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Do crude oil, gold and the US dollar contribute to Bitcoin investment decisions? An ANN-DCC-GARCH approach

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Abstract

Purpose – Bitcoin (BTC) is significantly correlated with global financial assets such as crude oil, gold and the US dollar. BTC and global financial assets have become more closely related, particularly since the outbreak of the COVID-19 pandemic. The purpose of this paper is to formulate BTC investment decisions with the aid of global financial assets.

Design/methodology/approach – This study suggests a more accurate prediction model for BTC trading by combining the dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model with the artificial neural network (ANN). The DCC-GARCH model offers significant input information, including dynamic correlation and volatility, to the ANN. To analyze the data effectively, the study divides it into two periods: before and during the COVID-19 outbreak. Each period is then further divided into a training set and a prediction set.

Findings – The empirical results show that BTC and gold have the highest positive correlation compared with crude oil and the USD, while BTC and the USD have a dynamic and negative correlation. More importantly, the ANN-DCC-GARCH model had a cumulative return of 318% before the outbreak of the COVID-19 pandemic and can decrease loss by 50% during the COVID-19 pandemic. Moreover, the risk-averse can turn a loss into a profit of about 20% in 2022.

Originality/value – The empirical analysis provides technical support and decision-making reference for investors and financial institutions to make investment decisions on BTC.

Keywords Correlation, Volatility, Portfolio, ANN, BTC

Paper type Research paper

1. Introduction

In January 2009, Bitcoin (BTC) was introduced as the world's pioneer cryptographic digital currency (Basher and Sadorsky, 2022). BTC offers lower transaction expenses compared to other cryptocurrencies (Kayal and Rohilla, 2021) and operates independently from central banks (Baur and Dimpfl, 2021). In addition, BTC allows individuals to mine, purchase, sell, or receive it, while ensuring user anonymity during transactions (Chen, 2023). Consequently, financial institutions and investors are increasingly attracted to the BTC market. There is also the fact that BTC is a high-risk, high-return financial asset (Baek and Elbeck, 2015; Huang *et al.*, 2019; Cheah *et al.*, 2022). During the COVID-19 pandemic, which is 2021, the BTC

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price exceeds $68,000 per coin. And at the end of 2022, the BTC price falls below $20,000 again. It is noted that, the BTC price is extremely volatile. This is why many speculators and financial institutions are keen on investing in BTC. Speculators are very interested in making good investment decisions or a better prediction of the BTC price.

At different stages, BTC trading decisions should be different. Figure 1 shows the daily closing prices for BTC from 2014 to 2022. After the outbreak of COVID-19 pandemic, BTC reflect into bull market from 2019 to early 2021, while the BTC market enters a complete bear market from the second half of 2021. BTC prices fall back to 2020 levels. This demonstrates that BTC proved to be a highly valuable investment until 2021. Undoubtedly, BTC investors should consider implementing distinct investment tactics prior to and following the outbreak of the COVID-19 pandemic. It is observed that BTC investors and financial institutions are keen to make more profits in bull markets and reduce investment risk in bear markets. Therefore, how should investors make BTC investment decisions in different periods? Is it possible to achieve this expectation through a forecasting methodology? These are the questions that need to be addressed in this study. Some scholars believe that the decrease in BTC's value is influenced by the price of the US dollar, gold and crude oil, (Dyhrberg, 2016; Bouri *et al.*, 2018; Grobys, 2021; Bani-Khalaf and Taspinar, 2023) etc. The US dollar, gold and crude oil also are regarded as traditional hedging assets (Wang *et al.*, 2021). Notably, as the BTC market has boomed, some researchers have found that BTC has also become an essential hedging asset (Bouri *et al.*, 2018; Wang *et al.*, 2019a). In addition, BTC and the traditional financial assets have become more closely related, particularly since the outbreak of the COVID-19 pandemic. BTC and the global financial assets have become more closely related, especially since the outbreak of the new crown epidemic. It is well known that the richer the information known, the more beneficial it is for our investment decisions. Based on this fact, an interesting question is whether the correlation between traditional financial assets and BTC can be beneficial for BTC investment transactions?

This paper aims to forecast BTC investment decisions by integrating the dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model and artificial neural network (ANN) methods. Briefly, we add the correlation and covariance between BTC and the global financial assets (gold, US dollar and crude oil) and volatility of BTC for predicting its trading decisions. We compare and analyze whether the inclusion of the correlation and volatility can enhance the precision of BTC trading prediction. On the other hand, we compare the differences of ANN-DCC-GARCH models for BTC trading prediction before and after the outbreak of COVID-19 pandemic.

