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## Article

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# Cryptocurrencies: hedging or financialization? behavioral time series analyses

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## ABSTRACT

This article investigates the time-series properties of cryptocurrency returns and compares them with currency and commodity returns. We perform and analyze the mean reversion, normality, unit root, high and low returns, correlation, *Autoregressive Moving Average* (ARMA) [2,2], *Autoregressive* (AR) [5], and long-run components in the *Generalized Autoregressive Conditional Heteroskedasticity* (GARCH) [1,1] estimates. We also perform regression analyses to evaluate two possible behavioral biases: familiarity and disposition effect. Our time series analysis documents that cryptocurrencies are neither currencies nor commodities. We also show that adding cryptocurrency to a portfolio increases market efficiency and uncertainty. We also document that cryptocurrency investors exhibit the same familiarity and disposition effect biases as commodity and currency investors. Overall, we conclude that investors in cryptocurrencies tend to underestimate risk and misestimate future prices, as they do in commodity and currency markets. This study makes at least three contributions to the literature. First, we evaluate whether cryptocurrencies tend to hedge or financialization. Second, our analysis includes both univariate and portfolio dimensions. Third, this is a pioneering study on using behavioral bias analysis to determine whether a cryptocurrency is a commodity or a currency.

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## 1. Introduction

The recent bitcoin crash has attracted considerable interest from industry and academia alike. According to recent news reports, the crash was valued 2 trillion USD (Nicolle & Kharif, 2022). Recent academic works on crashes have looked at how they impact regulatory (O'Halloran & Groll, 2019), market efficiency and volatility (Yaya et al., 2021), as well as bitcoin derivative (Hattori & Ishida, 2021). However, whether the nature of cryptocurrencies is hedging or financialization remains unexplored.

Understanding the nature of cryptocurrencies is essential because market participants, especially portfolio managers, need to align with their investment strategy and objectives. A separate analysis of cryptocurrencies themselves is incomplete because market participants shall evaluate any asset as an entire portfolio rather than individual (see standard finance textbooks such as Bodie et al. (2020) or CFA Institute (2023)). Hedging and financialization is a topic that has recently and extensively been discussed in commodity markets. For instance, Nguyen et al. (2020) document that most commodities, except gold, exhibit strong financialization. Kupabado and Kaehler (2021) reveal that financialization significantly contributes to commodity price movements. On the other hand, Ghosh et al. (2015) and Boroumand et al. (2000) examine the nature of hedging in commodity markets. Unfortunately, to the best of our knowledge, no study has yet been conducted that examines both hedging and financialization in cryptocurrencies. We understand that determining whether cryptocurrency is a commodity (Gronwald, 2019) or a currency (Hui et al., 2020) is not simple. However, this shall not stop us from investigating whether

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cryptocurrencies tend to exhibit hedging or financialization. There have been recent studies on bitcoin hedging; for instance, Koutmos et al. (2021) investigate bitcoin hedging to reduce economic uncertainties. Kinkyo (2022) examined how bitcoin can hedge Asian currencies. Several studies (Chemkha et al., 2022; Sharma & Karmakar, 2022; Wang et al., 2021; Yang et al., 2021) compare the safe heaven properties between bitcoin and other standard assets. Again, to the best of our knowledge, we did not find any study that examines cryptocurrencies' hedging and financialization properties.

Behavioral bias has been intensively examined in the stock, commodity, and currency markets. For example, recent articles from Mand and Sifat (2021) and Rubesam & Raimundo (2022) have investigated herding behavior in stock markets. Other studies on herding behavior can also be found, such as those by Sibande et al. (2021) on currencies and Youseff (2022) on commodities. Studies on herding behavior have also been expanded to include cryptocurrencies (for example, Gurdgiev and Loughlin (2020) and Zhao et al. (2022)). However, to the best of our knowledge, no study on herding bias in cryptocurrencies has been conducted to determine whether cryptocurrencies should be classified as commodities or currencies. There have been few studies on another bias, familiarity bias. A few examples are Seiler et al. (2013), who investigate future home price movements; Ayres and Dolvin (2021), who examine familiarity bias in firms' credit ratings; and Ashtiani et al. (2021), who analyze panic selling due to the IKEA effect. To the best of our knowledge, no study on familiarity bias in cryptocurrencies has been conducted. Another stock market bias, the disposition effect, has also been extensively discussed. Das (2012) attempts to calculate the loss from disposition bias in five stock markets. Trejos et al. (2019) and Winne (2021) recently examined whether the disposition effect is related to investors' confidence and decision-making processes. Our disposition effect analysis will explore a different perspective to classify cryptocurrencies. Overall, we can observe that previous studies on behavioral bias tended to document a specific bias in a financial asset. We found no studies that focused on behavioral bias to evaluate financial asset classification. Understanding this classification is also useful for evaluating whether a cryptocurrency exhibits hedging or financialization in relation to commodities, currencies, or both. This is the first study on bias to assess whether cryptocurrency should be classified as a currency or commodity. While two recent studies by Gronwald (2019) and Hui et al. (2020) concluded a classification of cryptocurrencies, they did not examine the behavioral bias dimension. We argue that a comprehensive analysis would also cover the behavioral aspects of cryptocurrencies. A legitimate reason can be found in Sun et al. (2021), who document that investors' behavioral factor is essential in adding cryptocurrencies to existing portfolios, or in Nazifi et al. (2021), who link cryptocurrencies and investors' feelings (i.e. happiness).

In summary, this study makes at least three contributions to the literature. First, we evaluate whether cryptocurrencies tend to hedging or financialization. On the one hand, if we find a strong indication of hedging, portfolio managers may use cryptocurrencies to be more conservative. Policymakers could also encourage cryptocurrencies as a component of a diversified portfolio to trigger stability in the financial markets. On the other hand, if we find a strong indication of financialization, we can suggest that portfolio managers leverage their aggressive positions by adding cryptocurrencies. Policymakers could then warn market participants that cryptocurrencies are suitable only for riskier positions. Second, our analysis includes both univariate and portfolio dimensions. We believe that our insight will generate practical input for the industry, especially for portfolio managers, because we provide clear comparisons between a single asset and an entire portfolio (for simplicity, we use an equally weighted portfolio). Another advantage of including portfolio analysis is that the portfolio series can be used to perform statistical tests on two behavioral biases of cryptocurrencies. This brings us to the third contribution, a pioneering study on using behavioral bias analysis to determine whether a cryptocurrency is a commodity or a currency. The classification analysis also indicates whether a cryptocurrency tends to exhibit hedging or financialization. This third analysis will provide additional and unique evidence supporting whether there is hedging or financialization of cryptocurrencies in relation to commodities or currencies. We believe that our behavioral analysis distinguishes this article from the current literature, particularly in the context of cryptocurrency markets.

Section 2 describes the literature review and the methods used to investigate the association between accounting policies and firms' performance. Section 3 discusses the examined data and presents the empirical findings. Section 4 presents the concluding remarks.

## 2. Literature review and method

### 2.1. Literature review

The proliferation of cryptocurrency as a financial asset has catalyzed numerous studies aimed at analyzing the dynamics of the crypto market and related assets. Initially, cryptocurrency was conceptualized as an alternative to traditional money and fiat currencies. A fundamental characteristic of money is its stable value, as it functions as a store of value. Consequently, users anticipate that a certain amount of money will enable them to purchase a similar amount of goods and/or services in the medium term, or ideally, over a longer time horizon. However, as cryptocurrency has evolved, this characteristic of stability has not been observed. The value of cryptocurrency exhibits significantly greater fluctuations compared to conventional currencies. An analysis by Kristoufek (2023), utilizing data from Bitcoin and the exchange rates of EUR, JPY, and GBP against the dollar from 1 January 2016, to 31 January 2022, indicates that Bitcoin exhibits much higher intra-day volatility than these three currencies. The volatility instability is even more pronounced when these currencies are compared.

