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Modeling climate policy uncertainty into cryptocurrency volatilities

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ABSTRACT

Climate change is a highly controversial topic within the socioeconomic context. Climate Policy Uncertainty (CPU) arises from the process of climate policies formulation and implementation. This uncertainty impacts financial market volatilities, including cryptocurrency markets. In this paper, we demonstrate the substantial role of CPU in forecasting volatilities in cryptocurrency markets using Genetic Programming (GP). Our study shows that different cryptocurrency markets respond differently to CPU across time scales. Our paper contributes to the literature by illustrating the impact of CPU on cryptocurrency market volatilities and analyzes it across different time horizons. Second, we build three volatility forecasting models for different cryptocurrency markets by incorporating CPU, which outperform traditional models. Our models can thereby illuminate portfolio construction and hedging strategies, providing valuable insights for investors and policymakers.

1. Introduction

Climate change can be characterized as one of the most disputable socioeconomic issues in the contemporary era. In response to the potential catastrophic risks imposed by climate change, governments are actively promoting various regulations and policies to mitigate such issue, which are known as the climate policies. Furthermore, the formulating and implementing of climate policies usually involve counterbalancing considerations, which engenders uncertainties of climate policies (Nesje et al., 2023), known as Climate Policy Uncertainty (CPU) (Fuss et al., 2008; Ren et al., 2022). This type of uncertainty places a complex layer of unpredictability into the financial market volatilities (Ding et al., 2021), creating a unique type of climate-related financial risk (Jin & Yu, 2023; Urom et al., 2020). As a result, scholars are gradually recognizing the interconnectivity between climate policies and financial market responses, particularly in cryptocurrency markets, which are sensitive to climate policy shifts, due to their energy-intensive characteristics (Wu & Ding, 2023; Zhang, Chen, et al., 2023; Zribi et al., 2023).

Further, the effect of cryptocurrency market volatility could be amplified because of the interconnectedness between the cryptocurrency market and other financial markets (Corbet et al., 2018; Demir et al., 2018; Gaies et al., 2021; Guesmi et al., 2023; Zhang et al., 2019; Zhang, Zhang, et al., 2023; Zhu et al., 2021). The volatility spillovers from the cryptocurrency market to traditional financial markets have been well documented, suggesting that the high volatility in cryptocurrencies can affect broader economic stability (Ahmed et al., 2024; Ding et al., 2022; Karim et al., 2023; Wang et al., 2022; Zhao & Park, 2024). Despite of the high volatility feature of the cryptocurrencies markets, they oftentimes exhibit low correlation with traditional financial markets during the high market volatility episodes (Feng et al., 2018; Hasan et al., 2022; Platanakis & Urquhart, 2020). As a result, high traditional financial market volatilities during the geopolitical events, such as Russia–Ukraine conflict, resulted in the financialization of the cryptocurrency markets, where investors envision cryptocurrencies markets as safe haven and thus allocate a large number of assets into cryptocurrencies markets (Hsu et al., 2024; Tarchella et al., 2024). Cryptocurrencies there have rapidly evolved from speculative assets into vital components of the global financial system in the past decade, profoundly impacting on investment strategies, financial risk management, and financial market stabilization. Volatilities in those markets can be used to estimate risk levels, and thereby guide decision-making processes for investors and policymakers. As a result, accurate volatility forecasting, becomes a crucial ingredient for navigating

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investments and regulations within those markets (Huang et al., 2023; Osman et al., 2023). Consequently, this unique asset characteristics necessitate portfolio risk diversification with cryptocurrencies. Concerning this uniqueness, it is therefore requisite to scrutinize cryptocurrency volatility, which is a worthwhile endeavor to understand the updated financial portfolio investment as well as the corresponding financial risk management.

As a result, because the CPU has a significant impact on cryptocurrency markets and more importantly, cryptocurrency markets are pivotal for constructing portfolios and managing financial risks. It is thereby essential to investigate the impact of CPU on cryptocurrency volatilities and thus how CPU can be useful in facilitating the cryptocurrency volatility forecasting. Consequently, in this paper, we demonstrate that the CPU plays a crucial role in forecasting volatilities in cryptocurrency markets and then we model the CPU into cryptocurrency volatility forecasting methods. In particular, we employ Genetic Programming (GP) to formulate a series of volatility forecasting models with explicit model format for three different cryptocurrency markets. Based on those three models, we are able to uncover different cryptocurrency markets respond to CPU differently, especially from the time scale perspective. The bitcoin market responds to both short and long-term CPU dynamics, whereas the other two cryptocurrency markets, i.e., Ethereum (ETH) and XRP, are less sensitive to the long-term CPU fluctuations.

On the basis, the contributions of this paper are twofold. Firstly, consisting with existing literature, the study has demonstrated the impact of CPU on cryptocurrency market volatilities, suggesting that CPU can provide effective information for predicting cryptocurrency volatility, which is a crucial consideration for investors to construct their portfolios and manage financial risks. With the help of Genetic Programming (GP), we modeled CPU into our cryptocurrency volatility forecasting models to take advantage of useful information embedded in the CPU. In addition, our study extends this analysis further, investigating impact of CPU on cryptocurrency market volatilities over daily, monthly, and quarterly horizons. We reveal that the Bitcoin market is sensitive toward CPU from all three types of time horizons, while the ETH and the XRP markets are only sensitive to daily and monthly CPU, and daily and quarterly CPU respectively. This result further strengthens the understanding that how the CPU factor drives the cryptocurrency market volatilities and how it contributes to the cryptocurrency market volatilities in different time horizons across different cryptocurrency markets.

Another contribution of our study is the development of three distinct volatility forecasting models tailored to each of the three cryptocurrency markets, with varying time horizons for CPU integration. Volatility forecasting, especially within the cryptocurrency markets, presents a formidable challenge due to the extreme price fluctuations and high unpredictability that characterize these markets. Traditional machine learning methods are often obstructed in providing interpretable models and necessitate considerable manual feature engineering (Cui et al., 2024). In response to these limitations, Genetic Programming (GP) emerges as a distinctive approach that evolves interpretable, symbolic models capable of inherently capturing non-linear relationships and interdependencies. Previous research into volatility forecasting has predominantly employed machine learning and econometric techniques, with few studies harnessing GP for models specifically customized to the cryptocurrency markets. A crucial strain of previous works is that these forecasting models often rely on black-box approaches, such as deep learning, which, despite their accuracy, lack of interpretability and fail to provide insights into market behavior, thereby limiting their practical usefulness in the financial markets.

