Risk forecasting comparisons in decentralized finance: An approach in constant product market makers.

Lucas Mussoi Almeida[a] (lucas.mussoi@ufrgs.br), Marcelo Scherer Perlin[a] (marcelo.perlin@ufrgs.br), Fernanda Müller[a] (fernanda.muller@ufrgs.br)

[a] Universidade Federal do Rio Grande do Sul, 90010460 - Porto Alegre, RS, Brazil.

Corresponding Author:

Lucas Mussoi Almeida

Universidade Federal do Rio Grande do Sul, 90010460 - Porto Alegre, RS, Brazil.

Tel: (+55) 51 98163.6144

Email: lucas.mussoi@ufrgs.br

Risk forecasting comparisons in decentralized finance: An approach in the constant product market makers.

Lucas Mussoi Almeida[a], Marcelo Scherer Perlin[a], Fernanda Müller[a]

[a] *Universidade Federal do Rio Grande do Sul, 90010460 - Porto Alegre, RS, Brazil.*

Abstract

Employing decentralized liquidity pool data from UNISWAP-V2, we forecast the Value-at-Risk (VaR) and Expected Shortfall (ES) using the GARCH model with different errors distributions, and, the deep learning probabilistic forecasting model algorithm *DeepAR*. The performances of the different forecasts are compared using an appropriate loss function. The GARCH model with normal distribution has been revealed to perform predominantly better, followed by the skewed t-student distribution when forecasting VaR. In contrast, the DeepAR model has demonstrated a poor forecasting capability for VaR in all cases - excluding liquidity pools with at least one stablecoin - however, prevails for the majority of the ES risk measures and data. Our findings recognize that, in part of the data, providing liquidity to a pair with at least one *stablecoin* is statistically significantly less risky than holding the same amount of crypto assets. Moreover, this research contributes to the development of new risk management tools and strategies for liquidity providers.

Keywords: DeFi, Risk, Cryptocurrency, Liquidity pool

*Corresponding author.

Email addresses: `lucas.mussoi@ufrgs.br` (Lucas Mussoi Almeida), `marcelo.perlin@ufrgs.br` (Marcelo Scherer Perlin), `fernanda.muller@ufrgs.br` (Fernanda Müller)

1. Introduction

Blockchain technology emerged in the blink of the 2007/2008 Subprime Mortgage crisis as a response to a deteriorated trust in the traditional financial sector (Earle, 2009). Blockchain literature body is initially composed of information systems genre researches (Labazova, 2019), where a decisive choke point is to acknowledge blockchain limitations (e.g., delay in recording) and performance metrics of different blockchain designs (Walsh et al., 2016; Xu et al., 2017). *Public permissionless* are fully decentralized blockchains where everyone can read, write, and validate information (Beck & Müller-Bloch, 2017; Beck et al., 2018), thus becoming useful for applications with a large number of untrusted participants, requiring exclusively *proof-of-work* (Gervais et al., 2016) or *proof-of-stake* (Saleh, 2021) consensus mechanisms to achieve agreements on system updates. Blockchains can support varied domains of the industry (Chauhan et al., 2018; Düdder & Ross, 2017), including execution and compilation of financial contracts, such as Bitcoin.

Almost a decade later, a complex financial environment - the architecture of Decentralized Finance (DeFi) - is gradually emerging on top of the existing blockchain platforms. DeFi is an arrangement of smart contracts where business logic - lending, trading, and derivatives - are executed in the *public permissionless* blockchain technology. In a *Decentralized Exchange* (DEX), the challenge of currency exchange was dealt with by imposing a *constant-function market maker* (CFMM) price mechanism (Hanson, 2003; Krishnamachari et al., 2021) - being one of decentralized finance most debated research area since Szabo (1996). A CFMM itself, then, is simply a set of liquidity pools (LP)[1], which, is a price mechanism that allows assets to be priced via a scoring rule which maps the current pool sizes to a marginal price (Angeris & Chitra, 2020; Aigner & Dhaliwal, 2021; Loesch et al., 2021) - liquidity providers are labeled as investors in decentralized exchanges and a fixed amount (0.05%, 0.3% or1% - depending on the exchange) is earned after each transaction executed in the LP. Research in cryptocurrencies mainly focuses on providing an overview of Bitcoin and its operations (Böhme et al., 2015; Narayanan et al., 2016), where user privacy and scams identification are substantial in the literature (Kosba et al., 2016; Alqassem et al., 2018; Maesa et al., 2019; Toyoda et al., 2019; Reyes-Macedo et al., 2019; Wang et al., 2020; Xia et al., 2021).

Impermanent loss is a concept that refers to the loss that liquidity providers may experience in a decentralized exchange due to the fluctuation of the price of the assets they have deposited. In particular, this phenomenon affects exchanges that use an automated market maker (AMM) algorithm, such as Uniswap V2. When a liquidity provider deposits two different assets in a Uniswap V2 pool, they receive a certain number of liquidity tokens that represent their share in the pool. Whenever someone wants to swap one asset for another, they need to pay a transaction fee, which is usually 0.3% of the transaction value. This fee is then distributed among all the liquidity providers in the pool, in proportion to their share.

To illustrate this, consider the following example: Suppose Alice is a liquidity provider on Uniswap V2 and deposits 1 ETH and 2000 USDC (which is a cryptocurrency pegged to the USD dollar) in a ETH-USDC pool, if the entire pool after the deposit contains 2 ETH and 4000 USDC than, Alice will receive a Liquidity Pool token that will portray a total share of 50%. Let's say the price of ETH stay's constant and there has been a total of 10 ETH worth of trade volumes before Alice's withdrawal, this would account for $0,03$ ETH earning for the liquidity thus, translating to $0,015$

[1] Traditional finance has a similar mechanism: Exchange Traded Funds (ETF).

ETH and 30 USDC; the liquidity pool now has $2,015$ ETH and 4030 USDC, than Alice would had made a profit. In another scenario, ETH price has inceased to 2500 USDC, Alice would have had a 500 USDC profit, but since she provided liquidity she is stuck with the original price, resulting in a 12,25% impermanent loss. Because the ETH price has gone up, an opportunity for arbitrage traders has been open by exploiting the price difference between the pool and the external market. For example, if the price of ETH is higher on another exchange liquidity pool, an arbitrageur can buy ETH on the aforementioned liquidity pool where ETH is 2000 and swap it for USDC on another exchange where, the price is at 2500 USDC, thus, realizing a profit. In this case, as UNISWAP-V2 uses a constanto product function for its AMM, the new liquidity pool balance - for ETH at 2500 USDC - would be of 1,7888 ETH and 4472,14 USDC, as Alice have 50% of the liquidity pool tokens, he would have made a total of 0,8944 ETH tokens and 2236,13 USDC tokens which, are equivalent to 4472 USDC - she has made a profit but less than if she had kept the tokens instead of providing liquidity. Overall, impermanent loss is a risk that liquidity providers need to be aware of when participating in decentralized exchanges with AMM algorithms like UNISWAP-V2. It can be particularly significant when the price of the assets in the pool is volatile or when there is a large discrepancy between the pool price and the external market price.

Risk management of cryptocurrencies such as Bitcoin is paramount as high losses can occur with substantial probability. According to Müller et al. (2022) an important aspect of appropriate risk management is accurate risk measures forecasting. Nowadays, the most common risk measures in the academic literature and practice of regulatory capital determination are Value-at-Risk (VaR) and Expected Shortfall (ES) (Basel Committee on Banking Supervision, 2013). Estimating the VaR and ES is imperative to permit an investor to make good decisions. Previous works have been attained to compare different VaR and ES forecasting procedures (Likitratcharoen et al., 2018; Troster et al., 2019; Trucíos, 2019; Acereda et al., 2020; Liu et al., 2020; Trucíos & Taylor, 2022), and Müller et al. (2022) make a further contribution by forecasting Range Value-at-Risk (RVaR). For the most part, investigations use econometric models, such as GARCH and GAS models. Few investigations consider Machine Learning models for risk prediction (Görgen et al., 2022), and rare works compare statistical and machine learning techniques (Shen et al., 2021). The aforementioned research data sources are all from exchanges or cryptoassets price-tracking websites - where prices are obtained by the volume-weighted average of all the prices from different exchanges. Bold investment alternatives in DeFI, such as providing liquidity to liquidity pools (LP), are more frequently - however, cautiously done - in a DeFi investor portfolio (Yousaf & Yarovaya, 2022).

This article stands out by elaborating on and analyzing the performance of the VaR and ES risk measures with decentralized data. In our analysis, we use individual liquidity pool's daily prices data, queried from *The Graph* - which is a decentralized protocol for indexing and querying data from ethereum blockchains - ranging from May 5th, 2020, to February 22nd, 2022, which comprehends 62808 - before cleaning procedure - distinct liquidity pools addresses from the UNISWAP-V2 decentralized exchange.

We use the traditional GARCH model as an estimation procedure for VaR and ES and the deep learning probabilistic forecasting model algorithm *DeepAR*. The standard GARCH model is implemented considering the normal and t-student distributions aligned with 25 (p, q) lags combinations. As a non-parametric approach, DeepAR (Salinas et al., 2020) is a recent probabilistic forecasting model, which uses Autoregressive Recurrent Neural Networks (ARNN) to estimate the probability distribution of a time series future given its past; instead of fitting separate models for each time series, it aims to create a global model that learns using all-time series in the dataset. The Value-at-Risk measure has already been used to forecasted forex pairs and demonstrated a competitive performance over other models (Fatouros et al., 2022). Comparison of risk prediction models is performed using loss functions, which is an established procedure for comparing risk prediction models (Gneiting, 2011; Müller et al., 2022).

There is a wide range of decentralized data that can be gathered from the *web 3.0* however, it is right to state that our data focus on one of the decentralized price formation mechanism - constant-function market maker (CFMM) - which allow the trade between assets without a fixed unit of exchange (Hanson, 2003; Daian et al., 2019; Angeris et al., 2022a,b; Goyal et al., 2022; Frongillo et al., 2023); this concept stands out by overturning the usage of order books in traditional finance. Besides the profuse contrast of structural concept between an AMM and an order book, traditional finance holds a parcel of the development in AMMs, due to the similarities between prediction markets (Othman & Sandholm, 2010; Slamka et al., 2012; Frongillo et al., 2023).

Serving not as only as a DEX, but concurrently Uniswap - which uses a constant-product function - has turned out to be an on-chain prominent decentralized authority on measuring the relative price of a pair of assets (Angeris & Chitra, 2020; Caldarelli & Ellul, 2021) - therefore, it is essential to scrutinize the risk of the instruments that are providing the price of cryptoassets to synchronize off-chain and on-chain. Another perspective of risk measures of decentralized data that requires allude is the increase of active users of non-custodial Metamask wallets[2] - growing the number of monthly active users in 1.800% in one year - and the integration with consolidated governmental payment methods[3]. Even noticing the limitation that not every active wallet means a different person or company (Tasca et al., 2018), nonetheless represents scalation in interest in the decentralized and *web3.0* environment, going objectively in the direction of *well-diversified* portfolios (Kajtazi & Moro, 2019).

Even facilitating trading volume of approximately US$2 billion a day of cryptocurrencies (Parlour, 2021), researches using Uniswap decentralized data are still scarce and limited to a small amount of selected LP; Lo & Medda (2022) observe the effectiveness of the Uniswap financial market through the ETH-USDT liquidity pool; Adachi et al. (2020) discuss the regulatory inconsistencies and systemic stability risk of stablecoins, similarly Klages-Mundt et al. (2020) approaches the economical modeling framework for stablecoins designers. Heimbach et al. (2021) examine the flow between UNISWAP-V2 liquidity pools and Berg et al. (2022) the inefficiencies between Uniswap and SushiSwap DEX, addressing sub-optimal trade routing; cyclical arbitrage using decentralized data is exploited in Wang et al. (2022b). Literature using the GARCH model in decentralized data is also restricted, Hansen et al. (2022) approaches the volatility of ETH/USDC pair in UNISWAP-V2 using GARCH(1,1) - our results demonstrate that for this LP pair, the best model is GARCH(1,5) and normal distribution.

As far as we know the only research approaching risk measures and employing decentralized data from liquidity pools is in Heimbach et al. (2022), where the ES of 9 LPs from UNISWAP-V2 are obtained by historical simulation. Regarding, exclusively, the discussion about methodological procedure, (Shen et al., 2021) compares bitcoin[4] returns volatility obtained via EWMA, GARCH, and *Recurrent Neural Network* (RNN) performances, by employing MAE and RMSE; when Value-at-Risk measure - and only - is approached, the efficiency of each method is measured by the

[2]https://consensys.net/blog/press-release/metamask-surpasses-10-million-maus-making-it-the-worlds-leading-non-custodial-crypto-wallet/

[3]https://consensys.net/blog/metamask/metamask-integrates-with-brazilian-payment-provider-pix-for-instant-crypto-purchases/

[4]Data extracted from https://coinmarketcap.com/

number of out-of-samples observations. The contribution of our work goes considerably further than the aforementioned works: our data is exclusively extracted from a decentralized exchange (UNISWAP-V2), VaR and ES risk measures are obtained via a parametric (GARCH) - adopting normal and t-student distributions, jointly with multiple sets of lags - and non-parametric (ARNN - *DeepAR*) approach, then the risk models are compared using the appropriate loss functions.

2. Background

2.1. Risk measures

Consider the random result X of any asset, where $X \geq 0$ is a gain and $X < 0$ is a loss, defined in the $\mathcal{X} := \mathcal{X}(\Omega, \mathcal{F}, \mathcal{P})$ probability space. F_X and F_X^{-1} are the cumulative distribution function and the inverse of X.

For $\forall X \in \mathcal{X}$ and $\alpha \in (0,1)$, VaR and ES of X are defined as follows:

$$VaR^{\alpha}(X) = -F_X^{-1}(\alpha) = -\inf\{x : F_X(x) \geq \alpha\}, \tag{1}$$

$$ES^{\alpha}(X) = \frac{1}{\alpha}\int_0^{\alpha} VaR^u(X)du, \tag{2}$$

VaR^{α} quantifies the maximum loss for a given significance level (α) and period. As a limitation of VaR, it ignores losses beyond the α-quantile of interest, and it is not coherent, as it does not satisfy the sub-additivity axiom. Thus, this measure does not satisfy the principle of diversification; that is, the VaR of the portfolio may be greater than the sum of the risk of individual assets. To overcome VaR shortcomings, there is ES, which quantifies the expected value of losses, given that these losses exceed the quantile of interest. Moreover, this measure is consistent.

