Agent-based Model of Initial Token Allocations: Simulating Distributions post Fair Launch

JOAQUIN DELGADO FERNANDEZ*, TOM BARBEREAU, and ORESTIS PAPAGEORGIOU, Interdisciplinary Centre for Security, Reliability and Trust (SnT), University of Luxembourg, Luxembourg

With advancements in distributed ledger technologies and smart contracts, tokenized voting rights gained prominence within Decentralized Finance (DeFi). Voting rights tokens (aka. governance tokens) are fungible tokens that grant individual holders the right to vote upon the fate of a project. The motivation behind these tokens is to achieve decentral control within a decentralized autonomous organization (DAO). Because the initial allocations of these tokens is often un-democratic, the DeFi project and DAO of Yearn Finance experimented with a fair launch allocation where no tokens are pre-mined and all participants have an equal opportunity to receive them. Regardless, research on voting rights tokens highlights the formation of timocracies over time. The consideration is that the tokens' tradability is the cause of concentration. To examine this proposition, this paper uses an agent-based model to simulate and analyze the concentration of voting rights tokens post three fair launch allocation scenarios under different trading modalities. The results show that regardless of the allocation, concentration persistently occurs. It confirms the consideration that the 'disease' is endogenous: the cause of concentration is the tokens' tradablility. The findings inform theoretical understandings and practical implications for on-chain governance mediated by tokens.

CCS Concepts: • **Applied computing** → IT governance; • **Social and professional topics** → *Centralization / decentralization*; • **Computing methodologies** → **Agent / discrete models**.

Additional Key Words and Phrases: blockchain, governance, decentralized finance, voting rights tokens, fair launch, agent-based modeling

1 INTRODUCTION

The digital representation of value and ownership, in the form of fungible and non-fungible tokens respectively, provides the basis for the *token economy*. Unlike traditional economies, the token economy does not rely on trusted third parties to verify transactions [61, 64], instead distributed ledger technology (DLT) and smart contracts ensure integrity in a pseudonymous peer-to-peer network of interactions [7, 73]. Advancements in the token economy with a focus on financial services and products materialized under the heading of Decentralized Finance (DeFi) [3, 6, 59, 71].

DLT enables people to coordinate themselves *on-chain*, that is, transactions and interactions are "mediated by a set of self-executing rules [i.e., smart contracts] deployed on a public blockchain" independently from central control [36, p. 1]. To achieve decentral control in DeFi, developers created and allocated so-called *voting rights tokens* – (fungible) tokens that stipulate voting entitlements to vote upon change proposals to a project [47]. An example is the decentralized exchange (DEX) Uniswap, a project which uses smart contracts to automate the exchange of fungible tokens of the Ethereum protocol. Its voting rights token, UNI, allows holders to cast votes and

*Corresponding author.

Authors' address: Joaquin Delgado Fernandez, joaquin.delgadofernandez@uni.lu; Tom Barbereau, tom.barbereau@uni.lu; Orestis Papageorgiou, orestis.papageorgiou@uni.lu, Interdisciplinary Centre for Security, Reliability and Trust (SnT), 29 Av. John F. Kennedy, University of Luxembourg, Luxembourg.

ACM 2158-656X/2024/2-ART
https://doi.org/10.1145/3649318

decide upon the use of resources stored in a treasury (defined in a smart contract). The participants and holders of voting rights tokens are typically refered to as members of a Decentralized Autonomous Organization (DAO).

The distribution of voting rights tokens, however, is considered as controversial given that the initial allocation often favors a minority of insiders (e.g., developers, investors, etc.). Tokens allocated to insiders are common within Initial Coin Offerings (ICOs) [14], hence a differentiation between initial allocations that favor insiders (labeled, "private") or those that do not (labeled, "public") [28, p. 10]. History repeats itself as insider allocations of voting rights tokens are common in DeFi DAOs [6].

One outlier to insider allocations is Yearn Finance. Its core developer, Andre Cronje, denoted that at inception voting rights tokens are majoritarily allocated to "friends and family" [20] – impossibly leading to decentral control. As solution, he implemented a type of initial token allocation for the voting rights tokens of the Yearn Finance (YFI) DAO — the *fair launch* – whereby all community members have an equal opportunity to receive a portion of the initial supply [63]. Though in theory this allocation strategy achieves equity through principles of fairness [see, 54], reality looks dire in the long run: Barbereau et al. [5] demonstrate how, as with most other voting rights tokens, for YFI concentration of wealth and voting power persists. Because holders rarely use these to cast votes, Barbereau et al. [6] denote a common theme and propose a purposefully *descriptive* theory of voting rights tokens as justification for concentration: they are *tradable* assets on cryptocurrency markets. This description may not seem surprising against the consideration that wealth in the token economy is concentrated (c.f. concentration in Bitcoin and Ethereum [32]), and so are capital markets more broadly [see, 52]. Indeed, the common feature of tradability appears to justify, on an intuitive level, the expectations that "wealth trickles up in free-market economies" [12].

The hypothesis whether the experiment of Andre Cronje's fair launch was inherently doomed to fail, given that the underlying tokens are *tradable* remains, unaccounted for. Taking the principle of a 'fair' launch (n.b., all tokens are allocated 'fairly'), one can consider weather alternative allocations are successful in achieving decentral control in the long run. Correspondingly, to challenge this consideration, this article addresses the following two research questions:

RQ1: Does trading behavior affect voting rights token distributions over time?
RQ2: Do alternative, 'fair launch' token allocations affect voting rights token distributions over time?

Provided the context in which these novel governance structures are deployed, our research topic – 'fair launch' token allocations – is of importance to Information System (IS) and requires the adoption of multidisciplinary perspectives [66]. Hence, we lean on previous theory on governance of public protocols / DAOs and token design, and use quantitative methods rooted in agent-based simulation; i.e., agent-based modeling (ABM). Guided by an ambition "for discovery and explanation" [8, p. 516], we specifically adopt ABM to simulate the trade and eventual distribution of voting rights tokens post three distinct 'fair launch' allocations (n.b., scenarios denoted S_n). The developed model is going from "real world to simulation world" [8, p. 516], an approach that is particularly suitable for the exploration of understudied, novel phenomena – here, the fair launch allocation. Within IS, the utility of ABM for the study of phenomena with "nonlinear behavior" [35, p. 158] is well-recognized. At large, the discipline is receptive of contributions emerging from simulation research [8, 21, 23, 72].

Davis et al. [21, p. 482] advise to ground the model within "simple theory"; theory, that provides the "basic concepts and process that describe a phenomenon" [8, p. 506]. Here, we focus on governance of public-permissionless systems in general, and DeFi DAOs in particular (Section 2). To establish further "epistemic credibility in the simulation model" [8, p. 517], aside from theory (deductive approach) we use empirical data (inductive approach) from Yearn Finance (Section 3). The development of our model (Section 4) is informed by the artificial cryptocurrency markets designed in Cocco et al. [19] and Roşu and Saleh [57]. Therein, agents represent traders that are endowed with an amount of fiat currency and seek to acquire the (artificially created) voting rights tokens (TKNs). The market rules are loosely based on understandings of clearing houses [41]. To investigate

RQ2, we developed two alternative scenarios to Andre Cronje's fair launch scenario (S_0) which respectively consider fairness in egalitarian terms (S_1) and 'at random' (S_2). The principles underlying these allocations build on political philosophy [43, 53]. We measure concentration in terms of the Gini Coefficient [31] and the Shannon Entropy [62]. With our work we make the following three contributions:

- We provide an agent-based model for the analysis of token distributions under various market conditions reflective of trading.
- Our simulation results show how over time, regardless of the 'fair' initial token allocation, concentration is imminent.
- We extend understandings on the governance of DAOs and tokenomics to formerly include initial token allocations as part of governance parameters.

2 RELATED WORK

2.1 Governance in public-permissionless Systems

Bitcoin [46] led to a burgeoning movement of developers that saw decentralization beyond technical terms; not least, as an ambiguous mix of political, economic, and organizational ideals [60] that materialized in the emergence of alternative protocols. Commonly the next generation of DLT includes *smart contracts* and the possibility to deploy tokens [7, 73]. Collectively, these technologies enable new, decentral business opportunities, modes of organization, and governance frameworks [61, 64].

While in public-permissionless systems, 'decentralization' in technical terms is achieved, in political terms, it is often contentious [11, 60]. Over the decision to increase the size of Bitcoin blocks, community debates led to an outright "civil war" [22, p. 8] that pitted parties against each other over socio-political motives. The core developers, who act as gatekeepers to protocol changes and are de facto in charge of governance, eventually took an autocratic decision against that increase – a behavior pejoratively described as "senatorial" [49]. Ethereum, too, faced its share of controversy. Following an exploited smart contract bug the Ethereum Foundation's leaders decided to irreversibly fork the ledger [26]. Against this backdrop, Penzo and Selvadurai [51, 19] denote how in public-permissionless systems, governing communities resort to informal adjudications, typically "immune [...] from state scrutiny".

Consequently, scholars distinguish between *on-chain* and *off-chain* governance of DLT systems. The former refers to rules that enforce the 'code-is-law' dictum; in other words, using smart contracts (and tokens) to define governance mechanisms and structures ("now the code runs itself") [55]. The greatest degree of on-chain governance, is typically achieved within and as part of DAOs [see the definition proposed in 36]. The informal resolution mechanisms in Bitcoin and Ethereum, however, are examples that demonstrated the shortcomings of the ditcum and shed light on ulterior powers and politics that are at play [22, 26]. Off-chain governance refers to the formalization of control via the intermediary of endogenous (e.g., through the foundation of institutions such as consortia, cooperatives, etc.) or exogenous (e.g., national laws, regulations, standards, etc.) structures [55, 74] that are typically registered and held liable [4].

