationship gradually becomes positive until late 2004. High volatility is observed between 2005 and 2009, with troughs in 2006/2007 and 2008. Post-2009, the relationship fluctuates around zero until early 2010, followed by another period of high volatility until 2015, with a peak correlation of about 0.8. In 2015, a positive correlation emerges but lasts briefly as the relationship turns volatile until 2018. Post-2018, a strictly negative correlation persists until a sudden spike in 2019, followed by a negative correlation until 2022, after which it remains positive.

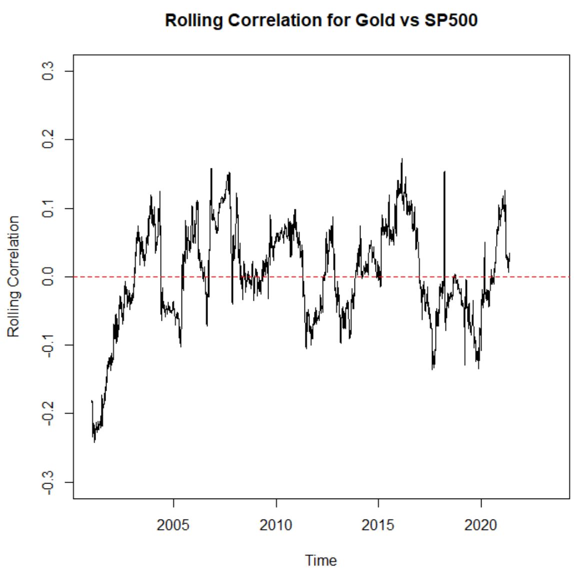
Lastly, in Figure 4(d), The relationship between Bitcoin and gold hovers around zero, with a strictly negative period from 2014 to 2016. From 2016 to 2019, it stabilizes around zero, dips into negatives in 2019, and rapidly turns positive in 2020. From 2021, it fluctuates around zero and gradually becomes positive. This observation alludes to gold being a zero-beta asset as suggested by [4] and having possible diversification benefits in a portfolio that includes Bitcoin.



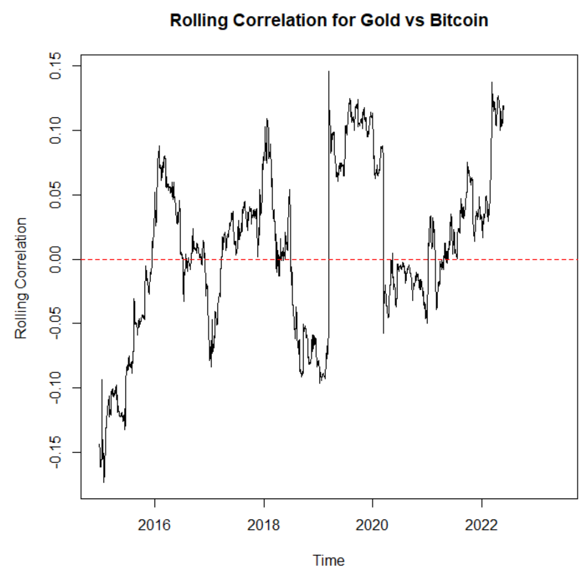
(a)



(b)



(c)



(d)

Fig. 4: The rolling window correlations of the respective indices with gold based on daily log returns with $\Delta T = 250$.

All the variables appear to maintain a negative relationship with gold during crisis periods, also known as bear markets. The World Index, S&P500 and FTSE100 experience prolonged negative correlations with gold in the early 2000s and this is possibly an indication that the indices themselves took a while to recover from the effects of 9/11 and the Dot.com bubble burst. FTSE100's relationship with gold is the most volatile prior to the GFC and S&P500's relationship with gold is the most volatile post the GFC. S&P500 also appears to be the first to have a negative relationship with gold leading up to the COVID-19 pandemic, with FTSE100 retaining a negative relationship for the longest period. Bitcoin on average maintains an independent relationship with gold, with the relationship even being positive in 2021 during the COVID-19 pandemic, this may be an indication that Bitcoin may have had hedging benefits during the pandemic, alluding to the observations made by [16] and [18] in their respective studies. In general, gold appears to exhibit negative relationships with the stock indices leading up to, during and after the periods of high volatility and decreasing prices identified in Sections 3.1 and 3.2.

