9. Network Dynamics of a Tokenized Financial Ecosystem

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1. Introduction

Blockchain technology, which until recently has been known mostly in small technological circles, is bursting throughout the globe. Recent years have witnessed a growing number of cryptographic tokens that are being introduced by researchers, private sector companies and NGOs. The expanding adoption of such Blockchain based cryptocurrencies gives birth to a new kind of rising economy which in turn presents a new type of challenges for policy makers and regulators, due to its potential economic and social impact that could fundamentally alter traditional financial and social structures.

Launched in July 2015 [1], the Ethereum Blockchain is a public ledger that keeps records of all Ethereum related transactions. The ability of the Ethereum Blockchain to store not only ownership, similarly to Bitcoin, but also execution code, in the form of *”Smart Contracts”*, has recently led to the creation of a large number of new types of ”tokens”, based on the Ethereum ERC20 protocol. These tokens are ”minted” by a variety of players, for a variety of reasons, having all of their transactions carried out by their corresponding Smart Contracts, publicly accessible on the Ethereum Blockchain. As a result, the ERC20 ecosystem constitutes one of the most fascinating examples for highly varied financial ecosystems, whose entire monetary activity is publicly available from its inception.

Our work presents an analysis of the dynamical properties of the ERC20 protocol compliant crypto-coins’ trading data, using a network theory prism. We first form a network from the monetary activity during two and a half years of ERC20 transactions over the Ethereum Blockchain. We show that the ERC20 financial ecosystem, despite being infinitely faceted and potentially comprised of unlimited amount of single-serving wallet addresses, still adheres to key properties known to characterize networks of human interactions.

Furthermore, we present a thorough model-based analysis of the dynamics of the underlying network of this rising economy. We propose observing γ, the power of the degree-distribution, as a meta-parameter of the network. We demonstrate how this meta-parameter is able to describe the dynamics and consolidation process of the network through time, unlike traditional economic indicators of ERC20 ecosystem which present highly unstable and unpredictable dynamics. In particular, we demonstrate that the dynamics of the Ethereum economy, as captured by γ can be *modeled* using an under-damped harmonic oscillator, substantiating the equilibration of this economy over time. Moreover, this analytical model enables the prediction of an economic network's future dynamics, and specifically the γ parameter associated with its popularity equality. In this work we have examined the accuracy of such prediction over 12 months' time.

In conclusion, by applying network theory methods, we demonstrate clear structural properties and converging dynamics, indicating that this ecosystem functions as a single coherent financial market stabilizing along time, despite major endogenous and exogenous forces that constantly act upon it. These results can hold great promise from several aspects. First, they demonstrate the use of network theory methodology on the emerging field of Blockchain economy, enabling to capture the maturity and stabilization of an otherwise apparently volatile economy. Secondly, the ability to estimate future dynamics of the ERC20 underlying network (or other digital economies) may provide policy makers with a useful tool for designing regulations and mechanisms intended to nip undesired interventions and manipulations in the bud. These anticipatory measures might aid in addressing a variety of economic and social challenges rising from the global use of the Blockchain technology. Lastly, these results suggest that a better understanding of traditional markets could become possible through the analysis of fine-grained, abundant and publicly available data of cryptomarkets.

2. Background and Related Work

Blockchain's ability to process transactions in a trust-less environment, apart from trading its official cryptocurrency, the *Ether*, presents the most prominent framework for the execution of "*Smart Contracts*" [2]. Smart Contracts are computer programs, formalizing digital agreements, automatically enforced to execute any predefined conditions using the consensus mechanism of the Blockchain, without relying on a trusted authority. They empower developers to create diverse applications in a Turing Complete Programming Language, executed on the decentralized Blockchain platform, enabling the execution of any contractual agreement and enforcing its performance.

Moreover, Smart Contracts allow companies or entrepreneurs to create their own proprietary tokens on top of the Blockchain protocol [3]. These tokens are often pre-mined and sold to the public through Initial Coin Offerings (ICO) in exchange of Ether, other crypto-currencies, or *Fiat Money*. The issuance and auctioning of dedicated tokens assist the venture to crowd-fund their project's development, and in return, the ICO tokens grant contributors with a redeemable for products or services the issuer commits to supply thereafter, as well as the opportunity to gain from their possible value increase due to the project's success. The most widely used token standard is Ethereums *ERC20* (representing Ethereum Request for Comment), issued in 2015. The protocol defines technical specifications giving developers the ability to program how new tokens will function within the Ethereum ecosystem.

This brand-new market of ERC20 compliant tokens is fundamental to analyze, as it is becoming increasingly relevant to the financial world. Issuing tokens on top of the Blockchain system by startups and other private sector companies is becoming a ubiquitous phenomenon, inducing the trade of these crypto-coins to an exponential degree. Since 2017, Blockchain startups have raised over 7 Billion dollars through ICOs. Among the largest offerings, *Tezos* raised $232M for developing a smart contracts and decentralized governance platform; *Filecoin* raised $205M to deploy a decentralized file storage network; *EOS* raised over $185M to fund scalable smart contracts platform and *Bancor*, who managed to raise $153M for deploying a Blockchain-based prediction market.

Apart from being formed by countless stake-holders and numerous tokens, the ERC20 transactional data also presents full data of prices, volumes and holders distribution. This, alongside with daily transactions of anonymized individuals is otherwise scarce and hard to obtain due to confidentiality and privacy control, hence providing a rare opportunity to analyze and model financial behavior in an evolving market over a long period of time.

There has been a surge in recent years in the attempt to model social dynamics via statistical physics tools [4], ranging from opinion dynamics, through crowd behaviors to language dynamics. The physical tools used are also varied, ranging from Ising models [5] to topology analysis [4]. More specifically, previous studies have implemented physics-based approaches to the analysis of economic markets. Econophysics have attempted to describe the dynamical nature of the economy with different, and increasingly sophisticated physical models. Frisch [6], who started this trend, has suggested to use a damped oscillator model to the economy post wars or disasters, with the assumption that there is an equilibrium state that has been perturbed. Since then, many new models have been suggested, ranging from quantum mechanical models [7][8] to chaos theory [9][10]. However, all of these models have attempted to describe the economy, represented by a singular *value*, e.g. stock market prices, whereas the underlying network of the economy has not been addressed.

Network science, however, has exceedingly contributed to multiple and diverse scientific disciplines in the past two decades, by examining exactly diverse network related parameters. Applying network analysis and graph theory have assisted in revealing the structure and dynamics of complex systems by representing them as networks, including social networks [11][12][13], computer communication networks [14], biological systems [15], transportation [16][17], IOT [18], emergency detection [19] and financial trading systems [20][21][22].

Most of the research conducted in the Blockchain world, was concentrated in Bitcoin, spreading from theoretical foundations [23], security and fraud [24][25], to some comprehensive research in network analysis [26][27] [28]. The world of Smart contracts has recently inspired research in aspects of design patterns, applications and security [29][30][31][32], policy towards ICOs has also been studied [3]. Some preliminary results examining network theory's applicability to ERC20 tokens has been made in [33]. In this work we aim to examine how this prominent field can enhance the understanding of the underlying structure of the ERC20 tokens trading data, and model it's stabilization process from a network perspective over time.

3. Methodology

3.1 Data

In order to preserve anonymity in the Ethereum Blockchain, personal information is omitted from all transactions. A User, represented by their wallet, can participate in the economy system through an address, which is attained by applying *Keccak-256* hash function on his public key. The Ethereum Blockchain enables users to send transactions in order to either send Ether to other wallets, create new Smart Contracts or invoke any of their functions. Since Smart Contracts are scripts residing on the Blockchain as well, they are also assigned a unique address. A Smart Contract is called by sending a transaction to its address, which triggers its independent and automatic execution, in a prescribed manner on every node in the network, according to the *data* that was included in the triggering transaction.

Smart Contracts representing ERC20 tokens comply with a protocol defining the manner in which the token is transferred between wallets and the form in which data within the token is accessed. Among these requirements, is the demand to implement a *transfer* method, which will be used for transferring the relevant token from one wallet to another. Therefore, each transfer of an ERC20 token will be manifested by a wallet sending a transaction to the relevant Smart Contract. The transaction will encompass a call to the *transfer* method in its *data* section, containing the amount being transferred and its recipient wallet. Each such token transfer results in altering the 'token's balance', which is kept and updated in its corresponding Smart Contract's storage.