Despite the advantages of ES, it does not satisfy an important statistical property satisfied by VaR, which is elicitability. A risk measure is elicitable when it is the minimizer of the expectation of some score function (Gneiting, 2011; Ziegel, 2016). For the practical use of the measures, this property is important, as it allows comparing competitive models using the score rule. In general, the VaR is elicitable under the following score function (Gneiting, 2011):

$$S^{VaR^{\alpha}}(x,y) = \alpha(x-y)^+ + (1-\alpha)(x-y)^- = \alpha\max\{x-y,0\} + (1-\alpha)\min\{x-y,0\}, \tag{3}$$

which is consistent for the α-quantile.

Although the ES is not elicitable, it is jointly elicitable with the VaR. Thus, the map $\rho(X) = (VaR^{\alpha}(X), ES^{\alpha}(X))$ is elicitable. The score function of ES is given by (Fissler & Ziegel, 2016; Gerlach et al., 2017):

$$\begin{aligned} S^{ES^{\alpha}}(x,y,z) =& y(I(x<y)) - \alpha) - xI(x<y) \\ &+ e^z\left(z - y + \frac{I(x<y)}{\alpha}(y-x)\right) \\ &- e^z + 1 - \log(1-\alpha), \end{aligned} \tag{4}$$

where $I(\cdot)$ is a indicator function that takes 1 as it value when the argument is true.

2.2. Risk forecast models

2.2.1. GARCH model

Consider that our random variable assumes a parametric approach given by: $X_t = \mu_t + \sigma_t z_t$, where μ_t and σ_t are the mean and standard deviation of the asset conditional on the information available at t, and z_t is white noise process that can assume different probability distributions. A common and competitive model to forecast the risk of the daily return of an asset (X_t) is the AR (autoregressive)-GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model.

Generally speaking, the formulation of AR(p)-GARCH(q,s) model can be described in this manner:

$$
\begin{aligned}
&X_t = \phi_0 + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t = \mu_t + \epsilon_t, \\
&\epsilon_t = \sigma_t z_t, \qquad z_t \sim i.i.d.\, F(\boldsymbol{\theta}), \\
&\sigma_t^2 = a_0 + \sum_{j=1}^{q} a_j \epsilon_{t-j}^2 + \sum_{k=1}^{s} b_k \sigma_{t-k}^2,
\end{aligned}
\tag{5}
$$

where p is the order of the autoregressive component, ϕ_i (for $i = 0, 1, \cdots, p$) are the parameters of the autoregressive model, ϵ_t is the error term, z_t is a white noise process with distribution $F(\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of parameters of the distribution, including zero mean and unit variance in addition to additional parameters that vary as the distribution. μ_t and σ_t^2 are the mean and variance conditional on past information, q and s are the orders of the GARCH model, and a_j and b_k, for $j = 0, 1, \cdots, q$ and $k = 0, 1, \cdots, s$ are the parameters of the GARCH model ($a_0 > 0$, $a_j \geq 0$, $b_k \geq 0$).

Based on the model defined in Equation (5), VaR and ES can be estimated in the following way:

$$
\begin{aligned}
\mathrm{VaR}_{t+1}^{\alpha} &= -\mu_{t+1} + \sigma_{t+1} \mathrm{VaR}^{\alpha}(z_{t+1}), \\
\mathrm{ES}_{t+1}^{\alpha} &= -\mu_{t+1} + \sigma_{t+1} \mathrm{ES}^{\alpha}(z_{t+1}),
\end{aligned}
$$

where μ_{t+1} and σ_{t+1} are, respectively, the forecast mean and conditional standard deviation obtained by the AR-GARCH model (see Section 3 for more details).

2.2.2. DeepAR

The *deep learning* architecture for the forecasting of time series has the proposal to predict the state of a system $h^{(t)}$ - hidden units of network - at time t. Following the construction of (Goodfellow et al., 2016), a dynamic system has the form of

$$
\mathbf{h}^{(t)} = f(\mathbf{h}^{(t-1)}, \mathbf{x}^{(t)}, \theta) \tag{6}
$$

where $\mathbf{h}^{(t-1)}$ is the state of the system at step $t-1$, $x^{(t)}$ is an external signal and θ are metadata - associated with layers weights and bias. Our problem needs to be tackled in a multivariate way, which equation 6 can be extended without loss of generality (Li et al., 2017; Sen et al., 2019; Salinas et al., 2020). More precisely, we explore the work of Salinas et al. (2020) which, given time series z_i, it models the conditional distribution $P(\mathbf{z}_{i,t_0:T} | \mathbf{z}_{i,1:t_0-1}, \mathbf{x}_{i,1:T})$ of the future of each time series $\mathbf{z}_i$ for times from t_0 to T. The *DeepAR* model assumes as distribution a product of multiples likelihood factors

$$
\begin{aligned}
Q_{\Theta}(\mathbf{z}_{i,t_0:T} | \mathbf{z}_{i,1:t_0-1}, \mathbf{x}_{i,1:T}) &= \prod_{t=t_0}^{T} Q_{\Theta}(z_{i,t} | \mathbf{z}_{i,1:t-1}, \mathbf{x}_{i,1:T}) \\
&= \prod_{t=t_0}^{T} p(z_{i,t} | \theta(\mathbf{h}_{i,t}, \Theta)
\end{aligned}
\tag{7}
$$

parametrized by the output $\mathbf{h}_{i,t}$ autorregressive recurrent network

$$\mathbf{h}_{i,t} = h(\mathbf{h}_{i,t-1}, z_{i,t-1}, \mathbf{x}_{i,t}, \Theta)$$

where h is a function given by a multi-layer recurrent neural network, parametrized by Θ with *long short-term memory* (LSTM) cells. For a fixed z, $p(z_{i,t}|\theta(\mathbf{h}_{i,t}, \Theta)$ is a distribution with the function $\theta(\mathbf{h}_{i,t}, \Theta)$ - $\mathbf{h}_{i,t-1}$ is the network output - as the input.

Thus, the algorithm of *DeepAR* is capable to learn the future distribution parameters of a time series; also, it can be fed with multiple time series concomitantly, then enabling cross-learning. The advantages of this algorithm permeates numerous research fields (Khan et al., 2020; Shan et al., 2022).

3. Data and methodological procedures

3.1. Data

Our data is gathered from the *The Graph* (https://thegraph.com/). The UNISWAP-V2 subgraph can be queried from *https://api.thegraph.com/subgraphs/name/uniswap/uniswap-v2*. At the first moment, a query command is executed in the *Python* language program to acquire, indiscriminately, all of the liquidity pools ever created in Uniswap-V2 until 22/02/2022. In the hands of the id of each LP, another appropriate Query is executed to retrieve all the essential data individually; `dailyVolumeToken0` and `dailyVolumeToken1` are self-described, `reserve0` and `reserve1` correspond respectively to the amount of tokens0 and tokens1 that compose the liquidity pool at a given timestamp, `dailyVolumeUSD` is accumulated at each trade and `reserveUSD` is derived liquidity both from a live conversion to USD; the data that comprehends the `totalSupply` - that varies depending on transactions, burning and mints.

Our dataset is of daily observations, intentionally, to reduce the risk models computational time processing but mainly to avoid the query performance going awry, besides being a prevailed practice of related works (Heimbach et al., 2021; Fatouros et al., 2022; Müller et al., 2022). The data itself is again given by a JSON type file where `dailyVolumeToken0` and `dailyVolumeToken1` are self-described, `reserve0` and `reserve1` corresponds respectively to the amount of tokens0 and tokens1 that compose the liquidity pool at a given timestamp. The `dailyVolumeUSD` is accumulated at each trade and `reserveUSD` is derived liquidity both from a live conversion to USD. The data that comprehends the `totalSupply` - that varies depending on transactions, burning, and mints - is the LP token quantity.

On February 22, 2022, at 12:00 AM (GMT) there was a total of $USD5.462.905.325, 26$ in the liquidity pools that have at least one transaction on that date. The longest liquidity pool is the pair USDC/ETH from May 5th, 2020 to February 22, 2022, corresponding to a total of 657 days. There is a sharp amount of liquidity pools being created just after the establishment of UNISWAP in the decentralized environment; from 4^{th} May 2020 to 15^{th} February 2022 a mean of 35.31 new liquidity pools arise daily, the data daily peak occurs in 21^{th} September 2020 where 115 liquidity pools where created. From the original 62808 liquidity pools set, 3896 are composed of at least one stablecoin and 87 pairs are strictly stable liquidity pools. All of the LPs are then ranked by their daily mean transaction volume and only the first 29 are considered. The chosen liquidity pools are unbiased and exceed substantially the amount in previous researches, where a certain amount - 12 Lp's in Heimbach et al. (2021) - are selected in a similar manner or restricted to a singular pair containing bitcoin or ethereum and a stablecoin (Kilimci et al., 2021; Sihananto et al., 2022; Hansen et al., 2022).

The studied period encompasses a troublesome season during the SARS-CoV-2 pandemic infection peaks, a USA presidential inauguration, global supply chain disruptions, and bitcoin's all-time high price, comprehends 465 days starting in 2020/11/14 to 2022/02/22, differing from the original data in 193 days. This is due to the individuality of each liquidity pool launch date - recalling that our analyzed LP samples were elected by their daily mean transaction volume, thus, suggesting the existence of an intrinsic utility given by users (investors); the period length decrease is because it includes the earliest recorded of the ranked observed liquidity pools, and to recognize patterns and compare models categorically, others had to follow the same period. The cycle of a liquidity pool is also a relevant consequence encompassed by the determined period (the pair ETH-TEND in Table 1 lost more than 99% of its value) together with the impetuous change from an unorthodox to widespread and debated investment option, by observing the increase of BTC and ETH price respectively of 130.24% and 456.38% during the same period.

		Mean	Variance	Standard Deviation	Kurtosis	Skewness	Return
0x08650bb9dc722c9c8c62e79c2bafa2d3fc5b3293	WETH-AMP	0.004835	0.003496	0.059131	6.651434	-0.028724	847.2704%
0x0d4a11d5eeaac28ec3f61d100daf4d40471f1852	ETH-USDT	0.002822	0.000725	0.026937	6.551293	-0.361439	271.5077%
0x27fd0857f0ef224097001e87e61026e39e1b04d1	ETH-RLY	0.003739	0.003966	0.062976	6.980647	0.229156	469.1284%
0x2fdbadf3c4d5a8666bc06645b8358ab803996e28	ETH-YFI	0.002570	0.003339	0.057785	7.899990	-0.473001	230.4784%
0x3041cbd36888becc7bbcbc0045e3b1f144466f5f	USDC-USDT	0.000213	2.954929×10^{7}	0.000543	5.923943	0.142786	10.4227%
0x32ce7e48debdccbfe0cd037cc89526e4382cb81b	ETH-CORE	0.002677	0.002995	0.054735	5.733394	0.280460	247.2963%
0x3b3d4eefdc603b232907a7f3d0ed1eea5c62b5f7	ETH-STAKE	0.002715	0.004217	0.064945	4.618415	-0.045599	253.5150%
0x3da1313ae46132a397d90d95b1424a9a7e3e0fce	ETH-CRV	0.004290	0.004242	0.065133	7.055627	-0.780321	635.2083%
0x3dd49f67e9d5bc4c5e6634b3f70bfd9dc1b6bd74	ETH-SAND	0.007203	0.004353	0.065980	6.220518	-0.108613	2748.6529%
0x43ae24960e5534731fc831386c07755a2dc33d47	ETH-SNC	0.002329	0.003374	0.058087	6.561864	-0.712413	195.3907%
0x4d5ef58aac27d99935e5b6b4a6778ff292059991	ETH-DPI	0.002552	0.003101	0.055695	7.927443	-0.736460	227.7467%
0x55d5c232d921b9eaa6b37b5845e439acd04b4dba	ETH-HEX	0.006898	0.003474	0.058947	5.664145	0.010645	2372.1325%
0x70ec2fa6eccf4010eaf572d1c1a7bcbc72dec983	ETH-ROOK	0.003751	0.005632	0.075049	6.037947	0.482729	472.2547%
0x7ba9b94127d434182287de708643932ec036d365	ETH-eRSDL	0.002866	0.006535	0.080840	4.692515	0.214629	279.2810%
0x819f3450da6f110ba6ea52195b3beafa246062de	ETH-MATIC	0.008094	0.004387	0.066239	6.945842	0.220924	4211.8296%
0xa2107fa5b38d9bbd2c461d6edf11b11a50f6b974	ETH-LINK	0.002358	0.003470	0.058911	7.828114	-0.763793	199.4007%
0xa478c2975ab1ea89e8196811f51a7b7ade33eb11	ETH-DAI	0.002536	0.000722	0.026871	6.715019	-0.364145	225.3140%
0xa5e79baee540f000ef6f23d067cd3ac22c7d9fe6	ETH-CEL	0.002978	0.002037	0.045140	5.512953	-0.304625	299.5654%
0xb4e16d0168e52d35cacd2c6185b44281ec28c9dc	ETH-USDC	0.002735	0.000724	0.026923	6.631192	-0.355365	256.7628 %
0xbb2b8038a1640196fbe3e38816f3e67cba72d940	ETH-BTC	0.003007	0.002031	0.045070	5.552948	-0.561386	304.8595%
0xc0bf97bffa94a50502265c579a3b7086d081664b	ETH-STRONG	0.005317	0.003375	0.058099	5.026098	0.329018	1085.2097%
0xc2adda861f89bbb333c90c492cb837741916a225	ETH-MKR	0.003442	0.003209	0.056651	7.716332	0.139178	395.6200%
0xc5be99a02c6857f9eac67bbce58df5572498f40c	ETH-AMPL	0.001130	0.003832	0.061905	4.481216	-0.049043	69.1578%
0xc730ef0f4973da9cc0ab8ab291890d3e77f58f79	ETH-AUDIO	0.004493	0.004204	0.064844	6.890275	-0.107408	708.1759%
0xcfb8cf118b4f0abb2e8ce6dbeb90d6bc0a62693d	ETH-TEND	-0.017247	0.025660	0.160188	11.063330	-0.479094	-99.9671%
0xcffdded873554f362ac02f8fb1f02e5ada10516f	ETH-COMP	0.002246	0.003301	0.057448	5.229382	-0.513556	184.2614%
0xd3d2e2692501a5c9ca623199d38826e513033a17	ETH-UNI	0.003045	0.003481	0.058999	7.517687	-0.370381	312.0683%
0xd90a1ba0cbaaaabfdc6c814cdf1611306a26e1f8	ETH-SWAP	0.003139	0.004722	0.068717	6.330821	0.027309	330.5442&
0xffa98a091331df4600f87c9164cd27e8a5cd2405	ETH-POLS	0.004425	0.004268	0.065330	5.904610	-0.279659	682.9748%

Table 1: Descriptive statistics of the Liquidity Pools tokens returns. The sample period runs from November 14, 2020, until February 02, 2022.