3.4 VAR model

3.4.1 VAR model estimates

The VAR model analysis examines how various variables interact with gold at different time lags, up to a lag of 7. The *VARselect* function on R was used to find the best possible lag to fit our model. This function returns information criterion such as the AIC (Akaike information criteria) and gives a final prediction of the lag order based on the variables from our dataset. In this function, a lag max of 100 was chosen as an initial guess. After running the function using the AIC as a main criterion, a lag of 7 was chosen for all the variables, see Table 3.

Table 3: VAR (7) model estimates (rounded to 6 decimal places) at each lag

Model	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
Gold	-0.045427	0.024252	0.025104	0.028782	-0.022237	-0.014046	-0.064761*
FTSE100	0.018858	-0.018983	-0.023179	0.045161 *	0.062845 *	0.060514 *	0.042681
Gold	-0.012387	-0.006724	0.012822	0.005546	-0.001875	-0.040896 *	-0.033375 *
S&P500	0.006099	0.003727	-0.005219	-0.026791 *	0.004486	-0.007411	0.031809 *
Gold	-0.012086	-0.006841	0.012199	0.005401	-0.001474	-0.039756 *	-0.034528 *
World Index	0.005728	-0.004585	-0.004657	-0.016107	0.009978	-0.016406	0.040059 *
Gold	-0.025546	-0.011009	0.029094	0.004608	-0.018825	-0.048685 *	-0.013911
Bitcoin	0.003383	0.002793	0.001231	-0.000144	-0.002029	-0.003786	-0.004550

* Displayed for significance level of 5%.

The study focuses on the interactions between gold and different indices, starting with the FTSE100 Index. Notable findings include significant interactions at lags 4, 5, 6, and 7. For instance, at lag 4, 5, and 6, a one-unit increase in FTSE100 returns positively influences gold returns. However, at lag 7, gold exhibits a negative self-impact, causing a decline in gold returns after 7 lags. This is an indication that the FTSE100 and gold have more significant effects on each other's returns over a longer lag period. The S&P500 and gold interaction also reveal significant estimates at lags 4, 6, and 7. Notably, at lag 4, a one-unit increase in S&P500 returns leads to a decrease in gold returns, while lag 6 shows a negative self-impact of gold. However, at lag 7, S&P500 returns positively affect gold returns, though gold itself negatively impacts its future returns. The interaction between the World Index and gold shows significance at lags 6 and 7. At both lags, gold negatively self-impacts its returns, while at lag 7, the World Index has a positive impact on gold returns. Conversely, the interaction between Bitcoin and gold only has a significant estimate at lag 6, where gold negatively impacts itself. In this study, gold generally appears to only be significantly impacted by the returns at latter lags and most of the effects from the other variables' returns are positive, with the negative impact being exerted by gold on itself, see also [12] for similar discussions.

3.4.2 Granger causality analysis

Table 4 employs a 95% confidence level (5% significance level) to assess the causal relationships between variables. In the case of the FTSE100 index and gold, the p-value for FTSE100's influence on gold is 0.00161, indicating a Granger causal effect of FTSE100 returns on gold returns. However, the converse, gold's causality on the FTSE100 index, is not supported, with a p-value of 0.34200, suggesting that gold does not significantly influence FTSE100 returns. For the S&P500 index and gold, both directions show causality effects. S&P500 has a causal effect on gold returns with a p-value of 0.04773, and gold has a causality effect on S&P500 returns with a p-value of 0.00158. This could be due to the global significance of gold, which is priced in US dollars and has a substantial impact on the S&P500 due to its status as a major commodity. The World Index exhibits minimal Granger causality on gold returns, as the p-value is 0.055090. However, the reverse direction, where gold returns influence the World Index returns, is supported with a very low p-value of 0.000001, indicating that gold returns do Granger cause World Index returns. In contrast, there is no causal relationship between Bitcoin returns and gold returns, as indicated by the p-value of 0.524800, and gold returns do not have a causal effect on Bitcoin returns. This lack of causality could be attributed to Bitcoin's decentralized and less regulated nature, which sets it apart from gold. In summary, the analysis identifies Granger causal effects in some interactions, especially involving S&P500 and gold, while others, like Bitcoin and gold, show no significant causal relationship.