2.2 Voting rights token-based governance

Within DeFi, beyond improvements made to the financial value chain [3, 59], experiments were made at implementing governance structures fully on-chain; most notably, by embedding voting rights into tokens. These tokens grant holders the ability to cast votes on proposals. While the features of these tokens are contextual to the individual project, the majority of these follow the fungible token standard ERC-20. Like most cryptocurrencies, they are tradable on regular and decentralized exchanges [5]. By nature, the study of these tokens is at the intersection of research of blockchain governance and *tokenomics* – subdomains of cross-disciplinary research on DLT – and contribute to research on DAOs [see, 6, 9, 34, 36, 58]

Oliveira et al. [47, p.8] define "Governance Parameters" of tokens as those parameters that "relate to what [it] effectively represents and how this connects to the way the platform is governed and managed". The authors introduce three parameters (Table 1): (1) "Representation" (the type of asset represented by a token), (2) "Supply" (the way tokens are distributed), and (3) "Incentive system" (the way a token exerts influence over the network and/or its holder). Given the focus on on-chain governance, our scope is on token allocations and distributions; hence, the prime subject of study being on the "Supply" parameter. Oliveira et al. [47, p. 9] note how "Supply" strategies can either be on a one-time basis ("fixed") or following increments ("schedule-based"). Tokens can also be "pre-mined" (or "pre-sold" [28]), that is a portion of the tokens is created and distributed before the official launch date. As such, they are means to overcome the chicken-and-egg problem [25].

Table 1. Excerpt of the Token Classification proposed in Oliveira et al. [47].

<table>
<tr><td rowspan="3">Governance Parameters</td><td>Representation</td><td colspan="2">Digital</td><td colspan="2">Physical</td><td colspan="2">Legal</td></tr>
<tr><td>Supply</td><td colspan="2">Schedule-based</td><td>Pre-mined, scheduled distribution</td><td colspan="2">Pre-mined, one-off distribution</td><td>Discretionary</td></tr>
<tr><td>Incentive system</td><td colspan="2">Enter Platform</td><td>Use Platform</td><td colspan="2">Stay Long-Term</td><td>Leave Platform</td></tr>
</table>

For the supply of voting rights tokens, whose fair deployment is motivated by a normative ambition of political decentralization, the story is more ambiguous. Uniswap developers pre-mined a part of all voting rights tokens (UNI) and allocated some to a group of insiders. Among others, the DeFi projects SushiSwap (SUSHI) and MakerDAO (MKR) followed similar paths, opting for an allocation that favored insiders. Over time, in all of these cases, wealth concentration was eminent [6]. Voting rights tokens are not exclusive to DeFi projects — they are also used to distribute governance power in blockchain-based metaverse projects – where, similarly, concentration was observed [34].

Concentration of wealth and power is inherent to human societies and economic systems [52]. Pareto [48] exposed the land concentration in the Italian *novecento* (XX$^{\text{th}}$ Century); subsequently lending his name to the Pareto Principle. Financial markets are no exception to the principle [42]. In cryptocurrency markets the same phenomena may be observed. Both Bitcoin and Ethereum have centralized token distributions, and the trend appears to only increase [32]. This is true even in the case of Proof-of-Stake cryptocurrencies where the project's security is closely tied to the level of dispersion [57]. Likewise, Nadini et al. [45] and Klein et al. [38] observe concentration of wealth in markets for non-fungible tokens. When it comes to voting rights tokens, Barbereau et al. [5] identified that the level of concentration among voting rights tokens is even higher, highlighting cases where a handful of people hold more than 50% of all tokens. Interestingly, these tokens are barely used by their holders to vote [6].

Andre Cronje's project Yearn Finance (YFI) sought to eliminate favoritism and insider allocations [63]. By opting for the first, "fixed" supply strategy, YFI were *not* allocated to a minority of insiders. Instead, the implemented *fair launch* allocation followed the principle of 'fair equality of opportunity' [see, 54]; effectively, the idea that each user has the same opportunity to obtain YFIs. Despite its failure to achieve an equitable distribution over time [5, 6], at least in theory, a fixed initial token allocation that is 'fair' would help achieve ambitions of decentral control. Evaluating this proposition is the subject of this study.

2.3 Agent-based modeling

To evaluate the phenomenon of initial token allocations and concentration of tokens we designed an agent-based modeling (ABM). ABM is a computational method used to simulate the actions and/or interactions of autonomous agents in order to understand how systems behave and what determines outcomes [40]. As analytical method, applications of ABM are found in a variety of disciplines from energy and pathology to risk management and finance. In IS research, the value of ABM was acknowledged given its methodological versatility to investigate systems whose "emergent properties unfold over time" [35, p. 158] and its supportive value in the development and/or verification of theory [10, 21, 23]. The literature studies of Beese et al. [8] and Dong [23] illustrate the breadth of ABM applications in IS research – citing the potential for scholars to embed theory in the exploration of complex phenomena.

For the study of cryptocurrencies and DLT-based systems, numerous works applied ABM. Bornholdt and Sneppen [13] proposed a model to study the emergence of cryptocurrencies vis-à-vis Bitcoin – considering factors such as trading, mining of new coins, and agent-to-agent interactions. Their findings show that Bitcoin may be interchangeable with cryptocurrencies of similar characteristics. Cocco et al. [19] built an artificial cryptocurrency marketplace based on an order book simulation of the Bitcoin market where agents trade autonomously. Their model is able to reproduce real price formations and market volatility; hence, our adaptation of it in this work. Roşu and Saleh [57] propose an environment to model the behavior of investors/agents in a Proof-of-Stake (PoS) based blockchain of cryptocurrency issuance. They denote, contrary to expectations, that agents seek to stabilize their portfolio instead of accumulating more wealth.

3 DATA PREPARATION

Given their open and auditable characteristics, DeFi projects, for the most part, are built on public-permissionless ledgers [3, 59]. These ledgers provide a rich source for the collection and analysis of quantitative data. Chen and Bellavitis [17] observe that 80% of DeFi platforms, are in fact, built on the Ethereum ledger. Ethereum records a variety of details, not least on tokens, data about their creation, their initial distribution, and transaction histories.

The fair launch was originally created as part of Yearn Finance, hence it's practice informs our study inductively [8]. Specifically, data on Yearn Finance is used to (1) define the base scenario S_0 ("Cronje"), (2) 'feed' our model based on reality, (3) calibrate the model, and (4) validate our model. For (2), we also extracted the price of YFI (from CoinGecko.com) and the Crypto Fear & Greed Index (FGI). The graphs for these two additional data sources are presented in Figure 1.

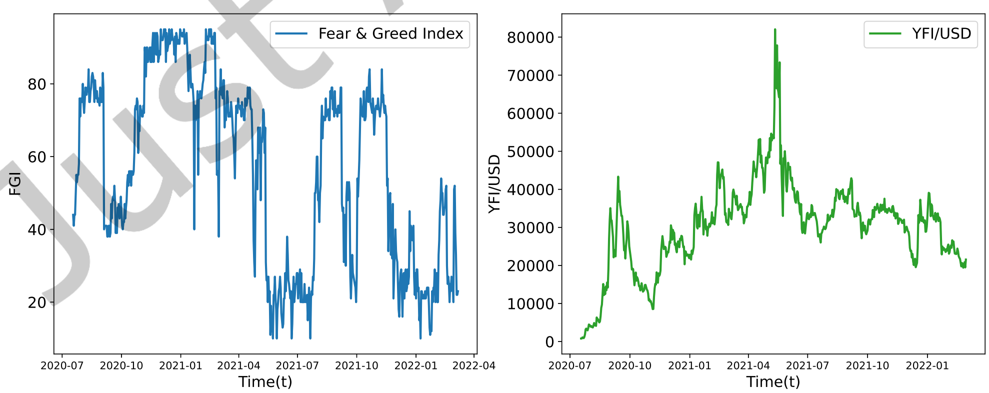

Fig. 1. Graphs for the Crypto FGI and YFI price.

Yearn Finance is built on Ethereum and uses the ERC-20 token standard for its voting rights token YFI. YFI was launched with a fixed supply whereby no tokens were allocated to insiders. Instead, the initial supply of 30,000 tokens in circulation was distributed via a liquidity providing scheme. Users could earn YFI by supplying liquidity into three distinct pools, allowing every user, regardless of their initial capital or other restrictions, to earn a portion of YFI's supply proportionate to the contributed liquidity. This type of allocation strategy was coined as a *fair launch* [63].

To generate data for our model, we used Dune to extract those addresses that have been holding YFI from Ethereum's public ledger. Then, we organized the data such that we could determine how many tokens are owned daily by each address. Finally, we excluded a number of address 'types' from the dataset: smart contracts (since they never utilized their voting rights, despite holding YFI [6]); addresses holding YFI valued less than $1 (since these rarely vote or trade their tokens owing to Ethereum's gas fees being significantly higher than the token's value), and; addresses used to burn tokens (e.g., 0x000…0000) (since no one controls them and YFI is effectively taken out of circulation). Table 2 presents our final data set.

Table 2. Overview of data extraction.

Extracted Addresses	96,227
Addresses used in Analysis	86,752
Extraction Period	2020-07-17 - 2021-08-15

Following the finalization of our data set, we utilized Exploratory Data Analysis (EDA) to determine the model's initial conditions and variables. We chose September 1st, 2020 (i.e., 45 days after the project's launch) as the starting date since at that point the Yearn Finance fair launch took place; in other words, all tokens were allocated to and claimed by liquidity providers. Using the Anderson-Darling test [2] and the Akaike information criterion [1], we identified that the probability distribution of the initial YFI allocation follows a Lomax distribution ($\lambda = 0.4$, $\alpha = 0.5$). Relying on the same methods, we found that the daily number of new addresses that have been holding YFI increases following an asymmetric Laplace distribution $ALap(0.71, 58, 76)$.

4 THE MODEL

The proposed model for initial allocations builds on an agent-based artificial cryptocurrency market (c.f. [19]). Subsequently, we describe the model in terms of the agents, the market rules, and the trading behavior. Then, we describe the initial token allocations of the three fair launch scenarios. Finally, we introduce the metrics used to evaluate concentration over time.

4.1 Agents

For our model, we take time steps $t \in \mathbb{N}_+ = \{1, 2, 3, ...\}$ which correspond to a single day and a new, individual trading round. The first time step in our model is at $t = 45$ (all tokens were allocated, claimed and are in circulation). For each time step, we define agents $i \in I$ as the addresses that hold voting rights tokens (TKNs) at the beginning of each trading round. The number of agents at time step t is given by $N_A(t) \in \mathbb{N}_+$. At the beginning of each trading round, a subset of I is selected to trade TKNs (the selection mechanism as well as the trading strategy of agents is described subsequently) and new agents (endowed *solely* with fiat currency) enter the market with the desire of placing buy orders to acquire TKNs. The new agents entering $(N_A(t+1) - N_A(t))$ follows $ALap(0.71, 58, 76)$ for every $t > 45$. In other words, at each trading round the 95% confidence interval (CI) of the number of new agents is $[114, 119]$. We run our model for 347 days ($t = 392$) and the 95% CI for the final number of agents ($N_A(392)$) is $[47113, 50890]$.

