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Financial Modelling of Cryptocurrency Price Dynamics

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ABSTRACT

The swift growth of cryptocurrencies in the global financial landscape has brought forth both significant opportunities and challenges. In this paper, a differential-equation model for cryptocurrency market dynamics based on the interaction of price, supply, demand, and mining hash rate is developed. The model captures the progression of these variables over time and is evaluated through numerical simulations by means of three illustrative settings. The outcomes provide insights into how different initial conditions influence cryptocurrency market behaviour and demonstrate the potential of the model for analysing price dynamics. The proposed framework provides a foundation for further research on the mathematical modelling and analysis of cryptocurrency markets.

1 Introduction

Cryptocurrencies have revolutionized the financial world by introducing decentralized digital currencies protected by cryptographic techniques. Bitcoin was introduced in 2009, and ever since, cryptocurrencies have gained traction from investors, regulators, and researchers. But the markets are volatile and uncertain, and factors like technology, regulation, market sentiment, and the economy have sway over these markets. This research intends to develop an extensive framework that can be employed to consider the cryptocurrency markets' behaviour by studying the supply-demand dynamics and the mining activity with the help of differential equations. The results will be added to the existing knowledge about cryptocurrencies and will be helpful for investors and the government.

One distinguishing element of cryptocurrencies is the usage of blockchain technology, which is also used in Bitcoin and many other cryptocurrencies. The Bitcoin blockchain is a public ledger that records all transactions, which are verified by network nodes using cryptography to ensure their security. Cryptocurrencies eliminate the requirement for a trusted third party (Catalini, de Gortari, & Shah, 2022). The degree of security a cryptocurrency provides and the number of agents ready to accept it determine its success (Brauneis, Mestel, Riordan, & Theissen, 2022). According to Chod and Lyandres (2023), transactions involving real estate or other assets like automobiles or houses usually involve cryptocurrencies. Furthermore, there is the risk of constantly fluctuating prices and extremely erratic transactions because they are exchanged (Katsiampa, Yarovaya, & Zięba, 2022). Research has demonstrated the relationship between the volume and exchange rates of Bitcoin and important macroeconomic factors such as consumer income, prices, and exchange rates. Some nations and organizations have begun regulating cryptocurrency exchanges despite their unregulated and anonymous character to safeguard consumers and stop illicit activities like money laundering and financing of terrorism (Foley, Karlsen, & Putniņš, 2019).

Cryptography protects cryptocurrencies, which are digital or virtual currencies that are hard to counterfeit or double-spend (Bonneau, Miller, Clark, Narayanan, Kroll, & Felten, 2015). A permissionless payment system can be developed and used thanks to cryptocurrencies (Gandal, Hamrick, Moore, & Oberman, 2018). They enable one side to exercise control over something developed and are intended to serve as a means of exchange (Manahov & Urquhart, 2021). The year 2009 saw the release of Bitcoin as open-source software. It was created under the pseudonym "Satoshi Nakamoto" by an individual or group (Shen, Urquhart, & Wang, 2020). Numerous other cryptocurrencies that have grown in popularity over time were made possible by Bitcoin (Dwyer, 2015). Since Bitcoin had no name at first, there were numerous attempts to find its founder (Jahanshahloo, Irresberger, & Urquhart, 2023). According to Corbet et al. (2020), the main function of Bitcoin is as a virtual currency that may be used as a means of payment, a store of value, a standard of value, a unit of account, and a medium of exchange.

Cryptocurrency transactions take place on certain platforms and give rise to their emergence as a distinct financial instrument with peculiar characteristics (Momtaz, 2019). According to Griffin and Shams (2020), a thorough examination of numerous actual cryptocurrencies reveals that they include characteristics common to money and other financial instruments and that they may even emerge organically from the financial transactions that take place between virtual communities. The characteristics of modern cryptocurrencies sometimes resemble those of uncommon and other global necessities (Jalan, Matkovskyy, Urquhart, & Yarovaya, 2023; Meng, Khan, 2024). Numerous scholars have invested a great deal of time and effort since the inception of cryptocurrencies in order to address these issues as well as numerous others that inevitably come up in relation to them (Duan, Li, Urquhart, & Ye, 2021). Researchers were curious to find out how the novel cryptographic concept of anonymous digital money functions and whether it has broad financial applications during the first phase of the study (2009–2011) (Makarov & Shoar, 2023). After that, they developed an interest in both their property and the features of numerous online platforms; nevertheless, no model of actual user transaction patterns has been developed on the platform (Borri, 2019).

The public's awareness of Bitcoin, the most well-known cryptocurrency, and other pertinent financial platforms and technologies has suddenly increased in recent years (Elsayed, Gozgor, & Yarovaya, 2022). Naturally, these developments have prompted several inquiries, such as: Does Bitcoin have any financial value (Symitsi & Chalvatzis, 2019; Grobys, Junttila, Kolari, & Sapkota, 2021)? Will Bitcoin ultimately result in the creation of a global currency (Karaa, Slim, Goyal, Goodell, & Kallinterakis, 2023; Yermack, 2015)? How do the exchange prices of cryptocurrencies and conventional currencies fluctuate (Hou, Li, Hu, & Oxley, 2023; Cheong, 2019)? Does this represent the disdain for the financial system and the decentralization of financial tools (De Vries, 2023)? Is it possible to make corrections for theoretical advancement and real-world application (Hoang & Baur, 2023)? Studying cryptocurrency features and concepts in depth is necessary to get the answers to these concerns (Cheong, 2019). Naturally, investigating it as a unique digital matter is the initial step in this direction (Shi, Zhai, & Wu, 2023).