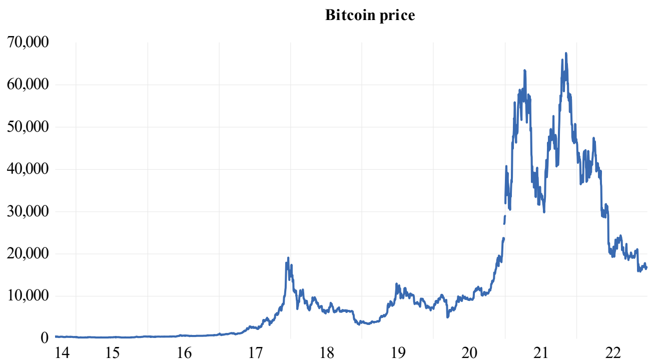

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Figure 1.
Bitcoin prices from Sept. 2014 to Dec. 2022

The main contributions of this paper are: first, this paper proposes the ANN-DCC-GARCH model for the first time and uses it for investment decision prediction in BTC. Second, from the perspective of empirical analysis, we validate the benefits of traditional financial assets on BTC investment trading decisions. Third, we compare the differences in BTC investment trading decisions prior to and following the occurrence of the COVID-19 pandemic. Fourth, we also find that for different risk preferences, the ANN-DCC-GARCH model predicts very large differences in BTC trading decisions.

The reminder of this study is organized as follows: Section 2 reviews and summarizes the previous studies related to BTC and the global financial assets, and Section 3 gives the data sources and makes the data descriptive. Section 4 introduces the DCC-GARCH models, ANN and the process of the ANN-DCC-GARCH approach. Section 5 exhibits the practical findings and the conclusion is given at the end.

2. Literature review

Some scholars have tried to infer the price trend of BTC by studying the association between BTC and other financial commodities to give suggestions for BTC investment (Erdas and Caglar, 2018; Al Mamun *et al.*, 2020; Okorie and Lin, 2020). For example, Baur and Dimpfl (2021) estimated the connection between gold and BTC and concluded that there is a substitution or catch-up effect between BTC and gold. According to Selmi *et al.* (2018), BTC was regarded as a hedge and a diversifier for oil price fluctuations. Additionally, investors can exchange gold for BTC or vice versa, in order to align their market exposure with the weight of gold. Kwon (2020) found that BTC and USD were negative correlated and figured out that BTC can be a hedge of the dollar.

Kang *et al.* (2019) studied on co-movements between BTC and Gold for easy diversification and hedge. By analyzing extreme relations, Das *et al.* (2020) discovered that BTC surpasses gold and commodity in terms of hedging crude oil implied volatility. Nguyen (2022), through correlation analysis, demonstrated the absence of a volatility spillover effect from BTC to the S&P500. Zhang and Mani (2021) found that dynamic correlation between gold and BTC is positive from 2020 to 2021. In addition to correlation analysis between BTC and other assets, there are also other kinds of relationship are focused, such as risk spillover effect or contagion (Khalfaoui *et al.*, 2023; Rehman *et al.*, 2023), causality relationship (Palazzi *et al.*, 2021; Rehman and Kang, 2021) and cointegration (Hu *et al.*, 2020; Tan *et al.*, 2021).

There have been various studies conducted by Jana and Das (2020), Arouxet *et al.* (2022), Sarkodie *et al.* (2022) and Liu *et al.* (2023), which demonstrate the notable influence of the COVID-19 pandemic on BTC's price fluctuations and volatility. Obviously, the association between BTC and other financial assets should also change significantly during the epidemic. Mariana *et al.* (2021) found a negative correlation between BTC and S&P500 during the epidemic. Jareño *et al.* (2021) showed a strong correlation between cryptocurrencies and crude oil during the COVID-19 pandemic. Bhuiyan *et al.* (2021) demonstrated a causal relationship between BTC and gold. Tiwari *et al.* (2024) measured the correlation between BTC and the clean renewable energy stock index, and their study shows that BTC offers a robust hedging and hedging mechanism comparing with investments in renewable energy. Dutta *et al.* (2020) confirmed that BTC can diversify the investment risk of crude oil during the epidemic. It is evident that BTC is more affected by the epidemic, and then the gap in BTC investments should be large before and after the epidemic.

It is observed from above discussion that there is an increasing amount of research on the association between BTC and the global financial assets following the occurrence of the COVID-19 epidemic. Some models, such as quantile-on-quantile regression, Wavelet quantile, quantile causality, time-varying parameter vector autoregression (TVP-VAR) and DCC-GARCH models are popular applied into association analysis between BTC and other financial assets. Kumar and Padakandla (2022) tested the applicability of gold and BTC as hedges based on the Wavelet quantile correlation method in the context of the COVID-19-related stock market crash. The results show that in the long and short term, gold consistently demonstrates its reputation as a safe haven asset across all markets, while BTC presents a combination of outcomes. Furthermore, gold can also serve as a reliable tool for hedging risks and diversifying investments. Nguyen (2022) examined the impact of COVID-19 and other periods of uncertainty in the stock market on BTC.