Cryptocurrency$_0$	Cryptocurrency$_1$	Mean Price$_0$	Cryptocurrency$_0$					Mean Price$_1$	Cryptocurrency$_1$				
			Mean	Variance	Standard Deviation	Kurtosis	Skewness		Mean	Variance	Standard Deviation	Kurtosis	Skewness
ETH	AMP	2,576.798000	0.003715	0.002910	0.053949	7.156692	−0.521456	0.039629	0.003862	0.006613	0.081322	9.705423	1.213413
ETH	USDT	2,576.443000	0.003756	0.002937	0.054195	6.935264	−0.472253	0.999861	0.000003	0.000002	0.001364	3.572743	−0.053854
ETH	RLY	2,576.344000	0.003732	0.002875	0.053617	7.238667	−0.328399	0.480201	0.003255	0.007897	0.088868	10.971050	1.448961
ETH	YFI	2,576.239000	0.003752	0.002898	0.053834	6.292930	−0.430969	33,928.230000	0.000399	0.005067	0.071179	8.862213	0.158323
USDC	USDT	0.999945	0.000002	0.000002	0.001352	3.379914	0.027884	0.999725	0.000002	0.000002	0.001278	3.161783	−0.066797
ETH	CORE	2,574.259000	0.003752	0.002827	0.053174	6.397469	−0.338812	7,288.235000	0.001404	0.005253	0.072479	13.061520	1.338530
ETH	STAKE	2,576.472000	0.003748	0.002843	0.053316	6.681321	−0.496940	13.665180	0.000410	0.008573	0.092588	4.900625	0.552868
ETH	CRV	2,575.556000	0.003718	0.002829	0.053192	6.554371	−0.467227	2.622400	0.002571	0.008373	0.091506	6.926974	−0.151684
ETH	SAND	2,576.310000	0.003722	0.002880	0.053661	7.068881	−0.340719	1.442368	0.009445	0.010114	0.100571	10.126230	1.169225
ETH	SNC	2,575.620000	0.003724	0.002809	0.053004	6.196467	−0.385209	11.318920	−0.000228	0.005288	0.072717	5.778087	−0.428910
ETH	DPI	2,576.310000	0.003708	0.002885	0.053714	7.072363	−0.500141	316.041700	0.001008	0.003878	0.062273	7.834940	−0.601946
ETH	HEX	2,576.157000	0.003716	0.002909	0.053932	6.954731	−0.487705	0.130329	0.006145	0.008370	0.091485	8.451836	0.659740
ETH	ROOK	2,575.905000	0.003726	0.002886	0.053724	6.892192	−0.334870	225.575200	0.001423	0.013054	0.114252	8.496467	1.282566
ETH	eRSDL	2,577.097000	0.003743	0.002804	0.052952	6.756162	−0.404310	0.191873	0.000435	0.015821	0.125782	4.574641	0.494054
ETH	MATIC	2,576.312000	0.003713	0.002900	0.053851	7.088253	−0.438195	1.058914	0.009564	0.008330	0.091270	7.555436	1.020352
ETH	LINK	2,576.106000	0.003748	0.002929	0.054120	6.987461	−0.475305	24.396320	0.000248	0.004938	0.070268	7.436274	−0.632928
ETH	DAI	2,576.411000	0.003734	0.002934	0.054167	6.999377	−0.474524	1.000595	−0.000007	0.000003	0.001849	3.323456	0.057716
ETH	CEL	2,576.766000	0.003732	0.002899	0.053841	7.059147	−0.519850	4.946063	0.000977	0.002376	0.048745	4.672689	0.478588
ETH	USDC	2,576.391000	0.003723	0.002936	0.054186	6.969951	−0.465659	0.999800	0.000003	0.000002	0.001248	5.638921	−0.280991
ETH	BTC	2,576.294000	0.003732	0.002928	0.054110	6.984472	−0.477380	43,921.190000	0.001858	0.001692	0.041131	4.717219	−0.181177
ETH	STRONG	2,576.789000	0.003730	0.002834	0.053233	5.746915	−0.300417	299.504300	0.004467	0.006541	0.080879	6.207320	0.753300
ETH	MKR	2,575.633000	0.003722	0.002887	0.053733	6.452788	−0.398992	2,450.356000	0.002598	0.004616	0.067942	11.662540	1.233368
ETH	AMPL	2,577.048000	0.003726	0.002921	0.054046	6.454133	−0.452025	1.032768	−0.000432	0.007754	0.088058	5.665211	−0.052187
ETH	AUDIO	2,576.602000	0.003730	0.002800	0.052918	6.602581	−0.423171	1.389826	0.003950	0.009341	0.096649	7.798530	0.846444
ETH	TEND	1527.455700	0.002553	0.020168	0.1420161	20.331780	−0.4051180	−0.008459	0.047284	0.217448	5.599527	−0.151933	0.010000
ETH	COMP	2,576.942000	0.003716	0.002878	0.053651	6.351021	−0.356908	334.097400	−0.000251	0.004916	0.070114	4.308399	−0.154392
ETH	UNI	2,575.660000	0.003731	0.002917	0.054006	7.035275	−0.483384	20.431720	0.001798	0.005313	0.072892	7.928103	0.334934
ETH	SWAP	2,575.525000	0.003732	0.002936	0.054185	6.925100	−0.473380	1.521191	0.001335	0.009462	0.097270	5.150701	0.499118
ETH	POLS	2,576.735000	0.003760	0.002872	0.053588	6.778563	−0.467907	2.210627	0.003879	0.008429	0.091811	5.438510	0.416447

Table 2: Descriptive statistics of the Portfolios tokens returns. The sample period runs from November 14, 2020, until February 02, 2022.

3.2. Methodological procedures

In order to assess the financial risk of liquidity pools and its counterpart portfolio, the LP returns and the individual tokens returns (Adams et al., 2020, 2021) are given, respectively, by

$$rLP_t = \log\left(\frac{reserveUSD_{t-1}totalSupply_t}{reserveUSD_t totalSupply_{t-1}}\right), \tag{8}$$

$$rtoken0_t = \log\left(\frac{reserveUSD_t reserve0_{t-1}}{reserveUSD_{t-1}reserve0_t}\right), \tag{9}$$

where rLP_t is the liquidity pool return at time t; $rtoken0$ and $rtoken1$ are the returns of each of the tokens belonging to the liquidity pool. Each time a investor desire to provide liquidity to any pair in UNISWAP-V2 an amount *liquidity pool* tokens is minted equivalently to the staked value; this tokens prices can be calculate by dividing the total amount $reserveUSD_t$ by $totalSupply_t$. The return for the second token is given in a similar way. From this point on, ADF (Dickey & Fuller, 1979) and PP (Phillips & Perron, 1988) tests were executed, and the stationarity of the *Liquidity Pool* tokens returns inferred, thus their adequacy to the procedure.

After the statistical tests, the methodological approach can be divided into two parts: (i) models implementations, (ii) and model score ranking. In (i) a combination of 5 lags for the GARCH(p,q) model - performed frequently in the risk forecasting literature of cryptocurrencies (Troster et al., 2019; Jiménez et al., 2020) and others risk forecasting studies (Righi & Ceretta, 2015; Diaz et al., 2017; Guo, 2022) - results in 25 different Var and ES values for each $\alpha = 0.01$ and $\alpha = 0.05$, which are held in common to the literature (Müller & Righi, 2017; Müller et al., 2022; Ardia et al., 2019; Trucíos, 2019), and, simultaneously for both normal and t-student distribution, on the other hand, the DeepAR (Salinas et al., 2020; Fatouros et al., 2022) approach forecast the probability distribution of a time series future given its past. Lastly, (ii) consists in obtaining VaR and ES score functions values, that are implemented to evaluate the forecasted risk models by computing the score mean function (Candelon et al., 2011; Nolde & Ziegel, 2017; Troster et al., 2019), which takes the following form

$$\bar{S} = \frac{1}{T}\sum_{i=1}^{T} S^{\rho}(x_i, y_i), \tag{10}$$

where y_i are the observed return history, x_i are the forecasted risk values performed by risk measure $\rho(\cdot)$ and S^{ρ} is the loss function of VaR and ES (which are defined in equations 1 and 2) which is negatively oriented, i.e., the lower the value, the better the performance of the risk forecasted model.

We perform a rolling window estimation with 250 observations (taking into account the period of rapid growth in market capitalization), which is the minimum required by the Basel Committee (Committee et al., 2013) to forecast market risk. In the parametric approach, the implementation for each modeling approach is straightforward, however, for the non-parametric (*DeepAR*) the time series data was divided into two non-overlapping sets, training, and testing. Training is used as the machine learning model input, and, the testing set is used to compute the *continuous ranked probability score* (CRPS) (Hersbach, 2000; Gneiting & Raftery, 2007) which is defined as the following

$$CRPS(F, x) = -\int_{-\infty}^{\infty} (F(y) - I(y \geq x))^2 dy, \tag{11}$$

where F is a cumulative distribution function, $I(\cdot)$ is a indicator function (*Heaviside*) and x is the true value. At some extent, CRPS resemble a distance between the forecasted value an the true one. Similarly to equation 10, an approach to find the most suitable model is by choosing the one with the minimized score mean function (Gasthaus et al., 2019; de Lima Silva et al., 2019).

Concerning the tuning of the *deepAR* hyperparameters, a grid search approach is implemented (de Lima Silva et al., 2019; Mathonsi & van Zyl, 2021; Wang et al., 2022a) at each forecasted step and are evaluated using CPRS, aforementioned. The tuning is then repeat exhaustively until the end of the rolling window procedure - time series observations. Displayed in Table 3.2 are the values of the two hyperparameters used to tune the *DeepAR* model; the number of LSTM cells holds an intersection set between the literature in probabilistic forecasting (Mathonsi & van Zyl, 2021) and the typical values recommended in the *DeepAR* guide[5], and, the number of hidden layers follows similar stratagem.

Hyperparameters	
LSTM cells	$\{10n \mid n \in \mathbb{N}, 4 \leq n \leq 10\}$
Hidden layers	1,2,3
Epochs	10
Learning rate	10^{-3}

Table 3: Hyperparameters used for the tunning of the *DeepAR* model.

Finally, the risk of 29 liquidity pools and the same tokens portfolio (at the same initial time) are forecasted. The daily price of the liquidity pool tokens is given by dividing `reserveUSD` by `totalSupply` - see section 3.1. The subtlety that lies in the difference between providing liquidity and holding the same assets necessary to merge a determined amount of liquidity pool tokens, after a period that the price of one or both had suffered variation, is called, *Impermanent Loss* (IL)(Aigner & Dhaliwal, 2021; Loesch et al., 2021), which, is the gap between then that investors are exposed. Considering the specific case of UNISWAP-V2, the portfolio of each liquidity pool accounts for an equal amount in USD for both of the constituting cryptocurrencies (Adams et al., 2020).

4. Results

Regarding the liquidity pools (LP), in tables 4 and 5 it is observed the predominance of the normal distribution in both risk measures, VaR and ES, and similarly in the significance levels; for the pair portfolio in Tables 6 and 7, the forecasted model's distributions results are analogous . For the two investment categories, liquidity pools and portfolios, there is a remarkably similar result, for both risk measures and significance levels the best top four forecasted models are those containing at least one stablecoin pegged to the USD dollar - pairs USDC-USDT, ETH-USDT, ETH-USDC, and ETH-DAI. The AMPL (Ampleforth) coin from the pair ETH-AMPL is also an algorithmic stablecoin pegged to the Consumer Price Index (CPI) rate, however, is not within the best-forecasted models. Moreover, the obtained GARCH

[5] `https://docs.aws.amazon.com/sagemaker/latest/dg/deepar_hyperparameters.html`

model lags p (lag variances) and q (lag residual errors) differ significantly from those in the literature; being the most practiced and predominant GARCH(1,1) - appering in decentralized finance (Hansen et al., 2022), cryptocurrencies (Troster et al., 2019; Jiménez et al., 2020) and risk forecast analysis literature (Righi & Ceretta, 2015; Diaz et al., 2017; Guo, 2022; Righi & Müller, 2022).

Previous research has documented the similarity in the performance of GARCH models to predict Value at Risk (VaR) and Expected Shortfall (ES), which tend to have the same model as the best candidate based on the realized loss for a given significance level (Righi & Müller, 2022; Meng & Taylor, 2020) . This result is observed for the majority of pairs in tables 5, 6 and 7 and the totality for the liquidity pool returns with significance level $\alpha = 1\%$ - table 4 - the best models are the same for VaR and ES. Exerting only the pairs that contain only one stablecoin pegged to the US dollar, all three pairs have the same model as the best candidate throughout all displayed results.

It is highlighted through tables 4 and 7, when the probabilistic forecasting $DeepAR$ model has a superior performance against the best GARCH model - based on the score function proposed in Fissler et al. (2016).

For the liquidity pool returns, $DeepAR$ shows poor performance in forecasting Value-at-Risk at both significance levels in all of the data, a result which corroborates with the literature (Shen et al., 2021) however, outperforms GARCH in forecasting Expected Shortfall risk in more than 89% and 96% for 1% and 5% significance level, respectively. Examining the model's performances for the Portfolios data - tables 6 and 7 - the GARCH model keeps outperforming $DeepAR$ forecasting in the majority of the cases in almost 80% and more than 93% for 1% and 5% significance level, respectively. Picking two particular samples, ETH-BTC, for both risks significance level $DeepAR$ overperform GARCH in VaR and ES; ML methods have demonstrated better predictability for cryptocurrencies portfolios (Alessandretti et al., 2018). A salient fact is the superior performance of the GARCH model for both VaR and ES and significance levels in the pairs with ETH and stablecoins pegged to the US dollar ETH-USDT, ETH-DAI and ETH-USDC (basically, all three pairs dictate the approximate same price of ETH in US dollars, recalling all the similar variables of basic statistics, see Table 2), which is endorsed by the literature, revealing that GARCH have the best performance for VaR and ES at 5% significance level among all other models (Trucíos & Taylor, 2022).