Due to the introduction of decentralized digital assets that function independently of conventional banking systems, cryptocurrencies have completely changed the financial landscape (Lucey, Vigne, Yarovaya, & Wang, 2022). It is imperative for investors, miners, policymakers, and researchers to comprehend the workings of cryptocurrencies (Dhawan & Putniņš, 2023). Robust models are required to study and predict the behaviour of cryptocurrency markets due to their quick and volatile nature (Catalini, de Gortari, & Shah, 2022). The public, regulatory agencies, and academia have all expressed a great deal of interest in the subject of cryptocurrency. Specifically, there have been intense discussions on how to distinguish between a cryptocurrency's "utility" and "exchange value." What influences each cryptocurrency's price is a crucial question as well (Shi, Zhai, & Wu, 2023). One of the most crucial problems for an economist or econometrician to address is the asset's valuation model (Gkillas, Katsiampa, Konstantatos, & Tsagkanos, 2023). But from a statistician's perspective, there don't seem to be many studies on cryptocurrency (Naeem, Nguyen, Karim, & Lucey, 2023).

The growth and resilience of cryptocurrency trading platforms were significantly aided by the Internet (Lyons & Viswanath-Natraj, 2023). Specifically, virtual computer networks have been developed for mining (or extracting cryptocurrencies) (Wei, 2018). The adoption of cryptocurrencies as a means of value storage, transmission, and

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remittance is linked to their utilitarian value (Amiram, Jorgensen, & Rabetti, 2022). Every cryptocurrency has its own characteristics that define its relative worth in relation to other non-proprietary and property-based items that can be used to measure the value of products and in the processes of accumulation, remittance, and exchange (Elsayed & Sousa, 2023). Following the broad adoption of the internet, it was evident that most users had simply shifted from being just present on a virtual network to utilizing a computer and software to conduct a variety of tasks (Grobys & Huynh, 2021). In these situations, network users' activities—that is, the creation of services and software—as well as the creation and distribution of information on the internet itself are important (Yao, Kong, Sensoy, Akyildirim, & Cheng, 2023). The present ICT industry and the development of specialized services, software, etc., all stem from this same activity. Thus, the rise of physical connections created along the Internet's axis is not the only factor contributing to its development; new business models functioning within it are also emerging and improving at the same time (Shen, Urquhart, & Wang, 2020).

Cryptocurrencies, which are decentralized digital assets with the potential to yield large returns and can be used as alternatives to traditional safe-haven investments, have completely changed the way people think about investing. To ensure that investors and policymakers make well-informed decisions, they must have a greater understanding of the pricing dynamics of cryptocurrency markets due to their inherent volatility and complexity.

Despite their growing prominence, the financial modeling of cryptocurrencies remains a relatively nascent field. Thus, the goal of this study is to show a theoretical framework and applications that affect the mathematical aspects of cryptocurrency pricing, which can help in making better decisions for various parties. An all-encompassing blueprint of their market dynamics is crucial. The aim of this study is therefore to contribute to this discourse by developing a suitable academic and practitioner- oriented model which would be in line with the needs and requirements of both groups.

2 Formation of the Model Dynamics

This section takes care of the model dynamics via the following assumptions:

2.1 Model Assumptions

i. The market responds to changes in supply and demand without delay (Market Efficiency).
ii. Parameters such as k_1, k_2, k_3, k_4 and C_m remain constant over the simulation period (Fixed Constants).
iii. Utility $U(t)$ and consumption $C(t)$ are constants (Constant Utility and Consumption).
iv. The model does not account for external factors such as regulations or technological advancements affecting cryptocurrency dynamics (Isolated System).

Consider the following model variables where $P(t)$ is the Price of the cryptocurrency at time t, $S(t)$ is the Supply of the cryptocurrency at time t, $D(t)$is the Demand for the cryptocurrency at time t, $H(t)$ is the Hash rate of the mining network at time t, and $M(t)$ is the Rate at which new cryptocurrency is mined at time t. The hash rate measures the processing capability of a proof-of-work (PoW) Bitcoin network, group, or individual. The hash rate determines the mining difficulty of a blockchain network and can be used to assess security.

For the constants and parameters definitions, let k_1, k_2, k_3, k_4 be the sensitivity constants for price, demand, mining rate, and hash rate dynamics, respectively, $U(t)$ the Utility or perceived value of the cryptocurrency, which can be modeled as a function of various factors such as technology adoption, regulatory news, and market trends, $C(t)$ the Consumption or burning rate of the cryptocurrency, which might be a constant or a function of other variables, and $C_m$the Average cost of mining per unit of the cryptocurrency. Then the following dynamics for Price, supply, demand, and hash rate functions are presented:

$$\frac{dP(t)}{dt} = k_1\left(\frac{D(t)}{S(t)} - P(t)\right). \tag{2.1}$$

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Equation (2.1) (Price Dynamics) models the price change based on the ratio of demand to supply.

$$\frac{dS(t)}{dt} = M(t) - C(t). \tag{2.2}$$

Equation (2.2), the supply dynamics, models the supply change as the difference between new mining and consumption.

$$\frac{dD(t)}{dt} = k_2(U(t) - D(t). \tag{2.3}$$

Equation (2.3), the demand dynamics equation, models demand change based on its deviation from perceived utility.

$$\frac{dH(t)}{dt} = k_4\left(\frac{P(t)}{C_m} - H(t)\right). \tag{2.4}$$

Equation (2.4), the hash rate dynamics equation, models the hash rate change based on the profitability of mining.

2.2.1. Economic Interpretation and Dimensional Consistency

The proposed model is formulated to make sure the terms in each differential equation are dimensionally consistent and have economic interpretations. The ratio of the two, $\frac{D(t)}{S(t)}$, is dimensionless because quantities of demand and supply are boh measured in the same units. So, $\left[\frac{D(t)}{S(t)} - 1\right]$ is a measure of relative excess demand. If $D(t) > S(t)$, then it exerts upward pressure on price, while $D(t) < S(t)$ exerts downward price pressure. As a result, the units of k_i are per second, so that the units of $\frac{dP(t)}{dt}$ are price per second.

The ratio $\frac{P(t)}{C_m}$ has no dimension in the hash-rate equation because both $P(t)$ and C_m are expressed as monetary value per unit of cryptocurrency. The ratio $\left[\frac{P)t)}{C_m} - 1\right]$ can thus be used as a simplified measure of the economic incentive for mining. If $P(t) > C_m$ then it is relatively more attractive to mine, and the hash rate will tend to rise, and vice versa. Therefore, the dimension of k_4 is $\frac{1}{time}$, and ensures the consistency of dimensions in $\frac{dH(t)}{dt}$.