Huang *et al.* (2023) employed a TVP-VAR model with stochastic volatility to examine the market relationship between BTC and green assets, both before and during the COVID-19 pandemic. Sharma *et al.* (2023) used quantile-to-quantile regression (QQR) and quantile Granger causality methods to investigate the association between BTC and the green economy. Meanwhile, Zhang and Mani (2021) employed various GARCH models, including Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH), Glosten-Jagannathan-Runkle (GJR)-GARCH and Multivariate GARCH (MGARCH) models, to explore the volatility, asymmetry and correlation among well-known cryptocurrencies and gold. The study also assessed asset correlations using the DCC approach and revealed that the linkage between gold and BTC intensified during the COVID-19 pandemic, reaching its highest point at the peak of the pandemic. Wang *et al.* (2021) also used the DCC-GARCH models to measure the dynamic correlation between hedge assets and global stock markets. A large number of studies have applied the DCC-GARCH models to analyze dynamic correlations and serve as a basis for other studies, such as value-at-risk, portfolio and systemic financial risk. We can find that the DCC-GARCH models are well used to measure time-varying correlations.

In recent years, many scholars directly studied on prediction of BTC (Adcock and Gradojevic, 2019; Atsalakis *et al.*, 2019; Pabuccu *et al.*, 2020; Hau *et al.*, 2021; Tripathi and Sharma, 2023; Wang and Hausken, 2022). Huang and Gao (2022) used least absolute shrinkage and selection operator (LASSO) approach to predict BTC returns from 2018 to 2019. Wang *et al.* (2019b) used the autoregressive jump intensity (ARJI) model to predict the volatility of BTC in 2018. Nakano *et al.* (2018) conducted experiments on high frequency BTC price data using artificial networks to evaluate various trading strategies. Adcock and Gradojevic (2019) utilized neural networks to make predictions on BTC prices. Pabuccu *et al.* (2020) employed several machine learning and Logit models as tools for forecasting BTC prices. Most of studies showed that machine learning methods have a better performance than time series models for BTC prediction.

From the aforementioned literature, it is clear that BTC and the global financial assets have some relationship. Numerous researchers have given special focus to the dependence of BTC and the financial assets as well as the risk premiums between them. Many scholars have pointed out that the estimation of financial product correlations and risk spillover is beneficial for portfolio and investment decisions. However, none of them adopt a quantitative approach to elucidate investment decisions regarding financial products. Since BTC and the global financial assets have certain relationships, is it beneficial to make investment decisions in BTC based on clarifying these relationships? If this assertion is correct, then the finding has important practical implications for both BTC investors and financial institutions.

3. The data

This study collects the data set from the Wind database. The data is daily and the sample period covers from September 17, 2014 to December 23, 2022. Input variables include daily high, low and open prices for BTC and binary variables for gold, US dollar and crude oil. A 0 represents a falling price and a 1 indicates a rising price. All input variables are one-period lag. All variables, except binary variables, are normalized using the entropy weight method. The 2019 data are regarded as out-of-sample data before the COVID-19 outbreak, and the 2022 data are out-of-sample after the outbreak of COVID-19.

Table 1 reports the data descriptive of the full sample and the sub-samples of 2019 and 2022. It is clear that the sample mean value in 2019 is 7383.25 and 28355.82 in 2022, which implies the price of BTC changes greatly prior to and following the occurrence of the COVID-19 pandemic. BTC price volatility is also high, as can be seen from the minimum and maximum values in both 2019 and 2022.

4. Methodology

We firstly introduce DCC-GARCH models and then demonstrate ANN method. Finally, steps of using the ANN-based DCC-GARCH models are summarized.

4.1 DCC-GARCH model

The GJR-GARCH (p, q) model can be defined as below:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (\alpha_i + \gamma_i I_{t-i}) \varepsilon_{t-i}^2 + \sum\nolimits_{j=1}^{q} \beta_j \sigma_{t-j}^2, \quad (1)$$

where:

$$I_{t-1} = \begin{cases} 0 \text{ if } \varepsilon_{t-1} \geq 0, \\ 1 \text{ if } \varepsilon_{t-1} < 0, \end{cases} \quad (2)$$

In addition, γ represents the leverage effect Also, the error term $\varepsilon_t = \sigma_t z_t$ and z_t is independently and identify student-t distribution.

The DCC structure is expressed as:

$$Q_t = \left(1 - \sum_{m=1}^{M} \theta_{1m} - \sum_{n=1}^{N} \theta_{2n}\right) \overline{Q} + \sum\nolimits_{m=1}^{M} \theta_{1m} \left(\varepsilon_{t-m} \varepsilon'_{t-m}\right) + \sum_{n=1}^{N} \theta_{2n} Q_{t-n}, \quad (3)$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \quad (4)$$

where $\overline{Q}$ represents the unconditional covariance of the standardized residuals that arise from the first step estimation and

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{q_{kk}} \end{bmatrix}, \quad (5)$$

Table 1.
The data descriptive and statistics

Bitcoin	Total sample	Subsample in 2019	Subsample in 2022
Mean	12860.64	7383.25	28355.82
Median	7106.54	7853.04	23222.24
Maximum	67566.83	13016.23	47465.73
Minimum	178.10	3399.47	15787.28
Std. Dev.	16197.13	2656.19	10183.79
Skewness	1.54	−0.057687	0.44
Kurtosis	4.28	1.80	1.55
Observations	2,134	258	254

Source(s): Authors' computation

So that Q_t^* for matrix Q_t^*, it will be a diagonal matrix where each element is the square root of the corresponding diagonal element of matrix Q_t. As for matrix R_t, its typical element will be in the form of $\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{ii}q_{jj}}}$.