The perception of crypto assets as more volatile has prompted several studies to investigate the factors driving the volatility of cryptocurrency values. Research by Kyriazis et al. (2023) reveals that investor sentiment influences the returns and volatility of major cryptocurrencies. Furthermore, cryptocurrencies with lower values are found to be unaffected by investor sentiment at extreme values; however, they prove to be profitable due to more aligned investor behavior. Factors such as increasing exchange volume, on-chain transfer value, and the intrinsic price of cryptocurrencies contribute to the heightened volatility of crypto assets, whereas an increase in the number of crypto users who do not actively trade correlates with a reduction in volatility levels (Kristoufek, 2023). Andersen et al. (2021) examine the variations in the equity markets under different regimes to explain the price formation when the information is incomplete. Their volatility estimation model relates to high-frequency statistics and the theory of market microstructure. This noisy analysis could trigger other uncertainty dimensions in cryptocurrency time series modeling. An example is the recent work from David et al. (2021), who propose the fractal and fractional process in advancing the time series analysis of cryptocurrency markets. They implement the Hurst and Lyapunov exponents in the fractal dimension of three methods: ARIMA (auto-regressive integrated moving average), ARFIMA (auto-regressive fractionally integrated moving average) and DFA (detrended fluctuation analysis). Their models incorporate four types of uncertainties: predictability, randomness, chaoticity, and persistence in the cryptocurrency markets.

In addition to examining factors influencing cryptocurrency market volatility, the unique nature of the cryptocurrency market necessitates research on investor strategies to protect asset values against extreme fluctuations, diversification strategies, and available hedging options (Matic et al., 2023; Nedved & Kristoufek, 2023). For instance, Dangi (2022) explores the potential of the cryptocurrency futures market to hedge the risk of a crypto asset portfolio. This study identifies a long-term interconnected relationship between the spot and futures markets, persistent volatility correlations, significant unidirectional long-term causality from futures to spot, and bidirectional short-term causality in all cryptocurrencies. Consequently, investors can mitigate their risk by engaging in positions in cryptocurrency futures (Dangi, 2022). Another study by Nedved and Kristoufek (2023) investigates whether commodities (i.e. gold, crude oil) and stock markets can serve as safe havens for Bitcoin. The findings suggest that while Bitcoin tends to move in tandem with the stock markets, oil and gold can function as safe havens, with gold specifically identified as a robust safe haven for Bitcoin.

Another extensively explored research area is the role of cryptocurrencies as an alternative investment and a source of diversification (Corbet et al., 2019). Practically, market participants, especially portfolio managers, need to align their investment strategies and objectives. Several previous studies have demonstrated that cryptocurrencies are integrated within broadly defined commodity markets (Ji et al., 2019). Dynamic correlation analyses between cryptocurrencies and other assets have been conducted in several prior studies (Corbet et al., 2019). Research by Koutmos et al. (2021) highlights the increasing role of cryptocurrencies as assets that reduce portfolio risk during the COVID-19 pandemic, with Bitcoin showing the highest effectiveness as a hedging instrument during this period. Furthermore, most cryptocurrencies consistently exhibit zero or negative betas, making them natural hedging instruments for investors

seeking to reduce their portfolio's comovement to the market. Cryptocurrencies also serve as superior hedges for economic uncertainties arising from equity and commodity markets. Another study by Kinkyo (2022) demonstrates that Bitcoin can provide a hedge against fiat currencies in Asia over various investment horizons. Moreover, Bitcoin offers better risk reduction than oil and gold, particularly over the medium and long terms.

## 2.2. Method

We perform our empirical analysis using relevant built-in functions from R and Wolfram Mathematica for double-checking and robustness. We start by reporting and evaluating the statistical descriptive of the observed assets (or portfolios). The statistical descriptive analysis includes the mean and standard deviation to analyze the mean reversion feature, normality, and unit root tests, and high positive (and low negative) to compare how frequently the actual returns deviate from their normal range. We perform the Jarque–Bera (JB) test by calculating the JB-Test statistics as follows:

$$JB = [n/6] * [S^2 + (K - 3)^2 / 4] \quad (1)$$

where  $S$  is the skewness and  $K$  is the kurtosis of a return series. We perform the unit root test by calculating the ADF -Test statistics to evaluate whether we can reject the null hypothesis of non-stationarity.

$$RET_t = \alpha_0 + \alpha_1 * RET_{t-1} + e_t \quad (2)$$

where  $RET_t$  is the return at time  $t$ . The ADF-Test is obtained by estimating the parameter and calculating the ADF-Test =  $[\hat{\alpha}_1 - 1] / \text{std dev}(\hat{\alpha}_1)$ . We executed both JB normality and unit root ADF tests using the tseries R package (Trapletti et al., 2022). Our definition of high positive (low negative) follows Longin and Solnik (2001), i.e. when a return is higher (lower) than its mean plus (minus) one standard deviation. Because we believed that 'extreme' was more appropriate for two or three standard deviations, we did not refer to this as such.

The basic idea of evaluating time series properties using ARMA (2,2) and AR(5) here follows Nguyen et al. (2020). They started their analysis from the main idea of strong form of market efficiency. Under the strong form, new information is captured into prices so that prices will depend on unpredictable future events. Thus, prices tend to follow a random walk process. They also argue that if the ARMA process can predict commodity prices, then commodity markets are not efficient. So, the closer ARMA properties between the two compared asset prices exhibit similarities and indicate financialization.

We follow the framework of Nguyen et al. (2020), who examine whether 11 commodities tend to provide hedging or financialization. They evaluated and compared the ARMA(p,q) properties of a return series. They argue that if a series can be estimated well using the ARMA(p,q) model, it indicates an inefficient market. Financialization occurs when two series exhibit the same type of efficient market hypothesis (EMH), whereas hedging occurs when two series exhibit different types. Nguyen et al. (2020) estimated up to ARMA(3,3) process, but in most series, they reported the estimates of ARMA(2,2) process. Therefore, the ARMA(2,2) process was performed as follows:

$$RET_t = \varphi_0 + \varphi_1 * RET_{t-1} + \varphi_2 * RET_{t-2} + \theta_1 * \epsilon_{t-1} + \theta_2 * \epsilon_{t-2} + \epsilon_t \quad (3)$$

Another property of commodities and cryptocurrencies is their predictability (Cheah et al., 2022; Liu et al., 2020). There are at least two points concerning the predictability level in commodities and cryptocurrencies. According to Liu et al. (2020), predictability is related to the 'Meese-Rogoff' puzzle and necessitates knowing how well a random walk model compares the commodities' predictability. On the other hand, Cheah et al. (2022) argue that the predictability of cryptocurrencies provides investors with a crucial signal regarding the factors driving cryptocurrency prices. From these two perspectives, we can infer that if two series have a similar level of predictability as their past values, it indicates financialization. By contrast, if these series differ, then hedging is indicated.



We estimate up to five days, AR(5) process, because we anticipate the possibility of a day or week (a week consisting of five working days) effect, as pointed out by Sewraj et al. (2019) and Baur (2012). We could also observe any possible variations among weekdays by estimating up to five lagged days. We realize that while cryptocurrencies are traded seven days a week, foreign exchange (FX) currencies and commodities are traded on weekdays only. Therefore, our 'balanced' return series contains (only) weekdays. The AR(5) process can be expressed as follows:

$$RET_t = \varphi_0 + \varphi_1 * RET_{t-1} + \varphi_2 * RET_{t-2} + \varphi_3 * RET_{t-3} + \varphi_4 * RET_{t-4} + \varphi_5 * RET_{t-5} + \epsilon_t \quad (4)$$

We also estimate the ARMA(2,2) and AR(5) models using the tseries R package (Trapletti et al., 2022).

Another important time-series property is the long-run component. According to Assaf et al. (2022), extracting a long-run component is a scientific method to evaluate a strong persistence in economics and financial markets. They also argue that the degree of this persistence is related to market efficiency. Jena et al. (2022) argue that if long-run memory exists, investors would find it easier to capture abnormal profits. This is also related to market efficiency. Assaf et al. (2022) also argue that the long memory component is essential to determine whether an asset return is predictable. If an asset return is predictable, then the weak form of the efficient market hypothesis is rejected. Following their logical framework, we extract the long memory of our sample asset prices and compare the extracted long memory properties to evaluate whether they exhibit similarities, implying a financialization. Analyzing long memory also implies long-run dependencies in financial modeling (Assaf et al., 2022). Therefore, we examine the properties of cryptocurrencies, currencies, and commodities to assess whether there is a similarity (financialization) or a difference (hedging). A standard method for extracting a long-run component is a GARCH(1,1), developed by Bollerslev (1986), and is as follows:

$$\begin{aligned} RET_t^2 &= \omega + \alpha_1 * \epsilon_{t-1}^2 + \beta_1 * RET_{t-1}^2 \\ 0 &\leq \alpha_1, \beta_1 \leq 1 \\ \alpha_1 + \beta_1 &< 1 \\ \omega &= LR / (1 - \alpha_1 - \beta_1) \end{aligned} \quad (5)$$

where  $\omega$ ,  $\alpha_1$ , and  $\beta_1$  are the GARCH(1,1) parameters to be estimated. LR refers to the long-run component of a series. We execute the GARCH(1,1) process using the fGarch R package (Wuertz et al., 2022).