Agents are endowed with fiat holdings $f_i(t)$ and TKN holdings $y_i(t)$. Based on Dragulescu and Yakovenko [24] and Brzezinski [15], the amount of fiat held by both, individual agents at $t = 45$ and those agents entering the market at each trading round, is drawn from a Pareto distribution with $\alpha = 2.1$ and $min(f_i(t)) = \$400k$ for the richest 10% of our agents and from an $Exp(\frac{1}{40000})$ for the remaining, bottom 90%. The amount of TKNs held by agents at $t = 45$ depends on the chosen fair launch scenario S_i with $i \in \{0, 1, 2\}$.

Independently of fiat or TKN holdings, each agent i is assigned to one of two populations, Diamond Hands (DH) and Random Traders (RT), representative of respective trading strategies. DHs are risk averse traders, who pragmatically invest in the market and are more likely to not incur in trades. RTs, then, are agents who enter to market for a variety of reasons (e.g., portfolio diversification, gambling, etc.). Following Cocco et al. [19], the agent populations is split into 30% DHs and 70% RTs.

4.2 Market rules

The TKN market is given by a mechanism *comparable* to a clearing house; whereby, buy and sell orders are accumulated over time and cleared ('matched') periodically [41]. The purpose of the model and developed market is not exploring how price is formed; instead, it is to simulate how tokens circulate (and concentrate) based on clear conditions. The mechanism we utilize is *not* a formal clearing house as it does not account for price formation, nor does it include adjustments of price after every transaction over time. Instead, at each time step the TKN price $T_p(t)$ is updated based on YFI's historical price data. Agents can autonomously decide whether they are willing to trade. Agents do not, however, have information about the orders other agents are placing. The scope of this work and the developed ABM is on token concentration, and not the way price is formed. Clearing houses offer a simple and effective system for matching orders between agents, requiring limited computation overhead and facilitating a realistic flow of tokens, which makes them suitable for large ABMs [18]

At $t \geq 45$, the total number of tokens in circulation is given by the constant $T_s = 36666$. For the trade of TKNs, we model a two-sided market with a number of buyers, each willing to buy TKNs, and several sellers, each willing to sell TKNs. Additionally, at every time step the buy/sell orders created by the agents are matched in a *first in first out* method, and at the end, the unmatched orders are canceled.

4.3 Trading behavior

Depending on the population agents belong to, they exert a choice – to trade (T) or not to trade – at every time step t. This decision is given by the probability $P_i(T)$. For RTs, who randomly wish to trade following a uniform distribution, $P_i(T) = 0.5$. For DHs, $P_i(T)$ is dependent on two independent variables. First, the Fear & Greed Index ($FGI(t)$) which fluctuates between a value of 0 ("Extreme Fear") and 100 ("Extreme Greed") [70]. In our case, we consider the values of the index as "Extreme" (FGI_e) when $FGI(t) > th_h$ or $FGI(t) < th_l$, and "Normal" (FGI_n) when $th_h > FGI(t) > th_l$ with th_h and th_l thresholds for the extreme values of Fear & Greed Index. Second, the agent's wealth (W), given by an agent's individual holding denominated in fiat $f_i(t)$. An agent's wealth at time t is considered "High" (W_h) when $f_i(t)$ is above the 90^{th} percentile of the wealth distribution and "Low" otherwise. Therefore, the probability of a DH agent to trade is given by:

$$\begin{aligned} P_i(T) = {} & P(T\|FGI_e, W_h)P(FGI_e)P(W_h) + P(T\|FGI_e, W_l)P(FGI_e)P(W_l) \\ & + P(T\|FGI_n, W_h)P(FGI_n)P(W_h) + P(T\|FGI_n, W_l)P(FGI_n)P(W_l) \end{aligned} \tag{1}$$

If an agent is willing to trade, the subsequent decision to execute a buy or sell order depends on the population they belong to. For RT, the buy and sell orders follow a Bernoulli distribution with $p = 0.5$. Initially, the same holds for DH but in their case the probability is calibrated at a later stage based on the data from Yearn Finance (c.f. Section 5). In the trading behavior, we do not consider protocols that allow to stake/sell voting rights token entitlements (e.g., Bribe Protocol) as these add yet another degree of complexity. At each time step the amount of fiat currency an agent spends on buying tokens follows a $\mathcal{N}(\mu = \frac{f_i(t)}{2},\ \sigma = \frac{\mu}{3})$ and the number of TKNs an agent sells follows a $\mathcal{N}(\mu = \frac{y_i(t)}{2},\ \sigma = \frac{\mu}{3})$. In our model, the average buy and sell values are considerably higher than those in [19]. This choice was intentional in order to increase the trading volume since agents trade at most once per day.

Admittedly, the agents of our model have limited intelligence since the only market factor that influences their decisions is the FGI. Although agents with more sophisticated decision-making (e.g., taking into consideration the price volatility of YFI) could potentially enhance the accuracy of the model, they are challenging to implement in our case due to the large number of agents considered. Despite that, existing literature indicates that ABMs that are composed of even less sophisticated agents (also known as *zero-intelligence* agents) have been able to capture some of the core characteristics of financial markets [see, 27, 33].

4.4 Fair launch scenarios

Our simulation is set up around three distinct scenarios representative of initial token allocations understood as 'fair'. Their design is informed on the basis of the epistemic dichotomy described in Beese et al. [8] as well as Dong [23].

The 'base' scenario, S_0, is created following an inductive approach (its design is informed by data extracted from Yearn Finance) and the distribution of T_s is modeled to follow a Lomax distribution with $\lambda = 0.4$ and $\alpha = 0.5$. The artificially created fair launch scenarios S_1 and S_2 are designed following a deductive approach on the basis of theory; here, philosophical interpretations of what might be seen as 'fair'.

The first alternative scenario, S_1 ("Bentham"), considers 'fairness' in egalitarian terms: equity is achieved in terms of uniformity such that the total supply of tokens is divided equally among the participants. Formerly, it considers Jeremy Bentham's dictum that "everybody to count for one, nobody for more than one" [see 43], without consideration of individual interests or material situation. For S_1, T_s is uniformly distributed such that each agent i at $t = 45$ holds $y_i(45) = \frac{T_s}{N_A(45)}$.

The second alternative scenario, S_2 ("Rawls"), considers randomness, and more specifically, the principle of a lottery as 'fair': equity is achieved in terms of a token allocation – at random –, and in our case, following a Normal distribution. It re-hashes the idea that the outcome of each individual's position, like the outcomes of ordinary lotteries, is a matter of good or bad "luck" [53, p. 74-5]. Randomness and chance are central to the theory of Darwinian evolution [68]. For S_2, T_s is distributed among agents following a truncated Normal Distribution ($\mu = 0.103, \sigma = 0.192$) defined on $[0, \infty]$.

In sum, we investigate two additional scenarios aside from the base scenario (Table 3). While keeping the market conditions and parameters fixed, changing the initial allocation of tokens provides further insight into the concentration of wealth.

Table 3. 'Fair' initial token allocation scenarios.

	Scenario	**Allocation**	**Perspective**
S_0	"Cronje" (Yearn Finance)	Everyone gets the same opportunity	Social liberalism
S_1	"Bentham"	Everyone gets the same	Egalitarianism
S_2	"Rawls"	Everyone gets a random amount	Darwinism

4.5 Metrics

Given the aim of analyzing the distribution of voting rights tokens post fair launch allocation, select metrics are computed at every time step. These metrics are the Gini Coefficient [31] and the Shannon Entropy [62]. This choice was made based on an evaluation of related works seeking to quantify and measure the distribution of tokens in a system; notably, as discussed in Gervais et al. [30], Gochhayat et al. [32], Barbereau et al. [6], and Klein et al. [38].

The Gini Coefficient is typically used to assess the distribution of wealth in a given country. It was, however, also applied to study wealth distribution in Bitcoin and Ethereum [32], in non-fungible tokens markets [38], and the distribution of voting rights tokens in DeFi projects [5, 6]. For our model, the Gini G indicates the concentration of TKNs amid agents. The Gini is given by:

$$G = \frac{\sum_{i=1}^{N_A} \sum_{j=1}^{N_A} |p_i - p_j|}{2N_A \cdot \sum_{j=1}^{N_A} p_j} \tag{2}$$

where p_i corresponds to the share of TKNs held by agent i and N_A the total number of agents. It is maximized through the Dirac distribution δ_{i_0}, i.e., $p_{i_0} = 1$ for some $i_0 \in \{1, \ldots, N_A\}$ and $p_i = 0$ for all $i \neq i_0$, and minimized through the uniform distribution, i.e., $p_i = \frac{1}{N_A}$ for all i.

The Shannon Entropy was initially developed to assess the information loss in telecommunication networks [62]. It has found application in multiple areas predominantly as a measure of uncertainty or randomness. In the context of blockchain technology, it was used to measure the level of decentralization in the consensus mechanism [32], network structure [29], and governance [67], of both Bitcoin and Ethereum.

The Normalized Shannon Entropy (NSE), then, takes values between 0 and 1, and determines the unpredictability of a distribution. We assume that a system where the voting tokens are distributed can exhibit high unpredictability (1), given that more agents influence the outcomes. The NSE is given by:

$$\text{NSE} = -\sum_{i=1}^{N_A} \frac{p_i \log(p_i)}{\log N_A} \tag{3}$$

where $0 \log(0) \equiv 0$ by convention since $\lim_{p \to 0} p \log(p) = 0$. It is 0 for δ_{i_0} and 1 for the uniform distribution (i.e., the extremes are interchanged compared to the Gini coefficient). To ease graphical observation, we opted to consider 1-NSE instead of NSE such that, as in Gini, higher values correspond to higher degrees of centrality.

5 IMPLEMENTATION AND CALIBRATION

The model was implemented in Python using the MESA framework [37]. The simulation and calibration of the model was performed in a High Performance Computing (HPC) facility. The hardware provided, depending on the allocation of the HPC, were a Dual Intel Xeon Broadwell or Skylake with 128GB of RAM.