4.2 Artificial neural network

ANNs are employed to model the non-linear connections between input and output variables (Mahdiani and Khamehchi, 2016; Rodriguez *et al.*, 2022). The main function of ANN is prediction. The ANN includes three layers of units, namely, the input, hidden and output layers. The ANN has also many nodes that are used to link the three layers and are called neurons. The basic principle of an ANN is that each neuron takes the initial input values and multiplies them by a certain weight, adds the values of the other inputs into this neuron and finally works out a sum, which is then adjusted by the bias of the neuron and finally normalizes the output values with an excitation function (Kulkarni and Haidar, 2009; Gupta and Nigam, 2020).

The more valid information is available as input variables, the more accurate the predictions of the ANN. The DCC-GARCH model can obtain dynamic correlations and volatilities, which are valuable information in financial market analysis (Yıldırım *et al.*, 2022). Therefore, we are well placed to use dynamic correlation and volatility as input variables for the ANN approach. In view of this, we merge the ANN and DCC-GARCH models and refer to them as the ANN-based DCC-GARCH model. Following Bahrambeygi and Moeinzadeh (2017), we construct the architecture of ANN-based DCC-GARCH model in Figure 2. The closing, opening, high and low prices of BTC at one-lag period are used as the most basic input variables. $Binary_{i,t-1}$ represents the binary variables of BTC and the global financial assets at time $t-1$. The binary variable is equal to 1 when the price rises and 0 otherwise. $\rho_{ij,t-1}$ is the correlation between BTC and the global financial assets, while $\sigma_{ij,t-1}$ represents their covariance and the volatility of BTC.

The model is performed in the following steps.

1. The information is separated into a grouping of data for training purposes and another for prediction.

2. The DCC-GARCH model is employed to approximate dynamic correlations, volatilities and covariances for the full sample. One-lag period of all variables, including the dynamic correlation, volatility, covariance as well as other indicators are used as input variables in the training dataset, while the dummy variable for log returns was the output variable.

3. All input variables in addition to the dummy variables are normalized (Kulkarni and Haidar, 2009). The normalized process is as follows:

$$X_{it} = \frac{x_{it}\text{-}\min(x_i)}{\max(x_i)\text{-}\min(x_i)}, \tag{6}$$

where x_{it} represents the i-th input variable at time t and X_{it} standards for normalized values.

4. A method is used to determine the number of hidden neurons. According to Rodriguez *et al.* (2022), there is currently no direct approach to ascertain the quantity of neurons. Following Zeng *et al.* (2023), the number of possible neurons is calculated as follows:

$$L = \sqrt{\varphi + \omega} + \alpha\,, \tag{7}$$

where φ and ω denote the number of nodes in the output layer and input layer, respectively, and α is an integer number from 1 to 10. L represents the number of nodes in the hidden layer.

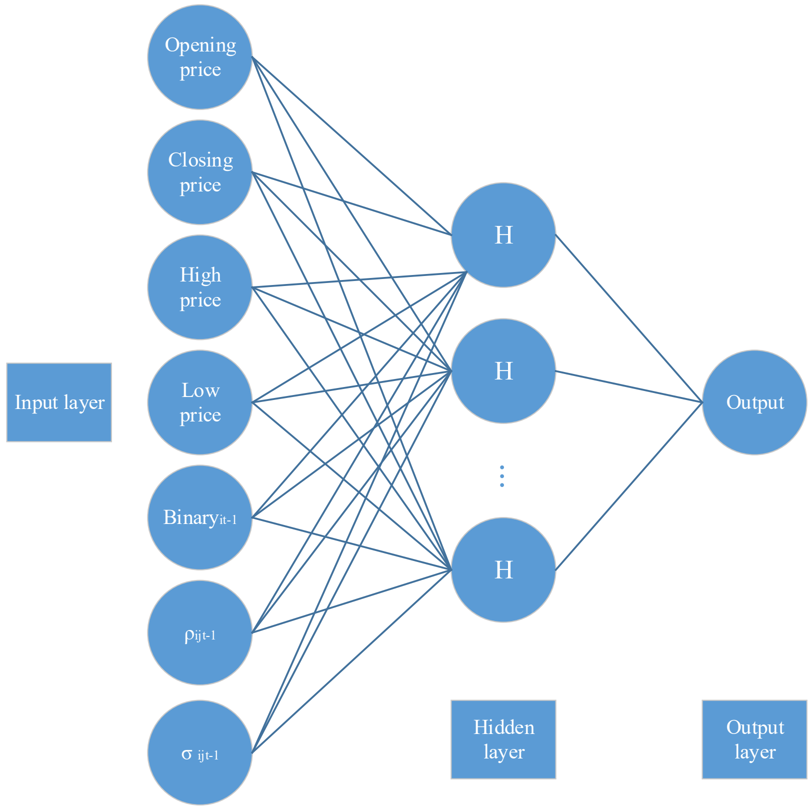

Figure 2.
The architecture of ANN-based DCC-GARCH model

Source(s): Figure by authors

5. The training of ANN models with varying numbers of hidden layers is conducted using the resilient back propagation algorithm, incorporating weight backtracking. The best model is determined based on its highest accuracy achieved on the training set. The accuracy of prediction is computed using the following formula:

$$AP = \frac{1}{T_1}\sum_{t=1}^{T_1}\left(I_{\left(\widehat{P}_t > 0.5\right)} * I_{(r_t > 0)}\right), \tag{8}$$

where T_1 represents the number of observations from 2014 to 2018, and from 2014 to 2021 in this study, respectively. $\widehat{P}_t$ denotes the estimated probability value, and I is an indicator function, r_t is the log return of BTC. The model is improved as the value of AP increases. From this we can determine the optimal number of neurons, i.e. the best model.

6. Finally, we bring the prediction dataset into the best ANN model to predict the output.

5. Empirical results

The empirical results in this study are calculated using the *R* Studio software. We mainly utilized the "rugarch" and "neuralnet" packages in the *R* software. In the ANN models, we used the algorithm of resilient backpropagation with weight backtracking and the cross-entropy method to calculate the convergence error. In the ANN-DCC-GARCH model, correlations between BTC and the three assets (crude oil, USD and gold), covariance of BTC with the three assets and volatility of BTC are normalized following Equation (8). The one-lag period data are regarded as the input variables.

5.1 Estimate results of the DCC-GARCH models

Figure 3 shows the DCC between BTC and the global financial assets. Obviously, the correlations between BTC and the global financial assets have a clear dynamic nature. Positive correlations dominate BTC and gold, as well as BTC and crude oil. The correlation between BTC and gold is slightly higher than that between BTC and crude oil for most of the time period, which was evidenced by Gkillas *et al.* (2022), BTC and the US dollar have a negative correlation, and the negative correlation becomes significantly stronger in 2020 and 2022. These findings facilitate the analysis of BTC and traditional financial asset portfolios. However, the results from the correlation estimates only do not allow for a substantive analysis of BTC investment decisions.

Figure 4 shows the volatility of BTC and the covariance of BTC with the global financial assets. We can clearly see that BTC has a high volatility, particularly in 2017 and 2020. Smales (2019) and Long *et al.* (2021) also evidence that BTC has a greater volatility than gold. In 2020, the covariance between BTC and gold and BTC and crude oil are quite stronger, which may attribute to the outbreak of the COVID-19 pandemic. In particular, the covariance between BTC and crude oil changes very much in 2020. The covariance between BTC and the US dollar exhibits a year-to-year strengthening trend, with the most pronounced strengthening trend in 2022.

5.2 Prediction analysis of the ANN-DCC-GARCH models

We bring the dynamic correlation and covariance obtained in the DCC-GARCH model as input variables into the ANN model, thus testing the predictive effect of the ANN-DCC-GARCH model on BTC transactions. In order to determine whether the results of the DCC-GARCH model contribute to the ANN predictions, four models are constructed. Model 1 is an ANN model that does not consider the estimated results of the DCC-GARCH model. Model 2 is an ANN model that adds only covariance as input variables. Model 3 is an ANN

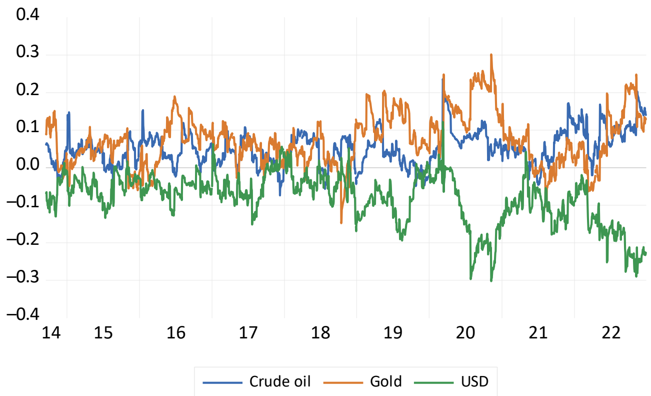

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Figure 3. Pairwise correlations between BTC and gold, crude oil and USD