There are two methods we employ to evaluate the bias components. First, we closely follow Seiler et al. (2013) to test whether familiarity bias exists according to the following regression equation:

$$RET_t = \eta_0 + \eta_1 * PCOM_t + \eta_2 * PFX_t + \xi_t \quad (6)$$

PFX refers to a portfolio series of equally weighted currencies, whereas PCOM refers to a portfolio series of equally weighted commodities. According to Seiler et al. (2013), a series tends to exhibit familiarity bias if the coefficient estimates are positive and significantly different from zero. Thus, in Equation (6), we will refer to the  $\eta_1$  and  $\eta_2$  parameters; if they are positive and significantly different from zero, then we can conclude that a cryptocurrency tends to be familiar with currencies, commodities, or both. This equation model of familiarity bias is based on the idea of measuring deviations from the standard usual benchmark (they wrote as 'status quo'). Investors familiar with certain assets tend to have lower risk assessments, indicating an underestimation of risk. Second, we closely follow Salisu et al. (2020) to test whether the observed series exhibits herding as follows:

$$RET_t = \gamma_0 + \gamma_1 * GI_{t-1} + \gamma_2 * GI_{t-2} + \gamma_3 * GI_{t-3} + \gamma_4 * GI_{t-4} + \gamma_5 * GI_{t-5} + \epsilon_t \quad (7)$$

$$\epsilon_t = \lambda_1 * PCOM_t + \lambda_2 * PFX_t + \mu_t \quad (8)$$

According to Salisu et al. (2020), the GI is a global fear factor. They argue and formulate that an asset return might be explained by a common global 'fear' index. Their idea of 'fear' here can be intuitively

explained by the fact that global panic eventually affects an asset return. Therefore, any statistically significant relationship could explore and explain whether the global fear component will be captured into an asset return. We use the MSCI World and FTSE All World as global indices representing the global fear factor. We also allow the equation up to five lags to accommodate more dynamics in the model, following Salisu et al. (2020). Then, we extract the residuals obtained in Equation (7) to test whether a cryptocurrency exhibits herding to currencies, commodities, or both in Equation (8). Equation (7) performs a statistical test to determine which lagged global factor may affect cryptocurrencies, whereas Equation (8) further analyzes whether a specific component of cryptocurrencies (after filtering the lagged global factor) exhibits herding. Therefore, we evaluate the sign and significance of  $\gamma$  and  $\lambda$  estimates. A positive and statistically significant indicates a specific lagged global factor and explains the herding tendency.

According to Das (2012), a disposition effect (DE) occurs when an investor tends to sell winners too early and holds losers too long. The underlying idea of their DE model is that we can extract the investors' propensity from their bias in selling winners (versus losers). Assuming investors are indifferent between two compared assets, evaluating and comparing DE factors could conclude whether those two assets tend to exhibit financialization. We define a return as a winner if today's return is higher than the return from yesterday. This implies that a return is called a loser if today's return is lower than the return from yesterday. Following Trejos et al. (2019) and Winne (2021), we model the probability of whether cryptocurrency is a winner in the following logistic regression model:

$$\Pr(W=1)_t = \Delta_0 + \Delta_1 * F_{t-1} + \Delta_2 * F_{t-2} + \Delta_3 * DF_{t-1} + \epsilon_t \quad (9)$$

where  $\Pr(W=1)$  is the dummy variable for a cryptocurrency's return (equals 1 if it is a winner and 0 otherwise), and  $F$  refers to the global index return, or PCOM or PFX.  $DF$  denotes a dummy variable for yesterday's  $F$ 's return (equals 1 if it is a winner and 0 otherwise). It should be noted that Equation (9) only allows up to two lags because the findings in Table 9 report that the second lag is the only significant determinant. We execute the logistic model using the R stats package. We must evaluate whether the coefficient in Equation (9) is statistically significant, as well as the sign or direction. A positive sign indicates that a positive return from a global factor increases the probability of a 'winner' cryptocurrency. This implies that a positive global return tends to prevent the DE, whereas a negative sign implies that a positive global return tends to trigger the DE.

We also evaluate which DE affects cryptocurrencies. Using our commodities and currencies sample, we calculate the DE as follows (somewhat similar to Trejos et al. (2019) and Winne (2021)):

$$DE = [\#POS - \#NEG] / [\#POS + \#NEG] \quad (10)$$

Then, we analyze how DE from both commodities and currencies is associated with the cryptocurrencies' returns in the following equation:

$$RET_t = \psi_0 + \psi_1 * DE_{COM,t} + \psi_2 * DE_{FX,t} + \epsilon_t \quad (11)$$

We must evaluate whether the coefficient in Equation (10) is statistically significant, as well as the sign or direction. A positive sign and statistically significant coefficient indicate that there is a DE from commodities or FXs (or both) associated with cryptocurrencies. Therefore, DE bias implies financialization, whereas absence of DE bias implies hedging for cryptocurrencies. We also conduct some of our empirical analyses using relevant built-in functions from Wolfram Mathematica for double-checking and robustness.

The last statistical analysis is the robustness test. We perform the dynamic conditional correlation (DCC) analysis to test whether each of the two paired variables in Table 8 and Table 9 models generate consistent results under different economic conditions. DCC analysis has also been widely used in recent commodity market research (see Liu et al., 2022 or Alshammari & Obeid, 2023). Our DCC analysis follows Danielsson (2011), and the technical implementation also follows Danielsson (2024). Our basic idea of the DCC analysis here assumes that each paired variable follows the standard GARCH(1,1) process (Bollerslev, 1986), and we perform a multivariate analysis to extract the conditional correlation of each daily observation.



### 3. Data and empirical analysis

Our daily return series includes two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), and six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USDCHF, and USD/CAD) from 2 November 2018 to 30 June 2022 (weekdays). We only consider a 'balanced' series; this implies a complete series containing no missing data for any other series. We also construct a portfolio series of equally weighted currencies (PFX) and commodities (PCOM), each portfolio equally weighted with each cryptocurrency (PFXBTC, PFXETH, PCOMBTC, and PCOMETH). [Table 1](#) provides detailed information on our daily return series.

[Table 2](#) reports the statistical description of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018, to 30 June 2022 (weekdays). We can observe several time-series properties of major cryptocurrencies (BTC and ETH). First, they exhibit mean reversion similar to currencies and commodities. However, unlike other assets and portfolios, their mean reversion tends to be slightly (even still lower than 0.5 percent) positive. This indicates that, on average, cryptocurrencies tend to generate a light positive return. Second, cryptocurrencies' returns exhibit non-normality, as indicated by the rejection of the normality null hypothesis (high JB-Test statistics values). Their non-normality properties are similar to currencies and portfolios. Their non-normality, however, seems to be closer to currencies than commodities. Third, cryptocurrencies' returns are stationary, as indicated by the rejection of the non-stationarity null hypothesis (high ADF-Test statistics values). Fourth, cryptocurrencies' high and low return proportions are surprisingly lower than those of currencies (except for USD.JPY), though still higher than those of commodities (except for Gold). A behavioral bias, likely as framing, occurs here. People tend to recall consecutive negative returns, called 'crash,' rather than objectively calculating the actual proportion of negative returns. We would have more concerns about negative returns in currencies because of a higher proportion of negative returns reported in the currency market. This might also indicate an inappropriate term for crash (for example, Kalyvas et al., 2022, and Hattori & Ishida, 2021). Or we shall redefine crashes as consecutive negative returns (similar to a recession in economics) rather than extreme returns because the proportions of negative returns are much higher in currencies (and we rarely or never heard of a crash in currencies).

[Table 3](#) reports a correlation matrix among two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018 to 30 June 2022 (weekdays). From [Table 3](#), we can observe that both BTC and ETH exhibit very low correlations to both currencies as well as commodities. This indicates that we cannot classify a cryptocurrency as either a currency or a commodity. We can also observe that BTC and ETH have a very high correlation to PFXBTC, PFXETH, PCOMBTC, and PCOMETH despite the portfolios' low correlation to each currency and commodity. This implies that adding BTC or ETH to existing currency or commodity portfolios will result in portfolios that are closer to cryptocurrencies rather than to currencies or commodities. For portfolio managers, this is an interesting signal. Any currency or commodity portfolio manager considering adding cryptocurrencies would be aware that this strategy will bring their existing portfolio closer to cryptocurrencies. This implies that they tend to incorporate cryptocurrency risks into their new portfolio compositions.