Table 4: VAR results from the Granger causality tests between gold, FTSE100, S&P500, World Index and Bitcoin

Null hypothesis	F-statistic	p - value	Direction
FTSE100 does not Granger cause gold returns	3.314300	0.00161*	FTSE100 ➔ Gold
Gold does not Granger cause FTSE100 returns	1.128300	0.342000	Gold ➔ FTSE100
S&P500 does not Granger cause gold returns	2.029500	0.047730*	S&P500 ➔ Gold
Gold does not Granger cause S&P500 returns	3.314500	0.001580*	Gold ➔ S&P500
World Index does not Granger cause gold returns	1.970400	0.055090	World Index ➔ Gold
Gold does not Granger cause World Index returns	5.842200	0.000001*	Gold ➔ World Index

Bitcoin does not Granger cause gold returns	0.087600	0.524800	Bitcoin ➔ Gold
Gold does not Granger cause Bitcoin returns	1.462800	0.175700	Gold ➔ Bitcoin

* Displayed for significance level of 5%.

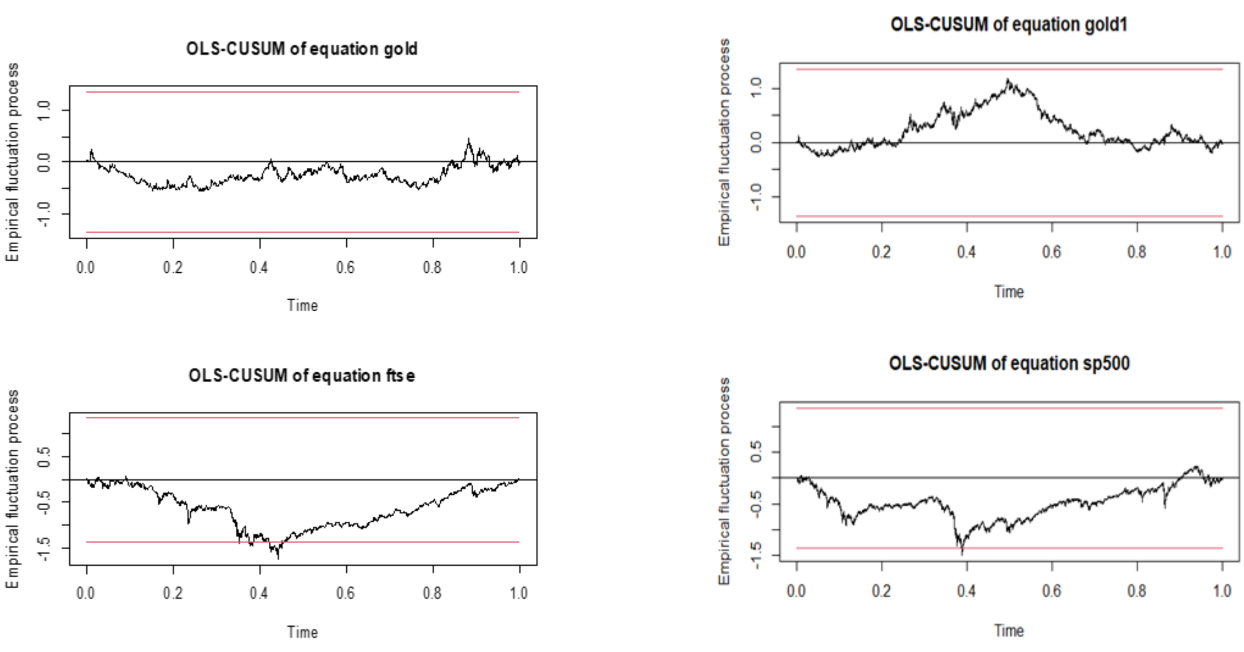
Table 4 employs a 95% confidence level (5% significance level) to assess the causal relationships between variables. In the case of the FTSE100 index and gold, the p-value for FTSE100's influence on gold is 0.00161, indicating a Granger causal effect of FTSE100 returns on gold returns. However, the converse, gold's causality on the FTSE100 index, is not supported, with a p-value of 0.34200, suggesting that gold does not significantly influence FTSE100 returns. For the S&P500 index and gold, both directions show causality effects. S&P 500 has a causal effect on gold returns with a p-value of 0.04773, and gold has a causality effect on S&P 500 returns with a p-value of 0.00158. This could be due to the global significance of gold, which is priced in US dollars and substantially impacts the S&P500 due to its status as a major commodity. The World Index exhibits minimal Granger causality on gold returns, as the p-value is 0.055090. However, the reverse direction, where gold returns influence the World Index returns, is supported with a very low p-value of 0.000001, indicating that gold returns do Granger cause World Index returns. In contrast, there is no causal relationship between Bitcoin returns and gold returns, as indicated by the p-value of 0.524800, and gold returns do not have a causal effect on Bitcoin returns. This lack of causality could be attributed to Bitcoin's decentralized and less regulated nature, which sets it apart from gold.

