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Exchange Market Liquidity Prediction with the K-Nearest Neighbor Approach: Crypto vs. Fiat Currencies

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Abstract: In this paper, we compare the predictions on the market liquidity in crypto and fiat currencies between two traditional time series methods, the autoregressive moving average (ARMA) and the generalized autoregressive conditional heteroskedasticity (GARCH), and the machine learning algorithm called the k-nearest neighbor (KNN) approach. We measure market liquidity as the log rates of bid-ask spreads in a sample of three cryptocurrencies (Bitcoin, Ethereum, and Ripple) and 16 major fiat currencies from 9 February 2018 to 8 February 2019. We find that the KNN approach is better suited for capturing the market liquidity in a cryptocurrency in the short-term than the ARMA and GARCH models maybe due to the complexity of the microstructure of the market. Considering traditional time series models, we find that ARMA models perform well when estimating the liquidity of fiat currencies in developed markets, whereas GARCH models do the same for fiat currencies in emerging markets. Nevertheless, our results show that the KNN approach can better predict the log rates of the bid-ask spreads of crypto and fiat currencies than ARMA and GARCH models.

Keywords: Bitcoin; digital money; Ethereum; investor behavior; Ripple; time series analysis



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1. Introduction

The popularity of cryptocurrency with financial intermediaries came about as a consequence of the perceived failures of the monetary authorities in the global financial crisis of 2008 and the European sovereign debt crisis during 2010 to 2013 [1]. In terms of monetary attributes, Yermack [2] explains that Bitcoin does not behave similarly to a fiat currency according to the criteria widely used by economists. For instance, some economists view the inelasticity in the supply of cryptocurrency as an advantage but some view it as a disadvantage.

Cryptocurrencies are digital coins not issued by any government or legal entity [3]; they only use cryptography and a clever system to regulate their supply, control trading operations and avoid frauds. The transactions are recorded digitally in a blockchain as an accounting system [4]. Digital currencies are based on peer-to-peer authentication with rules to determine the amount and condition produced [5]. These currencies plan the peer-to-peer network as a set of nodes in a self-organizing connected network. Hayes [6] has identified that the relative differences in the cost of mining on the margin determine the prices of cryptocurrencies. The most popular cryptocurrency is Bitcoin, which was developed in the seminal paper of Nakamoto [7]. Bitcoin, Ethereum, and Ripple are the main cryptocurrencies capitalized by the market as reported by Blas [8].

Conversely, Dwyer [5] reports that governments create and certify fiat currencies that are used by all. In terms of networks, this is similar to a client-server model in which one server receives requests from clients and responds to them. The server ensures the data precision of whatever information it provides. The issuer designs a fiat currency to hinder counterfeiting and enforces laws that make counterfeiting a crime.

What are the most important challenges in the cryptocurrency market? Encrybit [9], a cryptocurrency exchange platform, conducted a survey among 1108 traders between 23 April and 30 April 2018 and identified the three biggest problems in the cryptocurrency market: lack of security (40%), high trading fees (37%), and lack of liquidity (36%). The first problem deals with more sophisticated hackers who endanger the exchange platforms. The second problem arises because many exchanges split their trading fees into two separate fees in which the maker fee is higher than the taker fee because the former adds liquidity to the market. The third problem is price manipulation and high volatility in which brokers do not place orders or execute them on time.

Crook [10] argues that the illiquidity problem needs to be solved in order to democratize access to the cryptocurrency market, make it more efficient, and avoid perverse incentives from the different players. Jiang et al. [11] make a bibliometric research of 918 papers published between 2009 and 2019 about the cryptocurrency market and conclude that there was a shift in the main topic from technological to economic. Furthermore, the most important economic topic is explaining and forecasting the volatility in the cryptocurrency market. The most common statistical models that studies use to explain or predict market volatility are parametric such as the GARCH-type family.

The literature related to the liquidity of the cryptocurrency market is even more recent than the literature related to its volatility and has different strands: market microstructure explanations [12], the relation between liquidity and volatility [13,14], the factors that affect market liquidity [15,16], and how to measure liquidity in the cryptocurrency market [17].

None of the above strands have tried to explain or predict the liquidity in the cryptocurrency market. Furthermore, given the microstructure complexity of this liquidity, we assert that the use of nonparametric models would be better for predicting it. In this sense, we find that the *k*-nearest neighbor (KNN) approach, which is a supervised machine learning algorithm, is better suited to predict the liquidity of the cryptocurrency market than a classical linear model such as the autoregressive moving average (ARMA) model or a nonlinear model such as the generalized autoregressive conditional heteroskedasticity (GARCH) that are intensively used to predict volatility.

Although there have been several investors' clampdown events on cryptocurrency trading due to market news, these pieces of news are later incorporated into prices due to the short-term memory of Bitcoin returns that exhibit short term momentum and reversals [18]. It is important to clarify that the mechanism through which news may be added into cryptocurrency prices is short-term for cryptocurrencies' returns, but long-term for cryptocurrencies returns' volatility. Nevertheless, liquidity is at the bottom of the explanation.

Khuntia and Pattanayak [19] present an event history in the Bitcoin market from January 2015–June 2018 and suggest that these events impact the trading volume and the long-memory in volatility of bitcoin returns. Furthermore, Phillip et al. [20] found that slower transacted cryptocurrencies, such as Bitcoin, have less long memory, whereas faster transacted coins, such as Ripple display more long memory. In other words, the day-to-day volatility correlation (long memory in return volatility) is dependent on completion times and therefore liquidity.

Thus, the main objective of this study is to determine the best model for predicting the short-term log rates of the bid-ask spreads in the three biggest cryptocurrencies—Bitcoin, Ripple, and Ethereum—and in the 16 major fiat currencies listed by Bloomberg. Consequently, our research question is the following: Is the KNN approach a better predictor of the short-term liquidity of cryptocurrencies than classical time-series models? To the best of our knowledge, there is no other study that has addressed this question, and given the importance of market liquidity, we argue that it is necessary to find better ways to assess the liquidity of the cryptocurrency market (long-term memory in the cryptocurrency market liquidity is beyond the scope of our study).

This article is organized into five sections. In Section 2, we examine the literature on liquidity. Sections 3–5 present the methodology, results, and discussion of the study, respectively.

2. Literature Review

According to Jiang et al. [11], the research trend of the last decade in the published papers related to cryptocurrency has changed from a technological perspective to an economic one. Specifically, their focus has been to try to explain the volatility of cryptocurrencies with traditional statistical models such as generalized autoregressive conditional heteroskedasticity model (GARCH) and its derivations.

Financial time series, as Ruppert [21] mentions, often exhibit volatility clustering in assets returns, where periods of high volatility and periods of low volatility could be present, i.e., time-varying volatility is more common than constant volatility. In this sense, Nelson [22] comments that GARCH models elegantly capture the volatility and this feature accounts for both their theoretical appeal and their empirical success. Thus, as Venter and Maré [23] argue, the GARCH model has become increasingly popular among both academics and practitioners for modelling time-varying volatility in financial time series analysis, including cryptocurrencies.

GARCH-type models are actually used not only for examining mean returns but also a volatility return transmission within the VAR-GARCH model; for example, Loverta and Lopez [24] focus on credit default swap (CDS) spreads as a directly observable market indicator of default risk within the VAR-BEKK-GARCH framework.