[Table 4](#) reports the estimates of ARMA(2,2) process of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018 to 30 June 2022 (weekdays). From [Table 4](#), we can observe that both BTC and ETH have different ARMA(2,2) properties that set them apart from most of the commodities (Gold is an exception) and most of the currencies (USD.JPY). Again, this indicates that we cannot classify BTC and ETH as either currencies or commodities. Since there are no statistically significant ARMA(2,2) parameters in either BTC or ETH, we infer that cryptocurrencies are more efficient than currencies and commodities because their returns cannot be easily captured by the ARMA(2,2) process. This implies that forecasting cryptocurrencies will be a more challenging

**Table 1.** Detailed descriptions of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH), and two global indices (MSCI World and FTSE World) daily return series from 2 November 2018 to 30 June 2022 (weekdays).

Asset/Portfolio	Description of daily return series
BTC	Bitcoin/US Dollar FX Spot Rate
ETH	Ethereum/US Dollar FX Spot Rate
EUR.USD	Euro/US Dollar FX Spot Rate
USD.JPY	US Dollar/Japanese Yen FX Spot Rate
GBP.USD	UK Pound Sterling/US Dollar FX Spot Rate
AUD.USD	Australian Dollar/US Dollar FX Spot Rate
USD.CHF	US Dollar/Swiss Franc FX Spot Rate
USD.CAD	US Dollar/Canadian Dollar FX Spot Rate
Gold	COMEX Gold Composite Commodity
Silver	COMEX Silver Composite Commodity
Oil	NYMEX Light Sweet Crude Oil (WTI) Electronic Energy
Gas	NYMEX Henry Hub Natural Gas Electronic Energy
Corn	CBoT Corn Composite Commodity
Cattle	CME Live Cattle Electronic Commodity
PFX	Equally weighted FX portfolio (EUR, JPY, GBP, AUD, CHF, CAD)
PCOM	Equally weighted commodities portfolio (Gold, Silver, Oil, Gas, Corn, Cattle)
PFXBTC	Equally weighted BTC single asset and FX portfolio
PFXETH	Equally weighted ETH single asset and FX portfolio
PCOMBTC	Equally weighted BTC single asset and commodities portfolio
PCOMETH	Equally weighted ETH single asset and commodities portfolio
MSCI World	Morgan Stanley Capital International index
FTSE World	Derived from the FTSE Global Equity Index Series (GEIS)

**Table 2.** The statistical descriptive of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018 to 30 June 2022 (weekdays).

Asset/Portfolio	BTC	ETH	EUR.USD	USD.JPY	GBP.USD	AUD.USD	USD.CHF
Mean	0.22%	0.35%	-0.01%	0.02%	-0.01%	0.00%	0.00%
Std Dev	4.56%	5.92%	0.42%	0.47%	0.57%	0.63%	0.43%
Min	-26.60%	-33.34%	-2.05%	-2.81%	-3.63%	-3.84%	-2.77%
Max	24.06%	36.28%	1.61%	3.21%	2.66%	2.37%	1.86%
JB-Test	586.66	841.49	56.82	2471.69	431.56	466.70	263.18
ADF-Test	-8.81	-8.83	-10.87	-10.71	-10.90	-9.94	-10.66
High Positive	104	106	126	91	108	112	123
	11.30%	11.52%	13.70%	9.89%	11.74%	12.17%	13.37%
Low Negative	104	102	126	99	116	119	132
	11.30%	11.09%	13.70%	10.76%	12.61%	12.93%	14.35%
# Observations	920	920	920	920	920	920	920
Asset/Portfolio	USD.CAD	Gold	Silver	Oil	Gas	Corn	
Mean	0.00%	0.05%	-0.05%	-0.28%	0.13%	0.09%	
Std Dev	0.44%	1.02%	3.89%	11.56%	4.36%	1.75%	
Min	-1.86%	-4.98%	-100.00%	-305.97%	-25.95%	-17.39%	
Max	2.14%	5.95%	9.29%	37.66%	46.48%	6.41%	
JB-Test	157.71	966.73	8.63E + 06	1.15E + 07	11,113.66	5694.37	
ADF-Test	-9.62	-10.58	-9.71	-10.33	-9.64	-8.87	
High Positive	128	103	29	9	91	100	
	13.91%	11.20%	3.15%	0.98%	9.89%	10.87%	
Low Negative	128	104	25	7	89	95	
	13.91%	11.30%	2.72%	0.76%	9.67%	10.33%	
#Observations	920	920	920	920	920	920	
Asset/Portfolio	Cattle	PFX	PCOM	PFXBTC	PFXETH	PCOMBTC	PCOMETH
Mean	0.03%	0.00%	-0.01%	0.11%	0.18%	0.11%	0.17%
Std Dev	1.28%	0.15%	2.29%	2.30%	2.97%	2.66%	3.26%
Min	-7.98%	-0.83%	-49.51%	-13.70%	-17.07%	-26.10%	-24.43%
Max	7.25%	0.68%	8.34%	11.88%	18.05%	11.96%	18.60%
JB-Test	2133.29	228.98	2.43E + 06	594.10	834.42	6742.04	1932.09
ADF-Test	-11.35	-9.93	-10.32	-8.80	-8.84	-9.26	-9.13
High Positive	71	133	31	106	107	103	108
	7.72%	14.46%	3.37%	11.52%	11.63%	11.20%	11.74%
Low Negative	75	132	31	104	104	93	93
	8.15%	14.35%	3.37%	11.30%	11.30%	10.11%	10.11%
# Observations	920	920	920	920	920	920	920

task for portfolio managers. Similarities in the ARMA(2,2) parameters of three constructed portfolios (PFXBTC, PFXETH, and PCOMETH) indicate, again, that adding a cryptocurrency to existing currency or commodity portfolios will increase uncertainties in the portfolio returns, at least from ARMA(2,2) process. Overall, we might conclude that based on ARMA(2,2) properties, BTC and ETH do not seem to be financialization to currencies and commodities. However, we argue that hedging is also not a suitable term because we document that adding BTC or ETH to existing portfolios tends to increase uncertainty, contrary to the hedging purpose.

Table 5 reports the estimates of AR(5) process of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018 to 30 June 2022 (week-days). From Table 5, we can observe that compared to all commodities and currencies, BTC and ETH both have different AR(5) properties. We evaluate the difference from the sign of coefficient estimates and t-statistics of significance. This indicates, again, that BTC and ETH are neither currencies nor commodities. We also document that BTC and ETH are more efficient because the estimates of AR(5) in both cryptocurrencies do not generate any statistically significant coefficient. These are clearly different from currencies and commodities, which report a few significant coefficients from AR(5) process. The portfolios, however, are different from those in Table 4. We now see a few statistically significant coefficients in PFXETH, PCOMBTC, and PCOMETH in Table 5, in contrast to Table 4. This indicates that the predictability of portfolios' returns slightly increases with the addition of cryptocurrencies. Therefore, we could now draw the conclusion that cryptocurrencies tend to be (a little) hedging rather than financialization. However, this conclusion is not strong because it applies only to PFX and ETH, and most AR(5) parameters are still insignificant. We believe that cryptocurrencies are not financialized to the currencies and commodities markets.

Table 6 reports the most fitted univariate time series based on the Akaike Information Criterion (AIC). We performed the estimation using the built-in function in Wolfram Mathematica. Table 6 further justifies the results obtained in Table 5, as both cryptocurrencies exhibit different time series properties to commodities and currencies. This implies that cryptocurrencies tend to be classified as a new asset class, distinct from commodities and currencies.

Table 7 reports the estimates of GARCH(1,1) parameters of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018 to 30 June 2022 (week-days). Table 7 demonstrates that the long-run components of BTC and ETH are much higher than other currencies and commodities; a distinction can be seen in Silver, which exhibits a relatively high long-run component but is still below BTC and ETH. Referring to Assaf et al. (2022), the higher long-run components of cryptocurrencies demonstrate a stronger persistence in their markets. However, this might be contradictory if we only report a few market participants who can exploit. At least the number of investors profiting from cryptocurrencies must be higher than those profiting from currencies or commodities. Following Jena et al. (2022), a higher long-run component implies an easier sign to capture abnormal profits. Again, these time-series properties reveal that opportunities in cryptocurrency markets exist. Market participants would be cautious not only about the crash (downside) but also about opportunities (upside). An initial hypothesis of the risky asset for cryptocurrencies shall be negated with stronger persistence, meaning higher chances of earning abnormal profits. Evaluating the downside and upside of cryptocurrencies prevents us from confirmation bias because we can observe both challenges as well as opportunities.