Our study, on the other hand, adopts the GP method to aid the understanding of mechanism how CPU can be impacting on the cryptocurrency volatilities by providing explicit and interpretable volatility forecasting models. The inherent flexibility of GP enables the exploration and formulation of a diverse range of potential solutions, adapting its representational formats to achieve volatility forecasting goals. By accounting for the unique market features and different CPU time horizons, we have been able to apply GP to generate three distinct models that are both explicit and interpretable. These models unveil the relationships between cryptocurrency volatilities and CPU, offering precise volatility forecasting that can reinforce financial market decision-making, such as portfolio construction and hedging strategies, and providing actionable insights for investors and policymakers. Our empirical results also support that the performance of these models surpasses that of traditional volatility forecasting methods.

The remainder of the paper is structured as follows. Section 2 delivers the literature review of cryptocurrency volatility forecasting. In Section 3, we depict the methodology applied in this paper with the sample data and variable measures regarding the CPU and cryptocurrency market volatilities. The empirical results and the model performance of cryptocurrency market volatilities forecasting are presented in Section 4. Section 5 concludes the paper and gives research implications of the paper.

2. Relevant literature

Regarding the fluctuations of cryptocurrency markets, various models have been applied by the academic community to investigate the moving patterns of cryptocurrency market volatilities. Among those models, the GARCH model is the prevailing model that is widely used, which aims to study the market volatility of cryptocurrencies. However, Charles and Darné (2019) investigated six GARCH models and found that these models were not suitable for predicting Bitcoin volatility. This argument evoked the discussion of cryptocurrencies volatility prediction in the academic community.

2.1. GARCH model applications in cryptocurrency markets

Aharon et al. (2023) adopt an asymmetric GARCH model to reexamine the cryptocurrency asymmetric volatility patterns, where the model includes a structural break detection mechanism. Chi and Hao (2021) used price sequences of Bitcoin and Ethereum to study the effectiveness of various volatility models, and found that the univariate GARCH model has a sound performance, directly demonstrating the superiority of GARCH volatility forecasting over option-implied volatility in predicting future realized volatility. Building on this, Fang et al. (2023) has illustrated that the DCC-GARCH model is expertized in systemic risk forecasting. Furthermore, Wang et al. (2024) employed the DCC-GARCHCONNECTEDNESS method to study the dynamic volatility spillovers between cryptocurrency and energy markets, further affirming risk spillover structure from a multi-level analysis angle.

However, Ivanovski and Hailemariam (2023) proposed a GAS framework superior to the traditional DCC-GARCH model, using multivariate Generalized Autoregressive Score (GAS) model to study the time-varying dependencies between stock markets and cryptocurrency markets, capturing the persistence and nonlinearity of volatility between stocks and cryptocurrencies. Jiang et al. (2022) proposed a new model that integrates Accelerated Generalized Autoregressive Score (aGAS) technique with the Gaussian-Cauchy Mixture model. It is arguable that cryptocurrency returns, which are heavily tailed, can be well modeled with such method.

Nowadays, with the development of economy and scientific technology, advanced methods emerged for predicting the volatility of cryptocurrencies, such as machine learning models and high moments techniques (Bouri & Jalkh, 2023; Dias et al., 2022; Feng et al., 2024; Qiao et al., 2020). The significant fluctuations in non-stationary cryptocurrency prices have prompted the need for high-precision prediction models. Due to the lack of seasonal effects and other high-difficulty requirements, it is difficult to make accurate predictions using traditional methods, making machine learning, especially ensemble and deep learning, the best technology for cryptocurrency price prediction. Based on deep learning technology, D'Amato et al. (2022) developed a suitable model to capture the dynamic volatility of cryptocurrencies by capturing complex data interactions. This model is based on the Jordan neural network, which has stronger predictability compared to other models designed for time series. Similarly, Wang et al. (2023) demonstrated that machine learning application in terms of cryptocurrency volatility prediction can surpass traditional volatility models such as GARCH model by using internal and external determinants. Dudek et al. (2024) compared several models and forecasting methods and they suggest that no unanimous approach can be perceived as the most effective in forecasting the volatility of individual cryptocurrencies. The relative performance of different models can diverge depending on the characteristics of specific cryptocurrency markets.

In summary, various models have been applied for studying cryptocurrency market fluctuations, including traditional GARCH models and more advanced deep learning models. The selection of the suitable model in accommodating this issue has drawn plenty of concerns and the escalating levels of carbon dioxide emissions have positioned climate change as a critical challenge facing humanity, which attracted massive attention from the academia and the society. The interaction between the performance of cryptocurrencies and the flow of investments may constrain the shift toward low-carbon, sustainable alternatives (Yan et al., 2022). This has initiated a contentious discourse on the nexus between cryptocurrency mining and environmental conservation, drawing the gaze of numerous investors and market leaders (Arfaoui et al., 2023). Consequently, environmental, and particularly climate-related, policies have been identified as key influencers of cryptocurrency volatility (Pham et al., 2022).

2.2. Energy consumption of cryptocurrencies

The necessity of energy consumption for the mining and operation of cryptocurrency algorithms is considerable, exerting detrimental impacts on the environment (Howson, 2019). Academic research has been conducted to explore the correlation between environmental policy, its impact on the environment, and the volatility of cryptocurrencies. Empirical findings from (Jin & Yu, 2023) suggest that the uncertainty associated with climate policies has a markedly positive effect on the volatility of cryptocurrency prices, primarily due to extreme shocks in climate policy. In essence, abrupt and substantial modifications in climate policy contribute to increased cryptocurrency price volatility.

Moreover, energy-related assets volatility has also been scrutinized in the financial research field, coupled with cryptocurrencies. Sarker et al. (2023) examined the asymmetric effects of climate policy uncertainty (CPU) and the Global Energy Price Index (GEPI) on Bitcoin prices. Their longitudinal analysis revealed that changes, both increases and decreases, in CPU and GPEI significantly impact BTC, with both factors displaying a notable asymmetric influence on Bitcoin prices. The environmental impact of cryptocurrency mining embeds a direct linkage between CPU and cryptocurrency markets. Bitcoin and other proof-of-work cryptocurrencies rely on energy-intensive mining processes, which caused environmental concerns for their significant carbon footprints. Climate policies aimed at reducing greenhouse gas emissions, such as carbon taxes, create uncertainty for cryptocurrency miners, particularly in regions heavily reliant on fossil fuels (Zhang, Chen, et al., 2023). In fact, the CPU is difficult to accurately measure and quantify. Unlike traditional economic indicators, CPU is an inherently multidimensional measure and it stems from the proxy estimation such as textual analysis of newspaper and legislative documents (Xu et al., 2023). Although those estimations provide valuable approximations, they are prone to subjectivity and may fail to capture the full complexity of the whole policy blueprint.