Kyriazis et al. [25] study the volatility of the three most highly capitalized digital currencies (Bitcoin, Ethereum, and Ripple) during a bearish market and find that during distressed times, no possibilities for hedging exist between the majority of cryptocurrencies and the three major ones. Walther et al. [26] use the GARCH-MIDAS framework to identify drivers of cryptocurrency volatility and find that the global real economic activity provides superior volatility predictions for both bull and bear markets. Acereda et al. [27] study the expected shortfall of the main cryptocurrencies and find that the best results come from using a NGARCH.

Fakhfekh and Jeribi [28] model the volatility of 16 cryptocurrencies and find that the TGARCH was the best specification, whereas Cerqueti et al. [29] find that relaxing the normality assumption and considering skewed distributions, such as a skewed non-Gaussian GARCH models, yield better predictions for the cryptocurrencies' volatility. One of the most comprehensive studies about the usefulness of GARCH-type models for forecasting Bitcoin's volatility is the one by Köchling et al. [30]. Interestingly, the authors find that most GARCH-type models have equal predictive ability and that some specifications are outperformed on a regular basis.

In the last two years, several authors have focused their attention on cryptocurrencies' liquidity. Stenfors [31] defines the bid-ask spread as a bonus that is paid to market makers for standing ready to absorb the risk borne by others "immediately" and that the spread is closely connected to market liquidity. For the case of fiat exchange rate markets, Stenfors [31] uses the spread as a proxy, whereas Dyrberg et al. [12] use it for the case of cryptocurrency markets. Kim [32] finds that Bitcoin markets have bid-ask spreads that are approximately 2% lower than the main fiat currencies due to lower transaction costs.

Furthermore, there is a strong relation between the volatility and liquidity of the cryptocurrency market. Wei [13] shows that volatility decreases as liquidity increases in cryptocurrencies and that there is no sign of an illiquidity premium. Będowska-Sójka et al. [14] obtain a contrasting result in that high volatility in the cryptocurrency market attracts new investors and that this attraction causes an increase in the market liquidity. Brauneis et al. [15] and Scharnowski [16] show that the liquidity of cryptocurrencies depends specifically on the volatility of their returns, the dollar trading volume, and the number of transactions and that general financial market variables have no influence. Brauneis et al. [15] show that a universal best measure for the liquidity of cryptocurrencies does not exist yet because it depends on the application.

There is also research related to the long-term memory of cryptocurrencies returns' volatility, where the long memory describes the high order correlation structure of a series. Fakhfekha and Jeribi [28] studied sixteen of the most popular cryptocurrencies with five

GARCH-type models to predict long-term memory in cryptocurrencies returns' volatility and found the TGARCH with double exponential distribution to be the best model.

Lahmiri et al. [33] studied the nonlinear patterns of volatility in seven Bitcoin markets. They investigate the fractional long-range dependence in conjunction with the potential inherent stochasticity of volatility time series under four diverse distributional assumptions and found the existence of long memory in Bitcoin market volatility, irrespectively of distributional inference. Hence, in explaining long memory in cryptocurrencies returns' volatility it is useful to consider Markov-Switching Multifractal Models (MSM) or a sort of hybrid model between pure parametric models and non-parametric ones, such as the Fractionally Integrated GARCH model.

Finally, research has shifted towards non-parametric models to forecast cryptocurrencies returns' volatility. Khaldi et al. [34] compared different type-GARCH models and Artificial Neural Networks (ANN) models in an attempt to forecast the Bitcoin returns' volatility. They found that a type of ANN (the Multilayer Perceptron-MLP) outperformed all the parametric and nonparametric models, but it was only effective in short-term forecasting.

The previous review clearly finds that the most important economic concern in the cryptocurrency market has been its volatility, but now the focus is starting to shift to its liquidity. Nevertheless, so far there has been no attempt to predict this short-term liquidity. Furthermore, there is no consensus on what the best method is for predicting the market volatility (beyond a type of hybrid or a non-parametric model), nor what the best measure is for predicting liquidity, but it is possible to use the bid-ask spread as a measure of liquidity and a non-parametric model. Moreover, although there is a strong relation between volatility and liquidity, there is no consensus on the direction of the relation or whether all factors that affect this relation are within the market network.

3. Methodology

3.1. Data and Hypothesis

The study is motivated by empirical evidence based on the idea that even though cryptocurrencies exhibit similar features of fiat currencies their market structure is fundamentally different, as is noted by Dyhrberg et al. [12]. Furthermore, Saadah and Whafa [35] pointed out that cryptocurrencies are the most fluctuating product on the market and their high volatility makes liquidity prediction difficult. Therefore, modeling cryptocurrency prediction using classical time series methods coupled with the scarcity of a reliable data source could be a challenge. In this sense, KNN algorithm has been applied as a fundamental prediction technique when there is little or no prior knowledge about the distribution of the data [36]. Due to the complexity of the market microstructure in crypto and fiat currencies, we test whether nonparametric machine learning, such as the KNN approach, is better suited for predicting short-term liquidity in the cryptocurrency market rather than parametric time-series models that studies have widely used to predict volatility. Hence, we propose the following hypothesis based on Gandal and Halaburda [4], Stenfors [31], Kim [32], and Katsiampa [37].

Hypothesis 1. *The nonparametric KNN approach is a better method to predict the short-term liquidity of crypto and fiat currencies than classical ARMA and GARCH models.*

The data are the log rates of the daily closing bid-ask spreads from 9 February 2018 to 8 February 2019, for a total of 259 observations for each of the 19 currencies in the study. The log rates were calculated by taking the logarithm of the USD price ratio of the spreads for each currency.

The sample comprises three cryptocurrencies (Bitcoin, Ethereum, and Ripple) and 16 major fiat currencies: the Australian dollar, Brazilian real, British pound, Canadian dollar, Danish krone, euro, Japanese yen, Mexican peso, New Zealand dollar, Norwegian krone, Singaporean dollar, South African rand, South Korean won, Swedish krona, Swiss franc, and Taiwanese dollar. The data are publicly available on the Bloomberg database.

3.2. ARMA and GARCH Models

First, we used the augmented Dickey–Fuller (ADF) statistic to test for the presence of a unit root to rigorously verify the nonstationary nature of the log rates of the bid-ask spreads, $\{X_t\}$ with $t = 1, \dots, n$. If the null hypothesis of the presence of a unit root is rejected, then the stationarity autoregressive is guaranteed at least in the mean [38].

Once we applied the ADF test, we continued to analyze the ARMA model proposed by Box and Jenkins [39]. The generalized ARMA(p, q) model that includes both the p -autoregressive and the q -moving average terms is represented as follows:

$$\varnothing(L)X_t = \delta + \theta(L)\varepsilon_t \tag{1}$$

$$\varnothing(L)X_t = \theta(L)\varepsilon_t \text{ for } \delta = 0$$

where \varnothing and θ are the parameters for the autoregressive and moving average models, respectively, such as $\varnothing(L) = 1 - \varnothing_1L - \varnothing_2L^2 - \dots - \varnothing_pL^p$ and $\theta(L) = 1 - \theta_1L - \theta_2L^2 - \dots - \theta_qL^q$; L is the delay operator, and the value of its exponent indicates the order of the delay that means $L^sX_t = X_{t-s}, \forall s \geq 0$; δ is the constant parameter; and ε_t is the residuals with $\varepsilon_t \sim N(0, \sigma^2)$.