In table 8 are displayed the mean forecasted risks of the comprised models from Table 4 to 7; with these results, we show the risk difference between providing liquidity (*Liquidity Pool*) and simply holding the assets (*Portfolio*). Fixing a risk model and a significance level, say, $VaR^{0.01}$, for the ETH-BTC liquidity pool, the difference between them is that the mean risk of the portfolio is around 0.19% higher. Overall, all portfolios tend to have a higher mean risk value when compared to liquidity pools, and, to recognize the statistical significance of the difference we employed the unpaired Wilcoxon signed-rank test, in which the null hypothesis states that the forecasted risks of the liquidity pools and portfolios have equal medians.

In Table 8, the pairs with statistical significance are highlighted. The risk difference between investments with the ETH-BTC pair does not show statistical significance. However, we a have predominance of pairs with at least one stable coin in it. Regarding the USDC-USDT (*0x3041cbd36888becc7bbcbc0045e3b1f144466f5f*) liquidity pool, the high level of significance is due to the fact both are stablecoins and the investor income, in this liquidity pool, is due exclusively from the fee amount paid by the AMM contract - in UNISWAP-V2, 0.3% of each transaction in a liquidity pool is shared by the liquidity providers. Similar results are obtained for the ETH-USDT, ETH-DAI, and ETH-USDC. Specifically for the Value-at-Risk measure with 5% significance level, the ETH-HEX and ETH-AMPL

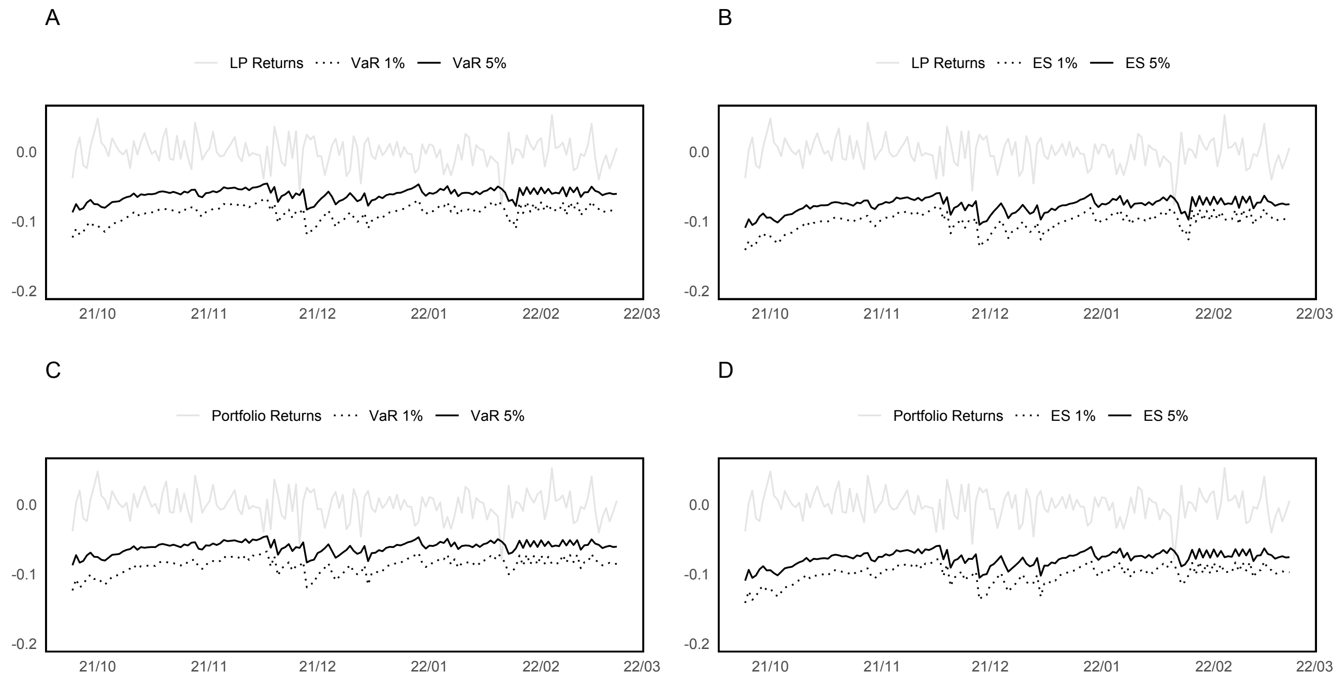

Figure 1: Evolution of risk forecasts for ETH-BTC pair returns and portfolio from September 24, 2021, until February 22, 2022. We present in figures 1.A the illustration of VaR 1% and VaR 5%, and, in figure 1.B ES 1% and ES5% forecastings adopting the GACRH models in Tables 4 and 5, as well as the ETH-BTC liquidity pool returns. We also include the the same forecastings for the ETH-BTC portfolio for the same period and models from Tables 6 and 7 in figures 1.C and 1.D

display statistical significance as well. However, in Table 9 the *DeepAR* shows that providing liquidity to the pairs has a higher risk than holding the assets for all risk measures and significance levels - besides the pair USDC-USDT (0x3041cbd36888becc7bbcbc0045e3b1f144466f5f) which, it is an already expect result due to the absence of influence from impermanent loss since, both cryptocurrencies are stable coins pegged to the US dollar and tend to stay the same price thus, the only effect on the liquidity token price is the protocol fees.

Figures 1 and 2 present the historical evolution of forecasts of VaR, ES, and returns - respectively from liquidity pools and portfolio pair - of the ETH-BTC pair considering the best forecasted GARCH model (Tables 4, through 7) and the probabilistic forecasting model *DeepAR*, respectively. Our data encompasses a period where on October 20, 2021, BTC achieved its all-time-high and declined to half of the price on January 22, 2022 - which could be due to the FED pushing higher rates and the development of cryptocurrency regulation guidance. Prominently, higher risk peaks are shown in around the date where BTC has decline to half of it all-time-high value in the DeepAR (Figure 2) forecasting than in the GARCH (Figure 1). The illustrations for the other pairs have been omitted for brevity and are available under request.

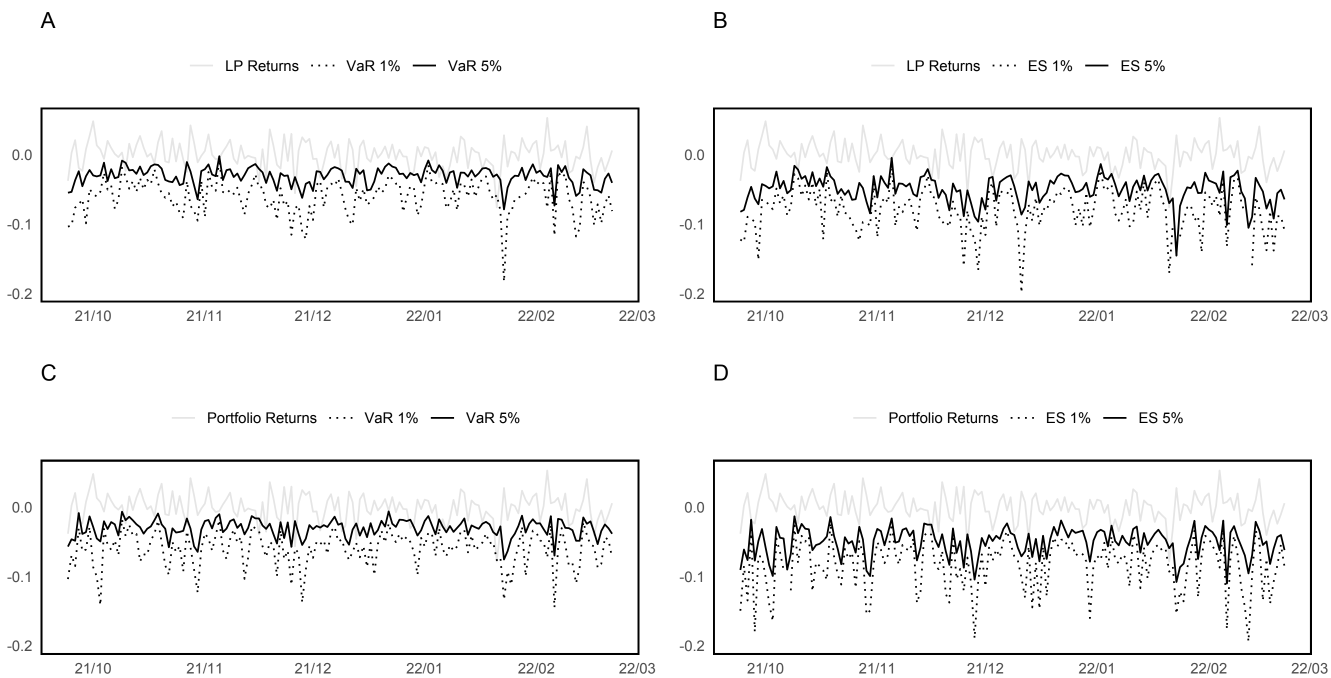

Figure 2: Evolution of risk forecasts for ETH-BTC pair returns and portfolio from September 24, 2021, until February 22, 2022. We present in figures 2.A the illustration of VaR 1% and VaR 5%, and, in figure 2.B ES 1% and ES5% forecastings adopting the DeepAR model, as well as the ETH-BTC liquidity pool returns. We also include the same forecastings for the ETH-BTC portfolio for the same period and model in figures 2.C and 2.D.

			GARCH(p,q)								DeepAR	
			$VaR^{0.01}$				$ES^{0.01}$				$VaR^{0.01}$	$ES^{0.01}$
	Pair address	Coin names	dist	lags (p,q)	best score	GARCH(1,1)	dist	lags (p,q)	best score	GARCH(1,1)		
1	0x08650bb9dc722c9c8c62e79c2bafa2d3fc5b3293	WETH-AMP	norm	(2,5)	0.110537	0.114278	norm	(2,5)	11.206531	11.559352	0.136869	**10.642572**
2	0x0d4a11d5eeaac28ec3f61d100daf4d40471f1852	ETH-USDT	norm	(1,5)	0.049155	0.049717	norm	(1,5)	5.339179	5.396811	0.060339	5.398263
3	0x27fd0857f0ef224097001e87e61026e39e1b04d1	ETH-RLY	norm	(4,5)	0.101179	0.105610	norm	(4,5)	10.349484	10.771329	0.114005	**9.180456**
4	0x2fdbadf3c4d5a8666bc06645b8358ab803996e28	ETH-YFI	norm	(5,1)	0.105053	0.106315	norm	(5,1)	10.669437	10.816516	0.118437	**9.512318**
5	0x3041cbd36888becc7bbcbc0045e3b1f144466f5f	USDC-USDT	norm	(2,5)	0.000678	0.000732	norm	(2,5)	0.087096	0.092726	0.001372	0.145823
6	0x32ce7e48debdccbfe0cd037cc89526e4382cb81b	ETH-CORE	norm	(5,2)	0.111400	0.117814	norm	(5,2)	11.156736	11.860632	0.139260	**10.425817**
7	0x3b3d4eefdc603b232907a7f3d0ed1eea5c62b5f7	ETH-STAKE	norm	(5,4)	0.114424	0.121097	norm	(5,4)	11.549600	12.156724	0.123707	**9.917462**
8	0x3da1313ae46132a397d90d95b1424a9a7e3e0fce	ETH-CRV	norm	(1,4)	0.129673	0.129832	norm	(1,4)	12.918344	12.947116	0.144094	**11.156872**
9	0x3dd49f67e9d5bc4c5e6634b3f70bfd9dc1b6bd74	ETH-SAND	norm	(5,3)	0.141204	0.146510	norm	(5,3)	13.888203	14.361028	0.164820	**12.055655**
10	0x43ae24960e5534731fc831386c07755a2dc33d47	ETH-SNC	norm	(2,5)	0.109797	0.113221	norm	(2,5)	11.140794	11.445907	0.125771	**10.104911**
11	0x4d5ef58aac27d99935e5b6b4a6778ff292059991	ETH-DPI	norm	(4,4)	0.104298	0.105059	norm	(4,4)	10.651153	10.732057	0.118290	**9.634707**
12	0x55d5c232d921b9eaa6b37b5845e439acd04b4dba	ETH-HEX	norm	(5,4)	0.109941	0.112234	norm	(5,4)	11.250528	11.457058	0.128046	**10.138075**
13	0x70ec2fa6eccf4010eaf572d1c1a7bcbc72dec983	ETH-ROOK	norm	(2,5)	0.131014	0.135082	norm	(2,5)	13.000207	13.358289	0.137403	**10.578605**
14	0x7ba9b94127d434182287de708643932ec036d365	ETH-eRSDL	norm	(5,5)	0.126908	0.141434	norm	(5,5)	12.942692	13.241017	0.143528	**10.850488**
15	0x819f3450da6f110ba6ea52195b3beafa246062de	ETH-MATIC	norm	(2,5)	0.119197	0.128442	norm	(2,5)	12.038714	12.851441	0.141206	**10.981544**
16	0xa2107fa5b38d9bbd2c461d6edf11b11a50f6b974	ETH-LINK	norm	(5,1)	0.108203	0.110196	norm	(5,1)	10.991557	11.179261	0.123366	**9.920849**
17	0xa478c2975ab1ea89e8196811f51a7b7ade33eb11	ETH-DAI	norm	(1,5)	0.049450	0.050041	norm	(1,5)	5.368848	5.429327	0.059238	**5.305143**
18	0xa5e79baee540f000ef6f23d067cd3ac22c7d9fe6	ETH-CEL	norm	(1,4)	0.081586	0.084194	norm	(1,4)	8.515402	8.768158	0.093546	**7.803606**
19	0xb4e16d0168e52d35cacd2c6185b44281ec28c9dc	ETH-USDC	norm	(1,5)	0.049371	0.049915	norm	(1,5)	5.361510	5.416968	0.060314	5.443156
20	0xbb2b8038a1640196fbe3e38816f3e67cba72d940	ETH-BTC	norm	(1,4)	0.086817	0.087618	norm	(1,4)	9.042431	9.117085	0.098572	**8.096807**
21	0xc0bf97bffa94a50502265c579a3b7086d081664b	ETH-STRONG	norm	(5,5)	0.091743	0.099667	norm	(5,5)	9.550507	10.296131	0.104592	**8.666080**
22	0xc2adda861f89bbb333c90c492cb837741916a225	ETH-MKR	norm	(1,5)	0.102762	0.104096	norm	(1,5)	10.528657	10.651819	0.110360	**9.070702**
23	0xc5be99a02c6857f9eac67bbce58df5572498f40c	ETH-AMPL	norm	(1,3)	0.132906	0.135895	norm	(1,3)	13.161910	13.411047	0.155162	**11.853173**
24	0xc730ef0f4973da9cc0ab8ab291890d3e77f58f79	ETH-AUDIO	norm	(5,5)	0.125389	0.128556	norm	(5,5)	12.523456	12.818210	0.137766	**10.612447**
25	0xcfb8cf118b4f0abb2e8ce6dbeb90d6bc0a62693d	ETH-TEND	norm	(5,3)	0.372560	0.376868	norm	(5,3)	26.179873	26.807428	0.492812	**17.530884**
26	0xcffdded873554f362ac02f8fb1f02e5ada10516f	ETH-COMP	norm	(4,4)	0.106495	0.107730	norm	(4,4)	10.842429	10.959961	0.116903	**9.409408**
27	0xd3d2e2692501a5c9ca623199d38826e513033a17	ETH-UNI	norm	(5,3)	0.109022	0.112764	norm	(5,3)	11.068185	11.419977	0.123090	**9.923797**
28	0xd90a1ba0cbaaaabfdc6c814cdf1611306a26e1f8	ETH-SWAP	norm	(1,5)	0.126153	0.127037	norm	(1,5)	12.597910	12.677193	0.139067	**10.785721**
29	0xffa98a091331df4600f87c9164cd27e8a5cd2405	ETH-POLS	norm	(3,2)	0.117789	0.121636	norm	(3,)	11.860530	12.204234	0.126297	**10.206392**

Notes: DeepAR that overperform GARCH are in bold, otherwise GARCH performs better.