Table 8 reports the regression results of Equation (6). As shown in Table 8, the covariates seem to be positive and statistically significant for both cryptocurrencies. This indicates that familiarity bias of cryptocurrencies tends to be associated with the biases of commodities and currencies. The result is a bit stronger in BTC than ETH. Further analysis in Figure 1 reveals that the familiarity bias of both BTC and ETH is stronger in PFX rather than PCOM (as indicated by scattered plots and regression line diagrams). However, both PFX and PCOM exhibit decent associations with both BTC and ETH. Overall, while this provides partial answers that cryptocurrencies exhibit familiarity with commodities and FXs, it is still not

2018 to 30 June 2022 (weekdays).

[illegible]

**Table 4.** The estimates of ARMA(2,2) process of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018 to 30 June 2022 (weekdays)

Asset/Portfolio	AR(1) $\phi_1$	AR(2) $\phi_2$	MA(1) $\theta_1$	MA(2) $\theta_2$	Intercept $\phi_0$
BTC	0.5059 1.11	0.4369 0.98	-0.5123 -1.10	-0.4003 -0.89	0.0001 0.66
ETH	0.4005 0.52	0.0968 0.11	-0.4204 -0.54	-0.0139 -0.02	0.0017 1.09
EUR.USD	-0.9476 -5.90***	-0.7122 -4.55***	0.9534 6.46***	0.7715 5.40***	-0.0001 -0.14
USD.JPY	0.1255 0.20	0.0753 0.11	-0.1765 -0.29	-0.0269 -0.04	0.0002 0.68
GBP.USD	-0.3962 -2.17**	0.5098 2.94***	0.4653 2.45**	-0.4803 -2.58***	0.0000 -0.23
AUD.USD	-0.5163 -9.73***	0.6300 12.89***	0.5866	-0.3778	-0.0103
USD.CHF	-1.1363 -15.98***	-0.8323 -9.89***	1.1729 19.00***	0.8871 12.71***	-0.0001 -0.26
USD.CAD	-0.9538 -2.60***	-0.0076 -0.02	0.9503 2.55**	-0.0302 -0.08	-0.0001 -0.38
Gold	0.5897	0.1898	-0.6089	-0.2274	0.0001 1.64
Silver	-0.1250 -0.26	-0.2775 -0.55	0.0866 0.18	0.3303 0.67	-0.0007 -0.40
Oil	0.1147 0.55	-0.2011 -2.37	0.2637 1.25	0.0639 0.52	-0.0031 -0.65
Gas	-0.5582 -15.59***	-0.9031 -21.52***	0.5646 13.42***	0.8699 13.98***	0.0040 1.17
Corn	1.1728 16.37***	-0.8935 -14.85***	-1.1395 -13.98***	0.8395 11.44***	0.0003 0.85
Cattle	-0.2093 -1.54	-0.8162 -11.20***	0.2781 2.23**	0.8433 9.60***	0.0005 0.53
PFX	1.1576 48.85***	-0.9017 -32.80***	-1.1910 -54.36***	0.9473 39.34***	-0.0001 -1.48
PCOM	-0.0532 -0.16	-0.1267 -0.88	0.3119 0.94	0.0452 0.23	-0.0001 -0.10
PFXBTC	0.5379 0.74	0.1541 0.16	-0.5405 -0.74	-0.1020 -0.10	0.0003 0.57
PFXETH	0.3197 0.65	0.1730 0.35	-0.3384 -0.68	-0.0883 -0.18	0.0009 1.13
PCOMBTC	-0.3951 -0.63	0.3933 1.09	0.4582 0.73	-0.3460 -0.94	0.0011 0.79
PCOMETH	0.1317 0.22	0.1708 0.42	-0.1047 -0.17	-0.1153 -0.29	0.0012 1.04

\*\*\*significant at 1%.

\*\*significant at 5%.

\*significant at 10%.

clear enough whether cryptocurrencies shall be classified as commodities or FXs. This implies that cryptocurrency investors tend to share the similar familiarity bias as those investing in commodities and currencies. Similar to Seiler et al. (2013), we conclude that investors understate risk and misestimate the future prices of cryptocurrencies, commodities, and currencies.

Table 9 reports the regression results of Equations (7) and (8). From Table 9 (upper panel), we can clearly see that only lagged 2 of the global factor affects cryptocurrencies. The direction of lagged 2 coefficients is positive. Figure 2 further clarifies that the associations between cryptocurrencies and lagged 2 global indices are quite strong, as indicated by scattered diagrams and regression lines between respective dependent and independent variables. This implies that a positive sentiment about the global factor tends to generate a positive return on the cryptocurrencies in the next two working days. We can conclude that there is a positive association between global factors and cryptocurrencies, but the association only appears after two working days. Table 9 (lower panel) demonstrates that a specific factor of cryptocurrencies tends to be associated with both commodities and currencies. A positive sign implies a tendency toward herding cryptocurrencies in the context of investors' familiarity bias. Therefore, we further justify the findings in Table 8 by demonstrating that investors tend to understate risk and misestimate the future prices of cryptocurrencies, commodities, and currencies.

**Table 5.** The estimates of AR(5) process of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018 to 30 June 2022 (weekdays).

Asset/Portfolio	AR(1) $\phi_1$	AR(2) $\phi_2$	AR(3) $\phi_3$	AR(4) $\phi_4$	AR(5) $\phi_5$	Intercept $\phi_0$
BTC	-0.0041 -0.12	0.0479 1.45	0.0385 1.17	0.0221 0.67	-0.0043 -0.13	0.0020 1.30
ETH	-0.0198 -0.60	0.0744 2.25	0.0251 0.76	0.0348 1.05	-0.0017 -0.05	0.0031 1.57
EUR.USD	0.0037 0.11	0.0725 2.20**)	-0.0493 -1.49	-0.0319 -0.97	-0.0244 -0.74	-0.0001 -0.60
USD.JPY	-0.0512 -1.55	0.0390 1.18	0.0095 0.29	-0.0018 -0.06	-0.0181 -0.55	0.0002 1.31
GBP.USD	0.0496 1.50	0.0354 1.07	0.0364 1.10	-0.0096 -0.29	-0.0274 -0.83	-0.0001 -0.28
AUD.USD	0.0871 2.64***)	0.0218 0.66	-0.0085 -0.26	-0.0096 -0.29	0.0011 0.03	0.0000 -0.15
USD.CHF	0.0328 1.00	0.0561 1.70*)	-0.0288 -0.87	0.0018 0.05	-0.0343 -1.04	0.0000 -0.35
USD.CAD	-0.0217 -0.66	-0.0371 -1.13	0.0108 0.33	0.0277 0.84	0.0153 0.46	0.0000 -0.07
Gold	-0.0100 -0.30	-0.0106 -0.32	0.0080 0.24	-0.0916 -2.79***)	-0.0313 -0.95	0.0005 1.61
Silver	-0.0412 -1.25	0.0538 1.63	-0.0058 -0.18	-0.0332 -1.01	-0.0270 -0.82	-0.0005 -0.42
Oil	0.3770 11.45***)	-0.2338 -6.65***)	0.0512 1.42	0.0166 0.47	0.0523 1.59	-0.0021 -0.58
Gas	-0.1003 -3.03***)	-0.0627 -1.89*)	-0.0009 -0.03	0.0590 1.78*)	-0.1031 -3.12***)	0.0016 1.09
Corn	0.0163 0.49	-0.0092 -0.28	-0.0278 -0.84	-0.0700 -2.12**)	0.0439 1.33	0.0009 1.59
Cattle	0.0740 2.24**)	-0.0338 -1.02	-0.0430 -1.30	0.0133 0.40	0.0334 1.01	0.0003 0.60
PFX	0.0620 1.88*)	0.0253 0.77	-0.0293 -0.89	0.0623 1.89*)	0.0232 0.70	0.0000 -0.14
PCOM	0.2573 7.80***)	-0.1602 -4.70***)	0.0461 1.34	0.0156 0.46	0.0417 1.26	-0.0001 -0.09
PFXBTC	-0.0030 -0.09	0.0502 1.52	0.0369 1.12	0.0224 0.68	-0.0032 -0.10	0.0010 1.29
PFXETH	-0.0193 -0.58	0.0764 2.32**)	0.0255 0.77	0.0346 1.05	-0.0017 -0.05	0.0015 1.56
PCOMBTC	0.0581 1.76	0.0236 0.71	0.0157 0.47	0.0154 0.47	0.0146 0.44	0.0009 1.05
PCOMETH	0.0269 0.82	0.0573 1.73*)	0.0032 0.10	0.0262 0.79	0.0075 0.23	0.0015 1.36

\*\*\*significant at 1%.