We obtain the ERC20 transactions basing on the further requirement of the ERC20 protocol, demanding that each call to the *transfer* method will be followed by sending a *Transfer* event and updating the event's logs with all relevant information regarding the token transfer. We therefore call an Ethereum full node's JSON API and fetch all logs matching to the *Transfer* event structure. Parsing these logs result in the following fields per transaction: *Contract Address* - standing for the address of the Smart Contract defining the transferred token, *Value* - specifying the amount of the token being transferred, *Sender* and *Receiver* addresses, being the wallet addresses of the token's seller and buyer, correspondingly.

We have retrieved all ERC20 tokens transactions spreading between February 2016 and June 2018, resulting in $88,985,493$ token trades, performed by $17,611,649$ unique wallets, trading $51,281$ token addresses. Due to the restriction on changing and tempering Smart Contracts, any modification made to a token's designated Smart Contract involves a definite change in its associated Contract Address. As a result, a token can change addresses throughout its lifespan, though for any point in time, it will only be assigned to a single relevant *Contract Address*. Therefore, the above-mentioned amount of unique contract addresses serves merely as an upper bound to the amount of unique tokens. Since we do not restrict ourselves to a specific type of token, but observe the network as a whole trading system, this non-unique identification of tokens doesn't affect our analysis of the network.

The dataset of ERC20 tokens transactions is extremely diverse and wide-ranging, where not only any ERC20 token might correspond to multiple contract addresses, and therefore being considered as various different tokens by our analysis, but also the characteristics of the different tokens are extremely varied. For instance, the tokens differ in their age, their economic value, activity volume and number of token holders, some merely serve as test-runs, others aren't tradable in exchanges yet, and some, according to popular literature, are frauds, all residing next to actual real-world valuable tokens.

3.2 Graph Analysis

In order to perceive the network's structure and assess the connectivity of its nodes, one should examine the network's degree distribution, considering both in-degree and out-degree, indicating the number of incoming and outgoing connections, correspondingly. The degree distribution $P(k)$ signifies the probability that a randomly selected node has precisely the degree k.

In random networks of the type studied by Erdős and Rényi [34], where each edge is present or absent with equal probability, the nodes' degrees follow a *Poisson* distribution. The degree obtained by most nodes is approximately the average degree $\bar{k}$ of the network. These properties are also manifested in dynamic networks [35]. In contrast to random networks, the nodes' degrees of social networks (such as the Internet or citation networks) often follow a *power law* distribution [36]:

$$P(k) = k^{-\gamma}$$

The power law degree distribution indicates that there is a non-negligible number of extremely connected nodes even though the majority of nodes have small number of connections. Therefore, the degree distribution has a long right tail of values that are far above the average degree. Power law distributions can be found in many real networks, Newman [13] summarized several of them, including word frequency, citations, telephone calls, web hits, or the wealth of the richest people.

3.3 Power-law Fit

The degree distribution of a given graph is plotted on a double logarithmic scale, over 20 logarithmically spaced bins, between the minimal and maximal degrees of relevant graph. We've selected splitting the data along 20 bins, in order to accommodate both small networks, having small sets of vertices and consequently possibly small degree sequences, and also large networks obtaining much larger variance of the degree set.

Several approaches are known in literature for fitting the power law distribution to a linear model in the double logarithmic scale and for estimating its *goodness-of-fit*, see for example [37]. We have chosen to fit the bins' heights to a Linear Model, using ordinary Least Squares Regression, while considering all binned data points, and not only their tail. We further chose to verify the *goodness-of-fit* of the power-law model to the degree distribution by calculating the coefficient of determination of the fit, i.e. its R^2, computed as follows:

$$R^2 = 1 - \frac{\sum_k (y_k - fk)^2}{\sum_k (y_k - \bar{y})^2}$$

where $y_k = P(k)$ are the degree distribution values, f_k are the modeled degrees by the fitted power-law model, and $\bar{y}$ is the means of the empirical degree distributions: $\frac{1}{n}\sum_k y_k$. A different methodology for estimating ERC20 network γ values and their goodness-of-fit can be found in [38].

3.4 Oscillation Dynamics

We consider the ERC20 system as a social physical system and thus use physical models to analyze it. We hypothesize that the ERC20 system behaves as a dynamical system approaching its equilibrium state, which can be modeled as a damped harmonics oscillator.

A harmonic oscillator is a system acted upon by a force negatively proportional to its perturbation from its equilibrium state. Physical systems that are modeled in this way are springs and swings. Systems that also experience a velocity-dependent friction-like force, e.g. air resistance, are modeled by a damped harmonic oscillator. The dynamical equation for these models is:

$$\frac{d^2x}{dt^2} = -kx - c\frac{dx}{dt}$$

where x is the perturbation from equilibrium, m is the mass, k is the spring constant and c is the viscous damping coefficient. The resonant frequency of the system is defined as $\omega_0 = \sqrt{m/k}$ and which represents how strong the damping is, compared to the resonant frequency, such that an over-damped system $\zeta > 1$ does not oscillate, but exponentially converges to the equilibrium state, whereas an under-damped system $\zeta < 1$ oscillates with a modified frequency $\omega_1 = \omega_0\sqrt{1-\zeta^2}$ during its exponential convergence. The case of critically damped system $\zeta = 1$ is an important one in physics, but does not relate to the analysis presented below.

Given an under-damped oscillator, the dynamics of the system can be described by the following function:

$$x(t) = A \cdot e^{-\omega_0 \zeta t} \cdot sin(\omega_0 \sqrt{1-\zeta^2 t} + \phi) + x_\infty$$

Here ϕ is the phase of the oscillation and x_∞ is the equilibrium state. In this work, we will use the under-damped oscillator in order to model the dynamics of the ERC20 network meta-parameter γ and extract the parameters of its dynamics.

4. Results

4.1 ERC20 Dynamics: A Semantic Approach

Our main objective in this paper is to explore and comprehend the dynamics of the diverse network of ERC20 over time. The first, and most obvious methodology to examine the network's evolvement through time, is using a traditional semantic approach, analyzing ERC20 data characteristics over time. We therefore observe weekly rolling window snapshots of the ERC20 transactional data, w_d, throughout FT :

$$wd = [d - 7, d), \forall d \in FT$$

and analyze the evolution of several intrinsic properties of the data.

We first observe the number of traded ERC20 tokens within each week of data, w_d, throughout the entire FT timespan, as is presented in Fig. 1. Due to the huge inflation in the number of ERC20 tokens created during FT , it's of no surprise that the rolling count of traded tokens presents a general increasing tendency. However, it's not monotonous, as there were times the number of weekly traded tokens presented evident and not negligible decreasing patterns.