Pham et al. (2023) discovered that the spillover effects between cryptocurrencies and assets related to green and fossil fuels vary over time, becoming more pronounced during periods of crisis. Anwer et al. (2023) utilized daily data from five global indices to investigate whether the green market mitigated the risks associated with cryptocurrencies and the carbon market, noting synchronous movements between the environmental sustainability index and the cryptocurrency index during the pandemic. Therefore, we argue that the climate policy can put heavy pressure on the cryptocurrency mining activities, which in turn, can affect the market price and market volatilities.

More recently, Ftiti et al. (2023) adopts heterogeneous autoregressive models to predict the realized volatility in cryptocurrency markets with volatility decomposition. In addition, Feng et al. (2024) developed a novel parameter tuning strategy applying in a number of regression models, including heterogeneous autoregressive model, Lasso regression and Ridge regression models to forecast volatility in cryptocurrency markets. In contrast, our paper uses GP method to generate new volatility forecasting models cryptocurrency markets rather using or optimizing existing volatility forecasting models such as the heterogeneous autoregressive model. Moreover, we propose different our volatility forecasting models for different cryptocurrency markets and we include the CPU factor to predict cryptocurrency market volatilities, which are unique compared with current research in cryptocurrency volatility forecasting. The inclusion of CPU factor in cryptocurrency volatility forecasting is also consistent with current study of climate finance (Xia et al., 2023; Zhao et al., 2024).

3. Data and methodology

3.1. Data and key variables

The data we employ in this paper covers the period of January 1, 2018 to December 31, 2023. There are three main cryptocurrency markets we investigate in this paper, namely, bitcoin, ETH and XRP markets, which are the most actively traded cryptocurrency markets. Based on the GARCH model, we obtained main condition volatility terms for all three cryptocurrency markets, and those terms constitute the key variables of cryptocurrency volatility forecasting. As we have argued in the previous section that cryptocurrency markets are firmly intercorrelated with the energy consumption because of their mining activities, the market price might be highly sensitive to the change of climate policy.[1] As a result, we incorporate the climate policy risk as another key variable to forecast the volatilities in those three markets. To measure the climate policy risk appropriately, we adopt the climate policy uncertainty (CPU) index proposed by Gavriilidis (2021), which is accessible from the online source.[2]

For the data sample period, we have divided into two different time horizons. We use the first three sample years as the in-sample period, namely, 2018–2020, and the 2021–2023 period as the out-of-sample period.

Before we define the conditional volatility for the cryptocurrency market, the daily return of cryptocurrency market serves as the fundamental variable, which is:

$$\boldsymbol{r_t} = ln\left(\frac{\boldsymbol{P_t}}{\boldsymbol{P_{t-1}}}\right), \tag{1}$$

where P_t is the daily cryptocurrency price for day t.

The CPU index, can be envisioned as a comprehensive metric for assessing the uncertainty surrounding climate-related policies. Therefore, the growth rate of climate policy uncertainty index also serves as the fundamental variable, which is:

$$r_t^{cpu} = \frac{I_t^{cpu} - I_{t-1}^{cpu}}{I_{t-1}^{cpu}}, \tag{2}$$

where I_t^{cpu} is the climate policy uncertainty index value for day t.

[1] see Figure 1

[2] see Gavriilidis (2021)

3.2. GARCH model

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, specifically the GARCH family models, have been extensively applied in financial literature for forecasting volatility, for both traditional financial and cryptocurrency markets (Çekin et al., 2024; Díaz-Hernández & Constantinou, 2019; Ding et al., 2019; Hassan et al., 2024; Li et al., 2023). It is because GARCH models enable the modeling of volatility as a function of both past variances and past forecasting errors, thereby capturing the time-varying moving patterns of conditional volatilities in traditional financial and cryptocurrency markets (Apostolakis, 2024; Bouazizi et al., 2023; Fakhfekh & Jeribi, 2020; Siu & Elliott, 2021).

The standard GARCH (1,1) model has the following form:

$$\sigma_t^2 = \alpha_0 + \alpha_1\sigma_{t-1}^2 + \alpha_2\varepsilon_{t-1}^2, \tag{3}$$

where σ_t is the volatility of the target cryptocurrency market volatility time series and ε_t is the residual term from the return prediction equation, which is:

$$r_t = \phi + \varepsilon_t, \tag{4}$$

where ϕ is the conditional mean, and $\varepsilon_t \sim N(0, \sigma_t^2)$.

3.3. Genetic programming

Genetic Programming (GP) (Hirsh et al., 2000; Poli et al., 2008) is a computational intelligence method within the domain of evolutionary computation that undertakes the evolution of a population of computer programs, typically represented as GP trees, through a series of genetic operations analogous to natural selection processes—namely, selection, crossover, mutation, and replacement. This methodology has garnered widespread application across a diverse array of engineering and optimization challenges, distinguishing itself from other computational methods. GP's first notable advantage in tackling forecasting issues is its highly flexible representation, which allows for a diverse range of potential solutions to be expressed and explored. Unlike more rigid algorithmic structures, GP is capable of adapting its representational form to better capture the complexities and nuances inherent in forecasting tasks. Secondly, the powerful search mechanisms inherent in GP enable it to navigate vast solution spaces with remarkable efficiency, thereby increasing the likelihood of identifying optimal or near-optimal solutions for forecasting problems. This robust search capability stems from the evolutionary principles underpinning GP, which guide the iterative refinement of program populations. The third significant merit of GP is the partial interpretability and exceptional execution efficiency of the heuristics it generates. This characteristic is particularly beneficial in practical applications, as it allows for a degree of understanding of the underlying decision processes, which is often a prerequisite in real-world scenarios. Moreover, the efficient execution of GP-generated solutions ensures that they can be readily deployed in dynamic and time-sensitive environments. In the traditional configuration of GP, a tree-based structure is employed, wherein each node of the tree functions as an operator and each internal terminal node serves as an operand. This architecture facilitates the straightforward encoding, evolution, and evaluation of mathematical expressions, which are fundamental to the problem-solving process. Furthermore, tree-based GP offers enhanced visualization of the evolved programs, contributing to improved comprehensibility and ease of analysis. The visual representation of GP trees can be particularly insightful, offering stakeholders a tangible depiction of the solution's structure and flow, which can be beneficial for refinement and explanation purposes.

