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Intensification Dimension of Prices Cryptocurrency with Hamiltonian Quantum Mechanics

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Aims: Cryptocurrency (CC) is a digital currency innovation that has impacted the financial sector's distribution mechanism since December 2013. This research aims to discover a non-linear mathematical Quantum relationship between the escalation of the development of cryptocurrency price fluctuations and prices in CC predictors.
Study Design: The research uses simulation techniques to operate numerical models that correspond to the process of dynamic observation behavior.
Place and Duration of Study: Types of crypto chosen based on this research data are Bitcoin (BTC), Ethereum (ETH), USD Coin (USDC), and Binance (BNB). The data collection period coverage is required with a number per week from 2019 to 2021 or 52 weeks.
Methodology: From the collection of crypto prices that have been selected, there are 157 data samples taken using a systematic sampling strategy with elements that are randomly selected and then followed by the next element from the column on the table after the first choice. The

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conceptual form of the research background is modeled by a multiple regression term equation which predicts a continuous variable unit as a non-linear mathematical function.
Results: The results of the research study found that the most prominent altcoins traded in the market are not affected by the price of Bitcoin securities. Percentage-wise, there were 40.33% of factors that influenced the movement of crypto coin price progress, with 59.67% being the remaining limiting factors in the study. Partial results show Bitcoin and altcoin assets have arbitrage potential with significant positives on put option volatility with asset discounting producing negative results and martingale strategies arising from a Hamiltonian perspective.
Conclusion: By time limitations, BTC and USDC have the most potential in martingale conditions, while the cryptocurrency ETH might be a solution in picking assets with growing values at medium risk. Meanwhile, crypto BNB is an asset that offers new data on many market indices.

Keywords: Cryptocurency; price intensification; price fluctuations; discount price; free option; hamiltonian.

1. INTRODUCTION

1.1 Background on Research

Price risk movements or volatility in crypto price variations are significantly associated with Bitcoin (BTC) asset price elements [1]. As the price of BTC assets rises, the measured evidence for the correlation between the demand levels of different crypto assets will increase. Baaquie et al. [2] define volatility as the options pricing of a derivative asset that is a predictor in economics and finance, where the emphasis is on the predictor, and provides an appropriate measuring instrument from the quantum mechanics approach as a possible price by volatility Hamiltonians.

1.2 Research Findings

Hou et al. [3] found that crypto coin securities can increase and be positive in outline when prices jump in a particular direction when calling or putting crypto options. Momtaz [4] reveals that 15% in 4 in 10 crypto samples measured on Initial Coin Offerings (ICOs) with three periods justifiably priced crypto assets have value conditions on liquidity, market capitalization, and risk that fluctuate with positive returns on price traded is below the level of readiness and correlates in the existence of an efficient market [5-7].

Alfeus & Kannan [8] found the existence of modeling crypto asset prices in the 30 Largest Cryptocurrency Market Cap Index (CCI30) with the Price Lookback Option method and the Normal Inverse Gaussian (NIG) distribution from a Monte-Carlo perspective that crypto asset prices are much lower from the results of consideration of option pricing decisions. Furthermore, it was discovered that price optimization in real-time can change prices with a degree of freedom in making decisions from option prices and is capable of making investor expectations depreciate due to the influence of a decentralized disequilibrium system from the market price of CCs with the risk effect of common currency indices such as fiat USD [9-13].

1.3 Object of Research

The acceleration of the price development of crypto assets starting from the BTC token in 2008 to 2009 on the Blockchain system, gave progressive results in market capitalization with the receipt of 795 billion US Dollars through its achievement in 2008 since it first appeared in the Bitcoin leaflet which aims as a moderator in the CC market. However, the BTC price now behaves like a "bubble" [14], with market pessimism demonstrating the importance of writing on the CC valuation process [15]. As a result, the availability of derivative assets with valuations comparable to option prices has attracted some scholars in recent years to simulate collective option techniques with varying returns and are employed in various sorts of complicated portfolios using a financial quantum mechanics approach [16,17].

1.4 Research Objectives

The de facto value of crypto assets will continue to change in the current regulatory process of technological progress, including the debate over the potential increase in crypto prices, which is the cause of the risk of realizing that it will be more difficult for someone to reap the technological civilization of transactions in the future. In the future, the verification process of centralized accounts without authorization will need recurring costs from the surrounding environment, increasing the danger of keeping data on their internet bandwidth [18]. This research will attempt to determine the instability element of the crypto price system indicator, which is translated into a potential particle of CCs flow (change from position) using a BTC moderator.

The illustration in Fig. 1 can explain the flux of the underlying crypto asset, which will be reflected in the emergence of sensitive transactions as long as the system has the potential to be hacked and has a low level of internet security protection, with the dynamics of the price of crypto assets as a line intersecting financial and economic charged fields as a link to the CCs flux sensitivity level [5,19].

2. MATERIALS AND METHODS

2.1 Materials

2.1.1 Hamilton's put option price volatility

The basic principle in the Hamiltonian option price, structured through the formalism concept of quantum mechanics, is a form of independent variables based on a system of potential positions [20].

$$H = -\frac{1}{2m}\left(\frac{\partial^2}{\partial x^2} + V(x)\right) \leftrightarrow H = -\frac{1}{2m}\frac{\partial^2}{\partial x^2} + \frac{1}{2}m\omega^2 x^2 \qquad (1)$$

In principle, Hamiltonian financial assumptions on the concept of strike prices (K) from K is the limit of the strike price which is an independent constant and serves as the initial focus of the price of Hamilton's put option in the form of the payout function in the remaining time (τ) with limits $C(t,x) = \langle x|C,t\rangle = \langle x|e^{-\tau H}|g\rangle$ which serves as the execution time by the holder of the option price alternately who will pay as much as the price of K in the future or until T (expiration) and as fulfillment in the conditions of the martingale strategy [21].

$$H = a + b\frac{\partial}{\partial x} - \frac{\sigma^2}{2}\left(\frac{\partial^2}{\partial x^2}\right) \qquad (2)$$

2.1.2 Dynamics of hermitian-hamiltonian discount prices

A feature of the interpretation of the potential price $V(x)$ that needs to be understood in financial observation is that the discounted price of $V(x)$ is a derivative in the martingale condition which has the potential to damage the conditional option price $S(t)$ meeting the conditions in Dirac's law $\langle x|S\rangle$, where $H|S >= 0$ as a characteristic of a martingale situation with $t \to e^{(t-t)H}|S$ as the arbitration time. The straight-line reflection of the Hamiltonian derivative in Black-Scholes that satisfies the discount condition can be determined by H_v [21]

$$H_V = -\frac{\sigma^2}{2}\frac{\partial^2}{\partial x^2} + \left(\frac{1}{2}\sigma^2 - V(x)\right)\frac{\partial}{\partial x} + V(x) \qquad (3)$$