For the period considered in this study, the analysis identifies Granger causal effects in some interactions, especially involving S&P500 and gold; however, Bitcoin and gold, show no significant causal relationship.

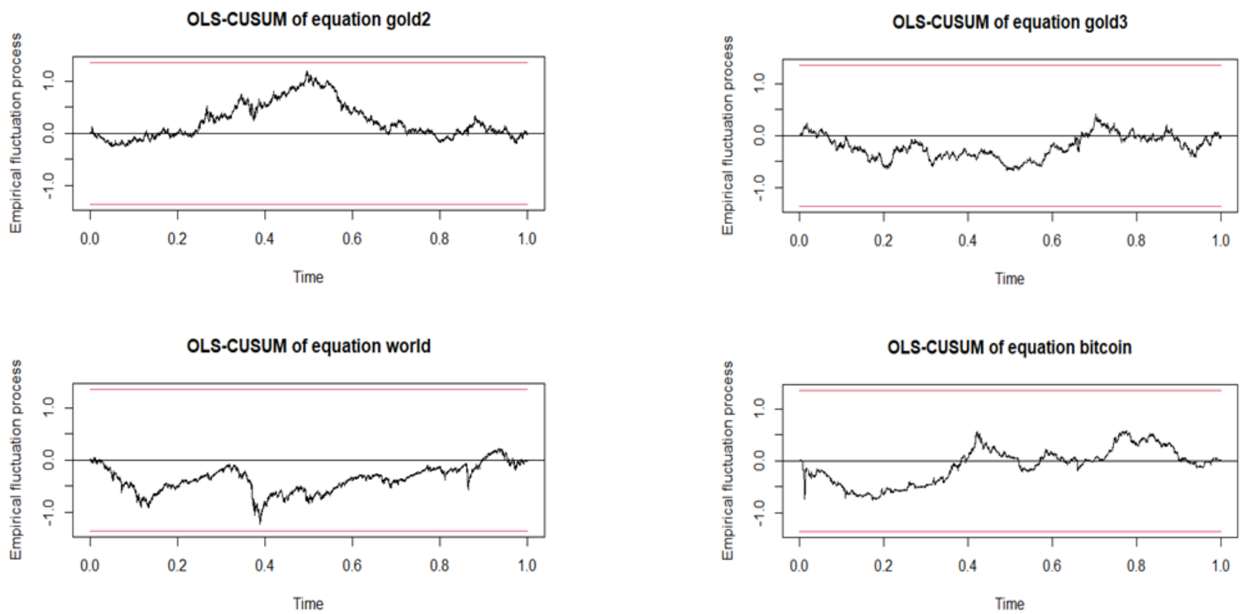
3.4.3 Structural analysis

CUSUM charts

Keeping in mind that the purpose of the CUSUM chart monitoring process stability over time, particularly in identifying shifts, structural breaks, and changes in the mean of a time series. Then in Figure 5, the FTSE100, S&P500, MSCI World index and Bitcoin are respectively compared with the corresponding empirical fluctuation of gold. Note that gold, gold1, gold2 and gold3 on Figures 5(a) to 5(d) denote the same period for the gold dataset, this is done to avoid confusing the reader when monitoring gold against each of the variables. More specifically, in Figure 5(a), the CUSUM chart demonstrates slight deviations in gold returns from the baseline, mainly in a negative direction. However, these deviations do not lead to a structural break in gold returns when the FTSE100 index is considered, as the fluctuations remain within the 95% confidence interval (or equivalently, there is no point that plots beyond the control limits). On the other hand, the FTSE100 index exhibits a significant negative deviation from the baseline, causing a structural break at around time 0.4 (there is a point that plots beyond the lower control limits for the FTSE100). This prominent structural break occurs in 2008 during the GFC, indicating a shift in FTSE100 returns. Although the fluctuations quickly recover, the returns remain negative.

