Adaptive Conformal Inference for computing Market Risk Measures: an Analysis with Four Thousands Crypto-Assets

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Abstract

This paper investigates the estimation of the Value-at-Risk (VaR) across various probability levels for the log-returns of a comprehensive dataset comprising four thousand crypto-assets. Employing four recently introduced Adaptive Conformal Inference (ACI) algorithms, we aim to provide robust uncertainty estimates crucial for effective risk management in financial markets. We contrast the performance of these ACI algorithms with that of traditional benchmark models, including GARCH models and daily range models. Despite the substantial volatility observed in the majority of crypto-assets, our findings indicate that ACI algorithms exhibit notable efficacy. In contrast, daily range models, and to a lesser extent, GARCH models, encounter challenges related to numerical convergence issues and structural breaks. Among the ACI algorithms, the Fully Adaptive Conformal Inference (FACI) and the Scale-Free Online Gradient Descent (SF-OGD) stand out for their ability to provide precise VaR estimates across all quantiles examined. Conversely, the Aggregated Adaptive Conformal Inference (AgACI) and the Strongly Adaptive Online Conformal Prediction (SAOCP) demonstrate proficiency in estimating VaR for extreme quantiles but tend to be overly conservative for higher probability levels. These conclusions withstand robustness checks encompassing the market capitalization of crypto-assets, time series size, and different forecasting methods for asset log-returns. This study underscores the promise of ACI algorithms in enhancing risk assessment practices in the context of volatile and dynamic crypto-asset markets.

Keywords: Value at Risk (VaR); Adaptive Conformal Inference (ACI); Aggregated Adaptive Conformal Inference (AgACI); Fully Adaptive Conformal Inference (FACI); Scale-Free Online Gradient Descent (SF-OGD); Strongly Adaptive Online Conformal Prediction (SAOCP), GARCH; Daily Range; Risk Management.

JEL classification: C14; C51; C53; C58; G17; G32.

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1 Introduction

In the realm of predictive modeling and decision-making, accurately quantifying uncertainty is as crucial as making accurate predictions themselves. This need for robust uncertainty estimation becomes particularly pronounced in high-stakes scenarios, where the consequences of erroneous decisions can be significant. One widely accepted approach for quantifying uncertainty is through the utilization of prediction sets, which associate each prediction with a range of potential outcomes, thereby providing a measure of the model's confidence in its predictions.

Conformal inference, introduced by [Vovk et al., 2005] and [Shafer and Vovk, 2008], offers a powerful framework for enhancing predictive models by constructing valid prediction sets with coverage guarantees. Unlike traditional methods that rely heavily on specific assumptions about data distributions, conformal prediction imposes minimal assumptions, primarily requiring exchangeability of the data, see [Angelopoulos and Bates, 2023] for a recent survey. However, in many real-world scenarios such as time series data or instances of distributional shift, the assumption of exchangeability may not hold, necessitating the development of adaptive techniques to handle such complexities.

Recent advancements in conformal inference have led to the emergence of Adaptive Conformal Inference (ACI) algorithms, designed explicitly to address scenarios where data arrives sequentially, without assuming exchangeability. These algorithms dynamically adjust the width of prediction intervals in response to observed data, thereby providing adaptive and accurate uncertainty quantification. Notably, ACI algorithms have been shown to be effective in various domains, including financial forecasting, epidemiology, and image classification.

Motivated by the success of ACI algorithms in handling sequential data, we turn our attention to the task of forecasting the Value at Risk (VaR) using adaptive conformal inference techniques. The VaR, a measure of the maximum potential loss that an investment portfolio may face over a specified time horizon, is of paramount importance in risk management across financial institutions and investment firms. Moreover, [Emmer et al., 2015] and [Kratz et al., 2018] showed that the Expected Shortfall (ES)[1] can be backtested through the approximation of several VaR estimates computed at different probability levels using a multinomial test. Accurate risk estimation is critical for ensuring financial stability and making informed investment decisions.

In this paper, we explore an innovative application of Adaptive Conformal Inference (ACI) methods, traditionally employed for generating prediction intervals in machine learning, to the domain of financial risk management, specifically for estimating Value-at-Risk (VaR) measures. While ACI methods have been predominantly used to construct robust confidence intervals around mean predictions, we adapt

[1]The ES is the average of the worst p losses, where p is the percentile of the returns distribution.

these methods to provide precise point estimates for tail quantiles. This adaptation leverages the ability of ACI to dynamically adjust prediction intervals based on the observed data, which is particularly useful in capturing the extreme quantiles necessary for accurate VaR estimation.

The conventional use of ACI methods involves creating prediction intervals for a given mean prediction model, adjusting the interval widths based on whether recent predictions have been included or excluded within these intervals. This adaptive mechanism ensures that the prediction intervals remain reliable over time, even as the underlying data distribution shifts. In our work, we repurpose this adaptive mechanism to estimate the quantiles of the prediction errors, which are then combined with point forecasts from a simple mean prediction model. This approach allows us to accurately predict the tail quantiles, which correspond to the VaR measures. By clearly delineating this novel application of ACI methods, we provide a fresh perspective on how these techniques can be utilized beyond their traditional scope. Our main interest lies not in constructing prediction intervals around mean forecasts, but in obtaining accurate point estimates for tail quantiles directly. This focus on quantile estimation for VaR calculation is crucial for effective financial risk management, where understanding the behavior of extreme values is more relevant than the central tendency. Thus, our work bridges the gap between robust prediction interval methodologies and the specific needs of financial risk estimation, offering a valuable contribution to the field.

Specifically, we will explore the application of various ACI algorithms, including the Aggregated ACI by [Zaffran et al., 2022], the Fully Adaptive Conformal Inference by [Gibbs and Candès, 2022], the Scale-Free Online Gradient Descent by [Bhatnagar et al., 2023], and the Strongly Adaptive Online Conformal Prediction by [Bhatnagar et al., 2023], in the context of VaR prediction. These algorithms offer different approaches to adaptively adjusting prediction intervals, thereby catering to diverse modeling requirements and data characteristics.

The primary objectives in this study are twofold. First, we aim to conduct a comprehensive empirical evaluation to assess the performance and applicability of the proposed ACI algorithms in VaR prediction tasks, to evaluate whether these methodologies can ensure accurate and reliable estimation of uncertainty in financial risk assessment. Secondly, we perform a wide range of robustness checks to verify that the results for the baseline case also hold in different settings. Therefore, we perform a series of checks considering the market capitalization of crypto-assets, time series size, and different forecasting methods for asset log-returns.

In the rapidly evolving landscape of cryptocurrencies, understanding risk measures is crucial for both investors and regulators. Previous empirical works have often focused on the most capitalized cryptocurrencies, such as Bitcoin and Ethereum, due to their high liquidity and significant market impact. However, the cryptocurrency market is highly diverse, encompassing assets with varying degrees of liquidity, capitalization, and investor profiles. It is for this reason that this paper aims to address this diversity by analyzing a comprehensive dataset of 4000 cryptocurrencies. This broad scope allows us to capture a wide range of market behaviors and dynamics, providing a more holistic view of risk measures across the entire cryptocurrency spectrum. By including assets with different characteristics, we can derive more robust and generalizable conclusions about the effectiveness of Adaptive Conformal Inference (ACI) methods for computing market risk measures.

The remainder of this paper is organized as follows. In Section 2, we review the literature devoted to Adaptive Conformal Inference algorithms, while Section 3 presents a description of the ACI algorithms under consideration, highlighting their key features and theoretical properties. Subsequently, in Section 4, we conduct extensive empirical evaluations with four thousand crypto-assets to compare the performance of these algorithms in VaR forecasting tasks, while robustness checks are discussed in Section 5. Finally, Section 6 summarizes our findings and outlines directions for future research in this domain.

2 Literature Review

Conformal Inference (CI), originally proposed by [Vovk et al., 1999] and [Vovk et al., 2005], has emerged as a versatile framework for constructing prediction intervals around point predictions, facilitating robust uncertainty quantification across various domains [Angelopoulos and Bates, 2023]. It has garnered significant attention for its utility in uncertainty quantification in regression and classification tasks, see [Papadopoulos, 2008], [Lei et al., 2013] [Lei and Wasserman, 2014], [Vovk et al., 2018], [Romano et al., 2019], [Romano et al., 2020], [Cauchois et al., 2021], [Barber et al., 2021] for several examples and detailed discussions.

However, traditional CI methods operate under the assumption of data exchangeability, wherein the joint distribution of observations remains invariant to their order. However, real-world datasets often deviate from this assumption, particularly in scenarios involving temporal dependence, such as time series data, see [Gibbs and Candes, 2021], [Zaffran et al., 2022], [Gibbs and Candès, 2022], and [Bhatnagar et al., 2023]. In this regard, several extensions of conformal prediction techniques have addressed challenges related to distribution shift, employing methods such as reweighting and distributionally robust optimization to maintain approximately valid coverage, see [Tibshirani et al., 2019], [Podkopaev and Ramdas, 2021], [Yang et al., 2022], and [Barber et al., 2023].

A recent line of research within the CI framework focuses on Adaptive Conformal Inference (ACI) algorithms, designed to handle non-exchangeable data by dynamically adjusting prediction intervals based on observed data [Gibbs and Candes, 2021]. The original ACI algorithm introduces a learning rate parameter to control the rate of adaptation, with subsequent research exploring meta-algorithms to optimize this parameter. Notable ACI algorithms include the Aggregated ACI by [Zaffran et al., 2022], the Fully Adaptive Conformal Inference by [Gibbs and Candès, 2022], the Scale-Free Online Gradient Descent by [Bhatnagar et al., 2023], and the Strongly Adaptive Online Conformal Prediction by [Bhatnagar et al., 2023].

Alternative lines of research have also started to explore the application of conformal prediction to time series data by using randomization, ensembles, and other meta-algorithms to produce valid prediction sets [Chernozhukov et al., 2018, Xu and Xie, 2021, Sousa et al., 2022]. Other approaches include simply using vanilla conformal prediction for time series without theoretical guarantees or resorting to weaker notions of exchangeability, see [Dashevskiy and Luo, 2008], [Wisniewski et al., 2020], [Stankeviciute et al., 2021] and [Kath and Ziel, 2021]. To keep track of the latest developments in conformal prediction, the reader may want to see the *Awesome Conformal Prediction* repository by [Manokhin, 2024].

Overall, the literature on Adaptive Conformal Inference algorithms underscores their significance in addressing the complexities of non-exchangeable data, offering the most promising avenues for robust uncertainty quantification in diverse application domains. It is for these reasons that we will use these methodologies to compute robust market risk measures with crypto-assets.

We remark that [Wisniewski et al., 2020] and [Kath and Ziel, 2021] are the only authors who employed (vanilla) conformal prediction to generate prediction intervals and rigorously tested their validity using unconditional and conditional coverage tests. However, their primary focus was on obtaining valid prediction intervals rather than on the tails of the distribution, which are critical for financial risk management. [Wisniewski et al., 2020] evaluated their models using 19 different confidence levels, ranging from 5% to 95%, while [Kath and Ziel, 2021] focused on 50% and 90% prediction intervals. Despite their thorough examination, the quantiles they considered do not align with the requirements of financial risk management. Regulatory frameworks such as the Basel II agreement mandate the use of Value-at-Risk (VaR) at the 1% probability level, while Basel III suggests using Expected Shortfall at the 2.5% probability level. The higher quantiles examined by [Wisniewski et al., 2020] and [Kath and Ziel, 2021] are less relevant for these purposes. Moreover, both studies revealed that although several models passed the unconditional coverage tests, almost none succeeded in the conditional coverage tests across all significance levels (see Table 2 in both papers). Such results highlight the limitations of existing models in providing reliable risk measures that are crucial for serious risk management applications. In contrast to these prior works, our study pioneers the application of ACI methods specifically for estimating tail quantiles relevant to financial risk management and that are robust to distributional shifts. By focusing on quantile estimation for VaR, we address a critical gap in the literature. Our approach not only leverages the adaptive nature of ACI to dynamically adjust prediction intervals but also repurposes these intervals to provide precise point estimates for the tail quantiles. This innovative use of ACI methods extends their applicability beyond traditional prediction interval construction, offering significant benefits for the accurate estimation of risk measures. To our knowledge, this alternative use of ACI for direct quantile estimation in the context of financial risk management has not been explicitly considered in previous literature. Thus, our work not only builds on the previous studies of [Wisniewski et al., 2020] and [Kath and Ziel, 2021] but also introduces a novel application that enhances the toolkit available for risk managers.

3 Materials and Methods

The aim of this study is to compare the performance of four ACI algorithms with traditional volatility models for daily data, such as GARCH models and daily range models, in computing the Value-at-Risk (VaR) at various probability levels for a large set of crypto-assets. Additionally, this comparison indirectly assesses the quality of the models' Expected Shortfall (ES), as proposed by [Kratz et al., 2018]. The ES represents the average of the worst p losses, where p is the percentile of the returns distribution. Although [Gneiting, 2011] demonstrated that the ES lacks a mathematical property known as elicitability and cannot be directly backtested, [Emmer et al., 2015] showed that the ES becomes elicitable when conditioned on the VaR and can be backtested by approximating multiple VaR levels. This concept was further refined by [Kratz et al., 2018], who introduced a multinomial test of VaR violations across multiple levels as a means of backtesting the ES.

Before presenting the outcomes of our extensive empirical evaluations, we first discuss the general structure of Adaptive Conformal Inference, four specific ACI algorithms used in our analysis, the benchmark volatility models for daily data, and backtesting procedures for market risk measures.

3.1 Adaptive Conformal Inference: the general structure

We delve into an online learning scenario where we have a sequential stream of crypto-assets log-returns $(y_t)_{t\geq 1}$, one at a time, see [Cesa-Bianchi and Lugosi, 2006] for a detailed discussion of online learning theory. Supposing that $\alpha \in (0,1)$ is our desired empirical coverage of prediction intervals, our objective is to produce, at each time step t, a prediction interval for the upcoming log-return y_t. This interval is generated using an interval construction function denoted as $\hat{C}_t$, that takes a parameter $\theta_t \in \mathbb{R}$ and produces a closed prediction interval $[l_t, u_t]$. It is essential that the interval construction function be nested, so that if $\theta' > \theta$, then $\hat{C}_t(\theta)$ must be a subset of $\hat{C}_t(\theta')$, thus indicating wider prediction intervals for larger values of θ. $\hat{C}_t(\theta)$ is indexed by t to highlight its potential dependence on other information available at each time point, such as a point prediction $\hat{\mu}_t$. Besides, let $r_t = \inf\{\theta \in \mathbb{R} : \mathbb{I}(y_t \in \hat{C}_t(\theta))\}$ be the radius at time t, i.e., the smallest θ ensuring that the prediction interval covers the log-return y_t, and $\mathbb{I}(\cdot)$ be the indicator function. A critical assumption used for the theoretical analysis of several ACI algorithms is the boundedness of these radii, so there exists a constant $D > 0$ such that $r_t < D$ for all t.

A straightforward approach to build prediction intervals involves directly employing the parameter θ_t to determine the interval width. Given the point prediction $\hat{\mu}_t$ at each time t, we can create a symmetric prediction interval around this point estimate as $\hat{C}_t(\theta_t) = [\hat{\mu}_t - \theta_t, \hat{\mu} + \theta_t]$. This method is known as the *linear interval constructor* and, in this setup, the radius is given by the absolute residual $r_t = |\hat{\mu}_t - y_t|$. The original work on Adaptive Conformal Inference (ACI) by [Gibbs and Candes, 2021] proposed constructing intervals based on past observed residuals . Assume to have a function S known as a "nonconformity score", where a common choice is given by the absolute residual $S(\mu, y) = |\mu - y|$. Moreover, if we denote with $s_t = S(\hat{\mu}_t, y_t)$ the nonconformity score of the t-th log-return, then the *quantile interval constructor* is formulated as follows:

$$\hat{C}_t(\theta_t) = [\hat{\mu}_t - \text{Quantile}(\theta, \{s_1, \dots, s_{t-1}\}), \hat{\mu}_t + \text{Quantile}(\theta, \{s_1, \dots, s_{t-1}\})],$$

where Quantile(θ, M) is the empirical θ-quantile of the elements in set M. It is easy to verify that $\hat{C}_t$ is nested within θ_t because the quantile function is non-decreasing in θ. The linear interval constructor will be used with the Scale-Free Online Gradient Descent by [Bhatnagar et al., 2023] and the Strongly Adaptive Online Conformal Prediction by [Bhatnagar et al., 2023], whereas the quantile interval constructor with the Aggregated ACI by [Zaffran et al., 2022] and the Fully Adaptive Conformal Inference by [Gibbs and Candès, 2022].

In this framework, the lower quantile l_t of the interval constructor $\hat{C}_t(\theta_t)$ corresponds to the 1-day ahead Value-at-Risk (VaR) at the probability level $p = (1 - \alpha)/2$, denoted as $VaR_{t,p}$. Conversely, the upper quantile u_t of the interval constructor $\hat{C}_t(\theta_t)$ corresponds to the 1-day ahead Value-at-Risk (VaR) at the probability level $1 - p = 1 - (1 - \alpha)/2$, denoted as $VaR_{t,1-p}$.

In general, the ACI algorithms interaction with the data and the computation of losses follow a similar pattern which is repeated sequentially for each time step $t = 1, \dots, T$:

- Predict θ_t and build the prediction interval $\hat{C}_t(\theta_t)$;
- Observe the true outcome y_t and compute the radius r_t;
- Verify whether y_t is not included in the prediction interval, $err_t := \mathbb{I}[y_t \notin \hat{C}_t(\theta_t)]$.
- Compute the so-called pinball loss $L^\alpha(\theta_t, r_t)$ defined as follows

$$L^\alpha(\theta_t, r_t) = \begin{cases} \alpha(\theta_t - r_t), & \theta_t \geq r_t \\ (1 - \alpha)(r_t - \theta_t), & \theta_t < r_t \end{cases}$$

This iterative process forms the foundation of the theoretical framework of online learning, from which theoretical results are then derived for each ACI algorithm.

The original Adaptive Conformal Inference (ACI) algorithm proposed by [Gibbs and Candes, 2021] dynamically adjusts the width of prediction intervals based on observed data. Their algorithm is outlined in pseudo-code format in Appendix A. It is possible to show that the updating mechanism for the estimated radius can be derived as an online subgradient descent scheme, using the subgradient of the pinball loss function. In simple terms, if the log-return y_t falls outside the prediction interval at time t ($err_t = 1$), the next interval widens ($\theta_{t+1} = \theta_t + \gamma\alpha$). Conversely, if y_t falls within the interval ($err_t = 0$), the next interval narrows ($\theta_{t+1} = \theta_t - \gamma(1 - \alpha)$). The learning rate γ governs the speed at which the interval width adapts to the data and is the primary tuning parameter. Theoretical considerations on coverage error bounds suggest a larger γ to expedite coverage error decay over time. However, in practice, overly large γ values lead to intervals exhibiting significant oscillations. Conversely, overly small γ values result in intervals that adapt too slowly to distribution shifts. Hence, selecting an appropriate γ value is crucial. This issue has spurred the development of ACI algorithms that are robust to the choice of this parameter. The theoretical guarantees concerning the performance of the ACI algorithm remain unaffected by the selection of the initial value θ_1. Therefore, in practical applications, any value can be chosen. Over time, the influence of the initial choice of θ_1 diminishes proportionally to the chosen learning rate. Following [Susmann et al., 2023], we set $\theta_1 = \alpha$ when employing the quantile interval predictor, and $\theta_1 = 0$ otherwise.

Finally, we remark that in the evaluation of Adaptive Conformal Inference (ACI) algorithms, traditional metrics such as the empirical coverage and the regret provide valuable insights into the overall performance of prediction intervals[2]. However, in the context of financial risk management, particularly concerning the estimation of risk measures in the tails of log-returns distributions, a more nuanced approach is required. Specifically, the focus is often directed towards assessing the quality of the estimated (tail) risk measures, such as quantiles (e.g., Value-at-Risk) or more comprehensive measures like the expected shortfall. Given the critical importance of accurately estimating tail risk, it is important to employ specialized evaluation techniques tailored to market risk measures. Consequently, backtesting procedures designed specifically for assessing the adequacy of these risk measures offer a more appropriate and rigorous means of evaluation in our case than the empirical coverage and the regret. An overview of the backtesting procedures employed in our empirical analysis will be provided in section 3.4.

[2]The empirical coverage is the proportion of log-returns y_t that fell within the corresponding prediction intervals, while the regret is the difference between the cumulative pinball loss given by a sequence θ_t versus the cumulative loss of the best possible fixed choice. [Gibbs and Candes, 2021] demonstrated that for all $\gamma > 0$, the ACI algorithm has the following finite sample bound on the coverage error (i.e., the difference between the empirical coverage and the nominal coverage): $|CovErr(T)| \leq (D+\gamma)/(\gamma T)$. This indicates that the coverage error is guaranteed to converge to zero for any choice of γ as T increases. Additionally, a similar bound exists for the regret, providing further insights into the algorithm's performance. For more comprehensive details, we refer to [Gibbs and Candes, 2021].

3.2 ACI algorithms: AgACI, FACI, SF-OGD, SAOCP

The **Aggregated ACI (AgACI)** by [Zaffran et al., 2022] resolves the challenge of selecting a suitable learning rate for ACI by executing multiple instances of the algorithm with varying learning rates. Subsequently, it combines the lower and upper interval bounds separately using an online aggregation of experts algorithm. Specifically, one aggregation algorithm aims to estimate the lower $(1-\alpha)/2$ quantile, while the other targets the upper $1-(1-\alpha)/2$ quantile. [Zaffran et al., 2022] explored several online aggregation algorithms and observed similar outcomes. Therefore, we adopt their recommendation and utilize the Bernstein Online Aggregation (BOA) algorithm, implemented in the `opera` R package [Wintenberger, 2017, Gaillard et al., 2023]. BOA operates as an online algorithm, deriving predictions for the lower (or upper) prediction interval bound through a weighted average of candidate ACI prediction interval bounds, with weights determined by each candidate's past performance concerning the quantile loss. Therefore, the prediction intervals produced by AgACI may not be symmetric around the point prediction, given the separate weights assigned to the lower and upper bounds. The primary parameter to tune in AgACI is the set of candidate learning rates γ. [Susmann et al., 2023] suggest using the following learning rates $\gamma \in \{0.001, 0.002, 0.004, 0.008, 0.016, 0.032, 0.064, 0.128\}$. Additionally, each candidate ACI algorithm requires a starting value for θ_1, which can be arbitrarily set to α, as previously discussed. The AgACI algorithm is outlined in pseudo-code format in Appendix B, and it is implemented in the `AdaptiveConformal` R package, see [Susmann et al., 2023] for more details. Finite sample bounds on the coverage error and the regret do not exist for the AgACI algorithm. [Zaffran et al., 2022] performed a wide range of experiments on synthetic time series with different time dependence structures, showcasing the robustness of the AgACI algorithm and its superior performance compared to baseline methods. However, they noted at the conclusion of their paper that future research would involve a theoretical analysis of the aggregation algorithm, particularly to determine if the experimentally observed asymptotic validity holds.

The **Fully Adaptive Conformal Inference (FACI)** by [Gibbs and Candès, 2022] was developed by the creators of the original ACI algorithm, in part to address the challenge of selecting the learning rate parameter γ. In this regard, FACI shares a similar objective with the AgACI algorithm, although it employs a slightly different approach. FACI also aggregates predictions from multiple instances of ACI, each executed with different learning rates. However, it differs in that it directly combines the estimated radii produced by each algorithm based on their pinball loss, employing an exponential reweighting scheme [Gradu et al., 2023]. Unlike AgACI, FACI does not separately aggregate the upper and lower bounds of the intervals, and this enables the development of theoretical guarantees regarding the algorithm's performance in a more straightforward manner. The FACI algorithm is outlined in pseudo-code format in Appendix C, and it is implemented in the `AdaptiveConformal` R package, see [Susmann et al., 2023] for more details. The process of tuning hyperparameters involves selecting a time interval length $|I|$ to control the pinball loss, which can be arbitrarily chosen. For the hyperparameter σ, [Gibbs and Candès, 2022] advocate for the optimal choice $\sigma = 1/(2|I|)$. Determining the third hyperparameter η poses a greater challenge. In the absence of distribution shifts, the optimal choice for η is,

$$\eta = \sqrt{\frac{3}{|I|}}\sqrt{\frac{\log(K \cdot |I|) + 2}{\alpha^2(1-\alpha)^3 + (1-\alpha)^2\alpha^3}}$$

where K is the number of multiple copies of the ACI algorithm with different learning rates. We remark that this solution is optimal only for the quantile interval constructor, where θ_t represents a quantile of previous nonconformity scores. Alternatively, [Gibbs and Candès, 2022] suggest learning η in an online manner using the following update rule:

$$\eta_t = \sqrt{\frac{\log(K \cdot |I|) + 2}{\sum_{s=t-|I|}^{t-1} L^{\alpha}(\theta_s, r_s)}}$$

Both approaches for selecting η yielded similar results in the empirical studies reported by [Gibbs and Candès, 2022]. Following [Susmann et al., 2023], we employed the former approach when the quantile interval construction function was selected, while we employed the latter approach for the linear interval construction function. Similar to AgACI, the grid for the learning parameter γ consists of values from the set $\gamma \in \{0.001, 0.002, 0.004, 0.008, 0.016, 0.032, 0.064, 0.128\}$. To establish a bound on the coverage error, [Gibbs and Candès, 2022] examined a slightly modified version of FACI in which θ_t is chosen randomly from the candidate $\theta_{t,k}$ with weights given by $p_{t,k}$, instead of taking a weighted average. They ensure that this randomized version of FACI yields results very similar to the deterministic version. The coverage error result also assumes that hyperparameters can change over time, meaning η_t and σ_t are specific to each time t, rather than being fixed. The authors demonstrate that the coverage error has the following specific bound, where $\gamma_{\min}$ and $\gamma_{\max}$ represent the smallest and largest learning rates in the grid, respectively:

$$|CovErr(T)| \leq \frac{1 + 2\gamma_{\max}}{T\gamma_{\min}} + \frac{(1 + 2\gamma_{\max})^2}{\gamma_{\min}} \exp(\eta_t(1 + 2\gamma_{\max}))\frac{1}{T}\sum_{t=1}^{T}\eta_t + 2\frac{1 + \gamma_{\max}}{\gamma_{\min}}\frac{1}{T}\sum_{t=1}^{T}\sigma_t$$

Therefore, if both η_t and σ_t converge to zero as $t \to \infty$, the coverage error will also converge to zero. Additionally, under mild distributional assumptions, they provide a type of short-term coverage error bound for arbitrary time spans, along with several regret bounds. For more details, we refer to [Gibbs and Candès, 2022].

The **Scale-Free Online Gradient Descent (SF-OGD)** is a versatile algorithm for online learning, initially proposed by [Orabona and Pál, 2018]. This algorithm involves updating θ_t through a gradient descent step, with the learning rate adapting to the scale of previously observed gradients. While SF-OGD was initially introduced within the context of Adaptive Conformal Inference (ACI) as a sub-algorithm for SAOCP (outlined below), it has demonstrated strong performance on its own in real-world applications, see [Bhatnagar et al., 2023]. The SF-OGD algorithm is outlined in pseudo-code format in Appendix D, and it is implemented in the `AdaptiveConformal` R package, see [Susmann et al., 2023] for more details. It is possible to show that the optimal selection for the learning rate is $\gamma = D/\sqrt{3}$, where D represents the maximum possible radius. In cases where D is unknown, it can be estimated by employing an initial subset of the time series as a calibration set. D can then be estimated as the maximum of the absolute residuals between the observed log-returns and the corresponding forecasts [Orabona and Pál, 2018, Bhatnagar et al., 2023]. [Bhatnagar et al., 2023] found a bound for the coverage error of this algorithm by showing that for any learning rate $\gamma = \Theta(D)$ (where $\gamma = D/\sqrt{3}$ is optimal) and any starting value $\theta_1 \in [0, D]$, then it holds that for any $T > 1$,

$$|CovErr(T)| \leq \mathcal{O}\big((1-\alpha)^{-2}T^{-1/4}\log T\big)$$

We remark that the coverage bounds for SF-OGD and SAOCP below (which is a generalization of SF-OGD) are distribution-free, see Theorems 4.2 and 4.3 and their proofs in [Bhatnagar et al., 2023] for the full details.