The variable x is arbitrage which allows verification of H_v (discount) Hamiltonian eliminates $S = e^x$ (security level) which if developed could increase the free-risk of someone's option pricing. The H_V functions equivalent to the effective Hermitian transform (H_{eff}) where $H_V = e^s H_{eff} e^{-s}$

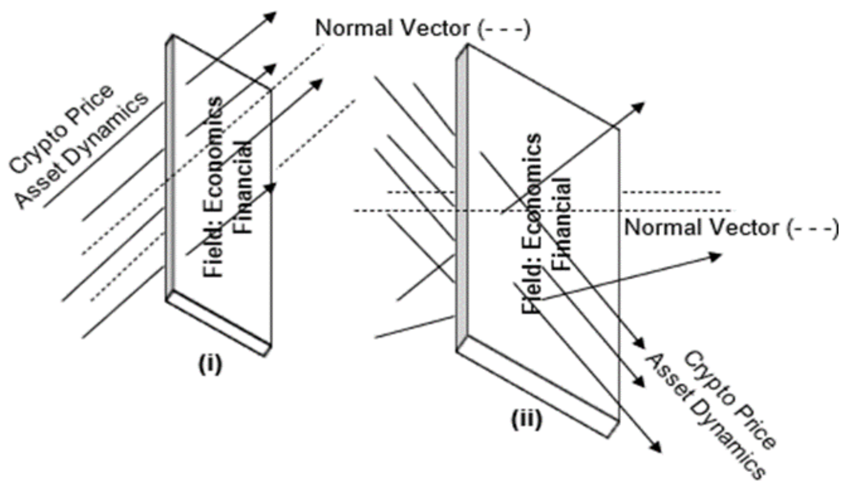

Fig. 1. Flux in the field of economic finance, (i) first field size 1/2 and (ii) second field size 1

$$H_{\text{eff}} = -\frac{\sigma^2}{2}\frac{\partial^2}{\partial x^2} + \frac{1}{2}\frac{\partial V}{\partial x} + \frac{1}{2\sigma^2}\left(V + \frac{1}{2}\sigma^2\right)^2$$
$$\rightarrow \hat{s} = \frac{1}{2}x - \frac{1}{\sigma^2}\int_0^x dyV(y) \quad (4)$$

By $H_{eff}|\phi_n >= E_n|\phi_n \rightarrow H_V|\psi_n >= E_n|\psi_n >$ and the pushing factors with using a
$\hat{H}_{BS} = e^{\alpha x}\left[-\frac{\sigma^2}{2}\frac{\partial^2}{\partial x^2} + \gamma\right]e^{-\alpha x}$
where $\gamma = \frac{1}{2\sigma^2}\left(r + \frac{1}{2}\sigma^2\right)^2; \alpha = \frac{1}{\sigma^2}\left(\frac{1}{2}\sigma^2 - r\right)$.

2.1.3 Hamilton securities free option price (martingale)

The term martingale is a development of the option price in a risk-neutral strategy where the Martingale is an instrument in the financial situation that is independent in any factor of random probability with arbitrage in nature. Arraut et al. [22] in the formulation of the Hamilton formula which is suitable in the martingale condition that under the time evolution of the option price is not obeying the rules in a symmetrical (ununited) manner where $\hat{\rho}C(x,t) = -i\left[\frac{\partial(x,t)}{\partial x}\right]$ and $i\hat{\rho}C(x,t) = \hat{\phi}$.

$$H \cdot C(t,x) = -\frac{\sigma^2}{2}\hat{\phi}^2{}_v + \left[\frac{1}{2}\sigma^2 - r\right]\hat{\phi}_v + rC(x,t) \quad (5)$$

2.1.4 Momenta fluctuations (η) particle prices

The formulation of the Langevin equation on price fluctuations in the movement of financial data is a derivative that is modeled by following from the Hamilton motion system with $\dot{x}$ as a reservoir (storage) in the measuring coefficient between two electrical circuit systems or couplings c and $\dot{p}$ is a moment reservoir [23].

$$\dot{x} = \frac{p}{M} \;\&\; \dot{p} = -\frac{dU(x)}{dx} + \sum_{i=1}^{N} c_i\left(r_i - \frac{c_i}{m\omega_i^2}x\right) \quad (6)$$

The reservoir model of $\dot{r}_i = \frac{p_i}{m}$ and $\dot{p}_i = -m\omega_i^2 r_i + c_i x$ becomes a dynamic model equal to zero (7) and with the addition by a requirement the result is in the form of a reservoir $(\dot{x}, \dot{r}_i, \dot{p}_i)$ can trigger an increase in velocity fluctuations by the particle mass (m) by moving $M\dot{v}$ following from the dispositional friction coefficient (γ) [24].

$$\left[r_i(0) - \frac{c_i}{m\omega_i^2}x(0)\right]\cos\omega_t t + \frac{p_i(0)}{m\omega_i}\sin\omega_i t - \frac{c_i}{m\omega_i^2}\int_0^t ds\,\dot{x}(s)\cos\omega_i(t-s) \quad (7)$$

Under the conditions in the disposition system by $\gamma(t) = \frac{1}{M}\sum(c_i^2/m\omega_i^2)\cos\omega_i t$ is modelled in the friction coefficient by approximating the moment strength of random particles in a correlated function by momenta η (8)

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$$\langle\eta(t)\eta(t')\rangle = k_B T\sum\left(\frac{c_i^2}{m\omega_i^2}\right)\cos\omega_i\,(t-t') \quad (8)$$

2.1.5 Hamiltonian potential price intensification

Limitations in asset trading in open markets can be structured by the Black-Scholes derived potential principle (H_{BS}) which can represent from option potential price depending on option barrier and option realization potential $V(x)$.

$$rC = \left(\frac{\partial C}{\partial t} + rS\frac{\partial C}{\partial S} + (\lambda + \mu V)\frac{\partial C}{\partial V} + \frac{1}{2}V\,S^2\frac{\partial^2 C}{\partial S^2}\right) + \rho\xi V^{\frac{1}{2}+\alpha}S\frac{\partial^2 C}{\partial S\partial V} + \xi^2 V^{2\alpha}\frac{\partial^2 C}{\partial V^2}$$

Considering the (Merton-Garman) equation as the price of capital options with stochastic volatility, *H* may be used to analyze financial system volatility in specific assets [25,26].

$$H_{BS} = -\frac{\sigma^2}{2}\frac{\partial^2}{\partial x^2} + \left(\frac{1}{2}\sigma^2 - r\right)\frac{\partial}{\partial x} + r \quad (9)$$

2.2 Hypotheses

Fig. 2 depicts the hypotheses on writing visualization that will be addressed in a study context connected to identifying the instability factor of the crypto pricing system, which is assessed as a potential flow partice.