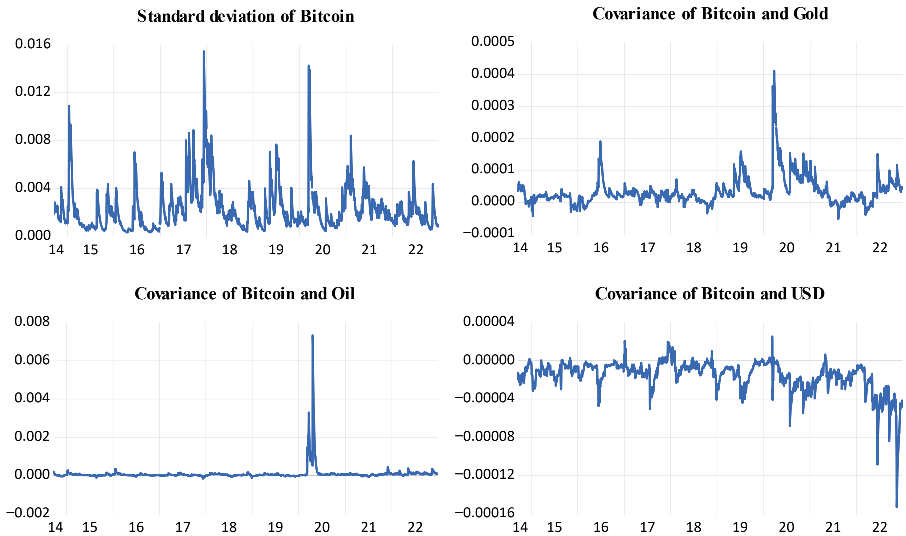

Figure 4.
Volatility of Bitcoin and covariance between BTC and the global financial assets

Source(s): Figure by authors

model that adds only dynamic correlation as input variables. Model 4 is an ANN model that puts both dynamic correlation and covariance as input variables. We first fit the four models using data within two in samples and select the number of hidden layers of the ANN model and the best models based on the prediction error. Secondly, we compare the fitting accuracy of the four models within two in samples based on the goodness-of-fit, i.e. the fitting accuracy. Again, we use each of the four models to predict BTC trading decisions for out-of-sample data and calculate the cumulative returns. Finally, we compare the cumulative returns in 2019 and 2022 for different risk preferences with the help of the best ANN-DCC-GARCH model.

Figures 5 and 6 displays the fitting errors of the four models for different numbers of hidden layers. We calculate the minimum and maximum number of hidden layers according to Zeng *et al.* (2023). Model 1 has a range of hidden layers spanning from 3 to 13, while the other models' range falls between 4 and 14. We can clearly find that the fitting error varies somewhat for different numbers of hidden layers, and the fitting errors of the four models also differ significantly. With the increase of the number of hidden layers, basically the fitting error of each model becomes smaller. Within the in-sample data from 2014–2018, we discovered that the ideal number of hidden layers for Model 1 and Model 2 is 13, whereas for Model 3 and Model 4 it is 14. Within the in-sample data from 2014–2021, we found that the optimal number of hidden layers for Model 1 is 12, and the other models are 14. Based on the minimum fitting error, Model 4 is the best fit model. This also demonstrates that the correlation and covariance are useful for the prediction of BTC transactions. This also indirectly verifies that the ANN-DCC-GARCH model is appropriate and reasonable.

Table 2 shows the goodness-of-fit of the four models. We can find that within the sample of 2014–2018, Model 4 has an accuracy of over 80% and predicts the rise with an accuracy of 87.38%. Within the sample of 2014–2021, the accuracy of Model 4 is 73.12%, but the accuracy of the rise is as high as 85.18%. By comparison of the four models, it can also be found that Models 2, 4 are all superior to Model 1, which indicates that the information obtained by the DCC-GARCH model is conducive to BTC trading forecasts.

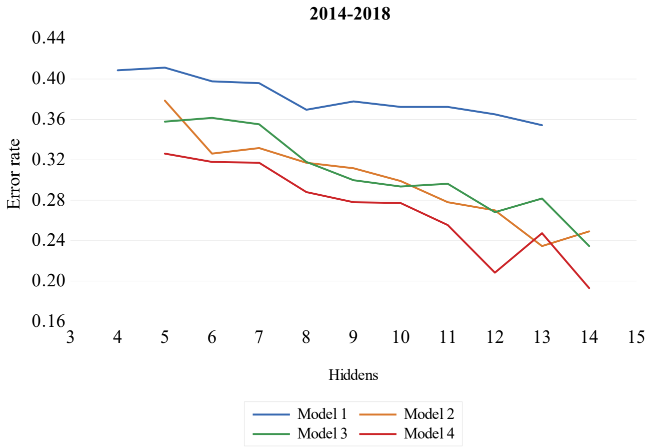

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Figure 5.
Error rates at different numbers of hidden neurons for the 2014–2018 dataset

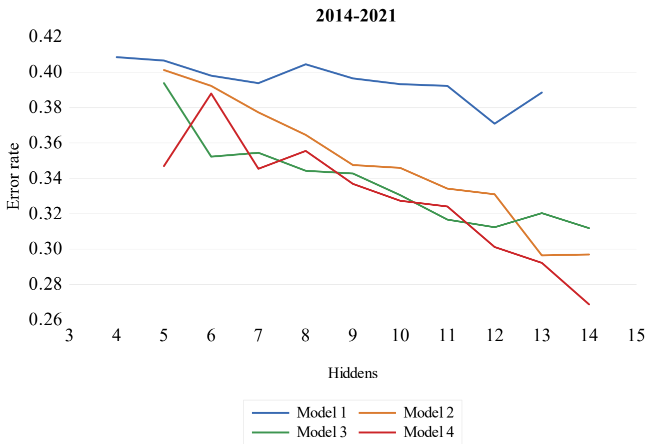

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Figure 6.
Error rates at different numbers of hidden neurons for the 2014–2021 dataset