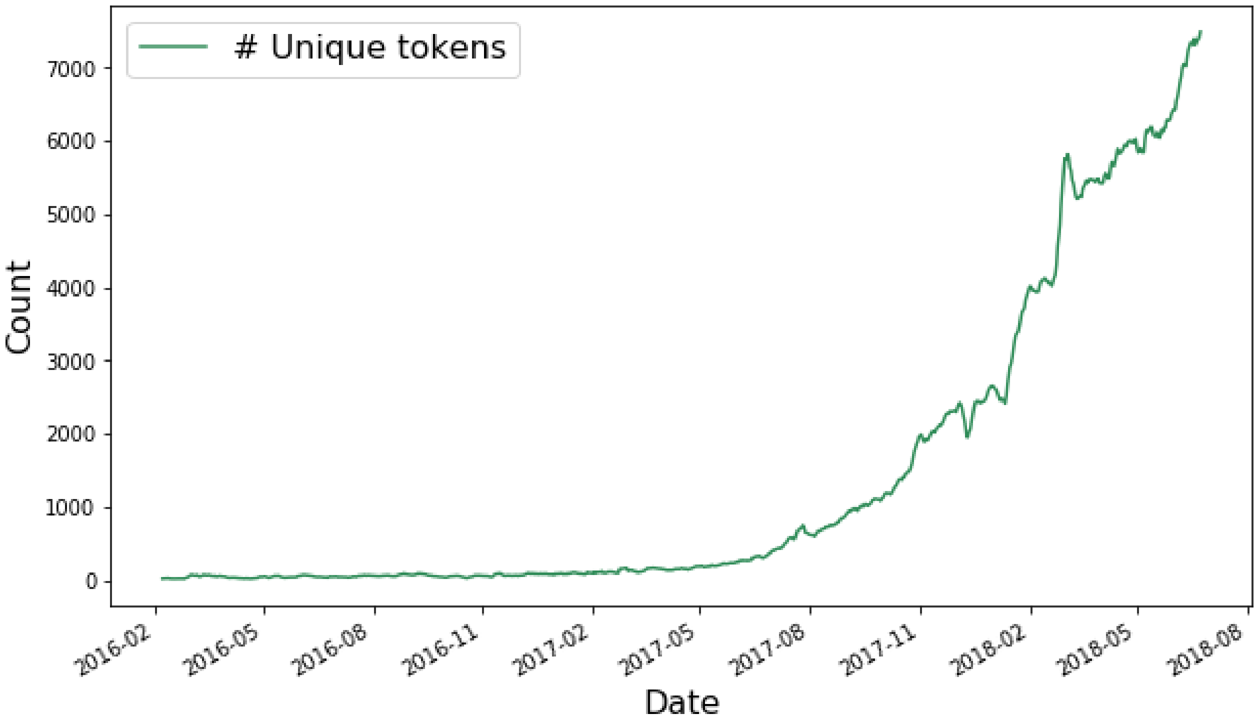
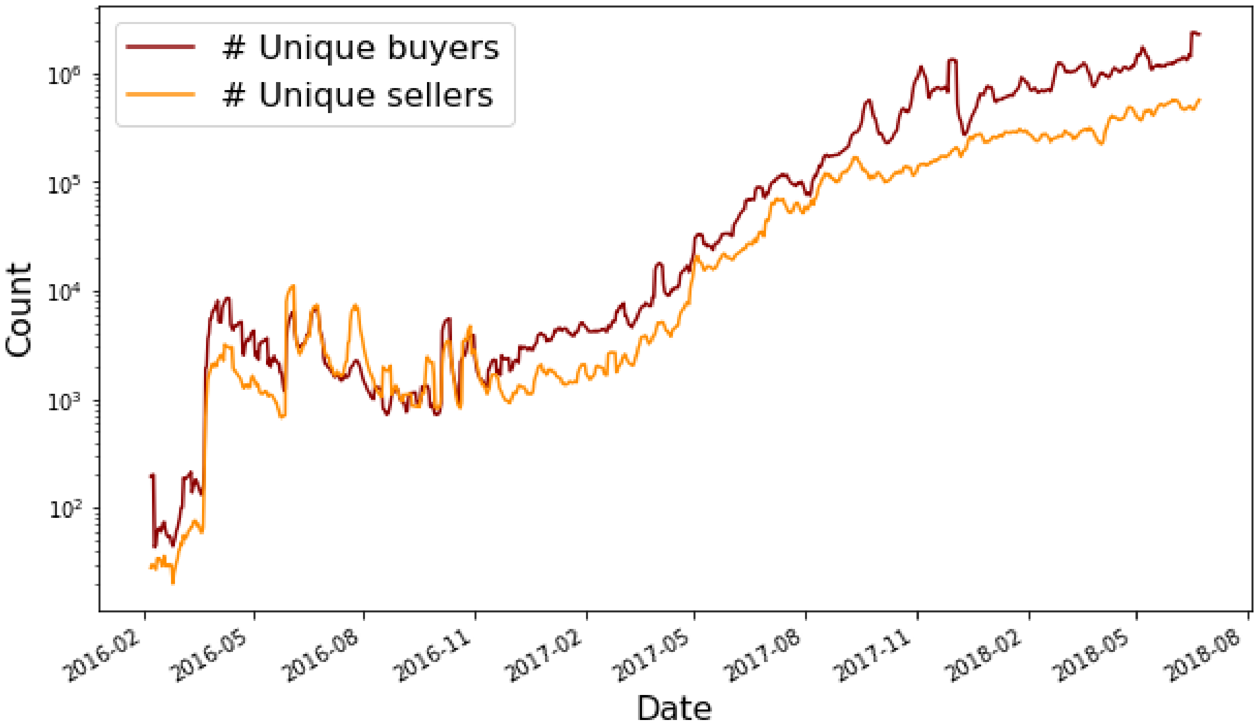


Figure 1: the number of unique traded tokens for each *d* related week, presented both in linear and logarithmic scale (right and left panels, correspondingly), where the logarithmic scale emphasizes signal diversity during the first year, and the logarithmic scale presents unstable behavior during the last year of data.

This instability becomes even clearer when observing the number of unique buying and selling wallets over time, depicted in Fig. 2. The first year of data presents not only unstable dynamics of these two properties, but also reveals how the ERC20 network shifts its vocation multiple times from a *Buyers Ecosystem*, where more unique buyers than sellers exist, into a *Sellers Ecosystem*, where more unique sellers take part in the weekly ERC20 transactions snapshot, and vice-versa. The second year of data reveals the network has transformed into a *Buyers Ecosystem*, though the ratios between unique buyers and sellers continue to undergo drastic changes.



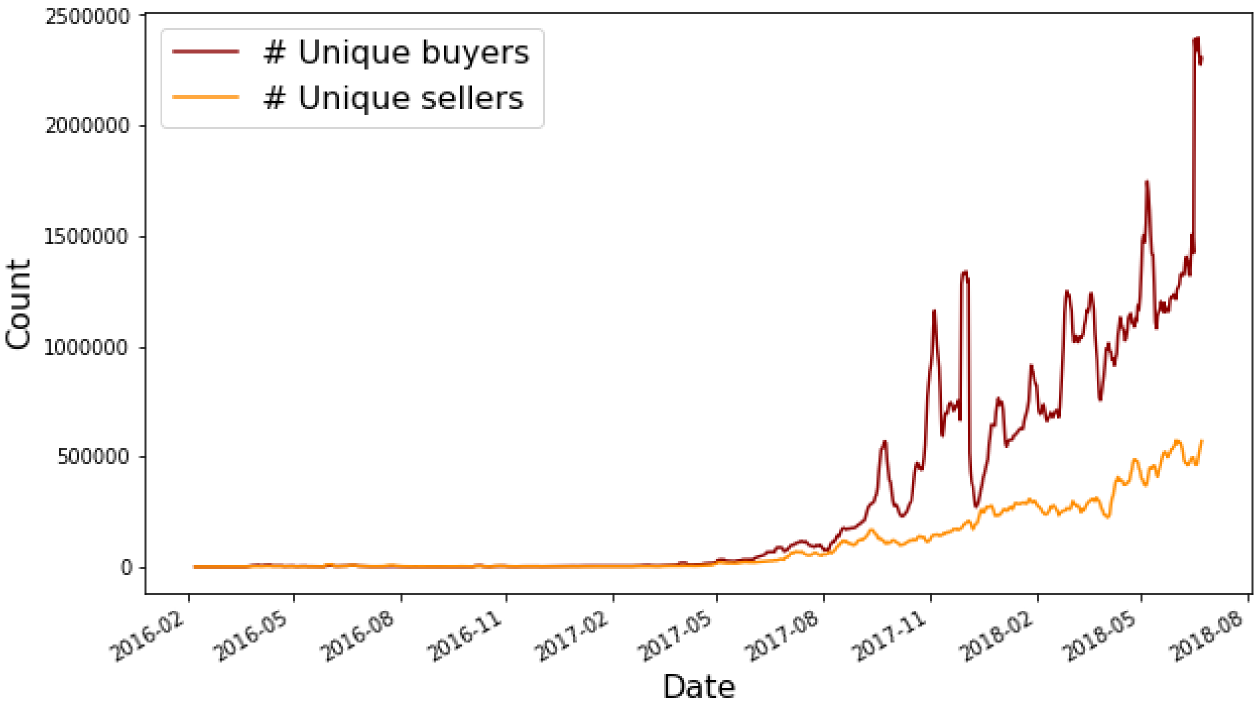
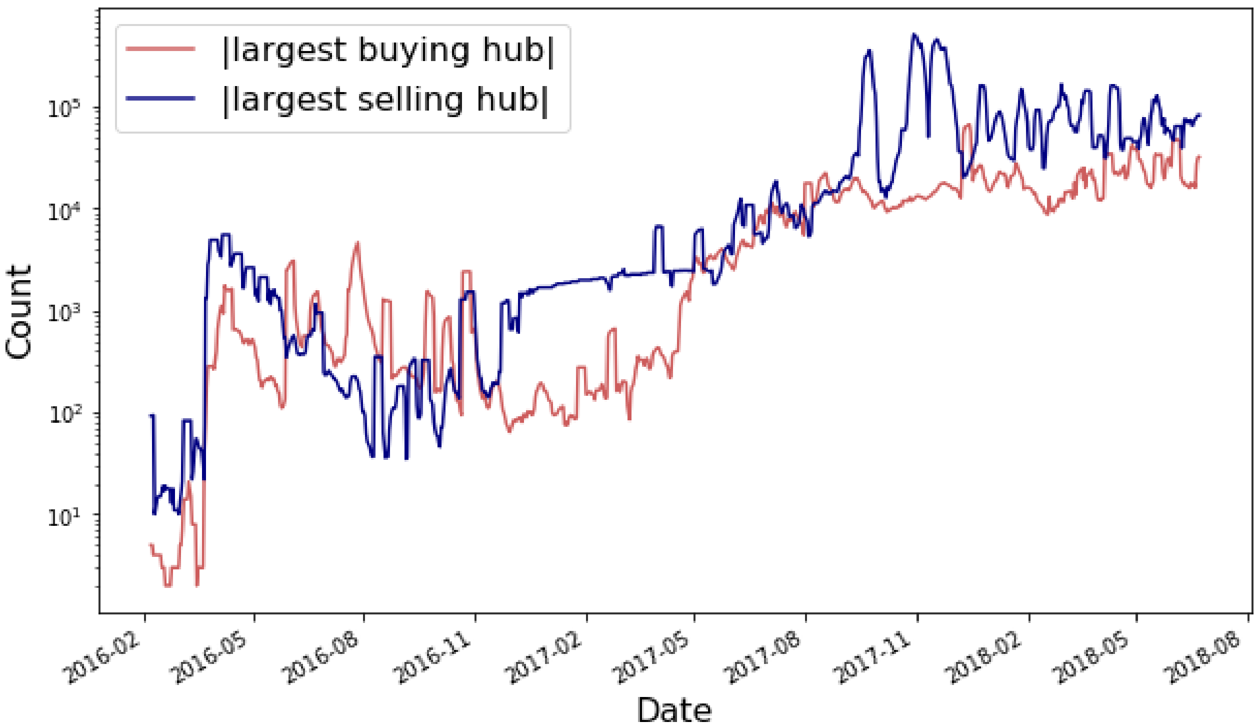