2.2.1 Put option volatility with CC price intensification

Fulfillment for the benefit of option price requirements in a martingale situation $e^{-\tau H}|S> = |S> \rightarrow \; He^{x} = 0$ that comes out of every potential price $V(x)$ can affect the potential price increase [21]. Thus, the orientation of someone holding a call or put option in the price of a crypto (such as a European option) through strike K at expiry date T will actualize the probability of a zero payout at time T when the call option is above option K in the put option price [27].

H_1: The volatility of Put options has a positive impact on the intensification of cryptocurrency prices.

2.2.2 Discount price dynamics with CC price intensification

The central to the discount price of the security at the spot interest rate r of the potential price $V(x)$ is the non-arbitrary basis of fixed deposits from within money market accounts [21]. The basic model may externally impact the amount of intensification of crypto prediction, allowing the generated asset trading simulation to make a profit of 69% of the price of Bitcoin securities [28,11].

H_2: Discount price dynamics have a positive potential for cryptocurrency price intensification

2.2.3 Securities free price options with CC price intensification

In the context of financial instruments, the premise in the form of a martingale condition is that it requires a risk-neutral requirement that transforms into an option price or any potential of security price arbitrage $S = e^{x}$ (safety level) at time T is a free price [22]. This is accompanied by a possible conduit of bitcoin price dynamics that exhibits a significant and continuous increase in speculative price volatility due to the period after the revelation of information in crypto prices [29].

H_3 : The security-free price option has a negative effect on the price intensification of cryptocurrencies.

2.2.4 Moment price fluctuations with CC price intensification

The position of the particle space in the quantum mechanical single-field theory Based on Hamilton, a mechanical system that has been recorded has an infinite number of degrees of freedom. In theory, the quantum is realized in a direction that can take any value at the time [16]. The financial particle will, however, change rapidly and in discrete leaps since the stimulus flow is non-directional [30]. As a result, price momentum and cryptocurrency returns are significantly correlated [31].

H_4: Moment price fluctuations have a positive effect on the intensification of cryptocurrency prices.

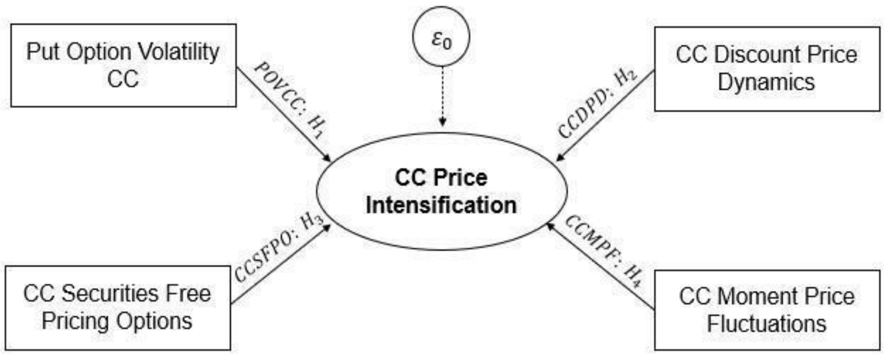


Fig. 2. Variable research path; information: (CC) cryptocurrency, (ε_0) the prediction margin of error of the research model

2.3 Methods

The research uses simulation techniques to operate numerical models that correspond to the process of dynamic observation behavior [32]. Baaquie [16] recommends measuring the use of asset price data populations in quantum finance principles that are applied to the distribution of asset log prices. In order to demonstrate how log data for cryptocurrency assets has come to dominate log return volatility [33].

This study uses the programming language Python 3.0 to prepare variable structures and is used to form plots, curves, or graphs to support research observations and is assisted by statistical tools programming Scipy Stats Python as the findings of descriptive statistics [34]. The conceptual form of the research background is modeled by a multiple regression term equation which predicts a continuous variable unit as a non-linear mathematical function [35].

$$\mathrm{CCPI}_t = \beta_0 + \beta_1 \mathrm{POVCC} + \beta_2 \mathrm{CCDPD} + \beta_3 \mathrm{CCSFPO} + \beta_4 \mathrm{CCMPF} + \varepsilon \qquad (10)$$

The nonlinear function arrangement comprises two distinct data sets. The first is a simple panel display of data in four cryptocurrencies, and the second is individual crypto data fragments. The significance between the variables was assigned to the test, and the test exposure was measured by the general acceptance of 10%, 5%, and .1%. The Chow and Hausman tests will be used to demonstrate panel data matrix testing [36].

In addition to fulfilling the assumptions of the panel and multiple regression predictors, an explanation for writing the results of crypto price intensification will be displayed with the probability distribution of data variables measured through the corresponding gamma distribution from Goos & David [37] that the distribution of gamma density values has positive double parameters (k, θ) as the event waiting time and the average waiting time for the arrival of the event following the expression $x \geq 0$.

$$f_x(x; k, \theta) = \frac{1}{\theta^k} \cdot \frac{1}{\Gamma(k)} x^{k-1} e^{-\frac{x}{\theta}} \rightarrow \Gamma(k) = \int_0^\infty t^{k-1}\, e^t dt \qquad (11)$$

The formulation of results (11) will follow the random variable from CCPI as the existence of the possibility of fluctuations is appropriate and correlated with price indicators [33,31].

3. RESULTS AND DISCUSSION

3.1 Results

3.1.1 Data review

Table 1 findings are appropriate discussion output decision materials, with data and information on the outcomes of panel data tabulation analysis and individual data descriptively between answers and exogenous factors displayed.