The **Strongly Adaptive Online Conformal Prediction (SAOCP)** algorithm by [Bhatnagar et al., 2023] was introduced as an enhancement over existing ACI algorithms, offering more robust theoretical guarantees. SAOCP operates similarly to AgACI and FACI, using a set of candidate online learning algorithms to generate prediction intervals, which are subsequently aggregated using a meta-algorithm. While SF-OGD was chosen as the candidate algorithm, any algorithm with anytime regret guarantees can be employed. Unlike AgACI and FACI, where each candidate employs a distinct learning rate but contributes consistently to the final prediction intervals, SAOCP assigns identical learning rates to all candidates. However, each candidate is allocated positive weight over a specific time interval. To address rapid distribution shifts, new candidate algorithms are continuously introduced, ensuring swift adaptation and positive weighting for the most recent candidates. In essence, SAOCP functions as a meta-algorithm overseeing multiple experts, with each expert constituting an independent online learning algorithm responsible for its own active interval with finite lifetime. At each time point t, a new expert is created, active over a finite "lifetime" that is defined as

$$L(t) = g \cdot \max_{n \in Z}\{2^n : t \equiv 0 \mod 2^n\},$$

where $g \in \mathbb{Z}_{\geq 1}$ is a multiplier for the lifetime of each expert. Experts are weighted based on their empirical performance relative to the pinball loss function, resulting in intervals with robust regret guarantees. The SAOCP algorithm is outlined in pseudo-code format in Appendix E, and it is implemented in the `AdaptiveConformal` R package, see [Susmann et al., 2023] for more details. The primary tuning parameter for SAOCP is the learning rate γ of the SF-OGD sub-algorithms, with the optimal choice established as $\gamma = D/\sqrt{3}$, as discussed earlier. [Bhatnagar et al., 2023] typically determine D by selecting the maximum residual from a calibration set. The second tuning parameter, which is the lifetime multiplier g, governs the duration of each expert's lifetime. Following [Bhatnagar et al., 2023], we set $g = 8$. [Bhatnagar et al., 2023] -Theorem 4.3- showed that a bound on the coverage error of SAOCP is given by:

$$|CovErr(T)| \leq \mathcal{O}\big(\inf_{\beta}(T^{1/2-\beta} + T^{\beta-1}S_\beta(T))\big)$$

for any $T \geq 1$, and where $S_\beta(T)$ is a technical measure of the smoothness of the cumulative gradients and expert weights for each of the candidate experts. For example, if there exists $\beta \in (1/2, 1)$, then $S_\beta(T) \leq \tilde{\mathcal{O}}(T^\gamma)$ for some $\gamma < 1 - \beta$, and the previous bound becomes $|CovErr(T)| \leq \tilde{\mathcal{O}}\big(T^{-\min\{1/2-\beta, \beta-1+\gamma\}}\big) = o_T(1)$. Finally, we remark that the previous bound is distribution-free, and mild regularity assumptions on the distributions of the data are only required if we need to achieve approximately valid coverage on *every* sub-interval of time. For more details, see Theorem C.3 in [Bhatnagar et al., 2023].

3.3 Benchmark volatility models for daily data

The GARCH(1,1) model remains a prominent benchmark model for computing market risk measures with daily data due to several reasons. Firstly, it captures essential characteristics of financial time series, such as volatility clustering and time-varying volatility, which are commonly observed in real-world financial markets. Secondly, the GARCH(1,1) model is relatively parsimonious compared to other volatility models, requiring only a small number of parameters to estimate. Given its widespread use in academic research and industry practice, the GARCH(1,1) model serves as a natural reference competitor when evaluating the performance of alternative market risk models. Its inclusion as a benchmark ensures that the proposed models undergo rigorous comparison against a well-established and widely recognized standard, thus enhancing the robustness and credibility of the assessment process in risk management applications. Specifically, a simple **GARCH(1,1) with constant mean μ and standardized errors**

z_t **following a symmetric Student's t-distribution with** ν **degrees of freedom** was used in this work to model the conditional variance σ_t^2 of the log-returns y_t:

$$\begin{aligned} y_t &= \mu + \varepsilon_t, \quad \varepsilon_t = z_t\sqrt{\sigma_t^2}, \quad z_t \sim t_\nu \\ \sigma_t^2 &= \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \end{aligned}$$

More complex model specifications and error distributions were discarded because they resulted in much higher rates of numerical convergence failures, see [Fantazzini, 2022] and [Fantazzini, 2023] for similar evidence with crypto-assets. The complexity of estimating GARCH models and the necessity for sizable samples have been extensively documented in the literature. The seminal work by [Fiorentini et al., 1996] highlighted the issues involved in GARCH model estimation, emphasizing the demand for large datasets. Furthermore, comprehensive simulation studies conducted by [Hwang and Valls Pereira, 2006], [Fantazzini, 2009], and [Bianchi et al., 2011] underscored the requirement of a sample size ranging from 250 to 500 observations for obtaining reliable model estimates of basic GARCH models. For scenarios involving more complex data generating processes, even larger sample sizes were necessary to ensure robust estimation. For GARCH models with Student's t errors, the calculation of the 1-day ahead Value-at-Risk (VaR) at the probability level p using information up to time $t-1$ is as follows:

$$VaR_{t,p} = \hat{\mu}_t + t_{p,\hat{\nu}}^{-1} \cdot \sqrt{(\hat{\nu}-2)/\hat{\nu}} \cdot \sqrt{\hat{\sigma}_t^2}$$

Here, $\hat{\mu}_t$ represents the 1-day-ahead forecast of the conditional mean, $\hat{\sigma}_t^2$ denotes the 1-day-ahead forecast of the conditional variance, and $t_{p,\hat{\nu}}^{-1}$ denotes the inverse function of the Student's t distribution with estimated $\hat{\nu}$ degrees of freedom at the probability level p. The term $\sqrt{(\hat{\nu}-2)/\hat{\nu}} \cdot \sqrt{\hat{\sigma}_t^2}$ represents the scale parameter of the Student's t distribution.

The second benchmark volatility model that we consider in our analysis employs the daily range to estimate the daily conditional variance of the log-returns y_t. The idea of using the price range has a rich history in both academic and professional literature, starting from the 19th century, see [Nison, 1994] and references therein. Notably, volatility measures derived from the daily range emerged as efficient alternatives to return-based volatility estimators, as demonstrated by several authors beginning with ([Parkinson, 1980]). Recent research has reignited interest in range-based estimators employing the open, high, low, and close (OHLC) prices for estimating daily volatility, see [Patton, 2011], [Molnár, 2012], [Chou et al.], and [Fiszeder et al., 2019]. Intriguingly, high-frequency volatility models have shown superior performance over low-frequency models using range-based estimators for short-term forecasts, typically one-day ahead [Lyócsa et al., 2021]. However, for longer forecast horizons, such as up to one month, the difference in forecast accuracy diminishes, particularly for most market indices. Moreover, [Fantazzini, 2023] conducted a comprehensive analysis on a dataset of over 2000 crypto-assets, evaluating their credit risk by computing their probability of "death", and found that ZPP-based models using range-based volatility estimators were a better choice for long-term forecasts up to 1 year ahead (which is the standard horizon for credit risk management). Building on [Molnár, 2012] and [Fantazzini, 2023], we will adopt the **Garman-Klass volatility estimator** [Garman and Klass, 1980]. This estimator has been shown to produce standardized returns that are normally distributed and yields estimates comparable to those obtained from high-frequency data. The Garman-Klass estimator assumes a Brownian motion with zero drift and no opening jumps. Nonetheless, for cases involving opening jumps, as seen with illiquid assets, the jump-adjusted Garman-Klass volatility estimator described in [Molnár, 2012] will be employed. The formula for the jump-adjusted Garman-Klass (GK) volatility estimator for the daily conditional variance σ_t^2 of the log-returns y_t is presented below:

$$\sigma^2_{GK,t} = \left[\log\left(O_t/C_{t-1}\right)^2 + \frac{1}{2}\log\left(H_t/L_t\right)^2 - (2\times\log 2 - 1)\log\left(C_t/O_t\right)^2\right]$$

To forecast the dynamics of range-based daily volatilities σ_t^2, we employed the Heterogeneous Autoregressive (HAR) model proposed by [Corsi, 2009], which posits that the daily volatility is influenced by past volatility over different time periods:

$$\begin{aligned}\sigma_t^2 &= \beta_0 + \beta_D\sigma^2_{t-1,D} + \beta_W\sigma^2_{t-1,W} + \beta_M\sigma^2_{t-1,M} + \epsilon_t, \quad \text{where} \\ &\sigma^2_{t-1,W} = \frac{1}{7}\sum_{j=1}^{7}\sigma^2_{t-j,D}, \quad \sigma^2_{t-1,M} = \frac{1}{30}\sum_{j=1}^{30}\sigma^2_{t-j,D}\end{aligned}$$

where σ_D^2, σ_W^2 and σ_M^2 denote the daily, weekly, and monthly volatility components, respectively. We adjusted the time periods for weekly and monthly volatilities to 7 and 30 days, respectively, instead of the usual 5 and 22 days, to accommodate the continuous trading in cryptocurrency exchanges. We will set the conditional mean of the log-returns y_t to zero when using the Garman-Klass volatility estimator. Therefore, in the case of the HAR model with daily range data, the 1-day ahead VaR can be computed as follows:

$$VaR_{t,p} = \Phi_p^{-1}\cdot\sqrt{\hat{\sigma}_t^2}$$

where Φ_p^{-1} denotes the inverse function of the normal distribution at the probability level p.

3.4 Backtesting Methods for Market Risk Measures

The assessment of different Value at Risk (VaR) models' forecasting performance entails comparing the forecasted VaR values against actual returns for each day. Initially, the process involves tallying the number of violations T_1 when the forecasted VaR is lower than the actual losses, with $T = T_1 + T_0$, where T_0 denotes the absence of VaR violations. The **unconditional coverage test** developed by [Kupiec, 1995] verifies whether the fraction of actual violations $\hat{\pi} = T_1/T$ is statistically significantly different from $p\%$, so the null hypothesis is given by $H_0 : \hat{\pi} = p$. This test employs the following likelihood ratio test statistic for the null hypothesis ([Kupiec, 1995]):

$$LR_{uc} = -2\ln\left[(1-p)^{T_0} p^{T_1} \,/\, \{(1 - T_1/T)^{T_0} (T_1/T)^{T_1}\}\right] \overset{H_0}{\sim} \chi^2_1$$

The **conditional coverage test** by [Christoffersen, 1998] tests the joint null hypothesis concerning the accuracy of the average number of VaR violations and the independence of violations. This test can identify models forecasting an excessive or insufficient number of clustered violations, but it requires at least several hundred observations for accuracy. The test statistic is presented as follows:

$$LR_{cc} = -2\ln\left[(1-p)^{T_0} p^{T_1}\right] + 2\ln\left[(1-\pi_{01})^{T00} \pi_{01}^{T01} (1-\pi_{11})^{T10} \pi_{11}^{T11}\right] \overset{H_0}{\sim} \chi^2_2$$

where T_{ij} is the number of observations with value i followed by j for $i, j = 0, 1$ and $\pi_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}$ denotes the corresponding probabilities.

In addition to the count of VaR violations, financial regulators are concerned with their magnitude. Thus, the **asymmetric quantile loss (QL) function** proposed by [González-Rivera et al., 2004] was computed in our analysis:

$$l(y_t, VaR_{p,t}) = (p - d_t^p)(y_t - VaR_{p,t})$$

where $d_t^p = \mathbf{1}(y_t < VaR_{p,t})$ is the indicator function for the VaR exceedances. This function penalizes realized losses below the p-th quantile level more heavily, facilitating cost comparison among different choices.

The previous asymmetric quantile loss functions are then used by the **Model Confidence Set** (MCS) by [Hansen et al., 2011] to select the best VaR forecasting models at a specified confidence level. Given the differences between the QLs of models i and j at time t (expressed as $d_{ij,t} = QL_{i,t} - QL_{j,t}$), the MCS approach is employed to evaluate the hypothesis of equal predictive capability, denoted as $H_{0,M} : E(d_{ij,t}) = 0$, for all i, j in M, where M represents the set of forecasting models. The initial step involves the computation of the following t-statistics:

$$t_{i\cdot} = \frac{\overline{d}_{i\cdot}}{\widehat{var}(\overline{d}_{i\cdot})} \quad \text{for} \quad i \in M,$$

where $\overline{d}_{i\cdot} = m^{-1} \sum_{j \in M} \bar{d}_{ij}$ is the simple loss of the i-th model relative to the average losses across models in the set M, $\bar{d}_{ij} = T^{-1} \sum_{t=1}^{T} d_{ij,t}$ measures the sample loss differential between model i and j, while $\widehat{var}(\overline{d}_{i\cdot})$ is a bootstrapped estimate of $var(\overline{d}_{i\cdot})$. Subsequently, the T-max statistic is calculated as follows: $T_{max,M} = \max_{i \in M}(t_{i\cdot})$. This statistic has a non-standard distribution, hence its distribution under the null hypothesis is determined via bootstrap methods involving 1000 replications. If the null hypothesis is rejected, one model is eliminated from the analysis, restarting the testing procedure anew, see [Hansen et al., 2011] for more details.

Building upon an idea introduced by [Emmer et al., 2015], [Kratz et al., 2018] introduced a **multinomial Value at Risk (VaR) test** that implicitly evaluates the Expected Shortfall (ES) by approximating it with various VaR levels. Their approximation is defined as:

$$ES_p \approx \frac{1}{4}[q(p) + q(0.75p + 0.25) + q(0.5p + 0.5) + q(0.25p + 0.75)]$$

where $q(\gamma) = VaR_{\gamma}$. A similar but more convenient approximation for the ES at the 2.5% level, as adopted by Basel III, was proposed by [Wimmerstedt, 2015] and [Fantazzini and Shangina, 2019]:

$$ES_{2.5\%} \approx \frac{1}{5}[VaR_{2.5\%} + VaR_{2.0\%} + VaR_{1.5\%} + VaR_{1.0\%} + VaR_{0.5\%}]$$

[Kratz et al., 2018] suggested using several VaR probability levels $p_1, \ldots, p_N$, where $p_j = p + [(j-1)/N](1-p)$ for $j = 1, \ldots, N$, starting from a given level p. If $\mathbb{I}_{t,j} = \mathbf{1}_{(Y_t < VaR_{p_j,t})}$ represents the usual indicator function for a VaR violation at level p_j and $X_t = \sum_{j=1}^{N} \mathbb{I}_{t,j}$, then the sequence $(X_t)_{t=1,\ldots,T}$ counts the number of VaR violations at level p_j. Now define $MN(T, (\pi_0, \ldots, \pi_N))$ as a multinomial distribution with T trials, each of which may result in one of $N+1$ outcomes $\{0, 1, \ldots, N\}$ with probabilities $\pi_0, \ldots, \pi_N$ that sum to one, while the observed cell counts are defined by $O_j = \sum_{t=1}^{T} I_{(X_t = j)}$, $j = 0, 1, \ldots, N$. Then, under the assumptions of unconditional coverage and independence as in Christoffersen (1998), it can be shown that the random vector $(O_0, \ldots, O_N)$ follows the multinomial distribution $MN(T, (p_1 - p_0, \ldots, p_{N+1} - p_N))$. Supposing that the estimated multinomial distribution is $MN(T, (\theta_1 - \theta_0, \ldots, \theta_{N+1} - \theta_N))$, where θ_j $(j = 1, \ldots, N)$ are the estimated distribution parameters, Kratz et al. (2018) consider the following null and alternative hypotheses:

$$
\begin{aligned}
H_0 : \quad & \theta_j = p_j, \quad \text{for} \quad j = 1, \ldots, N \\
H_1 : \quad & \theta_j \neq p_j, \quad \text{for at least one } j \in \{1, \ldots, N\}
\end{aligned}
$$

The null hypothesis can be tested using various test statistics. We refer to [Cai and Krishnamoorthy, 2006] for a comprehensive simulation study on the exact size and power properties of five possible tests, three of which were later employed by [Kratz et al., 2018]. In our empirical analysis, we utilized the *exact method*, the fifth test statistic reviewed by [Cai and Krishnamoorthy, 2006], which computes the probability of a given outcome under the null hypothesis using the multinomial probability distribution itself:

$$
P(O_0, O_1, \ldots, O_N) = \frac{T!}{O_0! O_1! \ldots O_N!} (p_1 - p_0)^{O_0} (p_2 - p_1)^{O_1} \ldots (p_{N+1} - p_N)^{O_N}
$$

[Cai and Krishnamoorthy, 2006] concluded that while the exact method performs well, it can be time-consuming for large numbers of cells N and sample sizes T. In such cases, simulation methods are preferable. For a comprehensive discussion on these backtesting methods and others, we refer to [Fantazzini, 2019], Chapter 11.

3.5 Structure of the Empirical Analysis

In this study, we conducted a comprehensive empirical analysis to evaluate the performance and robustness of various methods for estimating market risk measures across a diverse set of cryptocurrencies. Our analysis consists of a baseline case that considers all assets, as well as a series of robustness checks to verify that the results for the baseline case also hold in different settings. It is structured as follows:

- *Baseline Case: All 4000 Assets.* In the baseline analysis, we included all 4000 cryptocurrencies in our dataset to provide a broad assessment of the methods under study. This diverse dataset allows us to capture a wide range of market behaviors and characteristics.

- *Robustness Check 1: Market Capitalization of Crypto-Assets.* We conducted a robustness check based on the market capitalization of the assets. Our dataset included daily market capitalization data for 2310 out of the 4000 assets. The remaining assets lacked this data, which may indicate transparency issues regarding their circulating supply. For a comprehensive analysis, we divided these 2310 assets into four groups of approximately equal size based on their market capitalization. The first group consists of assets with the highest market capitalization, while the fourth group includes those with the lowest capitalization.

- *Robustness Check 2: Time Series size.* To examine the impact of time series length on our results, we divided the assets into four groups according to the number of daily data points available. Each group contains approximately the same number of assets. The first group includes assets with the longest time series (ranging from 1613 to 4939 daily data points), and the fourth group includes assets with the shortest time series (ranging from 731 to 836 daily data points).

- *Robustness Check 3: Different Forecasting Methods.* In the baseline case, we used a simple AR(1) model due to its ease of estimation and the generally weak mean dependence in crypto-assets' log-returns. As a third robustness check, we evaluated the impact of using a more complex model specification with a robust estimation method. Specifically, we employed a single-hidden-layer neural network, utilizing seven lagged daily log-returns as inputs and three hidden units:

$$y_t = \beta_0 + \sum_{j=1}^{3} \beta_j g\Big(\gamma_{0j} + \sum_{i=1}^{7} \gamma_{ij} y_{t-i}\Big)$$

  Feed-forward neural networks with a single hidden layer are implemented in the `nnet` R package, and we refer to [Venables and Ripley, 2002], Chapter 8, for the full theoretical details and the software implementation.

- *Robustness Check 4: Comparison with Methods that Predict Quantiles Directly.* [Engle and Manganelli, 2004] proposed an alternative approach to quantile estimation that focuses on modeling the quantile directly rather than the entire distribution. They introduced a class of semi-parametric conditional autoregressive quantile models, known as *CAViaR*, which utilize quantile regression and mild distributional assumptions. These models have a structure similar to GARCH models and are formally defined as follows:

$$\begin{aligned}
\text{Symmetric absolute value} : q_t(p) &= \beta_1 + \beta_2 q_{t-1}(p) + \beta_3 |y_{t-1}| \\
\text{Asymmetric slope} : q_t(p) &= \beta_1 + \beta_2 q_{t-1}(p) + \beta_3 (y_{t-1})^+ + \beta_4 (y_{t-1})^- \\
\text{Indirect GARCH(1,1)} : q_t(p) &= [\beta_1 + \beta_2 q_{t-1}^2(p) + \beta_3 y_{t-1}^2]^{1/2} \\
\text{Adaptive} : q_t(p) &= q_{t-1}(p) + \beta_1 \left\{ [1 + \exp(\beta_2 \cdot [y_{t-1} - q_{t-1}(p)])]^{-1} - p \right\}
\end{aligned}$$

  where $q_t(p)$ represents the p-quantile function associated with the conditional distribution of returns y_t, $(x)^+ = \max(x, 0)$, $(x)^- = -\min(x, 0)$ and β_i are the model parameters. The asymmetric slope model is specifically designed to capture the asymmetric leverage effect, which is the tendency for volatility to be higher following a negative return than a positive return of equal magnitude. The indirect GARCH(1,1) CAViaR model is correctly specified if the underlying data is generated by a GARCH(1,1) model with an i.i.d. innovation process. The adaptive specification adjusts to past errors to minimize the probability of consecutively underestimating the VaR. CAViaR parameters are estimated using the quantile regression minimization technique introduced by [Koenker and Bassett Jr, 1978]:

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \sum_t [p - I(y_t < q_t(\boldsymbol{\beta}, p))] \cdot [y_t - q_t(\boldsymbol{\beta}, p)]$$

where $\boldsymbol{\beta}$ is the vector of parameters to be estimated, while I is the indicator function. When the quantile model is linear, this minimization can be formulated as a linear programming problem, for which the dual problem is conveniently solved. For this reason and due to past empirical evidence, such as that provided by [Abad et al., 2014] and references therein, we will use only the Symmetric Absolute Value (SAV) model[3]. Moreover, given the computational burden of estimating the model for each quantile, we will limit our analysis to a selected group of crypto-assets: the two most capitalized assets (Bitcoin and Ethereum) and the two least capitalized assets (Bubble and Litecoin-Token) for which all models achieved numerical convergence.

The aim of this structure is to ensure that our empirical analysis is thorough and considers various factors that may influence the performance of the risk estimation methods.

4 Results

4.1 Data

Our study analyzed a dataset comprising 4000 crypto-assets spanning from July 2010 to January 2024. We obtained all assets freely available from `https://coinmarketcap.com/` in January 2024, ensuring that each had a time series consisting of at least 730 daily data points. We made this selection to ensure that all models used in our analysis had a minimum of one year's worth of data for initial training and calibration. The dataset included daily open, high, low, and close prices, as well as traded volume and market capitalization. Initially, we downloaded a dataset comprising 4003 assets. However, three assets were excluded due to their close prices remaining at zero throughout the entire time span, rendering them unusable. Additionally, approximately a dozen assets exhibited unusual reported prices in the weeks preceding their delisting from coinmarketcap.com. These anomalous trading days were excluded from our analysis to maintain its integrity. The names of the 4000 crypto assets used in our analysis are listed in Tables 14-21 in Appendix 5.

The first 365 daily observations were used to initialize the estimation of the GARCH model, with

[3]The R code using optimized C++ routines to estimate the CAViar model can be found at `https://github.com/Buczman/CaviaR`.

log-returns computed using the closing prices. For the HAR model, the daily range was estimated using the open, high, low, and close prices. Similarly, for the training and calibration of ACI models, log-returns were computed using the closing prices. An expanding window approach was then employed for the GARCH and HAR models, where one day of data was added incrementally to the initial sample. The models were re-estimated with the expanded dataset, and the Value at Risk (VaR) for the next day was computed. The ACI models were trained incrementally, one data point at a time, as detailed in the algorithms provided in Appendix B-E.

In our study, we utilize a dataset comprising 4000 cryptocurrencies, covering a wide range of market conditions and asset characteristics. This extensive dataset includes not only the most capitalized cryptocurrencies, like Bitcoin and Ethereum, but also those with lower capitalization and liquidity. The rationale behind this comprehensive approach is twofold. First, it allows us to assess the performance of ACI methods across a diverse set of assets, which is essential for understanding the general applicability and robustness of these methods. Second, by including a wide variety of cryptocurrencies, we can identify specific challenges and opportunities associated with different types of assets. This approach enables us to draw more nuanced and actionable insights that are relevant to a broader audience, including investors, portfolio managers, and regulators. Our analysis thus provides a detailed examination of market risk measures across the full spectrum of the cryptocurrency market, ensuring that our conclusions are both robust and broadly applicable.

As outlined in the previous section, we calculated the Value at Risk (VaR) across five probability levels (p_1 =0.5%, p_2 =1%, p_3 =1.5%, p_4 =2%, p_5 =2.5%) for the log-returns of each asset. This enabled us to conduct an approximate backtesting of the Expected Shortfall (ES) at the 2.5% level, a metric included in the Basel 3 agreement. While our primary focus was on the left tail of the distribution, given its significance in financial risk management, we also computed five quantiles for the right tail (p_6 =97.5%, p_7 =98%, p_8 =98.5%, p_9 =99%, p_{10} =99.5%) to ensure comprehensiveness and generality.

For the ACI models, we opted to employ a simple AR(1) model to capture the dynamics of crypto-assets' log-returns. Although we initially attempted to utilize the Hyndman and Khandakar [Hyndman and Khandakar, 2008] algorithm for automatic selection of the optimal ARIMA model[4], this approach encountered challenges, particularly with extremely volatile crypto-assets possessing relatively short time series (fewer than 1000 observations). Consequently, we reverted to employing a straightforward AR(1) model. In this regard, it is worth noting that the mean dependence of crypto-assets' log-returns is generally weak. Nevertheless, as part of our robustness checks, we will examine the impact on our results when employing a more complex model specification with a robust estimation method.

[4]The algorithm is implemented in the R package `forecast`.

4.2 Baseline Case: All 4000 Assets

In this section, we present the results of our comprehensive evaluation of Value at Risk (VaR) forecasting models applied to a dataset comprising 4000 crypto assets. Our analysis includes four Adaptive Conformal Inference (ACI) models, one Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, and one Heterogeneous Autoregressive (HAR) model using daily range volatilities.

Our evaluation begins with an examination of the performance of each model using the [Kupiec, 1995] test, the [Christoffersen, 1998] test, and the multinomial VaR test by [Kratz et al., 2018], see Table 1. Across all quantiles, we observed that the ACI models generally performed well, with FACI and SF-OGD emerging as the most effective models. However, AgACI and SAOCP, while providing accurate estimates for extreme quantiles (p_1 =0.5% and p_2 =1%), resulted to be too conservative when estimating quantiles between 1% and 2.5%, with less violations than expected. In the right tail of the distribution, AgACI demonstrated better results, instead, in line with the FACI and SF-OGD algorithms. According to the multinomial VaR test, FACI and SF-OGD were able to properly model the left and right tails of the distribution for the vast majority of crypto-assets (approximately 90% of assets), followed by AgACI (approximately 80%), while SAOCP had the worst performance among ACI algorithms, with only approximately 50% of assets where the multinomial VaR test was not rejected at the 5% probability level.

Differently from ACI algorithms, GARCH and HAR models faced challenges in achieving numerical convergence for approximately 2.5% of assets (96 and 104 assets, respectively), particularly those with extreme variability and/or relatively small datasets ($T < 1000$). Despite this, GARCH served as a reliable benchmark model, slightly underestimating VaR for the most extreme quantiles ($p_i \leq 1.0\%$) while maintaining accuracy for the other quantiles. Instead, the HAR model with daily range volatilities proved to be the least effective, underestimating lower quantiles up to $p_i = 1\%$, and severely overestimating higher quantiles. Similar problems emerged also for the right tail of the distribution. According to the multinomial VaR test, the GARCH model was able to model the left and right tails of the distribution for approximately 70% of assets, whereas the HAR model for only approximately 20% of assets, thus confirming the previous problems with the tests for the single quantiles.

Table 1: Average number of violations in % across all assets for each quantile; % of times the Christoffersen's conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec's unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by [Kratz et al., 2018] was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively. The results for the GARCH and HAR models only include assets for which numerical convergence was achieved.

Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.63	74.95	87.80	0.96	78.50	88.38	1.30	72.35	84.45	1.64	69.28	80.18	2.00	66.05	76.10	77.70
FACI	0.58	78.10	91.53	0.92	85.43	94.38	1.34	81.85	93.18	1.78	80.95	92.78	2.23	81.08	91.73	88.10
SF-OGD	0.51	96.03	95.18	0.94	96.35	96.25	1.37	95.88	95.10	1.81	94.50	93.53	2.24	94.00	92.55	86.73
SAOCP	0.64	94.03	90.00	0.96	93.83	89.08	1.31	89.58	83.73	1.56	83.03	75.25	1.86	75.18	66.80	55.15
GARCH	0.76	76.56	68.60	1.27	73.05	67.83	1.76	69.75	64.98	2.24	67.78	63.19	2.70	66.11	62.30	68.01 (*)
HAR_DR	1.08	66.50	58.24	1.33	60.24	56.03	1.53	51.18	46.05	1.71	42.51	38.73	1.88	36.40	33.21	21.36 (**)
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.51	70.30	88.00	97.94	71.68	88.35	98.35	71.58	87.68	98.75	75.23	86.75	99.17	68.50	80.58	79.95
FACI	97.17	76.08	92.55	97.70	77.73	92.55	98.24	78.15	92.40	98.78	82.63	93.03	99.25	74.38	87.25	88.80
SF-OGD	97.07	92.18	92.48	97.63	92.98	93.00	98.18	92.98	93.55	98.74	94.55	94.68	99.29	92.98	94.85	88.55
SAOCP	97.58	82.20	77.08	97.96	86.88	81.80	98.27	88.15	82.33	98.72	91.03	85.70	99.13	84.95	78.25	49.08
GARCH	96.82	68.55	66.83	97.35	69.57	66.68	97.89	70.41	66.68	98.45	72.52	68.31	99.05	73.31	67.88	69.62 (*)
HAR_DR	97.94	42.92	42.43	98.11	49.87	49.05	98.29	57.16	55.11	98.50	61.88	59.03	98.76	58.21	52.28	19.33 (**)

(*) The GARCH(1,1) model with standardized errors following a symmetric Student's t distribution did not reach numerical convergence for 96 assets (out of 4000).
(**) The HAR model used for the dynamics of range-based daily volatilities did not reach numerical convergence for 104 assets (out of 4000).

To identify the best VaR forecasting models, we utilized the asymmetric quantile loss (QL) function proposed by [González-Rivera et al., 2004] and employed the Model Confidence Set (MCS) method by [Hansen et al., 2011], see table 2 and 3. Notably, we considered only assets for which all six models reached numerical convergence. Such a choice clearly penalize ACI models, which were able to estimate quantiles for all assets, whereas this was not the case for GARCH and HAR models. Nevertheless, given that financial regulators are concerned not only with the number of VaR violations but also with their magnitude, we also compared the models using the asymmetric quantile loss and the MCS.

Our analysis reveals that the GARCH model consistently emerged as the top-ranked model for the majority of assets and was almost always included in the MCS. This underscores the enduring relevance of the GARCH(1,1) model with a student's t distribution in finance when using daily data, even nearly four decades after it was originally proposed.

While ACI models demonstrated proficiency in estimating quantiles for most assets, they exhibited challenges in estimating the most extreme quantiles ($p_i \leq 1\%$ and $p_i \geq 99\%$), particularly the AgACI and FACI models that showed rather large asymmetric losses and lower ranking. However, SF-OGD and SAOCP models displayed greater precision with smaller losses. These findings have significant implications for financial risk management: while a traditional benchmark like the GARCH model remains relevant, newer approaches such as ACI models offer promising alternatives, particularly for assets with complex dynamics such as crypto-assets, albeit with some caveats in extreme quantile estimation. Given that ACI models are more precise in terms of VaR violations, while GARCH models are better in terms of asymmetric quantile losses, forecasting combinations are a possibility. We leave this interesting issue as an avenue for further research.

Quantile	AgACI	FACI	SF.OGD	SAOCP	GARCH	HAR_DR
VaR_0.5	4.22	4.95	3.36	3.05	2.33	3.09
VaR_1.0	4.13	4.33	3.72	3.37	2.17	3.29
VaR_1.5	3.99	3.75	3.95	3.67	2.06	3.58
VaR_2.0	3.82	3.41	4.04	3.95	1.96	3.82
VaR_2.5	3.64	3.19	4.12	4.13	1.88	4.04
VaR_97.5	3.73	3.33	4.06	3.84	1.91	4.14
VaR_98.0	3.89	3.52	3.96	3.70	1.99	3.94
VaR_98.5	4.11	3.79	3.83	3.46	2.09	3.72
VaR_99.0	4.22	4.23	3.58	3.21	2.21	3.55
VaR_99.5	4.21	4.67	3.21	3.00	2.39	3.51

Table 2: Average rank of the models across all assets for each quantile based on the asymmetric quantile loss (QL) function proposed by [González-Rivera et al., 2004].

Quantile	AgACI	FACI	SF.OGD	SAOCP	GARCH	HAR_DR
VaR_0.5	57.23	43.52	68.56	76.71	89.56	81.70
VaR_1.0	68.85	61.57	69.01	75.17	93.32	78.20
VaR_1.5	75.22	75.93	69.82	74.73	94.83	73.71
VaR_2.0	78.38	83.08	69.16	70.99	95.80	68.80
VaR_2.5	82.19	86.55	67.21	68.22	95.98	64.02
VaR_97.5	89.45	93.26	76.29	79.16	97.44	69.32
VaR_98.0	87.00	90.10	79.19	81.78	97.08	73.97
VaR_98.5	83.32	85.51	80.68	85.69	96.87	79.45
VaR_99.0	79.40	75.40	82.72	87.55	96.06	82.79
VaR_99.5	73.26	61.36	85.17	90.23	94.99	85.72

Table 3: Number of times (in %) when the model was included into the Model Confidence Set (MCS) at the 10% confidence level across all assets.

4.3 Robustness check 1: Market capitalization of crypto-assets

In this section, we examined the 2310 assets with daily market capitalization data and categorized them into four groups, each containing approximately the same number of assets. The first group comprises assets with the highest market capitalization in dollars, while the fourth group consists of assets with the lowest capitalization.

We computed the [Kupiec, 1995] test, the [Christoffersen, 1998] test, and the multinomial VaR test by [Kratz et al., 2018] for each group, with the results presented in Tables 4-5.

The empirical analysis broadly confirms the findings of the baseline case. However, it reveals that the performance of the GARCH model and, to a lesser extent, the SAOCP algorithm deteriorated significantly when focusing on assets with the lowest market capitalization. It appears that the extreme volatility of this asset class strongly impacted the numerical stability of these models. As a result, the GARCH model exhibited too many VaR violations, while the SAOCP model demonstrated too few.

It is well known that crypto-assets with lower market capitalization tend to experience higher levels of volatility. This heightened volatility can pose challenges for several modeling approaches, which may struggle to adequately capture and predict extreme movements in these assets' prices. As such, future research could explore alternative modeling techniques specifically tailored to address the unique characteristics and dynamics of lower-capitalization crypto-assets, potentially enhancing the accuracy and robustness of risk management strategies in this segment of the market.

Table 4: Backtesting results based on **Market Capitalization** (first 2 groups): Average number of violations in % across all assets for each quantile; % of times the Christoffersen's conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec's unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by [Kratz et al., 2018] was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Highest Market capitalization: \$ 259874508 - \$ 1274831490851																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.50	73.31	89.95	0.81	68.11	82.84	1.12	60.83	74.00	1.48	52.34	68.28	1.86	49.74	62.91	71.75
FACI	0.50	74.87	93.41	0.90	78.86	93.07	1.34	74.87	91.85	1.80	74.18	92.03	2.28	75.56	92.03	90.12
SF-OGD	0.49	93.41	96.88	0.95	94.11	97.92	1.42	94.63	95.84	1.90	94.45	95.15	2.37	94.63	95.15	86.83
SAOCP	0.59	92.20	90.29	0.92	92.20	87.69	1.32	88.21	81.98	1.62	82.32	77.47	2.01	77.99	70.71	51.65
GARCH	0.47	83.10	76.83	0.88	76.66	70.91	1.30	70.38	68.29	1.71	69.51	67.25	2.12	69.51	65.85	72.65
HAR_DR	0.65	73.34	70.56	0.87	65.51	62.54	1.07	51.57	49.30	1.24	37.63	36.24	1.41	29.62	28.75	18.82
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.76	59.79	84.92	98.16	61.18	88.04	98.57	67.07	90.12	98.95	71.58	92.20	99.36	75.39	91.16	79.38
FACI	97.34	71.40	93.59	97.82	71.75	93.24	98.34	72.27	93.24	98.87	76.60	94.28	99.40	80.59	94.45	92.20
SF-OGD	97.28	88.39	94.97	97.79	89.95	94.63	98.31	90.12	94.45	98.84	91.16	97.05	99.36	93.93	96.01	88.21
SAOCP	97.72	80.59	76.78	98.08	86.31	81.63	98.42	89.60	84.92	98.84	92.03	87.00	99.27	89.25	84.40	50.95
GARCH	97.37	75.44	74.39	97.85	76.66	74.39	98.33	78.05	75.96	98.82	81.88	79.09	99.33	84.67	79.62	78.57
HAR_DR	98.25	43.73	47.39	98.43	54.18	56.62	98.63	63.59	66.03	98.84	69.16	68.12	99.10	59.06	57.14	17.42
Second Highest Market capitalization: \$ 56658794 - \$ 258810481																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.55	72.62	88.56	0.87	72.10	85.27	1.22	63.78	79.90	1.56	60.49	73.48	1.94	56.67	69.32	75.56
FACI	0.51	76.78	92.55	0.89	80.94	93.24	1.34	76.26	92.37	1.80	76.60	92.20	2.28	77.12	91.85	88.21
SF-OGD	0.49	95.84	96.53	0.94	95.84	95.84	1.40	95.49	95.67	1.86	92.72	93.93	2.32	95.32	94.63	88.04
SAOCP	0.59	95.49	93.59	0.93	93.76	87.69	1.28	87.52	80.24	1.55	79.38	71.75	1.86	71.58	63.43	48.18
GARCH	0.54	80.04	74.61	0.96	76.18	72.33	1.38	70.23	67.08	1.80	67.25	63.57	2.23	64.62	63.05	69.53
HAR_DR	0.72	69.79	65.72	0.93	58.66	56.01	1.11	44.52	41.52	1.28	32.51	31.10	1.44	26.68	25.97	16.96
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.63	68.28	90.64	98.05	69.84	92.20	98.44	71.92	91.51	98.84	75.56	92.37	99.28	75.74	89.77	83.36
FACI	97.24	72.27	93.07	97.75	75.04	94.11	98.28	75.04	93.41	98.82	80.94	93.24	99.34	80.94	92.89	92.03
SF-OGD	97.21	93.07	94.45	97.73	92.55	93.93	98.26	91.33	94.97	98.79	93.93	93.93	99.33	94.11	96.53	87.35
SAOCP	97.69	80.07	74.52	98.06	86.48	81.98	98.39	88.56	84.40	98.82	91.16	87.69	99.22	86.14	81.28	47.83
GARCH	97.16	73.03	71.10	97.66	75.83	74.78	98.16	77.06	73.73	98.66	78.63	75.13	99.22	78.98	75.66	74.61
HAR_DR	98.21	41.17	40.99	98.38	49.65	50.00	98.55	58.13	57.77	98.76	61.31	61.48	99.01	58.13	52.47	16.08

Table 5: Backtesting results based on **Market Capitalization** (last 2 groups): Average number of violations in % across all assets for each quantile; % of times the Christoffersen's conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec's unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by [Kratz et al., 2018] was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Third Highest Market capitalization: $ 12235621 - $ 56579279																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.57	74.52	90.99	0.90	77.12	88.56	1.25	70.71	85.44	1.59	67.42	77.30	1.94	62.05	71.75	74.70
FACI	0.52	78.68	93.24	0.89	84.40	96.01	1.32	80.94	93.59	1.77	79.90	93.41	2.23	81.28	92.03	90.12
SF-OGD	0.48	97.23	95.32	0.93	96.71	96.01	1.36	96.01	95.67	1.83	96.71	95.84	2.28	95.32	95.49	84.23
SAOCP	0.59	94.63	91.51	0.89	93.41	88.04	1.26	86.83	83.88	1.52	81.11	72.96	1.84	71.58	64.99	51.99
GARCH	0.61	78.57	69.82	1.09	75.89	68.21	1.55	71.61	65.54	1.99	70.00	64.46	2.44	66.43	63.04	70.01
HAR_DR	1.02	64.59	61.74	1.28	61.74	56.76	1.48	50.71	46.09	1.67	41.46	39.15	1.84	35.41	31.49	20.46
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.54	70.36	89.95	97.98	73.66	90.81	98.39	72.44	89.95	98.81	74.35	89.60	99.24	71.75	85.10	82.67
FACI	97.15	73.31	93.59	97.70	75.91	92.72	98.23	78.34	93.07	98.80	81.98	93.93	99.32	77.64	90.64	92.37
SF-OGD	97.14	94.11	94.28	97.67	93.93	94.28	98.19	93.24	93.93	98.75	94.11	94.11	99.29	94.45	94.45	88.39
SAOCP	97.63	80.76	74.52	97.97	86.48	81.46	98.30	89.25	83.54	98.74	91.33	85.62	99.17	84.92	79.90	45.75
GARCH	96.87	68.75	67.86	97.40	70.36	68.04	97.95	69.46	66.61	98.51	71.25	67.50	99.12	74.64	69.82	72.14
HAR_DR	97.89	43.06	44.48	98.07	50.71	50.89	98.26	58.19	57.12	98.49	60.32	60.32	98.77	51.60	49.82	18.51
Lowest Market capitalization: $ 2589 - $ 12233558																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.57	78.76	87.56	0.91	79.10	86.36	1.24	68.22	80.14	1.59	63.90	74.78	1.94	59.41	69.95	73.92
FACI	0.54	82.38	92.75	0.91	87.05	94.30	1.35	82.90	94.30	1.78	81.35	92.23	2.23	77.89	92.06	86.87
SF-OGD	0.49	96.37	93.96	0.92	95.68	95.51	1.36	96.03	94.82	1.83	94.65	93.26	2.27	93.78	93.96	86.01
SAOCP	0.61	93.26	89.98	0.93	89.98	83.42	1.27	83.07	76.34	1.53	73.92	66.67	1.80	63.56	56.13	45.08
GARCH	1.00	65.89	58.93	1.59	64.11	58.39	2.15	60.71	56.25	2.66	58.57	53.93	3.18	58.75	54.46	58.75
HAR_DR	1.26	54.51	44.96	1.54	54.34	49.38	1.75	50.62	43.72	1.94	44.42	39.29	2.11	37.70	35.93	15.22
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.62	66.15	80.83	98.05	69.26	82.38	98.47	70.98	84.63	98.86	75.82	85.49	99.26	72.54	83.77	77.37
FACI	97.22	73.40	93.78	97.75	78.93	93.96	98.30	82.73	93.09	98.84	86.01	93.44	99.32	78.76	91.02	90.33
SF-OGD	97.15	94.13	93.96	97.71	95.34	93.96	98.23	94.30	94.47	98.78	95.85	95.34	99.33	94.82	94.82	86.87
SAOCP	97.76	70.98	66.67	98.11	79.62	73.23	98.43	84.80	77.89	98.84	90.50	82.56	99.22	86.70	80.48	39.55
GARCH	96.38	57.86	56.43	96.93	58.57	54.46	97.51	58.21	53.57	98.12	60.71	55.00	98.80	58.21	52.14	56.96
HAR_DR	97.70	42.30	41.42	97.87	46.19	43.54	98.07	52.57	47.08	98.29	55.22	50.62	98.57	49.20	44.78	15.04

4.4 Robustness check 2: Time series size

As a second robustness check, we divided our assets into four groups based on the size of their time series, with each group containing approximately the same number of assets. The first group encompasses assets with the longest time series, ranging from 1613 daily data points to 4939 daily data points, while the fourth group comprises assets with the shortest time series, ranging from 731 daily data points to 836 daily data points.

We computed the [Kupiec, 1995] test, the [Christoffersen, 1998] test, and the multinomial VaR test by [Kratz et al., 2018] for each group, with the results presented in Tables 6-7.

The empirical analysis broadly confirms the findings of the baseline case. However, it unveils some intriguing trends: AgACI, FACI, and SF-OGD exhibit consistent performances across time series of varying lengths. Instead, GARCH models seem to perform best with time series close to 1000 observations. Assets with longer time series exhibit a higher number of VaR exceedances than expected, particularly in the extreme left tail, likely attributed to significant structural breaks. Conversely, shorter time series exhibit slightly inferior performance, likely due to relatively small datasets that are insufficient for accurate parameter estimation.

SAOCP and the HAR model with daily range data perform notably better with time series containing fewer than 1000 observations compared to longer time series. It appears that these methods are more sensitive to structural breaks, which occur more frequently in assets with longer time series. This evidence indirectly corroborates the simulation studies conducted by [Susmann et al., 2023], which demonstrated that SAOCP (and to some extent, SF-OGD) tend to underestimate the quantiles when faced with a distributional shift. A notable departure from the findings of [Susmann et al., 2023] is that the simple SF-OGD model turned out pretty robust across all time samples: despite showing slightly inferior performances compared to the FACI algorithm for very long time series, these differences were mostly statistically insignificant in terms of quantile losses (not reported). Moreover, SF-OGD emerged as the top-performing model for the shortest time series.

This evidence underscores the importance of considering both the length of the time series and the model's sensitivity to structural breaks when selecting appropriate risk forecasting methods. Future research could delve deeper into understanding the mechanisms underlying these performance disparities and explore potential refinements to enhance the accuracy and robustness of risk predictions across diverse time series lengths.

Table 6: Backtesting results based on **Time series size** (first 2 groups): Average number of violations in % across all assets for each quantile; % of times the Christoffersen's conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec's unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by [Kratz et al., 2018] was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Longest time series: 4939 - 1613 (daily data)																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.43	81.10	89.50	0.77	67.10	78.10	1.11	57.20	67.50	1.46	48.40	56.60	1.84	43.00	49.30	62.60
FACI	0.44	84.80	93.50	0.90	82.00	93.10	1.36	77.80	91.70	1.81	76.90	91.00	2.29	75.30	91.10	90.10
SF-OGD	0.47	97.50	95.90	0.93	93.80	94.90	1.40	94.50	94.70	1.89	92.90	93.90	2.37	93.80	95.40	83.30
SAOCP	0.50	96.00	91.40	0.80	86.80	77.90	1.16	76.40	67.70	1.43	62.40	53.50	1.73	49.30	41.30	31.00
GARCH	0.83	68.70	61.98	1.37	66.01	58.99	1.90	63.43	57.23	2.39	62.50	57.02	2.88	59.40	55.68	59.19
HAR_DR	1.01	56.72	50.92	1.25	51.83	47.15	1.44	43.08	38.59	1.61	34.22	32.69	1.78	29.84	27.90	3.05
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.86	52.90	80.50	98.27	57.40	83.80	98.67	62.30	86.50	99.05	68.10	92.80	99.44	80.40	93.90	76.50
FACI	97.35	62.90	94.90	97.87	68.10	94.60	98.38	72.10	94.50	98.92	76.90	94.90	99.46	85.30	96.70	93.90
SF-OGD	97.34	91.40	96.40	97.86	91.70	94.90	98.36	90.60	95.40	98.89	91.90	96.20	99.42	95.80	97.10	85.90
SAOCP	98.06	63.50	57.40	98.36	77.30	69.70	98.67	85.30	79.20	99.04	92.80	87.90	99.40	92.40	89.00	35.30
GARCH	96.70	57.95	57.02	97.24	59.61	56.30	97.80	58.26	56.40	98.38	61.67	57.23	99.00	62.60	56.71	58.26
HAR_DR	97.99	36.97	38.09	98.17	42.87	44.09	98.36	50.61	50.41	98.57	52.55	51.73	98.84	42.16	40.02	3.87
Second Longest time series: 1612 - 1039 (daily data)																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.59	74.90	88.90	0.94	78.00	90.40	1.28	69.40	87.10	1.64	65.90	82.50	2.01	62.30	79.60	80.30
FACI	0.54	78.50	93.90	0.94	85.20	94.90	1.42	79.80	95.00	1.91	78.30	95.40	2.40	78.20	94.80	91.10
SF-OGD	0.53	95.50	97.60	1.00	97.70	98.00	1.48	96.00	96.30	1.96	95.40	95.80	2.44	94.80	95.10	86.60
SAOCP	0.65	92.70	89.90	1.00	95.70	91.30	1.38	92.10	86.60	1.65	86.40	77.90	1.98	80.70	72.20	50.20
GARCH	0.73	72.91	71.30	1.22	69.69	65.56	1.69	66.06	61.63	2.15	62.84	59.52	2.61	62.64	60.62	66.06
HAR_DR	1.04	63.97	63.36	1.29	60.29	55.78	1.48	48.11	42.89	1.66	36.23	33.37	1.81	28.15	26.41	17.60
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.81	72.60	88.90	98.20	75.30	91.20	98.58	76.80	92.40	98.95	81.60	92.90	99.34	77.70	90.70	82.70
FACI	97.42	79.60	95.40	97.89	82.60	95.60	98.40	83.00	95.50	98.91	86.50	95.40	99.40	83.10	95.70	92.90
SF-OGD	97.33	94.60	96.20	97.84	94.90	96.10	98.35	94.90	96.40	98.86	96.50	96.90	99.37	95.60	97.60	86.80
SAOCP	97.89	84.80	78.90	98.21	87.70	84.00	98.50	92.00	87.20	98.89	94.10	89.40	99.26	91.40	86.70	49.20
GARCH	97.16	70.80	68.48	97.63	71.70	69.08	98.12	74.92	69.69	98.63	76.74	72.61	99.18	77.95	73.11	70.09
HAR_DR	98.11	37.15	36.13	98.27	47.08	44.42	98.43	57.83	55.78	98.62	64.48	62.54	98.87	62.13	58.96	15.35

Table 7: Backtesting results based on **Time series size** (last 2 groups): Average number of violations in % across all assets for each quantile; % of times the Christoffersen's conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec's unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by [Kratz et al., 2018] was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Third Longest time series: 1038 - 837 (daily data)																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.72	69.20	87.70	1.04	83.60	92.20	1.37	78.80	92.10	1.71	79.60	90.90	2.05	76.80	87.50	82.20
FACI	0.65	72.90	90.80	0.94	86.90	95.20	1.34	84.40	94.20	1.77	83.10	94.30	2.20	84.20	93.50	88.00
SF-OGD	0.51	93.90	95.40	0.92	97.30	96.30	1.32	96.80	95.80	1.74	95.40	93.90	2.16	94.90	92.90	88.90
SAOCP	0.68	92.40	92.40	1.00	96.70	93.80	1.35	95.60	91.10	1.59	91.80	84.60	1.88	86.20	78.20	65.70
GARCH	0.70	80.57	74.79	1.19	79.31	73.11	1.64	73.63	71.43	2.11	72.16	68.70	2.55	69.43	66.07	73.74
HAR_DR	1.17	69.23	61.12	1.43	62.80	58.48	1.64	52.37	48.58	1.83	43.94	41.41	2.00	38.67	34.88	27.82
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.41	79.10	93.60	97.85	82.40	92.40	98.28	78.90	91.60	98.69	80.60	86.30	99.12	64.90	78.70	84.20
FACI	97.11	82.80	92.70	97.66	85.10	93.80	98.23	82.00	93.20	98.77	86.70	93.90	99.24	71.00	87.60	90.10
SF-OGD	96.95	93.00	91.80	97.52	94.30	92.50	98.08	93.80	92.80	98.67	95.10	94.50	99.24	91.30	94.30	90.80
SAOCP	97.37	91.60	86.70	97.77	92.10	87.90	98.10	90.90	85.80	98.59	90.90	85.40	99.05	81.00	74.90	56.30
GARCH	96.88	75.00	74.89	97.42	77.21	74.68	97.97	77.73	73.74	98.52	77.52	72.90	99.11	78.68	75.32	77.84
HAR_DR	97.83	42.99	43.52	98.00	51.32	50.16	98.18	57.01	55.32	98.39	63.96	58.38	98.66	61.85	55.22	25.40
Shortest time series: 836 - 731 (daily data)																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.77	74.60	85.10	1.10	85.30	92.80	1.44	84.00	91.10	1.76	83.20	90.70	2.10	82.10	88.00	86.30
FACI	0.69	76.20	87.90	0.89	87.60	94.30	1.25	85.40	91.80	1.64	85.50	90.40	2.05	86.60	87.50	83.30
SF-OGD	0.53	97.20	91.80	0.91	96.60	95.80	1.28	96.20	93.60	1.64	94.30	90.50	1.99	92.50	86.80	88.40
SAOCP	0.73	95.00	86.30	1.01	96.10	93.30	1.36	94.20	89.50	1.59	91.50	85.00	1.83	84.50	75.50	74.20
GARCH	0.78	84.06	66.40	1.31	77.30	73.66	1.82	75.88	69.73	2.30	73.66	67.61	2.77	72.96	66.80	73.56
HAR_DR	1.09	76.11	57.69	1.35	66.09	62.75	1.56	61.13	54.15	1.74	55.57	47.47	1.92	48.89	43.62	37.25
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	96.97	76.60	89.00	97.43	71.60	86.00	97.86	68.30	80.20	98.30	70.60	75.00	98.78	51.00	59.00	76.40
FACI	96.80	79.00	87.20	97.36	75.10	86.20	97.95	75.50	86.40	98.52	80.40	87.90	98.90	58.10	69.00	78.50
SF-OGD	96.68	89.70	85.50	97.30	91.00	88.50	97.93	92.60	89.60	98.54	94.70	91.10	99.13	89.20	90.40	90.70
SAOCP	97.03	88.90	85.30	97.49	90.40	85.60	97.81	84.40	77.10	98.36	86.30	80.10	98.83	75.00	62.40	56.10
GARCH	96.53	70.43	67.00	97.10	69.83	66.70	97.66	70.74	66.90	98.26	74.07	70.43	98.92	73.97	66.40	72.45
HAR_DR	97.84	54.45	51.92	98.00	58.20	57.49	98.19	63.16	58.91	98.42	66.60	63.46	98.69	66.80	55.06	33.00

4.5 Robustness check 3: Different forecasting methods

As a third robustness check, we wanted to assess the impact on our results by employing a more complex model specification than an AR(1) model, namely a single-hidden-layer neural network using seven lagged daily log-returns as inputs and three hidden units.

We computed the [Kupiec, 1995] test, the [Christoffersen, 1998] test, and the multinomial VaR test by [Kratz et al., 2018] for the four ACI algorithms using the neural network as forecasting model, and the results are presented in Table 8. We also computed the asymmetric QL function proposed by [González-Rivera et al., 2004] and employed the MCS method by [Hansen et al., 2011], see table 9 and 10. Similarly to the baseline case, we considered only assets for which all six models reached numerical convergence.

In terms of VaR violations, there are no notable differences among the models, except for SAOCP, where the number of instances where the Christoffersen's test, the Kupiec test, and the multinomial VaR test did not reject the null hypothesis was 5%-12% lower than the baseline case. This evidence suggests that the more volatile mean forecasts computed using a neural network penalized this algorithm. A similar phenomenon, albeit on a smaller scale (3%-5% lower), was also observed for the AgACI algorithm.

Regarding quantile loss functions, all four ACI algorithms were strongly penalized in terms of average ranking, with SAOCP exhibiting the largest decline in ranking across all competing models. Likewise, all four ACI algorithms demonstrated a decrease in the percentage of times the models were included in the Model Confidence Set (20%-30% lower), particularly affecting the left tail of the distribution.

In general, employing a more complex forecasting model for the mean of the assets' log-returns with ACI algorithms did not result in more precise risk estimates. This outcome can probably be attributed to the lower model bias being outweighed by the higher variance of the model estimates. These findings underscore the intricate trade-offs involved in selecting forecasting models for risk management purposes, highlighting the importance of considering both model complexity and estimation accuracy in decision-making processes.