Figure 2: Number of unique selling and buying wallets within $[d-7, d)$ presented both in linear and logarithmic scale (right and left panels, correspondingly), where the logarithmic scale emphasizes signal diversity during the first year, and the logarithmic scale presents unstable behavior during the last year of data.

We further analyze the sizes of the largest buying and selling hubs, in other words, the maximal in and out-degrees over time, presented in Fig. 3. We note that similarly to the dynamics of total number of buyers and sellers presented in Fig. 2, this semantic property also displays major volatility, where the network frequently shifts from having a largest selling hub to having a largest buying hub and vice-versa.



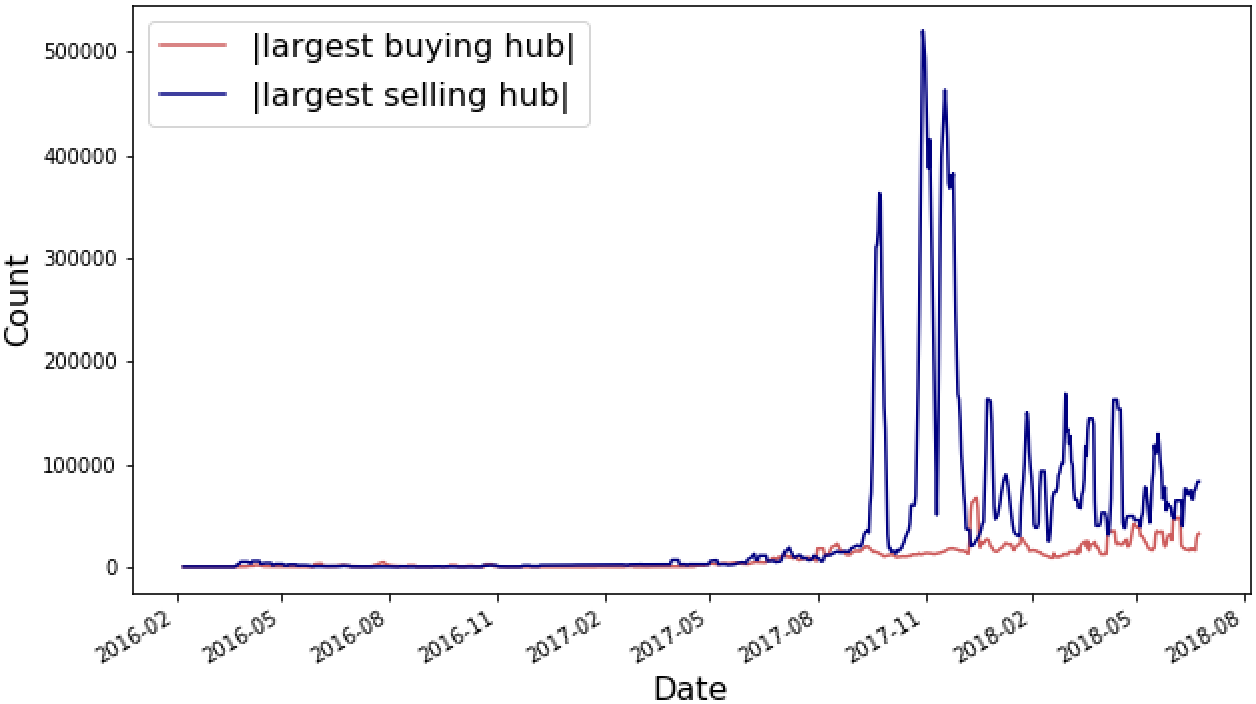


Figure 3: Size of largest selling hub and largest buying hub within $[d-7, d)$ presented both in linear and logarithmic scale (right and left panels, correspondingly), where the logarithmic scale emphasizes signal diversity during the first year, and the logarithmic scale presents unstable behavior during the last year of data.

We finally observe the dynamics of total number of active wallets throughout time, and the evolution of number of transactions among them over time, depicted in Fig. 4. These two properties present the same phenomena of instability, where smooth and monotonic trends are not evident, and drops of over 60% exist along FT, and no consolidation process is evident in this prism.