Likewise, in the demand equation, $U(t)$ and $D(t)$ are expressed in the same units, so that $\frac{U(t)}{D(t)}$ is dimensionless, meaning that the value of k_2 must have the dimension of inverse time. The coefficient k_3 can be used to convert hash-rate units into cryptocurrency units per unit time, as the $M(t) = k_3(t)$. Consequently, the model is dimensionally consistent and offers a meaningful economic representation of interactions between price, supply, demand and mining activity.

In summary, these models form a system of differential models given as follows:

$$\begin{cases} \frac{dP(t)}{dt} = k_1\left(\frac{D(t)}{S(t)} - P(t)\right), \\ \frac{dS(t)}{dt} = M(t) - C(t), \\ \frac{dD(t)}{dt} = k_2(U(t) - D(t)), \\ M(t) = k_3 H(t) \\ \frac{dH(t)}{dt} = k_4\left(\frac{P(t)}{C_m} - H(t)\right). \end{cases} \tag{2.5}$$

The solution of this, and similar differential models can be obtained using numerical or semi-analytical methods (Edeki, Okagbue, Opanuga, & Adeosun, 2014; Opanuga, Edeki, Okagbue, Akinlabi, Osheku, & Ajayi, 2014; Hu, Ye, & Jianwei, 2021; Edeki, Ugbebor, & Owoloko, 2016; Lipton, Gal, & Lasis, 2014; Ouyang, Zheng, & Jiang, 2015).

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3 Brief Overview of Euler's Solution Method and Applicable Cases

Euler's method is a straightforward numerical methodology for solving ordinary differential equations (ODEs) with a known initial value. It is one of the most straightforward and intuitive approaches to approximating the solutions of differential equations (Behera & Ray, 2022; Yang, Yang, & Liu, 2023).

Euler's method approximates the solution of the differential equation over a given interval by using

$$y' = f(t, y) \tag{3.1}$$

and the following iterative formula:

$$y_{n+1} = y_n + h \cdot f(t_n, y_n) \tag{3.2}$$

where y_n is the approximate value of the solution at step n, t_n is the current time or position, h is the step size (a small positive number), and $f(t, y)$ is the function defining the derivative y'.
Using Euler's Method involves the following steps:

S1: Initialization:

a. Set the initial condition $y(0) = y_0$.
b. Choose a step size h.
c. Determine the number of steps N such that $N \cdot h$ covers the desired interval.

S2: Iteration:

- For each step n from 0 to $N - 1$:
  - Compute $y_{n+1} = y_n + h \cdot f(t_n, y_n)$
  - Update $t_{n+1} = t_n + h$.

S3: Output:

- The pairs (t_n, y_n) represent the approximate solution at discrete points.

Euler's method is used because of the simplicity of the method and the fact that it can be used to illustrate the qualitative behavior of the proposed system. The reliability of the numerical results was checked by varying the step sizes in the simulations progressively, and comparing the resulting trajectories. The qualitative behavior of the solutions was shown to be consistent between the various simulations of the illustrative test cases, which suggests that the chosen step size is sufficient for the present simulations.

3.1 Numerical Simulation

We employ Euler's method to approximate the solutions of the differential system over a time period of 10 units with a time step $dt = 0.1$. A step size of $dt = 0.1$ was adopted for the simulations after checking the stability and consistency of the resulting trajectories.

3.1.1. Initial Conditions and Parameters

The system is initialized with:

$$\left.\begin{aligned} P(0) &= 1000 \\ S(0) &= 21000000 \\ D(0) &= 5000 \\ H(0) &= 20000 \end{aligned}\right\}. \tag{3.3}$$

The constants are set as:

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$$\left.\begin{aligned} &k_1 = 0.01, k_2 = 0.02, \\ &k_3 = 0.1, k_4 = 0.05, \\ &C_m = 1000, \\ &U(t) = 50000, C(t) = 10 \end{aligned}\right\}. \tag{3.4}$$

The initial conditions and parameter values for the simulations are merely illustrative and have not been calibrated from the real world. They are chosen to give a uniform set of numbers for the analysis of the qualitative properties of the proposed differential model and to allow comparisons between the various cases of simulation. In particular, the baseline values $P(0) = 1000$, $S(0) = 21{,}000{,}000$, $D(0) = 5000$, and $H(0) = 20{,}000$ provide the starting state of the model, while the parameters $k_1 = 0.01$, $k_2 = 0.02$, $k_3 = 0.1$, $k_4 = 0.1$, $C_m = 1000$, $U(t) = 50{,}000$, and $C(t) = 10$ are chosen to produce meaningful interactions among price, supply, demand, and mining activity. The above values are not meant to be an estimation of a specific cryptocurrency or of a specific period of time. Instead, they offer a set of fixed target points to study the impact of initial demand and hash rate changes. Therefore, the numerical results should be viewed as examples of possible model behavior, and not as predictions of real outcomes.

The simulations are basically illustrative and are not intended to provide empirical forecasts of actual cryptocurrency prices. The results of the model should be viewed and interpreted as theoretical insights into the possible dynamics of price, supply, demand, and hash rate under the specified conditions, since the model has not been calibrated against any observed cryptocurrency data.

3.1.2. Illustrative Cases

The illustrative cases are constructed by varying the selected initial conditions while keeping the remaining parameters fixed at the baseline values in Eqs. (3.3)–(3.4). This allows the effects of initial demand and hash rate on the model dynamics to be examined in a controlled manner. These are visualized in Figs. 1-Fig. 4. In addition, comprehensive interpretations follow to that effect accordingly.