We used the Schwarz criterion (SC) developed by Schwarz [40] that penalizes the inclusion of a greater number of parameters compared with the Akaike Information Criterion (AIC) proposed by Akaike [41] and therefore avoids errors in the estimation of models with large numbers of parameters. For ARMA models, Koehler and Murphree [42] confirms in an empirical study that the SC is a better criterion than AIC and validates the results of others that the AIC will overfit the data. To select the best ARMA(p, q), we used the model with the lowest SC. Second, we applied the GARCH(p, q) model proposed by Bollerslev [43] that considers the dependence of the conditional variance (σ_t^2) on the past squared residuals of the model ($\zeta_{t-j}^2, j = 1, \dots, p$) and the past values of the variance ($\sigma_{t-k}^2, k = 1, \dots, q$) for the $\{X_t\}$ time series. In this context, the modeling of the conditional mean and conditional variance is governed by the following:

$$X_t = X_{t-1} + \zeta_t \tag{2}$$

$$\zeta_t = N(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^p \alpha_j \zeta_{t-j}^2 + \sum_{k=1}^q \delta_k \sigma_{t-k}^2$$

$$Z_t = \frac{\zeta_t}{\sigma_t}$$

where p is the time delay parameter of the squared residuals; q is the time delay parameter of the past values of the variance; α_0, α_j with $j = 1, \dots, p$ and δ_k with $k = 1, \dots, q$ are the estimated coefficients; and Z_t represents the standardized residuals with $Z_t \sim N(0, 1)$. To select the parameters p, q , we also applied the SC, which has been shown to exhibit a higher degree of accuracy in identifying the true data generating process than AIC [44].

3.3. Nearest Neighbor Method

Fix and Hodges [45] introduced the nearest neighbor rule as a non-parametric method for pattern classification. Later, Cover and Hart [46] formalized mathematically the method. As a nonparametric method, in the KNN algorithm no explicit assumptions about the underlying data distribution are needed. The KNN besides a classification tool is also used as forecasting technique that considers the spatial correlation between the points of a phase space to improve short-term prediction.

Bajo-Rubio et al. [47] apply the KNN to the foreign exchange market to indicate the potential utility not only as a tool for the prediction of the daily exchange rate but also for the rules of purchase or sales in the technical analysis. Fernández-Rodríguez et al. [48]

state that the basic idea behind these predictors is that pieces of the time series in the past might resemble pieces in the future.

The KNN algorithm used in this study can be explained following the next steps from Finkenstädt and Kuhbier [49], and Arroyo and Maté [50]:

- (1) The time series considered, $\{X_t\}$, is transformed into a series of d -dimensional vectors:

$$X_t^{d,\tau} = \left(X_t, X_{t-\tau}, \dots, X_{t-(d-1)\tau} \right) \quad t = 1, \dots, n \tag{3}$$

where $d, \tau \in \mathbb{N}$ with d being the number of lags and τ being the delay parameter. In the KNN forecasting algorithm, d and τ are pre-determined parameters.

- (2) To simplify, we shall only consider the case of $\tau = 1$, then the resulting time series of vectors is denoted by $\{X_t^d\}$, with $t = d, \dots, n$, which represents a vector of d consecutive observations that can be characterized as a point in d -dimensional space:

$$X_t^d = \left(X_t, X_{t-1}, \dots, X_{t-d+1} \right) \quad t = 1, \dots, n \tag{4}$$

These d -dimensional vectors are often called d -histories, whereas the d -dimensional space is referred to as the phase space of time series.

- (3) The distance between the last vector, also called focal, $X_n^d = (X_n, X_{n-1}, \dots, X_{n-d+1})$ and each vector in the time series $\{X_t^d\}$ with $t = d, \dots, n - 1$ is computed. The distance used in this study is the sum over all dimensions of the absolute difference between the values of the cases (X_n^d and X_t^d with $t = d, \dots, n - 1$) also called the Manhattan distance or city block metric.

$$D(X_t^d, X_n^d) = \sum_{i=1}^{n-1} |X_t^d - X_n^d| \tag{5}$$

- (4) The k vector closest to X_n^d is selected and denoted by $X_{T1}^d, X_{T2}^d, \dots, X_{Tk}^d$. The k parameter is also pre-determined using a criteria selection, generally the k with the lowest sum of squares residuals (SSRs).
- (5) Given the k neighboring vectors $X_{T1}^d, X_{T2}^d, \dots, X_{Tk}^d$; their subsequent values, $X_{T1+1}^d, X_{T2+1}^d, \dots, X_{Tk+1}^d$, are averaged to obtain the forecast, X_{n+1} .

$$X_{n+1} = \frac{\sum_{T=T1}^{Tk} X_{T+1}^d}{Tk} \tag{6}$$

Thus, the KNN searches for segments with similar dynamic behavior and uses them to produce the forecast. In this sense, the future short-term evolution of the time series will then be calculated using the historical patterns. To compare the above time-series methods and select the best model, we calculated the average of the sum-of-squares residual (SSR) for the ARMA, GARCH, and KNN methods. The selected model had the lowest SSR.

4. Results

4.1. Descriptive Statistics

Table 1 lists the main descriptive statistics of the depreciation rates of crypto and fiat currencies. Practically all currencies appreciate versus the USD during the time span considered in this study, but the greatest appreciations occur for the cryptocurrencies. The highest kurtosis and volatility values are quantified in the cryptocurrencies and emerging market currencies, such as the Brazilian real and Mexican peso.

Table 1. Depreciation rates, descriptive statistics.

Currency	Mean ^a		SD ^a		Skewness ^a		Kurtosis ^a	
	%	Rank ^b	%	Rank ^b	Value	Rank ^b	Value	Rank ^b
Brazilian real	−0.049%	15	0.973%	05	0.697	02	3.242	01
Ripple ^c	−0.342%	18	6.355%	01	0.737	01	2.170	02
Ethereum ^c	−0.737%	19	6.066%	02	0.308	04	2.063	03
Bitcoin ^c	−0.315%	17	4.181%	03	−0.345	18	1.597	04
Mexican peso	−0.004%	02	0.785%	06	−0.398	19	1.478	05
New Zealand dollar	−0.026%	08	0.537%	09	0.081	08	1.120	06
Danish krone	−0.031%	11	0.437%	13	−0.260	16	0.803	07
British pound	−0.028%	09	0.498%	12	0.028	09	0.780	08
Euro	−0.030%	10	0.436%	14	−0.249	15	0.643	09
Swedish krona	−0.051%	16	0.585%	07	0.223	05	0.602	10
Japanese yen	−0.004%	01	0.391%	16	0.025	10	0.514	11
Australian dollar	−0.036%	13	0.553%	08	0.003	11	0.435	12
South Korean won	−0.009%	04	0.501%	11	0.092	07	0.389	13
Taiwanese dollar	−0.018%	05	0.270%	18	0.187	06	0.384	14
Swiss franc	−0.026%	07	0.378%	17	−0.112	13	0.294	15
Norwegian krone	−0.033%	12	0.523%	10	−0.137	14	0.143	16
Singaporean dollar	−0.008%	03	0.265%	19	−0.020	12	0.099	17
Canadian dollar	−0.020%	06	0.426%	15	0.341	03	0.067	18
South African rand	−0.043%	14	1.029%	04	−0.283	17	−0.045	19

Notes: ^a Depreciation rates are calculated as the first logarithmic difference of the last prices. Prices are based on U.S. dollars. ^b Statistics are ordered from highest to lowest, and numbers in each rank's column represent the place in the list of currencies. ^c Cryptocurrency. Source: Own elaboration with Eviews7 and data from Bloomberg.