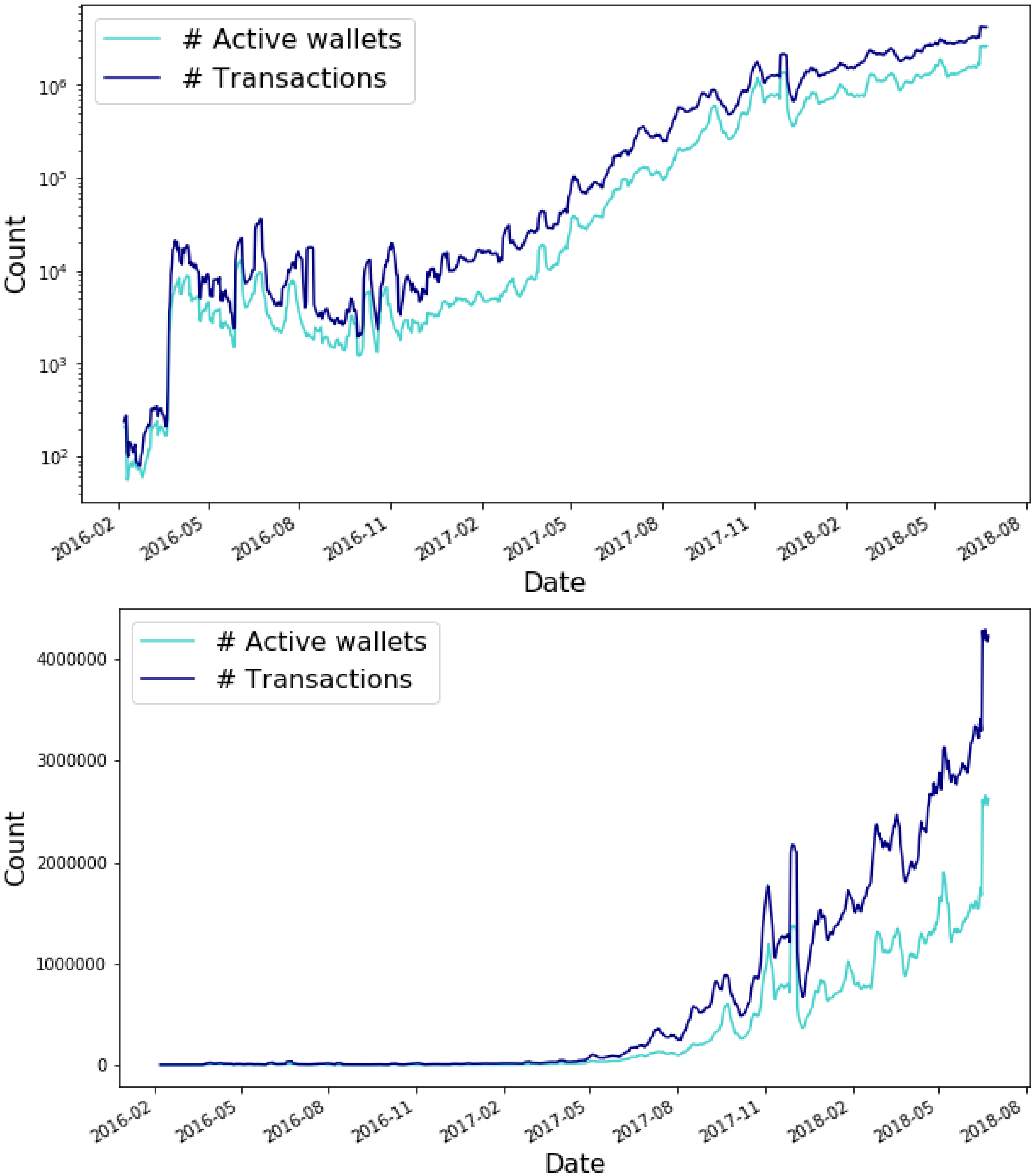


Figure 4: Number of weekly active wallets and transactions volume, presented both in linear and logarithmic scale (right and left panels, correspondingly), where the logarithmic scale emphasizes signal diversity during the first year, and the logarithmic scale presents unstable behavior during the last year of data.

Concluding, the semantic, more traditional approach for reviewing the network's evolution through time, manifests a highly unstable, unpredictable ecosystem. This erratic behavior, across multiple properties, might imply the network's inability to reach equilibrium.

4.2 ERC20: Network Theory Applicability

Throughout the last two decades, network theory has aided in modeling and comprehending a variety of complex systems, including social networks, transportation networks, financial trading systems and many more. We'd therefore like to examine whether a more network-related prism could be of use to explore whether the ERC20 network undergoes a consolidation process throughout the examined timespan.

Network theory states that degree distributions of human related networks, and economic systems in particular, strongly aspire to be arranged in a scale free, power-law governed regime. Thus, we first explore its networks' degree distribution, and verify that the ERC20 network satisfies this known characteristic of other real-world networks. We therefore construct a directed graph, consisting of all ERC20 transactions during the examined 2 years period, namely:

Definition 1 *Let FT denote the Full Timespan between February 2016 and June 2018. The ERC20 Full Transactions Graph, $G_{FT}(V, E)$, is a directed graph based on all transactions made during FT, with any of the traded ERC20 tokens. The set of vertices V consists of all ERC20 trading wallets in the period:*

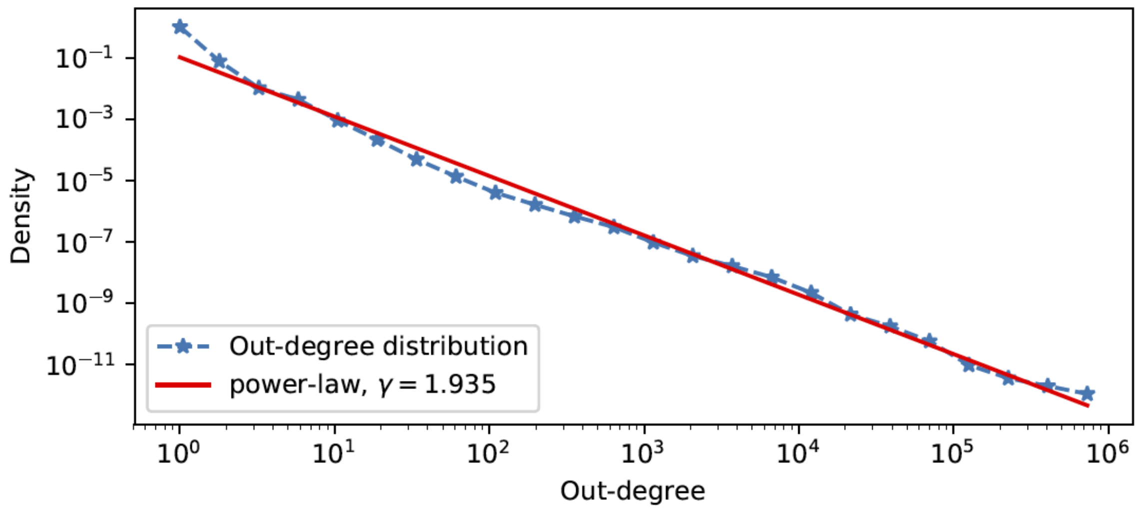
> $V := \{v i$ wallet w_v bought or sold any token during $FT\}$ (5)

and the set of edges $E \subseteq V \times V$ is defined as:

> $E := \{(u, v) i$ wallet w_u sold any token to w_v during $FT\}$ (6)

The resulting graph consists of $6, 890, 237$ vertices and $17, 392, 610$ edges. Out-going edges depict transactions in which wallet w_u sold any type of ERC20 token to other wallets, and in-coming edges to u are formed as result of transactions in which w_u bought any ERC20 token from others. Out-degree of vertex u represents the number of unique wallets buying tokens from w_u and its in-degree depicts the number of unique wallets selling tokens to it.

Surprisingly, despite the great variance between the traded tokens in the network, we discovered that the degree distribution depicts a strong power-law pattern, as presented in Fig. 5. Hence the *ERC20 Full Transactions Graph*, G_{FT}, displays similar connectedness structure to other real-world networks, such as [11] [12] [13], presenting a non-negligible number of highly connected nodes even though the majority of nodes have small number of connections, both in buying and selling transactions.



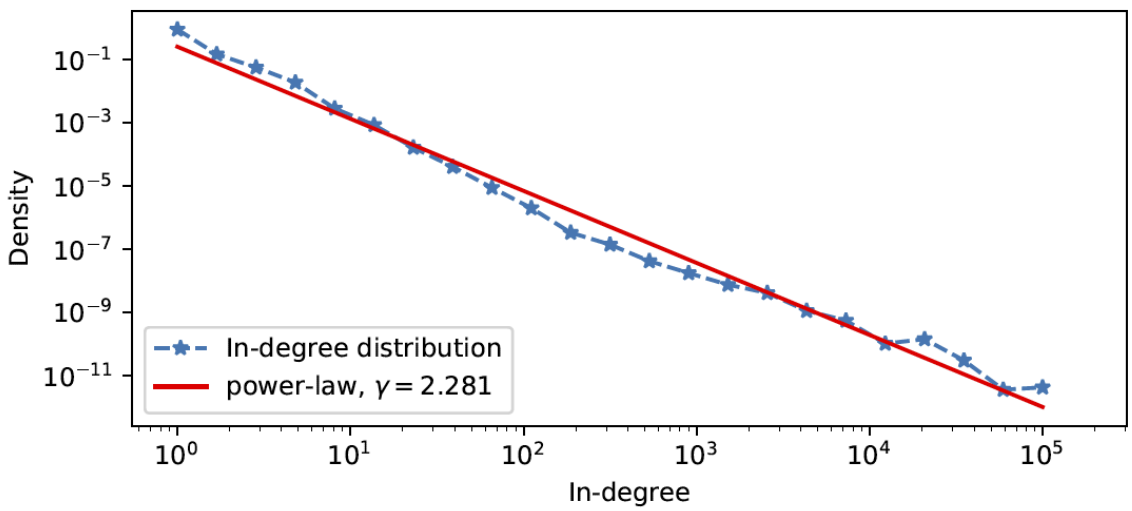


Figure 5: Analysis of Blockchain network dynamics for a 2 years period from February 2016 to June 2018. The networks nodes represent ERC20 wallets and edges are formed by ERC20 buy-sell transactions. Outgoing degree of a node reflects the number of unique wallets receiving funds from that node, regardless of the token being transferred, and vice-versa for incoming degree. Both outgoing and incoming degrees present a power-law distribution, similarly to what was demonstrated in analysis of mobile phone, citation data and many other real-world networks (see citation 13).