\*\*significant at 5%.

\*significant at 10%.

**Table 6.** The fitted univariate time-series estimation, based on AIC criteria using Wolfram Mathematica built-in function.

Asset/Portfolio	Time Series Fit	Asset/Portfolio	Time Series Fit
BTC	MA(0)	Oil	AR(3)
ETH	MA(0)	Gas	MA(2)
EUR.USD	GARCH(1,1)	Corn	MA(0)
USD.JPY	GARCH(1,1)	Cattle	MA(1)
GBP.USD	GARCH(1,1)	PFX	AR(1)
AUD.USD	AR(1)	PCOM	MA(2)
USD.CHF	GARCH(1,1)	PFXBTC	MA(0)
USD.CAD	GARCH(1,1)	PFXETH	MA(0)
Gold	GARCH(1,1)	PCOMBTC	AR(1)
Silver	MA(0)	PCOMETH	GARCH(1,1)

Wolfram Mathematica TimeSeriesFit function based on AIC criteria.

Figure 3 depicts the dynamic conditional correlation (DCC) between BTC and PCOM, BTC and PFX, ETH and PCOM, and ETH and PFX variables for daily trading days from 9 November 2018 to 30 June 2022. We can see that, though there are variations in the correlations, the correlations between



**Table 7.** The estimates of GARCH(1,1) parameters of two major cryptocurrencies (BTC and ETH), six commodities (Gold, Silver, Crude Oil, Natural Gas, Corn, and Cattle), six FX currencies (EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF, and USD/CAD), and six constructed portfolios (PFX, PCOM, PFXBTC, PFXETH, PCOMBTC, and PCOMETH) daily return series from 2 November 2018 to 30 June 2022 (weekdays).

Asset/Portfolio	LR	Omega	Alpha1	Beta1
	LR	$\omega$	$\alpha_1$	$\beta_1$
BTC	0.2072%	0.0309%	7.1776%	77.9168%
ETH	0.3600%	0.0386%	9.5524%	79.7199%
EUR.USD	0.0018%	0.0000%	6.3781%	91.6382%
USD.JPY	0.0019%	0.0002%	12.8375%	78.5517%
GBP.USD	0.0031%	0.0004%	13.1881%	74.8338%
AUD.USD	0.0044%	0.0001%	6.8507%	91.5673%
USD.CHF	0.0019%	0.0002%	11.7425%	78.3524%
USD.CAD	0.0019%	0.0001%	6.0149%	91.1913%
Gold	0.0100%	0.0007%	8.7122%	84.5892%
Silver	0.1515%	0.0425%	0.0000%	71.9385%
Oil	0.0000%	0.0000%	43.4549%	84.3339%
Gas	-0.0944%	0.0010%	11.5549%	89.4696%
Corn	0.0363%	0.0009%	9.3465%	88.3084%
Cattle	0.0278%	0.0018%	32.1783%	61.1928%
PFX	0.0002%	0.0000%	7.8650%	87.6695%
PCOM	0.0000%	0.0000%	10.4002%	93.4585%
PFXBTC	0.0525%	0.0081%	7.4172%	77.1758%
PFXETH	0.0910%	0.0100%	9.6370%	79.3877%
PCOMBTC	0.0726%	0.0022%	4.4245%	92.5222%
PCOMETH	0.1121%	0.0053%	6.5786%	88.6883%

**Table 8.** The regression results of equation (6). The asterisk indicates a significant explanatory variable at the(\*) 10% significance level,\*\*) 5% significance level,\*\*) 1% significance level.

RET <sub>t</sub> = $\eta_0 + \eta_1^* \text{PCOM}_t + \eta_2^* \text{PFX}_t + \xi_t$ (6)		
Independent Variable	Dependent Variable	
	BTC	ETH
Intercept	0.00 (1.53)	0.00* (1.84)
PCOM	0.17*** (2.63)	0.15* (1.83)
PFX	5.37*** (5.54)	7.22*** (5.73)
Adjusted R-squared	0.04	0.04

\*\*\*significant at 1%,

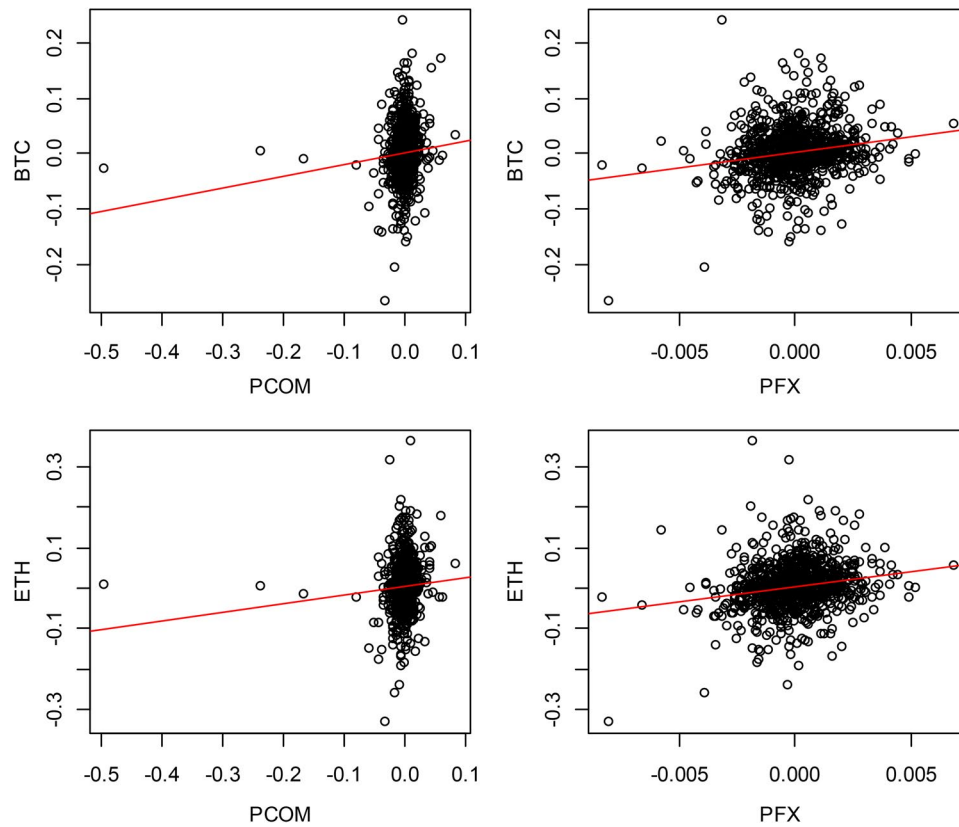
\*\*significant at 5%,

\*significant at 10%.

cryptocurrencies and PFX are slightly stronger than those between PCOM. This indicates that the familiarity bias tends to be slightly toward PFX (rather than PCOM), and the bias is consistent under different economic conditions.

Figure 4 depicts the dynamic conditional correlation (DCC) plots between BTC and MSCI lagged 2, BTC and FTSE lagged 2, ETH and MSCI lagged 2, and ETH and FTSE lagged 2 variables for daily trading days from 9 November 2018 to 30 June 2022. We can observe that though there are some variations, the correlations tend to be stable, and there are no significant differences between the global factor MSCI and FTSE. This indicates that the global fear factor lagged 2 tends to have an association with cryptocurrencies, and the bias is consistent under different economic conditions.

Table 10 reports the regression results of Equation (9). According to Table 10, the previous global factor and currencies (not commodities) tend to decrease the likelihood of a 'winner' cryptocurrency. The signs are different for lagged 1 and 2 covariates in ETH. We tend to refer to the lagged one because the results are stronger and more consistent. We conclude that a positive sentiment toward the global factor and currencies is associated with the disposition effect, but the correlation is negative, however. This means that a negative global factor and currencies that occurred yesterday will trigger global investment allocation into cryptocurrencies, causing an increase in the demand for cryptocurrencies. Finally, a higher return for cryptocurrencies is realized on the next working day. This is understandable because a negative sentiment in an asset class triggers investors to shift their investments to another asset class.