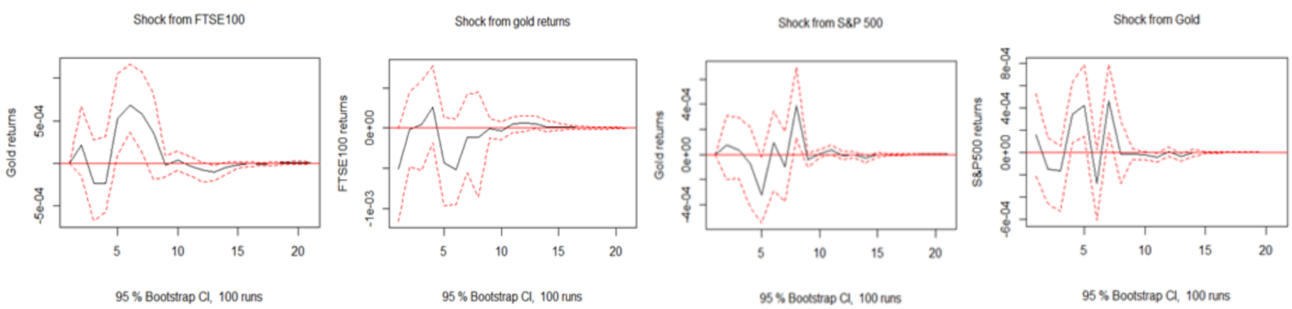


(a) (b)

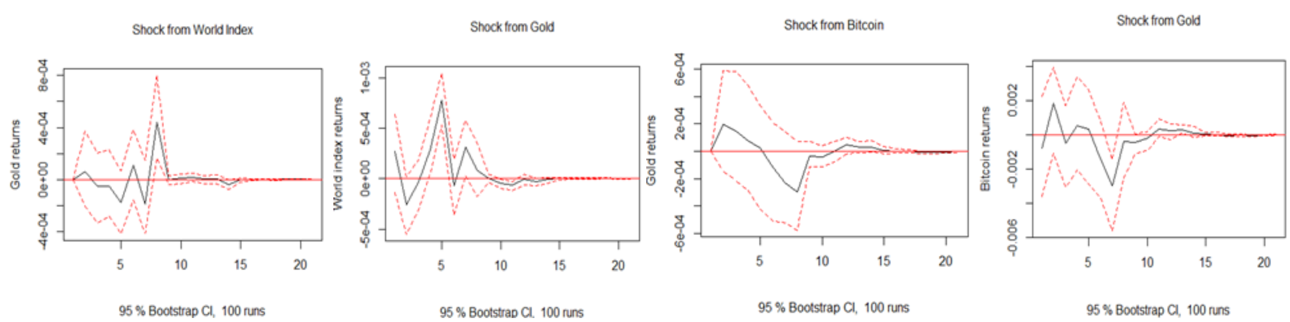


(c) (d)

Fig. 5: Cumulative sum chart of the independent variables (FTSE100, S&P500, World Index and Bitcoin) against the dependent variable (gold).



(a) (b) (c) (d)



(e) (f) (g) (h)

Fig. 6: Impulse response functions. (a) shows a shock on FTSE100 and how gold returns respond; (b) shows a shock on gold returns and how FTSE100 returns respond; (c) shows a Shock on S&P500 and how gold returns respond; (d) shows a shock on gold returns and how S&P500 returns respond; (e) shows a shock on the World Index and how gold returns respond; (f) shows a shock on gold returns and how World Index returns respond; (g) shows a shock on the Bitcoin and how gold returns respond; (h) shows a shock on gold returns and how Bitcoin returns respond.

Similar negative deviations are observed in the S&P500, see Figure 5(b), with another structural break occurring during the GFC (there is a point that plots beyond the control limits for S&P500). However, this break is not as severe as in the

FTSE100 index. This unexpected result may be due to the ability of the US, represented by the S&P500, to recover relatively quickly from the crisis. Notably, during most of the period, gold shows a positive deviation in the presence of S&P500 returns, possibly reflecting the S&P500's ability to recover from the crisis. In contrast, there are no structural breaks in gold returns when considering the World Index and Bitcoin returns, see Figure 5(c) and 5(d), and similarly in the opposite direction. Overall, when testing the model's stability, it becomes evident that gold does not exhibit any structural breaks in the presence of the variables analysed.

Impulse Response analysis

The results below determine all the factors stated in Section 2.4 under Impulse response analysis. Figure 6 examines the response of gold to shocks in various indices. When FTSE100 returns experience a shock, Figure 6(a), they initially have a strong positive effect on gold for the first two periods, followed by a slight decline until just before period 5. Then, there's an increased positive effect until period 10, with a minor dip just before period 10 before settling at zero. Conversely, the shock on gold returns does not appear to have a significant impact on FTSE100 returns.