However, in order to apply network theory to modeling ERC20s' dynamics over time, we must also verify that temporal snapshots of this network also adhere to a power-law model. We therefore form and analyze *weekly transactions graphs*, each of which is based on one week of all ERC20 transactions. Formally:

Definition 2 *Let FT denote the Full Timespan between February 2016 and June 2018. Given a day $t \in FT$, the ERC20 Weekly Transactions Graph, $G_t(V_t, E_t)$, is a directed graph based on all transactions made during $[t-7, t)$, trading any of the ERC20 tokens. The set of vertices V_t consists of all ERC20 trading wallets in that period:*

> $V_t := \{vi$ wallet w_v bought or sold any token during $[t-7, t)\}$ (7)

and the set of edges $E_t \subseteq V_t \times V_t$ is defined as:

> $E_t := \{(u, v)i$ wallet w_u sold any token to w_v during $[t-7, t)\}$ (8)

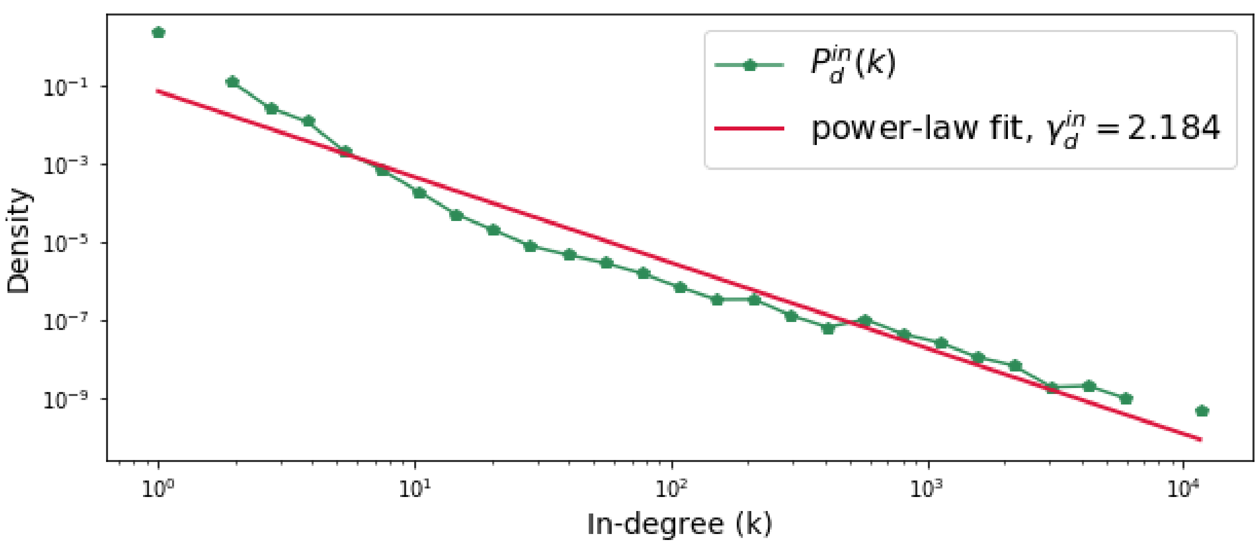
The out (in) degree distributions, $P_t^{out}(k)(P_t^{in}(k))$, signifies the probability that a randomly selected node $v \in V_t$ has precisely out-degree (in-degree) k. When out-degree distribution follows a power-law model, it satisfies:

$$P_t^{out}(k) = k^{-\gamma_t^{out}}$$

And correspondingly, the in-degree complies with:

$$P_t^{in}(k) = k^{-\gamma_t^{in}}$$

Fig. 6 demonstrates that empirical observations, in form of ERC20 *weekly transactions graphs* coincide with theory, presenting a strong fit of both weekly out and in-degree distributions to the power-law model.



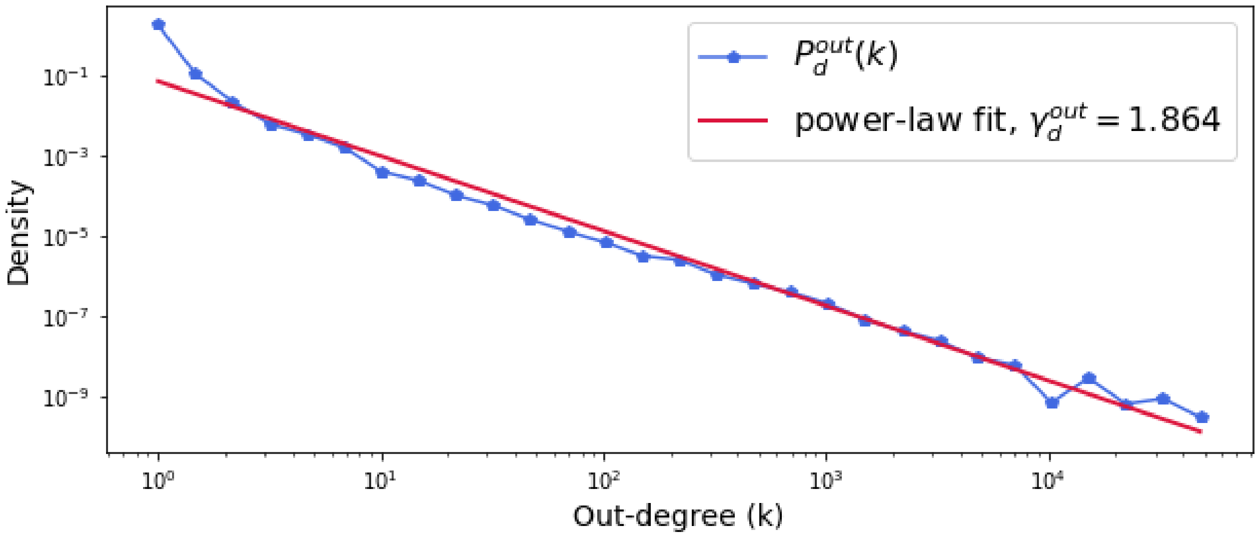


Figure 6: In-Degree distribution ($P^{in}_{t_0}(k)$, left panel) and out-degree distribution ($P^{out}_{t}(k)$, right panel) of the weekly transactions graph $G_{t_0}(V_{t_0}, E_{t_0})$, for t_0 = January 31st, 2018. Outgoing degree of a vertex reflects the number of unique wallets receiving funds from that vertex, and vice-versa for incoming degree. Both outgoing and incoming degrees present a power-law distribution, obtaining similar $\gamma^{out}_{t_0}$ and $\gamma^{in}_{t_0}$ values to the achieved corresponding γ-s for the *Full Transactions Graph* (See Fig. 5)

It is also to be noted that a different methodology to model the ERC20 temporal degree distribution and to estimate its γ parameters was applied in [38] and also presented high agreement with a truncated power-low model. These fits to the power-law model demonstrate that Network Theory is applicable to the ERC20 network, despite its extremely diverse and non-homogeneous nature, giving rise to the possibility of harnessing this domain’s power in order to investigate and model the dynamics of ERC20 network over time.

4.3 ERC20 Dynamics: The Oscillating Network Model

During the examined timespan of 2.5 years of ERC20 transactions, the network keeps evolving and changing its dynamics. Not only does the rising public interest in Blockchain and tokens induce an exponential growth in transactions’ volume, but the traded tokens on the network change as well, as new tokens are established and others lose their impact and decay.

This dynamical nature of the ERC20 economy leads us to examine the degree distribution over time, as manifested by its associated γ values. We thereby construct 878 *weekly transactions graphs*, by a sliding window of 1 day, for each day in the 2.5 years period between February 2016 to June 2018:

$$\bigcup_{t \in FT} Gt(V_t, E_t)$$

We calculate both in and out degree distributions for each of these weekly graphs, P_d^{in} and P_d^{out}respectively, and fit each of them to the power-law model.

In order to examine the *goodness-of-fit* of the power-law model to the empirical degree distribution for each of the weekly graphs, we've calculated the R^2 of each such fit. The results are depicted in Fig. 8, presenting that for over 99% of $t \in FT$, both P_t^{in} and P_t^{out}, fits to power-law yield an $R^2 \geq 0.8$. Moreover, both P_t^{in} and P_t^{out} display an improving fit to power-law as t increases, manifested by the convergence of R^2 towards 1.

We next examine the dynamics of the power-law fit, and explicitly the dynamics of its associated γ values along time. We postulate that any network of human related transactions, has a characteristic *stable state*, in the form of γ_∞^{in} and γ_∞^{out}, to which the network strives to converge:

$$\gamma_t^{in} \xrightarrow[t \to \infty]{} \gamma_\infty^{in}, \gamma_\infty^{out} \xrightarrow[t \to \infty]{} \gamma_\infty^{out}$$

Empirical observations of both γ^{in} and γ^{out} coincide with this hypothesis, as can be seen in Fig. 7, and can be efficiently modeled as an Harmonic Under-Damped Oscillator, formally $\forall t \in FT$:

$$osc(t) = A \cdot e^{-\omega 0 \zeta t} \cdot sin(\omega 0 \sqrt{1 - \zeta 2t} + \phi) + \gamma_\infty$$

The oscillator fitted to the entire data of γ values along time FT is referred to $osc_{FT}(t)$.