Example 1: Base Setting

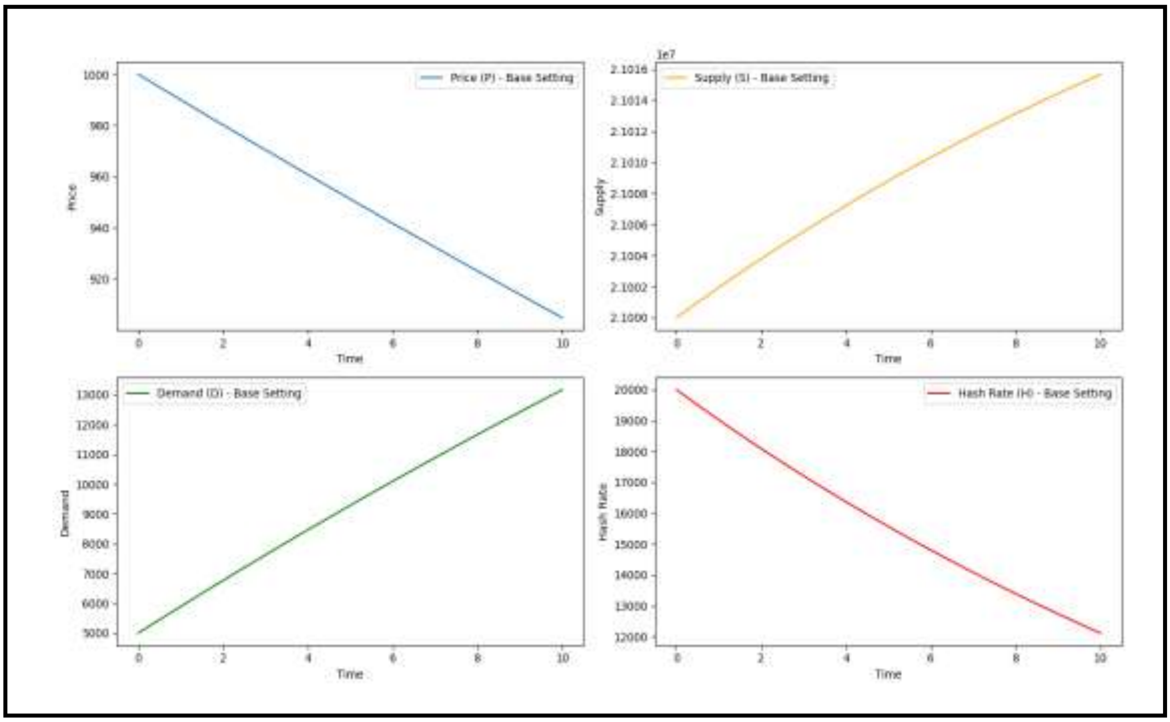

Fig. 1: Base Setting effects on Price, supply, demand, and hash rate functions

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An initial increase in price is seen, then it stabilizes gradually as shown in Fig. 1. Demand grows slowly towards its level of utilisation and supply is increased steadily. The hash rate is also steadily raised as the price goes up.

Example 2: High Initial Demand

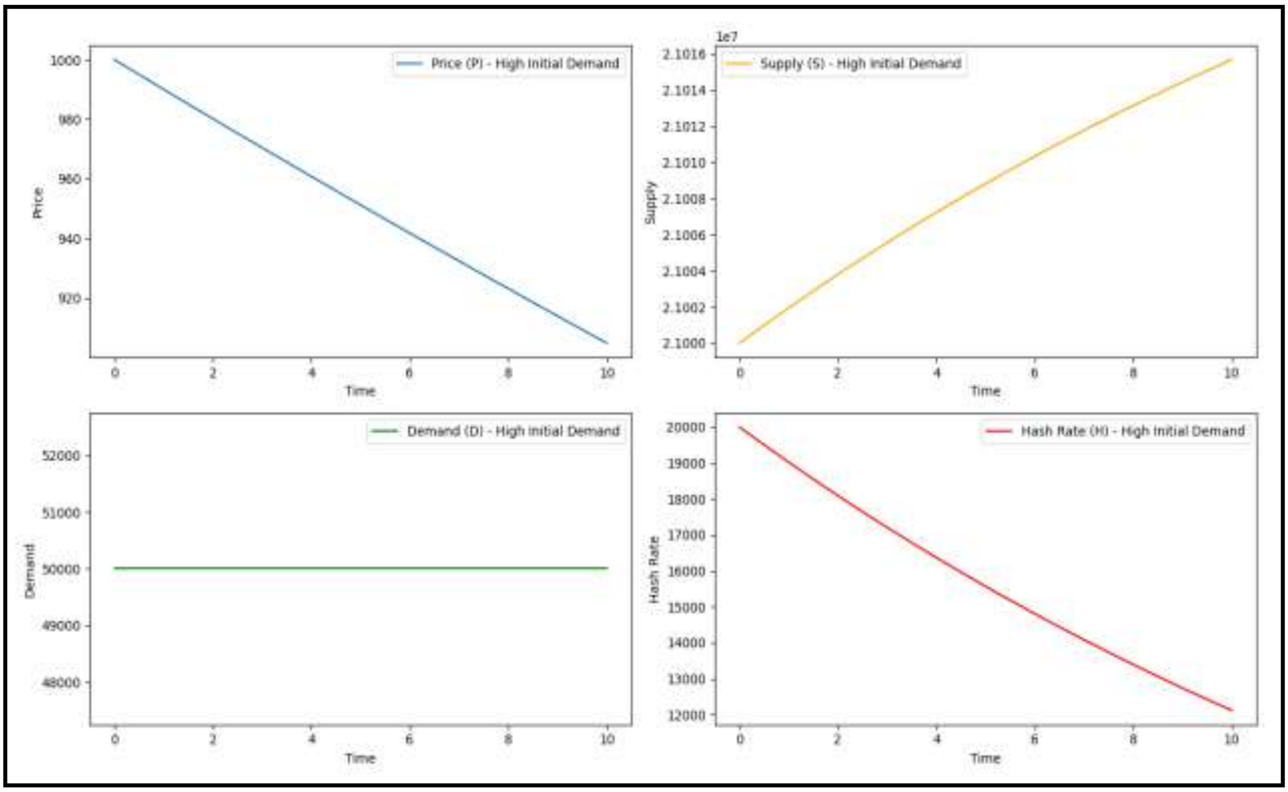

Fig. 2: Initial demand effects on price, supply, demand, and hash rate functions

The initial rise in price is very steep, with a subsequent leveling off at a comparatively high price level (see Fig. 2). Supply increases gradually, while demand declines from its high initial level towards the utility level. As the price goes up, the hash rate goes up.