Table 8: Average number of violations in % across all assets for each quantile **using a neural network**; % of times the Christoffersen's conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec's unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by [Kratz et al., 2018] was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.65	70.00	87.80	0.97	73.48	87.43	1.29	66.58	82.58	1.63	63.60	77.70	1.98	61.98	73.88	74.20
FACI	0.61	75.18	92.18	0.94	83.20	95.43	1.37	80.63	94.33	1.81	78.90	93.18	2.27	78.20	93.08	87.90
SF-OGD	0.52	95.38	95.98	0.96	96.58	97.35	1.40	96.30	96.23	1.86	95.60	95.15	2.31	95.18	94.28	83.03
SAOCP	0.60	93.25	89.65	0.88	88.55	83.10	1.16	78.55	72.43	1.40	71.85	63.38	1.64	62.58	55.25	46.23
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.62	63.20	83.55	98.03	64.70	84.90	98.41	64.48	85.75	98.79	69.13	86.40	99.19	63.05	79.95	76.60
FACI	97.22	73.63	93.43	97.75	75.30	93.58	98.29	75.95	94.25	98.81	80.40	94.38	99.25	70.60	87.53	88.00
SF-OGD	97.18	93.70	93.90	97.72	94.85	95.15	98.24	95.25	95.95	98.79	95.85	95.93	99.33	92.93	95.20	84.48
SAOCP	97.97	67.70	61.80	98.27	74.35	68.58	98.55	77.85	73.30	98.90	87.90	82.60	99.24	86.95	83.15	42.40

Quantile	AgACI	FACI	SF.OGD	SAOCP	GARCH	HAR_DR
VaR_0.5	4.45	5.26	3.68	3.39	1.84	2.37
VaR_1.0	4.25	4.67	4.03	3.84	1.71	2.51
VaR_1.5	4.12	4.16	4.24	4.17	1.62	2.69
VaR_2.0	3.97	3.83	4.35	4.47	1.53	2.85
VaR_2.5	3.84	3.62	4.43	4.64	1.48	2.98
VaR_97.5	3.89	3.75	4.39	4.49	1.44	3.05
VaR_98.0	4.06	3.91	4.31	4.30	1.51	2.91
VaR_98.5	4.26	4.22	4.14	4.04	1.57	2.76
VaR_99.0	4.34	4.65	3.93	3.75	1.68	2.66
VaR_99.5	4.46	5.12	3.62	3.38	1.80	2.62

Table 9: Average rank of the models across all assets for each quantile based on the asymmetric quantile loss (QL) function proposed by [González-Rivera et al., 2004]. ACI algorithms use a neural network.

Quantile	AgACI	FACI	SF.OGD	SAOCP	GARCH	HAR_DR
VaR_0.5	0.39	0.27	0.44	0.51	0.90	0.81
VaR_1.0	0.46	0.37	0.43	0.48	0.94	0.76
VaR_1.5	0.51	0.48	0.43	0.46	0.95	0.72
VaR_2.0	0.56	0.56	0.42	0.44	0.96	0.68
VaR_2.5	0.59	0.62	0.40	0.41	0.97	0.67
VaR_99.5	0.67	0.70	0.48	0.50	0.99	0.74
VaR_99.0	0.64	0.65	0.51	0.53	0.98	0.76
VaR_98.5	0.59	0.58	0.52	0.55	0.97	0.78
VaR_98.0	0.55	0.48	0.53	0.58	0.96	0.82
VaR_97.5	0.50	0.37	0.57	0.62	0.95	0.84

Table 10: Number of times (in %) when the model was included into the Model Confidence Set (MCS) at the 10% confidence level across all assets. ACI algorithms use a neural network.

4.6 A comparison with methods that predict quantiles directly

As a fourth robustness check, we employed the Symmetric Absolute Value (SAV)-CAViar model with a selected group of crypto-assets: the two most capitalized assets (Bitcoin and Ethereum) and the two least capitalized assets (Bubble and Litecoin-Token) for which all models achieved numerical convergence. The plots of the prices of these four cryptoassets are reported in Figure 1, while the main descriptive statistics of their log-returns in Table 11.

We computed the [Kupiec, 1995] test, the [Christoffersen, 1998] test, and the multinomial VaR test by [Kratz et al., 2018] for the four ACI algorithms using the AR(1) as forecasting model, for the GARCH model with student's t errors, for the HAR model with the daily range, and for the CAViaR-SAV model. We also computed the asymmetric QL function proposed by [González-Rivera et al., 2004] and employed the MCS method by [Hansen et al., 2011]. The results for Bitcoin and Ethereum are presented in Table 12, while for Bubble and Litecoin-Token in Table 13.

In terms of VaR violations, all four ACI algorithms were able to properly model both the left and right tails of the return distributions, with the exception of SAOCP, which continued to show issues

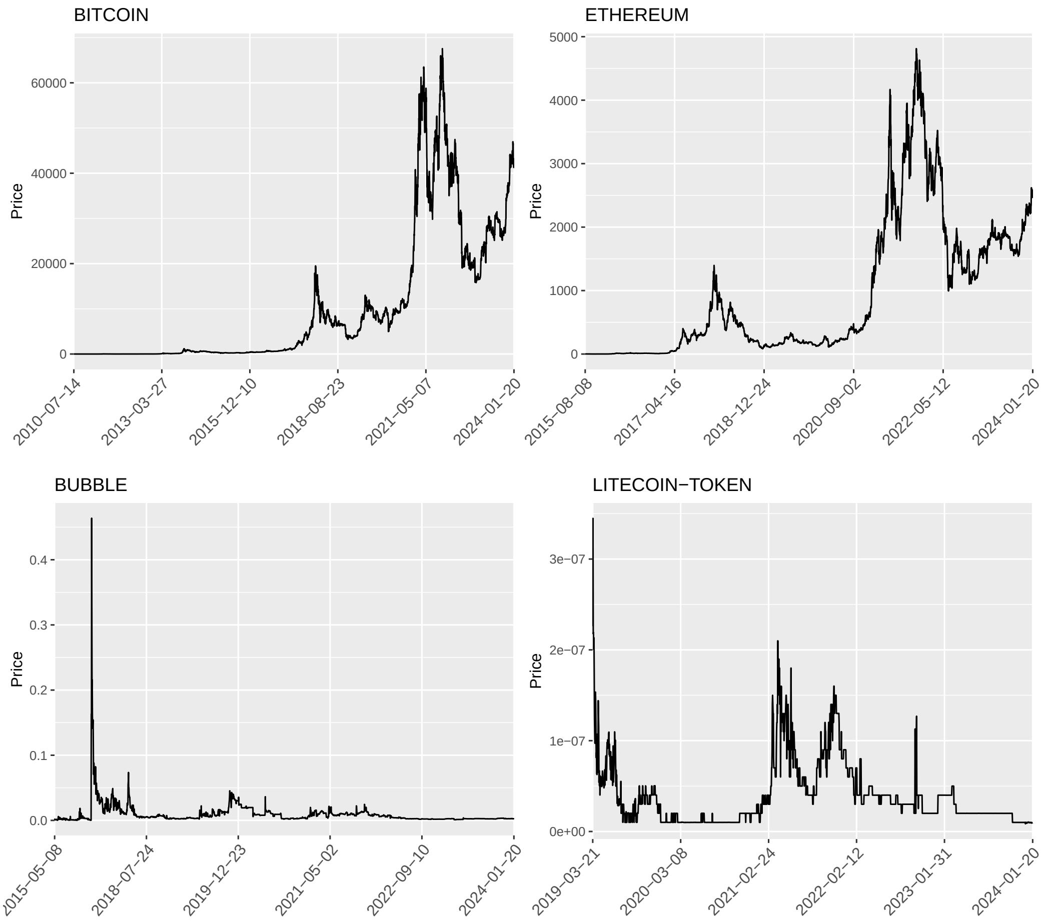

Figure 1: Plots of the prices of these four crypto-assets: Bitcoin, Ethereum, Bubble, Litecoin-Token.

Asset	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Bitcoin	0.27%	0.05	-0.68	0.40	0.00	-1.02	24.03
Ethereum	0.26%	0.06	-0.55	0.41	0.00	0.01	11.75
Bubble	0.05%	0.26	-2.45	6.67	0.00	6.93	192.23
Litecoin-token	-0.18%	0.19	-1.15	1.73	0.00	0.08	16.32

Table 11: Log-returns' main descriptive statistics: Bitcoin, Ethereum, Bubble, Litecoin-Token.

when modeling the right tail of the distribution. The GARCH model worked well with Ethereum but was unable to correctly estimate the quantiles for Bitcoin and the assets with the lowest capitalization. The HAR model performed the worst across all assets, while the CAViaR model passed all coverage tests for the left tail of the assets with the highest market capitalization but failed the tests for the right tail and for the assets with the lowest capitalization.

Regarding quantile loss functions, the GARCH model generally exhibited the lowest asymmetric loss functions for Bitcoin and Ethereum, followed by the CAViaR model and the ACI models. However, the GARCH model showed the worst losses (along with the HAR model) for the assets with the lowest market capitalization, whereas the ACI methods performed the best. This confirms that the extreme volatility of these types of assets strongly impacts their numerical stability. Interestingly, the CAViaR model demonstrated remarkably low losses across all assets, indicating its greater computational robustness compared to the GARCH and HAR models. It is important to note that in most instances, the differences between the models' losses were not statistically significant, resulting in the vast majority of the considered models being included in the model confidence set.

In summary, while traditional models like GARCH and HAR exhibit strengths and weaknesses across different assets, the adaptive nature of ACI methods, particularly their robustness in highly volatile markets, highlights their potential as valuable tools in financial risk management. The CAViaR model's consistent performance across various assets further underscores its reliability, making it an interesting alternative to more conventional approaches.

Table 12: Number of VaR violations in % across **Bitcoin** and **Ethereum** for each quantile and model; p-values in % for the Christoffersen's conditional coverage (CC) test; p-values in % for the Kupiec's unconditional coverage (UC) test; Asymmetric quantile loss (QL) function by [González-Rivera et al., 2004]; the model was included in the Model Confidence Set (MCS): YES or NO; p-values in % for the multinomial VaR test by [Kratz et al., 2018], for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

BITCOIN (ID = 1)

Model	VaR_0.5	CC_0.5	UC_0.5	Asymmetric QL	MCS	VaR_1.0	CC_1.0	UC_1.0	Asymmetric QL	MCS	VaR_1.5	CC_1.5	UC_1.5	Asymmetric QL	MCS	VaR_2.0	CC_2.0	UC_2.0	Asymmetric QL	MCS	VaR_2.5	CC_2.5	UC_2.5	Asymmetric QL	MCS	ES_2.5_test
AgACI	0.46	0.00	69.10	5.76	YES	0.96	0.00	79.47	8.99	YES	1.49	0.00	94.08	11.74	YES	1.95	0.02	79.25	14.00	NO	2.32	0.00	42.34	15.73	YES	84.26
FACI	0.83	0.00	0.38	5.67	YES	1.27	0.00	8.03	8.86	YES	1.75	0.00	17.70	11.18	YES	2.27	0.00	19.56	13.24	YES	2.84	0.00	14.68	15.09	YES	10.04
SF-OGD	0.66	15.12	15.39	5.18	YES	1.22	3.54	14.08	8.76	YES	1.84	0.01	7.05	11.27	YES	2.34	1.47	11.03	13.60	YES	3.06	0.73	1.89	15.70	YES	18.25
SAOCP	0.68	22.07	10.60	5.22	YES	1.20	37.81	18.23	8.27	YES	1.57	91.36	68.25	10.93	YES	2.14	37.98	49.60	13.28	YES	2.60	28.32	66.17	15.60	YES	43.33
GARCH	0.83	1.10	0.38	4.69	YES	1.64	0.04	0.01	7.91	YES	2.36	0.01	0.00	10.57	YES	3.08	0.00	0.00	12.88	YES	3.72	0.00	0.00	14.96	YES	0.01
HAR_DR	1.29	0.00	0.00	5.80	YES	1.64	0.00	0.01	9.13	YES	2.14	0.17	0.08	12.12	YES	2.43	10.21	4.60	14.88	NO	2.60	29.07	66.17	17.42	NO	0.00
CAViar	0.33	20.20	7.83	5.13	YES	0.72	10.81	4.63	8.33	YES	1.03	1.26	0.53	10.89	YES	1.60	12.78	4.31	13.20	YES	2.10	16.28	7.40	15.15	YES	12.59

Model	VaR_97.5	CC_97.5	UC_97.5	Asymmetric QL	MCS	VaR_98.0	CC_98.0	UC_98.0	Asymmetric QL	MCS	VaR_98.5	CC_98.5	UC_98.5	Asymmetric QL	MCS	VaR_99.0	CC_99.0	UC_99.0	Asymmetric QL	MCS	VaR_99.5	CC_99.5	UC_99.5	Asymmetric QL	MCS	ES_97.5_test
AgACI	98.56	0.00	0.00	14.38	NO	98.91	0.00	0.00	12.59	NO	99.23	0.00	0.00	10.58	NO	99.54	0.00	0.00	7.99	NO	99.80	0.40	0.09	4.90	NO	0.01
FACI	97.86	2.19	11.26	13.92	NO	98.25	22.60	21.55	12.05	NO	98.73	19.34	18.49	10.01	NO	99.34	1.91	1.26	7.68	NO	99.72	0.71	2.43	4.78	NO	10.97
SF-OGD	98.05	1.42	1.25	13.59	NO	98.34	20.05	9.23	11.91	NO	98.84	5.14	4.80	9.64	NO	99.23	2.32	9.59	7.55	NO	99.67	20.20	7.83	4.29	YES	8.26
SAOCP	98.51	0.00	0.00	13.55	NO	98.62	0.26	0.14	11.82	NO	98.91	3.40	1.74	9.69	NO	99.39	1.49	0.45	7.20	NO	99.74	4.18	1.22	4.29	YES	0.00
GARCH	96.87	0.48	0.90	12.18	YES	97.46	1.23	1.29	10.40	YES	98.19	22.03	9.01	8.46	YES	98.97	60.32	85.21	6.34	YES	99.43	70.13	52.08	3.87	YES	3.73
HAR_DR	97.44	0.10	80.26	15.83	NO	97.79	0.12	32.26	13.46	NO	98.05	0.01	1.77	10.91	NO	98.36	0.00	0.01	8.11	NO	98.84	0.00	0.00	4.98	NO	0.00
CAViar	98.25	0.26	0.06	12.59	NO	98.67	0.28	0.06	10.83	NO	98.84	5.14	4.80	8.92	NO	99.21	18.47	13.27	6.93	NO	99.58	13.36	40.33	4.22	YES	0.29

ETHEREUM (ID = 1027)

Model	VaR_0.5	CC_0.5	UC_0.5	Asymmetric QL	MCS	VaR_1.0	CC_1.0	UC_1.0	Asymmetric QL	MCS	VaR_1.5	CC_1.5	UC_1.5	Asymmetric QL	MCS	VaR_2.0	CC_2.0	UC_2.0	Asymmetric QL	MCS	VaR_2.5	CC_2.5	UC_2.5	Asymmetric QL	MCS	ES_2.5_test
AgACI	0.46	0.00	69.10	3.29	YES	0.96	0.00	79.47	5.35	YES	1.49	0.00	94.08	7.31	YES	1.95	0.02	79.25	8.87	YES	2.32	0.00	42.34	10.20	YES	84.26
FACI	0.83	0.00	0.38	3.49	YES	1.27	0.00	8.03	5.45	YES	1.75	0.00	17.70	7.25	YES	2.27	0.00	19.56	8.77	YES	2.84	0.00	14.68	10.11	YES	10.04
SF-OGD	0.66	15.12	15.39	3.53	YES	1.22	3.54	14.08	5.65	YES	1.84	0.01	7.05	7.36	YES	2.34	1.47	11.03	9.08	NO	3.06	0.73	1.89	10.56	NO	18.25
SAOCP	0.68	22.07	10.60	3.44	YES	1.20	37.81	18.23	5.68	YES	1.57	91.36	68.25	7.45	YES	2.14	37.98	49.60	9.16	NO	2.60	28.32	66.17	10.74	NO	43.33
GARCH	0.55	85.93	71.12	3.22	YES	0.95	75.64	81.13	5.36	YES	1.29	40.58	34.49	7.10	YES	1.69	24.45	23.42	8.63	YES	2.09	29.67	16.21	9.98	YES	61.43
HAR_DR	1.21	0.00	0.00	3.44	YES	1.58	0.99	0.51	5.26	YES	1.95	12.83	6.68	6.84	YES	2.39	35.24	16.14	8.29	YES	2.75	57.88	40.29	9.64	YES	0.04
CAViar	0.37	56.64	30.25	3.19	YES	0.88	66.03	52.55	5.39	YES	1.32	58.87	43.57	7.18	YES	1.91	94.41	73.44	8.64	YES	2.57	12.37	81.40	10.06	YES	71.25

Model	VaR_97.5	CC_97.5	UC_97.5	Asymmetric QL	MCS	VaR_98.0	CC_98.0	UC_98.0	Asymmetric QL	MCS	VaR_98.5	CC_98.5	UC_98.5	Asymmetric QL	MCS	VaR_99.0	CC_99.0	UC_99.0	Asymmetric QL	MCS	VaR_99.5	CC_99.5	UC_99.5	Asymmetric QL	MCS	ES_97.5_test
AgACI	98.56	0.00	0.00	9.34	YES	98.91	0.00	0.00	8.07	YES	99.23	0.00	0.00	6.57	YES	99.54	0.00	0.00	4.95	YES	99.80	0.40	0.09	3.05	YES	0.01
FACI	97.86	2.19	11.26	9.31	YES	98.25	22.60	21.55	7.90	YES	98.73	19.34	18.49	6.46	YES	99.34	1.91	1.26	4.81	YES	99.72	0.71	2.43	3.02	YES	10.97
SF-OGD	98.05	1.42	1.25	9.71	NO	98.34	20.05	9.23	8.23	NO	98.84	5.14	4.80	6.48	YES	99.23	2.32	9.59	4.80	YES	99.67	20.20	7.83	2.84	YES	8.26
SAOCP	98.51	0.00	0.00	9.83	NO	98.62	0.26	0.14	8.18	NO	98.91	3.40	1.74	6.68	NO	99.39	1.49	0.45	4.81	YES	99.74	4.18	1.22	2.81	YES	0.00
GARCH	97.91	29.67	16.21	8.87	YES	98.38	14.74	13.87	7.57	YES	98.90	14.32	7.28	6.14	YES	99.38	9.56	3.43	4.59	YES	99.63	56.64	30.25	2.81	YES	41.02
HAR_DR	96.73	2.52	1.41	9.20	YES	97.25	2.38	0.78	7.84	YES	97.80	1.58	0.47	6.40	YES	98.13	0.02	0.00	4.82	YES	98.68	0.00	0.00	2.99	YES	0.01
CAViar	98.46	0.25	0.06	8.98	YES	98.79	0.44	0.15	7.64	YES	99.27	0.11	0.03	6.13	YES	99.52	0.89	0.23	4.51	YES	99.67	39.72	18.13	2.80	YES	0.48

Table 13: Number of VaR violations in % across **Bubble** and **Litecoin-Token** for each quantile and model; p-values in % for the Christoffersen's conditional coverage (CC) test; p-values in % for the Kupiec's unconditional coverage (UC) test; Asymmetric quantile loss (QL) function by [González-Rivera et al., 2004]; the model was included in the Model Confidence Set (MCS): YES or NO; p-values in % for the multinomial VaR test by [Kratz et al., 2018], for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

	BUBBLE (ID = 918)																									
Model	VaR_0.5	CC_0.5	UC_0.5	Asymmetric QL	MCS	VaR_1.0	CC_1.0	UC_1.0	Asymmetric QL	MCS	VaR_1.5	CC_1.5	UC_1.5	Asymmetric QL	MCS	VaR_2.0	CC_2.0	UC_2.0	Asymmetric QL	MCS	VaR_2.5	CC_2.5	UC_2.5	Asymmetric QL	MCS	ES_2.5_test
AgACI	0.28	30.18	12.39	9.11	YES	0.76	44.77	23.79	13.42	YES	1.18	4.17	20.98	17.09	YES	1.65	2.93	24.03	20.41	YES	2.08	8.19	20.09	23.22	YES	70.88
FACI	0.43	85.55	61.61	9.54	YES	0.99	82.57	97.03	13.25	YES	1.65	25.43	56.81	16.99	YES	1.94	2.42	83.44	20.46	YES	2.36	8.75	68.11	22.92	YES	55.15
SF-OGD	0.38	69.08	40.51	8.56	YES	0.99	82.57	97.03	13.14	YES	1.46	74.03	89.22	17.20	YES	2.17	19.42	57.52	20.40	YES	2.69	45.03	57.52	22.80	YES	72.42
SAOCP	0.43	85.55	61.61	8.97	YES	0.80	56.74	34.56	14.00	YES	1.13	27.19	14.74	17.40	YES	1.42	9.31	4.34	20.98	YES	1.94	21.67	8.41	23.91	YES	45.28
GARCH	2.69	0.00	0.00	13.74	NO	3.73	0.00	0.00	17.64	NO	4.68	0.00	0.00	20.45	NO	5.05	0.00	0.00	22.73	YES	5.90	0.00	0.00	24.66	YES	0.00
HAR_DR	0.19	7.06	2.15	9.09	YES	0.29	0.05	0.01	15.98	NO	0.33	0.00	0.00	22.13	NO	0.43	0.00	0.00	27.73	NO	0.48	0.00	0.00	32.96	NO	0.00
CAViar	1.81	0.00	0.00	10.82	YES	2.10	0.00	0.00	14.54	YES	2.14	1.63	2.24	17.79	YES	2.76	0.47	1.80	21.17	YES	2.86	17.09	30.18	23.64	YES	0.00
Model	VaR_97.5	CC_97.5	UC_97.5	Asymmetric QL	MCS	VaR_98.0	CC_98.0	UC_98.0	Asymmetric QL	MCS	VaR_98.5	CC_98.5	UC_98.5	Asymmetric QL	MCS	VaR_99.0	CC_99.0	UC_99.0	Asymmetric QL	MCS	VaR_99.5	CC_99.5	UC_99.5	Asymmetric QL	MCS	ES_97.5_test
AgACI	98.16	0.26	4.21	27.13	YES	98.39	2.38	18.02	24.26	YES	98.72	9.55	38.29	20.53	YES	99.06	4.45	79.64	16.77	YES	99.43	85.25	66.95	11.26	YES	19.94
FACI	97.64	9.91	68.11	26.77	YES	98.16	38.78	59.93	22.99	YES	98.35	5.77	56.81	20.49	YES	98.91	7.24	69.34	16.14	YES	99.48	93.65	89.89	10.86	YES	33.70
SF-OGD	97.73	23.42	48.62	26.37	YES	98.21	8.14	49.30	23.79	YES	98.49	4.22	96.51	19.60	YES	99.01	5.55	97.03	15.58	YES	99.39	14.48	47.25	10.57	YES	60.98
SAOCP	98.16	5.65	4.21	26.29	YES	98.35	16.40	24.03	23.61	YES	98.68	12.54	49.33	19.70	YES	98.91	7.24	69.34	15.31	YES	99.39	71.29	47.25	9.99	YES	5.37
GARCH	93.72	0.00	0.00	27.10	YES	94.47	0.00	0.00	24.68	YES	95.23	0.00	0.00	21.88	YES	96.08	0.00	0.00	18.52	YES	97.50	0.00	0.00	13.96	NO	0.00
HAR_DR	99.24	0.00	0.00	34.99	NO	99.29	0.00	0.00	29.54	NO	99.48	0.01	0.00	23.71	NO	99.52	2.61	0.73	17.35	YES	99.62	70.17	42.11	10.13	YES	0.00
CAViar	98.24	2.90	2.27	25.24	YES	98.57	2.95	4.95	22.48	YES	99.05	0.41	2.73	19.26	YES	99.29	0.57	16.68	15.05	YES	99.14	3.74	3.50	10.68	YES	0.00
	LITECOIN-TOKEN (ID = 3807)																									
Model	VaR_0.5	CC_0.5	UC_0.5	Asymmetric QL	MCS	VaR_1.0	CC_1.0	UC_1.0	Asymmetric QL	MCS	VaR_1.5	CC_1.5	UC_1.5	Asymmetric QL	MCS	VaR_2.0	CC_2.0	UC_2.0	Asymmetric QL	MCS	VaR_2.5	CC_2.5	UC_2.5	Asymmetric QL	MCS	ES_2.5_test
AgACI	0.21	22.85	8.65	5.56	YES	0.50	10.96	3.70	9.41	YES	1.14	2.12	24.87	12.51	YES	1.43	2.63	10.61	15.12	YES	1.78	4.13	7.02	17.67	YES	21.56
FACI	0.29	45.82	21.49	5.78	YES	0.64	33.36	14.93	8.62	YES	1.14	20.37	24.87	11.35	YES	1.43	15.40	10.61	14.42	YES	2.00	14.02	21.16	16.67	YES	57.56
SF-OGD	0.29	45.82	21.49	5.80	YES	0.71	48.74	25.54	9.21	YES	1.14	42.73	24.87	12.82	YES	1.71	53.42	42.95	15.36	YES	1.93	29.80	15.15	17.67	YES	43.39
SAOCP	0.43	90.24	69.49	5.64	YES	0.64	33.36	14.93	8.94	YES	1.07	32.08	16.27	12.49	YES	1.21	6.17	2.32	15.08	YES	1.57	4.01	1.67	17.47	YES	11.95
GARCH	4.35	0.00	0.00	16.43	NO	5.35	0.00	0.00	18.53	NO	5.92	0.00	0.00	20.03	NO	6.70	0.00	0.00	21.08	NO	6.85	0.00	0.00	21.91	YES	0.00
HAR_DR	4.49	0.00	0.00	14.24	NO	4.85	0.00	0.00	17.06	NO	4.85	0.00	0.00	19.19	NO	4.92	0.00	0.00	20.98	NO	5.06	0.00	0.00	22.57	YES	0.00
CAViar	0.36	71.19	42.23	5.74	YES	0.50	10.96	3.70	9.49	YES	0.86	8.80	3.10	12.51	YES	1.43	20.29	10.61	15.20	YES	1.85	16.43	10.50	17.38	YES	26.40
Model	VaR_97.5	CC_97.5	UC_97.5	Asymmetric QL	MCS	VaR_98.0	CC_98.0	UC_98.0	Asymmetric QL	MCS	VaR_98.5	CC_98.5	UC_98.5	Asymmetric QL	MCS	VaR_99.0	CC_99.0	UC_99.0	Asymmetric QL	MCS	VaR_99.5	CC_99.5	UC_99.5	Asymmetric QL	MCS	ES_97.5_test
AgACI	98.00	2.47	21.16	17.82	YES	98.22	16.68	55.47	15.96	YES	98.50	1.01	99.47	13.61	YES	99.00	2.08	99.57	10.61	YES	99.22	0.01	16.33	7.10	YES	10.63
FACI	97.15	6.10	40.74	17.33	YES	97.57	1.55	27.10	15.60	YES	98.15	13.03	29.22	12.69	YES	98.93	2.69	79.48	9.97	YES	99.43	0.15	71.39	6.45	YES	80.43
SF-OGD	97.00	50.19	24.87	18.12	YES	97.79	43.48	57.87	16.02	YES	98.22	45.17	39.69	13.04	YES	98.79	60.89	43.89	9.76	YES	99.36	73.19	47.05	6.86	YES	72.73
SAOCP	98.72	0.46	0.13	17.87	YES	99.00	1.09	0.31	15.79	YES	99.00	22.71	10.02	13.53	YES	99.07	86.00	78.16	10.02	YES	99.57	90.63	69.49	6.55	YES	0.03
GARCH	92.72	0.00	0.00	21.00	YES	93.30	0.00	0.00	20.16	NO	93.72	0.00	0.00	19.18	NO	94.72	0.00	0.00	17.89	NO	95.93	0.00	0.00	15.95	NO	0.00
HAR_DR	95.08	0.00	0.00	22.68	NO	95.44	0.00	0.00	21.11	NO	95.44	0.00	0.00	19.36	NO	95.51	0.00	0.00	17.28	NO	95.86	0.00	0.00	14.57	NO	0.00
CAViar	98.57	1.50	0.52	18.27	YES	98.86	3.69	1.25	16.66	YES	98.79	53.36	35.98	14.08	YES	99.22	64.28	39.96	10.78	YES	99.57	90.24	69.49	6.42	YES	0.75

5 Discussion and Conclusions

This paper compared the performance of four Adaptive Conformal Inference (ACI) algorithms with traditional volatility models for daily data, such as GARCH models and daily range models, in computing the Value-at-Risk (VaR) at various probability levels for 4000 crypto-assets observed between 2010 and 2024. Additionally, this comparison indirectly assessesed the quality of the models' Expected Shortfall (ES) by using a multinomial test of VaR violations across multiple levels as a means of backtesting the ES, as proposed by [Kratz et al., 2018].