Table 4: Selected GARCH and DeepAR models through mean score value criteria for Value-at-Risk and Expected Shortfall at $\alpha = 0.01$ considering Liquidity Pool tokens time series valuation.

			GARCH(p,q)								DeepAR	
			$VaR^{0.05}$				$ES^{0.05}$				$VaR^{0.05}$	$ES^{0.05}$
	Pair address	Coin names	dist	lags	best score	GARCH(1,1)	dist	lags (p,q)	best score	GARCH(1,1)		
1	0x08650bb9dc722c9c8c62e79c2bafa2d3fc5b3293	WETH-AMP	norm	(2,5)	0.077272	0.079895	norm	(2,5)	1.754686	1.811341	0.136730	**1.194265**
2	0x0d4a11d5eeaac28ec3f61d100daf4d40471f1852	ETH-USDT	norm	(1,5)	0.034527	0.034902	norm	(1,5)	0.849329	0.858107	0.060325	**0.620118**
3	0x27fd0857f0ef224097001e87e61026e39e1b04d1	ETH-RLY	norm	(4,5)	0.071035	0.074048	norm	(4,5)	1.620945	1.682890	0.114227	**1.050466**
4	0x2fdbadf3c4d5a8666bc06645b8358ab803996e28	ETH-YFI	norm	(3,4)	0.074708	0.075357	norm	(3,4)	1.692886	1.707029	0.118563	**1.120290**
5	0x3041cbd36888becc7bbcbc0045e3b1f144466f5f	USDC-USDT	norm	(2,5)	0.000486	0.000531	norm	(2,5)	0.062957	0.063930	0.001367	0.065771
6	0x32ce7e48debdccbfe0cd037cc89526e4382cb81b	ETH-CORE	norm	(5,2)	0.078443	0.082745	norm	(5,2)	1.762701	1.861694	0.138965	**1.259035**
7	0x3b3d4eefdc603b232907a7f3d0ed1eea5c62b5f7	ETH-STAKE	norm	(5,4)	0.081466	0.085984	norm	(5,4)	1.831322	1.922889	0.123426	**1.204123**
8	0x3da1313ae46132a397d90d95b1424a9a7e3e0fce	ETH-CRV	norm	(3,2)	0.091636	0.091794	norm	(1,3)	2.041059	2.042482	0.143908	**1.321751**
9	0x3dd49f67e9d5bc4c5e6634b3f70bfd9dc1b6bd74	ETH-SAND	norm	(5,3)	0.099642	0.103503	norm	(5,3)	2.202969	2.279403	0.164725	**1.467087**
10	0x43ae24960e5534731fc831386c07755a2dc33d47	ETH-SNC	norm	(2,5)	0.077330	0.079819	norm	(2,5)	1.747462	1.795168	0.125441	**1.156473**
11	0x4d5ef58aac27d99935e5b6b4a6778ff292059991	ETH-DPI	norm	(3,5)	0.073193	0.073832	norm	(3,5)	1.667771	1.679895	0.118169	**1.118866**
12	0x55d5c232d921b9eaa6b37b5845e439acd04b4dba	ETH-HEX	norm	(5,4)	0.075408	0.077007	norm	(5,4)	1.741347	1.774161	0.127891	**1.190156**
13	0x70ec2fa6eccf4010eaf572d1c1a7bcbc72dec983	ETH-ROOK	norm	(2,5)	0.092241	0.094993	norm	(2,5)	2.046744	2.101794	0.137186	**1.266456**
14	0x7ba9b94127d434182287de708643932ec036d365	ETH-eRSDL	sstd	(55,)	0.083428	0.089924	sstd	(5,5)	1.931518	2.122399	0.143390	**1.280987**
15	0x819f3450da6f110ba6ea52195b3beafa246062de	ETH-MATIC	norm	(1,5)	0.083712	0.090106	norm	(1,5)	1.890270	2.017160	0.140925	**1.283172**
16	0xa2107fa5b38d9bbd2c461d6edf11b11a50f6b974	ETH-LINK	norm	(4,2)	0.076198	0.077773	norm	(4,2)	1.726452	1.757468	0.123279	**1.149690**
17	0xa478c2975ab1ea89e8196811f51a7b7ade33eb11	ETH-DAI	norm	(1,5)	0.034723	0.035115	norm	(1,5)	0.853966	0.863178	0.059171	**0.624399**
18	0xa5e79baee540f000ef6f23d067cd3ac22c7d9fe6	ETH-CEL	norm	(1,4)	0.058033	0.059892	norm	(1,4)	1.350160	1.388652	0.093448	**0.919983**
19	0xb4e16d0168e52d35cacd2c6185b44281ec28c9dc	ETH-USDC	norm	(1,5)	0.034635	0.035024	norm	(1,5)	0.852467	0.860939	0.060223	**0.621842**
20	0xbb2b8038a1640196fbe3e38816f3e67cba72d940	ETH-BTC	norm	(2,2)	0.061348	0.061898	norm	(1,4)	1.424740	1.435443	0.098501	**0.939946**
21	0xc0bf97bffa94a50502265c579a3b7086d081664b	ETH-STRONG	sstd	(4,5)	0.058677	0.066140	sstd	(4,5)	1.474985	1.651552	0.104639	**1.017600**
22	0xc2adda861f89bbb333c90c492cb837741916a225	ETH-MKR	norm	(1,5)	0.072394	0.073229	norm	(1,5)	1.654147	1.672088	0.110237	**1.051723**
23	0xc5be99a02c6857f9eac67bbce58df5572498f40c	ETH-AMPL	sstd	(4,1)	0.090953	0.097585	norm	(1,3)	2.088956	2.126360	0.155011	**1.378297**
24	0xc730ef0f4973da9cc0ab8ab291890d3e77f58f79	ETH-AUDIO	norm	(5,5)	0.088257	0.090110	norm	(5,5)	1.964091	2.006747	0.137624	**1.239211**
25	0xcfb8cf118b4f0abb2e8ce6dbeb90d6bc0a62693d	ETH-TEND	norm	(5,3)	0.268424	0.270284	norm	(5,3)	4.494257	4.583930	0.491966	**2.671407**
26	0xcffdded873554f362ac02f8fb1f02e5ada10516f	ETH-COMP	norm	(4,4)	0.075006	0.076127	norm	(4,4)	1.701026	1.719047	0.116510	**1.102668**
27	0xd3d2e2692501a5c9ca623199d38826e513033a17	ETH-UNI	norm	(4,3)	0.076672	0.079130	norm	(4,3)	1.735136	1.787555	0.122950	**1.145125**
28	0xd90a1ba0cbaaaabfdc6c814cdf1611306a26e1f8	ETH-SWAP	norm	(1,5)	0.088281	0.088940	norm	(1,5)	1.976625	1.989445	0.138879	**1.243612**
29	0xffa98a091331df4600f87c9164cd27e8a5cd2405	ETH-POLS	norm	(3,2)	0.083222	0.085770	norm	(3,5)	1.869857	1.922296	0.126135	**1.209683**

Notes: DeepAR that overperform GARCH are in bold, otherwise GARCH performs better.

Table 5: Selected GARCH and DeepAR models through mean score value criteria for Value-at-Risk and Expected Shortfall at $\alpha = 0.05$ considering Liquidity Pool tokens time series valuation.

			GARCH(p,q)								DeepAR	
			$VaR^{0.01}$				$ES^{0.01}$				$VaR^{0.01}$	$ES^{0.01}$
	Pair address	Coin names	dist	lags (p,q)	best score	GARCH(1,1)	dist	lags (p,q)	best score	GARCH(1,1)		
1	0x08650bb9dc722c9c8c62e79c2bafa2d3fc5b3293	WETH-AMP	norm	(5,5)	0.110547	0.114377	norm	(5,5)	11.197764	11.556494	0.132428	**10.176505**
2	0x0d4a11d5eeaac28ec3f61d100daf4d40471f1852	ETH-USDT	norm	(1,5)	0.049766	0.050245	norm	(1,5)	5.395777	5.444305	0.057375	**5.153269**
3	0x27fd0857f0ef224097001e87e61026e39e1b04d1	ETH-RLY	norm	(4,5)	0.101164	0.105574	norm	(4,5)	10.346308	10.766429	0.110648	**8.933284**
4	0x2fdbadf3c4d5a8666bc06645b8358ab803996e28	ETH-YFI	norm	(2,4)	0.104980	0.106253	norm	(5,1)	10.666163	10.808608	0.116301	**9.365135**
5	0x3041cbd36888becc7bbcbc0045e3b1f144466f5f	USDC-USDT	norm	(4,5)	0.000728	0.000754	norm	(4,5)	0.092240	0.095211	0.001308	0.139327
6	0x32ce7e48debdccbfe0cd037cc89526e4382cb81b	ETH-CORE	norm	(5,2)	0.111263	0.117931	norm	(5,2)	11.145173	11.871797	0.132955	**10.158141**
7	0x3b3d4eefdc603b232907a7f3d0ed1eea5c62b5f7	ETH-STAKE	norm	(5,4)	0.114691	0.120838	norm	(5,4)	11.567431	12.126022	0.129150	**10.286160**
8	0x3da1313ae46132a397d90d95b1424a9a7e3e0fce	ETH-CRV	norm	(3,2)	0.129180	0.130142	norm	(3,2)	12.883941	12.950867	0.139921	**10.919891**
9	0x3dd49f67e9d5bc4c5e6634b3f70bfd9dc1b6bd74	ETH-SAND	norm	(5,4)	0.140224	0.145747	norm	(5,4)	13.816197	14.292898	0.155981	**11.820627**
10	0x43ae24960e5534731fc831386c07755a2dc33d47	ETH-SNC	norm	(2,4)	0.109858	0.113271	norm	(2,4)	11.138664	11.444318	0.120490	**9.733591**
11	0x4d5ef58aac27d99935e5b6b4a6778ff292059991	ETH-DPI	norm	(4,4)	0.104372	0.105114	norm	(4,4)	10.655442	10.734864	0.114297	**9.332866**
12	0x55d5c232d921b9eaa6b37b5845e439acd04b4dba	ETH-HEX	norm	(5,4)	0.110272	0.112503	norm	(5,4)	11.250818	11.451606	0.129616	**10.337795**
13	0x70ec2fa6eccf4010eaf572d1c1a7bcbc72dec983	ETH-ROOK	norm	(3,5)	0.130922	0.134945	norm	(3,5)	12.985780	13.339493	**0.098988**	**8.136261**
14	0x7ba9b94127d434182287de708643932ec036d365	ETH-eRSDL	sstd	(5,5)	0.128133	0.141891	norm	(5,5)	12.954618	13.245787	0.131557	**10.462088**
15	0x819f3450da6f110ba6ea52195b3beafa246062de	ETH-MATIC	norm	(1,5)	0.119131	0.128305	norm	(2,5)	12.018798	12.825315	0.137530	**10.560426**
16	0xa2107fa5b38d9bbd2c461d6edf11b11a50f6b974	ETH-LINK	norm	(4,2)	0.108364	0.110392	norm	(5,1)	11.003766	11.193314	0.139902	**10.894965**
17	0xa478c2975ab1ea89e8196811f51a7b7ade33eb11	ETH-DAI	norm	(1,5)	0.050056	0.050547	norm	(1,5)	5.427474	5.476727	0.117668	9.486044
18	0xa5e79baee540f000ef6f23d067cd3ac22c7d9fe6	ETH-CEL	norm	(1,5)	0.081751	0.084795	norm	(1,5)	8.527430	8.817545	**0.060732**	**5.393880**
19	0xb4e16d0168e52d35cacd2c6185b44281ec28c9dc	ETH-USDC	norm	(1,5)	0.049974	0.050454	norm	(1,5)	5.417637	5.466093	0.092870	7.762717
20	0xbb2b8038a1640196fbe3e38816f3e67cba72d940	ETH-BTC	norm	(2,2)	0.086911	0.087743	norm	(2,2)	9.048198	9.127403	**0.059734**	**5.377882**
21	0xc0bf97bffa94a50502265c579a3b7086d081664b	ETH-STRONG	norm	(5,5)	0.091038	0.099237	norm	(5,5)	9.464559	10.239384	0.094797	**8.002285**
22	0xc2adda861f89bbb333c90c492cb837741916a225	ETH-MKR	norm	(1,5)	0.102764	0.104131	norm	(1,5)	10.526427	10.652716	0.109914	**8.974013**
23	0xc5be99a02c6857f9eac67bbce58df5572498f40c	ETH-AMPL	norm	(1,4)	0.132319	0.135034	norm	(1,4)	13.130934	13.362145	**0.106813**	**8.889347**
24	0xc730ef0f4973da9cc0ab8ab291890d3e77f58f79	ETH-AUDIO	norm	(5,5)	0.126570	0.128637	norm	(5,5)	12.602571	12.816310	0.145406	**11.207232**
25	0xcfb8cf118b4f0abb2e8ce6dbeb90d6bc0a62693d	ETH-TEND	norm	(5,3)	0.370137	0.375209	norm	(5,3)	26.176703	26.976024	**0.133977**	**10.418136**
26	0xcffdded873554f362ac02f8fb1f02e5ada10516f	ETH-COMP	norm	(5,4)	0.106415	0.107900	norm	(5,4)	10.825724	10.970069	0.507971	18.104094
27	0xd3d2e2692501a5c9ca623199d38826e513033a17	ETH-UNI	norm	(4,3)	0.109757	0.112787	norm	(5,3)	11.070963	11.419499	0.114631	**9.250653**
28	0xd90a1ba0cbaaaabfdc6c814cdf1611306a26e1f8	ETH-SWAP	norm	(1,5)	0.126091	0.126995	norm	(1,5)	12.585852	12.666756	**0.119599**	**9.719383**
29	0xffa98a091331df4600f87c9164cd27e8a5cd2405	ETH-POLS	norm	(2,2)	0.117705	0.121575	norm	(2,2)	11.848580	12.194568	0.137179	**10.755402**

Notes: DeepAR that overperform GARCH are in bold, otherwise GARCH performs better.