Table 1. Symbol terms and coefficients in regression analysis variables

Symbol	Variable names	Variable coefficient
CCPI	Cryptocurrency Price Intensification	β_0
POVCC	Put Option Volatility Cryptocurrency	β_1
CCDPD	Cryptocurrency Discount Price Dynamics	β_2
CCSFPO	Cryptocurrency Securities Free Pricing Option	β_3
CCMPF	Cryptocurrency Moment Price Fluctuations	β_4

Table 2. Statistics descriptive panel analysis

Variable	Panel description					
	Mean	**SD**	σ^2	Min	Max	N
0. CCPI	0.3519	1.1097	1.2314	0	9.3239	628
1. POVCC	0.4039	1.3068	1.7077	0	9.2918	628
2. CCDPD	1,77E+09	2,26E+10	5.1293	0.0127	4,66E+11	628
3. CCSFPO	0.0673	0.0831	0.0069	0.0002	0.2483	628
4. CCMPF	-233.21	233.74	54,634.3	-956.32	0	628

The price fluctuation of cryptocurrencies (Table 2) is generally higher than the average price value. The phenomena of discrepancies in these predictors suggest an information storage inequality, causing the market's pricing system to fluctuate toward an equilibrium situation [38]. Similarly, the Hamiltonian formulation can characterize the degree of price distribution to be worthless, or there is a potential for securities owned by investors to form precisely the same or the same price [39].

Table 3 outlines the USDC predictors with the highest values in the search results between the Put volatility price factor and the asset discount rate which makes the USDC intensification value soar. The highest free price security factor occurs by the BTC coin of $H \cdot C(t,x) = 0.2483$ which is multiplied by the time evolution limit in the asset. In addition, the effect of fluctuations in the price fluctuations of BTC, ETH, USDC, and BNB crypto assets is zero (constant) with the highest amount of price reduction fluctuations held in BNB assets or equal to $\langle \eta(t)\eta(t^{'}) \rangle = -956.32$.

3.1.2 OLS output regression

Research data processing results are depicted in Table 4 (the first data are done with a fixed model), while Table 5 depicts Ordinary Least Square data for sub-regression display between samples.

The study concludes that the panel regression in Table 4 is symmetrical or unidirectional in estimating predictor answers to responses where Put option volatility and discounted asset dynamics have the potential to be significantly positive and free choice prices have the potential to be significantly negative measured across four cryptocurrencies [27-29,11]. However, crypto price changes are thought to be beneficial but not substantial. Table 5 demonstrates that different altcoins have price returns that are unrelated to price momentum.

Table 5 has two characteristics that do not affect the intensification of crypto prices, namely BTC and BNB assets, where BTC assets at a reduced-price experience huge arbitrage event, contradicting the conclusions [28]. BTC is becoming a significant asset price and has some speculative free pricing options [29]. While the price of cryptocurrency BNB does not derive from all available prices and does not fluctuate from discrete returns, the issue of BNB securities is contradictory [31,30] because the risk with a free price rate approaches that of the BNB asset price, allowing it to become a price mover.

Table 3. Statistics descriptive sub-analysis

	Variable	Mean	SD	σ^2	Min	Max	N
BTC	0. CCPI	0.0282	0.0094	0.0000885	0.02	0.0435	157
	1. POVCC	0.027	0.0093	0.0000866	0.019	0.0421	157
	2. CCDPD	29.943	161.22	25,993.1	0.0127	920.24	157
	3. CCSFPO	0.0862	0.1005	0.0101	0.0062	0.2483	157
	4. CCMPF	-61.54	34.839	1,213.8	-199.98	0	157
ETH	0. CCPI	0.0417	0.0107	0.00014	0	0.0586	157
	1. POVCC	0.04	0.0105	0.00011	0	0.0565	157
	2. CCDPD	73.957	453.21	205,407.2	0.0277	2,895.9	157
	3. CCSFPO	0.0731	0.0852	0.0072	0.0052	0.212	157
	4. CCMPF	-152.94	86.584	7,496.9	-298.18	0	157
USDC	0. CCPI	1.285	19.443	37.805	0	93.239	157
	1. POVCC	14.982	22.927	52.566	0	92.918	157
	2. CCDPD	7,08e+09	4,49e+10	2,02e+21	1,50e+00	4,65e+11	157
	3. CCSFPO	0.0453	0.0616	0.0037	0.0029	0.1548	157
	4. CCMPF	-198.09	112.14	12,576.7	-386.21	0	157
BNB	0. CCPI	0.0527	0.0118	0.00014	0	0.0728	157
	1. POVCC	0.0506	0.0114	0.00013	0	0.0699	157
	2. CCDPD	70.307	36.141	1,306.2	0.0443	231.15	157
	3. CCSFPO	0.0649	0.0756	0.0057	0.0046	0.1904	157
	4. CCMPF	-520.29	279.23	77,969.4	-956.32	0	157

Table 4. Panel tabulation results

Variable	Panel Regression		Sample	Fixed Effects
	Coeff.	**Prob.**		
CCPI	0.2769*** (0.0811)	0.0007	BTC	-0.1783
POVCC	0.3373*** (0.0304)	0.0000	ETH	-0.1739
CCDPD	8.11E-12*** (1.54E-12)	0.0000	USDC	0.4991
CCSFPO	-0.8704* (0.4550)	0.0562	BNB	-0.1468
CCMPF	7.29E-05 (0.0002)	0.7572		
				χ^2
Durbin-Watson	1.5864	< 2DW		
S.D. Endogenous	1.1097		Chow-Test	0.0000**
S.E. Endogenous	0.8572			
Adj. R	0.4033	100%	Hausman-Test	0.0000**

**Description: ***sig. .1%, **sig. 5%, *sig. 10%; (*Coeff. | Std. Error)*

Table 5. Subsection regression results

Sample	Coeff.	Variable				Prob.
		POVCC	**CCDPD**	**CCSFPO**	**CCMPF**	
BTC	-0.0003*** (5.08*e*-05)	1.0781*** (0.002)	7.235e-09 (5.12e-09)	-0.0065** (0.000)	7.918e-07*** (8.79e-08)	0.00***
ETH	0.0006*** (2.84*e*-05)	1.0408*** (0.001)	1.53e-08** (5.61e-09)	-0.0039*** (8.08e-05)	1.78e-06*** (6.32e-08)	0.00***
USDC	2.5143*** (0.565)	0.2525*** (0.063)	8.31e-12** (2.99e-12)	-14.579*** (3.668)	0.0051** (0.002)	4.82e-11***
BNB	-0.0003*** (7.35e-05)	1.0522*** (0.002)	6.66e-07** (2.54e-07)	-0.0033*** (0.000)	1.50e-08 (3.34e-08)	6.36e-308***

**Description: ***sig. .1%, **sig. 5% (*Coeff. | Std. Error)*

3.2 Discussion

3.2.1 Distribution analysis

Valuation Table 2 shows that two predictors are close to each other between the mean values, the variables CCDPD and CCSFPO in the illustration of Fig. 3, which can be visualized as the average distribution with a standard deviation simulated by the normal Gaussian distribution $N(\mu,\sigma)$ shows that the price distribution discount scalable crypto assets on the potential interpretation of $V(x)$ quantum [21,40] in the spot interest rate on crypto assets has at least a trading score on a relatively comparable basis to the average price of the asset adapting a number of external factors to crypto trading [28].