Figure 7 predicts the trading returns for BTC in 2019 and presents the cumulative trading returns for long-term hold, Models 1–4 and two random investment strategies. First, Model 4 has a cumulative return of 318%. In other words, an investment of \$1m at the beginning of 2019 may achieve a return of \$3.18m by the end of 2019. Among all models, Model 4 has the best prediction result, which fully illustrates the practicability of the ANN-DCC-GARCH model. Second, the investment decision to hold for the long term can achieve a return of 192%, which indicates that the BTC market is in a bull market in 2019. Also, the profitability of the two random investment strategies serves as additional confirmation. Moreover, Model 2 and Model 3 can be profitable by 189 and 266%, respectively, which indicates that the information of dynamic correlation is more beneficial for BTC investment decisions.

Figure 8 shows the predicted trading returns for each model in 2022. The BTC market is in a bear market in 2022 due to the COVID-19 epidemic, rising energy prices and the Russian–Ukrainian war and long-term BTC holdings will lose about 64%. In contrast, investment strategies using Models 1–4 would significantly reduce the percentage loss. For example, Model 4 predicts a cumulative return of 84.8% and 86% for Model 2, which is much higher than the 36% for long-term holdings. This indicates that the ANN-DCC-GARCH models are effective in reducing investment losses in BTC during the bear market phase. We can also find that two random investment strategies outperform the long-term holding, which implies that the long-term holding is a very unwise investment strategy during a bear market period.

In the above investment decision, we use a predicted probability above 50% as a buy and a probability below 50% as a no trade. But different risk-averse people have different preference settings. Thus, we use 50% as the risk-neutral preference setting, 20% as the risk-loving preference setting and 80% as the risk-averse preference setting. Figure 9 shows the cumulative returns of the three risk preferences and long-term holdings in 2019. We can clearly see that risk-neutral is the most profitable in 2019. Risk averse and risk lovers receive much smaller returns than risk neutrals, but larger than long term holders. The finding suggests that risk-neutral is the best option during BTC's bull market phase. Figure 10 shows

Table 2.
Goodness of fit of ANN, ANN-DCC-GARCH models for BTC

Periods	Models	Accuracy rate	Accuracy rate for buying	Accuracy rate for selling
2014–2018	Model 1	0.6458	0.7656	0.4980
	Model 2	0.7654	0.8230	0.6943
	Model 3	0.7654	0.8328	0.6822
	Model 4	0.8071	0.8738	0.7247
2014–2021	Model 1	0.6291	0.8126	0.4116
	Model 2	0.7036	0.7782	0.6151
	Model 3	0.6881	0.7792	0.5802
	Model 4	0.7312	0.8518	0.5884

Source(s): Authors' computation

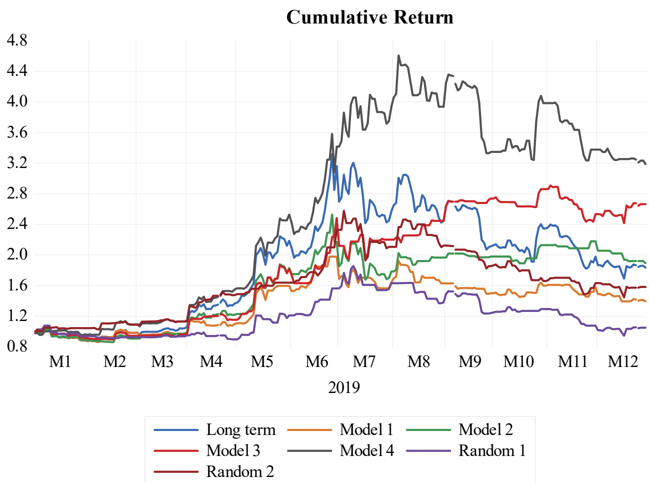

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Figure 7.
Predicted return of BTC in 2019 (before the COVID-19)

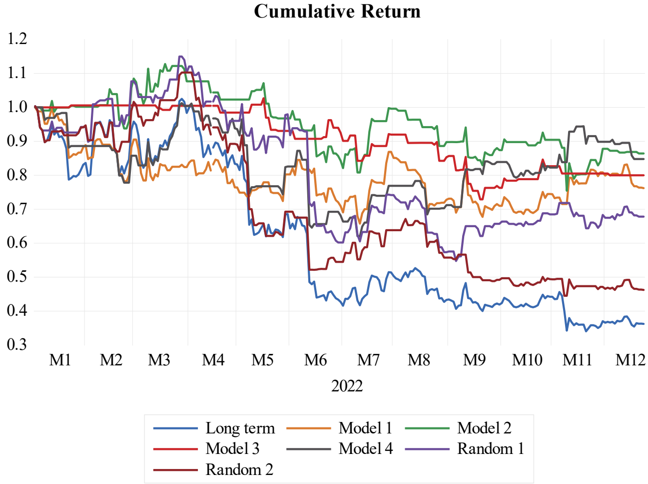

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Figure 8.
Predicted return of Bitcoin in 2022 (during the COVID-19)