Example 3: Low Initial Mining Hash Rate

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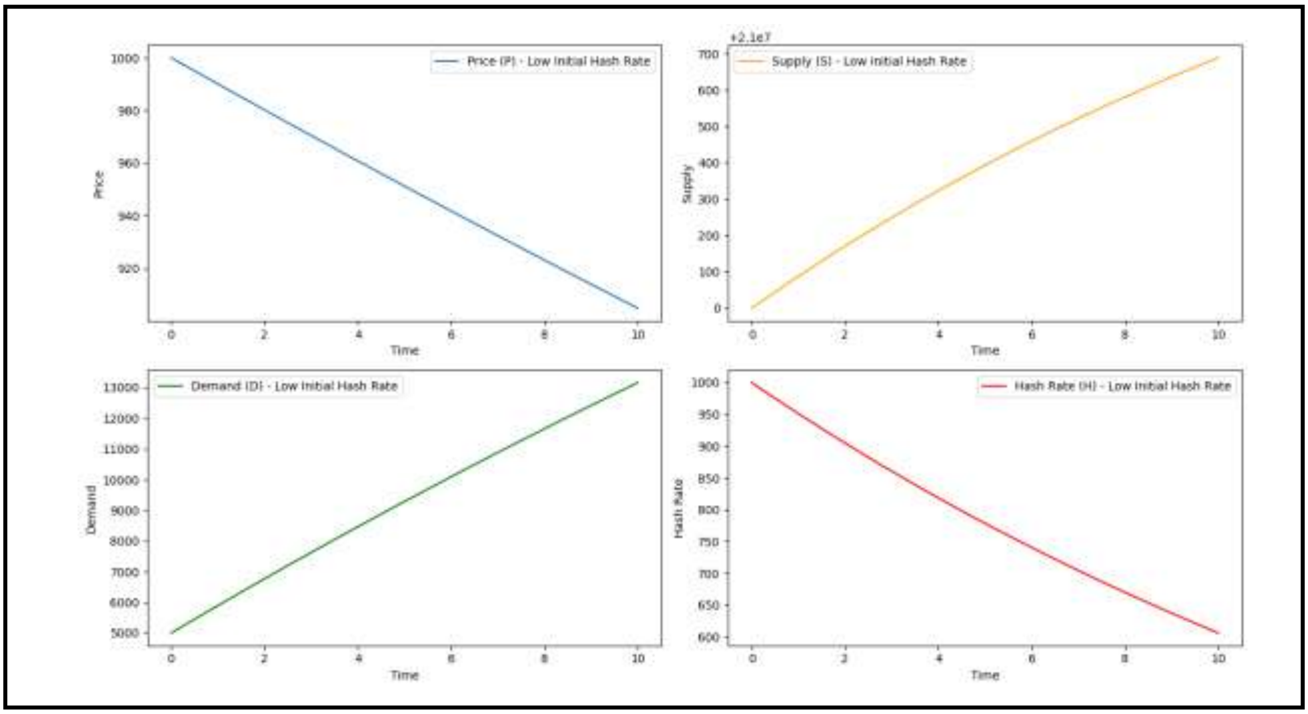

Fig. 3: Low initial mining hash rate effects on price, supply, demand, and hash rate functions

As seen in Fig. 3, a lower initial hash rate is correlated with slower supply growth and an initial price increase. Demand slowly moves towards the utility level, while the hash rate slowly rises from its low starting point.

Example 4: Combined Effects

To visualize and compare the different Settings, we plot the results together.

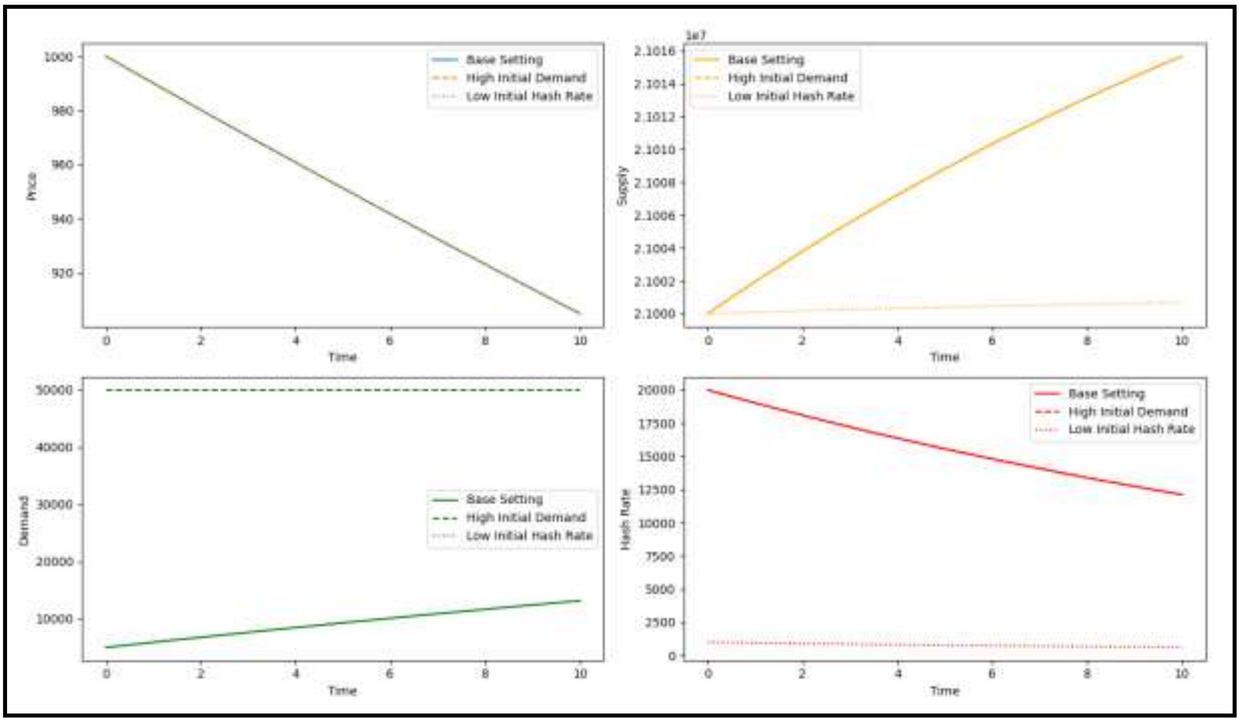

Fig. 4: Combined Rate effects on Price, supply, demand, and hash rate functions

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The price dynamics of the settings are clearly different, as represented in Fig. 4, where the highest demand setting had the most strongly pronounced initial price reaction. The initial hash rate is more sensitive to Supply, while the demand slowly transitions towards the Utility across the settings. The other initial condition is also reflected in the hash-rate evolution