For the calibration, we followed the recommendations of Richiardi et al. [56, p. 4] whereby a "full exploration" of the parameters is required. To do so, we implemented a grid search (GS) to find a set of optimal values of parameters. GS performs an exhaustive search over all the possible combinations of parameters until finding the optimal one. The goodness of the fit and the stopping condition of GS are computed using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) between the actual (extracted from the dataset) and calibrated model. The respective equations are given by:

$$\text{RMSE} = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^{n} (x_i - \hat{x}_i)^2} \quad \text{and} \quad \text{MAPE} = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{x_i - \hat{x}_i}{x_i} \right| \tag{4}$$

where x_i is the actual observation and $\hat{x}_i$ is the simulated value.

The optimization was executed over all eligible parameters. The FGI threshold takes values from 0 to 100. For all other parameters, we considered values between 0 and 1. The optimal parameter values are displayed in Table 4.

Table 4. Optimal parameter values.

Parameter	Description	Optimal Value
$P_{DH}(Buy)$	Buy probability of DH	0.7
$DH/N_A(t)$	Population share of DH	0.3
th_h	FGI threshold high	80
th_l	FGI threshold low	20
$P(T\|FGI_e)$	Trading probability under extreme market conditions	0.7
$P(T\|W_h)$	Trading probability under high wealth	0.7
$P(T\|FGI_n)$	Trading probability under normal market conditions	0.8
$P(T\|W_l)$	Trading probability under low wealth	0.9

The optimal values of the DH/RT population ratio were close to the ratio used by Cocco et al. [19]. Therefore, we fixed it at 30% DHs and 70% RTs. Similarly, the buy probability was optimized to be 70% for DH. For the DHs, we found that high trading probabilities indeed lead to lower error rates (Table 5). This, as demonstrated in Roşu and Saleh [57], represents an expected behavior as more trading is linked with higher wealth concentration. Diametrically opposed to the high trading probability parameter set, is an artificially created parameter set, with relatively low trading probabilities. The error rates for this parameter set are relatively worse than the optimal set of high trading probabilities. We also artificially generated and investigated a compromise between the two sets (medium probability) without extreme trading probabilities.

Table 5. Diamond Hand trading probabilities parameter sets with their correspondent error rates

Parameters	High	Medium	Low
$P(T\|FGI_e)$	0.7	0.3	0.1
$P(T\|W_h)$	0.7	0.4	0.1
$P(T\|FGI_n)$	0.8	0.3	0.2
$P(T\|W_l)$	0.9	0.5	0.2
$P_i(T)$	0.77	0.38	0.15
$MAPE$	0.1859	0.224	0.255
$RMSE$	0.007	0.009	0.012

In sum, we investigate three scenarios (Table 3) under three trading probabilities (Table 5). The results might vary due to the stochastic nature of ABM. In anticipation of this variance and to ensure the robustness of our results, we applied a Monte-Carlo method [39] by repeating the experiment of the three simulation sets within the HPC; resulting in more than 1000 simulations (or, approximately 300 per set of trading probabilities). For all simulations, the agents can place buy or sell orders depending on the probability defined in $P_{DH} = 0.7$ for DH (optimized value) and $P_{RT} = 0.5$ for RT (constant) respectively.

6 SIMULATION RESULTS

6.1 Effects of trading probabilities on the three scenarios

The first simulation considers the model's behavior under high trading probability (Figure 2). High trading probability refers to a relatively high likelihood for DH agents to place an order. The second simulation is the artificially created edge case with low trading probabilities (Figure 3). It is diametrically opposed to the former, and explores the behavior of DH agents when the market dictates a relatively low likelihood to place a trade. (The graphs for S_0 and S_2 are visually coinciding.) The third simulation set was created artificially as middle ground between the high and low trading probabilities (Figure 4).

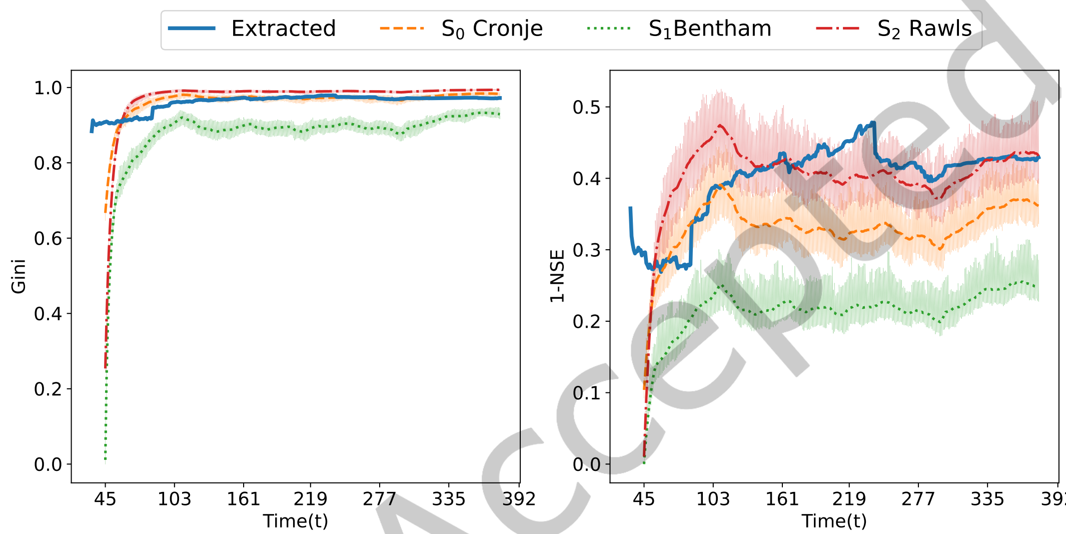

Fig. 2. Simulations for the parameter set representative of high trading probabilities.

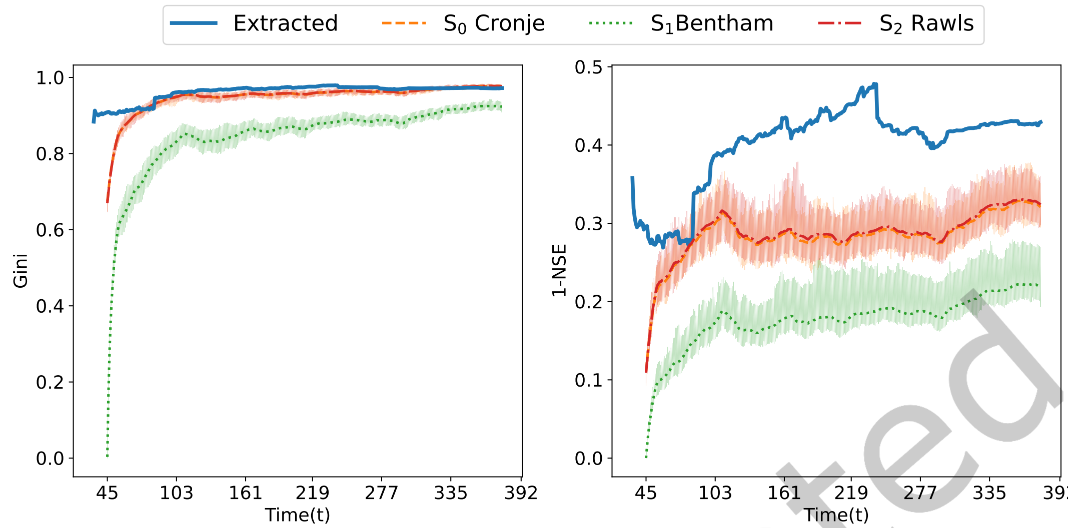

Fig. 3. Simulations for the parameter set representative of low trading probabilities.

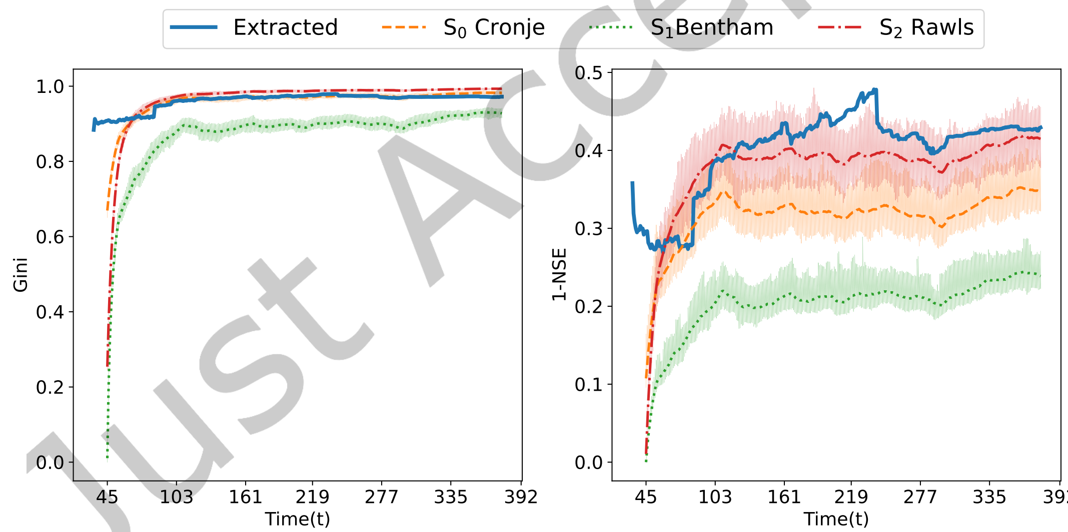

Fig. 4. Simulations for the parameter set representative of medium trading probabilities.

Across all trading probabilities, for S_0 and S_2, the Gini values of the simulated data overlap considerably with the extracted YFI data for $t \geq 100$. Until the end of the simulation time frame, the Gini values of the extracted data diverge by at most by 1.1% on S_0 and 1.7% on S_2 across all trading probability scenarios. The close fit between the extracted data from Yearn Finance and the three simulations, and in particular for S_0, is expected given the performed optimizations. The exception to the convergence is S_1, whose graph is below the extracted data in all three simulations. It appears that an egalitarian initial token allocation would then lead to relatively less concentration in the time frame of the simulation.

We expect variations in the initial values of Gini and NSE because, even though our model starts with the same number of agents at each simulation, the initial token allocation is not fixed and as discussed above, the token distribution in S_0 follows a Lomax distribution. Regardless of the scenario and trading probability, after the 1-NSE stabilizes, all distributions move in a lateral and parallel direction with regards to the extracted 1-NSE values from YFI. Although our simulation results seem to coincide with the Yearn Finance data for Gini we observe high variations of the NSE. This divergence may be interpreted in two ways.