However, if we consider the log rates of the bid-ask spreads (see Table 2), the results are mixed. Bitcoin and the main emerging currencies have lower log rates and volatilities than Ripple and Ethereum, but all the cryptocurrencies of the sample are situated in the lowest kurtosis values, which indicate fewer outliers.

Table 2. Bid-ask spread rate (log-transformation), descriptive statistics.

Currency	Mean		SD		Skewness		Kurtosis	
	%	Rank ^a	%	Rank ^a	Value	Rank ^a	Value	Rank ^a
Mexican peso	0.097%	10	0.090%	10	6.895	03	74.027	01
Singaporean dollar	0.049%	12	0.125%	05	7.413	02	67.219	02
South Korean won	0.208%	02	0.333%	01	7.653	01	60.429	03
South African rand	0.299%	01	0.232%	02	3.635	04	17.463	04
Brazilian real	0.047%	14	0.056%	12	3.060	05	14.781	05
New Zealand dollar	0.192%	03	0.177%	03	2.836	06	13.686	06
Swedish krona	0.110%	08	0.081%	11	2.550	07	9.588	07
Japanese yen	0.024%	19	0.023%	19	2.356	10	7.302	08
Canadian dollar	0.045%	15	0.045%	15	2.548	08	7.232	09
Swiss franc	0.055%	11	0.053%	13	2.430	09	6.807	10
British pound	0.105%	09	0.107%	08	2.284	11	6.206	11
Euro	0.038%	17	0.037%	18	1.990	12	4.188	12
Ethereum ^b	0.134%	06	0.108%	07	1.870	13	4.099	13
Norwegian krone	0.169%	05	0.120%	06	1.732	14	3.860	14
Australian dollar	0.114%	07	0.095%	09	1.548	15	2.264	15
Bitcoin ^b	0.049%	13	0.040%	17	1.302	16	2.167	16
Danish krone	0.042%	16	0.048%	14	1.125	18	1.363	17
Ripple ^b	0.181%	04	0.133%	04	1.135	17	0.912	18
Taiwanese dollar	0.037%	18	0.042%	16	0.877	19	−0.246	19

Notes: ^a Statistics are ordered from highest to lowest and numbers in each rank's column represent the place in the list of currencies. ^b Cryptocurrency. Source: Own elaboration with Eviews7 and data from Bloomberg.

4.2. ARMA Models

Table 3 presents the ADF test. This test rejects the null hypothesis of the presence of unit roots in all cases, which means the series is stationary, at least for the mean; thus, the ARMA models can be applied. The research generally uses the Ljung–Box test to validate the ARMA models. This test can confirm the null hypothesis that the residuals of the model do not present a linear correlation. However, it does not allow for a distinction between random and nonlinear dependence. Therefore, we consider the Brock, Dechert, and Scheinkman (BDS) test to detect the presence of nonlinear dependence [51].

Table 3. Augmented Dickey–Fuller test and ARMA(p,q) model.

Currency	ADF ^a	ARMA(p,q) ^b	Dim2 ^c	Dim3 ^c	Dim4 ^c	Dim5 ^c
Canadian dollar ^f	−4.949	7,2	0.009 ^d	0.009 ^d	0.008 ^d	0.006 ^d
British pound ^f	−2.940	5,8	0.003 ^d	0.002 ^d	−0.002 ^d	−0.006 ^d
Ethereum	−3.725	5,7	0.014	0.020	0.026	0.030
Australian dollar	−4.024	5,7	0.011 ^e	0.019	0.023	0.020 ^e
Euro ^f	−4.023	5,5	0.007 ^d	0.003 ^d	0.004 ^d	−0.001 ^d
Japanese yen	−3.993	5,5	0.014	0.017 ^d	0.019 ^d	0.015 ^d
Danish krone	−4.881	5,5	0.012	0.018	0.026	0.027
Mexican peso	−4.424	5,5	0.002 ^d	0.014 ^d	0.025	0.027
South African rand ^f	−4.908	5,4	0.002 ^d	−0.001 ^d	−0.010 ^d	−0.016 ^d
Swedish krona	−5.232	5,4	0.034	0.044	0.039	0.036
Norwegian krone	−4.298	5,4	0.018	0.032	0.036	0.036
Swiss franc ^f	−4.260	5,0	0.014 ^e	0.018 ^d	0.017 ^d	0.014 ^d
New Zealand dollar ^f	−4.910	4,5	0.009 ^d	0.011 ^d	0.008 ^d	0.005 ^d
Bitcoin	−12.554	3,2	0.008 ^e	0.018	0.022	0.025
Taiwanese dollar ^f	−13.999	2,2	0.008 ^d	0.009 ^d	0.009 ^d	0.010 ^d
Brazilian real	−8.028	1,2	0.007 ^d	0.014 ^d	0.021 ^e	0.034
Ripple	−2.913	1,1	0.016	0.033	0.039	0.042
Singaporean dollar ^f	−16.508	1,0	−0.015 ^d	−0.017 ^d	−0.017 ^d	−0.020 ^d
South Korean won	−16.017	0,1	−0.014 ^d	−0.030 ^e	−0.041	−0.034 ^e

Notes: ^a ADF: Augmented Dickey–Fuller test statistic. ^b ARMA(p,q): Parameter p for the autoregressive model; table is ordered from highest to lowest p , followed by the parameter q for the moving average model. ^c Dim#: BDS statistic for dimension # from residuals. ^d H_0 :BDS = 0 is not rejected (5% significance, bootstrap probabilities). ^e H_0 :BDS = 0 is not rejected (1% significance, bootstrap probabilities). ^f There is no evidence to reject the hypothesis that the residuals of the model are *iid* (BDS test). Source: Own elaboration with Eviews7 and data from Bloomberg.

Eight currencies could be estimated through a linear stochastic model such as the ARMA, as there was no evidence to reject the hypothesis that the residuals of the model are an independently and identically distributed (*iid*) series: Canadian dollar, British pound, euro, South African rand, Swiss franc, New Zealand dollar, Taiwanese dollar, and Singaporean dollar. In addition, six of them had complex models with parameters p and q above five. If we compare these results with Table 1, none of these currencies are among the first five currencies with the highest kurtosis.

4.3. GARCH Models

The GARCH(p,q) method was also applied, and in the case of cryptocurrencies, the GARCH(1,1) model was the best because it had the lower SC for a range of p and q from one to three. For this reason and to compare the estimated coefficients between currencies, Table 4 shows the results of the GARCH(1,1) models. The coefficient that was estimated for the lagged square residuals indicates the sudden changes in the conditional variance in response to strong changes in the unexpected component or unexpected news. In this sense, cryptocurrencies and emerging market currencies, such as the Mexican peso and Brazilian real, show higher values for these coefficients than do the euro or British pound.