4 The modified model in relation to Time-dependent

Here, we consider how the above-mentioned model with its terms can be modified. Firstly, a situation of modifying the parameters to be time-dependent is considered. In this case, the variables such as market efficiency $(k_{1)}$, utility $U(t)$ and consumption $C(t)$ are considered as constants but are redefined and made functions of time, thus better reflecting the influence of external factors on the cryptocurrency market. This change would allow for the shifting regulatory landscape, advancements in technology, and other external changes.
Traditionally, market efficiency is considered static; that is, it is assumed that it reacts to changes in the market immediately. This assumption, however, doesn't go far enough to account for how long it could take for markets to do information processing or adjust to a shock. A market efficiency that is modeled as a time- dependent function $\eta(t)$ can be used to simulate the changes in market efficiency that follow events such as changes in regulation, news releases, and changes in trading volume. For example, $\eta(t)$ can be raised with positive regulatory changes or lowered with market shocks to simulate the speed or slowness of market response to different market conditions.
The value of owning cryptocurrency as a utility parameter is also very dynamic and dependent on technological advancements, adoption rates, and economic sentiment. The utility function is a function of time, $U(t)$, and can reflect changes in the utility function: technological advances increase the utility of a commodity, while economic recession decreases the utility of a commodity. This method enables the model to simulate fluctuations in investor behavior over time and generate scenarios in which the demand for cryptocurrencies changes depending on the utility's availability, impacting the price.

Consumption is the combined amount of spending power or capital invested in buying cryptocurrencies. It is influenced by factors such as inflation, disposable income, and macroeconomic conditions. The model can thus be used to account for changes in available capital with time, as the capital may increase as a result of an expansion of the economy, or be reduced as a result of a recession. Also, since $C(t)$ is time-dependent, the model can also be used to simulate changes in demand as a result of macroeconomic pressures or market-specific pressures which affect the overall demand and consequently the price stability. The extensions discussed in this section are proposed directions for future research and are not implemented or numerically evaluated in the present study.

4.1 Mathematical Formulation of Time-Dependence

These time-dependent parameters can be represented as:

$$\left.\begin{array}{l}\eta(t) = \eta_0 + f_1(t) \\ U(t) = U_0 + f_2(t) \\ C(t) = C_0 + f_3(t)\end{array}\right\} \tag{4.1}$$

where $\eta_0, U_0,$ and C_0 represent the initial values of market efficiency, utility, and consumption, respectively, and $f_1(t), f_2(t),$ and, $f_3(t)$ are functions representing time-dependent changes, capturing the effects of external influences like economic cycles, regulatory announcements, and technological advancements.

Consequently, the Revised Assumptions are:

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i. Market Efficiency as Time-Dependent: Rather than assuming a fixed market efficiency, we introduce a function $k_1(t)$ to capture shifts in market responses due to varying liquidity, transaction volumes, or market access changes.
ii. Utility as a Variable Function of Time and External Factors: Define utility as U(t), which could vary based on regulatory news, public sentiment, or technological changes.
iii. Consumption as Time-Dependent: Consumption C(t) could vary with transaction volume or economic activity, which we can represent through a variable function, such as $C(t) = C_0 + C_{\text{ext}}(t)$, where $C_{\text{ext}}(t)$ represents fluctuations from external economic pressures.

4.2 The Adjusted Model Equations

Here, the model equations are rewritten to incorporate these time-dependent variables. Thus:

$$\left.\begin{aligned}
\frac{dP(t)}{dt} &= k_1(t)\left(\frac{D(t)}{S(t)} - P(t)\right) \\
\frac{dS(t)}{dt} &= M(t) - C(t) \\
\frac{dD(t)}{dt} &= k_2(U(t) - D(t)) \\
M(t) &= k_3 H(t) \\
\frac{dH(t)}{dt} &= k_4\left(\frac{P(t)}{C_m} - H(t)\right)
\end{aligned}\right\}. \tag{4.2}$$

4.3 Specific Time-Dependent Functions

For the variability of these parameters, the Market Efficiency, Utility, and Consumption functions are considered.

Market Efficiency: $k_1(t) = k_1^0 + \alpha\, sin(\omega t)$, where k_1^0 is the baseline efficiency, while α and ω are parameters that introduce fluctuations.

Utility: $U(t) = U_0 + \beta e^{-\lambda t} + \gamma(t)$, where U_0 is baseline utility, and $\gamma(t)$ models abrupt changes from regulatory news.

Consumption: $C(t) = C_0 + \delta t$, where C_0 is the baseline consumption, and d captures growth in usage over time.

Hence, the system becomes:

$$\left.\begin{aligned}
\frac{dP(t)}{dt} &= (k_1^0 + \alpha\, sin(\omega t))\left(\frac{D(t)}{S(t)} - P(t)\right) \\
\frac{dS(t)}{dt} &= M(t) - (C_0 + \delta t) \\
\frac{dD(t)}{dt} &= k_2\left(\left(U_0 + \beta e^{-\lambda t} + \gamma(t)\right) - D(t)\right) \\
M(t) &= k_3 H(t) \\
\frac{dH(t)}{dt} &= k_4\left(\frac{P(t)}{C_m} - H(t)\right)
\end{aligned}\right\}. \tag{4.3}$$

Regulatory changes and announcements can trigger substantial cryptocurrency price fluctuations by altering investor sentiment, risk perception, and trading activity. Their effects can be incorporated into the model as stochastic shocks influencing demand, market efficiency, and price volatility.