Building upon the aforementioned strengths of GP, this study introduces a novel approach that leverages a data-driven GP model, rigorously trained with real market datasets, to forecast the volatility of three cryptocurrency markets by using conditional volatility terms with climate policy uncertainty. In an effort to construct this model, we have distilled the forecasting challenge into the task of calculating a specific function:

$$f\left(\mathbf{X_{t-1}}, \boldsymbol{\sigma}_{t-1}^{2,cpu}\right) = r_t^2, \tag{5}$$

where r_t^2 is the realized volatility of different cryptocurrency markets estimated from daily squared returns of different cryptocurrency markets, $\mathbf{X_t}$ is a vector of conditional volatilities and residual terms extracted from GARCH model, $\boldsymbol{\sigma}_t^{2,cpu}$ is a vector of the volatility of climate policy uncertainty with different time horizon, namely, 1-day, 1-month and 3-month climate policy index volatilities. Specifically, our data-driven GP approach consists of the following parts:

- *Terminal Set*: $\mathbf{X_{t-1}}$, $\boldsymbol{\sigma}_{t-1}^{2,cpu}$,
- Function Set: $+$, $-$, $\times$,
- *Fitness measure*: the error between the value forecasted from the individual function GP generated and the corresponding desired output r_t^2,
- *GP parameters*: population = 10,000, the maximum length of the program = 1000 (i.e. up to 1000 subitems within one polynomial function), probability of crossover operation = 0.8 (i.e. 80 % of population functions will be mixed with other functions to generate new functions) and probability of mutation operation = 0.1 (i.e. 10 % of population functions will be mutated to generate new functions).
- *Termination criterion*: when the fitness measure reaches 0 or the system runs up to 100 generations, the system will terminate (For our work, the fitness measure will never reach 0, therefore the system will terminate after 100 generations).

This function (5) is derived and refined through our data-driven GP methodology, which employs a comprehensive data sample spanning the period from January 1, 2018 to December 31, 2023. The GP model's development is underpinned by a systematic process that commences with the acquisition of real-world cryptocurrency market data. This data acts as the foundational bedrock upon which the GP evolves and validates its predictive capabilities. By applying the evolutionary mechanisms intrinsic to GP (selection, crossover, mutation, and replacement), the model iteratively improves through generations, with the aim of enhancing its predictive accuracy and reliability in forecasting cryptocurrency volatility. To ensure the robustness of our model, we have meticulously curated our dataset to encompass a representative sample of the cryptocurrency market within the specified time frame. This dataset encapsulates a variety of market volatility prediction variables, including conditional volatility terms and climate policy uncertainty, which serve as inputs to the GP model.

3.4. Model setup

In order to setup the cryptocurrency market volatility models using GP, it is essential to construct the input dataset. Firstly, by employing the GARCH model, we extracted four variables to forecast cryptocurrency market volatilities, namely, $\sigma_t^{2,i}$ and $\sigma_{t-1}^{2,i}$, which are conditional variance for cryptocurrency market i, at day t and t-1, $\varepsilon_t^{2,i}$ and $\varepsilon_{t-1}^{2,i}$, which are squared residual terms for cryptocurrency market i, at day t and t-1, as the input. In addition, we obtain three different time horizon CPU variance, namely, $\sigma_{t,d}^{2,cpu}$, $\sigma_{t,m}^{2,cpu}$, $\sigma_{t,q}^{2,cpu}$, which are CPU conditional variance at daily, monthly and quarterly time horizon, respectively, extracted from GARCH model, also as the input.

By putting those aforementioned seven variables into the input dataset, we apply GP method to develop volatility forecasting models for three different cryptocurrency markets with climate policy risks using this dataset. By using GP, we can incorporate the climate policy risk into the volatility forecasting models at different time horizons. We use 1-day, 1-month and 3-month climate policy index volatilities to represent three different policy effects, namely, short-term policy effect, middle-term policy effect and long-term policy effect, respectively. It is arguable that different cryptocurrency markets might respond to the climate policy in distinct manners. We employ those climate policy risk factors to distinguish the effect of climate policy on cryptocurrency markets.

Therefore, we use the approach based on function (5) and its corresponding parts for the data mining of the three datasets for three different cryptocurrency markets. The GP approach can automatically identify the most relevant factors that can be used to predict cryptocurrency market volatilities by targeting the fitness measure proposed.[3]

By processing the three datasets, we obtain three different volatility forecasting model regarding three cryptocurrency markets, namely, bitcoin, ETH and XRP.

In particular, the model for predicting bitcoin volatility is exhibited in Eq. (6):

$$r_t^{2,btc} = \left[\left(\sigma_{t-1,d}^{2,cpu} - \sigma_{t-1,m}^{cpu} * \sigma_{t-1,q}^{cpu}\right) \Big/ \left(\sigma_{t-1}^{btc} + \sigma_{t-2}^{btc}\right)\right]^2 + \varepsilon_{t-1}^{btc} * \left(\sigma_{t-1,d}^{cpu} - \sigma_{t-1,q}^{cpu}\right) + \varepsilon_{t-1}^{btc} * \sigma_{t-1,d}^{cpu} * \left(\sigma_{t-1,m}^{cpu} + \sigma_{t-1,q}^{cpu}\right), \tag{6}$$

the model for predicting ETH volatility is exhibited in Eq. (7):

$$r_t^{2,eth} = \left[\sigma_{t-1,m}^{cpu} * \left(\sigma_{t-2}^{eth} - \varepsilon_{t-2}^{eth}\right) \Big/ \sigma_{t-1}^{eth}\right]^2 + \varepsilon_{t-1}^{eth} * \left(\varepsilon_{t-2}^{eth} + \sigma_{t-1,d}^{cpu} + \sigma_{t-1,m}^{cpu}\right), \tag{7}$$

and the model for predicting XRP volatility is exhibited in Eq. (8):

$$r_t^{2,xrp} = \left[\sigma_{t-1,q}^{2,cpu} * \left(\sigma_{t-1}^{2,xrp} - \varepsilon_{t-2}^{xrp} + \sigma_{t-1,d}^{cpu}\right)\right] \Big/ \left(\sigma_{t-1}^{2,xrp} + \sigma_{t-1,m}^{2,cpu}\right) - \varepsilon_{t-2}^{xrp} * \left(\sigma_{t-1,q}^{cpu} - \sigma_{t-1,d}^{cpu}\right). \tag{8}$$

It is noticeable that roles that climate policy risk played in three cryptocurrency markets are quite different. The volatility forecasting model for Bitcoin, in Eq. (6), highlights the significant roles played by climate policy risks over daily, monthly, and quarterly time horizons in predicting Bitcoin's volatility. It is thereby arguable that Bitcoin market volatility is quite sensitive to the change of climate policy. The responsiveness of Bitcoin market volatility to climate policy risk tends to be rigorous at the initial stage, with policy effects that persist over extended periods, including both monthly and quarterly influences.