Table 4. GARCH(1,1).

Currency	ARCH ^a		GARCH ^b		Dim2 ^d	Dim3 ^d	Dim4 ^d	Dim5 ^d
	Coeff.	Rank ^c	Coeff.	Rank ^c				
New Zealand dollar	−0.022	18	1.014	01	−0.010 ^e	−0.023 ^f	−0.030 ^f	−0.033
South Korean won [§]	0.041	10	1.013	02	0.000 ^e	0.000 ^e	−0.001 ^e	−0.001 ^e
British pound [§]	0.031	13	0.939	03	−0.002 ^e	−0.012 ^e	−0.026 ^f	−0.032 ^f
Swiss franc [§]	0.037	11	0.936	04	0.000 ^e	−0.006 ^e	−0.013 ^e	−0.016 ^e
Canadian dollar	0.023	14	0.907	05	−0.006 ^e	−0.028 ^f	−0.049	−0.056
Euro	0.016	15	0.886	06	−0.005 ^e	−0.021 ^e	−0.032 ^f	−0.033
Danish krone [§]	0.016	16	0.862	07	0.008 ^e	0.006 ^e	0.003 ^e	0.001 ^e
Japanese yen [§]	0.050	09	0.839	08	0.002 ^e	0.004 ^e	0.002 ^e	0.001 ^e
Bitcoin [§]	0.111	07	0.835	09	0.000 ^e	−0.003 ^e	−0.003 ^e	−0.003 ^e
Taiwanese dollar [§]	0.084	08	0.834	10	0.002 ^e	0.009 ^e	0.008 ^e	0.005 ^e
Mexican peso [§]	0.205	04	0.717	11	−0.012 ^e	−0.022 ^f	−0.029 ^f	−0.032 ^f
Norwegian krone [§]	0.036	12	0.712	12	−0.003 ^e	−0.010 ^e	−0.010 ^e	0.001 ^e
Ripple [§]	0.262	03	0.663	13	0.002 ^e	0.005 ^e	0.000 ^e	0.003 ^e
Brazilian real [§]	0.491	01	0.644	14	0.004 ^e	0.001 ^e	−0.004 ^e	0.000 ^e
Ethereum [§]	0.274	02	0.605	15	0.003 ^e	0.003 ^e	0.002 ^e	0.001 ^e
Singaporean dollar [§]	−0.009	17	0.558	16	−0.021 ^f	−0.027 ^e	−0.029 ^e	−0.032 ^e
Australian dollar [§]	−0.034	19	0.490	17	−0.010 ^e	−0.017 ^e	−0.022 ^e	−0.022 ^e
South African rand [§]	0.120	06	−0.208	18	0.000 ^e	0.004 ^e	−0.002 ^e	−0.010 ^e
Swedish krona [§]	0.124	05	−0.859	19	0.001 ^e	−0.002 ^e	−0.004 ^e	−0.002 ^e

Notes: ^a Coefficient from GARCH(1,1) for square residuals lagged once. ^b Coefficient from GARCH(1,1) for conditional variance lagged once. ^c Coefficients are ranked from highest to lowest values. ^d Dim#: BDS statistic for dimension # from standardized residuals. ^e H0:BDS = 0 is not rejected (5% significance, bootstrap probabilities). ^f H0:BDS = 0 is not rejected (1% significance, bootstrap probabilities). [§] There is no evidence to reject the hypothesis that the standardized residuals are *iid* (BDS test). Source: Own elaboration with Eviews7 and data from Bloomberg.

Conversely, the estimated coefficients of the lagged conditional variance show inverse results. Cryptocurrencies and emerging market currencies, such as the Mexican peso and Brazilian real, have a lower probability of following trends (or lower persistence) in the conditional variance than do the euro or British pound. The BDS test for the standardized residual practically validated the GARCH models of all log-rate series, except for the euro, the Canadian dollar, and the New Zealand dollar (Table 4). However, these three currencies were validated by the BDS test for ARMA models.

4.4. KNN Approach

The last method applied to the log-rate series was the KNN approach. To choose the best number of k , we considered a range between one and five, with the lowest SSRs from the forecast. Figure 1 shows the predictor space charts based on three lags for the spreads of Bitcoin, euro, Japanese yen, and Mexican peso as examples to visualize the dispersion of the data. The points of the Bitcoin's spreads are more dispersed over time than those visualized in fiat currencies, which are more concentrated between each other. For instance, the presence of outliers is more visible in the Mexican peso than the points in the space chart of Bitcoin. As it was noted in Table 2, the highest kurtosis was found in emerging countries' currencies in comparison with cryptocurrencies. Therefore, due the complexity of the liquidity microstructure of cryptocurrencies, and hence the greater dispersions distance between each point of the chart space, more neighbor points should be considered to improve predictions compared with fiat currencies. Thus, based in the distance between each point and the k neighbors, we classify the charts into four categories as follows:

- I. Very large distance: Bitcoin ($k = 2$), Ethereum ($k = 3$), and Ripple ($k = 3$)
- II. Large distance: Australian dollar ($k = 2$), Danish krone ($k = 3$), Japanese yen ($k = 3$), Norwegian krone ($k = 2$), and Taiwanese dollar ($k = 2$)

- III. Medium distance: British pound ($k = 1$), Canadian dollar ($k = 2$), euro ($k = 2$), Swedish krona ($k = 3$), and Swiss franc ($k = 2$)
- IV. Small distance: Brazilian real ($k = 2$), Mexican peso ($k = 1$), New Zealand dollar ($k = 1$), Singaporean dollar ($k = 1$), South African rand ($k = 2$), and South Korean won ($k = 1$)