To achieve this objective, we employed four ACI algorithms, including the Aggregated ACI by [Zaffran et al., 2022], the Fully Adaptive Conformal Inference by [Gibbs and Candès, 2022], the Scale-Free Online Gradient Descent by [Bhatnagar et al., 2023], and the Strongly Adaptive Online Conformal Prediction by [Bhatnagar et al., 2023]. These algorithms, explicitly designed to address scenarios where data arrives sequentially, dynamically adjust the width of prediction intervals in response to observed data, thereby providing adaptive and accurate uncertainty quantification. As benchmark models for daily data, we used the GARCH(1,1) model with a symmetric Student's t-distribution for the standardized errors and the daily range volatilities computed using the Garman-Klass estimator together with an HAR model.

In terms of VaR violations across all quantiles, FACI and SF-OGD were able to properly model the left and right tails of the distribution for the vast majority of crypto-assets, followed by AgACI, while SAOCP exhibited the poorest performance among ACI algorithms. Conversely, GARCH and HAR models faced challenges in achieving numerical convergence for approximately 2.5% of assets, particularly those with extreme variability and/or relatively small datasets ($T < 1000$). Despite this, GARCH served as a reliable benchmark model, slightly underestimating the VaR for the most extreme quantiles ($p_i \leq 1.0\%$) while maintaining accuracy for the other quantiles. In contrast, the HAR model with daily range volatilities proved to be the least effective, underestimating lower quantiles up to $p_i = 1\%$ and severely overestimating higher quantiles. Similar issues emerged for the right tail of the distribution.

Regarding asymmetric quantile loss functions, our analysis revealed that the GARCH model consistently emerged as the top-ranked model for the majority of assets and was almost always included in the Model Confidence Set. While ACI models demonstrated proficiency in estimating quantiles for most assets, they exhibited challenges in estimating the most extreme quantiles ($p_i \leq 1\%$ and $p_i \geq 99\%$), particularly the AgACI and FACI models, which showed rather large asymmetric losses and lower ranking. However, SF-OGD and SAOCP models displayed greater precision with smaller losses.

These findings have significant implications for financial risk management: while a traditional benchmark like the GARCH model remains relevant, newer approaches such as ACI models offer promising alternatives, particularly for assets with complex dynamics such as crypto-assets, albeit with some caveats in extreme quantile estimation. Given that ACI models are more precise in terms of VaR violations, while GARCH models are better in terms of asymmetric quantile losses, forecasting combinations are a possibility, and we leave this issue as an avenue for further research.

Finally, we performed a set of robustness checks to verify that our results also held with different settings. In terms of market capitalization of crypto-assets, the results are similar to the baseline case. However, we found that the performance of the GARCH model and, to a lesser extent, the SAOCP algorithm deteriorated significantly when focusing on assets with the lowest market capitalization. It is well known that crypto-assets with lower market capitalization tend to experience higher levels of volatility. This heightened volatility can pose challenges for several modeling approaches, which may struggle to adequately capture and predict extreme movements in these assets' prices. As such, future research could explore alternative modeling techniques specifically tailored to address the unique characteristics and dynamics of lower-capitalization crypto-assets, potentially enhancing the accuracy and robustness of risk management strategies in this segment of the market.

As a second robustness check, we divided our assets into four groups based on the size of their time series: AgACI, FACI, and SF-OGD exhibited consistent performances across time series of varying lengths. Instead, GARCH models seemed to perform best with time series close to 1000 observations. SAOCP and the HAR model with daily range data performed notably better with time series containing fewer than 1000 observations compared to longer time series. It appears that these methods are more sensitive to structural breaks, which occur more frequently in assets with longer time series. This evidence indirectly corroborates the simulation studies conducted by [Susmann et al., 2023], which demonstrated that SAOCP tends to underestimate the quantiles when faced with a distributional shift. This evidence underscores the importance of considering both the length of the time series and the model's sensitivity to structural breaks when selecting appropriate risk forecasting methods. Future research could delve deeper into understanding the mechanisms underlying these performance disparities and explore potential refinements to enhance the accuracy and robustness of risk predictions across diverse time series lengths.

As a third robustness check, we assessed the impact on our results by employing a single-hidden-layer neural network instead of a simple AR(1) like in the baseline case. In terms of VaR violations, there are no notable differences among the models (except for SAOCP), while, regarding quantile loss functions, all four ACI algorithms were strongly penalized in terms of average ranking, with SAOCP exhibiting the largest decline in ranking across all competing models. In general, employing a more complex forecasting model for the mean of the assets' log-returns with ACI algorithms did not result in more precise risk estimates. This outcome can probably be attributed to the lower model bias being outweighed by the higher variance of the model estimates. These findings underscore the intricate trade-offs involved in selecting forecasting models for risk management purposes, highlighting the importance of considering both model complexity and estimation accuracy in decision-making processes.

As a fourth robustness check, we tested the Symmetric Absolute Value (SAV)-CAViaR model with four crypto-assets, including the most and least capitalized. ACI algorithms effectively modeled both tails of the return distributions, except for SAOCP on the right tail. The GARCH model performed well for Ethereum but struggled with Bitcoin and low-capitalization assets. The HAR model performed the worst, while the CAViaR model passed coverage tests for the left tail of high-capitalization assets but failed for the right tail and low-capitalization assets. The GARCH model had the lowest asymmetric losses for Bitcoin and Ethereum but performed poorly for low-capitalization assets, where ACI methods excelled. Overall, ACI methods demonstrated robustness in highly volatile markets, and the CAViaR model showed consistent performance, making it a reliable alternative to traditional approaches.

The general recommendation for investors that emerges from our analysis is to utilize the Fully Adaptive Conformal Inference (FACI) and the Scale-Free Online Gradient Descent (SF-OGD) algorithms. These algorithms exhibit remarkable precision in providing VaR estimates across all examined quantiles, applicable to various types of crypto-assets and different market conditions. The risk estimates offered by these ACI algorithms can then be compared or even combined with those from traditional GARCH models, especially considering the latter's proficiency in offering small asymmetric quantile losses, provided a large dataset is available. We leave this issue as an avenue for future research. We note that while GARCH(1,1) is a parsimonious and analytically appealing model, its performance is highly dependent on the size and characteristics of the data sample. Our study found that GARCH(1,1) faces computational difficulties and often fails to achieve numerical convergence for smaller datasets (fewer than 1000 observations). Furthermore, for longer datasets, the model struggles with structural breaks, leading to suboptimal performance, particularly in the extreme parts of the left tail of the distribution, as observed with Bitcoin. In contrast, the ACI algorithms offer several advantages. They are computationally more efficient and robust across a wider range of dataset sizes, from small to medium. This makes them particularly suitable for crypto-assets, which often have limited historical data or exhibit high volatility. The ACI models dynamically adjust to new data, providing more accurate and adaptive risk estimates without the computational burdens associated with GARCH models. Additionally, the simplicity and speed of ACI models enhance their tractability, making them more practical for real-time risk management and forecasting in the fast-evolving cryptocurrency market. While GARCH(1,1) remains valuable for its analytical properties and its capacity to support further financial modeling, such as deriving explicit asset valuation formulas, the ACI models fill an important gap by offering robust performance and computational efficiency across various market conditions and data constraints. Therefore, incorporating ACI models into risk management frameworks provides a complementary approach, leveraging their strengths in scenarios where traditional models like GARCH may falter.

An important limitation of this paper is the reliance on time series consisting of at least 730 daily data points, ensuring each model had a minimum of one year's worth of data for initial training and calibration. This condition inevitably excluded a significant number of young crypto-assets, thereby restricting the depth of our analysis. One potential solution could involve utilizing high-frequency data if available, although alternative approaches should also be explored. Further research endeavors could address these limitations by incorporating additional data sources, exploring alternative model specifications, and examining the performance of forecasting models across varying time horizons and market conditions. This would enhance the robustness and applicability of risk management strategies in the dynamic landscape of crypto-assets.

As a final note, we wish to underscore that our findings align with the existing literature, highlighting the necessity of robust risk management frameworks for cryptoassets. For instance, [Liu et al., 2020] emphasize the challenges and rewards of investing in cryptocurrencies, suggesting that Value-at-Risk (VaR) forecasting can benefit from parsimonious models. Although they discuss models under the Generalized Autoregressive Score (GAS) framework, our study similarly finds that simpler models, such as GARCH, remain highly relevant and effective for VaR forecasting in specific scenarios. This resonates with [Liu et al., 2020]'s assertion that more elaborate models do not always outperform simpler alternatives, particularly when considering the varying dynamics of crypto-assets. [Trucíos and Taylor, 2023] further contribute to the discourse by comparing various advanced risk forecasting methods, including long-memory processes and quantile regression-based models, and highlighting the efficacy of certain models for specific cryptocurrencies. Their exploration of the robustness of these models during turbulent periods, such as the COVID-19 pandemic, parallels our findings that no single model universally outperforms others. Additionally, their investigation into forecast combination strategies aligns with our suggestion that combining traditional models like GARCH with ACI approaches could enhance predictive performance. [Müller et al., 2022] introduce the concept of Range Value at Risk (RVaR) and demonstrate that GARCH models with various error distributions can effectively forecast RVaR for major cryptocurrencies. Our study corroborates their observation that non-normal distributions are often more suitable for VaR and Expected Shortfall (ES) predictions, reinforcing the notion that the choice of model and distribution significantly impacts the accuracy of risk measures and that simple volatility models, such as GARCH with a Student's t-distribution, can produce accurate risk forecasts. [Alexander and Dakos, 2023] provide one of the most comprehensive review of the cryptocurrency risk forecasting literature, advocating for the practical application of relatively simple models over more complex alternatives. Their extensive backtesting with hourly and daily data reveals that models capturing asymmetric volatility and heavy-tailed distributions are just as effective as more sophisticated models. Our results echo this sentiment, demonstrating that models like FACI and SF-OGD can achieve reliable forecasts for cryptoassets without the need for overly computationally complex specifications, thus addressing the practical constraints faced by investors.

In conclusion, our study situates itself within the broader context of cryptocurrency risk forecasting literature, aligning with key findings from [Liu et al., 2020], [Müller et al., 2022], [Trucíos and Taylor, 2023], and [Alexander and Dakos, 2023]. By validating the efficacy of newer ACI models and recognizing the conditions under which they excel, our research contributes to a nuanced understanding of risk management in the cryptocurrency market. Future research should continue to explore the interplay between model complexity, data availability, and forecasting accuracy to develop robust risk management strategies that can withstand the unique challenges posed by cryptoassets.

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Appendix A: The original Adaptive Conformal Inference (ACI) algorithm.

```
Input:  starting value θ_1, user-specified learning rate γ > 0.
for t = 1, 2, ..., T do
    Output:  prediction interval Ĉ_t(θ_t).
    Observe y_t.
    Evaluate err_t = 𝕀[y_t ∉ Ĉ_t(θ_t)].
    Update θ_{t+1} = θ_t + γ(err_t − (1 − α)).
end for
```

Appendix B: The Aggregated Adaptive Conformal Inference (AgACI) algorithm.

```
Input:  candidate learning rates (γ_k)_{1≤k≤K}, starting value θ_1.
Initialize lower and upper BOA algorithms:
    B^l = BOA(α ← (1 − α)/2)
    B^u = BOA(α ← (1 − (1 − α)/2)).
for k = 1, ..., K do
    Initialize ACI A_k = ACI(α ← α, γ ← γ_k, θ_1 ← θ_1).
end for
for t = 1, 2, ..., T do
    for k = 1, ..., K do
        Retrieve candidate prediction interval [l_t^k, u_t^k] from A_k.
    end for
    Compute aggregated lower bound l̃_t = B^l((l_t^k : k ∈ {1, ..., K})).
    Compute aggregated upper bound ũ_t = B^u((u_t^k : k ∈ {1, ..., K})).
    Output:  prediction interval [l̃_t, ũ_t].
    Observe y_t.
    for k = 1, ..., K do
        Update A_k with log-return y_t.
    end for
    Update B^l with observed log-return y_t.
    Update B^u with observed log-return y_t.
end for
```

Appendix C: The Fully Adaptive Conformal Inference (FACI) algorithm.

```
Input: starting value θ_1, candidate learning rates (γ_k)_{1≤k≤K},
        parameters σ, η.
for k = 1, ..., K do
    Initialize expert A_k = ACI(α ← α, γ ← γ_k, θ_1 ← θ_1).
end for
for t = 1, 2, ..., T do
    Define the probabilities p_t^k = w_t^k / Σ_{i=1}^K w_t^i, for all 1 ≤ k ≤ K.
    Set θ_t = Σ_{k=1}^K θ_t^k p_t^k.
    Output: prediction interval Ĉ_t(θ_t).
    Observe the log-return y_t and compute r_t.
    w̄_t^k ← w_t^k exp(−η L^α(θ_t^k, r_t)), for all 1 ≤ k ≤ K.
    W̄_t ← Σ_{i=1}^K w̄_t^i
    w_{t+1}^k ← (1 − σ) w̄_t^k + W̄_t σ / K
    Set err_t = 𝕀[y_t ∉ Ĉ_t(θ_t)]
    for k = 1, ..., K do
       Update ACI A_k with y_t and obtain θ_{t+1}^k
    end for
end for
```

Appendix D: The Scale-Free Online Gradient Descent (SF-OGD) algorithm.

```
Input: starting value θ_1, learning rate γ > 0.
for t = 1, 2, ..., T do
    Output: prediction interval Ĉ_t(θ_t)
    Observe the log-return y_t and compute r_t
    Update θ_{t+1} = θ_t − γ ∇L^α(θ_t, r_t) / sqrt(Σ_{i=1}^t ||∇L^α(θ_i, r_i)||_2^2)
end for
```

Appendix E: The Strongly Adaptive Online Conformal Prediction (SAOCP) algorithm.

Input: initial value θ_0, learning rate $\gamma > 0$.

for $t = 1, 2, \ldots, T$ do

Initialize expert $\mathcal{A}_t = \text{SF-OGD}(\alpha \leftarrow \alpha, \gamma \leftarrow \gamma, \theta_1 \leftarrow \theta_{t-1})$,

set weight $w_t^t = 0$

Compute active set Active(t) $= \{i \in \{1, \ldots, T\} : t - L(i) < i \leq t\}$ (see

below for definition of $L(t)$),

Compute prior probability $\pi_i \propto i^{-2}(1 + \lfloor \log_2 i \rfloor)^{-1} \mathbb{I}[i \in \text{Active}(t)]$.

Compute un-normalized probability $\hat{p}_i = \pi_i [w_{t,i}]_+$ for all $i \in \{1, \ldots, t\}$

Normalize $p = \hat{p} / \|\hat{p}\|_1 \in \Delta^t$ if $\|\hat{p}\|_1 > 0$, else $p = \pi$.

Set $\theta_t = \sum_{i \in Active(t)} p_i \theta_t^i$ (for $t \geq 2$), and $\theta_t = 0$ for $t = 1$

Output: prediction set $\hat{C}_t(\theta_t)$.

Observe log-return y_t and compute r_t.

for $i \in$ Active(t) do

Update expert $\mathcal{A}_t$ with y_t and obtain θ_{t+1}^i

Compute $g_t^i = \begin{cases} \frac{1}{D}\left(L^\alpha(\theta_t, r_t) - L^\alpha(\theta_t^i, r_t)\right) & w_t^i > 0 \\ \frac{1}{D}\left[L^\alpha(\theta_t, r_t) - L^\alpha(\theta_t^i, r_t)\right]_+ & w_t^i \leq 0 \end{cases}$

Update expert weight $w_{t+1}^i = \frac{1}{t-i+1}\left(\sum_{j=i}^t g_j^i\right)\left(1 + \sum_{j=i}^t w_j^i g_j^i\right)$

end for

end for

Appendix F: List of crypto-assets IDs and names

ID	NAME	ID	NAME	ID	NAME	ID	NAME	ID	NAME
1	Bitcoin	760	Okcash	1353	TajCoin	1817	Voyager Token	2178	Upfiring
2	Litecoin	764	PayCoin	1368	Veltor	1826	Particl	2184	Privatix
3	Namecoin	788	Circuits of Value	1376	Neo	1828	SmartCash	2191	Paypex
4	Terracoin	799	SmileyCoin	1382	NoLimitCoin	1830	SkinCoin	2205	Phantomx
5	Peercoin	815	Kobocoin	1389	Zayedcoin	1831	Bitcoin Cash	2208	EncrypGen
6	Novacoin	819	Bean Cash	1392	Pluton	1834	Pillar	2209	Ink
8	Feathercoin	825	Tether USDt	1395	Dollarcoin	1838	OracleChain	2212	Quantstamp
10	Freicoin	831	Wild Beast Block	1396	MustangCoin	1839	BNB	2213	QASH
13	Ixcoin	833	Gridcoin	1414	Firo	1846	GeyserCoin	2215	Energo
16	WorldCoin WDC	837	X-Coin	1437	Zcash	1850	Cream	2222	Bitcoin Diamond
18	Digitalcoin	853	LiteDoge	1439	AllSafe	1853	OAX	2223	BLOCKv
25	Goldcoin	857	SongCoin	1447	ZClassic	1856	district0x	2230	MONK
35	Phoenixcoin	859	Woodcoin	1455	Golem	1861	Stox	2231	Flixxo
42	Primecoin	873	NEM	1466	Hush	1866	Bytom	2237	EventChain
43	Anoncoin	894	Neutron	1468	Kurrent	1876	Dentacoin	2241	Ccore
45	CasinoCoin	895	Xaurum	1473	Pascal	1878	Shadow Token	2242	Qbao
52	XRP	898	Californium	1474	Eternity	1881	DeepOnion	2243	Dragonchain
53	Quark	916	MedicCoin	1492	Obyte	1883	Adshares	2245	Presearch
56	Zetacoin	918	Bubble	1495	PoSW Coin	1886	Dent	2247	BlockCDN
61	TagCoin	921	Universal Currency	1500	Wings	1888	InvestFeed	2248	Cappasity
66	Nxt	934	ParkByte	1503	Jupiter	1896	0x Protocol	2249	Eroscoin
67	Unobtanium	938	ARbit	1505	Alias	1902	MyBit	2255	Social Send
69	Datacoin	945	Bata	1511	PureVidz	1903	HyperCash	2256	Bonpay
72	Deutsche eMark	948	AudioCoin	1514	ICOBID	1908	Nebulas	2273	Uquid Coin
74	Dogecoin	951	Synergy	1515	iBank	1916	BiblePay	2274	MediShares
77	Diamond	978	Ratecoin	1518	Maker	1918	Achain	2276	Ignis
78	HoboNickels	986	CrevaCoin	1521	Komodo	1925	Waltonchain	2277	SmartMesh
83	Omni	993	BowsCoin	1522	FirstCoin	1930	Primas	2279	Playkey
87	FedoraCoin	1004	HNC COIN	1528	Iconic	1934	Loopring	2280	Filecoin
90	Dimecoin	1019	Manna	1546	Centurion	1935	Bitcoin Dominica	2281	BitcoinX
93	42-coin	1020	Axiom	1552	Enzyme	1937	Po.et	2282	Super Bitcoin
99	Vertcoin	1027	Ethereum	1556	Chrono.tech	1947	Monetha	2286	MicroMoney
109	DigiByte	1032	TransferCoin	1558	Argus	1948	Aventus	2287	LockTrip
118	ReddCoin	1033	GuccioneCoin	1562	Swarm City	1949	Agrello	2288	Worldcore
122	PotCoin	1035	AmsterdamCoin	1567	Nano	1950	Hiveterminal Token	2289	Gifto
128	Maxcoin	1037	Agoras: Currency of Tau	1578	Zero	1954	Moeda Loyalty Points	2290	YENTEN
131	Dash	1038	Eurocoin	1582	Netko	1955	Neblio	2291	Genaro Network
132	Counterparty	1042	Siacoin	1586	Ark	1958	TRON	2293	United Bitcoin
141	MintCoin	1044	KWD	1596	Edgeless	1962	BUZZCoin	2295	Starbase
145	DopeCoin	1052	VectorAI	1609	Asch	1966	Decentraland	2296	OST
148	Auroracoin	1053	Bolivarcoin	1619	Skycoin	1967	Indorse Token	2297	StormX
154	Marscoin	1066	Pakcoin	1623	BlazerCoin	1968	XPA	2299	aelf
162	Magic Internet Money	1070	Expanse	1624	Atmos	1970	ATBCoin	2300	WAX
168	Uniform Fiscal Object	1082	SIBCoin	1629	Zennies	1974	Propy	2303	MediBloc
170	BlackCoin	1085	Swing	1630	Coinonat	1975	Chainlink	2305	NAGA
184	DNotes	1090	Save and Gain	1632	Concoin	1982	Kyber Network Crystal Legacy	2306	Bread
213	MonaCoin	1104	Augur	1636	XTRABYTES	1983	VIBE	2307	Bibox Token
215	Rubycoin	1106	StrongHands	1637	iExec RLC	1984	Substratum	2310	Bounty0x
217	Bela	1107	PAC Protocol	1638	WeTrust	1991	Rivetz	2313	SIRIN LABS Token
234	e-Gulden	1120	DraftCoin	1651	SpeedCash	1993	Kin	2315	HTMLCOIN
258	Groestlcoin	1135	ClubCoin	1654	BitCore	1996	SALT	2316	DeepBrain Chain
260	PetroDollar	1136	Adzcoin	1657	Bitvolt	1998	Ormeus Coin	2318	Neumark
263	PLNcoin	1146	AvatarCoin	1658	Lunyr	2001	ColossusXT	2320	xMoney
268	WhiteCoin	1154	Validity	1659	Gnosis	2002	TrezarCoin	2323	HEROcoin
276	Bitstar	1155	Litecred	1660	Monolith	2006	Cobinhood	2324	BigONE Token
278	Quebecoin	1156	Yocoin	1669	Humaniq	2009	Bismuth	2329	Hyper Pay
290	BlueCoin	1159	SaluS	1674	Bitcoin Palladium	2010	Cardano	2332	STRAKS
291	MaidSafeCoin	1164	Francs	1678	InsaneCoin	2011	Tezos	2335	Lightning Bitcoin
293	Bitcoin Plus	1165	Evil Coin	1680	Aragon	2019	Viberate	2336	Game.com
298	NewYorkCoin	1168	Decred	1681	PRIZM	2022	Internxt	2337	Lamden
313	Pinkcoin	1169	PIVX	1684	Qtum	2034	Everex	2341	SwftCoin
316	Dreamcoin	1175	Rubies	1693	Theresa May Coin	2041	BitcoinZ	2344	AppCoins
328	Monero	1185	FreedomCoin	1694	Sumokoin	2043	Cindicator	2345	High Performance Blockchain
333	Curecoin	1191	Memetic / PepeCoin	1697	Basic Attention Token	2044	Enigma	2346	WaykiChain
360	Motocoin	1194	Independent Money System	1698	Horizen	2047	Zeusshield	2348	Measurable Data Token
362	CloakCoin	1200	NevaCoin	1700	¡U+00C6¿ternity	2058	AirSwap	2349	Mixin
366	BitSend	1209	PosEx	1703	Metaverse ETP	2062	Aion	2354	GET Protocol
367	Coin2.1	1210	Cabbage	1706	Aidos Kuneen	2070	DomRaider	2359	Polis
372	Bytecoin	1212	MojoCoin	1710	Veritaseum	2071	Request	2363	Zap
377	Navcoin	1214	Lisk	1712	Quantum Resistant Ledger	2076	Blue Protocol	2364	TokenClub
389	Startcoin	1216	EDRCoin	1720	IOTA	2081	AirDAO	2367	Aigang
405	DigitalNote	1218	PostCoin	1721	Mysterium	2083	Bitcoin Gold	2370	Bitcoin God
416	HempCoin	1223	BERNcash	1727	Bancor	2087	KuCoin Token	2371	United Traders Token
460	Clams	1229	DigixDAO	1731	GlobalToken	2088	EXRNchain	2379	Kcash
463	BitShares	1230	Steem	1732	Numeraire	2090	LATOKEN	2386	KZ Cash
470	Viacoin	1241	FuzzBalls	1736	Unify	2092	NULS	2387	Bitcoin Atom
501	Cryptonite	1244	HiCoin	1745	Dinastycoin	2096	Ripio Credit Network	2391	EchoLink
502	Carboncoin	1247	AquariusCoin	1747	Onix	2099	ICON	2392	Bottos
506	CannabisCoin	1248	Bitcoin 21	1750	GXChain	2100	JavaScript Token	2394	Telcoin
512	Stellar	1250	Zurcoin	1757	FUNToken	2104	iEthereum	2395	Ignition
541	Syscoin	1252	2GIVE	1758	TenX	2110	OLD DOVU	2396	WETH
551	Donu	1254	PlatinumBAR	1759	Status	2112	Phoenix Global [old]	2398	SelfKey
558	Emercoin	1257	LanaCoin	1762	Ergo	2120	Etherparty	2399	INT
572	RabbitCoin	1259	PonziCoin	1765	EOS	2126	FlypMe	2405	IOST
576	GameCredits	1273	Citadel	1768	AdEx	2130	Enjin Coin	2407	AICHAIN
584	NativeCoin	1274	Waves	1769	Denarius	2131	iBTC	2410	SpaceChain
597	Opal	1279	PWR Coin	1772	Storj	2132	Powerledger	2415	ArbitrageCT
601	Acoin	1281	ION	1774	SocialCoin	2135	Revain	2416	Theta Network
624	bitCNY	1282	High Voltage	1779	Wagerr	2136	ATLANT	2424	SingularityNET
638	Trollcoin	1285	GoldBlocks	1784	Polybius	2137	Electroneum	2427	ChatCoin
644	GlobalBoost	1291	Comet	1785	Gas	2143	Streamr	2428	Scry.info
656	Prime-XI	1297	ChessCoin	1786	SunContract	2147	ELTCOIN	2429	Mobius
659	Bitswift	1298	LBRY Credits	1787	Jetcoin	2148	Desire	2430	Hydro Protocol
693	Verge	1299	PUTinCoin	1788	Metal DAO	2151	Autonio	2438	Double-A Chain
702	SpreadCoin	1306	Cryptojacks	1789	Populous	2153	Aeron	2443	Trinity Network Credit
703	Rimbit	1312	Steem Dollars	1799	Rupee	2158	Phore	2444	CRYPTO20
707	Blocknet	1320	Ardor	1807	Santiment Network Token	2160	Innova	2447	Crypterium
720	Crown	1321	Ethereum Classic	1808	OMG Network	2161	Raiden Network Token	2448	SparksPay
730	GCN Coin	1343	Stratis	1814	Metrix Coin	2162	Delphy	2452	Tokenbox
733	Quotient	1351	Aces	1816	Civic	2165	ERC20	2454	Bitcoin Unlimited

Table 14: Names and crypto-assets' coinmarketcap.com IDS: 1-500.