On the other hand, the volatility forecasting model for Ethereum (ETH), in Eq. (7), indicates that long-term climate policy risk exhibits limited impact on ETH market volatility. However, short-term and medium-term climate policy risks affect ETH market volatility, as evidenced by the absence of the quarterly CPU volatility term in Eq. (7). This implies that the ETH market is more responsive to immediate and intermediate changes in climate policy rather than long-term shifts of the policy. Finally, the volatility forecasting model for XRP, as illustrated in Eq. (8), reveals that medium-term climate policy risk has little effect on XRP market volatility. In contrast, short-term and long-term climate policy risks influence XRP market volatility, which can be observed by the absence of a monthly CPU volatility term in Eq. (8). It is thereby arguable that XRP market volatility is more susceptible to immediate and long-time changes in climate policy, while medium-term risks are less influential.

As a result, the distinguishing impacts of climate policy risks on the volatility of Bitcoin, Ethereum, and XRP unveils the fact that the responses of three cryptocurrency markets to climate policy changes are the nuanced and varied over our sample period. Bitcoin market volatility demonstrates a broad sensitivity across multiple time horizons. On the other side, Ethereum volatility is primarily influenced by short- and medium-term climate policy risks, and XRP volatility is affected by both short- and long-term climate policy risks. Our results therefore unravel the impact climate policy on cryptocurrency market volatilities through a time horizon lens.

4. Empirical findings

In order to verify the model performance of our GP-developed models, we established a comparative framework by benchmarking our models against existing volatility forecasting models. Specifically, we employed both the traditional GARCH model and the CPU-adjusted GARCH model. The inclusion of the latter is intended to eliminate the information advantage that our models may take from the CPU index. Therefore, we compare the volatility forecasting errors with both GARCH model and GARCH-CPU model, which is a GARCH model added with a daily CPU volatility term. We compare our model across all three cryptocurrency markets to strengthen the result robustness of our paper.

By using the data from our sample period, we undertake both in-sample and out-of-sample period volatility forecasting. The performance of our GP-developed models is compared against the performance of both GARCH and CPU-GARCH model, which is CPU-adjusted GARCH model. The volatility forecasting performance of all three models in Bitcoin, Ethereum and XRP markets is presented in Tables 1, 2 Tables 3, 4 and Tables 5, 6, respectively.

Specifically, the traditional GARCH model is displayed as in Eq. (3), which is the basic model for our performance comparison. The CPU-GARCH incorporates the CPU conditional variance term into the GARCH model, which serves a more advanced version of GARCH model, taking the following form in Eq. (9):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 \sigma_{t-1,d}^{2,CPU}. \tag{9}$$

Furthermore, in order to compare the model performance, we use both Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The MAE is a widely used measure of prediction accuracy in time series analysis, providing an average of the absolute differences between predicted and actual values. The MAE measure can be defined as follows in Eq. (10) for market i:

$$MAE_t^i = \frac{1}{n} \sum_{i=1}^{n} \left| r_t^{2,i} - \widehat{r}_t^{2,i} \right|, \tag{10}$$

where $r_t^{2,i}$ is the actual value of volatility for cryptocurrency market i, $\widehat{r}_t^{2,i}$

[3] see Figure 2

Table 1
Model performance comparison of all three models for Bitcoin volatility forecasting using MAE measure.

Year/Model	GARCH	GP-Model	Improve rate	CPU-GARCH	GP-Model	Improve rate
2018	0.002130	0.001841	13.57 %	0.001977	0.001841	6.91 %
2019	0.001615	0.001388	14.05 %	0.001542	0.001388	10.00 %
2020	0.003124	0.002184	30.08 %	0.002724	0.002184	19.82 %
2021	0.001919	0.001401	26.99 %	0.003657	0.001401	61.68 %
2022	0.001993	0.001554	22.04 %	0.001711	0.001554	9.11 %
2023	0.001152	0.000882	23.42 %	0.001094	0.000882	19.39 %

Table 2
Model performance comparison of all three models for Bitcoin volatility forecasting using RMSE measure.

Year/Model	GARCH	GP-Model	Improve rate	CPU-GARCH	GP-Model	Improve rate
2018	0.003827	0.003294	13.95 %	0.003577	0.003294	7.94 %
2019	0.003397	0.002878	15.28 %	0.003138	0.002878	8.29 %
2020	0.011612	0.006201	46.60 %	0.008174	0.006201	24.13 %
2021	0.003298	0.000822	75.08 %	0.004597	0.000822	82.12 %
2022	0.003959	0.002497	36.93 %	0.002977	0.002497	16.13 %
2023	0.001327	0.001176	11.39 %	0.001286	0.001176	8.57 %

Table 3
Model performance comparison of all three models for Ethereum volatility forecasting using MAE measure.

Year/Model	GARCH	GP-Model	Improve rate	CPU-GARCH	GP-Model	Improve rate
2018	0.003744	0.003223	13.92 %	0.003573	0.003223	9.79 %
2019	0.002289	0.002139	6.54 %	0.002183	0.002139	2.01 %
2020	0.006485	0.005165	20.36 %	0.006401	0.005165	19.32 %
2021	0.003388	0.002579	23.87 %	0.007848	0.002579	67.14 %
2022	0.002535	0.002228	12.11 %	0.002743	0.002228	18.77 %
2023	0.001277	0.000614	51.93 %	0.000903	0.000614	32.04 %

Table 4
Model performance comparison of all three models for Ethereum volatility forecasting using RMSE measure.