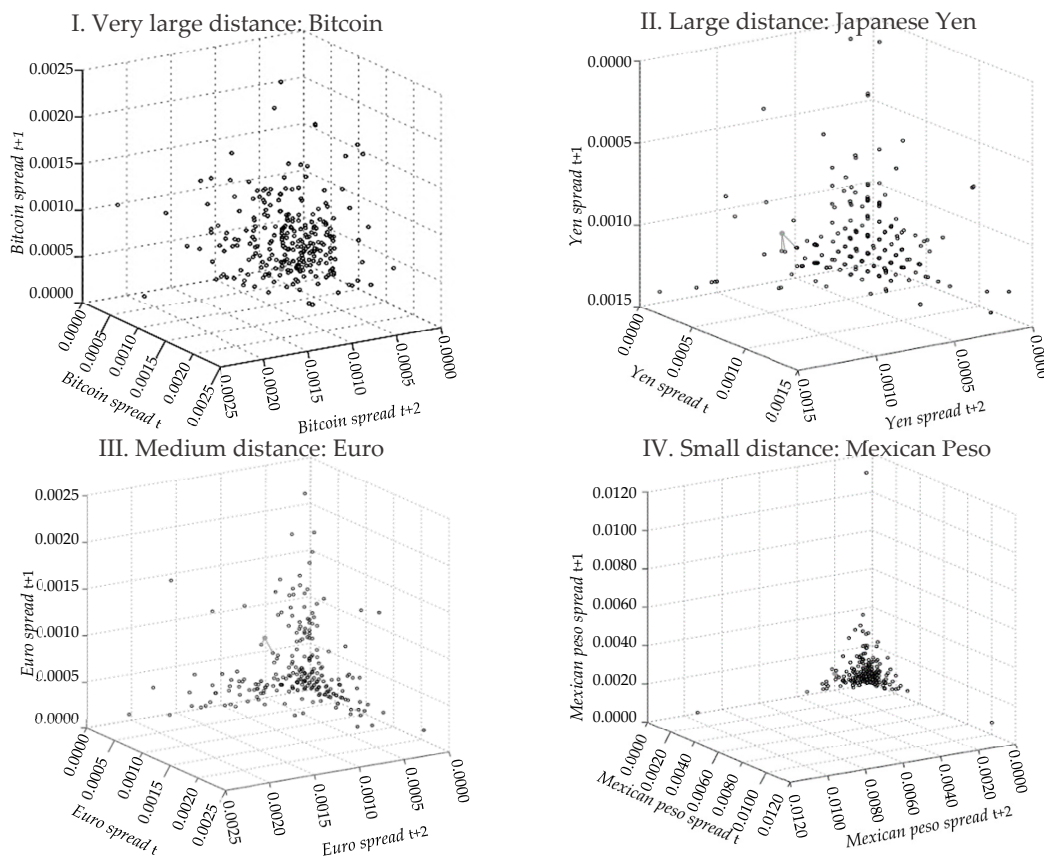


Figure 1. Dispersion points in the predictor space chart for the k -nearest neighbor (KNN) approach. **Source:** Own elaboration with SPSS 21 from Bloomberg data.

Figure 1 shows that the log rates of cryptocurrencies are more dispersed over time than are those of fiat currencies. For this reason, more neighbor points must be considered in cryptocurrencies than for fiat currencies to improve predictions. As an example of the KNN prediction, Table 5 shows the results for 6 February 2019, which is the third-to-last date of the study, as a selected focal case for the 19 currencies.

4.5. Comparative Analysis

Further, the SSRs for the three methods (ARMA, GARCH, and KNN) were calculated to compare the prediction ability and select the method with the minimum squared residual mean. Table 6 shows that the KNN approach produced the best results in predicting the spread of the log rates of the bid-ask spreads compared with the ARMA and GARCH models.

In terms of fiat currencies, the KNN approach provided the best prediction performance for the Canadian dollar, euro, and Japanese yen. In the case of cryptocurrencies, the prediction of the Bitcoin spread was better than that of Ripple and Ethereum.

Table 5. Nearest neighbor predictions for 6 February 2019.

Currency	Neighbor(s) ^a	Distance(s) ^b	Observed/Predicted ^c
Ethereum	13 November 2018, 7 November 18, 21 November 2018 7 August 2018, 16 November 2018, 12 June 2018	0.000002, 0.000003, 0.000005 0.000232, 0.000274, 0.000326	0.000001/0.000001 0.000727/0.000744
Japanese yen	26 December 2018, 14 February 2018, 27 September 2018	0.000112, 0.000141, 0.000194	0.000110/0.000111
Ripple	5 June 2018, 2 July 2018, 5 April 2018	0.000353, 0.000432, 0.000843	0.000000/0.000253
Swedish krona	25 April 2018, 26 September 2018, 24 October 2018	0.000174, 0.000254, 0.000259	0.000460/0.000470
Australian dollar	24 October 2018, 1 August 2018	0.000146, 0.000255	0.000281/0.000415
Bitcoin	16 April 2018, 11 September 2018	0.000094, 0.000084	0.000407/0.000404
Brazilian real	10 January 2019, 30 January 2019	0.000391, 0.00111	0.002959/0.002774
Canadian dollar	4 May 2018, 27 April 2018	0.000166, 0.00017	0.000529/0.000449
Euro	22 August 2018, 12 November 2018	0.000205, 0.000264	0.000176/0.000132
Norwegian krone	12 December 2018, 16 January 2019	0.000013, 0.00003	0.000854/0.000855
South African rand	9 May 2018, 17 October 2018	0.001357, 0.002655	0.002545/0.002034
Swiss franc	26 December 2018, 20 November 2018	0.000239, 0.000308	0.000301/0.000299
Taiwanese dollar	20 February 2018, 10 May 2018	0.00024, 0.000244	0.000555/0.000558
British pound	11 December 2018	0.000303	0.000696/0.000641
Mexican peso	14 November 2018	0.000295	0.000764/0.001021
New Zealand dollar	9 January 2019	0.00034	0.000885/0.000884
Singaporean dollar	21 February 2018	0.000786	0.000136/0.000265
South Korean won	21 January 2019	0.001488	0.000224/0.001702

Notes: ^a Nearest cases from the focal point (6 February 2019). ^b The distance between two cases (focal and its neighbor) is the sum, over all dimensions, of the absolute difference between values for the cases.

^c As a focal case, 6 February 2019, the third-to-last date of the study, was selected. Source: Own elaboration with SPSS21 and data from Bloomberg.

Table 6. Sum-of-squares residuals (SSR).

Currency	ARMA ^a		GARCH ^b		KNN ^c	
	SSR ^d	Rank ^e	SSR ^d	Rank ^e	SSR ^d	Rank ^e
South African rand	0.0010380	02	0.0037240	02	0.0000134	01
New Zealand dollar	0.0004680	03	0.0026110	03	0.0000078	02
Mexican peso	0.0001520	07	0.0004550	14	0.0000068	03
Ethereum	0.0000846	10	0.0007740	06	0.0000019	04
Swedish krona	0.0000825	11	0.0004860	12	0.0000017	05
Ripple	0.0002380	05	0.0022430	04	0.0000016	06
Norwegian krone	0.0001480	08	0.0020730	05	0.0000015	07
Singaporean dollar	0.0003930	04	0.0004710	13	0.0000014	08
Australian dollar	0.0000995	09	0.0005720	10	0.0000010	09
British pound	0.0001540	06	0.0005830	09	0.0000008	10
South Korean won	0.0028720	01	0.0039790	01	0.0000008	11
Brazilian real	0.0000651	12	0.0007250	07	0.0000004	12
Swiss franc	0.0000524	13	0.0001520	15	0.0000004	13
Bitcoin	0.0000283	16	0.0001020	17	0.0000002	14
Danish krone	0.0000307	15	0.0001060	16	0.0000002	15
Taiwanese dollar	0.0000373	14	0.0000810	18	0.0000002	16
Canadian dollar	0.0000275	17	0.0006370	08	0.0000001	17
Euro	0.0000136	18	0.0005300	11	0.0000001	18
Japanese yen	0.0000085	19	0.0000280	19	0.0000001	19

Notes: ^a Autoregressive moving average model. ^b Autoregressive conditional heteroscedasticity model. ^c Nearest neighbor approach. ^d SSR is the sum-of-squares residual from each model. ^e SSR are ordered from highest to lowest and numbers in each rank's column represent the place in the list of currencies. Source: Own elaboration with SPSS21 and data from Bloomberg.