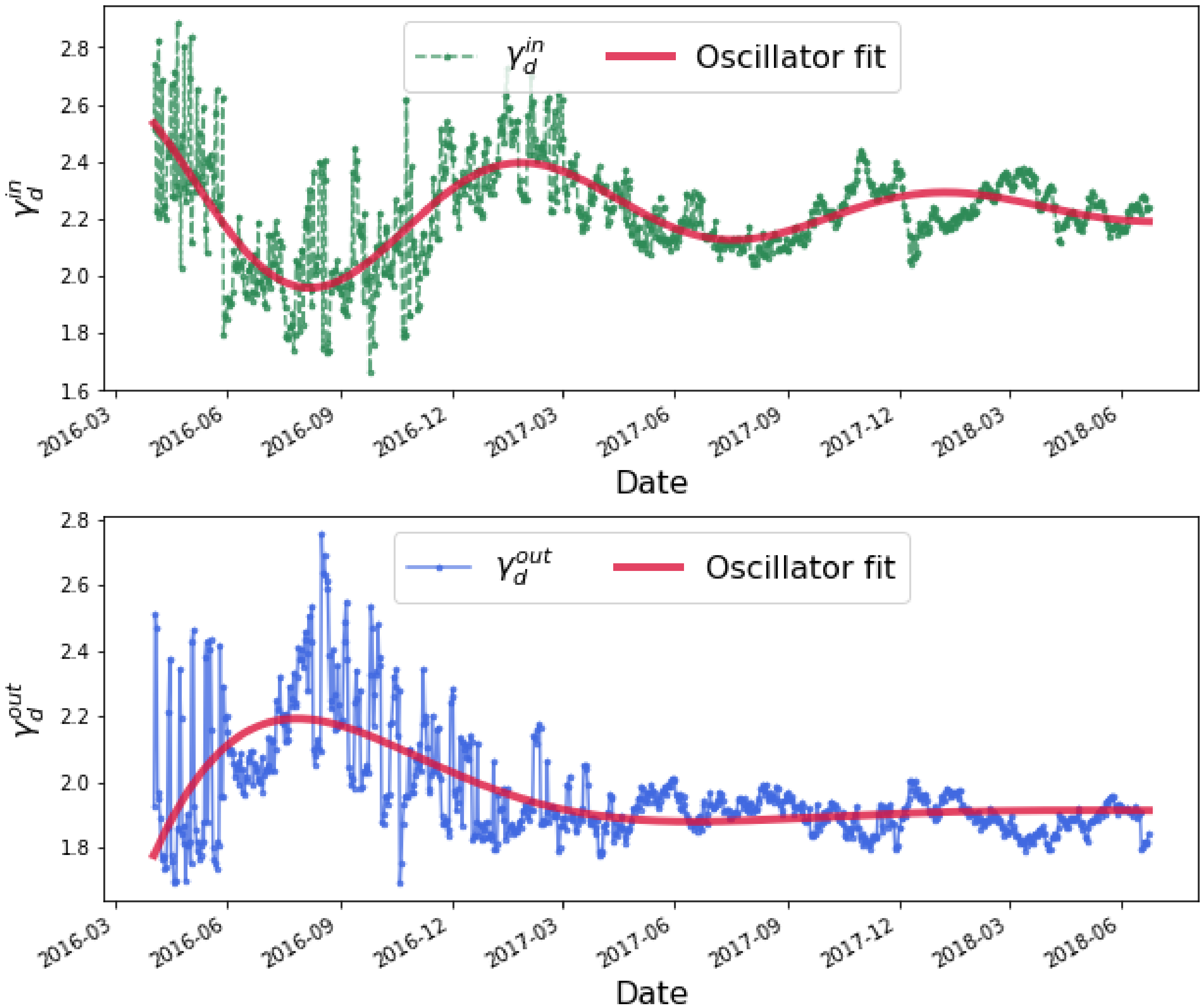


Figure 7: ERC20 transactional network temporal development, in a network related prism, demonstrating the underlying consolidation process the network undergoes. Evolvement of incoming degree distribution gradient, γ_t^{in}, is depicted in the upper panel and out-degree distribution gradient γ_t^{out} is displayed in the lower panel. Both gradients converge to their *stable states* γ_∞^{in} and γ_∞^{out} correspondingly, following a Harmonic Under-Damped Oscillator model.

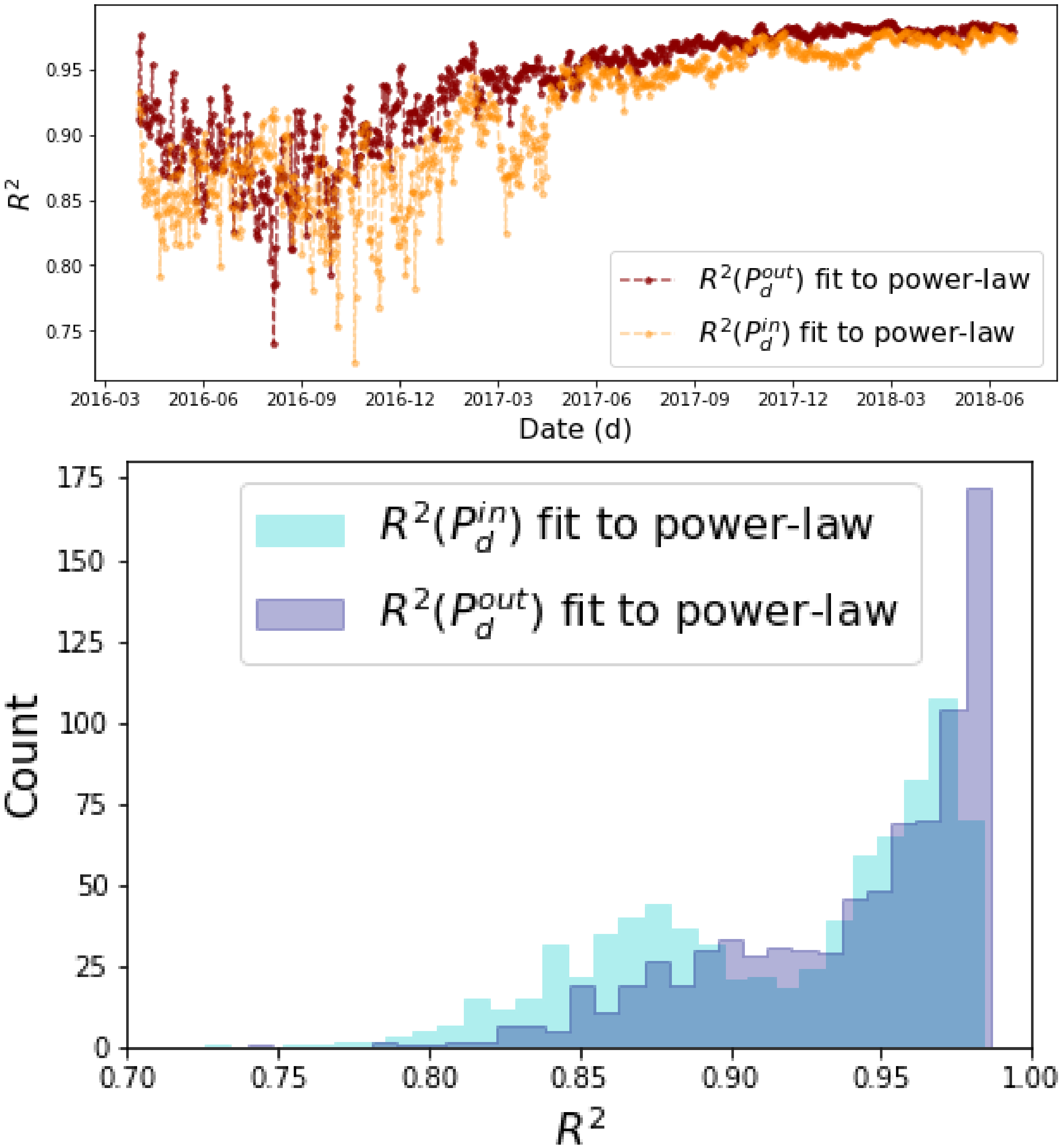


Figure 8: Left panel presenting R^2 of both Incoming and outgoing degree distributions fits to power-law, for each *Gt*, $t \in FT$. Right panel presents and compares the G_t-s' R^2 distributions. As can be noted for both P_t^{in} and P_t^{out}, over 99% ofthe fits to power-law yield $R^2 \geq 0.8$, and both present an improvement pattern over time, as they converge to 1 throughout time.