Table 6: Selected GARCH and DeepAR models through mean score value criteria for Value-at-Risk and Expected Shortfall at $\alpha = 0.01$ considering the pair Portfolio time series valuation.

			GARCH(p,q)								DeepAR	
			$VaR^{0.05}$				$ES^{0.05}$				$VaR^{0.05}$	$ES^{0.05}$
	Pair address	Coin names	dist	lags (p,q)	best score	GARCH(1,1)	dist	lags (p,q)	best score	GARCH(1,1)		
1	0x08650bb9dc722c9c8c62e79c2bafa2d3fc5b3293	WETH-AMP	norm	(5,5)	0.077539	0.080123	norm	(5,5)	1.755745	1.812320	0.132464	**1.143914**
2	0x0d4a11d5eeaac28ec3f61d100daf4d40471f1852	ETH-USDT	norm	(1,5)	0.034996	0.035344	norm	(1,5)	0.858108	0.865579	0.057307	**0.619695**
3	0x27fd0857f0ef224097001e87e61026e39e1b04d1	ETH-RLY	norm	(4,5)	0.071047	0.074052	norm	(4,5)	1.620583	1.682297	0.110910	1.037966
4	0x2fdbadf3c4d5a8666bc06645b8358ab803996e28	ETH-YFI	norm	(2,4)	0.074647	0.075337	norm	(2,4)	1.690194	1.705368	0.116505	**1.099954**
5	0x3041cbd36888becc7bbcbc0045e3b1f144466f5f	USDC-USDT	norm	(4,5)	0.000530	0.000546	norm	(4,5)	0.063721	0.064110	0.001304	0.064241
6	0x32ce7e48debdccbfe0cd037cc89526e4382cb81b	ETH-CORE	norm	(5,2)	0.078337	0.082823	norm	(5,2)	1.760470	1.863206	0.132697	**1.201590**
7	0x3b3d4eefdc603b232907a7f3d0ed1eea5c62b5f7	ETH-STAKE	norm	(5,4)	0.081719	0.085864	norm	(5,4)	1.835702	1.919788	0.128814	**1.206233**
8	0x3da1313ae46132a397d90d95b1424a9a7e3e0fce	ETH-CRV	norm	(3,2)	0.091084	0.092154	norm	(3,2)	2.027524	2.044916	0.139759	**1.283176**
9	0x3dd49f67e9d5bc4c5e6634b3f70bfd9dc1b6bd74	ETH-SAND	norm	(5,4)	0.099074	0.102936	norm	(5,4)	2.190947	2.266993	0.155824	**1.419038**
10	0x43ae24960e5534731fc831386c07755a2dc33d47	ETH-SNC	norm	(1,4)	0.077447	0.079907	norm	(2,4)	1.747415	1.795169	0.120163	**1.139026**
11	0x4d5ef58aac27d99935e5b6b4a6778ff292059991	ETH-DPI	norm	(3,5)	0.073255	0.073891	norm	(3,5)	1.667620	1.680215	0.114104	**1.084935**
12	0x55d5c232d921b9eaa6b37b5845e439acd04b4dba	ETH-HEX	norm	(5,4)	0.075870	0.077410	norm	(5,4)	1.742142	1.773666	0.129371	**1.157031**
13	0x70ec2fa6eccf4010eaf572d1c1a7bcbc72dec983	ETH-ROOK	norm	(3,5)	0.092230	0.094954	norm	(3,5)	2.044641	2.098956	0.098632	**0.910844**
14	0x7ba9b94127d434182287de708643932ec036d365	ETH-eRSDL	sstd	(5,5)	0.084576	0.090731	sstd	(5,5)	1.949702	2.128478	0.131282	**1.265228**
15	0x819f3450da6f110ba6ea52195b3beafa246062de	ETH-MATIC	norm	(1,5)	0.083823	0.090184	norm	(1,5)	1.887834	2.015276	0.137376	**1.241573**
16	0xa2107fa5b38d9bbd2c461d6edf11b11a50f6b974	ETH-LINK	norm	(4,3)	0.076285	0.077920	norm	(4,2)	1.726948	1.759497	0.139531	**1.278608**
17	0xa478c2975ab1ea89e8196811f51a7b7ade33eb11	ETH-DAI	norm	(1,5)	0.035155	0.035524	norm	(1,5)	0.862327	0.870012	0.117650	1.141510
18	0xa5e79baee540f000ef6f23d067cd3ac22c7d9fe6	ETH-CEL	norm	(1,5)	0.058217	0.060378	norm	(1,5)	1.351619	1.396331	0.060659	**0.623518**
19	0xb4e16d0168e52d35cacd2c6185b44281ec28c9dc	ETH-USDC	norm	(1,5)	0.035122	0.035471	norm	(1,5)	0.861190	0.868655	0.093053	0.918352
20	0xbb2b8038a1640196fbe3e38816f3e67cba72d940	ETH-BTC	norm	(2,2)	0.061348	0.062005	norm	(2,2)	1.424167	1.437188	**0.059631**	**0.614887**
21	0xc0bf97bffa94a50502265c579a3b7086d081664b	ETH-STRONG	sstd	(5,5)	0.058675	0.065804	sstd	(5,5)	1.469863	1.639668	0.094716	**0.945801**
22	0xc2adda861f89bbb333c90c492cb837741916a225	ETH-MKR	norm	(1,5)	0.072417	0.073265	norm	(1,5)	1.653749	1.672261	0.109694	**1.009871**
23	0xc5be99a02c6857f9eac67bbce58df5572498f40c	ETH-AMPL	norm	(1,4)	0.094449	0.096039	norm	(1,4)	2.082562	2.116159	0.106713	**1.049893**
24	0xc730ef0f4973da9cc0ab8ab291890d3e77f58f79	ETH-AUDIO	norm	(5,5)	0.089205	0.090266	norm	(5,5)	1.978063	2.007305	0.145346	**1.371571**
25	0xcfb8cf118b4f0abb2e8ce6dbeb90d6bc0a62693d	ETH-TEND	norm	(5,3)	0.266078	0.268341	norm	(5,3)	4.505484	4.620253	**0.133779**	**1.233053**
26	0xcffdded873554f362ac02f8fb1f02e5ada10516f	ETH-COMP	norm	(5,4)	0.075041	0.076288	norm	(5,4)	1.699577	1.720762	0.506464	2.806211
27	0xd3d2e2692501a5c9ca623199d38826e513033a17	ETH-UNI	norm	(4,3)	0.077089	0.079164	norm	(5,3)	1.742396	1.787470	0.114209	**1.096037**
28	0xd90a1ba0cbaaaabfdc6c814cdf1611306a26e1f8	ETH-SWAP	norm	(1,5)	0.088296	0.088973	norm	(1,5)	1.974655	1.987751	0.119387	**1.160948**
29	0xffa98a091331df4600f87c9164cd27e8a5cd2405	ETH-POLS	norm	(2,2)	0.083202	0.085767	norm	(2,2)	1.868452	1.920937	0.136953	**1.254584**

Notes: DeepAR that overperform GARCH are in bold, otherwise GARCH performs better.

Table 7: Selected GARCH and DeepAR models through mean score value criteria for Value-at-Risk and Expected Shortfall at $\alpha = 0.05$ considering the pair Portfolio time series valuation.

	Liquidity Pool ($VaR^{0.01}$)	Portfolio ($VaR^{0.01}$)	Liquidity Pool ($VaR^{0.05}$)	Portfolio ($VaR^{0.05}$)	Liquidity Pool($ES^{0.01}$)	Portfolio ($ES^{0.01}$)	Liquidity Pool ($ES^{0.05}$)	Portfolio Pool ($ES^{0.05}$)
0x08650bb9dc722c9c8c62e79c2bafa2d3fc5b3293	0.11174237	0.11224682	0.07794033	0.07871530	0.12854961	0.12891955	0.09866610	0.09931201
0x0d4a11d5eeaac28ec3f61d100daf4d40471f1852	**0.04888758****	**0.05006601****	**0.03377637*****	**0.03482035*****	**0.05640127****	**0.05764654****	**0.04304183****	**0.04416825****
0x27fd0857f0ef224097001e87e61026e39e1b04d1	0.10408440	0.10415983	0.07269431	0.07279540	0.11969236	0.11975503	0.09194119	0.09202654
0x2fdbadf3c4d5a8666bc06645b8358ab803996e28	0.10525844	0.10557526	0.07394827	0.07406974	0.12078579	0.12124062	0.09332918	0.09338740
0x3041cbd36888becc7bbcbc0045e3b1f144466f5f	**0.00055032*****	**0.00072215*****	**0.00035130*****	**0.00051194*****	**0.00064928*****	**0.00082667*****	**0.00047333*****	**0.00064083*****
0x32ce7e48debdccbfe0cd037cc89526e4382cb81b	0.11292210	0.11292836	0.07870198	0.07872914	0.12993723	0.12993309	0.09968410	0.09969844
0x3b3d4eefdc603b232907a7f3d0ed1eea5c62b5f7	0.11463284	0.11528299	0.08039113	0.08099231	0.13165869	0.13233319	0.10138649	0.10201769
0x3da1313ae46132a397d90d95b1424a9a7e3e0fce	0.12957700	0.12994493	0.09080840	0.09084267	0.14887135	0.14938757	0.11502477	0.11481828
0x3dd49f67e9d5bc4c5e6634b3f70bfd9dc1b6bd74	0.13613642	0.13586699	0.09438965	0.09448180	0.15689398	0.15644477	0.11998674	0.11985719
0x43ae24960e5534731fc831386c07755a2dc33d47	0.11323927	0.11357958	0.07991960	0.08029344	0.12980666	0.13012845	0.10033225	0.10070672
0x4d5ef58aac27d99935e5b6b4a6778ff292059991	0.10658698	0.10683581	0.07451911	0.07471291	0.12245845	0.12271634	0.09425728	0.09445222
0x55d5c232d921b9eaa6b37b5845e439acd04b4dba	0.11208646	0.11412934	**0.07648903***	**0.07859740***	0.12978641	0.13179673	0.09831564	0.10038386
0x70ec2fa6eccf4010eaf572d1c1a7bcbc72dec983	0.13269385	0.13295233	0.09334388	0.09368032	0.15225966	0.15247938	0.1174713	0.11776001
0x7ba9b94127d434182287de708643932ec036d365	0.13462642	0.13633898	0.08852283	0.09019430	0.16117253	0.16278352	0.1171553	0.11883813
0x819f3450da6f110ba6ea52195b3beafa246062de	0.11831324	0.11893224	0.08174492	0.08247979	0.13649595	0.13705733	0.1041668	0.104830667
0xa2107fa5b38d9bbd2c461d6edf11b11a50f6b974	0.10993679	0.11032840	0.07667179	0.07709971	0.12647701	0.12689879	0.0970682	0.097520274
0xa478c2975ab1ea89e8196811f51a7b7ade33eb11	**0.04948407****	**0.05043267****	**0.03427177****	**0.03505804****	**0.05704802****	**0.05807733****	**0.04359921****	**0.04448501****
0xa5e79baee540f000ef6f23d067cd3ac22c7d9fe6	0.08237832	0.08296524	0.05780368	0.05836359	0.09459745	0.09519781	0.07287165	0.07358174
0xb4e16d0168e52d35cacd2c6185b44281ec28c9dc	**0.04922459****	**0.05032466****	**0.03403530*****	**0.03499559*****	**0.05677709****	**0.05794666****	**0.04334864****	**0.04439463****
0xbb2b8038a1640196fbe3e38816f3e67cba72d940	0.08737006	0.08754128	0.06099551	0.06108957	0.10048355	0.10069375	0.07722288	0.07730847
0xc0bf97bffa94a50502265c579a3b7086d081664b	0.09202550	0.09276157	0.05779694	0.05919773	0.11380064	0.10705903	0.07955977	0.08091967
0xc2adda861f89bbb333c90c492cb837741916a225	0.10426774	0.10440429	0.07310337	0.07324589	0.11976347	0.11989705	0.09221185	0.09235071
0xc5be99a02c6857f9eac67bbce58df5572498f40c	0.13305149	0.13242513	**0.08987552*****	**0.0932209*****	0.15240533	0.15191846	0.12534770	0.11725904
0xc730ef0f4973da9cc0ab8ab291890d3e77f58f79	0.12852062	0.13005341	0.08991294	0.09119385	0.14771734	0.14937539	0.11358530	0.11502064
0xcfb8cf118b4f0abb2e8ce6dbeb90d6bc0a62693d	0.38870399	0.37260988	0.27819085	0.26300362	0.96119738	0.92292419	0.57534800	0.53774826
0xcffdded873554f362ac02f8fb1f02e5ada10516f	0.11013112	0.11014891	0.07696045	0.07724257	0.12641347	0.12651080	0.09721270	0.09741913
0xd3d2e2692501a5c9ca623199d38826e513033a17	0.11205987	0.11293886	0.07825326	0.07895633	0.12886939	0.12945043	0.09898183	0.09979277
0xd90a1ba0cbaaaabfdc6c814cdf1611306a26e1f8	0.12759520	0.12790509	0.08905704	0.08940940	0.14675736	0.14704610	0.12407943	0.12509411
0xffa98a091331df4600f87c9164cd27e8a5cd2405	0.11800402	0.11813190	0.08289306	0.08307161	0.13546209	0.13556476	0.10443148	0.10456889

Notes: * $p < 0.1$, **$p < 0.05$, *** $p < 0.01$. Statistical significance obtained by the Unpaired Wilcoxon signed-rank test.