Then, Arraut et al. [22], in a study emphasizing the conditions of the quantum martingale requirements in Fig. 3 (right), make it possible for the price distribution of crypto assets as an instrument to have arbitrage opportunities at the time of payment T (maturity) with free risk under-price options for someone who invests. The most significant impact on the two distributions (Fig. 3) can then be simulated on the measurable value of crypto price intensification via a random gamma distribution [37] so that the two predictors of the distribution of Fig. 3 can explain the optimality and evaluation of financial risk with increasing crypto asset prices measured at the average event rate and event arrival time by Fig. 4, which is assumed in minutes from the two previous p values [41].

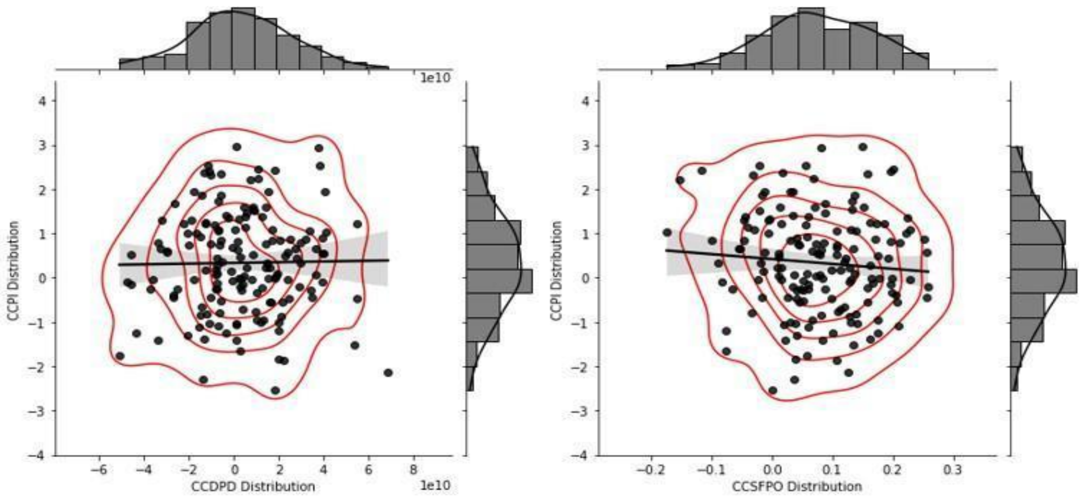


Fig. 3. Normal distribution plot with variable OLS Plot CCDPD (Left), CCSFPO (Right)

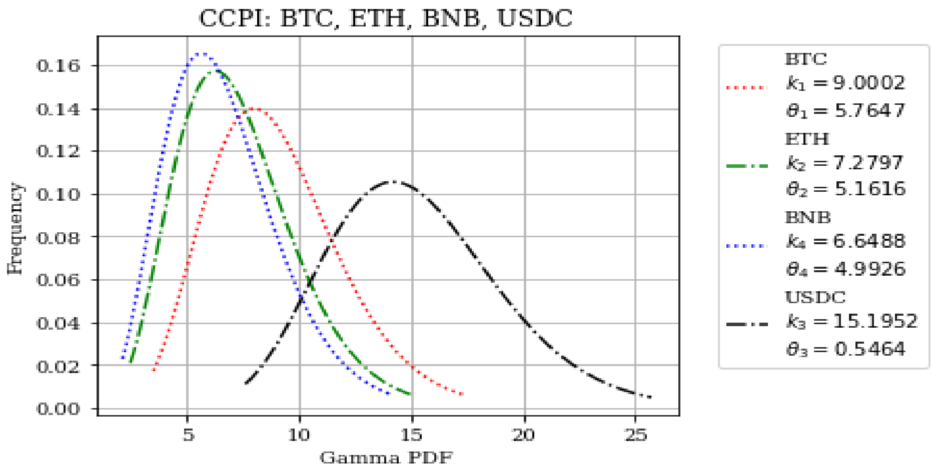


Fig. 4. The random distribution plot and the odds of the gamma function with crypto price intensification measures

It is found in Table 3 that the average level of asset price intensification combined in Fig. 4 and the valuation of Table 2 with both predictors result in an average waiting time of events of 6 to 15 minutes of rising crypto coin prices simultaneously with an estimated event arrival time of 0.50 seconds to 5 minutes. It occurs from the price increase process by the progress of the distribution of crypto asset intensification in trading transactions.

3.2.2 Full interpretation analysis

The indications in Table 4 in the price momentum indicator are consistent with the hypothesis statement, like positive but not significant or departing from the arguments of the [30] and [31] panels. However, it is significant and positive in Table 5 with cryptocurrency BNB, which has become an asset that the spread of momentum flows cannot be determined.

Statistical analysis Table 2 can serve as a warning by identifying the relationship between the level of distribution of price fluctuation moments and the standard deviation of moments away from the average level of price fluctuation moments (pictured left). Fig. 5 depicts the issue of the intensification of crypto assets (shown on the left), which is exacerbated by the fact that the moment of fluctuation is impacted by a range of bound attitudes from various sectors of crypto trading activity [42]. Compared to three other cryptocurrencies, BNB has varied returns that are not restricted by price momentum [31]. However, the panel of discrete results (right figure) is only partly connected [30].

3.2.3 Subsection analysis

Table 5 output demonstrates that the discounted price of BTC crypto assets is modest but positive at the value of 7.23×10^{-9}. Generally, the risks associated with any crypto investment vary depending on the type of crypto invested [43]. This means that there has been a constant arbitrage problem in financial markets in BTC assets, which stimulated [27] payments occur at time T when the martingale condition appears as a potential price effect increases with the call price above the strike price for the put option in an extended position $(S_T - K)$.