At inception of Yearn Finance some contracts held a large amount of YFI and distributed them shortly after. Given the scope of our model we did not consider such behavior. We argue that the smart contracts that emitted YFI rapidly result in sharper rises in the metrics' values. This is consistent with our findings which indicate that when there is a large amount of YFI accessible for trading in a short period of time, the metrics rise.

The second interpretation pertains to the token supply (T_s). Formerly, the supply of YFI was "schedule-based" [47]: it began with a supply of 30000 YFI allocated following the fair launch, and subsequently an additional 6666 YFI tokens were distributed. For simplicity, we start with 36666 supply dispersed to the starting holders in our simulations. Again, the distribution of 6666 YFI in a short period of time theoretically results in higher concentration than our model, which in contrast, distributes YFI more slowly over time. The schedule-based supply of YFI can be observed in the 'bumps' around t=100. While the change is more subtle in Gini, within 1-NSE the change is more clearly observable. This is due to the comparatively higher sensitivity of the latter metric with regards to minor fluctuations [see, 6] which can also be observed in the Figures above, where the standard deviation of NSE is substantially higher than that of Gini.

6.2 Actual concentration of wealth amid *whales*

Following the three simulation sets focusing on the trading probabilities, we performed a more granular analysis of the actual concentration of TKNs amid the population of agents ($N_A(392)$). Particularly, we sought to investigate the share of agents that hold 90% of all tokens in circulation. These agents are so called *whales*, "'wealthy', above-average token-holders" [6]. In consideration of the amount of available data following the Monte-Carlo simulations, in Table 6 we present a more feasible analysis on the basis of the results from the first simulation round. For the sake of comparison, the extracted column refers to reality (i.e., the Yearn Finance data).

Table 6. Share of agents that control 90% of TKNs in circulation at t=392.

	High probability		**Medium probability**		**Low probability**		**Extracted**	
Scenario	Percentage	Actual	Percentage	Actual	Percentage	Actual	Percentage	Actual
S0 Cronje	2,59%	1137 / 43830	2,63%	1188 / 45092	3,63%	1499 / 41248	2,02%	849/41926
S1 Bentham	10,80%	4777 / 44214	10,73%	4847 / 44950	11,38%	4999 / 43895		
S2 Rawls	0,76%	376 / 49397	1,29%	572 / 44300	2,83%	1250 / 44056		

Unsurprisingly, in consideration of the values metrics took in the previous analysis, we observe a concentration of TKNs in the hands of the few. These few individuals are de facto in control as they may exert significant political pressure. In relative terms, as reflected in the metrics, the egalitarian allocation S_1 shows that the actual number of whales is higher. Regardless, our results align and support the timocratic description of DeFi governance by Barbereau et al. [6] and the observations on whales (in metaverse DAOs) by Goldberg and Schär [34].

6.3 Extending the simulation of S_1 "Bentham"

After running the first set of simulations, we opted to run a separate simulation to explore whether S_1 indeed demonstrates more or less concentration over time. To do so, we extended the simulation rounds from t=392 (August 15th 2021, the last data point extracted from Yearn Finance) to t=545 (March 1st 2022, the last point of the simulations). This represents an extension of 44.39%. The results of the simulation are presented in Figure 5.

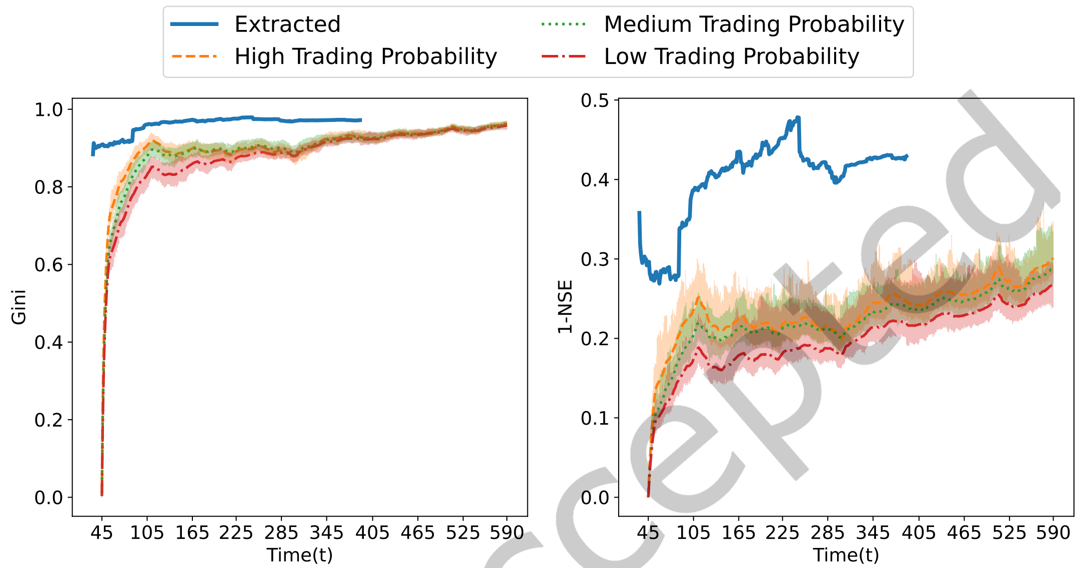

Fig. 5. Simulation for the Bentham scenario under the three trading probabilities.

From our previous simulations on the effects of different trading probabilities, we observe how S_1 Bentham's initial token allocation positively affects both metrics. It is to be expected that an equal distribution of tokens at origination will reduce concentration, at least early on. In this simulation we observe similar phenomena to what was demonstrated in Roşu and Saleh [57]: even though the delayed effect of an egalitarian initial token allocation (like the one simulated) might generate, concentration is, judging from our simulation results, inevitable in the long run. To corroborate this observation, we fitted linear regressions (LR) on Gini from the three trading scenarios. In the worst case scenario, the slope of the LR is $4 * 10^{-4}$.

7 VALIDATION OF THE MODEL

Validation is an essential part of ABM [8, 21, 23]. There are numerous techniques for validation, all of which are used to establish credibility in the simulations [8]. To validate our model we opt to use three different techniques: *event validity*, *parameter variability (sensibility analysis)*, and *extreme condition tests*.

7.1 Event validity

For the event validity, simulated events are compared with those occurring in real world systems [8]. Specifically, we take the share of agents that control 90% of TKNs in circulation between t=1 and t=392 for S_0 Cronje. (The values at t=392 are identical to those displayed in Table 6.) The real world (extracted) data is taken from Yearn Finance (c.f. Section 3). The comparison between these datasets is displayed in Figure 6.

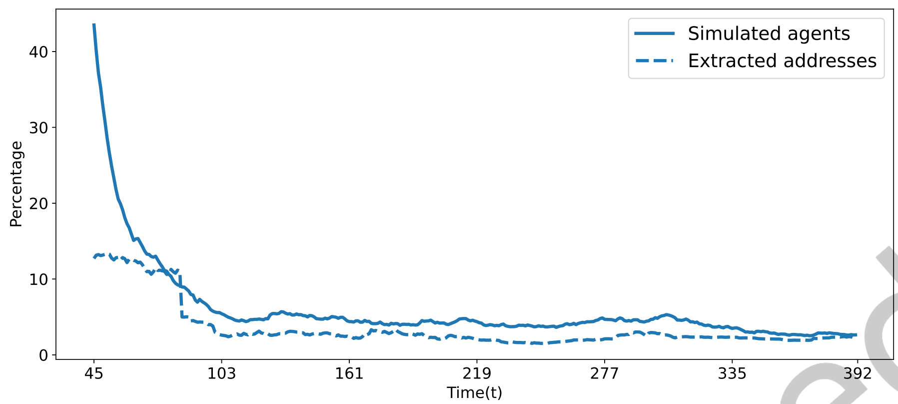

Fig. 6. Validation through event validity for the share of agents that control 90% of the circulation between Yearn Finance and S_0.

The model during calibration was not given any information regarding the token concentration. From Figure 6, we visualize how both the simulated and real world values converge after approximately 100 steps (100 natural days). At the end of the simulations the difference is 0.4 percent points. These results present a solid base for the validity of the model as it closely replicates reality [21].

7.2 Parameter variability

For the parameter variability, input parameters are modified and the resulting changes analyzed [8]. We evaluated the impact of alternative DH/RT population ratios – with 10%, 30%, 50%, 70%, and 90% DH – on the scenario S_0 relative to reality. The change was observed in terms of the metrics. Here too, we applied the Monte-Carlo method using the HPC. Figure 7 gives the simulated metrics for the five ratios along the actual distribution of the Yearn Finance token.

The procedure yields variability between the different population ratio and reality. We define the Δ as the difference between the simulated scenario and the extracted data. The simulations with 90% (Δ_{Gini}=1.95%; Δ_{NSE}=34.89%), 70% (Δ_{Gini}=1.30%; Δ_{NSE}=29.42%), and 50% DH (Δ_{Gini}=0.71%, Δ_{NSE}=25%) perform relatively worse than those with 30% (Δ_{Gini}=0.015%; Δ_{NSE}=19.65%) and 10% (Δ_{Gini}=0.4%; Δ_{NSE}=16.52%). In consideration of the Δ values and Cocco et al. [19] (who take 70% irrationality), the 30% DH is most appropriate and therefore justifies the models' validity [21].

7.3 Extreme conditions test

For the extreme conditions tests, we tested whether our model behaves reasonably when extreme values are selected for specific parameters [8]. To do so, we selected parameters to be tinkered with, all while keeping the other parameters at their optimal value (refer to Table 4). Here, the considered scenario is S_0 relative to reality.

In the first analysis, we considered extreme values for the ratio of DH. Figure 8 displays our model if the population share of DH ($DH/N_A(t)$) is at 0.01 and 0.99. The results displayed here support our argument that the more the tokens are traded, the more concentration is to be observed. Conversely, fewer trades yield less concentration.