ID	NAME	ID	NAME	ID	NAME	ID	NAME	ID	NAME
2457	TrueChain	2725	Skrumble Network	3132	EtherGem	3519	Breezecoin	3843	BOLT
2458	Odyssey	2726	DAOstack	3133	Arepacoin	3580	Crystal Token	3849	WHEN Token
2459	indaHash	2737	Global Social Chain	3138	Noku	3581	Kleros	3850	OTOCASH
2462	AidCoin	2739	Digix Gold Token	3139	DxChain Token	3589	Ethereum Meta	3853	MultiVAC
2465	BUX Token	2742	Sakura Bloom	3140	Ubex	3600	Hippocrat	3854	Unification
2466	Moola	2745	Joint Ventures	3141	Blockpass	3602	Bitcoin SV	3855	Locus Chain
2467	OriginTrail	2748	Oxen	3142	BaaSid	3607	VestChain	3856	SF Capital
2468	LinkEye	2752	Datarius Credit	3149	Netkoin	3610	Micromines	3863	UGAS
2469	Zilliqa	2757	Callisto Network	3152	Obitan Chain	3611	Noir	3866	CONUN
2474	Matrix AI Network	2758	Unibright	3155	Quant	3613	Dash Green	3869	Alpha Token
2475	Garlicoin	2760	Cred	3156	Airbloc	3617	ILCOIN	3870	Lition
2476	Ruff	2762	Open Platform	3158	ZCore (old)	3620	Atlas Protocol	3871	Newton
2478	CoinFi	2763	Morpheus.Network	3159	Apollon	3621	BitNautic Token	3873	botXcoin
2481	Zeepin	2764	Silent Notary	3162	YoloCash	3625	QuadrantProtocol	3874	IRISnet
2482	CPChain	2765	XYO	3164	PumaPay	3626	Rootstock Smart Bitcoin	3875	Valor Token
2489	BitWhite	2771	RED	3166	Bitcoin Incognito	3627	Block-Logic	3877	WebDollar
2490	CargoX	2772	Digitex	3171	HeartBout	3628	MXC	3878	Swap
2492	Elastos	2776	AVA	3175	Maro	3632	Opacity	3880	OceanEx Token
2496	Polymath	2777	IoTeX	3179	Arbidex	3633	BitGuild PLAT	3884	Function X
2497	Medicalchain	2780	NKN	3181	ShowHand	3634	Kambria	3890	Polygon
2499	SwissBorg	2827	Phantasma	3182	HitChain	3635	Cronos	3893	ChangeNOW Token
2502	Huobi Token	2828	SPINDLE	3189	Mainstream For The Underground	3637	Aergo	3894	Crypto Sports Network
2503	DMarket	2830	Seele-N	3194	DPRating	3639	PlayGame	3897	OKB
2505	Bluzelle	2837	0xBitcoin	3198	KingXChain	3640	Livepeer	3898	Axe
2511	WePower	2838	Plian	3200	Nasdacoin	3644	TravelNote	3902	MoneroV
2513	GoldMint	2840	QuarkChain	3205	VeriDocGlobal	3645	Shivers	3908	Decimated
2529	Cashaa	2846	FuturoCoin	3208	YUKI	3646	Herbalist Token	3911	Ocean Protocol
2530	Fusion	2847	Abyss	3210	MIB Coin	3652	ZumCoin	3913	Titan Coin
2535	Edge	2856	CEEK VR	3217	Ontology Gas	3656	Beacon	3914	GlitzKoin
2536	Neurotoken	2859	XMax	3218	Energi	3657	Lambda	3915	Merebel
2537	Gems	2861	GoChain	3219	FUTURAX	3659	QUINADS	3918	Safe
2539	Ren	2862	Smartshare	3220	DAV Coin	3661	Stronghold Token	3925	Tratok
2540	Litecoin Cash	2866	Sentinel Protocol	3238	ABCC Token	3662	HedgeTrade	3928	IDEX
2542	Tidex Token	2868	Constellation	3242	Beetlecoin	3663	Footballcoin (XFC)	3930	ThunderCore
2544	Nitro Network	2870	FantasyGold	3243	Moneytoken	3664	AgaveCoin	3931	Elementeum
2545	Arcblock	2873	Metronome	3247	Fire Lotto	3667	Atomic Wallet Coin	3934	CNNS
2546	Remme	2874	Aurora	3255	CyberMusic	3672	DogeCash	3935	SparkPoint
2548	POA Network	2878	DigiFinexToken	3256	Bitether	3673	ASD	3936	GNY
2552	IHT Real Estate Protocol	2882	Zus	3260	AMO Coin	3686	Conscious Value Network	3939	Tronipay
2553	Refereum	2883	ZINC	3261	EvenCoin	3687	BitBall	3945	Harmony
2554	Lympo	2889	Bob's Repair	3263	Dinero	3698	Observer	3946	Carry
2556	Credits	2890	KanadeCoin	3265	Havy	3701	Rootstock Infrastructure Framework	3948	TERA
2561	BitTube	2891	Cardstack	3266	Carebit	3702	Beam	3950	Neom
2562	Education Ecosystem	2894	OTCBTC Token	3273	IQ.cash	3703	ADAMANT Messenger	3951	Pirate Chain
2563	TrueUSD	2896	Mainframe	3279	Rotharium	3704	v.systems	3953	Evedo
2565	StarterCoin	2901	FansTime	3280	RealTract	3708	Exosis	3956	BOMB
2566	Ontology	2906	Essentia	3285	Birake	3709	Grin	3957	UNUS SED LEO
2569	CoinPoker	2907	Karatgold Coin	3287	Abulaba	3712	Cloudbric	3964	Reserve Rights
2570	Viction	2908	HashCoin	3294	Bitcoin Adult	3714	LTO Network	3968	Elitium
2572	BABB	2909	LikeCoin	3296	MINDOL	3715	Cajutel	3973	Aryacoin
2573	Electrify.Asia	2912	TENT	3304	MobilinkToken	3716	Amoveo	3974	Bitcoin 2
2576	Tokenomy	2913	Databroker	3306	Gemini Dollar	3717	Wrapped Bitcoin	3976	Bitcoin Confidential
2577	Ravencoin	2915	Moss Coin	3316	smARTOFGIVING	3718	BitTorrent	3978	Chromia
2578	TE-FOOD	2916	Nimiq	3317	Cryptrust	3721	Huobi Pool Token	3986	StakeCubeCoin
2585	CENNZnet	2921	OneLedger	3325	Robotina	3722	TEMCO	3987	Beldex
2586	Synthetix	2927	sUSD	3327	SIX	3724	SOLVE	3992	COTI
2588	Loom Network	2930	IQ	3328	CMITCOIN	3730	The Currency Analytics	4001	MenaPay
2595	NANJCOIN	2933	BitMart Token	3330	Pax Dollar	3731	PlayChip	4003	Zenon
2603	Pundi X (Old)	2934	BitKan	3332	Gossip Coin	3733	S4FE	4006	STP
2605	BnkToTheFuture	2937	VITE	3334	X-CASH	3737	BTU Protocol	4013	SpectreSecurityCoin
2606	Wanchain	2938	Hashgard	3335	Shard	3738	Decentralized Crypto Token	4014	Mobile Crypto Pay Coin
2607	AMLT	2941	CoinEx Token	3337	QChi	3741	EurocoinToken	4017	EOSDT
2608	Mithril	2943	Rocket Pool	3344	Ecoreal Estate	3742	Chimpion	4018	Klimatas
2614	BlitzPick	2945	ContentBox	3345	DAPS Coin	3748	HXRO	4023	Bitcoin BEP2
2616	Stipend	2947	SoPay	3354	TRONCLASSIC	3750	eXPerience Chain	4024	Raven Protocol
2620	Carbon Protocol	2949	Kryll	3361	MintMe.com Coin	3752	uPlexa	4026	LiquidApps
2624	Sentinel Chain	2950	LemoChain	3362	Auxilium	3754	EveryCoin	4027	DeVault
2626	Friendz	2958	TurtleCoin	3364	PLATINCOIN	3759	Jinbi Token	4028	MotaCoin
2628	Rentberry	2960	Tourist Token	3366	SafeInsure	3760	Scanetchain	4030	Algorand
2630	PolySwarm	2965	VikkyToken	3371	MIR COIN	3763	Oduwacoin	4033	Native Utility Token
2631	ODEM	2976	Ryo Currency	3383	Knekted	3764	Save Environment Token	4035	Honest
2634	XDC Network	2980	WABnetwork	3388	FREEdom Coin	3768	PIBBLE	4036	Contentos
2638	Cortex	2982	MVL	3395	SteepCoin	3769	HashBX	4038	MovieBloc
2642	CyberVein	2988	Pigeoncoin	3397	Neural Protocol	3770	CustomContractNetwork	4039	ARPA
2643	Sentinel	2989	STASIS EURO	3404	Wixlar	3773	Fetch.ai	4041	MX TOKEN
2644	eosDAC	2991	NIX	3408	USDC	3779	CoTrader	4043	PayRue (Propel)
2645	U Network	2992	Apollo Currency	3417	Future1coin	3783	Ankr	4047	Naka Bodhi Token
2653	Auctus	2994	Bitcoin File	3418	Metadium	3792	USDe	4051	Parachute
2655	Monero Classic	2998	Vexanium	3422	SHPING	3794	Cosmos	4054	IG Gold
2658	Smart MFG	3006	Niobio	3432	Rapids	3795	ZEON	4056	Ampleforth
2660	Aditus	3008	Vivid Coin	3435	Snetwork	3798	Xuez	4058	FIBOS
2662	Haven Protocol	3012	VeThor Token	3437	ABBC Coin	3799	SafeCoin	4060	TrustVerse
2665	Dero	3013	PRiVCY	3441	Divi	3800	FidexToken	4064	USDK
2666	Effect Network	3018	Kalkulus	3446	Zenswap Network Token	3801	BORA	4066	Chiliz
2667	FintruX Network	3024	Arionum	3449	MMOCoin	3805	BoatPilot Token	4069	Blockburn
2674	Masari	3029	Flux	3452	Etho Protocol	3806	TigerCash	4074	ScPrime
2675	Dock	3052	GoCrypto Token	3454	Decentralized Asset Trading Platform	3807	LitecoinToken	4075	CryptoFranc
2677	Linker Coin	3056	Thore Cash	3456	PlusOneCoin	3809	DOS Network	4076	ETHplode
2682	Holo	3071	EUNO	3459	GoHelpFund	3810	Ethereum Gold Project	4077	Maya Preferred
2685	Zebi Token	3077	VeChain	3464	Cheesecoin	3814	Celer Network	4078	Super Zero Protocol
2689	Rublix	3079	X8X Token	3468	Fivebalance	3816	Verasity	4090	Wirex Token
2694	Nexo	3089	AVINOC	3469	TrueDeck	3820	BuckHathCoin	4092	Dusk
2696	DAEX	3097	XOVBank	3479	MODEL-X-coin	3822	Theta Fuel	4096	Switch
2700	Celsius	3106	PKG Token	3481	Peony	3826	TOP	4097	x42 Protocol
2704	Transcodium	3118	Graviocoin	3482	Teloscoin	3829	Nash	4102	TranslateMe Network Token
2705	Amon	3121	IGToken	3484	Waletoken	3830	Veil	4104	FUZE Token
2709	Morpheus Labs	3123	GSENetwork	3489	Escroco Emerald	3831	Safe Haven	4105	Coinmetro Token
2712	MyToken	3125	XDNA	3501	CryptoSoul	3835	Orbs	4114	Golden Token
2717	BoutsPro	3126	ProximaX	3512	Alpha Coin	3839	xRhodium	4116	TOKPIE
2724	Zippie	3128	SiaCashCoin	3513	Fantom	3840	1irstcoin	4118	ForTube

Table 15: Names and crypto-assets' coinmarketcap.com IDS: 501-1000.

ID	NAME	ID	NAME	ID	NAME	ID	NAME	ID	NAME
4119	VinDax Coin	4705	PAX Gold	5175	Bitcoin Vault	5552	Hathor	5925	Pkoin
4120	Prom	4709	XcelToken Plus	5176	Tether Gold	5560	Idea Chain Coin	5926	CoinZoom
4121	Sapphire	4710	Cere Network	5179	Celeum	5563	CryptoBharatCoin	5931	Darwinia Commitment Token
4122	CCA	4712	AmonD	5181	BiLira	5566	Keep Network	5939	Wrapped NXM
4124	EOS TRUST	4715	Tokenize Xchange	5185	KOK	5567	Celo	5945	Temtum
4134	Akropolis	4746	Quiztok	5187	Jarvis Network	5577	Litecoin SV	5947	TokenPocket
4139	Brazilian Digital Token	4747	Velas	5189	AK12	5578	LEVELG	5956	MUX Protocol
4144	TrueFeedBack	4757	Robonomics.network	5190	FLEX	5583	Hacken Token	5957	DFI.Money
4150	GLOBEX	4758	dForce	5198	Creditcoin	5589	DXdao	5963	Centric Swap
4157	THORChain	4761	NuCypher	5200	Gleec Coin	5590	GeoDB	5964	Trust Wallet Token
4160	Ycash	4769	EOS Force	5204	CitiOs	5595	MultiCoinCasino	5966	Student Coin
4162	Storeum	4777	Azbit	5219	USD Bancor	5599	XTRM COIN	5985	Limestone Network
4165	CREDIT	4779	HUSD	5220	QURAS	5600	Attila	5989	BNS Token
4166	Realio Network	4787	BitcoinV	5221	Handshake	5601	STAKE	5994	Shiba Inu
4167	Bitrue Coin	4793	D Community	5224	Juventus Fan Token	5604	Secret	5999	XT.com Token
4172	Terra Classic	4794	FinexboxToken	5225	FC Barcelona Fan Token	5608	BTCUP	6025	DigiMax DGMT
4173	Levolution	4797	SMILE	5226	Paris Saint-Germain Fan Token	5609	BTCDOWN	6039	Connectome
4174	BitcoinRegular	4801	Codex	5227	Atletico De Madrid Fan Token	5612	SOMESING	6051	888tron
4180	DDKoin	4804	ROOBEE	5228	Galatasaray Fan Token	5614	Zelwin	6053	Mineral
4182	GoWithMi	4805	VNDC	5229	AS Roma Fan Token	5616	MATH	6062	Shuffle
4183	Safex Cash	4807	Shentu	5236	Kemacoin	5617	UMA	6069	Assemble Protocol
4189	Ultra	4808	Bincentive	5246	ViteX Coin	5618	Dawn Protocol	6111	Ecoin official
4191	Syntropy	4809	Project WITH	5253	The Hustle App	5623	Skillchain	6113	BlackPearl Token
4193	Dynamite	4824	SymVerse	5263	Compound Dai	5625	LUKSO (Old)	6118	BitoPro Exchange Token
4195	FTX Token	4826	ZUM TOKEN	5266	MiL.k	5626	King DAG	6138	DIA
4197	ShareToken	4834	Golos Blockchain	5268	Energy Web Token	5630	WaykiChain Governance Coin	6156	Donut
4200	ChainX	4841	suterusu	5274	Edgeware	5631	Orion	6176	Mobility Coin
4206	WINkLink	4846	Kava	5275	Paycoin	5632	Arweave	6179	SeChain
4213	Uptrennd	4847	Stacks	5277	SynchroBitcoin	5633	UCROWDME	6180	Suku
4215	Eminer	4850	LINKA	5279	Sologenic	5634	Fuse	6187	Serum
4217	BOSagora	4860	Era Swap	5300	Inex Project	5640	PointPay	6193	Cream Finance
4224	Mcashchain	4862	DAD	5305	BTSE Token	5644	Blue Baikal	6194	Geeq
4228	Ferrum Network	4865	Nahmii	5309	OG Fan Token	5647	Kadena	6209	Spheroid Universe
4229	Yobit Token	4866	Grimm	5313	CONTRACOIN	5648	BlockNoteX	6210	The Sandbox
4245	Enecuum	4867	BeatzCoin	5320	Bonorum	5651	CryptoBet	6216	AXEL
4249	Findora	4881	Guider	5326	Orbit Chain	5659	Xank	6218	Arcona
4253	CryptoBonusMiles	4885	Diligence	5328	WOM Protocol	5662	Sylo	6236	Offshift (old)
4256	Klaytn	4887	Receive Access Ecosystem	5330	Shardus	5665	Helium	6237	MDsquare
4257	Bitball Treasure	4890	Newscrypto	5332	Cofinex	5667	Bitgesell	6243	DeFiPie
4261	Sucrecoin	4909	Merge	5336	Homeros	5673	EYES Protocol	6245	SocialGood
4264	Ritocoin	4915	UCX	5338	Somnium Space Cubes	5674	PhoenixDAO	6248	Coalculus
4268	NewYork Exchange	4916	Modex	5343	Five Star Coin	5686	Vectorium	6249	Ziktalk
4269	GateToken	4917	DEXA COIN	5350	XPR Network	5690	Render	6257	Berry
4275	COMBO	4920	Aerotoken	5354	PEAKDEFI	5691	SKALE	6262	Jubi Token
4279	Solar	4927	RigoBlock	5355	Chainpay	5692	Compound	6264	Dark Energy Crystals
4280	12Ships	4929	JD Coin	5358	IBStoken	5698	GM Holding	6283	Blocery
4283	BitForex Token	4940	Kuverit	5365	Historia	5702	MONNOS	6323	LinkCoin Token
4286	ZENZO	4943	Dai	5366	GoalTime N	5705	tGOLD	6375	ASTA
4287	Jobchain	4944	Tellor	5370	Hive	5713	Ravencoin Classic	6405	MiniSwap
4289	IOEX	4948	Nervos Network	5375	Hive Dollar	5721	SorachanCoin	6410	Feellike
4291	Krypton Galaxy Coin	4950	LCX	5380	Hunt Town	5728	Balancer	6430	Electric Vehicle Zone
4292	Nibble	4951	Zynecoin	5382	ELYSIA	5741	DMM: Governance	6447	Fisco Coin
4293	PERL.eco	4953	FirmaChain	5383	B ONE PAYMENT	5748	mStable Governance Token	6457	Globaltrustfund Token
4298	Rapidz	4956	MAP Protocol	5392	Scopuly	5765	sETH	6470	Hiblocks
4299	Tokoin	4957	Minter Network	5397	Castweet	5776	tBTC	6482	Jur
4306	BSOV Token	4974	EXMO Coin	5399	TILWIKI	5777	renBTC	6490	ITAM Games
4307	UNICORN Token	4983	Demeter Chain	5400	Charg Coin	5781	CashBackPro	6493	KStarCoin
4361	Bitpanda Ecosystem Token	4985	ArdCoin	5401	CoinLoan	5782	Bestay	6498	Metacoin
4365	Streamit Coin	4997	Blockzero Labs	5407	KingdomStarter	5785	STPAY	6500	ThreeFold
4366	MixMarvel	5002	SafeCapital	5409	4P FOUR	5792	Bananatok	6507	Kulupu
4381	MYCE	5005	ARCS	5410	PARSIQ	5794	pNetwork	6511	Strong
4388	ExchangeCoin	5007	TROY	5420	SonoCoin	5798	Darwinia Network	6520	HOPR
4411	TenUp	5011	ALLY	5423	DSLA Protocol	5800	Treecle	6535	NEAR Protocol
4424	XDAG	5015	HEX	5425	Mesefa	5802	SORA	6536	MANTRA
4427	BITICA COIN	5016	Innovative Bioresearch Coin	5426	Solana	5804	DeFiChain	6537	RioDeFi
4430	VNX	5024	ALL BEST ICO	5429	DEAPcoin	5805	Avalanche	6538	Curve DAO Token
4431	VIDY	5025	Jade Currency	5434	pTokens BTC	5809	Cap	6539	YAM V1
4441	Vectorspace AI	5026	Orchid	5435	Epic Cash	5815	BitcoinPoS	6542	Happy Birthday Coin
4452	BidiPass	5031	MimbleWimbleCoin	5437	BIZZCOIN	5816	Rewardiqa	6543	Barter
4460	PirateCash	5034	Kusama	5444	Cartesi	5818	Ormeus Cash	6554	GamerCoin
4466	Ormeus Ecosystem	5038	Litecash	5445	LBK	5821	Aleph.im	6564	ZenSports
4467	Nestree	5046	Streamity	5446	USDJ	5824	Smooth Love Potion	6565	TideBit Token
4487	Secure Cash	5049	VerusCoin	5449	Beer Money	5828	VN Token	6588	Etherisc DIP Token
4490	Emirex Token	5052	Apple Network	5450	WiBX	5829	TrustSwap	6598	Aureus Nummus Gold
4491	Flits	5060	XeniosCoin	5453	KardiaChain	5833	ASKO	6602	XFUEL
4502	Altbet	5062	Bepro	5455	Bitcoin XT	5835	Decentr	6607	MixTrust
4512	FINSCHIA	5067	MAX Exchange Token	5468	Isiklar Coin	5836	Idena	6609	Decentrahub Coin
4520	Decentralized Vulnerability Platform	5068	Neutrino Index	5473	CRDT	5837	CEREAL	6611	DuckDaoDime
4525	Lightyears	5070	Tap	5474	Ixinium	5841	NEST Protocol	6622	Hakka.Finance
4542	Scrypta	5072	Rakon	5478	ECOSC	5847	Defis	6626	SPACE-iZ
4546	01coin	5079	apM Coin	5479	UCA Coin	5857	FLAMA	6627	Meter Stable
4552	Aircoins	5084	PlayFuel	5480	Bali Coin	5858	QANplatform	6636	Polkadot
4558	Flow	5086	Pawtocol	5482	CCX	5864	yearn.finance	6638	UniLayer
4566	XDB CHAIN	5088	Guapcoin	5486	Jack Token	5865	FIO Protocol	6641	AhaToken
4568	JFIN Coin	5103	Tachyon Protocol	5488	JUST	5866	DEXTools	6649	Cat Token
4571	HEdpAY	5109	FRED Energy	5508	Algory Project	5873	NextDAO	6651	USDX [Kava]
4586	ProBit Token	5113	inSure DeFi	5513	Crypto Holding Frank Token	5877	Rarible	6653	FolgoryUSD
4630	Sierracoin	5114	Coinsbit Token	5518	Torex	5880	Props Token	6655	Krosscoin
4642	Hedera	5117	Origin Protocol	5520	Martkist	5882	StaFi	6665	LGCY Network
4647	PUBLISH	5130	K-Tune	5521	EzyStayz	5886	Rowan Token	6668	PROXI
4660	Telos	5135	AfroDex	5522	SENSO	5892	Anyswap	6669	PowerPool
4677	Tepleton	5143	Documentchain	5524	TNC Coin	5893	Frontier	6670	Axis DeFi
4678	Global Digital Content	5155	Nyzo	5529	ASYAGRO	5899	Casper	6679	WHALE
4679	Band Protocol	5159	Waves Enterprise	5530	REBIT	5900	DigiDinar	6680	Digex
4680	FYDcoin	5160	Dune Network	5536	AtromG8	5906	NerveNetwork	6682	Pollux Coin
4687	BUSD	5161	WazirX	5538	Buzzshow	5908	dKargo	6684	Dextoken
4691	Zano	5165	Freight Trust & Clearing Network	5539	VeraOne	5914	Intexcoin	6693	OC Protocol
4702	Rupiah Token	5168	Bitcoin Classic	5541	Xaya	5918	ModiHost	6697	TriipMiles
4703	BonusCloud	5169	PYRO Network	5544	Aluna.Social	5919	Meter Governance	6701	Burency
4704	Banano	5174	Buxcoin	5548	Massnet	5922	Swingby	6704	JBOX

Table 16: Names and crypto-assets' coinmarketcap.com IDS: 1001-1500.

ID	NAME	ID	NAME	ID	NAME	ID	NAME	ID	NAME
6705	Lien	7096	Bridge Oracle	7486	Rari Governance Token	7878	MobileCoin	8258	CUDOS
6709	Vidya	7102	Linear Finance	7497	Marlin	7881	sKLAY	8259	Furucombo
6714	Libfx	7105	Permission Coin	7498	Yield Protocol	7882	Efforce	8260	Indexed Finance
6715	Sperax	7110	New BitShares	7501	WOO	7908	Guarded Ether	8264	Basis Gold Share
6719	The Graph	7116	Crypto Accept	7505	Everscale	7931	Forj (Bondly)	8265	Helmet.insure
6724	Klever	7126	Giftedhands	7512	Unistake	7933	Alpha5	8267	OKT Chain
6726	YUSRA	7127	Velo	7513	BitOnyx	7942	Curate	8270	Gera Coin
6727	Reserve	7129	TerraClassicUSD	7533	Oraichain	7952	Venus SXP	8271	Poolz Finance
6731	Tokamak Network	7131	YAM V3	7535	Keep3rV1	7957	Venus USDT	8276	Arianee
6735	Nexalt	7133	Ducato Finance Token	7539	Colibri Protocol	7958	Venus USDC	8278	VEROX
6739	ONBUFF	7150	Flamingo	7548	WEMIX	7959	Venus BUSD	8279	e-Money
6742	DxSale.Network	7158	BurgerCities	7552	Hyve	7960	Venus XVS	8282	Koinos
6744	Chain Games	7169	Chicken	7553	unFederalReserve	7964	Venus LTC	8284	TokenAsset
6747	Crust Network	7182	Billion Happiness	7570	Blurt	7965	Venus XRP	8290	SuperVerse
6748	Centrifuge	7186	PancakeSwap	7576	Kava Lend	7972	Honey	8292	Router Protocol
6754	Polkaswap	7187	S.Finance	7579	Mars Network	7974	Venus BCH	8294	Cometh
6758	SushiSwap	7189	Origin Dollar	7583	Auric Network	7975	Venus LINK	8295	CPUcoin
6765	ESR Coin	7190	PowerTrade Fuel	7585	Freeway Token	7976	Venus DOT	8296	KLAYswap Protocol
6766	Satopay Network	7192	Wrapped BNB	7586	Yearn Classic Finance	7977	Unit Protocol Duck	8298	Paralink Network
6771	DataHighway	7199	Ultra Clear	7588	Gameswap	7978	Bonfida	8299	Stake DAO
6773	FUTUREXCRYPTO	7200	Bidao	7590	Dvision Network	7980	MinePlex	8307	DIGG
6783	Axie Infinity	7202	OctoFi	7591	Misbloc	7986	Hub - Human Trust Protocol	8309	ARMOR
6789	Blockchain Cuties Universe Governance	7206	TitanSwap	7593	DefiDollar DAO	7988	Zugacoin	8310	TosDis
6801	TriumphX	7208	Polkastarter	7594	Smoothy	8000	Lido DAO	8320	PolkaBridge
6804	MiraQle	7216	LuaSwap	7596	SmartCredit Token	8002	SpiderDAO	8329	PAID Network
6810	Cyclub	7217	Morpher	7616	Lattice Token	8020	DeFiato	8335	Mdex
6824	Epanus	7219	Rubic	7617	saffron.finance	8029	Oxygen	8339	xFund
6829	Pearl	7222	yAxis	7618	Alpaca City	8031	governance ZIL	8340	Natus Vincere Fan Token
6830	KILT Protocol	7224	DODO	7619	Bitcoiva	8034	BioPassport Token	8341	Young Boys Fan Token
6833	Litentry	7225	DeFiner	7622	UBIX.Network	8035	Grom	8349	Onooks
6836	Moonbeam	7226	Injective	7623	Libartysharetoken	8036	YVS.Finance	8351	OptionRoom
6841	Phala Network	7227	APY.Finance	7628	Coral Swap	8037	Vanar Chain	8353	Beacon ETH
6843	Radworks	7228	DerivaDAO	7632	Rake Finance	8043	MahaDAO	8357	Bitcicoin
6852	Akropolis Delphi	7229	Gelato	7635	UniWorld	8044	Adappter Token	8358	Potentiam
6855	BIDR	7230	Opium	7636	Team Heretics Fan Token	8045	APY Vision	8364	Bridge Mutual
6859	Harvest Finance	7231	Nsure.Network	7637	Trabzonspor Fan Token	8049	Tornado Cash	8365	Seascape Crowns
6865	Crypton	7232	Stella	7638	Apollon Limassol	8056	UNION Protocol Governance Token	8368	Xeno Token
6866	TAI	7236	Celo Dollar	7639	Club Atletico Independiente	8057	AnRKey X	8372	XNODE
6867	STABLE ASSET	7242	cVault.finance	7641	Medicalveda	8063	Duck DAO (DLP Duck Token)	8376	MASQ
6868	Seigniorage Shares	7244	SaTT	7645	WadzPay Token	8066	Yield App	8377	SX Network
6870	OIN Finance	7245	Stobox Token	7647	Azuki	8068	Coinbase tokenized stock FTX	8378	Akita Inu
6872	Carrot	7255	Aitra	7653	Oasis Network	8071	OnX Finance	8384	CLV
6874	SalmonSwap	7256	Mettalex	7654	RFOX	8075	Rally	8385	Umbrella Network
6881	DefiDollar	7257	APEcoin.dev	7661	GYSR	8080	Dypius [Old]	8386	Gourmet Galaxy
6882	EXNT	7262	extraDNA	7664	UNCX Network	8083	Tokenlon Network Token	8387	Auto
6883	KittenFinance	7263	HLP Token	7665	NestEGG Coin	8085	Lido Staked ETH	8389	BambooDeFi
6887	Archethic	7270	SAFE DEAL	7669	UNCL	8100	Ankr Staked ETH	8394	Anime Token
6889	TRONbetLive	7276	Kirobo	7672	Unifi Protocol DAO	8104	1inch Network	8398	YFIONE
6890	TON Token	7278	Aave	7676	Axion	8105	ROCKI	8405	Butterfly Protocol
6891	Niftyx Protocol	7281	Persistence	7677	ReapChain	8107	Cobak Token	8406	Apron Network
6892	MultiversX	7288	Venus	7678	Rook	8117	Dymmax	8408	Govi
6896	CORN	7296	Truebit	7681	Ideaology	8119	SafePal	8409	Razor Network
6898	JackPool.finance	7301	AurusX	7684	ORO	8120	Whiteheart	8411	Marginswap
6901	Swerve	7305	Jackpot	7687	Folder Protocol	8123	Australian Dollar Token	8416	Finxflo
6905	Upper Euro	7310	Gem Exchange and Trading	7691	Farmland Protocol	8124	DRC Mobility	8419	APYSwap
6906	Upper Pound	7311	Beefy	7692	e-Radix	8125	Unique One	8420	DAO Maker
6907	Upper Dollar	7320	Neutrino Token	7694	Governor DAO	8129	Fire Protocol	8421	Argon
6911	BNSD Finance	7321	yOUcash	7697	Experty Wisdom Token	8130	Supreme Finance	8422	Pangolin
6928	Bella Protocol	7326	DeXe	7698	CorionX	8131	Curio Governance	8423	Public Mint
6929	Hegic	7332	EasyFi	7699	CyberFi Token	8132	BiFi	8424	Deri Protocol
6930	KIRA	7334	Conflux	7703	MileVerse	8133	Skey Network	8425	JasmyCoin
6933	Nuco.cloud	7336	Index Cooperative	7705	ANIVERSE	8136	WAXE	8426	Filda
6938	YFDAI.FINANCE	7349	Centaur	7725	TrueFi	8141	Mithril Share	8427	Lendhub
6940	Lead Wallet	7355	Reflex	7726	ICHI	8143	Nord Finance	8431	G999
6941	Huobi BTC	7363	POP Network Token	7732	Brother Music Platform	8144	OVR	8438	Hoge Finance
6942	Juggernaut	7367	SnowSwap	7737	API3	8145	SparkPoint Fuel	8442	EthicHub
6945	Amp	7375	SUP	7739	DexKit	8146	Zipmex	8443	LUXO
6949	Hedget	7377	Dogeswap	7740	Polaris Share	8156	GGDApp	8444	Gains Farm
6950	Perpetual Protocol	7380	Dracula Token	7742	88mph	8159	One Cash	8445	SharedStake
6951	Reef	7381	CoFiX	7749	Paypolitan Token	8160	One Share	8448	MCOBIT
6952	Frax	7382	ACoconut	7750	Eden	8162	AME Chain	8449	Goose Finance
6953	Frax Share	7386	Spaceswap MILK2	7755	Handy	8163	Exeedme	8452	Shield Protocol
6958	Alchemy Pay	7390	Spaceswap SHAKE	7761	BuildUp	8164	JulSwap	8458	Peanut
6960	DefiBox	7392	Talent Token	7762	Lyra	8166	MAPS	8463	Tapx
6975	YFFII Finance	7396	r/CryptoCurrency Moons	7772	Leverj Gluon	8167	Wise Token	8469	LavaSwap
6989	Zeedex	7398	Coreto	7784	BLink	8168	Bao Finance (old)	8476	Premia
6991	Sashimi	7399	Global Gaming	7789	OASISBloc	8173	Loon Network	8479	VAIOT
6992	Spartan Protocol	7404	Value Liquidity	7791	Pancake Bunny	8174	CircleSwap	8483	Berry Data
6993	REVV	7411	Covalent	7795	Bird.Money	8177	KnoxFS	8484	Olyverse
6997	SakeToken	7412	UniLend	7805	Muse	8182	VidyX	8487	TBCC
7009	BNBUP	7414	Behodler	7809	Carbon	8185	Trism	8489	XSGD
7010	BNBDOWN	7420	Digital Reserve Currency	7813	Basis Cash	8188	MoneySwap	8492	Vesper
7016	ETHUP	7422	PlotX	7814	Alaya	8191	NFTX	8494	Modefi
7022	Pickle Finance	7424	Hermez Network	7816	Basis Share	8196	Mantis	8495	Everest
7024	Autobahn Network	7425	PayAccept	7817	Bifrost	8200	Shapeshift FOX Token	8497	ApeSwap
7030	Betherchip	7429	Liquity	7819	Unicap.finance	8202	ZKBase	8499	300FIT NETWORK
7033	Empty Set Dollar	7430	Zenfuse	7821	Royale Finance	8206	QuickSwap [Old]	8500	NitroEX
7034	Golff	7431	Akash Network	7824	Vai	8212	Earn Defi Coin	8501	Luxurious Pro Network Token
7041	Gather	7436	BonFi	7826	Zoracles	8213	Venus Filecoin	8508	PoolTogether
7046	Aavegotchi	7438	ZeroSwap	7838	Base Protocol	8214	Venus DAI	8509	XMON
7048	Wing Finance	7440	BarnBridge	7841	Idle	8216	Electra Protocol	8510	QiSwap
7055	DeFi Pulse Index	7445	cCOMP	7844	ACryptoS	8224	Dequant	8519	Xend Finance
7064	BakeryToken	7455	Audius	7846	Unbound	8230	AI Network	8522	TOZEX
7074	Oracolxor	7460	Alpha Quark Token	7857	Mirror Protocol	8232	UniDex	8524	Wrapped Huobi Token
7077	UniFi Protocol	7461	PlayDapp	7859	Badger DAO	8236	Glitch	8525	Rai Reflex Index
7080	Gala	7462	United	7860	ClinTex CTi	8245	Hydra	8526	Raydium
7083	Uniswap	7463	RAMP	7864	DGPayment	8249	LP 3pool Curve	8528	HashBridge Oracle
7087	Dego Finance	7467	Swirge	7866	Monavale	8252	pBTC35A	8530	StarLink
7094	dHedge DAO	7474	Axia Protocol	7870	Plasma Finance	8255	Prosper	8531	Quantfury Token
7095	Unisocks	7475	Camp	7876	SORA Validator Token	8256	HollyGold	8534	Chintai