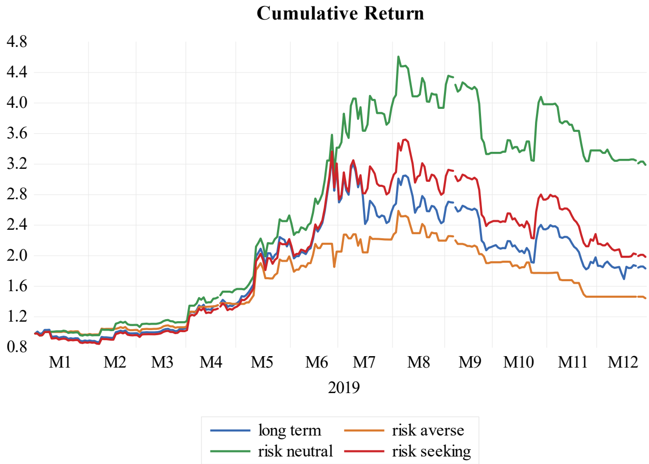

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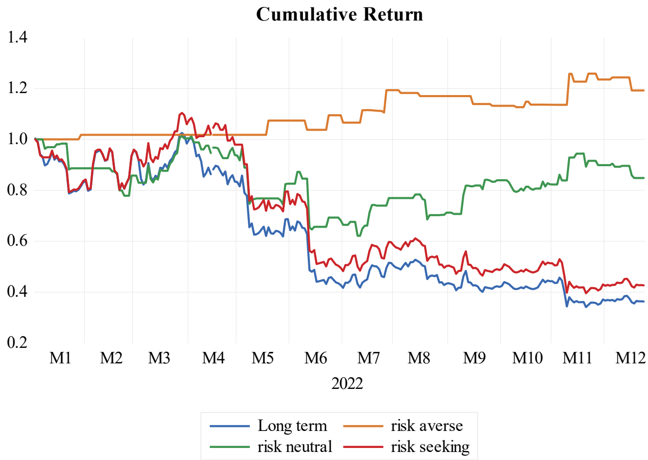
Figure 9.
Cumulative returns of BTC for different risk preference in 2019

the cumulative returns in 2022 for the three risk preferences and long-term holdings. We can find that in the bear market phase in 2022, the risk averse can turn a loss into a profit of about 20%. With the analysis in Figures 9 and 10, the practicability of the ANN-DCC-GARCH model is reconfirmed.

6. Conclusion

The BTC market has attracted numerous investors, which has prompted the need for developing investment strategies specifically for BTC. Therefore, in this study, we propose a unique model called ANN-DCC-GARCH that combines both econometric and machine learning models. We apply this model for the first time to make investment trading decisions



Source(s): Figure by authors

Figure 10.
Cumulative returns of BTC for different risk preference in 2022

regarding BTC. Additionally, we make predictions on BTC investment trading strategies prior to and following the occurrence of the COVID-19 pandemic. Our BTC prediction results show that the ANN-DCC-GARCH model is highly practical and effective, further confirming its superiority over the traditional ANN model.

The ANN-DCC-GARCH model supports the important value of dynamic correlation and volatility in investment decisions on the one hand. On the other hand, it directly quantifies the investment trading strategies of financial assets. Before the COVID-19 outbreak, i.e. during 2019, the investment trading strategy of the ANN-DCC-GARCH model could achieve a return of 318%. This suggests that the ANN-DCC-GARCH model has a very strong predictive power during the bull market phase of BTC and can capture excess profits. During the bear phase of BTC, the utilization of the ANN-DCC-GARCH model can greatly minimize losses for investors. Moreover, the ANN-DCC-GARCH model can set different investment strategies for different risk-averse people. We find that risk-neutral is the best choice in the bull phase of BTC and risk-averse is the best choice in the bear phase. Obtaining information in the DCC-GARCH models such as DCC, volatility and covariance can be very useful for investment decisions in BTC, prior to and following the occurrence of the COVID-19 epidemic. The ANN-DCC-GARCH model utilizes the binary variable of the current period as the output variable and all the historical information as the input variable. Therefore the model is completely capable of being applied to real-world BTC investment trading.

Although the analysis in this paper is significant for BTC investment, there are some limitations in this paper. Firstly, we can affirm that the ANN-DCC-GARCH model has good results for investment decisions in BTC, but we are not sure how well the model predicts other financial assets. Secondly, according to the theory of diversification, investing in the BTC market alone might be risky. In this way, the application of the ANN-DCC-GARCH model has some limitations. From this, our future research can explore the ANN-DCC-GARCH model in a diversified portfolio of financial assets and also further analyze the model's predictive effect on investment transactions in other financial assets.

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