For the shock in S&P500 returns and its effect on gold, Figure 6(c), there is a low positive effect for the first four periods, followed by a negative period between 4 and 6, with an increase starting from period 5. The response remains slightly positive for a brief time before turning negative again after period 9. The shock in gold returns, Figure 6(d), initially has a negative effect on S&P500 returns for four periods but becomes positive for a short time between period 4 and 6. The response fluctuates between negative and positive from the 6th period to the 8th, and it settles at zero after period 8.

In the case of a shock on the World Index and its effect on gold, Figure 6(e), there's an initial positive reaction that declines after approximately the 2nd period. Negative effects occur from period 2 to 5 and briefly between period 7 and 8. The response settles at zero before period 10, and the confidence intervals suggest that the World Index would have a significant impact on gold if a shock were to occur, particularly after period 7. Conversely, the shock in gold returns on the World Index, Figure 6(f), shows a continuous rise and fall in the effect. The confidence intervals indicate periods of higher significance, with a lower margin for error occurring from period 4 to 6.

For the shock in Bitcoin and its impact on gold, Figure 6(g), there is an initial positive effect that persists until the 5th period, followed by a dip and a negative effect up to the 11th period. The room for error in the plot suggests that the effect of a Bitcoin shock on gold is likely to be minor but not entirely negligible. Conversely, the response to a shock in gold on Bitcoin, Figure 6(h), follows a similar pattern of initially positive, then alternating between negative and positive for the remaining periods, eventually settling at zero. The effect of a gold shock on Bitcoin is also likely to be insignificant but not entirely dismissible.

Additionally, the upper and lower bound confidence intervals show a range within which the impulse response may vary. For instance, in Figures 6(g) and (h) it can be seen that the impulse response functions between gold and Bitcoin appear to have the largest room for variation, which may be an indication of the independence between the two assets' returns. The impulse response functions of gold and S&P500 returns, Figures 6(c) and 6(d), do however appear to have little room for variation, which may be an indication of them being quite dependent on each other. We can also see that the upper and lower bound confidence intervals in Figure 6 remain on opposite sides of zero for all the plots, so it is difficult to say whether the impact of the various shocks is strictly positive or negative.

Forecast error variance decomposition (FEVD)

Key observations from the variance decomposition plots in Figures 7(a) to 7(d) for each of the four variables against gold are as follows: (NB: gold, gold1, gold2 and gold3 on Figure 7 denote the same period for the gold dataset, this is done to avoid confusing the reader when conducting time horizon comparison against other variables)

- **Gold's Self-Variability:** In all four plots, gold is found to contribute to its own variability, indicating that changes in gold prices are largely driven by its own past values. Gold's price movements are not significantly influenced by the independent variables included in the model. This is in line with sub-section 3.4.1 where previous gold returns appear to have significant impact on its current returns.
- **Influence on Independent Variables:** In contrast, when considering the influence of gold on the independent variables, a small percentage of the variability in the independent variables is attributed to gold. This suggests that while gold's price changes are self-driven, it does have a minor impact on the variability of the other variables, albeit over varying time horizons.
- **Differing Time Horizons:** One notable difference among the variabilities is the time horizons at which they manifest. The World Index and S&P 500 begin to show the influence of gold at periods 4 and 5, respectively, indicating a delayed response. FTSE 100 starts at period 0, indicating an immediate impact, while Bitcoin shows the influence of gold after a delay, starting at period 6.