Year/Model	GARCH	GP-Model	Improve rate	CPU-GARCH	GP-Model	Improve rate
2018	0.005888	0.005124	12.97 %	0.005639	0.005124	9.12 %
2019	0.004099	0.003731	8.98 %	0.003947	0.003731	5.48 %
2020	0.01638	0.01251	23.69 %	0.01393	0.01251	10.22 %
2021	0.007583	0.005217	31.20 %	0.01207	0.005217	56.78 %
2022	0.004621	0.003863	16.03 %	0.004479	0.003863	13.76 %
2023	0.00218	0.001282	41.17 %	0.001641	0.001282	21.86 %

Table 5
Model performance comparison of all three models for XRP volatility forecasting using MAE measure.

Year/Model	GARCH	GP-Model	Improve rate	CPU-GARCH	GP-Model	Improve rate
2018	0.005555	0.004699	15.40 %	0.005441	0.004699	13.61 %
2019	0.002242	0.001707	23.87 %	0.001848	0.001707	7.63 %
2020	0.005565	0.004963	10.82 %	0.005168	0.004963	3.97 %
2021	0.007183	0.005812	19.09 %	0.007389	0.005812	21.34 %
2022	0.004164	0.002312	44.47 %	0.003362	0.002312	31.23 %
2023	0.003098	0.002688	13.22 %	0.002747	0.002688	2.15 %

Table 6
Model performance comparison of all three models for XRP volatility forecasting using RMSE measure.

Year/Model	GARCH	GP-Model	Improve rate	CPU-GARCH	GP-Model	Improve rate
2018	0.012411	0.010244	17.46 %	0.011804	0.010244	13.22 %
2019	0.004425	0.003699	16.40 %	0.003885	0.003699	4.78 %
2020	0.020463	0.017935	12.36 %	0.019267	0.017935	6.92 %
2021	0.018559	0.01558	16.05 %	0.017884	0.01558	12.89 %
2022	0.005621	0.004257	24.27 %	0.005167	0.004257	17.62 %
2023	0.017223	0.016001	7.09 %	0.016288	0.016001	1.76 %

is predicted value of volatility for cryptocurrency market i from volatility forecasting models, and n is the number of observations in one year. By calculating the MAE for our GP-developed models and comparing it with the MAE values obtained from the traditional GARCH and CPU-GARCH models, we can assess the relative accuracy of each model in forecasting cryptocurrency market volatility. Lower MAE values indicate superior model performance, reflecting a closer alignment between predicted and actual volatility levels. In addition to MAE, we utilize the Root Mean Square Error (RMSE) to further evaluate the forecasting performance of our models. RMSE is a robust metric that penalizes larger errors more heavily, thus providing a more comprehensive assessment of prediction accuracy. The RMSE measure can be defined as follows in Eq. (11) for market i:

$$RMSE_t^i = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(r_t^{2,i} - \widehat{r}_t^{2,i}\right)^2}, \tag{11}$$

where $r_t^{2,i}$ is the actual value of volatility for cryptocurrency market i, $\widehat{r}_t^{2,i}$ is predicted value of volatility for cryptocurrency market i from volatility forecasting models, and n is the number of observations in one year. We estimate the RMSE for our GP-developed models and comparing it with the RMSE values from the GARCH and CPU-GARCH models, we can determine the effectiveness of each model in minimizing forecasting errors. Lower RMSE values signify better model performance, indicating that the predictions are more accurate and reliable in capturing the volatility dynamics of cryptocurrency markets.

In Tables 1 and 2, we present the volatility forecasting results for the Bitcoin market. It is observable that our GP-model is overwhelmingly precise than both GARCH and CPU-GARCH model in predicting Bitcoin market volatilities. On average, our model is approximately 20 % improved than the two benchmark models using MAE[4] and approximately 25 % improved than the two benchmark models using RMSE.[5] The comparison of forecasting accuracy for individual years reveals noteworthy improvements in 2020 and 2021, demonstrated by the empirical results presented in the two tables. These enhancements of forecasting accuracy may be largely attributed to the volatile fluctuations in Bitcoin market during this period because of the outbreak of COVID-19. Moreover, the in-sample period and out-of-sample period performance have trivial differences, indicating that our model performance is stable for both periods. This stability illuminates the robustness of our model, indicating its effectiveness in both historical and forward-looking market conditions.

In addition, we present the volatility forecasting results for the Ethereum market in Tables 3 and 4. It is clear that our GP-model is exceedingly accurate than both GARCH and CPU-GARCH model in predicting Ethereum market volatilities. On average, our model is approximately 28 % improved than the two benchmark models using MAE[6] and approximately 20 % improved than the two benchmark models using RMSE.[7] For the individual forecasting year performance comparison, it can be observable in the two tables that forecasting accuracy improvements in year 2021 and year 2023 are more significant. These years are in the episodes of pronounced volatility in the Ethereum market, unraveled by substantial price peaks.[8] Our model's ability to accurately forecast during these turbulent periods demonstrates that our model can particularly aid the volatility forecasting accuracy in rapidly evolving markets like Ethereum. Notably, the performance during the out-of-sample period surpasses that of the in-sample period, which further highlights the robustness of our model, indicating that our model refrains the overfitting problem.

[4] see Table 1
[5] see Table 2
[6] see Table 3
[7] see Table 4
[8] see Figure 1

The volatility forecasting results for the XRP market, as shown in Tables 5 and 6, indicate that our GP model is remarkably more precise than both the GARCH and CPU-GARCH models. On average, our model shows an improvement of approximately 13 % over the benchmark models using the MAE metric, shown in Table 5. Our GP model demonstrates an average improvement of approximately 10 %, as presented in Table 6 using RMSE. For individual year forecasting performance, all forecasting performance for XRP market is stable, where the performance of year 2023 is relative weak, which can be attributed to the stable movement of XRP in 2023.

We also show the volatility forecasting results for the XRP market in Tables 5 and 6. It is observed that our GP-model is overwhelmingly precise than both GARCH and CPU-GARCH model in predicting XRP market volatilities. On average, our model is approximately 13 % improved than the two benchmark models using MAE[9] and approximately 10 % improved than the two benchmark models using RMSE (see Tables 6). For individual year forecasting performance, all forecasting performance for XRP market is stable, where the performance of year 2023 is relative weak, which can be attributed to the stable movement of XRP in 2023. Furthermore, the volatility forecasting performance of our GP-developed models for XRP market is substantially lower than the performance for Bitcoin market. In fact, such performance difference, technological foundations of these cryptocurrencies have contributed in a significant way. Bitcoin works under the energy-intensive proof-of-work (PoW) consensus mechanism. This mechanism requires massive amount of computational power and thus consumed tremendous energy during the Bitcoin mining. Therefore, the climate policy uncertainty can have a considerable impact on the Bitcoin market as new policy may require lower carbon emissions and impose energy usage quota. On the other hand, the operation framework of XRP tends to be less energy-intensive than the Bitcoin market, which alleviates its exposure to climate policy uncertainty. This fundamental difference in energy consumption directly influences the extent to which climate policy affects market volatility, with Bitcoin being more susceptible due to its higher energy consumption.