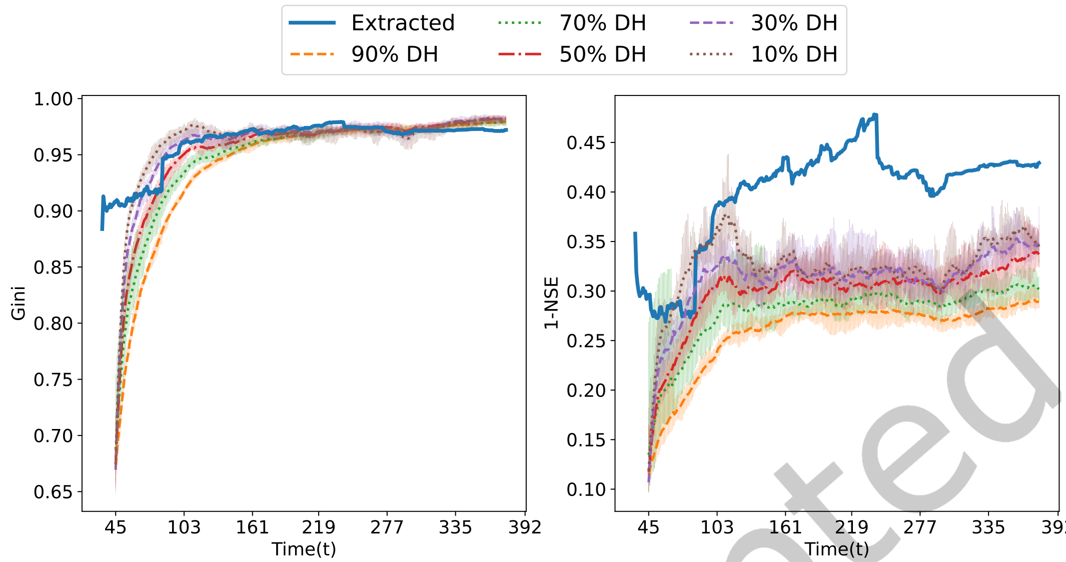

Fig. 7. Impact of different population allocations on Gini and NSE

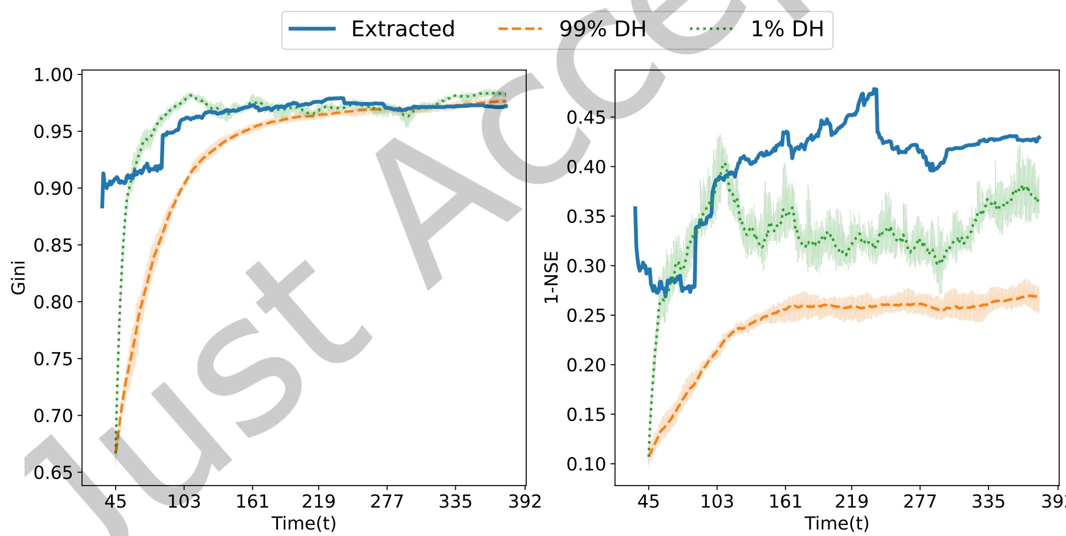

Fig. 8. Impact of extreme population allocations on Gini and NSE

In the second analysis, we considered extreme values for the FGI threshold (th). Figure 9 displays our model under different th_h and th_l. As we note minor differences ($0.33 < \Delta_{Gini} < 0.54$; $2.71 < \Delta_{NSE} < 4.56$) between the extreme FGI scenarios and the optimal scenario, we conclude that the impact of extreme values for the FGI threshold is moderate on the model. This meets expectations as the model ought to behave "reasonably" when extreme values are selected [8, p. 512].

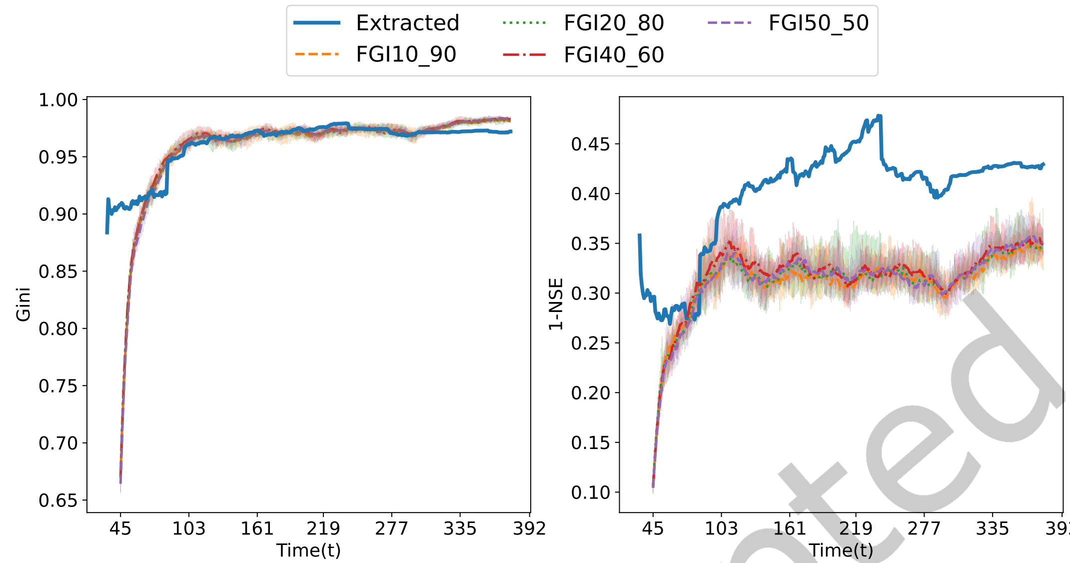

Fig. 9. Impact of extreme FGI thresholds on Gini and NSE

8 DISCUSSION

Using agent-based modeling (ABM), we evaluated how trading probabilities affect distribution over time within three distinct scenarios representative of 'fair' initial token allocations. Our findings are consistent with Barbereau et al. [6] timocratic description as the ability to trade voting rights tokens appears to be one of the causes of concentration (RQ1). Amid all three simulation sets with high, medium, and low trading probabilities, the three scenarios tend towards concentration (RQ2). Subsequently, we discuss our contributions, implications, and limitations.

8.1 Contributions and implications

The concentration of wealth in the long term, as observed in our constructed ABM, aligns with findings on the concentration of wealth in public-permissionless [6, 32, 34], and general understandings on the concentration of wealth [52]. The implications of our findings are of theoretical and practical nature.

Our findings allow to "sharpen" theory [21, p. 440] on tokenomics and DAO governance. Specifically, we contribute to the token classification of Oliveira et al. [47] as we refine the "Governance Parameters" in favor a distinction of the "Supply" parameter in terms of "Distribution" and "Allocation". The "Distribution" parameter is accounted for already as it is equivocally used for the "Supply" of tokens. For "Allocations" we distinguish between "Fair Launch" allocations (such as the ones described) and all other token allocations that may favor a minority of insiders (e.g., like Uniswap did). This contribution parallels research on ICOs which account for these 'unfair' allocations as so-called "private pre-sale[s]" [28, p. 10] – a terminology we adopt here.

Table 7 showcases our refinement vis-à-vis the original classification of Oliveira et al. [47]. While our findings do not allow to distinguish causation or correlation between allocation and concentration of tokens over time, the inclusion of "Allocations" in the token classification provides an indication for the normative ambitions of on-chain governance frameworks. Certainly, these are of value to research on DAOs, their governance, and concentration of power [see, 6, 9, 34, 36, 58]

Table 7. Italicized refinements to the Token Classification of Oliveira et al. [47].

<table>
<tr><td rowspan="4">Governance Parameters</td><td colspan="2">Representation</td><td colspan="2">Digital</td><td colspan="2">Physical</td><td colspan="2">Legal</td></tr>
<tr><td rowspan="2">Supply</td><td>Distribution</td><td>Schedule-based</td><td colspan="2">Pre-mined, scheduled distribution</td><td colspan="2">Pre-mined, one-off distribution</td><td>Discretionary</td></tr>
<tr><td>Allocation</td><td colspan="3">Fair launch</td><td colspan="3">'Unfair' launch, pre-sale</td></tr>
<tr><td colspan="2">Incentive system</td><td>Enter Platform</td><td colspan="2">Use Platform</td><td colspan="2">Stay Long-Term</td><td>Leave Platform</td></tr>
</table>

The practical implications of our findings are for the design of future governance frameworks that leverage voting rights tokens. Our work provided additional evidence that trading largely determines the extent to which governance power is concentrated. Hence, beyond the alternative to move governance of DAOs 'off-chain' (which carries a high risk of concentration of power [see, 22, 26, 49, 55]), the possibility to transfer tokens must be addressed.

In practice, this can be achieved through a new class of tokens described as *soulbound*. The introduced definition refers to "accounts, or wallets, that hold publicly visible, non-transferable (but possibly revocable-by-the-issuer) tokens" [69, p. 2]. In other words, the (albeit pseudonymous) identity of a holder is encrypted into an Soulbound Token (SBT) that is linked to the respective wallet. The opportunities for on-chain governance are promising:

- They mitigate Sybil attacks.
- They (could) grant more voting power to reputable holders.
- They enable for "proofs-of-personhood".
- They allow to correlate between SBTs which support particular causes and prevent a "tyranny of the majority" [44].

These opportunities provide avenues for research as they require contextual analysis. To date, we note the intended application of SBTs for Know-Your-Customer processes and user credentials as the cryptocurrency exchange Binance stipulated the intent to explore SBT on its native blockchain. Binance's SBT would grant access to specific functions of the BNB Chain [50]. Another, experimental application of SBTs is in electronic health records [see, 65]. It remains to be seen how these are implemented in practice and to what extent they achieve said promises.

8.2 Limitations

The research is subject to a number of limitations. In turn, some also offer potential research directions in the field of modeling cryptocurrency/token markets and organizational works in IS research.

The first limitation pertains to the defined market rules. Though these followed the principles stipulated in Mendelson [41], the clearing mechanism lacks a formal price clearing method. As we aim to replicate the behavior of YFI and evaluate the concentration of tokens, we acknowledge that the defined market mechanics may result in an oversimplification of reality. Fitting a model that accurately replicates the price of the mentioned asset poses challenges due to the high volatility and stochasticity observed in cryptocurrency markets. (This limitation was acknowledged in Cocco et al. [19].)