Table 8: Mean forecasted risks values of the GARCH model which performed the better in VaR and ES considering two significance levels - 1% and 5%. The risk models are assessed by employing the apoppriate score function (loss function). Samples range from 2020/11/14 to 2022/02/22.

	Liquidity Pool ($VaR^{0.01}$)	Portfolio ($VaR^{0.01}$)	Liquidity Pool ($VaR^{0.05}$)	Portfolio ($VaR^{0.05}$)	Liquidity Pool($ES^{0.01}$)	Portfolio ($ES^{0.01}$)	Liquidity Pool ($ES^{0.05}$)	Portfolio Pool ($ES^{0.05}$)
0x08650bb9dc722c9c8c62e79c2bafa2d3fc5b3293	0.137591	0.133804	0.067497	0.065060	0.195542	0.199094	0.113424	0.112537
0x0d4a11d5eeaac28ec3f61d100daf4d40471f1852	0.060211	0.057705	0.030409	0.030647	0.086641	0.081373	0.050761	0.049040
0x27fd0857f0ef224097001e87e61026e39e1b04d1	0.116685	0.113552	0.059679	0.058421	0.165249	0.166483	0.097127	0.096650
0x2fdbadf3c4d5a8666bc06645b8358ab803996e28	0.118328	0.115555	0.060310	0.058940	0.170175	0.166359	0.099514	0.097338
0x3041cbd36888becc7bbcbc0045e3b1f144466f5f	$\boxed{0.001248^{*}}$	$\boxed{0.001304^{**}}$	0.000617	0.000661	0.001884	0.001875	0.001066	0.001093
0x32ce7e48debdccbfe0cd037cc89526e4382cb81b	0.140305	0.133780	0.071922	0.067839	0.212767	0.186867	0.121199	0.111427
0x3b3d4eefdc603b232907a7f3d0ed1eea5c62b5f7	0.122707	0.128761	0.065082	0.065953	0.184150	0.183216	0.107355	0.107752
0x3da1313ae46132a397d90d95b1424a9a7e3e0fce	0.143977	0.140711	0.073736	0.070950	0.208615	0.197839	0.122517	0.117210
0x3dd49f67e9d5bc4c5e6634b3f70bfd9dc1b6bd74	0.159325	0.151596	0.079585	0.076299	0.243275	0.221736	0.136644	0.128249
0x43ae24960e5534731fc831386c07755a2dc33d47	0.128272	0.123595	0.065592	0.064465	0.179050	0.174883	0.106456	0.104757
0x4d5ef58aac27d99935e5b6b4a6778ff292059991	0.120076	0.116018	0.061621	0.059347	0.167894	0.159149	0.100165	0.095891
0x55d5c232d921b9eaa6b37b5845e439acd04b4dba	0.129042	0.132491	0.067126	0.066098	0.190817	0.180304	0.110958	0.107932
0x70ec2fa6eccf4010eaf572d1c1a7bcbc72dec983	0.103389	0.101327	0.051947	0.050065	0.155249	0.145540	0.087917	0.083721
0x7ba9b94127d434182287de708643932ec036d365	0.138509	0.132517	0.071808	0.070045	0.206226	0.180513	0.118490	0.110656
0x819f3450da6f110ba6ea52195b3beafa246062de	0.149541	0.143402	0.076754	0.073283	0.207585	0.203213	0.124661	0.119016
0xa2107fa5b38d9bbd2c461d6edf11b11a50f6b974	0.140352	0.139708	0.070967	0.070403	0.204287	0.209794	0.117699	0.119028
0xa478c2975ab1ea89e8196811f51a7b7ade33eb11	0.124605	0.118675	0.062982	0.061811	0.181674	0.170781	0.104894	0.100588
0xa5e79baee540f000ef6f23d067cd3ac22c7d9fe6	0.059334	0.061134	0.030675	0.030848	0.086447	0.088707	0.050443	0.051302
0xb4e16d0168e52d35cacd2c6185b44281ec28c9dc	0.093732	0.093479	0.047746	0.048321	0.130474	0.129014	0.078170	0.077598
0xbb2b8038a1640196fbe3e38816f3e67cba72d940	0.060311	0.060293	0.030392	0.030398	0.082153	0.084264	0.049667	0.050121
0xc0bf97bffa94a50502265c579a3b7086d081664b	0.098224	0.094958	0.048956	0.048720	0.143451	0.131304	0.082021	0.078823
0xc2adda861f89bbb333c90c492cb837741916a225	0.105242	0.111713	0.054782	0.055828	0.149841	0.157859	0.089090	0.092389
0xc5be99a02c6857f9eac67bbce58df5572498f40c	0.110978	0.107049	0.056202	0.056039	0.158536	0.150108	0.092208	0.089498
0xc730ef0f4973da9cc0ab8ab291890d3e77f58f79	0.155094	0.144127	0.077023	0.074433	0.220406	0.202866	0.128510	0.120425
0xcfb8cf118b4f0abb2e8ce6dbeb90d6bc0a62693d	0.140271	0.137038	0.071523	0.070414	0.207488	0.194554	0.118735	0.114571
0xcffdded873554f362ac02f8fb1f02e5ada10516f	0.500123	0.502687	0.261711	0.262716	0.774459	0.754614	0.436420	0.435929
0xd3d2e2692501a5c9ca623199d38826e513033a17	0.120504	0.118272	0.062125	0.060923	0.169627	0.165705	0.100969	0.099181
0xd90a1ba0cbaaaabfdc6c814cdf1611306a26e1f8	0.125330	0.122440	0.064083	0.064674	0.176889	0.168782	0.104898	0.102564
0xffa98a091331df4600f87c9164cd27e8a5cd2405	0.139688	0.138638	0.070780	0.071646	0.202562	0.199762	0.117194	0.116428

Notes: * $p < 0.1$, **$p < 0.05$, *** $p < 0.01$. Statistical significance obtained by the Unpaired Wilcoxon signed-rank test.

Table 9: Mean forecasted risks values of the probabilistic DeepAR model which performed the better in VaR and ES considering two significance levels - 1% and 5%. The risk models are assessed by employing the appropriate score function (loss function). Samples range from 2020/11/14 to 2022/02/22.

5. Conclusion

We perform in this paper research in risk prediction contemplating decentralized finance investment products using VaR and ES. The risk liquidity pools and simply holding the assets are predicted using GARCH models and the *DeepAR* probabilistic forecasting model algorithm. The risk forecasts are compared by using score functions (Gneiting & Raftery, 2007; Fissler et al., 2016).

The score functions allow us to infer that, for our data, the most suitable GARCH models are not the typical GARCH(1,1) commonly used and adopted by the risk forecast literature for both VaR and ES. The higher lags observed in the GARCH modeling can be interpreted as an indicator of a more complex and persistent volatility pattern in the returns from Liquidity Pools and Portfolios, these emerging assets exhibit distinctive characteristics, which are reflected in their properties (Liu et al., 2020). These higher lag values also show that there is greater inter-temporal autocorrelation in our data. We found that stablecoins pegged to the US dollar tend to have the lowest score values. Moreover, a distinctive pattern in the mean forecasted values indicates that investments in liquidity pools (providing liquidity) are, altogether, less risky than simply holding the assets. To give legitimacy to the results the unpaired Wilcoxon signed-rank test is employed, which, only corroborates with statistical significance for pairs with at least one stablecoin pegged to the US dollar. These results indicate that liquidity pools are an investment product with a lower risk than simply holding the assets and, when there is no impermanent loss, it has a higher return due to the UNISWAP-V2 protocol 0.3% fee. Also, we found that DeepAR, a probabilistic forecasting method, outperforms the best GARCH model for forecasting Value-at-Risk and Expected Shortfall of six distinct liquidity pools, including the ETH-BTC pair, at both 1% and 5% significance levels. However, the Wilcoxon test results indicate that only the USDC-USDT pair in the liquidity pool is less risky than simply holding the assets.

Our research using decentralized data from UNISWAP-V2 has demonstrated that there are decentralized finance products for investors that are more risk-averse but, want to expose their portfolios to cryptocurrencies. Our use of Value-at-Risk and Expected Shortfall at 1% and 5% significance levels allowed us to perform a thorough analysis of risk forecasting in this area. Our findings suggest that investing in liquidity pools that contain at least one stablecoin is less risky than simply holding the assets. This is an important finding for investors seeking to mitigate risk using the environment of decentralized finance. Further research could focus on veryfing the results using data from other decentralized exchanges in the ethereum blockchain and extending the number of observations in order to embrace other relevant periods; also, including other models, such as GAS. Similarly, an investigation to identify the dissonances between the risk comparisons with GARCH and *DeepAR* can be carried on, complemented by density forecast tests Dufour et al. (2000).

6. Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Acereda, B., Leon, A., & Mora, J. (2020). Estimating the expected shortfall of cryptocurrencies: An evaluation based on backtesting. *Finance Research Letters*, *33*, 101181.

Adachi, M., Cominetta, M., Kaufmann, C., van der Kraaij, A. et al. (2020). A regulatory and financial stability perspective on global stablecoins. *Macroprudential Bulletin*, *10*.

Adams, H., Zinsmeister, N., & Robinson, D. (2020). Uniswap v2 core. 2020. *URL: https://uniswap. org/whitepaper. pdf*, .

Adams, H., Zinsmeister, N., Salem, M., Keefer, R., & Robinson, D. (2021). Uniswap v3 core.

Aigner, A. A., & Dhaliwal, G. (2021). Uniswap: Impermanent loss and risk profile of a liquidity provider. *arXiv preprint arXiv:2106.14404*, .

Alessandretti, L., ElBahrawy, A., Aiello, L. M., & Baronchelli, A. (2018). Anticipating cryptocurrency prices using machine learning. *Complexity*, *2018*, 1–16.

Alqassem, I., Rahwan, I., & Svetinovic, D. (2018). The anti-social system properties: Bitcoin network data analysis. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *50*, 21–31. doi:`10.1109/TSMC.2018.2883678`.

Angeris, G., Agrawal, A., Evans, A., Chitra, T., & Boyd, S. (2022a). Constant function market makers: Multi-asset trades via convex optimization. In *Handbook on Blockchain* (pp. 415–444). Springer.

Angeris, G., & Chitra, T. (2020). Improved price oracles: Constant function market makers. In *Proceedings of the 2nd ACM Conference on Advances in Financial Technologies* AFT '20 (p. 80–91). New York, NY, USA: Association for Computing Machinery. URL: `https://doi.org/10.1145/3419614.3423251`. doi:`10.1145/3419614.3423251`.

Angeris, G., Evans, A., Chitra, T., & Boyd, S. (2022b). Optimal routing for constant function market makers. In *Proceedings of the 23rd ACM Conference on Economics and Computation* (pp. 115–128).

Ardia, D., Bluteau, K., & Rüede, M. (2019). Regime changes in bitcoin garch volatility dynamics. *Finance Research Letters*, *29*, 266–271.

Basel Committee on Banking Supervision (2013). Fundamental review of the trading book: A revised market risk framework. *Consultative Document, October*, . Available in: `https://www.bis.org/publ/bcbs265.pdf`.

Beck, R., & Müller-Bloch, C. (2017). Blockchain as radical innovation: a framework for engaging with distributed ledgers as incumbent organization, .

Beck, R., Müller-Bloch, C., & King, J. L. (2018). Governance in the blockchain economy: A framework and research agenda. *Journal of the Association for Information Systems*, *19*, 1.

Berg, J. A., Fritsch, R., Heimbach, L., & Wattenhofer, R. (2022). An empirical study of market inefficiencies in uniswap and sushiswap. *arXiv preprint arXiv:2203.07774*, .

Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives*, *29*, 213–38. URL: `https://www.aeaweb.org/articles?id=10.1257/jep.29.2.213`. doi:`10.1257/jep.29.2.213`.

Caldarelli, G., & Ellul, J. (2021). The blockchain oracle problem in decentralized finance—a multivocal approach. *Applied Sciences*, *11*, 7572.

Candelon, B., Colletaz, G., Hurlin, C., & Tokpavi, S. (2011). Backtesting value-at-risk: a gmm duration-based test. *Journal of Financial Econometrics*, *9*, 314–343.

Chauhan, A., Malviya, O. P., Verma, M., & Mor, T. S. (2018). Blockchain and scalability. In *2018 IEEE International Conference on Software Quality, Reliability and Security Companion (QRS-C)* (pp. 122–128). doi:10.1109/QRS-C.2018.00034.

Committee, B. et al. (2013). Fundamental review of the trading book: A revised market risk framework. *Consultative Document, October*, .

Daian, P., Goldfeder, S., Kell, T., Li, Y., Zhao, X., Bentov, I., Breidenbach, L., & Juels, A. (2019). Flash boys 2.0: Frontrunning, transaction reordering, and consensus instability in decentralized exchanges. *arXiv preprint arXiv:1904.05234*, .

Diaz, A., Garcia-Donato, G., & Mora-Valencia, A. (2017). Risk quantification in turmoil markets. *Risk Management*, *19*, 202–224.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*, 427–431.

Düdder, B., & Ross, O. (2017). Timber tracking: reducing complexity of due diligence by using blockchain technology. *Available at SSRN 3015219*, .

Dufour, A., Engle, R. F. et al. (2000). The acd model: predictability of the time between consecutive trades. *University of Reading and University of California at San Diego*, *35*, 463–497.

Earle, T. C. (2009). Trust, confidence, and the 2008 global financial crisis. *Risk Analysis*, *29*, 785–792. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1539-6924.2009.01230.x. doi:https://doi.org/10.1111/j.1539-6924.2009.01230.x. arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1539-6924.2009.01230.x.