The performance of our GP-developed models in volatility forecasting, exhibits substantial improvements over traditional GARCH and CPU-GARCH models. The utilization of the GP method to identify the exact format of volatility forecasting models by integrating climate risk factors represents a novel and powerful approach in financial modeling. This method allows for the discovery of complex, non-linear relationships that traditional models may fail to capture, thereby enhancing the accuracy and robustness of volatility predictions.

It is arguable that the capability of the GP-developed model to outperform traditional models across different cryptocurrencies (Bitcoin, Ethereum, and XRP) emphasizes the adaptability of evolutionary algorithms in financial volatility forecasting. The inclusion of climate risk factors into the model structure not only reflects the growing crucial effect environmental policy in financial markets but also provides a deep understanding of cryptocurrency market dynamics under the current climate policy framework. Our method coincides with the increasing emphasis on sustainable finance, where environmental risks are integrated into financial decision-making processes.

In Fig. 1, it is observable that high volatilities in different cryptocurrency markets all concentrate in similar periods. In fact, volatility clustering is not only a characteristic of traditional financial markets but is also featured in the cryptocurrency markets, resulting from their dynamic and speculative nature (Ahmed et al., 2024). In those three cryptocurrency markets, volatility clustering is particularly pronounced,[10] as these markets are prevailing in their inherent volatility and the rapid transmission of information and sentiment across market participants. Our GP models' superior performance in volatility

[9] see Tables 5
[10] see Figure 1

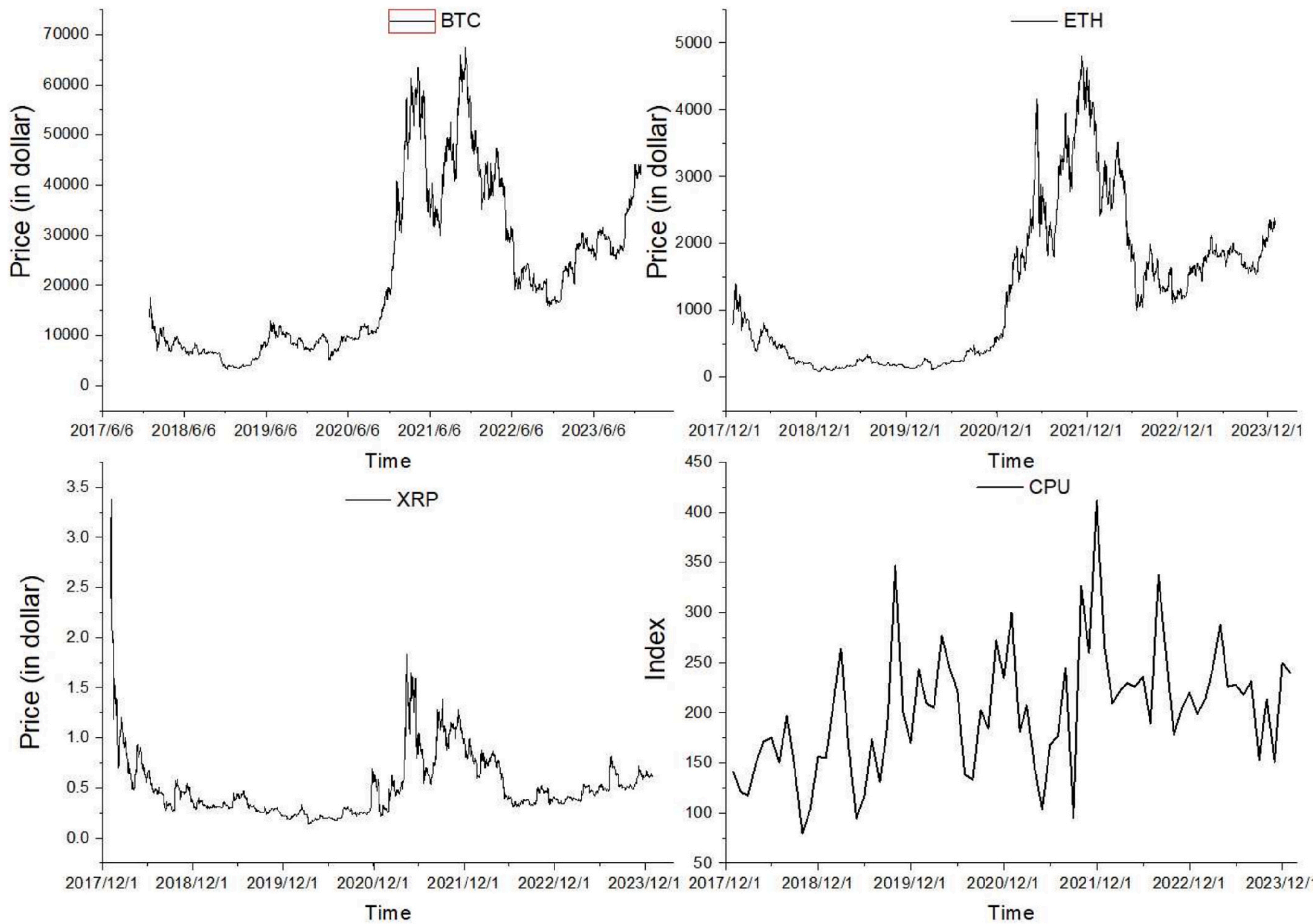

Fig. 1. Plotting of price movement trend of three main cryptocurrency markets with the climate policy uncertainty index movement trend from January 1, 2018 to December 31, 2023.

forecasting stems from the precise capture of volatility clustering phenomenon. It is because cryptocurrency markets usually exhibit complex interdependencies with CPU variations (Guo et al., 2024). Our GP framework thereby takes advantage of volatility clustering insights with CPU factor through its model evolvement, allowing our framework to effectively identify and exploit the underlying volatility clustering mechanisms. This is further supported by the finding that the cryptocurrency markets can be segmented into a few clustering periods, with a majority of the market activity concentrated within these periods (Lorenzo & Arroyo, 2022), which, in turn, connected cryptocurrency markets to the climate-related financial risk.