The second limitation pertains to the awareness of agents. In the designed model the decision making of individual agent's does not depend on past decisions or those of other agents. To address these shortcomings, future work may build upon and extend our model to include a public order book where agents are aware about other orders. Further, a distinction may be made between trading mechanisms and clearing methods on centralized and decentralized exchanges.

The third limitation pertains to the trading behavior of agents. For our simulations, we heavily rely on the FGI as a proxy for market conditions. Subsequent work could opt for the use of more granular indicators, such as the price or the volatility of different DeFi assets or social media data.

At last, because this study focused on initial token allocations, we did not consider the different techniques to cast the actual votes. While the allocation might lead to concentration, specific voting techniques may prevent whales from skewing the outcomes of elections. *Quadratic voting* – whereby preferences in terms of strength instead of a simple ballot are cast [16] – is now effectively used in some DAOs (e.g., Synthetix) and discussed in others (e.g., OlympusDAO, CurveDAO). That method, however, is yet to prove fruitful in the long run: one of the considered cases in Barbereau et al. [6], Synthetix, uses quadratic voting and although the findings reveal relatively less concentration, all metrics are still high. The evaluation of different voting techniques represents a notable research direction for interdisciplinary IS research.

9 CONCLUSION

Within the DeFi space, recent scholarship observed the implementation of on-chain governance frameworks for DAOs that leverage tokens embedded with voting rights. The initial allocation of these voting rights tokens ought to follow principles of fairness in order to achieve normative goals of political decentralization. The fair launch allocation of Andre Cronje gained prominence as it did not allocate any tokens to a minority of insiders. However, in practice it fell short as over time YFI tokens became highly concentrated.

The contributions of this study are threefold. First, on the basis of Cocco et al. [19] and Roşu and Saleh [57], we proposed an agent-based modeling (ABM) to simulate fair launch initial token allocation. Using the model, we simulated alternative initial token allocation scenarios understood as ’fair’ [43, 53]. Second, as our simulation results show, over time, independently of market conditions and agents’ willingness to trade, concentration is imminent. At last, the implications of our results allowed to extend understandings on DAOs and tokenomics to formerly include allocations as formal part of developed governance understandings.

ACKNOWLEDGMENTS

The authors thank Reilly Smethurst and Joachim Geske for their friendly reviews. The authors also thank Gilbert Fridgen for his valuable feedback as part of the first submission.

This research was funded by the Luxembourg National Research Fund (FNR) and PayPal PEARL (grant reference 13342933) as well as by the FNR in the FiReSPArX (grant reference 14783405) and PABLO (grant reference 16326754) projects. Additionally, research is supported by the European Union (EU) within its Horizon 2020 program, project MDOT (grant reference 814654). For the purpose of open access, the authors have applied a Creative Commons Attribution 4.0 International (CC BY 4.0) license to any author accepted manuscript version arising from this submission.

PayPal’s financial support is administered via the FNR, and by contractual agreement, PayPal has no involvement in the authors’ research.

REFERENCES

[1] H. Akaike. 1974. A new look at the statistical model identification. *IEEE Trans. Automat. Control* 19, 6 (Dec. 1974), 716–723. https://doi.org/10.1109/TAC.1974.1100705 Conference Name: IEEE Transactions on Automatic Control.

[2] T. W. Anderson and D. A. Darling. 1952. Asymptotic Theory of Certain "Goodness of Fit" Criteria Based on Stochastic Processes. *Ann. Math. Statist.* 23, 2 (June 1952), 193–212. https://doi.org/10.1214/aoms/1177729437

[3] Raphael Auer, Bernhard Haslhofer, Stefan Kitzler, Pietro Saggese, and Friedhelm Victor. 2023. *The Technology of Decentralized Finance (DeFi).* Technical Report. Bank for International Settlements. https://www.bis.org/publ/work1066.htm

[4] Tom Barbereau and Balázs Bodó. 2023. Beyond financial regulation of crypto-asset wallet software: In search of secondary liability. *Computer Law & Security Review* 49 (2023), 105829. https://doi.org/10.1016/j.clsr.2023.105829

[5] Tom Barbereau, Reilly Smethurst, Orestis Papageorgiou, Alexander Rieger, and Gilbert Fridgen. 2022. DeFi, Not So Decentralized: The Measured Distribution of Voting Rights. In *Proceedings of the 55th Annual Hawaii International Conference on System Sciences.* https://doi.org/10.24251/HICSS.2022.734

[6] Tom Barbereau, Reilly Smethurst, Orestis Papageorgiou, Johannes Sedlmeir, and Gilbert Fridgen. 2023. Decentralised Finance's timocratic governance: The distribution and exercise of tokenised voting rights. *Technology in Society* 73 (May 2023), 102251. https://doi.org/10.1016/j.techsoc.2023.102251

[7] Roman Beck, Christoph Müller-Bloch, and John Leslie King. 2018. Governance in the blockchain economy: A framework and research agenda. *Journal of the Association for Information Systems* 19, 10 (2018), 1. https://aisel.aisnet.org/jais/vol19/iss10/1

[8] Jannis Beese, M Kazem Haki, Stephan Aier, and Robert Winter. 2019. Simulation-based research in information systems. *Business & Information Systems Engineering* 61, 4 (2019), 503–521. https://doi.org/10.1007/s12599-018-0529-1

[9] Cristiano Bellavitis, Christian Fisch, and Paul P Momtaz. 2022. The rise of decentralized autonomous organizations (DAOs): a first empirical glimpse. *Venture Capital* (2022), 1–17. https://doi.org/10.1080/13691066.2022.2116797

[10] Nicholas Berente, Stefan Seidel, and Hani Safadi. 2018. Research Commentary—Data-Driven Computationally Intensive Theory Development. *Information Systems Research* (Dec. 2018). https://pubsonline.informs.org/doi/epdf/10.1287/isre.2018.0774

[11] Balázs Bodó, Jaya Klara Brekke, and Jaap-Henk Hoepman. 2021. Decentralisation: A multidisciplinary perspective. *Internet Policy Review* 10, 2 (2021), 1–21. https://doi.org/10.14763/2021.2.1563

[12] Bruce M Boghosian. 2019. Is inequality inevitable? *Scientific American* 321, 5 (2019), 70–77.

[13] Stefan Bornholdt and Kim Sneppen. 2014. Do Bitcoins make the world go round? On the dynamics of competing crypto-currencies. *arXiv preprint arXiv:1403.6378* (2014).

[14] Thomas Bourveau, Emmanuel T De George, Atif Ellahie, and Daniele Macciocchi. 2022. The role of disclosure and information intermediaries in an unregulated capital market: evidence from initial coin offerings. *Journal of Accounting Research* 60, 1 (2022), 129–167. https://doi.org/10.1111/1475-679X.12404

[15] Michal Brzezinski. 2014. Do wealth distributions follow power laws? Evidence from 'rich lists'. *Physica A: Statistical Mechanics and its Applications* 406 (July 2014), 155–162. https://doi.org/10.1016/j.physa.2014.03.052

[16] Vitalik Buterin. 2019. Quadratic Payments: A Primer. https://vitalik.ca/general/2019/12/07/quadratic.html

[17] Yan Chen and Cristiano Bellavitis. 2020. Blockchain disruption and decentralized finance: The rise of decentralized business models. *Journal of Business Venturing Insights* 13 (June 2020), e00151. https://doi.org/10.1016/j.jbvi.2019.e00151

[18] Silvano Cincotti, Marco Raberto, and Andrea Teglio. 2010. Credit Money and Macroeconomic Instability in the Agent-based Model and Simulator Eurace. *Economics* 4, 1 (Dec. 2010). https://doi.org/10.5018/economics-ejournal.ja.2010-26

[19] Luisanna Cocco, Giulio Concas, and Michele Marchesi. 2017. Using an artificial financial market for studying a cryptocurrency market. *Journal of Economic Interaction and Coordination* 12, 2 (2017), 345–365. https://doi.org/10.1007/s11403-015-0168-2

[20] Andre Cronje. 2021. Fair launches, decentralized collaboration, and Fixed Forex. *Medium* (July 2021). https://andrecronje.medium.com/

[21] Jason P Davis, Kathleen M Eisenhardt, and Christopher B Bingham. 2007. Developing theory through simulation methods. *Academy of Management Review* 32, 2 (2007), 480–499. https://doi.org/10.5465/amr.2007.24351453

[22] Primavera De Filippi and Benjamin Loveluck. 2016. The invisible politics of Bitcoin: governance crisis of a decentralised infrastructure. *Internet Policy Review* 5, 3 (Sept. 2016). https://doi.org/10.14763/2016.3.427

[23] John Qi Dong. 2022. Using Simulation in Information Systems Research. *Journal of the Association for Information Systems* 23, 2 (2022), 408–417. https://doi.org/10.17705/1jais.00743

[24] Adrian Dragulescu and Victor M. Yakovenko. 2001. Exponential and power-law probability distributions of wealth and income in the United Kingdom and the United States. *Physica A: Statistical Mechanics and its Applications* 299, 1-2 (Oct. 2001), 213–221. https://doi.org/10.1016/S0378-4371(01)00298-9

[25] Benedict J Drasch, Gilbert Fridgen, Tobias Manner-Romberg, Fenja M Nolting, and Sven Radszuwill. 2020. The token's secret: the two-faced financial incentive of the token economy. *Electronic Markets* 30, 3 (2020), 557–567. https://doi.org/10.1007/s12525-020-00412-9

[26] Quinn DuPont. 2017. Chapter 8: Experiments in algorithmic governance – A history and ethnography of "The DAO," a failed decentralized autonomous organization. In *Bitcoin and Beyond: Cryptocurrencies, Blockchains and Global governance*. Routledge, Taylor & Francis