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4.4 Modeling regulatory shock function and Market lagged Responses

Define a regulatory shock function $R(t)$ that introduces random or scheduled shocks to the system based on regulatory announcements. Each shock can be represented as a sudden change in parameters, such as a drop in market efficiency $\eta(t)$, an increase in volatility $\sigma(t)$, or a consumption adjustment in $C(t)$.

Mathematically, this can be represented as:

$$\left.\begin{aligned} \eta(t) &= \eta_0 + f_1(t) + R(t) \\ \sigma(t) &= \sigma_0 + f_4(t) + R(t) \end{aligned}\right\}, \tag{4.4}$$

Where $R(t)$ follows a stochastic process, such as a Poisson jump process to introduce discrete events, or a Gaussian noise term to represent continuous fluctuations in response to regulatory news.

The inclusion of lagged responses and feedback mechanisms shows delayed market reactions to supply-demand imbalances and previous price levels. A time-lagged parameter for market response, creating a delay function $D(\tau)$ in supply-demand adjustments, is of the form:

$$S(t) = f(D(\tau)) \cdot D(\tau - t) \tag{4.5}$$

where $D(\tau)$ represents the delayed adjustment of supply based on past demand changes.

This will create unique simulation patterns in which prices oscillate or stabilize gradually, demonstrating realistic market feedback behaviours rather than rapid modifications. Future work should incorporate all of these elements. This is in addition to a rigorous validation across numerous cryptocurrencies, especially with varying market size and features, to enhance the model's prediction power and robustness for diverse market conditions. Numerical experiments for these extensions are beyond the scope of the present study and are left for future work

5 Concluding Remarks

This study developed a differential-equation model for the analysis of cryptocurrency price dynamics via the interaction of price, supply, demand, and mining hash rate. The numerical simulations show how these stated variables evolve and reveal that changes in initial demand and hash rate can significantly impact the resulting market path. In particular, higher initial demand gives stronger price responses, whereas a lower initial hash rate constrains supply growth and affects successive price and mining dynamics. These outcomes highlight the unified nature of market demand and mining activity in shaping cryptocurrency price behaviour.

The proposed model offers a suitable mathematical structure for studying cryptocurrency markets and provides a foundation for further financial modelling and analysis. Nevertheless, its simplifying assumptions, including constant parameters, utility and consumption, and the exclusion of external market influences, limit its representation of real-world cryptocurrency markets. Consequently, future work should incorporate stochastic market movements, regulatory shocks, market sentiment, macroeconomic factors, transaction fees, block rewards, and delayed market responses, in addition to empirical validation across different cryptocurrencies. Such extensions would improve the model's realism, robustness, and potential for practical forecasting and decision-making.

Declaration of competing interests

The author(s) declare no known conflicts of interest regarding this work.

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References

[1.] Amiram, D., Jorgensen, B. N., & Rabetti, D. (2022). Coins for bombs: The predictability of on-chain transfers for terrorist attacks. Journal of Accounting Research, 60, 427–466. https://doi.org/10.1111/1475-679X.12430.

[2.] Behera, S., & Ray, S. S. (2022). An efficient numerical method based on Euler wavelets for solving fractional order pantograph Volterra delay-integro-differential equations. Journal of Computational and Applied Mathematics, 406, 113825.

[3.] Bonneau, J., Miller, A., Clark, J., Narayanan, A., Kroll, J. A., & Felten, E. W. (2015). Sok: Research perspectives and challenges for bitcoin and cryptocurrencies. In 2015 IEEE Symposium on Security and Privacy (pp. 104-121). IEEE.

[4.] Borri, N. (2019). Conditional tail-risk in cryptocurrency markets. Journal of Empirical Finance, 50, 1–19. https://doi.org/10.1016/j.jempfin.2018.11.002.

[5.] Brauneis, A., Mestel, R., Riordan, R., & Theissen, E. (2022). Bitcoin unchained: Determinants of cryptocurrency exchange liquidity. Journal of Empirical Finance, 69, 106–122. https://doi.org/10.1016/j.jempfin.2022.08.004.

[6.] Catalini, C., de Gortari, A., & Shah, N. (2022). Some simple economics of stablecoins. Annual Review of Financial Economics, 14, 117–135. https://doi.org/10.1146/annurev-financial-111621-101151.

[7.] Cheong, C. W. (2019). Cryptocurrencies vs global foreign exchange risk. The Journal of Risk Finance, 20(4), 330-351.

[8.] Corbet, S., Larkin, C., Lucey, B. M., Meegan, A., & Yarovaya, L. (2020). The impact of macroeconomic news on bitcoin returns. The European Journal of Finance, 26, 1396–1416. https://doi.org/10.1080/1351847X.2020.1737168.

[9.] Duan, K., Li, Z., Urquhart, A., & Ye, J. (2021). Dynamic efficiency and arbitrage potential in bitcoin: A long-memory approach. International Review of Financial Analysis, 75, 101725. https://doi.org/10.1016/j.irfa.2021.101725.

[10.] Dwyer, G. P. (2015). The economics of bitcoin and similar private digital currencies. Journal of Financial Stability, 17, 81–91. https://doi.org/10.1016/j.jfs.2014.11.006.

[11.] Edeki, S. O., Okagbue, H. I., Opanuga, A. A., & Adeosun, S. A. (2014). A semi-analytical method for solutions of a certain class of second- order ordinary differential equations. Applied Mathematics, 5(13), 2034-2041. https://doi.org/10.4236/am.2014.514197

[12.] Edeki, S. O., Ugbebor, O. O., & Owoloko, E. A. (2016). He's polynomials for analytical solutions of the Black-Scholes pricing model for stock option valuation. Lecture Notes in Engineering and Computer Science. Retrieved from https://www.worldcat.org/title/hes-polynomials-for-analytical-solutions-of-the-black-scholes-pricing-model-for-stock-option-valuation/oclc/953245692

[13.] Foley, S., Karlsen, J. R., & Putninš, T. J. (2019). Sex, drugs and bitcoin: How much illegal activity is financed through cryptocurrencies? The Review of Financial Studies, 32, 1798–1853. https://doi.org/10.1093/rfs/hhz015.