5. Conclusion

To conclude, because climate change is a highly debated socioeconomic issue, governments implement climate policies to address its risks. Nevertheless, formulation and implementation involve counterbalancing considerations, resulting in Climate Policy Uncertainty (CPU). This paper shows that CPU significantly affects cryptocurrency markets and thus, how CPU can be modeled into cryptocurrency market volatilities. By employing Genetic Programming (GP), the paper formulates volatility forecasting models for three cryptocurrency markets with the incorporation of CPU. We reveal that different cryptocurrency markets respond to CPU differently in terms of time scale. Based on the empirical analysis from our framework, this study uncovers the varying responsiveness of Bitcoin, Ethereum, and XRP markets to CPU across daily, monthly, and quarterly horizons, highlighting the importance of CPU in cryptocurrency volatility forecasting. Then, we propose tailored GP volatility forecasting models for each market, demonstrating their superiority volatility forecasting performance over traditional forecasting methods. GP's flexibility allows the models to encapsulate market intricacies, offering explicit and interpretable relationships that facilitate more informed financial decision-making and risk hedging strategies. Attributing to our explicit and interpretable models, they could be exceedingly helpful to investors and policymakers for constructing portfolios and formulating hedging strategies.

On the basis, our study can yield fruitful research implications. This paper delivers a pronounced understanding on how CPU can permeate into cryptocurrency market dynamics over various time horizons. Market participants can thereby adjust their trading and hedging strategies accordingly. Our multi-time horizon analysis reveals that the impact of CPU on cryptocurrency markets may be transient in the daily time horizon, suggesting that market participants can capitalize on short-term volatility by adjusting their trading strategies and positions in response to CPU fluctuations. In addition, our research implications expand beyond short-term trading adjustments. For longer time horizons, the more pronounced relationship between CPU and cryptocurrency volatility, can navigate investors to formulate a strategic approach for their risk management and investment in cryptocurrency markets for their long-run plan.

Our study also yields pivotal policy implications. Firstly, inclusion of CPU in cryptocurrency volatility forecasting can produce more accurate and reliable volatility forecasts, enabling better risk assessment and management for financial institutions. Accurate cryptocurrency

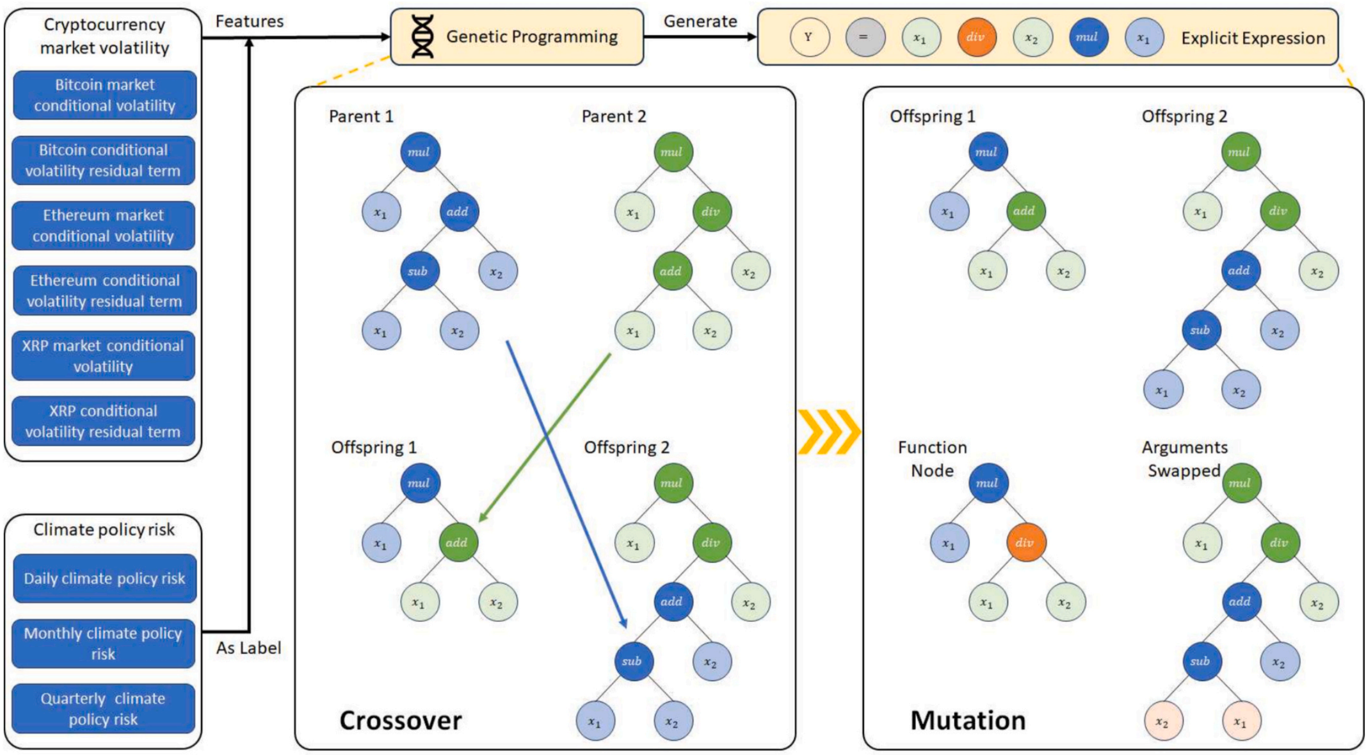

Fig. 2. The process of GP to generate the best function for forecasting cryptocurrency market volatilities.

volatility forecasting, can help regulators anticipate market turbulence and implement precautious measures to mitigate potential risks, such as stress testing for cryptocurrency related financial products issued by financial institutions. Additionally, stable climate policies can attract long-term investment into the cryptocurrency markets, thereby reducing their overall volatility and enhancing their role in the broader financial ecosystem. By understanding how climate policy uncertainty affects market volatility, policymakers can develop risk management strategies that enhance the resilience of the financial system against climate-related shocks. Therefore, accurate volatility forecasting in cryptocurrency markets can be a stabilizer in the financial ecosystem.

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Declaration of competing interest

The authors report no conflicts of interest in this work. The sponsors had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

Data availability

Data will be made available on request.

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