5. Discussion

We compare the predictions on the short-term market liquidity of the major crypto and fiat currencies by using classical time-series models such as ARMA and GARCH and a nonparametric learning machine algorithm called the KNN approach. We find that the KNN algorithm is a better predictor of the log rate of the bid-ask spreads of crypto and fiat currencies than the ARMA and GARCH models given the nonlinearity of the market liquidity and the complexity of its market microstructure, as stated by Bouoiyour et al. [3].

We also find that the log rates of cryptocurrencies behave differently than those of the fiat currencies in developed markets. However, the short-term prediction (KNN approach) is similar in the emerging markets with fiat currencies when using a wider prediction timespan (GARCH model). The result of the cryptocurrency's log rates is in accordance with its more complex pattern than the fiat currencies, as mentioned in Gandal and Halaburda [4], due to its time spatial dispersion performance derived from the KNN approach and with the absence of outliers, as noted by the kurtosis statistic.

Considering a classical time-series analysis, ARMA models are better at capturing the short-term liquidity of the fiat currencies in developed countries, whereas GARCH models are better suited for estimating the behavior of the fiat currencies in the emerging market countries because their currencies are more susceptible to sudden changes or unexpected news with a lower probability of following trends. Nevertheless, the KNN approach is better suited to capture the short-term liquidity of cryptocurrencies than the ARMA and GARCH models.

The practical implications of this study are twofold. First, as the number of entities that accept cryptocurrencies increases, this study shows that using the KNN approach better explains the short-term liquidity of the cryptocurrency market than traditional time-series models. This ability is important given the speculative nature of investors in the cryptocurrency market. Second, other machine learning models are worth trying to compare the results among them.

Despite the above results, three limitations of the study can be observed. First, the sample used in this study is small because Bloomberg has a short time publishing cryptocurrencies data and it is difficult to obtain a reliable and complete data, i.e., bid-ask rates. Secondly, the cryptocurrencies analyzed in this paper are limited to three, and according to Ong et al. [52], there is a large array of cryptocurrency variants, alternative coins, or altcoins, that are introduced to the market on a daily basis; although, the information about cryptocurrencies can be sparse [53].

For future research, other types of GARCH models could be reviewed in the comparison analyses, such as the VAR-BEKK-GARCH model proposed by Lovreta and López [24] for log spreads time series. On the other hand, it is also possible to consider besides KNN other different intelligent algorithms that can be a route for cryptocurrencies behavior analysis, for example, the Support Vector Machine (SVM) and the Long Short-Term Memory (LSTM) model that was applied by Saadah and Wafa [36]. In addition, other possible directions for future research might include a systematic quantitative analysis of the popularity and impact of cryptocurrencies and how they spread in a macro level as suggested by Park and Park [54].

Finally, in this field it is necessary to deal with the interplay between liquidity, returns, and volatility in the context of long-term memory while at the same time using more nonparametric methods, such as machine learning, that may be better suited to deal with the microstructure complexity of the cryptocurrency markets.

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References

- Balcilar, M.; Bouri, E.; Gupta, R.; Roubaud, D. Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Econ. Model* **2017**, *64*, 74–81. [CrossRef]
- Yermack, D. Is Bitcoin a Real Currency? An Economic Appraisal. In *Handbook of Digital Currency: Bitcoin, Innovation, Financial Instruments, and Big Data*; Chuen, D.L.K., Ed.; Academic Press: London, UK, 2015; pp. 31–43. [CrossRef]
- Bouoiyour, J.; Selmi, R.; Tiwari, A.K.; Olayeni, O.R. What drives Bitcoin price. *Econ. Bull.* **2016**, *36*, 843–850.
- Gandal, N.; Halaburda, H. Can we predict the winner in a market with network effects? Competition in cryptocurrency market. *Games. SSRN Electron. J.* **2016**, *7*, 16. [CrossRef]
- Dwyer, G.P. The economics of Bitcoin and similar private digital currencies. *J. Financ. Stab.* **2015**, *17*, 81–91. [CrossRef]
- Hayes, A.S. Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telemat. Inform.* **2017**, *34*, 1308–1321. [CrossRef]
- Nakamoto, S. Bitcoin: A Peer-to-Peer Electronic Cash System. Available online: <https://bitcoin.org/bitcoin.pdf/> (accessed on 27 December 2016).
- Bas, D.S. Hayek and the cryptocurrency revolution. *Iber. J. Hist. Econ. Thought* **2020**, *7*, 15–28. [CrossRef]
- Encrybit Revealed Real-Time Cryptocurrency Exchange Problems—Survey Insights. Available online: <https://medium.com/@enbofficial/encrybit-revealed-real-time-cryptocurrency-exchange-problems-survey-report-announced-650bba659a6d/> (accessed on 18 May 2020).
- Crook, M. Bringing liquidity to the new crypto economy. *J. Digit. Bank.* **2019**, *3*, 279–287.
- Jiang, S.; Li, X.; Wang, S. Exploring evolution trends in cryptocurrency study: From underlying technology to economic applications. *Financ. Res. Lett.* **2020**, status (in press; corrected proof). [CrossRef]
- Dyhrberg, A.H.; Foley, S.; Svec, J. How investible is Bitcoin? Analyzing the liquidity and transaction costs of Bitcoin markets. *Econ. Lett.* **2018**, *171*, 140–143. [CrossRef]
- Wei, W.C. Liquidity and market efficiency in cryptocurrencies. *Econ. Lett.* **2018**, *168*, 21–24. [CrossRef]