[14.] Gandal, N., Hamrick, J. T., Moore, T., & Oberman, T. (2018). Price manipulation in the bitcoin ecosystem. Journal of Monetary Economics, 95, 86–96.

[15.] Griffin, J. M., & Shams, A. (2020). Is bitcoin really untethered? The Journal of Finance, 75, 1913–1964. https://doi.org/10.1111/jofi.12903.

[16.] Grobys, K., & Huynh, T. L. D. (2021). When tether says "JUMP!" bitcoin asks "How low?". Finance Research Letters, 47, 102644.

[17.] Grobys, K., Junttila, J., Kolari, J. W., & Sapkota, N. (2021). On the stability of stablecoins. Journal of Empirical Finance, 64, 207–223. https://doi.org/10.1016/j.jempfin.2021.09.002.

[18.] Hoang, L. T., & Baur, D. G. (2023). How stable are stablecoins? European Journal of Finance, forthcoming.

[19.] Hou, Y., Li, Y., Hu, Y., & Oxley, L. (2023). Time-varying spillovers of higher moments between bitcoin and crude oil markets and the impact of the US-China trade war: A regime-switching perspective. European Journal of Finance, forthcoming.

[20.] Hu, L., Ye, J., & Jianwei, E. (2021). A novel integrated approach for analyzing the financial time series and its application on the stock price analysis. Acta Physica Polonica B, 52(6), 837-846. https://doi.org/10.5506/APhysPolB.52.837

[21.] Jalan, A., Matkovskyy, R., Urquhart, A., & Yarovaya, L. (2023). The role of interpersonal trust in cryptocurrency adoption. Journal of International Financial Markets, Institutions and Money, 83, 101715. https://doi.org/10.1016/j.intfin.2022.101715.

[22.] Karaa, R., Slim, S., Goodell, J. W., Goyal, A., & Kallinterakis, V. (2023). Do investors feedback trade in bitcoin – and why? European Journal of Finance, forthcoming.

[23.] Katsiampa, P., Yarovaya, L., & Zięba, D. (2022). High-frequency co-movements and correlations between bitcoin and other top-traded cryptocurrencies during the COVID-19 crisis. Journal of International Financial Markets Institutions & Money, 79, 101578. https://doi.org/10.1016/j.intfin.2022.101578.

[24.] Lipton, A., Gal, A., & Lasis, A. (2014). Pricing of vanilla and first-generation exotic options in the local stochastic volatility framework: survey and new results. Quantitative Finance, 14(12), 2003-2022. https://doi.org/10.1080/14697688.2014.946254

[25.] Lucey, B. M., Vigne, S. A., Yarovaya, L., & Wang, Y. (2022). The cryptocurrency uncertainty index. Finance Research Letters, 22, 102147.

[26.] Lyons, R. K., & Viswanath-Natraj, G. (2023). What keeps stablecoins stable? Journal of International Money and Finance, 131, 102777. https://doi.org/10.1016/j.jimonfin.2022.102777.

[27.] Makarov, I., & Shoar, A. (2023). Blockchain analysis of the bitcoin market. Available on SSRN: https://ssrn.com/abstract=3942181.

[28.] Manahov, V., & Urquhart, A. (2021). The efficiency of bitcoin: A strongly typed genetic programming approach to smart electronic bitcoin markets. International Review of Financial Analysis, 73, 101629. https://doi.org/10.1016/j.irfa.2020.101629.

[29.] Meng, K., Khan, K. Is cryptocurrency Efficient? A High-Frequency Asymmetric Multifractality Analysis. Comput Econ 63, 2225–2246 (2024). https://doi.org/10.1007/s10614-023-10402-6

[30.] Momtaz, P. P. (2019). The pricing and performance of cryptocurrency. The European Journal of Finance, 27, 367–380. https://doi.org/10.1080/1351847X.2019.1647259.

[31.] Naeem, M. A., Nguyen, T. T. H., Karim, S., & Lucey, B. (2023). Extreme downside risk transmission between green cryptocurrencies and energy markets: The diversification benefits. Finance Research Letters, 58, 104263. https://doi.org/10.1016/j.frl.2023.104263.

[32.] Opanuga, A. A., Edeki, S. O., Okagbue, H. I., Akinlabi, G. O., Osheku, A. S., & Ajayi, B. (2014). On numerical solutions of systems of ordinary differential equations by numerical-analytical method. Applied Mathematics & Information Sciences, 8(164), 8199-8207.

[33.] Ouyang, F.-Y., Zheng, B., & Jiang, X.-F. (2015). Intrinsic multi-scale dynamic behaviors of complex financial systems. PLoS ONE, 10(6), e0129672. https://doi.org/10.1371/journal.pone.0129672

[34.] Symitsi, E., & Chalvatzis, K. J. (2019). The economic value of Bitcoin: A portfolio analysis of currencies, gold, oil and stocks. Research in International Business and Finance, 48, 97-110.

[35.] Shen, D., Urquhart, A., & Wang, P. (2020). Forecasting the volatility of bitcoin: The importance of jumps and structural breaks. European Financial Management, 26, 1294–1323. https://doi.org/10.1111/eufm.12254.

[36.] Wei, W. C. (2018). Liquidity and market efficiency in cryptocurrencies. Economics Letters, 168, 21–24.

[37.] Yang, H., Yang, Z., & Liu, S. (2023). Numerical Threshold of Linearly Implicit Euler Method for Nonlinear Infection-Age SIR Models. Discrete & Continuous Dynamical Systems-Series B, 28(1).

[38.] Yao, Y., Kong, W., Sensoy, A., Akyildirim, E., & Cheng, Z. (2023). How do cryptocurrencies behave before and after COVID-19: Volatility persistence and transmission. International Review of Financial Analysis, 81, 101778. https://doi.org/10.1016/j.irfa.2022.101778.

[39.] Yermack, D. (2015). Is Bitcoin a real currency? An economic appraisal. In Handbook of digital currency (pp. 31-43). Academic Press.