Table 17: Names and crypto-assets' coinmarketcap.com IDS: 1501-2000.

ID	NAME	ID	NAME	ID	NAME	ID	NAME	ID	NAME
8536	Mask Network	8801	Light	9104	AIOZ Network	9466	Edgecoin	9783	Roseon
8537	Channels	8813	LABS Group	9107	ZilSwap	9467	Celo Euro	9789	ETH2x Flexible Leverage
8538	AC Milan Fan Token	8823	Poodl Token	9110	Kattana	9468	Spore	9792	ACENT
8540	HecoFi	8826	Moss Carbon Credit	9111	Push Protocol	9473	Unicly CryptoPunks Collection	9797	Avalaunch
8541	SifChain	8827	Boson Protocol	9115	WorkQuest Token	9479	KSwap	9798	VELOREX
8543	Kangal	8829	Pig Finance	9119	Alien Worlds	9481	Pendle	9805	EVAI
8544	Fractal ID	8831	Aurix	9120	Franklin	9487	Sheesha Finance [ERC20]	9816	APENFT
8545	Launchpool	8833	DeGate	9125	Gains	9488	ZooKeeper	9819	PalGold
8547	RamenSwap	8837	Scholarship Coin	9131	Alchemist	9492	Etherland	9825	NiiFi
8548	Aloha	8840	DailySwap Token	9132	MobiFi	9493	Reflexer Ungovernance Token	9827	Sportcash One
8549	Polkacity	8841	Arro Social	9134	NBX	9498	EnreachDAO	9828	Nafter
8554	PRivaCY Coin	8844	SPRINK	9148	Drep [new]	9502	Pippi Finance	9837	Flux Protocol
8558	BT.Finance	8849	AXIS Token	9155	DEFIT	9503	CryptoTycoon	9839	blockbank
8560	WhaleRoom	8850	Viper Protocol	9158	moonwolf.io	9504	NAOS Finance	9840	Pleasure Coin
8561	KeyFi	8857	Anchor Protocol	9169	MMAON	9505	Lever Token	9844	Atlantic Finance Token
8565	Exen Coin	8858	Cub Finance	9172	Professional Fighters League Fan	9507	Goztepe S.K. Fan Token	9848	Moonlight Token
8566	Ballswap	8862	Rage Fan	9173	Raze Network	9508	Universidad de Chile Fan	9854	Tiger King Coin
8567	HAPI Protocol	8863	SHOPX	9175	MOBOX	9509	Legia Warsaw Fan Token	9855	EthereumMax
8579	Polkamarkets	8865	vBSWAP	9176	RocketX exchange	9510	Fortuna Sittard Fan Token	9856	Knit Finance
8590	Cyclone Protocol	8866	BSC TOOLS	9177	Pitbull	9511	Dfyn Network	9859	YUMMY
8593	FileStar	8867	DeHive	9179	Defi For You	9512	Cubiex Power	9862	Sishi Finance
8602	Bounce Token	8868	50x.com	9180	myDID	9518	MemePad	9863	TrustBase
8605	WOWswap	8874	DAFI Protocol	9188	Globe Derivative Exchange	9522	Bonfire	9865	Ispolink
8607	Xion Finance	8875	Uno Re	9191	Occam.Fi	9524	Media Network	9866	FEAR
8610	DMEX(Decentralized Mining E.)	8877	KIWIGO	9193	Prostarter	9526	LOCGame	9867	Hot Cross
8611	VKENAF	8879	Pika	9194	Saito	9530	FaraLand	9868	XCAD Network
8612	Float Protocol (Bank)	8880	MacaronSwap	9196	Genesis Shards	9533	GreenTrust	9869	Spherium
8613	Alchemix	8882	Alliance Fan Token	9198	Hord	9537	EpiK Protocol	9870	xWIN Finance
8615	Ethernity	8883	Sint-Truidense Voetbalvereniging Fan	9200	Revomon	9543	Biconomy	9872	TheFutbolCoin
8616	Aurox	8884	Istanbul Basaksehir Fan Token	9205	K21	9544	POLKARARE	9879	Exohood
8617	Red Kite	8885	Novara Calcio Fan Token	9207	Metaverse Index	9545	NFTb	9889	Bistroo
8620	TOWER	8886	USDP Stablecoin	9212	CumRocket	9547	tSILVER	9891	BinaryX (old)
8621	yieldwatch	8891	Bitcoin Standard Hashrate Token	9214	MoonStar	9549	Mercurial Finance	9892	YooShi
8622	Bancor Governance Token	8894	Deeper Network	9217	XFai	9550	PERI Finance	9900	HODL
8625	SaltSwap Finance	8895	ORAO Network	9218	Mist	9553	B-cube.ai	9903	Convex Finance
8633	Nodestats	8897	KickPad	9220	StrikeX	9562	Coldstack	9904	GeroWallet
8635	xDAI	8899	xSUSHI	9225	Rigel Protocol	9566	Liquity USD	9905	Rune
8637	Tranche Finance	8904	renZEC	9237	Horizon Protocol	9576	Vulkania	9906	Bunicorn
8642	Fei USD	8905	BitSong	9241	Satozhi	9578	Dungeonswap	9908	Ki
8643	Shadows	8908	ImpulseVen	9245	Signata	9583	MELX	9920	RUSH COIN
8644	Kylin	8909	Stater	9247	Whole Earth Coin	9586	PRIVATEUM GLOBAL	9928	Space Token
8646	Mina	8910	Daily	9251	Standard	9588	O3 Swap	9931	SONM (BEP-20)
8647	MurAll	8911	Strike	9253	Twinci	9590	Obortech	9932	ElonDoge
8648	ChainGuardians	8912	Tidal Finance	9258	Chia	9592	Fortress Lending	9936	Elephant Money
8649	Oxbull.tech	8915	Hello Pets	9259	TheForce Trade	9595	CaliCoin	9938	OpenOcean
8657	wanUSDT	8916	Internet Computer	9260	Zignaly	9597	dFund	9941	Chihuahua
8658	Wrapped WAN	8917	Shyft Network	9262	UniFarm	9598	Lion Token	9943	American Shiba
8659	Jetfuel Finance	8925	Wrapped Matic	9263	Unizen	9604	Privapp Network	9946	Your Future Exchange
8660	BSCPAD	8926	A2DAO	9265	Porta	9605	TruePNL	9951	WaultSwap
8662	Starter	8936	Trias Token (New)	9269	Refinable	9607	Bankless DAO	9954	Netvrk
8665	Parallel	8937	Woonkly Power	9270	Bitcoin Bam	9608	SpookySwap	9958	SafeMoon Inu
8666	DFX Finance	8938	Ellipsis	9279	SuperLauncher	9613	Trustpad (Old)	9962	STARSHIP
8669	Sovryn	8942	Paybswap	9284	Secured MoonRat Token	9615	Polylastic	9967	SafeBlast
8670	Vow	8943	WHITEX	9285	Moonriver	9620	Wrapped Statera	9968	Corgidoge
8673	TotemFi	8961	Futureswap	9286	Doge Killer	9628	Raptor Finance	9976	Freela
8675	Minds	8962	ETNA Network	9288	BENQI	9632	UMI	9982	DINGO TOKEN (old)
8677	Symbol	8963	UnMarshal	9291	Ternoa	9635	SaveYourAssets	9984	CluCoin
8678	EHash	8964	Blizzard.money	9295	CLIMB TOKEN FINANCE	9637	Altura	9989	Solrise Finance
8679	Unido EP	8966	Safemars	9299	NFT Art Finance	9638	SingularityDAO	9991	Charli3
8681	Funder One Capital	8968	Polychain Monsters	9300	Zeppelin DAO	9639	Pussy Financial	9996	Bezoge Earth
8683	Asva	8970	Lokr	9302	MoMo KEY	9640	MetisDAO	9997	METANOA
8690	CAD Coin	8971	MerchDAO	9308	Vulcan Forged (PYR)	9643	Don-key	9998	Unicly
8691	Domani Protocol	8972	Seedify.fund	9316	Shipit pro	9651	Ethermon	10005	Zoo Token
8695	BlockWallet	8978	PooCoin	9318	BeforeCoinMarketCap	9653	Nabox	10011	CoinWind
8697	Konomi Network	8981	WardenSwap	9326	ROPE Token	9654	CryptoBlades	10023	Planet
8702	Ares Protocol	8985	Efinity Token	9342	Community Business Token	9656	CateCoin	10029	USD mars
8704	Playcent	8992	Cellframe	9344	1MillionNFTs	9663	ArGo	10030	Mars Ecosystem Token
8705	Bifrost	8994	Delta	9345	BSCS	9665	My DeFi Pet	10031	TEN
8707	Alpaca Finance	8996	Mogul Productions	9348	Crowny	9666	Terran Coin	10033	NFTMart Token
8708	Big Data Protocol	8997	Cook Finance	9353	Kalata	9670	GogolCoin	10036	BSClaunch
8709	ETHA Lend	9002	Busy DAO	9364	Unlock Protocol	9673	Loser Coin	10040	Wall Street Games
8710	bAlpha	9007	ZooCoin	9368	Euler Tools	9674	Wilder World	10042	Karura
8711	Pando	9008	AMMYI Coin	9377	TreeDefi	9675	Drops Ownership Power	10046	Dotmoovs
8715	Taraxa	9016	DAOhaus	9386	Kishu Inu	9679	MoonStarter	10047	EPIK Prime
8716	Convergence	9017	Polkadex	9395	Strite	9686	My Crypto Heroes	10049	Manchester City Fan Token
8717	Oddz	9020	Toko Token	9413	Vira-lata Finance	9691	Venus Reward Token	10052	Gitcoin
8719	Illuvium	9021	Wrapped XDAI	9416	The Crypto Prophecies	9693	DOGGY	10055	Crust Shadow
8720	Inverse Finance	9024	disBalancer	9417	Maple	9694	Upfire	10059	Pandora Finance
8723	Bogged	9025	Tribe	9421	Ampleforth Governance Token	9698	Tycoon	10061	CumInu
8726	Idavoll DAO	9026	Blind Boxes	9423	Phuture	9700	Phutuber	10079	Quidax Token
8730	Belt Finance	9027	Uhive	9428	Venus Cardano	9710	Kabosu	10081	SafeMoonCash
8732	Swop	9029	Graphlinq Chain	9430	Alphr finance	9711	Sanshu Inu	10083	ClassZZ
8733	BasketCoin	9035	Vidiachange	9436	Dogelon Mars	9712	Shih Tzu	10088	PolyDoge
8738	Pastel	9040	Pundi X (New)	9437	CherrySwap	9720	PlatON	10090	Friends With Benefits Pro
8741	Sovi Finance	9043	Stone DeFi	9438	Nominex	9721	Samoyedcoin	10093	Gold Secured Currency
8745	A2A	9045	JPY Coin v1	9440	Mochi Market	9737	Hummingbird Finance (Old)	10095	Elk Finance
8752	Landbox	9046	8PAY	9441	Jigstack	9740	Dot Finance	10098	Greenheart CBD
8755	Nerve Finance	9047	CARD.STARTER	9443	Step Finance	9741	Solanium	10099	KALM
8757	SafeMoon	9055	BerrySwap	9444	Kyber Network Crystal v2	9742	ElonTech	10101	Kwikswap Protocol
8759	ZCore Finance	9061	Rainicorn	9447	Synthetify	9747	Cryption Network	10102	BankSocial
8766	MyNeighborAlice	9062	LinkPool	9449	Sienna (ERC20)	9749	WallStreetBets DApp	10103	Lossless
8769	MeetPle	9065	Realfinance Network	9450	BLACKHOLE PROTOCOL	9752	AFEN Blockchain Network	10109	Feeder.finance
8771	GYEN	9067	Olympus v2	9451	Verso	9756	Virtue Poker	10117	Moonarch.app
8772	ZUSD	9070	CFX Quantum	9452	Bandot Protocol	9757	WeStarter	10121	ByteNext
8789	EDDASwap	9071	Chainge	9453	Agave	9760	Stratos	10127	JINDO INU
8790	KINE	9073	Popsicle Finance	9455	Lemond	9763	Copiosa Coin	10128	TeraBlock
8795	Mute	9083	Equalizer	9456	Australian Safe Shepherd	9764	MILC Platform	10134	Polycat Finance
8797	Chronicle	9089	Tenset	9458	HOKK Finance	9766	Rentible	10145	DeFinity
8798	Ramifi Protocol	9091	CPCoin	9461	X World Games	9767	Frenchie Network	10155	Vanity
8799	InsurAce	9103	GAMEE	9462	Wrapped AVAX	9780	Snowball	10158	SpaceGrime

Table 18: Names and crypto-assets' coinmarketcap.com IDS: 2001-2500.

ID	NAME	ID	NAME	ID	NAME	ID	NAME	ID	NAME
10160	Swaperry	10502	SafeMars	10888	NewB.Farm	11223	MetaMUI	11530	Roush Fenway Racing Fan
10161	OptionPanda	10506	HitBTC Token	10889	DRIFE	11230	Sakura	11531	Portugal National Team Fan
10165	PornRocket	10508	Instadapp	10891	Only1	11232	Highstreet	11532	Arsenal Fan Token
10166	AstroElon	10514	HUNNY FINANCE	10893	Brokoli Network	11233	Monsoon Finance	11533	UFC Fan Token
10167	SpaceY	10519	Curio Stable Coin	10894	StorX Network	11234	Position Exchange	11534	Levante U.D. Fan Token
10172	DekBox	10522	Pacoca	10897	Alitas	11240	HI	11539	Vendit
10174	CreamPYE	10524	reBaked	10898	Wrapped Centrifuge	11242	Moonpot	11541	Ariva
10178	Rabbit Finance	10526	TribeOne	10899	Daddy Doge	11245	Landshare	11552	Talken
10180	Gomining	10527	Lithium	10900	Hachiko Inu	11247	Kephi Gallery	11556	CryptoZoo (new)
10182	Manifold Finance	10529	Sun (New)	10901	Shiba Floki Inu	11251	Dexlab	11557	The Doge NFT
10183	DeSpace Protocol	10530	CrossWallet	10903	Coin98	11254	Minifootball	11560	DeHub
10185	Moonlana	10532	Divergence	10904	BunnyPark	11258	Creaticles	11562	Kava Swap
10188	Automata Network	10554	Sekuritance	10905	AirNFTs	11271	Colana	11563	aiRight
10201	BitBook	10555	Canary	10908	KuSwap	11275	BinStarter	11566	ASH
10202	Starcoin	10556	B.Protocol	10914	BABY DOGE INU	11278	Project TXA	11568	Adventure Gold
10217	Cykura	10557	Swapz	10918	Crypto Village Accelerator	11279	Block Ape Scissors	11570	The Recharge
10221	Fanadise	10563	Decubate	10919	CoinsPaid	11283	Ryoshis Vision	11578	Cirus Foundation
10222	Vodra	10566	BlackHat	10928	DOJO	11289	Spell Token	11579	Cryptomeda
10223	Vega Protocol	10570	Binance Smart Chain Girl	10929	ZoidPay	11291	Kryptomon	11582	Lumi Credits
10225	Pera Finance	10576	MoonLift Capital	10932	Impossible Finance	11292	Unreal Finance	11584	Braintrust
10228	Omchain	10585	TrustFi Network	10933	Impossible Finance Launchpad	11293	Avaware	11586	Story
10232	MakiSwap	10586	TABOO TOKEN	10935	Aldrin	11294	SuperRare	11591	Raid Token
10234	Draken	10593	Flurry Finance	10949	Baanx	11299	POTENT	11596	SingularFarm
10237	QiDao	10603	Immutable	10953	Kaby Arena	11301	YEL.Finance	11599	Alita Finance
10238	MAI	10613	Empire Token	10954	MContent	11307	Beta Finance	11603	MarketMove
10239	SpiritSwap	10622	XCarnival	10967	YIN Finance	11308	Fenerbahce Token	11612	Sunny Aggregator
10240	Wrapped Fantom	10630	Guild of Guardians	10970	BabyDoge ETH	11309	OneRare	11614	Theos
10251	The Corgi of PolkaBridge	10631	Gods Unchained	10973	PureFi Protocol	11314	CWallet	11616	Score Token
10257	Shibaken Finance	10640	Kawakami	10974	Tranchess	11317	Relay Token	11620	IX Swap
10260	Thorstarter	10641	RichQUACK.com	10977	Mint Club	11318	Goldex Token	11621	Punk Vault (NFTX)
10262	KleeKai	10644	SafeBull	10984	Witch Token	11322	Mobius Finance	11646	Regen Network
10264	Charged Particles	10648	Eifi FInance	10987	AVME	11323	Crypto Carbon Energy	11649	Wicrypt
10265	Gold Fever	10657	YetiSwap	11013	LIQ Protocol	11324	Forest Knight	11654	VelasPad
10269	Cheems	10665	KogeCoin.io	11015	Team Vitality Fan Token	11329	KamPay	11660	MCFinance
10272	AladdinDAO	10666	Lanceria	11017	PolygonFarm Finance	11330	VIMworld	11663	Elemon
10275	Catgirl	10669	Pallapay	11018	CryptoArt.Ai	11336	Nobility	11664	YAY Games
10277	TRONPAD	10674	Synapse Network	11020	ZOO Crypto World	11338	Block Commerce Protocol	11670	DeFi Warrior (FIWA)
10278	Genshiro	10675	Hare Token	11023	Wrapped KuCoin Token	11340	Immutable	11672	Pocoland
10285	Bitspawn	10677	Pollen	11024	KingDeFi	11344	Mate	11678	Lumenswap
10289	Daisy Launch Pad	10685	Olive Cash	11033	RedFEG	11345	Civilization	11682	DeathRoad
10290	RFOX Finance	10686	Evanesco Network	11035	Splintershards	11346	RACA	11685	BetU
10291	Convex CRV	10688	Yield Guild Games	11036	Alkimi	11348	Identity	11690	Magic Beasties
10293	Swarm	10695	MoonEdge	11038	BFG Token	11349	ADAPad	11695	ChronoBase
10294	DeFi Land	10700	KickToken	11042	NFTBooks	11350	NFTLaunch	11696	Wrapped Harmony
10295	IOI Token	10704	Binamon	11053	Cogecoin	11352	Moonie NFT	11697	Phantom Protocol
10303	AutoShark	10705	CoinSwap Space	11056	Golden Doge	11354	WagyuSwap	11700	Life Crypto
10307	Project Quantum	10712	Flourishing AI	11060	Baby Shiba Inu	11366	Paribus	11701	Copycat Finance
10311	NFT STARS	10713	Burp	11061	Multiverse	11367	Aurory	11706	Acet
10312	EscoinToken	10714	Babylons	11066	DinoX	11368	Feisty Doge NFT	11707	Sona Network
10324	Gravity Finance	10715	AirCoin	11067	Step Hero	11371	RoboFi	11713	Shambala
10325	Safe Energy	10720	Black Phoenix	11076	JOJO	11373	Metaverse Miner	11714	Brazil National Football Team Fan
10326	BullPerks	10722	SolanaSail	11078	IAGON	11374	Mines of Dalarnia	11715	Snook
10334	BabySwap	10723	Waves Ducks	11079	Bitgert	11380	Dogecoin 2.0	11726	SideShift Token
10336	Hamster	10725	WaultSwap Polygon	11082	Arena Token	11387	CropperFinance	11727	Phoenix Token
10337	Sheesha Finance [BEP20]	10729	UFO Gaming	11083	TripCandy	11390	Hibiki Finance	11736	CryptoMines
10347	Human	10740	Liti Capital	11086	Gamerse	11392	Moon Rabbit	11739	Blox Token
10348	Sarcophagus	10742	NEXTYPE	11088	Enjinstarter	11394	Green Climate World	11740	DeFIL
10350	Black Eye Galaxy	10744	DeRace	11090	Invitoken	11395	BOHR	11746	Megatech
10351	HTMOON	10746	Biswap	11092	Bitget Token	11396	JOE	11750	Buying.com
10364	APWine Finance	10747	ETHPad	11093	Drip Network	11397	Kaiken Shiba	11752	XP NETWORK
10366	Cake Monster	10748	PolkaWar	11104	Artery Network	11409	Tarot	11753	Cycle Finance
10367	April	10750	Qredo	11105	PearZap	11412	Binemon	11765	BigShortBets
10368	Cryptex Finance	10753	Evodefi	11107	Birb	11413	Ceres	11770	EverETH Reflect
10372	Dacxi	10756	Omni Real Estate Token	11109	Electric Cash	11414	Qubit	11772	DeMon Token
10373	Tulip Protocol	10759	rhino.fi	11110	Spores Network	11415	Yield Yak	11779	Dreams Quest
10376	dAppstore	10763	Aston Martin Cognizant Fan	11112	MyBricks	11417	Gaj Finance	11783	GameFi.org
10386	Bitcoin Latinum	10768	KAKA NFT World	11114	xNFT Protocol	11419	Toncoin	11794	handleFOREX
10388	SupremeX	10774	Sonar	11126	Hypersign Identity	11420	Tune.FM	11796	Inter Milan Fan Token
10391	Creator Platform	10776	Signum	11129	CryptoZoon	11421	Marnotaur	11797	Cricket Foundation
10392	The Everlasting Parachain	10777	DinoSwap	11130	Plant Vs Undead	11422	Wanaka Farm	11801	Daily COP
10393	LEOPARD	10778	Metahero	11132	Wrapped OKT	11423	VEMP	11802	Project X
10394	Kuma Inu	10784	KCCPAD	11134	OEC BTC	11427	Coinary Token	11805	Structure finance
10403	Kommunitas	10789	Tether EURt	11146	Jswap.Finance	11431	Minimals	11809	Ref Finance
10404	Integral	10791	eCash	11148	Proxy	11437	DEEPSPACE	11810	Pirate Coin Games
10407	Baby Doge Coin	10793	Alfa Romeo Racing ORLEN Fan	11150	DeFine	11446	S.C. Corinthians Fan Token	11813	Afreum
10408	Formation Fi	10798	MiniDOGE	11153	EmiSwap	11448	The HUSL	11814	Potato
10409	Opulous	10800	Hungarian Vizsla Inu	11156	dYdX (ethDYDX)	11450	Skyrim Finance	11818	Waggle Network
10411	Moonfarm Finance	10803	RealFevr	11160	BOY X HIGHSPEED	11451	Shiden Network	11820	TORG
10412	HoDooi.com	10804	FLOKI	11164	Vabble	11455	Polinate	11821	Swarm Markets
10421	Torum	10805	Throne	11165	Orca	11456	SnowCrash Token	11823	Pocket Network
10427	POLKER	10807	CoinW Token	11168	Vent Finance	11458	EVRYNET	11835	Monsters Clan
10428	Alium Finance	10808	Ubeswap	11171	Mango	11461	Marinade Staked SOL	11836	Citadel.one
10429	HaloDAO	10810	Jetswap.finance	11178	Wrapped LUNA Classic	11463	Husky Avax	11838	MilkshakeSwap
10430	Argentine Football Association Fan	10814	One Basis	11181	Saber	11464	ApeXit Finance	11842	PolkaFantasy
10434	SafeLaunch	10818	Penguin Finance	11185	TABANK	11465	CATO	11848	Strips Finance
10436	Xiglute Coin	10820	Yieldly	11186	Vention	11469	Solpad Finance	11851	Crosschain IOTX
10439	StakeWise	10821	Starlink	11188	Dopex	11470	Boring Protocol	11854	ArbiNYAN
10442	Decentralized Social	10824	Hertz Network	11190	KittyCake	11486	WifeDoge	11857	GMX
10452	SolAPE Token	10831	Mimo Governance Token	11191	Lydia Finance	11492	TCGCoin 2.0	11861	PlanetWatch
10455	EQIFI	10832	Etherlite	11197	Sukhavati Network	11495	Tomb	11862	Arix
10461	Memecoin	10833	ADAX	11202	Tokemak	11497	Scream	11864	Meme Lordz
10462	SHILL Token	10839	Yield Parrot	11206	Bloktopia	11498	Chainbing	11865	Bone ShibaSwap
10463	Anypad	10841	Wolf Safe Poor People	11209	TRAVA.FINANCE	11499	AMATERAS	11869	Realm
10465	Polytrade	10853	ETHDOWN	11211	DNAxCAT Token	11500	Biconomy Exchange Token	11871	GameZone
10467	IRON Titanium Token	10854	Railgun	11212	Star Atlas	11503	Manga Token	11878	Arbidoge
10469	iMe Lab	10861	Gamestarter	11213	Star Atlas DAO	11512	Kalao	11880	EpicHero 3D NFT
10482	BULL FINANCE	10866	Million	11218	BoringDAO	11516	Ekta	11882	Bitcashpay (new)
10484	Iron	10868	Super Floki	11220	Port Finance	11522	Jenny Metaverse DAO	11885	HurricaneSwap Token
10494	Octopus Protocol	10875	ChainCade	11221	BitDAO	11528	Valencia CF Fan	11887	Mission Helios
10501	BaconDAO	10877	Ainu Token	11222	Nine Chronicles	11529	Clube Atletico Mineiro Fan	11888	Matrix Labs

Table 19: Names and crypto-assets' coinmarketcap.com IDS: 2501-3000.