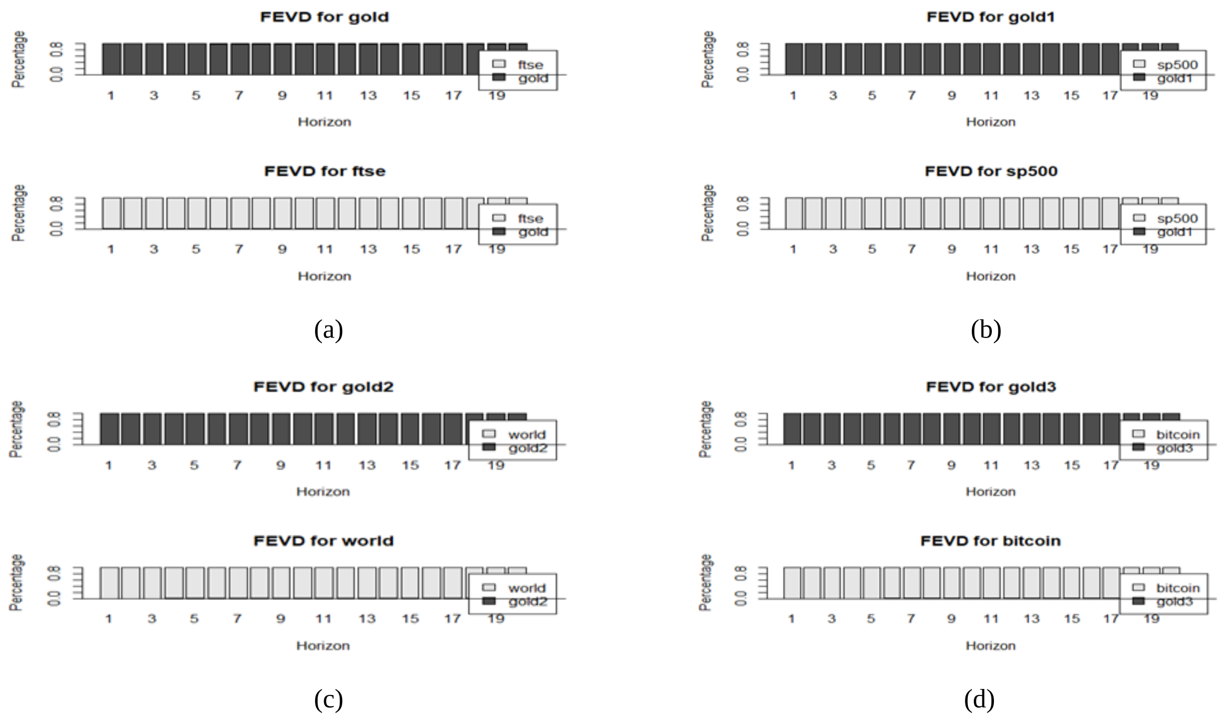


Fig. 7: Forecast Error Variance Decomposition

3.5 Hedging and safe haven properties

All the analysis in this section is based on Equation (12b). In Table 5, the hedge coefficient represents c_0, the 0.1 coefficient represents c_1, the 0.05 coefficient represents c_2 and the 0.01 coefficient represents c_3.

Table 5: The estimation results of the role of gold as a safe haven asset and hedge for daily returns.

Index	Hedge	0.1	0.05	0.01
World Index	0.0002768*	0.0012242.	-0.0010751	-0.0010171
S&P 500	0.0002952*	0.0013545**	-0.0017560*	-0.0007587
FTSE 100	0.0002850*	0.0009545	-0.0001303	-0.0038313**
Bitcoin	0.0001571	0.0018280**	-0.0030807**	0.0017540

'**' statistically significant at a 5% significance level.

'*' statistically significant at a 10% significance level.

The regression results show that for the World Index, none of the coefficients ($c_1, c_2,$ or c_3) in are significantly different from zero, indicating no strong evidence of a non-linear relationship between gold and the World Index. However, in the cases of Bitcoin, S&P500, and FTSE100, there is some evidence of a non-linear relationship with gold. For Bitcoin, two coefficients, c_1 and c_2, are significantly different from zero at the 0.05 significance level, suggesting a non-linear relationship during extreme stock market movements exceeding the 10% and 5% quantiles. S&P500 and FTSE100 each have one coefficient, c_1 and c_3, respectively, that is statistically different from zero at a 5% significance level, indicating a non-linear relationship during extreme market movements exceeding the 10% and 1% quantiles, respectively.

The intercept term (c_0) for the World Index, FTSE100, Bitcoin, and S&P500 is positive but very close to zero, and only one of the coefficients ($c_0, c_1,$ or c_3) is positive. This suggests that gold's role as a safe haven for these indices appears to be weak. Gold's returns do not substantially increase during extreme market events, but they also do not decline significantly, indicating a weak safe haven effect.