Group, London; New York.
[27] J Doyne Farmer, Paolo Patelli, and Ilija I Zovko. 2005. The predictive power of zero intelligence in financial markets. (2005).
[28] Gilbert Fridgen, Ferdinand Regner, André Schweizer, and Nils Urbach. 2018. Don't Slip on the Initial Coin Offering (ICO): A Taxonomy for a Blockchain-enabled Form of Crowdfunding. In *26th European Conference on Information Systems (ECIS)*.
[29] Adem Efe Gencer, Soumya Basu, Ittay Eyal, Robbert van Renesse, and Emin Gün Sirer. 2018. Decentralization in Bitcoin and Ethereum Networks. arXiv:1801.03998 [cs.CR]
[30] Arthur Gervais, Ghassan O. Karame, Vedran Capkun, and Srdjan Capkun. 2014. Is Bitcoin a Decentralized Currency? *IEEE Security & Privacy* 12, 3 (May 2014), 54–60. https://doi.org/10.1109/MSP.2014.49
[31] C. Gini. 1912. *Variabilità e mutabilità*. https://ui.adsabs.harvard.edu/abs/1912vamu.book.....G
[32] Sarada Prasad Gochhayat, Sachin Shetty, Ravi Mukkamala, Peter Foytik, Georges A. Kamhoua, and Laurent Njilla. 2020. Measuring Decentrality in Blockchain Based Systems. *IEEE Access* 8 (2020), 178372–178390. https://doi.org/10.1109/ACCESS.2020.3026577
[33] Dhananjay K. Gode and Shyam Sunder. 1993. Allocative Efficiency of Markets with Zero-Intelligence Traders: Market as a Partial Substitute for Individual Rationality. *Journal of Political Economy* 101, 1 (Feb. 1993), 119–137. https://doi.org/10.1086/261868
[34] Mitchell Goldberg and Fabian Schär. 2023. Metaverse governance: An empirical analysis of voting within Decentralized Autonomous Organizations. *Journal of Business Research* 160 (2023), 113764. https://doi.org/10.1016/j.jbusres.2023.113764
[35] Kazem Haki, Jannis Beese, Stephan Aier, and Robert Winter. 2020. The Evolution of Information Systems Architecture: An Agent-Based Simulation Model. *MIS Quarterly* 44, 1 (2020).
[36] Samer Hassan and Primavera De Filippi. 2021. Decentralized Autonomous Organization. *Internet Policy Review* 10, 2 (2021), 1–10. https://doi.org/10.14763/2021.2.1556
[37] Jackie Kazil, David Masad, and Andrew Crooks. 2020. Utilizing Python for Agent-Based Modeling: The Mesa Framework. In *Social, Cultural, and Behavioral Modeling*, Robert Thomson, Halil Bisgin, Christopher Dancy, Ayaz Hyder, and Muhammad Hussain (Eds.). Springer International Publishing, Cham, 308–317.
[38] Niklas Konstantin Klein, Fritz Lattermann, and Dirk Schiereck. 2023. Investment in non-fungible tokens (NFTs): the return of Ethereum secondary market NFT sales. *Journal of Asset Management* (May 2023), 1–14. https://doi.org/10.1057/s41260-023-00316-1
[39] Thomas Lux. 2018. Estimation of agent-based models using sequential Monte Carlo methods. *Journal of Economic Dynamics and Control* 91 (2018), 391–408. https://doi.org/10.1016/j.jedc.2018.01.021
[40] Charles M Macal. 2016. Everything you need to know about agent-based modelling and simulation. *Journal of Simulation* 10, 2 (2016), 144–156. https://doi.org/10.1080/14649350802481470
[41] Haim Mendelson. 1982. Market behavior in a clearing house. *Econometrica: Journal of the Econometric Society* (1982), 1505–1524. https://doi.org/10.2307/1913393
[42] Loretta J Mester. 2007. Some thoughts on the evolution of the banking system and the process of financial intermediation. *Economic Review-Federal Reserve Bank of Atlanta* 92, 1/2 (2007), 67.
[43] John Stuart Mill. 1864. *Chapter V - Of The Connection Between Justice and Utility*. Cambridge University Press, 62–96. https://doi.org/10.1017/CBO9781139923927.005
[44] John Stuart Mill. 1998. *On Liberty and other Essays*. Oxford University Press, USA.
[45] Matthieu Nadini, Laura Alessandretti, Flavio Di Giacinto, Mauro Martino, Luca Maria Aiello, and Andrea Baronchelli. 2021. Mapping the NFT revolution: market trends, trade networks, and visual features. *Scientific reports* 11, 1 (2021), 20902. https://doi.org/10.3389/fbloc.2019.00012
[46] Satoshi Nakamoto. 2008. Bitcoin: A Peer-to-Peer Electronic Cash System. (2008). -.
[47] Luis Oliveira, Liudmila Zavolokina, Ingrid Bauer, and Gerhard Schwabe. 2018. To Token or not to Token: Tools for Understanding Blockchain Tokens. In *39th International Conference of Information Systems*.
[48] Vilfredo Pareto. 1964 [1919]. *Cours d'économie politique*. Vol. 1. Librairie Droz. https://doi.org/10.3917/droz.paret.1964.01
[49] Jack Parkin. 2019. The senatorial governance of Bitcoin: making (de)centralized money. *Economy and Society* 48, 4 (Oct. 2019), 463–487. https://doi.org/10.1080/03085147.2019.1678262
[50] Helen Partz. 2022. First Binance soulbound token BAB targets KYC user credentials. https://cointelegraph.com/news/first-binance-soulbound-token-bab-targets-kyc-user-credentials
[51] Stephen Penzo and Niloufer Selvadurai. 2021. A hard fork in the road: developing an effective regulatory framework for public blockchains. *Information & Communications Technology Law* (2021), 1–27.
[52] Thomas Piketty. 2014. *Capital in the Twenty-First Century*. Belknap Press.
[53] John Rawls. 1971. *A Theory of Justice*. Harvard University Press Boston. https://doi.org/10.4159/9780674042605
[54] John Rawls. 1991. Justice as fairness: Political not metaphysical. In *Equality and Liberty*. Springer, 145–173. https://doi.org/10.1007/978-1-349-21763-2_10
[55] Wessel Reijers and Mark Coeckelbergh. 2018. The Blockchain as a Narrative Technology: Investigating the Social Ontology and Normative Configurations of Cryptocurrencies. *Philosophy & Technology* 31, 1 (March 2018), 103–130. https://doi.org/10.1007/s13347-016-0239-x

[56] Matteo G Richiardi, Roberto Leombruni, Nicole J Saam, and Michele Sonnessa. 2006. A common protocol for agent-based social simulation. *Journal of artificial societies and social simulation* 9 (2006).

[57] Ioanid Roşu and Fahad Saleh. 2021. Evolution of shares in a proof-of-stake cryptocurrency. *Management Science* 67, 2 (2021), 661–672. https://doi.org/10.1287/mnsc.2019.3515

[58] Carlos Santana and Laura Albareda. 2022. Blockchain and the emergence of Decentralized Autonomous Organizations (DAOs): An integrative model and research agenda. *Technological Forecasting and Social Change* 182 (2022), 121806. https://doi.org/10.1016/j.techfore.2022.121806

[59] Fabian Schär. 2021. Decentralized finance: On blockchain-and smart contract-based financial markets. *Federal Reserve Bank of St. Louis Review* (2021).

[60] Nathan Schneider. 2019. Decentralization: an incomplete ambition. *Journal of Cultural Economy* 12, 4 (July 2019), 265–285. https://doi.org/10.1080/17530350.2019.1589553

[61] Jan Schwiderowski, Asger Balle Pedersen, and Roman Beck. 2023. Crypto Tokens and Token Systems. *Information Systems Frontiers* (March 2023), 1–14. https://doi.org/10.1007/s10796-023-10382-w

[62] C. E. Shannon. 1948. A Mathematical Theory of Communication. *Bell System Technical Journal* 27, 3 (July 1948), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

[63] Laura Shin and Andre Cronje. 2020. Andre Cronje of Yearn Finance on YFI and the Fair Launch: 'I'm Lazy'. *Unchained Podcast* (July 2020). https://unchainedpodcast.com/andre-cronje-of-yearn-finance-on-yfi-and-the-fair-launch-im-lazy/

[64] Ali Sunyaev, Niclas Kannengießer, Roman Beck, Horst Treiblmaier, Mary Lacity, Johann Kranz, Gilbert Fridgen, Ulli Spankowski, and André Luckow. 2021. Token economy. *Business & Information Systems Engineering* (2021), 1–22.

[65] Namrta Tanwar and Jawahar Thakur. 2023. Patient-centric soulbound NFT framework for electronic health record (EHR). *Journal of Engineering and Applied Science* 70, 1 (Dec. 2023), 1–11. https://doi.org/10.1186/s44147-023-00205-9

[66] Horst Treiblmaier, Melanie Swan, Primavera De Filippi, Mary Lacity, Thomas Hardjono, and Henry Kim. 2021. What's Next in Blockchain Research? -An Identification of Key Topics Using a Multidisciplinary Perspective. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems* 52, 1 (2021), 27–52. https://doi.org/10.1145/3447934.3447938

[67] Rowan van Pelt, Slinger Jansen, Djuri Baars, and Sietse Overbeek. 2021. Defining Blockchain Governance: A Framework for Analysis and Comparison. *Information Systems Management* 38, 1 (2021), 21–41. https://doi.org/10.1080/10580530.2020.1720046

[68] Andreas Wagner. 2012. The role of randomness in Darwinian evolution. *Philosophy of Science* 79, 1 (2012), 95–119.

[69] E Glen Weyl, Puja Ohlhaver, and Vitalik Buterin. 2022. Decentralized Society: Finding Web3's Soul. *Available at SSRN 4105763* (2022).

[70] Jackson Wood. 2022. The Crypto Fear and Greed Index, Explained. https://www.coindesk.com/learn/the-crypto-fear-and-greed-index-explained/

[71] Dirk A Zetzsche, Douglas W Arner, and Ross P Buckley. 2020. Decentralized Finance. *Journal of Financial Regulation* 6, 2 (Sept. 2020), 172–203. https://doi.org/10.1093/jfr/fjaa010

[72] Meng Zhang and Guy Gable. 2014. Rethinking the value of simulation methods in the information systems research field: A call for reconstructing contribution for a broader audience. In *35th International Conference on Information Systems*. Association for Information Systems (AIS).

[73] Rui Zhang, Rui Xue, and Ling Liu. 2019. Security and privacy on blockchain. *ACM Computing Surveys (CSUR)* 52, 3 (2019), 1–34.

[74] Rafael Ziolkowski, Gianluca Miscione, and Gerhard Schwabe. 2020. Decision problems in blockchain governance: Old wine in new bottles or walking in someone else's shoes? *Journal of Management Information Systems* 37, 2 (2020), 316–348. https://doi.org/10.1080/07421222.2020.1759974