14. Sójka, B.B.; Hinc, T.; Kliber, A. Volatility and Liquidity in Cryptocurrency Markets—The Causality Approach. In *Contemporary Trends and Challenges in Finance*; Jajuga, K., Junge, H.L., Orłowski, L., Staehr, K., Eds.; Springer: Cham, Switzerland, 2020; pp. 1–43. [[CrossRef](#)]
15. Brauneis, A.; Mestel, R.; Theissen, E. What Drives the Liquidity of Cryptocurrencies? A Long-Term Analysis. *Financ. Res. Lett.* **2020**, status (in press; corrected proof). [[CrossRef](#)]
16. Scharnowski, S. Understanding bitcoin liquidity. *Financ. Res. Lett.* **2020**, status (in press; corrected proof). [[CrossRef](#)]
17. Brauneis, A.; Mestel, R.; Riordan, R.; Theissen, E. How to measure the liquidity of cryptocurrencies? *SSRN Electron. J.* **2020**, 3503507. [[CrossRef](#)]
18. Hong, K. Bitcoin as an alternative investment vehicle. *J. Inf. Technol. Manag.* **2017**, *18*, 265–275. [[CrossRef](#)]
19. Khuntia, S.; Pattanayak, J.K. Adaptive long memory in volatility of intra-day bitcoin returns and the impact of trading volume. *Financ. Res. Lett.* **2020**, *32*, 101077. [[CrossRef](#)]
20. Phillip, A.; Chan, J.; Peiris, S. On long memory effects in the volatility measure of cryptocurrencies. *Financ. Res. Lett.* **2019**, *28*, 95–100. [[CrossRef](#)]
21. Ruppert, D. GARCH Models. In *Statistics and Data Analysis for Financial Engineering*; Springer: New York, NY, USA, 2011.
22. Nelson, D.B. Conditional heteroskedasticity in asset returns: A new approach. *Econom. J. Econom. Soc.* **1991**, *59*, 347–370. [[CrossRef](#)]
23. Venter, P.J.; Maré, E. GARCH Generated Volatility Indices of Bitcoin and CRIX. *J. Risk Financ. Manag.* **2020**, *13*, 121. [[CrossRef](#)]
24. Lovreta, L.; Pascual, J.L. Structural breaks in the interaction between bank and sovereign default risk. *Ser. J. Span. Econ. Assoc.* **2020**, *11*, 531–559. [[CrossRef](#)]
25. Kyriazis, N.A.; Daskalou, K.; Arampatzis, M.; Prassa, P.; Papaioannou, E. Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. *Heliyon* **2019**, *5*, e02239. [[CrossRef](#)]
26. Walther, T.; Klein, T.; Bouri, E. Exogenous drivers of Bitcoin and Cryptocurrency volatility—A mixed data sampling approach to forecasting. *J. Int. Financ. Mark. Inst. Money* **2019**, *63*, 101133. [[CrossRef](#)]
27. Acereda, B.; Leon, A.; Mora, J. Estimating the expected shortfall of cryptocurrencies: An evaluation based on backtesting. *Financ. Res. Lett.* **2020**, *33*, 101181. [[CrossRef](#)]
28. Fakhfekh, M.; Jeribi, A. Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. *Res. Int. Bus. Financ.* **2020**, *51*, 101075. [[CrossRef](#)]
29. Cerqueti, R.; Giacalone, M.; Mattera, R. Skewed non-Gaussian GARCH models for cryptocurrencies volatility modelling. *Inf. Sci.* **2020**, *527*, 1–26. [[CrossRef](#)]
30. Köchling, G.; Schmidtke, P.; Posch, P.N. Volatility forecasting accuracy for Bitcoin. *Econ. Lett.* **2020**, *191*, 108836. [[CrossRef](#)]
31. Stenfors, A. Bid-ask spread determination in the FX swap market: Competition, collusion or a convention? *J. Int. Financ. Mark. Inst. Money* **2018**, *54*, 78–97. [[CrossRef](#)]
32. Kim, T. On the transaction cost of Bitcoin. *Financ. Res. Lett.* **2017**, *23*, 300–305. [[CrossRef](#)]
33. Lahmiri, S.; Bekiros, S.; Salvi, A. Long-range memory, distributional variation and randomness of bitcoin volatility. *Chaos Solitons Fractals* **2018**, *107*, 43–48. [[CrossRef](#)]
34. Khaldi, R.; El Afia, A.; Chiheb, R. Forecasting of BTC volatility: Comparative study between parametric and nonparametric models. *Prog. Artif. Intell.* **2019**, *8*, 511–523. [[CrossRef](#)]
35. Saadah, S.; Whafa, A.A. Monitoring Financial Stability Based on Prediction of Cryptocurrencies Price Using Intelligent Algorithm. In Proceedings of the 2020 International Conference on Data Science and Its Applications (ICoDSA), Bandung, Indonesia, 5–6 August 2020; pp. 1–10.
36. Devroye, L.; Györfi, L.; Krzyżak, A.; Lugosi, G. On the strong universal consistency of nearest neighbor regression function estimates. *Ann. Stat.* **1994**, *22*, 1371–1385. [[CrossRef](#)]
37. Katsiampa, P. Volatility estimation for Bitcoin: A comparison of GARCH models. *Econ. Lett.* **2017**, *158*, 3–6. [[CrossRef](#)]
38. Dickey, D.A.; Fuller, W.A. Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* **1979**, *74*, 427–431. [[CrossRef](#)]
39. Box, G.; Jenkins, G. *Time Series Analysis: Forecasting and Control, Time Series Analysis: Forecasting and Control*; Holden-Day Inc.: San Francisco, CA, USA, 1976.
40. Schwarz, G. Estimating the dimension of a model. *Ann. Stat.* **1978**, *6*, 461–464. [[CrossRef](#)]
41. Akaike, H. A new look at the statistical model identification. *IEEE Trans. Autom. Control.* **1974**, *19*, 716–723. [[CrossRef](#)]
42. Koehler, A.B.; Murphree, E.S. A comparison of the Akaike and Schwarz criteria for selecting model order. *Appl. Stat.* **1988**, *37*, 187–195. [[CrossRef](#)]
43. Bollerslev, T. Generalized autoregressive conditional heteroskedasticity. *J. Econ.* **1986**, *31*, 307–327. [[CrossRef](#)]
44. Mitchell, H.; McKenzie, M.D. GARCH model selection criteria. *Quant. Financ.* **2003**, *3*, 262–284. [[CrossRef](#)]
45. Fix, E.; Hodges, J.L. *Discriminatory Analysis, Nonparametric Discriminators: Consistency Properties*; Technical Report 4; School of Aviation Medicine, Randolph Field: Texas, CA, USA, 1951.
46. Cover, T.M.; Hart, P.E. Nearest neighbor pattern classification. *IEEE Trans. Inf. Theory* **1967**, *13*, 21–27. [[CrossRef](#)]
47. Rubio, O.B.; Sosvilla-Rivero, S.; Rodríguez, F.F. *Non-Linear Forecasting Methods: Some Applications to the Analysis of Financial Series*; FEDEA Working Paper 2002-01; Fundación de Estudios de Economía Aplicada: Madrid, Spain, 2002. [[CrossRef](#)]

48. Fernández-Rodríguez, F.; Sosvilla-Rivero, S.; Andrada-Félix, J. Exchange-rate forecasts with simultaneous nearest-neighbour methods: Evidence from the EMS. *Int. J. Forecast.* **1999**, *15*, 383–392. [[CrossRef](#)]
49. Finkenstädt, B.; Kuhbier, P. Forecasting nonlinear economic time series: A simple test to accompany the nearest neighbor approach. *Empir. Econ.* **1995**, *20*, 243–263. [[CrossRef](#)]
50. Arroyo, J.; Maté, C. Forecasting histogram time series with k-nearest neighbours methods. *Int. J. Forecast.* **2009**, *25*, 192–207. [[CrossRef](#)]
51. Brock, W.A.; Scheinkman, J.A.; Dechert, W.D.; LeBaron, B. A test for independence based on the correlation dimension. *Econ. Rev.* **1996**, *15*, 197–235. [[CrossRef](#)]
52. Ong, B.; Lee, T.M.; Li, G.; Chuen, D.L.K. Evaluating the Potential of Alternative Cryptocurrencies. In *Handbook of Digital Currency: Bitcoin, Innovation, Financial Instruments, and Big Data*; Chuen, D.L.K., Ed.; Academic Press: London, UK, 2015; pp. 81–135. [[CrossRef](#)]
53. Jahani, E.; Krafft, P.M.; Suhara, Y.; Moro, E.; Pentland, A.S. Scamcoins, s*** posters, and the search for the next bitcoinTM: Collective sensemaking in cryptocurrency discussions. *Proc. ACM Hum. Comput. Interact.* **2018**, *2*, 1–28. [[CrossRef](#)]
54. Park, S.; Park, H.W. Diffusion of cryptocurrencies: Web traffic and social network attributes as indicators of cryptocurrency performance. *Qual. Quant.* **2020**, *54*, 297–314. [[CrossRef](#)]