Fig. 6 (left) depicts the practical kernel density estimation (KDE) level for calculating the parameter level of variance and covariance of the BTC crypto put option volatility as a depiction of the option density variance interpolation [44]. The depiction of interpolation in the research [45] can highlight the link between transaction volume and market activity. As a consequence of complicated computations, these pattern indicators may be identified to be predicted in connection to BTC activity in a particular market [46,47].

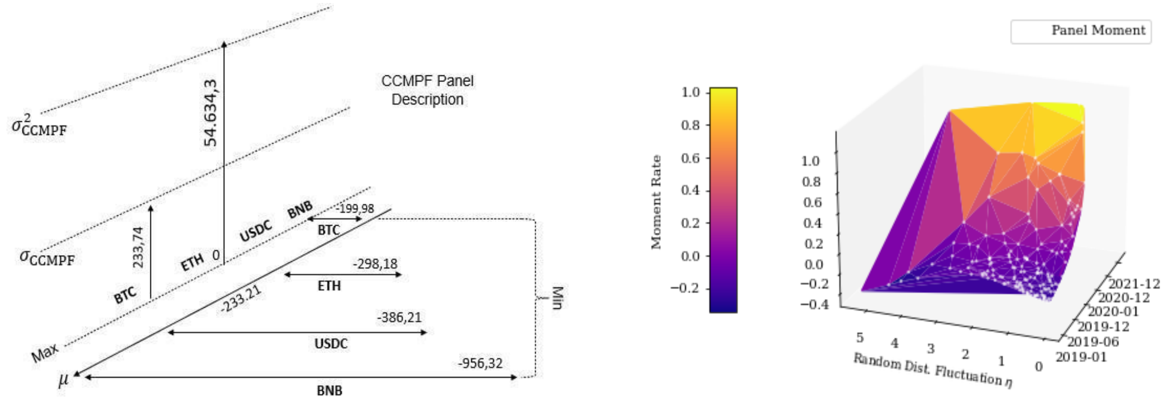


Fig. 5. Panel descriptive statistical analysis (left) with price fluctuation momentum particle position $\gamma(t)$ (right)

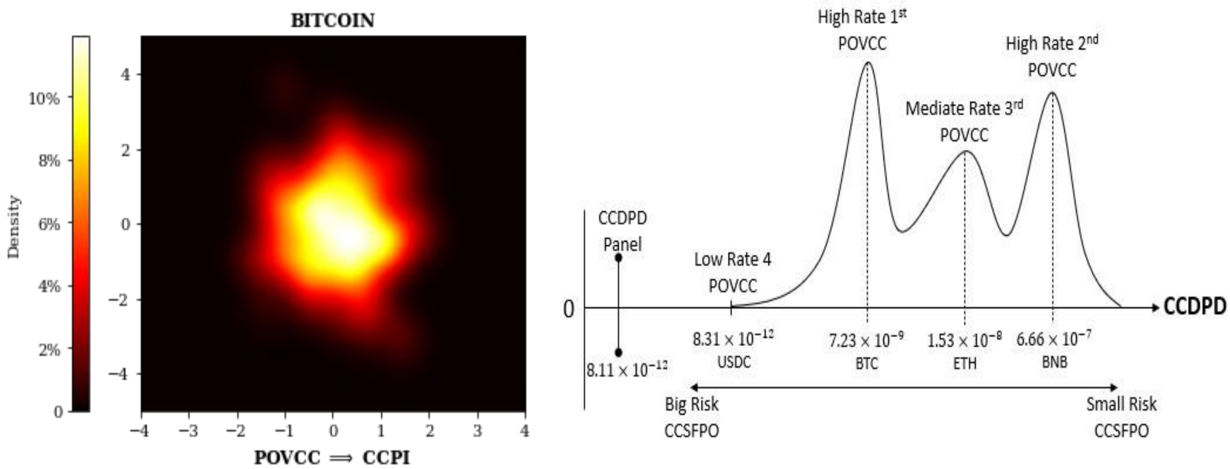
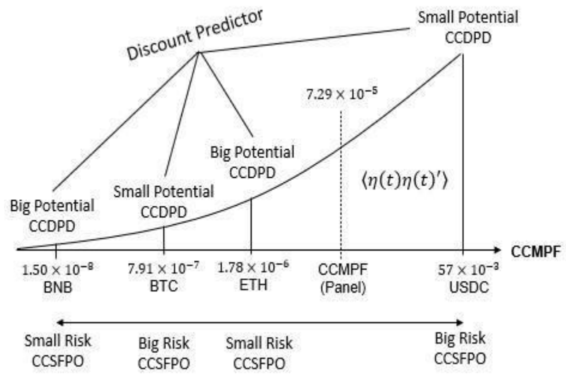


Fig. 6. Put options volatility density parameter polarization plot (left) with crypto discount rate dynamics and martingale risk parameters (right)



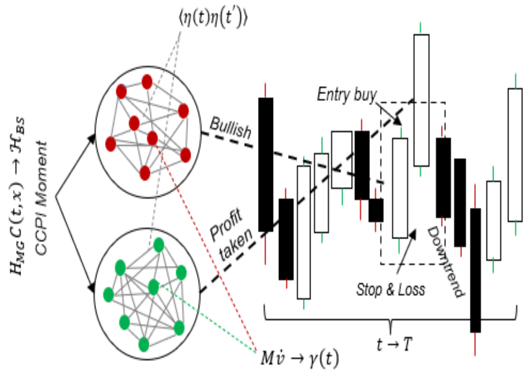


Fig. 7. Levels of Crypto Asset Price Fluctuation Moments (left) and Illustration of the two-way acceleration of bullish and bearish CCs CCPI models by derivatives H_{MG} (right)

According to Giudici & Polinesi [48], crypto price patterns are difficult to translate, as shown in Fig. 6 (left), the dynamics of estimated BTC put volatility density ranges from 0% to 10% due to variations in the intensity of BTC crypto price increases in certain markets, which are assumed to be linear in comparison to Fig. 6 (right). At freepricing, BTC assets are still categorized as hazardous assets, based on the conclusions of Table 5. Thus, the implementation that arbitrage-capable BTC assets with the Hamiltonian H_v quantum financial optimization structure can be a cost to the underlying person to transact between non-constructive price factors [49].

Unlike BNB assets which are the second tier by price factor in put options after BTC with arbitrage influence, BNB is at the highest level in potential asset discount dynamics, which has a significant positive effect on price intensification results. This means that from a quantum financial perspective, the spot interest rate and potential determine the probability that the arbitrage term does not occur from securities [21]. El-Berawi et al. [28] and T. Li et al. [11] that BNB prices can be developed to generate profits but are not affected by Bitcoin prices.