Fatouros, G., Makridis, G., Kotios, D., Soldatos, J., Filippakis, M., & Kyriazis, D. (2022). Deepvar: a framework for portfolio risk assessment leveraging probabilistic deep neural networks. *Digital finance*, (pp. 1–28).

Fissler, T., & Ziegel, J. F. (2016). Higher order elicitability and osband's principle. *The Annals of Statistics*, *44*, 1680–1707. URL: http://www.jstor.org/stable/43974729.

Fissler, T., Ziegel, J. F., & Gneiting, T. (2016). Expected shortfall is jointly elicitable with value at risk-implications for backtesting. *Risk Magazine*, .

Frongillo, R., Papireddygari, M., & Waggoner, B. (2023). An axiomatic characterization of cfmms and equivalence to prediction markets. *arXiv preprint arXiv:2302.00196*, .

Gasthaus, J., Benidis, K., Wang, Y., Rangapuram, S. S., Salinas, D., Flunkert, V., & Januschowski, T. (2019). Probabilistic forecasting with spline quantile function rnns. In *The 22nd international conference on artificial intelligence and statistics* (pp. 1901–1910). PMLR.

Gerlach, R., Walpole, D., & Wang, C. (2017). Semi-parametric bayesian tail risk forecasting incorporating realized measures of volatility. *Quantitative Finance*, *17*, 199–215.

Gervais, A., Karame, G. O., Wüst, K., Glykantzis, V., Ritzdorf, H., & Capkun, S. (2016). On the security and performance of proof of work blockchains. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security* (pp. 3–16).

Gneiting, T. (2011). Making and evaluating point forecasts. *Journal of the American Statistical Association*, *106*, 746–762.

Gneiting, T., & Raftery, A. E. (2007). Strictly proper scoring rules, prediction, and estimation. *Journal of the American statistical Association*, *102*, 359–378.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press. `http://www.deeplearningbook.org`.

Görgen, K., Meirer, J., & Schienle, M. (2022). Predicting value at risk for cryptocurrencies using generalized random forests. *arXiv preprint arXiv:2203.08224*, .

Goyal, M., Ramseyer, G., Goel, A., & Mazières, D. (2022). Finding the right curve: Optimal design of constant function market makers. *arXiv preprint arXiv:2212.03340*, .

Guo, Z.-Y. (2022). Risk management of bitcoin futures with garch models. *Finance Research Letters*, *45*, 102197.

Hansen, P. R., Kim, C., & Kimbrough, W. (2022). Periodicity in Cryptocurrency Volatility and Liquidity*. *Journal of Financial Econometrics*, . URL: `https://doi.org/10.1093/jjfinec/nbac034`. doi:`10.1093/jjfinec/nbac034`. `arXiv:https://academic.oup.com/jfec/advance-article-pdf/doi/10.1093/jjfinec/nbac034/46459144/nbac034.pdf`. Nbac034.

Hanson, R. (2003). Combinatorial information market design. *Information Systems Frontiers*, *5*, 107–119.

Heimbach, L., Schertenleib, E., & Wattenhofer, R. (2022). Risks and Returns of Uniswap V3 Liquidity Providers. In *4th ACM Conference on Advances in Financial Technologies (AFT), Cambridge, Massachusetts, USA*.

Heimbach, L., Wang, Y., & Wattenhofer, R. (2021). Behavior of liquidity providers in decentralized exchanges. *arXiv preprint arXiv:2105.13822*, .

Hersbach, H. (2000). Decomposition of the continuous ranked probability score for ensemble prediction systems. *Weather and Forecasting*, *15*, 559–570.

Jiménez, I., Mora-Valencia, A., & Perote, J. (2020). Risk quantification and validation for bitcoin. *Operations Research Letters*, *48*, 534–541.

Kajtazi, A., & Moro, A. (2019). The role of bitcoin in well diversified portfolios: A comparative global study. *International Review of Financial Analysis*, *61*, 143–157.

Khan, M. A., Saqib, S., Alyas, T., Rehman, A. U., Saeed, Y., Zeb, A., Zareei, M., & Mohamed, E. M. (2020). Effective demand forecasting model using business intelligence empowered with machine learning. *IEEE Access*, *8*, 116013–116023.

Kilimci, H., Yıldırım, M., & Kilimci, Z. H. (2021). The prediction of short-term bitcoin dollar rate (btc/usdt) using deep and hybrid deep learning techniques. In *2021 5th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)* (pp. 633–637). doi:10.1109/ISMSIT52890.2021.9604741.

Klages-Mundt, A., Harz, D., Gudgeon, L., Liu, J.-Y., & Minca, A. (2020). Stablecoins 2.0: Economic foundations and risk-based models. In *Proceedings of the 2nd ACM Conference on Advances in Financial Technologies* AFT '20 (p. 59–79). New York, NY, USA: Association for Computing Machinery. URL: https://doi.org/10.1145/3419614.3423261. doi:10.1145/3419614.3423261.

Kosba, A., Miller, A., Shi, E., Wen, Z., & Papamanthou, C. (2016). Hawk: The blockchain model of cryptography and privacy-preserving smart contracts. In *2016 IEEE Symposium on Security and Privacy (SP)* (pp. 839–858). doi:10.1109/SP.2016.55.

Krishnamachari, B., Feng, Q., & Grippo, E. (2021). Dynamic curves for decentralized autonomous cryptocurrency exchanges. *arXiv preprint arXiv:2101.02778*, .

Labazova, O. (2019). Towards a framework for evaluation of blockchain implementations. In *ICIS*.

Li, Y., Yu, R., Shahabi, C., & Liu, Y. (2017). Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. *arXiv preprint arXiv:1707.01926*, .

Likitratcharoen, D., Ranong, T. N., Chuengsuksomboon, R., Sritanee, N., & Pansriwong, A. (2018). Value at risk performance in cryptocurrencies. *The Journal of Risk Management and Insurance*, *22*, 11–28.

de Lima Silva, P. C., Sadaei, H. J., Ballini, R., & Guimarães, F. G. (2019). Probabilistic forecasting with fuzzy time series. *IEEE Transactions on Fuzzy Systems*, *28*, 1771–1784.

Liu, W., Semeyutin, A., Lau, C. K. M., & Gozgor, G. (2020). Forecasting value-at-risk of cryptocurrencies with riskmetrics type models. *Research in International Business and Finance*, *54*, 101259.

Lo, Y. C., & Medda, F. (2022). Do DEXs work? using uniswap v2 to explore the effectiveness of decentralized exchanges. *Journal of Financial Market Infrastructures*, . URL: https://doi.org/10.21314/jfmi.2022.004. doi:10.21314/jfmi.2022.004.

Loesch, S., Hindman, N., Richardson, M. B., & Welch, N. (2021). Impermanent loss in uniswap v3. *arXiv preprint arXiv:2111.09192*, .

Maesa, D., MArino, A., & Ricci, L. (2019). The bow tie structure of the bitcoin users graph. *Applied Network Science*, *4*, 21–31. doi:https://doi.org/10.1007/s41109-019-0163-y.

Mathonsi, T., & van Zyl, T. L. (2021). A statistics and deep learning hybrid method for multivariate time series forecasting and mortality modeling. *Forecasting*, *4*, 1–25.

Meng, X., & Taylor, J. W. (2020). Estimating value-at-risk and expected shortfall using the intraday low and range data. *European Journal of Operational Research*, *280*, 191–202. URL: https://www.sciencedirect.com/science/article/pii/S0377221719305752. doi:https://doi.org/10.1016/j.ejor.2019.07.011.

Müller, F. M., & Righi, M. B. (2017). Numerical comparison of multivariate models to forecasting risk measures. *Risk Management*, *20*, 29–50. URL: https://doi.org/10.1057/s41283-017-0026-8. doi:10.1057/s41283-017-0026-8.

Müller, F. M., Santos, S. S., Gössling, T. W., & Righi, M. B. (2022). Comparison of risk forecasts for cryptocurrencies: A focus on range value at risk. *Finance Research Letters*, *48*, 102916. URL: https://www.sciencedirect.com/science/article/pii/S1544612322001878. doi:https://doi.org/10.1016/j.frl.2022.102916.

Narayanan, A., Bonneau, J., Felten, E., Miller, A., & Goldfeder, S. (2016). *Bitcoin and cryptocurrency technologies: a comprehensive introduction*. Princeton University Press.

Nolde, N., & Ziegel, J. F. (2017). Elicitability and backtesting: Perspectives for banking regulation. *The annals of applied statistics*, *11*, 1833–1874.

Othman, A., & Sandholm, T. (2010). Automated market-making in the large: the gates hillman prediction market. In *Proceedings of the 11th ACM conference on Electronic commerce* (pp. 367–376).

Parlour, C. A. (2021). Decentralized exchanges. *SSRN Electronic Journal*, . URL: https://doi.org/10.2139/ssrn.3905316. doi:10.2139/ssrn.3905316.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*, 335–346.

Reyes-Macedo, V. G., Salinas-Rosales, M., & Gallegos Garcia, G. (2019). A method for blockchain transactions analysis. *IEEE Latin America Transactions*, *17*, 1080–1087. doi:10.1109/TLA.2019.8931194.

Righi, M., & Müller, F. (2022). Range based risk measures and their applications. *Available at SSRN 4051687*, .

Righi, M. B., & Ceretta, P. S. (2015). A comparison of expected shortfall estimation models. *Journal of Economics and Business*, *78*, 14–47.

Saleh, F. (2021). Blockchain without waste: Proof-of-stake. *The Review of financial studies*, *34*, 1156–1190.

Salinas, D., Flunkert, V., Gasthaus, J., & Januschowski, T. (2020). Deepar: Probabilistic forecasting with autoregressive recurrent networks. *International Journal of Forecasting*, *36*, 1181–1191.

Sen, R., Yu, H.-F., & Dhillon, I. S. (2019). Think globally, act locally: A deep neural network approach to high-dimensional time series forecasting. *Advances in neural information processing systems*, *32*.

Shan, F., He, X., Armaghani, D. J., Zhang, P., & Sheng, D. (2022). Success and challenges in predicting tbm penetration rate using recurrent neural networks. *Tunnelling and Underground Space Technology*, *130*, 104728.

Shen, Z., Wan, Q., & Leatham, D. J. (2021). Bitcoin return volatility forecasting: A comparative study between garch and rnn. *Journal of Risk and Financial Management*, *14*, 337.

Sihananto, A. N., Sari, A. P., Prasetyo, M. E., Fitroni, M. Y., Gultom, W. N., & Wahanani, H. E. (2022). Reinforcement learning for automatic cryptocurrency trading. In *2022 IEEE 8th Information Technology International Seminar (ITIS)* (pp. 345–349). doi:10.1109/ITIS57155.2022.10010206.

Slamka, C., Skiera, B., & Spann, M. (2012). Prediction market performance and market liquidity: A comparison of automated market makers. *IEEE Transactions on Engineering Management*, *60*, 169–185.

Szabo, N. (1996). Smart contracts: building blocks for digital markets. *EXTROPY: The Journal of Transhumanist Thought,(16)*, *18*, 28.

Tasca, P., Hayes, A., & Liu, S. (2018). The evolution of the bitcoin economy: Extracting and analyzing the network of payment relationships. *The Journal of Risk Finance*, *19*, 94–126.

Toyoda, K., Takis Mathiopoulos, P., & Ohtsuki, T. (2019). A novel methodology for hyip operators' bitcoin addresses identification. *IEEE Access*, *7*, 74835–74848. doi:`10.1109/ACCESS.2019.2921087`.

Troster, V., Tiwari, A. K., Shahbaz, M., & Macedo, D. N. (2019). Bitcoin returns and risk: A general garch and gas analysis. *Finance Research Letters*, *30*, 187–193.

Trucíos, C., & Taylor, J. W. (2022). A comparison of methods for forecasting value at risk and expected shortfall of cryptocurrencies. *Journal of Forecasting*, .

Trucíos, C. (2019). Forecasting bitcoin risk measures: A robust approach. *International Journal of Forecasting*, *35*, 836–847. URL: `https://www.sciencedirect.com/science/article/pii/S0169207019300184`. doi:`https://doi.org/10.1016/j.ijforecast.2019.01.003`. Forecasting issues in developing economies.

Walsh, C., O'Reilly, P., Gleasure, R., Feller, J., Li, S., & Cristoforo, J. (2016). New kid on the block: a strategic archetypes approach to understanding the blockchain. In *2016 International Conference on Information Systems, ICIS 2016* (p. 6). Association for Information Systems. AIS Electronic Library (AISeL).

Wang, H., He, D., & Ji, Y. (2020). Designated-verifier proof of assets for bitcoin exchange using elliptic curve cryptography. *Future Generation Computer Systems*, *107*, 854–862.

Wang, J., Wang, S., Zeng, B., & Lu, H. (2022a). A novel ensemble probabilistic forecasting system for uncertainty in wind speed. *Applied Energy*, *313*, 118796.

Wang, Y., Chen, Y., Wu, H., Zhou, L., Deng, S., & Wattenhofer, R. (2022b). Cyclic arbitrage in decentralized exchanges. WWW '22 (p. 12–19). New York, NY, USA: Association for Computing Machinery. URL: `https://doi.org/10.1145/3487553.3524201`. doi:`10.1145/3487553.3524201`.

Xia, P., Wang, H., Gao, B., Su, W., Yu, Z., Luo, X., Zhang, C., Xiao, X., & Xu, G. (2021). Trade or trick? *Proceedings of the ACM on Measurement and Analysis of Computing Systems*, *5*, 1–26. URL: `https://doi.org/10.1145/3491051`. doi:`10.1145/3491051`.

Xu, X., Weber, I., Staples, M., Zhu, L., Bosch, J., Bass, L., Pautasso, C., & Rimba, P. (2017). A taxonomy of blockchain-based systems for architecture design. In *2017 IEEE international conference on software architecture (ICSA)* (pp. 243–252). IEEE.

Yousaf, I., & Yarovaya, L. (2022). Static and dynamic connectedness between nfts, defi and other assets: Portfolio implication. *Global Finance Journal*, *53*, 100719. URL: `https://www.sciencedirect.com/science/article/pii/S1044028322000217`. doi:`https://doi.org/10.1016/j.gfj.2022.100719`.

Ziegel, J. F. (2016). Coherence and elicitability. *Mathematical Finance*, *26*, 901–918.