In the case of FTSE 100, the coefficient for $'D(r_{stock}q_1)'$ is negative and statistically significant at the 0.05 significance level, indicating that when FTSE100 exceeds the 1% quantile of the return distribution, gold's returns tend to decrease significantly. This suggests a negative relationship between gold and FTSE100 during extreme events, indicating the presence of the safe haven property. Similarly, for Bitcoin, the coefficient for $'D(r_{stock}q_5)'$ is negative and statistically significant at the 0.05 significance level, suggesting that when Bitcoin exceeds the 5% quantile of the return distribution, gold's returns tend to decrease significantly, indicating a negative relationship between gold and Bitcoin during extreme events.

The intercept term (c_0) for the World Index, S&P500, FTSE100, and Bitcoin is positive, indicating a weak hedge effect. Gold's returns do not necessarily move in the opposite direction of these markets during extreme events, but they also don't increase significantly. Since only some of the coefficients ($c_1, c_2,$ or c_3) are negative, with only two being statistically significant and not jointly exceeding the value of c_0, this suggests that gold does not serve as an effective hedge for these markets.

4 Conclusion

Our study covers a large period, contrary to most of our primary references that only cover parts of the 21st century, so it allows us to make a broader comparative analysis of gold's role and its evolution in financial markets. The study finds that gold appears to be a relatively stable asset during periods of market instability, as suggested by most of the available literature, suggesting its potential role as a safe haven for other financial variables. Three distinct periods of instability (2001-2002, 2007-2009, and 2019-2021) are identified, during which all variables, including gold, are adversely impacted. However, gold sustains the lowest impact compared to other assets. The analysis revealed that during crises, gold's conditional volatility is lower compared to the considered stock indices and Bitcoin, highlighting its stability. The relationships between different financial assets, such as gold, stock indices, and Bitcoin, exhibit diverse patterns of correlation over the years, with significant deviations during crisis periods. Most of the financial indices sustained the largest volatility shock in the COVID-19 pandemic but the relationships between the indices and gold are most volatile after the GFC. The CUSUM chart for the VAR model reaffirms gold's log returns' stability in the presence of various financial indices and highlights the resilience of some indices, such as the S&P500, in recovering from economic crises, which could influence the dynamics of gold log returns.

The S&P500 and FTSE100 interestingly appear to Granger cause gold, which may be an indication of potential deterioration in gold's hedging and safe haven capabilities due to growing dependence between the returns of the indices and gold. Granger causality analysis provides insights into the predictive relationships between past values of financial variables and gold returns, with a bidirectional relationship observed between gold and the S&P500 due to gold's role as a global commodity priced in U.S. dollars.

The results obtained from the Impulse Response Function analysis offered a comprehensive understanding of how shocks in one variable influence others within the VAR model, gold and S&P500 returns appeared to have the biggest impact on each other taking longer to recover and having narrow margins for error bidirectionally. Variance decomposition clarifies the relationships between gold and other independent variables, indicating that gold's price movements are primarily driven by its own historical values, with a relatively minor influence on other financial indices at varying time intervals. This can aid in forecasting, risk management, and decision-making in financial markets.

The regression results suggest that gold's safe haven property varies depending on the context of different financial indices and the extent of market instability as suggested by [6]. Gold does not exhibit a strong safe haven effect in most cases, except for specific negative relationships during extreme events. It also appears to have a weak hedge effect, with its returns not showing substantial increases or consistent inverse movements during extreme market events.

Overall, the findings shed light on the behavior of gold in relation to various financial indices, highlighting its potential role as a safe haven asset and its limited effectiveness as a hedge in the long-term, contrary to the findings of [2]. The findings differ from previous research and suggest that gold's hedging and safe haven properties may be fading over time. The study also points out that Bitcoin has the potential to serve as a hedge or safe haven asset in the future due to its independence from gold, although investor confidence in its ability to fulfill this role may take time to develop.

Additionally, the study acknowledges the limitation of not being able to fully explore the effects of the aftermath of the COVID-19 pandemic on gold's safe haven and hedging properties due to data constraints. This area could be explored in future research including the research topics that are listed in [1-21]. Other areas of further research could include:

- The evolution of gold's role in emerging markets.
- Gold's hedging properties for other assets such as bonds in the 21st century.
- The effects of behavioral finance on the evolution of gold's role as a safe haven asset.

Data Availability Statement: All the data are publicly available on the following links:

https://www.investing.com/commodities/gold-historical-data.

https://www.investing.com/indices/us-spx-500-historical-data.

https://www.investing.com/indices/uk-100-historical-data.

https://za.investing.com/indices/msci-world-historical-data.

https://www.investing.com/crypto/bitcoin/historical-data.

Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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