Table 5 displays the results. BNB has no chance of experiencing a price fluctuation and is not influenced by price momentum (Panel Interpretation). Based on Bazzani [50], the Hamiltonian motion of particle dynamics, accessible in a restricted sense when based on a non-homogeneous data model, might result in average impermanence between particle densities of the distribution. BNB is based on outcomes [31], but not in the same way as [30]. Clearly, under modest martingale circumstances, the regression of free price options BNB may theoretically get substantial discount price dynamics, allowing it to be successful without the price fluctuation influence of BTC assets.

4. CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

4.1 Conclusions

The results of the study found from the output valuation in the result and discussion section in the combined state of the level of crypto coin price movements on the essential Hamiltonian fluctuations of the price system towards an equilibrium condition or $\langle \eta(t)\eta(t)^{\wedge\prime} \rangle = 0$, which shows in the descriptive statistical sample that the prices fluctuate with the smallest value being negative and the most significant price is zero; this fact proves that the crypto price potential is simultaneously dynamic. By time limitations, BTC and USDC have the most potential in martingale conditions, while the cryptocurrency ETH might be a solution in picking assets with growing values at medium risk. Meanwhile, crypto BNB is an asset that offers new data on many market indices [51,52].

The results of this study also provide evidence of the phenomenon through non-homogeneous data with non-linear mathematical assumptions in testing between dependent and independent variables by Hamiltonian financial quantum material in transactions on crypto prices. That has been confirmed in specific markets that crypto asset prices can potentially move 40.33% of the CC price predictor with the remaining 59.67% outside the research limits in results and discussion, so this problem has the opportunity to be an attack by the system unconditionally.

4.2 Limitations and Recommendations

This paper gives limitations to simulate the price of protection by crypto assets during the transaction process. These limitations can increase the evolution of crypto prices, which can be a study for future research. However, investors and institutions or banks can prefer medium-risk crypto assets such as ETH and needs to prepare strategies in handling assets such as BTC and USDC as two assets that have the potential to change the martingale paradigm in terms of trading in the market. In contrast, BNB assets can be flexible regarding price return information held (in BNB assets).

5. MANAGERIAL IMPLICATIONS

Investigations into the realization of the potential price writing in cryptocurrencies as the influential particle price of the change in price position by BTC (as the primary market moderator), both in full sample findings and some types of altcoins, have shown positive and negative results (CCPI variable findings) with it can be said that the price moves dynamically regardless of various predictors based on Hamiltonian financial quantum mechanics studies. As a final mediation of the study, it can be warned that several value predictions and estimations on the simulation of the past discussion and collection time of crypto prices may change in the future. Thus, a coherent study is needed to develop the subsequent cryptocurrency price potential research.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. S Kumar A, Ajaz T. Co-movement in crypto-currency markets: evidences from wavelet analysis. Financ Innov. 2019;5(1). DOI: 10.1186/s40854-019-0143-3.
2. Baaquie BE, Corianò C, Srikant M. Hamiltonian and potentials in derivative pricing models: Exact results and lattice simulations. 2003. DOI: 10.48550/arXiv.cond-mat/0211489.
3. Hou AJ, Wang W, Chen CYH, Härdle WK. Pricing cryptocurrency options. J Financ Econ. 2020;18(2):250-79. DOI: 10.1093/jjfinec/nbaa006.
4. Momtaz PP. The pricing and performance of cryptocurrency. Eur J Fin. 2021;27(4-5):367-80. DOI: 10.1080/1351847X.2019.1647259.
5. Nieto-Chaupis H IEEE CHIL Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON). IEEE Publications. 2019; 2019
6. Rohde PP, Mohan V, Davidson S, Berg C, Allen D, Brennen GK et al. Quantum crypto-economics: blockchain prediction markets for the evolution of quantum technology. SSRN Journal. 2021. DOI: 10.2139/ssrn.3777706.
7. Zulfiqar N, Gulzar S. Implied volatility estimation of bitcoin options and the stylized facts of option pricing. Financ Innov. 2021;7(1):67. DOI: 10.1186/s40854-021-00280-y
8. Alfeus. M, & Kannan, S; 2021. Pricing Exotic Derivatives for Cryptocurrency Assets-à Monte Carlo Perspective. Available: https://ssrn.com/abstract=3862655.
9. Stegink T, de Persis C, van der Schaft A. A port-Hamiltonian approach to optimal frequency regulation in power grids; 2015. Available: http://arxiv.org/abs/1509.07318. DOI: 10.1109/CDC.2015.7402703.
10. Saef D, Wang Y, Aste T. Regime-based implied stochastic volatility model for crypto option pricing. SSRN Journal. 2022. DOI: 10.2139/ssrn.4190481.
11. Li L, Arab A, Liu J, Liu J, Han Z. Bitcoin options pricing using LSTM-Based prediction model and blockchain statistics. Proceedings 2nd IEEE International Conference on Blockchain, Blockchain. 2019:67-74. DOI: 10.1109/Blockchain.2019.00018.
12. Tse W-M, Hai C. Crypto-asset pricing models and their efficiency-dependent trading strategies; 2021. Available:https://ssrn.com/abstract=3898534.
13. Venter PJ, Mare E, Pindza E. Price discovery in the cryptocurrency option market: A univariate GARCH approach.