ID	NAME	ID	NAME	ID	NAME	ID	NAME	ID	NAME
11893	Teddy Cash	12253	WOOF	12590	AutoShark DEX	12971	Lunr Token	13592	Silva Token
11896	Morpheus Token	12254	Gro DAO Token	12591	LunaChow	12972	DEUS Finance	13606	Great Bounty Dealer
11907	Fantom Oasis	12255	BitOrbit	12595	Filecoin Standard Hashrate Token	12979	Sentre Protocol	13618	Shiba Girlfriend
11910	SokuSwap	12256	cheqd	12599	ASPO World	12981	BHAX Token	13626	ACA Token
11911	Larix	12257	XTRA Token	12604	FRAKT Token	12987	SatoshiStreetBets Token	13630	OOGI
11913	AcknoLedger	12258	StrongNode Edge	12607	Solberg	12988	LABEL Foundation	13632	Genopets
11916	Minerva Wallet	12265	Investin	12609	Sway Protocol	12991	MagnetGold	13636	GMCoin
11921	Nether NFT	12269	WELD	12613	Solareum Wallet	12996	FastSwap (BSC)	13637	XRdoge
11923	Elpis Battle	12271	CryptoBlades Kingdoms	12614	Dragon Kart	12999	ssv.network	13649	Energy8
11925	Monsta Infinite	12272	Boo Finance	12641	OBRok Token	13009	ITSMYNE	13655	Crabada
11926	Thetan Arena	12275	Dynamix	12644	The Three Kingdoms	13011	UNKJD	13656	Jacy
11930	HALO network	12278	Playermon	12648	Wrapped Curio Ferrari F12tdf	13012	Synchrony	13659	Crypto Global United
11931	Traders coin	12279	PixelVerse	12649	Alanyaspor Fan Token	13018	Paras	13663	Gains Network
11933	HalfPizza	12280	BHO Network	12650	GAIA Everworld	13020	Flare Token	13675	Kintsugi
11935	Parrot Protocol	12284	Bantu	12652	Hanu Yokia	13021	Moola Market	13676	BLOCKS
11939	Heroes & Empires	12293	Beyond Protocol	12653	ROCO FINANCE	13026	FOHO Coin	13698	Real Realm
11941	Xfinite Entertainment Token	12294	Ertha	12661	HashBit BlockChain	13030	Pegaxy	13702	STEMX
11945	My Master War	12295	Dinamo Zagreb Fan Token	12664	Scallop	13038	StarLaunch	13708	BFK Warzone
11948	Radix	12297	Lido Staked SOL	12671	FANG Token	13041	Solarbeam	13715	Fancy Games
11952	Wrapped Moonriver	12301	Retreeb	12675	Dark Matter DeFi	13047	Piccolo Inu	13718	GAMINGDOGE
11958	Knight War - The Holy Trio	12306	Raptoreum	12678	FireStarter	13051	ARC	13721	NovaXSolar
11961	Vee Finance	12307	Warena	12682	DecentraWeb	13068	COGI	13726	ENNO Cash
11962	Bright Token	12312	NASDEX	12687	S.S. Lazio Fan Token	13071	SquidGameToken	13727	Shiryo
11967	Hero Arena	12313	Kawaii Islands	12690	Wrapped PKT	13074	Baby Moon Floki	13731	Leeds United Fan Token
11973	Thales	12315	DOSE	12691	Safle	13080	dForce USD	13735	SolDoge
11977	Infinity PAD	12319	DeFi Kingdoms	12692	Poken	13103	Vigorus	13746	FLOOF
11978	Revolve Games	12325	MarsRise	12695	PolyPup Finance	13105	MetaWars	13748	Spartacus
11983	Hudi	12329	DBX	12703	Gyro	13118	Yoshi.exchange	13749	BabyXape
11993	HappyFans	12333	DAO Invest	12705	Pollchain	13119	Wolf Safe Poor People	13751	Liquid Collectibles
12040	Buff Doge Coin	12338	ShibaCorgi	12709	HZM Coin	13121	Atlantis Loans	13760	Shib Army
12041	Dimitra	12344	Affinity	12710	Shakita Inu	13133	Decentral Games ICE	13768	ZeLoop Eco Reward
12042	Sypool	12345	Steam Exchange	12722	Cryowar	13136	Kitty Inu	13769	World Mobile Token
12043	Octopus Network	12350	Triall	12731	Ideanet Token	13138	SugarBounce	13783	Afrostar
12044	Vera	12351	GreenZoneX	12735	Piggy Finance	13142	BTRIPS	13813	ENTERBUTTON
12046	Idexo Token	12355	Baby Floki Billionaire	12737	Umi Digital	13157	PolkaPets	13827	SavePlanetEarth
12049	Green Beli	12359	Wojak Finance	12739	Revolotto	13167	Mimir Token	13831	Crypto Classic
12050	Symmetric	12364	Youclout	12743	Open Rights Exchange	13197	KnoxDAO	13842	Bunscake
12051	Cryptopolis	12365	Lovely Inu Finance	12749	Nakamoto Games	13198	NuNet	13850	Santa Coin
12054	MatrixETF	12366	Demeter	12751	Blockchain Monster Hunt	13211	Algebra	13855	Ethereum Name Service
12057	Dopex Rebate Token	12373	ArchAngel Token	12752	ORE Token	13212	Ethera	13864	Shiba Lite
12058	Light DeFi	12380	PolyDragon	12754	Revault Network	13216	Ninneko	13868	Baby Squid Game
12060	XTblock	12381	Smile Coin	12760	Socean Staked Sol	13229	PaintSwap	13871	TaleCraft
12064	Cratos	12382	Zamio	12761	Angle	13236	Galaxy War	13874	GAMI World
12066	Shirtum	12387	Ribbon Finance	12767	FODL Finance	13237	FantomStarter	13877	e-Money EUR
12070	Quidd	12393	Lightcoin	12769	Ardana	13243	FoxGirl	13881	Hector Network
12071	XcelPay	12395	Merchant Token	12773	DfiStarter	13244	Beethoven X	13887	P2P Solutions foundation
12074	Gem Guardian	12397	Moonbeans	12775	Waste Digital Coin	13246	LiquidDriver	13889	ZUNA
12077	Zenith Coin	12398	Spain National Fan Token	12778	Ojamu	13250	ScarQuest	13901	Bit2Me
12078	DogeSwap	12400	Decimal	12780	French Connection Finance	13251	CryptoXpress	13913	Blockster
12082	CyberDragon Gold	12409	Lido wstETH	12781	xHashtag	13256	Flokimooni	13914	Oobit
12089	Coinweb	12411	Balkari	12784	Red Floki	13265	Fidira	13916	Omax Coin
12090	YoCoin	12414	MRHB DeFi Network	12785	Colony	13271	QUARTZ	13920	Popcorn
12100	Crystl Finance	12416	PulsePad	12797	ShoeFy	13272	Credefi	13932	Genesis Worlds
12109	Poof.cash	12417	Lovelace World	12799	Internet of Energy Network	13276	Squid Game	13933	ArcadeNetwork
12115	Orion Money	12418	Jax.Network	12807	DAOSquare	13277	UNIFEES	13936	Ari10
12118	Celestial	12431	StarSharks (SSS)	12813	Sinverse	13286	CorgiCoin	13937	Catena X
12119	Planet Sandbox	12432	StarSharks SEA	12814	Dexsport	13319	Flamengo Fan Token	13938	Game Coin
12120	AstroSwap	12435	Battle Hero	12815	CryptoPlanes	13323	Integritee Network	13943	GINZA NETWORK
12125	RazrFi	12436	Timeleap Finance	12818	gotEM	13326	RBX	13953	Scotty Beam
12131	Fruits	12439	BRCP TOKEN	12820	Treat DAO [new]	13336	Newsolution2.0	13967	Goldfinch
12133	X Protocol	12440	Buffer Finance	12833	Mech Master	13337	MMScash	13969	Phoenix
12136	IjasCoin	12448	EverGrow	12834	Envoy	13342	SoulSwap Finance	13973	nSights DeFi Trader
12137	NFTrade	12451	Mondo Community Coin	12835	FalconsInu	13351	ADACash	13977	DoragonLand
12140	RMRK	12452	TETU	12836	AutoCrypto	13352	Dinger Token	13978	MetaVPad
12147	Synapse	12457	ZEDXION	12843	Graphene	13383	CropBytes	13987	DYOR Token
12148	Swash	12458	Karus Starter	12844	The Flash Currency	13400	MojitoSwap	13989	BabyFlokiZilla
12150	Little Angry Bunny v2	12459	Holdex Finance	12851	BODA Token	13403	Howl City	13994	MetaDoge V2
12153	Kurobi	12460	United Emirate Decentralized Coi	12854	PAPPAY	13411	Titan Hunters	13996	AVNRich Token
12154	Everest Token	12463	Timechain Swap Token	12859	DogeBonk	13420	PlaceWar	14020	Samsunspor Fan Token
12156	Asia Coin	12464	Lox Network	12870	The CocktailBar	13425	NFT Champions	14027	Snowbank
12166	Starpad	12465	Ridotto	12873	KlimaDAO	13429	Doge Floki Coin	14052	FC Porto Fan Token
12172	Moniwar	12468	Equilibrium Games	12878	BEMIL Coin	13431	Agricoin	14053	GovWorld
12173	Revuto	12472	Elysian	12885	Astar	13436	ftm.guru	14063	FantOHM
12176	Hummingbird Egg	12480	Starchi	12886	bloXmove Token	13437	Kiba Inu	14069	FIA Protocol
12179	PolyAlpha Finance	12485	Arowana Token	12889	Hundred Finance	13439	CashCow	14073	Vagabond
12180	Rainbow Token	12487	Dark Frontiers	12890	Uplift	13449	GameStation	14075	POOMOON
12182	Blocto Token	12488	Dogira	12892	Linked Finance World	13453	Waifer	14079	Shibalana
12186	Songbird	12489	Guardian	12895	Lil Floki	13465	Altbase	14089	Tempus
12192	RugZombie	12494	Melo Token	12898	GooseFX	13471	Omni Consumer Protocols	14094	AlgoGems
12193	AquaGoat.Finance	12495	XGOLD COIN	12901	King Shiba	13472	XDEFI Wallet	14099	Mobius Money
12194	Baby Floki (BSC)	12500	Orca AVAI	12907	Vires Finance	13473	Apricot Finance	14114	Superalgos
12196	Kollect	12501	Qrkita Token	12912	Digital Bank of Africa	13479	WePiggy Coin	14119	Upper Swiss Franc
12198	Boss Token	12506	NFTY Token	12919	Universal Basic Income	13485	Smarty Pay	14133	WAM
12199	FUFU	12511	Wrapped NewYorkCoin	12924	XDoge Network	13493	Wanaka Farm Wairere	14161	1NFT
12200	Digital Swiss Franc	12516	Dog Collar	12929	OneArt	13509	Mytheria	14172	ADToken
12203	Defina Finance	12517	DEI	12930	Cpos Cloud Payment	13518	Ethereans	14179	Pintu Token
12208	Taxa Token	12524	Farmers Only	12932	Little Bunny Rocket	13521	Numbers Protocol	14188	Plugin
12212	Allbridge	12526	USD Open Dollar	12938	Catena	13523	Merit Circle	14195	Solar
12214	Shibaverse	12532	TTcoin	12942	THORSwap	13524	Solend	14205	Wakanda Inu
12215	Falcon 9	12536	Decentralized Community Investment P.	12949	Toucan Protocol: Base Carbon Tonne	13531	Keeps Coin	14210	Construct
12218	Continuum World	12537	PolyBeta Finance	12951	Riot Racers	13532	xDollar	14222	StrongHands Finance
12220	Osmosis	12546	Liquidus (old)	12952	MetaverseX	13534	xDollar Stablecoin	14235	Shiba Interstellar
12221	Rangers Protocol	12549	Dinosaureggs	12954	Vetter Token	13542	Stabledoc	14251	Freedom. Jobs. Business.
12225	TryHards	12562	Mononoke Inu	12956	Wanda Exchange	13543	Bamboo Coin	14253	Baby Samo Coin
12229	DogeGF	12566	PinkSale	12957	Galactic Arena: The NFTverse	13546	BabyDogeZilla	14256	QuizDrop
12230	Revest Finance	12573	Clearpool	12959	Pontoon	13548	BecoSwap Token	14261	Strip Finance
12236	Jet Protocol	12576	Geist Finance	12961	BullionFx	13560	ShibaZilla2.0 (old)	14265	MetaDoge
12238	OwlDAO	12577	PLĜnet	12965	Good Games Guild	13567	SmarterCoin (SMRTr)	14271	GM Wagmi
12240	MARS4	12581	CZodiac Farming Token	12967	GoldMiner	13571	All.Art Protocol	14285	OnGO
12252	Bombcrypto	12585	Demole	12969	Gari Network	13574	Neos Credits	14292	Coin Of Champions

Table 20: Names and crypto-assets' coinmarketcap.com IDS: 3001-3500.

ID	NAME	ID	NAME	ID	NAME	ID	NAME	ID	NAME
14299	JUNO	14921	Microverse	15516	Pi INU	16080	Power Cash	16671	Multiverse
14319	dHealth	14925	Witnet	15517	WoopMoney	16086	BitTorrent (New)	16675	Ctomorrow Platform
14322	UPFI Network	14926	JPool Staked SOL (JSOL)	15528	Zodium	16091	MetaGods	16678	NFT Worlds
14324	Shiba Inu Empire	14928	Crypto Royale	15532	Moomonster	16093	Bitkub Coin	16679	AgeOfGods
14325	SmartNFT	14938	Jade Protocol	15535	Flux	16100	Crafting Finance	16686	AvaOne Finance
14327	SmartLOX	14943	Unique Venture Clubs	15539	NOSHIT	16103	SOLCash	16687	Galaxy Coin
14336	TRVL	14950	Operon Origins	15557	Mother of Memes	16105	Chumbi Valley	16706	Meta MVRS
14338	PlayPad	14968	Viral Inu	15563	Cornucopias	16116	Wrapped Solana	16727	X
14339	Cypherium	14969	Dragon Mainland Shards	15564	DEXGame	16128	Predictcoin	16742	Monster Galaxy
14340	MELI	14978	Let's Go Brandon Token	15565	CheeseSwap	16130	Wrapped Staked HEC	16749	FOX TOKEN
14341	BitShiba	14990	MetaSoccer	15572	Charm	16133	Frontrow	16751	Infinity Skies
14342	DKEY BANK	14996	MEDIA EYE NFT Portal	15574	KaraStar UMY	16135	Shib Generating	16753	Wild Island Game
14345	Botto	14997	Outrace	15575	Plastiks	16137	BTC 2x Flexible Leverage Index	16757	GroupDao
14349	Tutellus	15002	Kryxivia	15584	Humans.ai	16148	FreeRossDAO	16768	Dibs Share
14362	SportsIcon	15006	MetalSwap	15585	GuildFi	16160	Multi-Chain Capital (new)	16769	Sunflower Farm
14363	Pancake Games	15013	ReSource Protocol	15589	The Crypto You	16162	SafeMoon V2	16781	ZURRENCY
14371	Inflation Hedging Coin	15024	Angle Protocol	15592	MetaBrands	16168	Nitro League	16817	Wrapped EGLD
14374	Green Ben	15028	UXD Protocol	15608	TabTrader Token	16178	Imperium Empires	16819	Recovery Right Token
14382	Kitty Solana	15035	KEYS	15610	Terra Classic USD (Wormhole)	16181	Solice	16820	Blin Metaverse
14389	Sator	15039	MADworld	15617	Kyrrex	16182	ManuFactory	16821	Mean DAO
14391	Dali	15041	youves uUSD	15638	Ltradex	16185	Dingocoin	16831	Fantom USD
14392	Golden Ball	15050	Milk	15641	Kounotori	16191	TravGoPV	16832	Web3 Inu
14397	Dragon Crypto Aurum	15056	Wolf Game Wool	15652	GOGOcoin	16197	Luna Rush	16837	Covenant
14399	Cross-Chain Bridge Token	15060	Rocket Pool ETH	15659	Decentralized Eternal Virtual T.	16201	Day By Day	16842	Stargaze
14404	Etherconnect	15069	CRODEX	15664	BlockchainSpace	16209	Olympus v1	16849	OUSE Token
14421	SpritzMoon Crypto Token	15080	Suteku	15669	The Parallel	16218	Marvelous NFTs (Bad Days)	16863	Crypto Raiders
14422	HeroesTD	15084	Symbiosis	15678	Voxies	16219	FireBotToken	16868	Shadow Token
14446	Laqira Protocol	15085	The Killbox	15683	Musk Metaverse	16230	ETH Fan Token Ecosystem	16900	Optimus
14447	Swole Doge	15090	Cirrus	15687	Grim Finance	16231	Platypus Finance	16913	Millonarios FC Fan Token
14449	Jaiho Crypto	15097	Boryoku Dragonz	15688	Domi Online	16251	BitcoinBR	16923	Gamma
14452	Transhuman Coin	15098	Robo Inu Finance	15691	WX Token	16253	Tr3zor	16928	Elon GOAT
14458	Kaby Gaming Token	15100	RaceFi	15698	GFORCE	16254	OMarket Global LLC	16929	Experimental Finance
14461	Sphynx Labs	15110	MEGAWEAPON	15700	Cryptotem	16256	REDMARS	16936	2omb Finance
14463	Realy	15128	Niftify	15720	MetaFabric	16258	World of Defish	16937	2SHARE
14488	JK Coin	15131	Everton Fan Token	15721	MagicCraft	16260	impactMarket	16943	Tomb Shares
14489	CheckDot	15132	Davis Cup Fan Token	15723	HorizonDollar	16271	Jolofcoin	16946	Metacraft
14490	Bit Hotel	15134	Aston Villa Fan Token	15731	SORA Synthetic USD	16272	PLT	16962	XELS
14492	Nemesis PRO	15135	TFS Token	15734	bePAY Finance	16277	Ari Swap	16963	POW
14495	HappyLand	15138	Koda Cryptocurrency	15736	LUCA	16279	Changer	16979	Hillstone Finance
14515	MMPRO Token	15140	EVERY GAME	15737	Soldex	16283	ARTi Project	16981	Moola Celo
14516	DAOLaunch	15142	Katana Inu	15744	Prism	16290	GreenTek	16982	Moola Celo EUR
14519	VVS Finance	15175	DAWG	15747	MODA DAO	16296	Battle Saga	17002	BAHA
14522	Moonscape	15178	Gunstar Metaverse	15752	Blockasset	16300	Adana Demirspor Token	17010	Step
14523	SolChicks Token	15180	GamesPad	15758	LimoCoin Swap	16304	Astroport Classic	17017	VCGamers
14532	Wrapped CRO	15181	MonoX Protocol	15759	AAG	16305	Izumi Finance	17025	MarsColony
14534	ParaSwap	15182	Chives Coin	15762	Bitlocus	16326	Kitsumon	17027	CUBE
14535	NFTBomb	15185	Kujira	15764	Hololoot	16330	Chikn Egg	17047	WeWay
14538	Pundi X PURSE	15187	H3RO3S	15779	basis.markets	16334	APX	17049	Black Whale
14540	VLaunch	15188	DappRadar	15782	Geopoly	16350	Phaeton	17050	Multichain
14543	Treasure Under Sea	15193	Pexcoin	15784	LIT	16352	Green Satoshi Token (SOL)	17054	Comb Finance
14553	Panda Coin	15194	Sportium	15788	Royal Gold	16355	Tranquil Staked ONE	17057	Diyarbekirspor Token
14556	Boba Network	15211	Atlantis	15789	ThorFi	16357	TRYC	17059	Erzurumspor Token
14557	Cindrum	15212	RPS LEAGUE	15790	Propel	16359	Calo	17061	ClearDAO
14562	VIP Token	15231	Baby Bali	15799	LIFEBIRD	16363	Minto	17076	Wonderful Memories
14567	MetaCash	15235	GoldenWspp	15806	Attack Wagon	16386	Meblox Protocol	17081	LooksRare
14580	Greyhound	15236	CheersLand	15830	GAMER	16387	Poopsicle	17084	Quantum
14582	Embr	15240	SENATE	15840	Stamen Tellus Token	16388	Governance OHM	17088	chikn feed
14586	ShibElon	15241	Candylad	15841	KnightSwap	16394	SUPE	17097	SHIBIC
14587	Crypto Cavemen Club	15245	WingSwap	15842	Bedrock	16395	Kayserispor Token	17111	TheSolanDAO
14594	Maximus	15246	Surviving Soldiers	15853	Axl Inu	16397	Woozoo Music	17118	DarkCrypto
14599	PANDAINU	15248	Santos FC Fan Token	15857	QUASA	16402	Smart Marketing Token	17131	Planet IX
14613	XSwap Protocol	15250	Thetan Coin	15858	Galaxy Fight Club	16405	Brewlabs	17133	TopManager
14625	CronaSwap	15253	Infinite Launch	15862	Dash Diamond	16406	CakeSwap	17140	ArbiSmart
14627	SonarWatch	15257	EverRise	15866	PayNet Coin	16411	iPulse	17142	Shiba Inu Pay
14631	Notional Finance	15266	Metagalaxy Land	15870	League of Ancients	16412	Conjee	17157	Dream
14650	Andus Chain	15268	GalaxyGoggle DAO	15876	Bomb Money	16421	TinyBits	17169	Betswap.gg
14653	Tranquil Finance	15270	Vita Inu	15881	Voxel X Network	16430	Tectonic	17172	Revolution
14660	Reflecto	15284	SwinCoin	15882	Monetas	16434	Ooki Protocol	17183	Lum Network
14661	Sao Paulo FC Fan Token	15286	Degree Crypto Token	15889	Metaverse Face	16447	CryptoTanks	17186	Mindfolk Wood
14665	Centaurify	15288	TemplarDAO	15891	CryptoCart V2	16463	OpenDAO	17203	Deesse
14681	Fabwelt	15305	Calamari Network	15893	Ruby Currency	16466	BALI TOKEN	17207	Giveth
14682	EarthFund	15312	Hashtagger.com	15898	Metakings	16481	Kasta	17208	Chihuahua
14711	1Sol	15313	BunnyPark Game	15899	Last Survivor	16488	Artem Coin	17212	EVE Token
14713	Comdex	15326	XIDR	15906	Snap Token	16500	ShibaDoge	17213	Square Token
14721	RealLink	15338	CoreStarter	15907	HarryPotterObamaSonic10Inu	16503	A4 Finance	17215	Flag Network
14723	GenshinFlokiInu	15355	Baby Lovely Inu	15918	Artube	16509	Dreamverse	17228	Shitcoin
14728	Interstellar Domain Order	15366	XIDO FINANCE	15921	Poollotto.finance	16516	Ancient Kingdom	17242	UBXS Token
14734	Arker	15368	Egoras Credit	15922	New Order	16517	VaporNodes	17284	Dogelana
14745	Kromatika	15388	RIZON	15924	NvirWorld	16525	Scarab Finance	17285	Sperax USD
14767	The Coop Network	15395	Monster	15926	Rainmaker Games	16526	NanoMeter Bitcoin	17290	Solvent
14783	Treasure	15397	Firulais	15929	Metagame Arena	16528	Sivasspor Token	17299	Kingdom Karnage
14795	SappChat	15398	Rome	15931	FrogSwap	16529	Sakaryaspor Token	17302	ChinaZilla
14798	Pacific	15419	Zenlink	15933	Bomb Money	16531	Antalyaspor Token	17306	LaserEyes
14803	Aurora	15428	Euro Shiba Inu	15936	99Starz	16534	iDypius	17318	CATCOIN
14806	ConstitutionDAO	15438	ForthBox	15946	Polygen	16537	Marvin Inu	17334	JumpToken
14820	Infinity Rocket Token	15439	Age of Tanks	15951	Ftribe Fighters (F2 NFT)	16543	Avocado DAO Token	17336	Apollo Crypto DAO
14822	Victoria VR	15440	Txbit Token	15959	Vader Protocol	16552	RAI Finance	17354	Puli
14825	Viblos	15447	Lyra	15970	Agro Global	16555	ULAND	17364	linSpirit
14836	Day Of Defeat 2.0	15456	Juicebox	15973	ZERO	16559	Cherry Network	17374	Zamzam Token
14838	Artificial Intelligence	15463	SIDUS	15985	Mongoose	16575	Walter Inu	17399	Moebius
14840	ClassicDoge	15469	Sipher	16001	DarkShield Games Studio	16580	Traverse	17410	Thoreum V3
14843	Spintop	15471	4JNET	16003	TATA Coin	16582	SouloCoin	17420	Grape Finance
14849	Centcex	15476	LUXY	16007	Revenue Coin	16589	Dogewhale	17429	Puff
14871	Windfall Token	15478	Decentral Games	16010	Silo Finance	16600	NftEyez	17433	Topshelf Finance
14872	HUGHUG Coin	15480	Umami Finance	16013	XY Finance	16606	Gas DAO	17444	Froyo Games
14878	Alephium	15486	PumpETH	16016	Portuma	16607	Islander	17445	LORDS
14885	Coinscope	15489	Wizarre Scroll	16019	NKCL Classic	16612	Nosana	17447	Nova finance
14896	Tag Protocol	15493	Multiverse Capital	16032	HUH Token	16630	Evulus Token	17459	veDAO
14899	xExchange	15502	Peoplez	16035	Crypto Fight Club	16638	Metoshi	17468	Dhabi Coin
14915	Unix Gaming	15510	Decentral Games Governance	16049	THORWallet	16652	The Winkyverse	17483	ELIS

Table 21: Names and crypto-assets' coinmarketcap.com IDS: 3501-4000.