**Figure 1.** The scattered plot between BTC and PCOM, BTC and PFX, ETH and PCOM, and ETH and PFX variables. The linear regression line between the two variables is plotted in red.

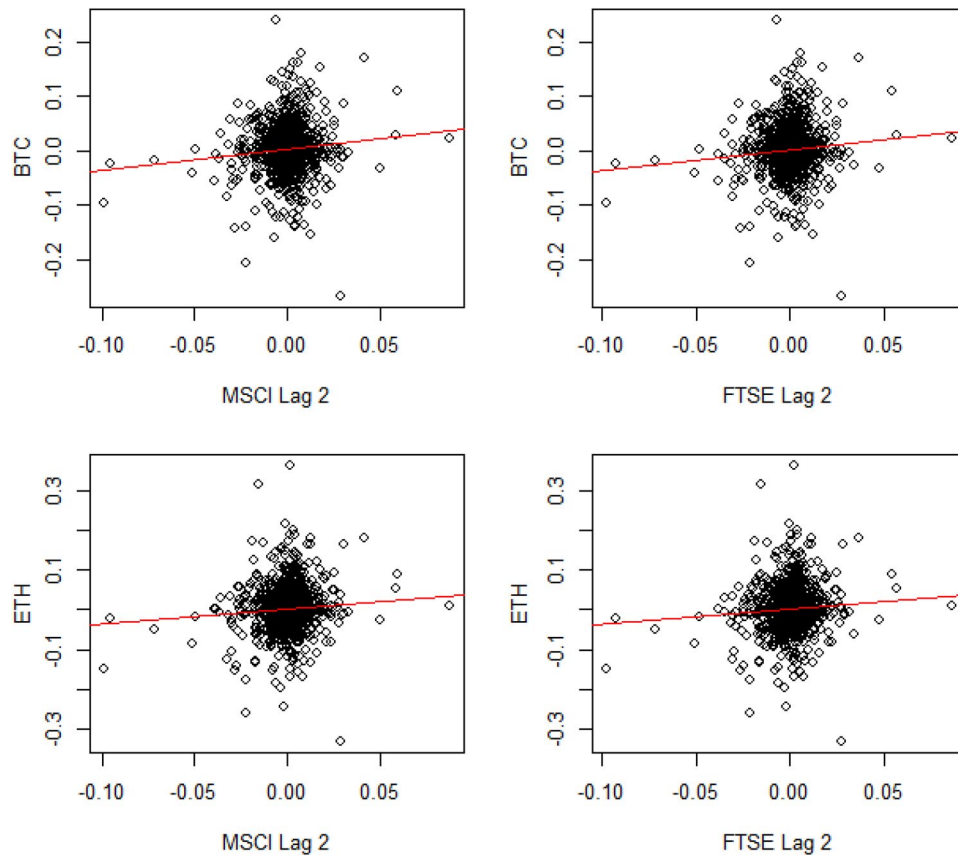
**Table 9.** The regression results of equations (7) and (8). The asterisk indicates a significant explanatory variable at the \*) 10% significance level, \*\*) 5% significance level, \*\*\*) 1% significance level.

$RET_t = \gamma_0 + \gamma_1 * Glt-1 + \gamma_2 * Glt-2 + \gamma_3 * Glt-3 + \gamma_4 * Glt-4 + \gamma_5 * Glt-5 + \epsilon_t$ (7)				
Independent Variable	Dependent Variable: BTC		Dependent Variable: ETH	
	GI = MSCI	GI = FTSE	GI = MSCI	GI = FTSE
Intercept	0.00 (1.41)	0.00 (1.41)	0.00* (1.71)	0.00 (1.72)
Glt-1	-0.05 (-0.40)	-0.05 (-0.39)	-0.12 (-0.73)	-0.12 (-0.75)
Glt-2	0.37*** (2.97)	0.37*** (2.86)	0.57*** (3.53)	0.58*** (3.46)
Glt-3	-0.06 (-0.45)	-0.08 (-0.61)	-0.01 (-0.04)	-0.02 (-0.14)
Glt-4	0.03 (0.25)	0.05 (0.40)	0.06 (0.39)	0.09 (0.53)
Glt-5	0.02 (0.17)	0.02 (0.16)	-0.06 (-0.35)	-0.06 (-0.34)
Adjusted R-squared	0.01	0.01	0.01	0.01
$\epsilon_t = \lambda_1 * PCOM_t + \lambda_2 * PFX_t + \mu_t$ (8)				
Independent Variable	Dependent Variable: BTC		Dependent Variable: ETH	
	GI = MSCI	GI = FTSE	GI = MSCI	GI = FTSE
PCOM	0.16** (2.50)	0.16** (2.51)	0.14* (1.66)	0.14* (1.67)
PFX	5.03*** (5.21)	5.04*** (5.21)	6.71*** (5.36)	6.71*** (5.35)
Adjusted R-squared	0.04	0.04	0.03	0.03

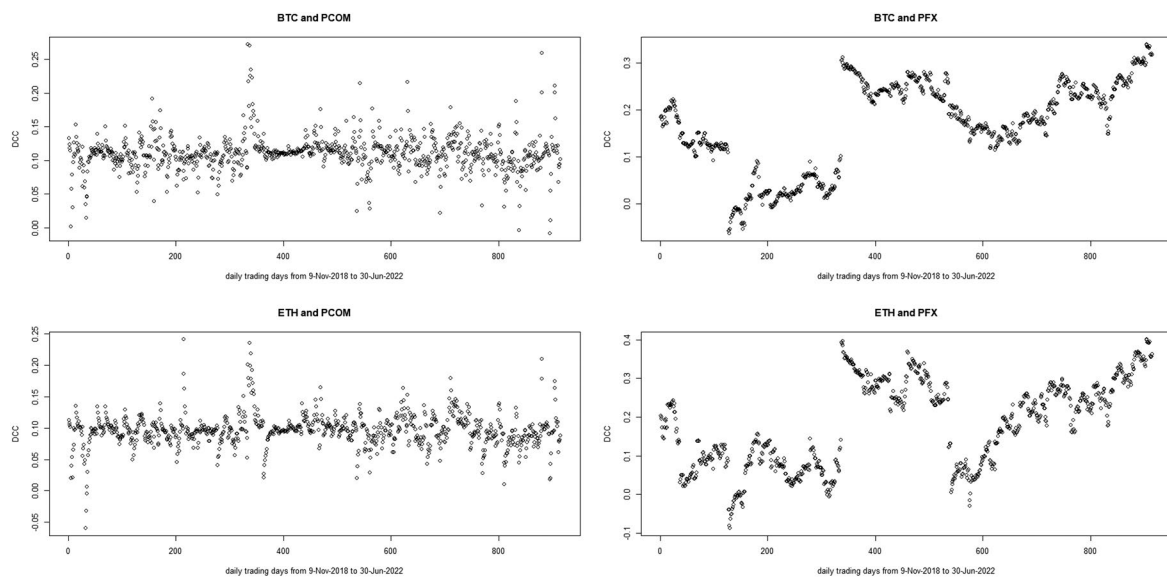
\*\*\*significant at 1%.

\*\*significant at 5%.

\*significant at 10%.