Cogent Econ Fin. Cogent OA. 2020; 8(1).
DOI: 10.1080/23322039.2020.1803524.
14. Cheung A, Roca E, Su J (Wai K. Crypto-currency bubbles: an application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin prices. Appl Econ. 2015;47(23):2348-58.
DOI: 10.1080/00036846.2015.1005827.
15. Karl W. VCRIX-A Volatility Index for Crypto-Currencies Standard-Nutzungsbedingungen; 2019.
Available: http://irtg1792.hu-berlin.de.
16. Baaquie B, E. Quantum field theory for economics and finance; 2018.
DOI: 10.1017/9781108399685.
17. Hu Y, Rachev ST, Fabozzi FJ. Modelling crypto asset price dynamics, optimal crypto portfolio, and crypto option valuation. 2019.
DOI: 10.3905/jai.2021.1.133.
18. Demertzis M, Wolff GB, Demertzis M. The economic potential and risks of crypto assets: is a regulatory framework needed? Standard-Nutzungsbedingungen: is deputy director of bruegel; 2018.
Available:http://hdl.handle.net/10419/208022.
19. Narváez F, R, Vallejo D, F, Morillo P, A et al. Smart technologies, systems and applications Narváez FR, Vallejo DF, Morillo PA, Proaño JR, editors. Vol. 1154. Springer International Publishing; 2020.
DOI: 10.1007/978-3-030-46785-2.
20. Deriglazov A. Classical mechanics: Hamiltonian and Lagrangian formalism. 2nd ed. Springer International Publishing; 2017.
DOI: 10.1007/978-3-319-44147-4.
21. Baaquie BE. Quantum finance: path integrals and Hamiltonians for options and interest rates; 2004.
Available:http://www.cambridge.org/9780521840453.
22. Arraut I, Au A, Tse AC. On the multiplicity of the martingale condition: spontaneous symmetry breaking in Quantum Finance; 2020.
Available: http://arxiv.org/abs/2004.11270.
23. Paul W, Baschnagel J. Stochastic processes from physics to finance. 2nd ed; 2013.
DOI: 10.1007/978-3-319-00327-6.
24. Morin D. The Hamiltonian method; 2008.
Available:http://www.people.fas.harvard.edu/˜djmorin/book.html.
25. Guéant O. Optimal execution and block trade pricing: A general framework. Appl Math Fin. 2015;22(4):336-65.
DOI: 10.1080/1350486X.2015.1042188.
26. Bagarello F. Appearances of pseudo-bosons from Black-Scholes equation. J Math Phys. 2016;57(4):5-14.
DOI: 10.1063/1.4944583.
27. Azimbayev N, Kitapbayev Y. On the valuation of multiple reset options: integral equation approach; 2021.
Available: http://arxiv.org/abs/2109.09302.
28. El-Berawi AS, Belal MAF, Ellatif MMA. Adaptive Deep Learning based Cryptocurrency Price Fluctuation Classification. IJACSA. 2021;12(12).
DOI: 10.14569/IJACSA.2021.0121264.
29. Akyildirim E, Corbet S, Cumming D, Lucey B, Sensoy A. Riding the wave of crypto-exuberance: the potential misusage of corporate blockchain announcements. Technol Forecasting Soc Change. 2020;159.
DOI: 10.1016/j.techfore.2020.120191.
30. Lee RST. Quantum finance intelligent forecast and trading systems; 2020.
DOI: 10.1007/978-981-32-9796-8.
31. Falcon A, Lyu T. Daily cryptocurrency returns forecasting and trading via machine Learning. J Stud Res. 2021;10(4):1-2.
DOI: 10.47611/jsrhs.v10i4.2217.
32. Kothari CR. Research methodology. New age international (P). 2nd ed Kothari CR, editor; 2004.
Available:http://www.newagepublishers.com.
33. Van der Auwera E, Schoutens W, Giudici MP, Alessi L. Financial risk management for cryptocurrencies. Springer Briefs Fin; 2020.
DOI: 10.1007/978-3-030-51093-0.
34. Hejase AJ, Hejase HJ. Research methods a practical approach for business students. 2nd ed. Philadelphia: Masadir Inc; 2013.
35. Little TD. The Oxford handbook of quantitative methods. Statistical analysis. 2013;2.
36. Biørn E. 198 Madison Avenue: Oxford University Press; 2017. Econometrics of panel data. 1st ed.
Available:https://www.pdfdrive.com/econometrics-of-panel-data-methods-and-applications e181234705.html.
37. Goos P, David M. Statistics with JMP: graphs, descriptive statistics, and

probability (WILEY, editor. 1st ed. John Wiley & Sons Ltd; 2015.
38. Arraut I, Lobo Marques JAL, Gomes S. The probability flow in the stock market and spontaneous symmetry breaking in quantum finance. Mathematics. 2021; 9(21).
DOI: 10.3390/math9212777.
39. Schaden M. Quantum finance. Physica A: Statistical Mechanics and its Applications. 2002;316(1-4):511-38.
DOI: 10.1016/S0378-4371(02)01200-1.
40. Gonçalves CP. Quantum financial economics - risk and returns. *Risk Management*; 2011.
DOI: 10.48550/arXiv.1107.2562.
41. Bouland A, van Dam W, Joorati H, Kerenidis I, Prakash A. Prospects and challenges of quantum finance. J Comp Fin. 2020;31-40.
42. Coulter KA. The impact of news media on Bitcoin prices: modelling data driven discourses in the crypto-economy with natural language processing. R Soc Open Sci. 2022;9(4):220276.
DOI: 10.1098/rsos.220276.
43. Teker D, Deniz EA. Crypto currency applications in financial markets: factors affecting crypto currency prices. Pressacademia. 2020;11(1):34-7.
DOI: 10.17261/Pressacademia.2020.1235.
44. D'Emilio V, Green R, Raymond V. Density estimation with Gaussian processes for gravitational wave posteriors. Mon Not R Astron Soc. 2021;508(2):2090-7.
DOI: 10.1093/mnras/stab2623.
45. Gonçalves CPdS, Gonçalves C. An evolutionary quantum game model of financial market dynamics − theory and evidence. SSRN Journal. 2007.
DOI: 10.2139/ssrn.982086.
46. Choustova O. Toward quantum-like modeling of financial processes. J Phys Conf S. 2007;70(1).
DOI: 10.1088/1742-6596/70/1/012006.
47. Jogenfors J. Quantum bitcoin: an anonymous and distributed currency secured by the no-cloning theorem of quantum mechanics. Quantum physics. 2016;1-10.
DOI: 10.1109/BLOC.2019.8751473.
48. Giudici P, Polinesi G. Crypto price discovery through correlation networks. Ann Oper Res. 2021;299(1-2):443-57.
DOI: 10.1007/s10479-019-03282-3.
49. Orús R, Mugel S, Lizaso E. Quantum computing for finance: overview and prospects. Rev Phys. 2019;4. Elsevier B.V.
DOI: 10.1016/j.revip.2019.100028.
50. Bazzani A. Hamiltonian systems and Stochastic processes. Lecture notes, University of Bologna; 2018.
51. Baaquie BE, Coriandò C, Srikant M. Hamiltonian and potentials in derivative pricing models: exact results and lattice simulations. Phys A. 2004;334(3-4):531-57.
DOI: 10.1016/j.physa.2003.10.080.
52. Li T, Shin D, Wang B, Barber B, Barberis N, Ben-David I et al. Cryptocurrency pump-and-dump schemes. SSRN Journal; 2019.
DOI: 10.2139/ssrn.3267041

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