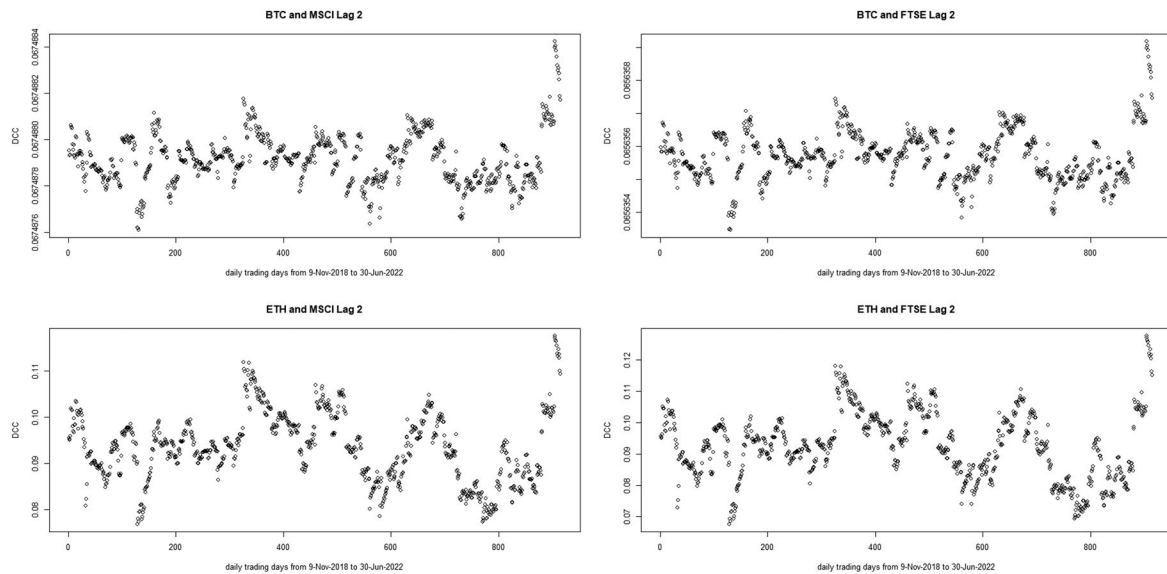


**Figure 2.** The scattered plot between BTC and MSCI lagged 2, BTC and FTSE lagged 2, ETH and MSCI lagged 2, and ETH and FTSE lagged 2 variables. The linear regression line between the two variables is plotted in red.



**Figure 3.** The DCC plots between BTC and PCOM, BTC and PFX, ETH and PCOM, and ETH and PFX variables for daily trading days from 9 November 2018 to 30 June 2022.

Table 11 reports the regression results of Equation (11). We also note that Table 11 is different from Table 10. While Table 10 analyzes the association between yesterday and today, Table 11 analyzes the association on the same day. According to Table 11, the DE biases of commodities and currencies tend to be associated with cryptocurrencies. This demonstrates that investors experience a similar DE bias



**Figure 4.** The DCC plots between BTC and MSCI lagged 2, BTC and FTSE lagged 2, ETH and MSCI lagged 2, and ETH and FTSE lagged 2 variables for daily trading days from 9 November 2018 to 30 June 2022.

**Table 10.** The regression results of equation (9). The asterisk indicates a significant explanatory variable at the \*) 10% significance level, \*\*) 5% significance level, \*\*\*) 1% significance level.

Pr (W=1)t=Δ0 + Δ1* Ft-1 + Δ2* Ft-2 + Δ3* DFt-1 + εt (9)				
Dependent variable: BTC				
Independent variable	F = MSCI	F = FTSE	F = PCOM	F = PFX
Intercept	0.00 (-0.04)	0.06 (0.58)	-0.04 (-0.39)	-0.20 (-1.62)
Ft-1	-32.64*** (-3.99)	-28.70*** (-3.56)	-9.12* (-1.72)	-238.23*** (-3.83)
Ft-2	10.44 (1.43)	7.47 (1.03)	0.26 (0.06)	115.95** (1.97)
DFt-1	-0.11 (-0.62)	-0.26 (-1.41)	-0.04 (-0.23)	0.27 (1.30)
AIC	1237.30	1238.20	1269.30	1255.00
Dependent variable: ETH				
Independent variable	F = MSCI	F = FTSE	F = PCOM	F = PFX
Intercept	-0.05 (-0.41)	-0.04 (-0.37)	0.07 (0.70)	-0.18 (-1.50)
Ft-1	-34.94*** (-4.15v)	-34.63*** (-4.05)	-1.22 (-0.36)	-234.43*** (-3.78)
Ft-2	18.23** (2.38)	18.23** (2.32)	-1.27 (-0.38)	122.16** (2.08)
DFt-1	0.05 (0.27)	0.04 (0.23)	-0.19 (-1.24)	0.33 (1.54)
AIC	1238.70	1240.90	1273.90	1257.50

\*\*\*significant at 1%,

\*\*significant at 5%,

\*significant at 10%.

across different asset classes: commodities, currencies, and cryptocurrencies. Overall, we can conclude that the DE bias tends to be similar for investors in these three asset classes, but yesterday's bias could cause investors to shift their asset allocation.

#### 4. Conclusion

There has been a sharp rise in interest in the discussion surrounding bitcoin crashes in both industry and academia. A behavioral bias that could harm market participants could result from focusing only on the crash and ignoring other facts. We analyze and evaluate cryptocurrencies' time-series properties to

**Table 11.** The regression results of equation (11). The asterisk indicates a significant explanatory variable at the\*) 10% significance level,\*\*) 5% significance level,\*\*\*) 1% significance level.

RET <sub>t</sub> = $\psi_0 + \psi_1 \text{ DECOM}_{t-1} + \psi_2 \text{ DEFX}_{t-1} + 3t$ (11)		
Dependent variable		
Independent variable	BTC	ETH
Intercept	0.00* (1.68)	0.00** (2.08)
DECOM	0.01*** (2.76)	0.02*** (3.30)
DEFX	0.01** (2.56)	0.01*** (3.40)
Adjusted R-squared	0.01	0.02

\*\*\*significant at 1%,

\*\*significant at 5%,

\*significant at 10%.

determine whether BTC and ETH exhibit hedging or financialization to the currencies and commodities markets. Our analyses include mean reversion, normality, unit root, the proportion of high and low returns, correlation, ARMA(2,2), AR(5), and long-run GARCH(1,1) estimates. We also performed a behavioral analysis by assessing two behavioral biases, namely familiarity and disposition effect.

According to our univariate time-series analyses, BTC and ETH are neither currencies nor commodities. Further evaluation of the impact of adding cryptocurrencies to a portfolio reveals that cryptocurrencies increase uncertainty and efficiency. This implies that adding cryptocurrencies is more suitable for aggressive portfolio managers. While this confirms that cryptocurrencies are riskier, arbitrage opportunities exist due to high long-run components. We document a double-edged sword, both upside and downside, of cryptocurrencies. According to our behavioral bias analysis, we find a strong and consistent bias association between cryptocurrencies and both commodities and currencies. We document consistent behavioral issues in the context of familiarity bias and disposition effect (DE). This implies that investors treat cryptocurrencies in a manner similar to how they treat commodities and currencies, including how they exhibit bias. Therefore, it is not surprising that cryptocurrency investors also understate risk and misestimate future prices.

Overall, from a univariate perspective, we can conclude that cryptocurrencies are neither currencies nor commodities. From an academic perspective, we expect that unless there is a significant extension, univariate models used in currencies or commodities would not work properly in cryptocurrencies. From a practical perspective, market participants would expect different paths when predicting future price. However, from a behavioral perspective, cryptocurrencies tend to be close to both currencies and commodities. This implies that cryptocurrency investors, like those who invest in currencies and commodities, tend to understate risk and misestimate future prices. An academic implication in quantitative finance is that a sophisticated economic model shall factor this risk due to behavioral bias in cryptocurrency markets. Another academic implication is that behavioral bias tends to emerge in all asset classes, at least in the case of currencies, commodities, and cryptocurrencies. Our findings also lead to some practical implications. First, portfolio managers and investors should use a higher discount factor when evaluating cryptocurrency returns since cryptocurrencies tend to possess higher actual risks than they expect. Second, analyzing the risks of cryptocurrencies cannot be limited only to the rational asset pricing model. Practitioners shall also factor in the behavioral bias in cryptocurrency markets to prevent underestimating risk factors.

However, there are some remarks on our findings. Those remarks can be a direction for future research. First, our model and analysis heavily assume that the behavior of cryptocurrencies, commodities, and FXs is captured only by prices. Adding another variable, such as volume, could enrich the analysis and bring further research questions. Second, our robustness test on different economic conditions uses a dynamic conditional correlation method. Further analysis using the regime-switching or quantile method could quantify the degree of dependence (or associations) between examined variables.

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## Authors' contributions

Dony Abdul Chalid (Author 1) contributed to the conception and design of the research, the drafting of the paper and revising it critically for intellectual content. Rangga Handika (Author 2) contributed to the conception and design of the research, collected data, analysis of the results, the drafting of the paper and revising it critically for intellectual content. All authors read and approved the version to be published, and all authors agree to be accountable for all aspects of the work.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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## Data availability statement

The data that support the findings of this study are available from Datastream. Restrictions apply to the availability of these data, which were used under license for this study. The data are available from the corresponding author, Dony Abdul Chalid, upon reasonable request.

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