The under-damped oscillator model is in fact an extension of the regular single-parameter model, which suggested γ as a constant *stable state*, to a new model governed by five parameters: (*i*) $\lambda = \omega_0 \zeta$ representing the exponential decay, (*ii*) $\omega = \omega_0 \sqrt{1-\zeta^2}$ standing for the angular frequency, (*iii*) γ_∞ for the stable state to which the system converges, (*iv*) A representing the maximal amplitude of the oscillation and (*v*) ϕ for the phase shift. The parameters of fitted oscillators to γ^{in} and γ^{out} on the entire FT, $osc^{in}_{FT}(t)$ and $osc^{out}_{FT}(t)$ correspondingly, are presented in Table 1 and Table 2.

Table 9.1: Under-Damped Oscillator Models Parameters

Type	A	φ	γ_∞	$\frac{2\pi}{\omega_0}$ (days)	ζ
$osc^{out}_{FT}(t)$	-0.77	2.96	1.91	530.2	0.577
$osc^{in}_{FT}(t)$	0.39	2.23	2.23	341.1	0.152

Table 9.2: Under-Damped Oscillator Models Derived Parameters

Type	$\frac{1}{\lambda}$ (days)	$\frac{2\pi}{\omega}$ (days)	k	c
$osc^{out}_{FT}(t)$	146.3	649.1	1.40e−4	1.37e−2
$osc^{in}_{FT}(t)$	356.6	345.6	3.38e−4	5.61e−3

Once the modeling of the ERC20 network dynamics by an under-damped oscillator is established, this analytical model can also be used for predictive purposes. We have examined the accuracy of predicting the γ parameter, associated with popularity equality, over 12 months' time. Full details of these predictive abilities can be found in [33].

4.4 ERC20 Dynamics: Network Theory VS Traditional Approaches

In order to determine that the variances of γ^{out}_t and γ^{in}_t form a unique indicator for unveiling the network's consolidation process, we explicitly compare their variance dynamics to the variance of the previously analyzed, traditional properties, including network's evolving size, both in vertices and in edges perspectives, number of unique buyers, sellers and of ERC20 tokens traded over each such weekly transactions network. Since the mean values of the compared standard deviations are highly different in value and scale, we compare their normalized versions, i.e. the *Coefficients of Variation*:

$$CV(x) := \frac{std(x)}{mean(x)}$$

Fig. 9 presents a comparison between the coefficients of variation of traditional indicators and network originated parameters. It demonstrates that the traditional parameters exhibit higher variance than those of γ_t^{in} and γ_t^{out}) along the entire two years timespan. Furthermore, the economic indicators do not present consistent decay, indicating lack of convergence of the associated properties. Nevertheless, both $CV(\gamma_t^{in})$ and $CV(\gamma_t^{out})$ present a consistent decreasing trend, indicating ongoing convergence of the degree distribution gradients along time.

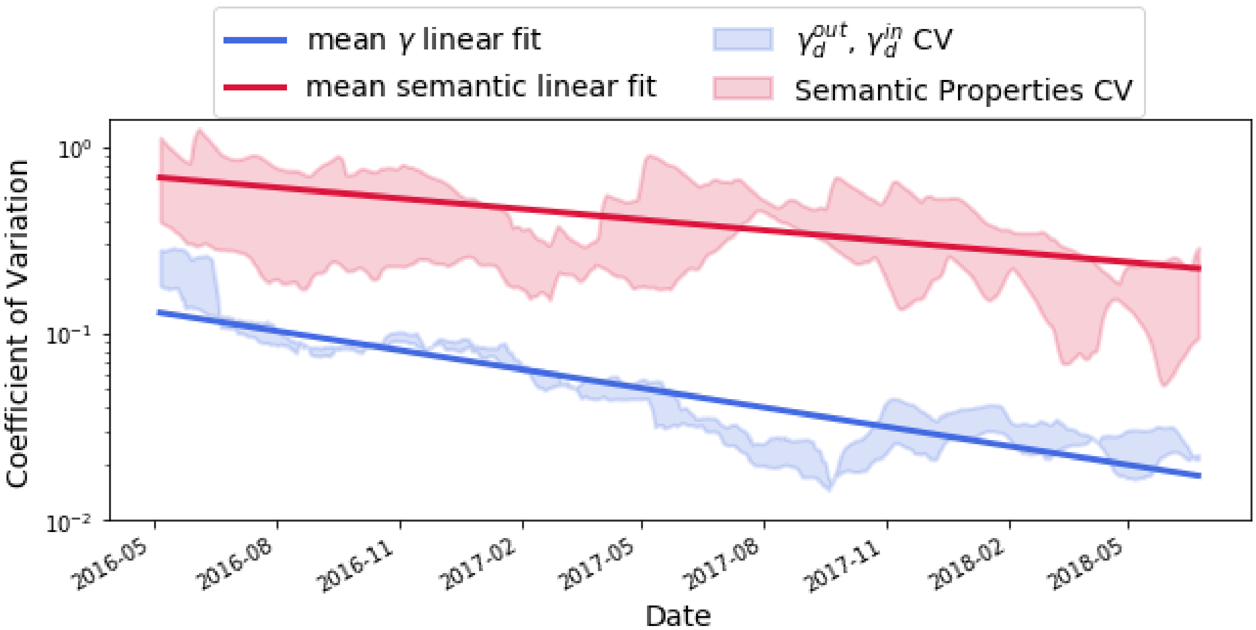


Figure 9: Network stabilizing process manifested by the decreasing trend of coefficient of variation of degree distribution gradients, γ_t^{out} and γ_t^{in}. The variance comparison between the latter and other basic aspects s.a. number of buyers, sellers, vertices, edges and number of traded tokens for each *Gt, t ∈ FT*, affirms this network-related measure as a significant, and so far unique, index for the ERC20 network's consolidation process.

To conclude, this analysis demonstrates the underlying temporal consolidation process the ERC20 ecosystem undergoes along 30 months of its activity, until reaching an equilibrium with respect to the essential network characteristics, γ_t^{out} and γ_t^{in}. Though unstable and erratic in many aspects, amongst all in rates, number of active wallets and activity volume, when observing the ERC20 economy from a network theory prism, one can conclude the network undergoes a steady consolidation process, reaching an equilibrium, in a network sense.

5. Discussion

In this contribution, we presented evidence suggesting that the extremely non-homogeneous [38] ERC20 economy still conforms to the statistics of other social networks [11] [13] [14] [15] [17] [21]. This was demonstrated by examining both the incoming and outgoing degree distributions, and verifying their compliance to a scale-free power-law model, evident in Fig. 5. *A-priori* there is no theoretical justification that an amalgamation of non-related tokens, each with a different source and functionality, will result in a cohesive, single network behaving according to the well-established principles of network theory. Our results support the hypothesis that the ERC20 assembles a single community.

We further wished to go beyond a static view of the ERC20 ecosystem, and explored its dynamics along time. We first presented how observing the dynamics of ERC20 throughout semantic, more traditional, characteristics of the data, such as number of traded tokens over time, number of active wallets and transaction counts over time, manifest a highly unstable and unpredictable system, as can be seen in figures 1, 2 and 4. These observations raised the concern of whether the ERC20 system can be considered as a stabilizing, equilibrating economy.

We have shown that each weekly transactions network along the examined 2.5 years period, still conforms to a power-law degree distribution, as shown by the goodness-of-fit parameter, R^2 in Fig. 8, signifying that each individual week behaves as a scale-free network. This observation enabled reassessing the dynamics of ERC20 using a network-theory perspective. Numerous network-related meta-parameters have been analyzed in the study of social networks, ranging from the degree distribution of the network, its average path length, the clustering coefficient and to network's spectral properties (see [36]).

Here we have chosen to focus on the dynamics analysis of the most basic and the highly investigated network characteristic of them all, studying the development of the network's degree distribution, manifested by its associated power, γ, throughout time. Inspired by macro-scale market dynamics [6] [9], which demonstrated an oscillatory stabilization process, we analyzed the exponents of in and out-degree distribution (γ^{in} and γ^{out}) and studied to which extent their dynamics can be modeled by an under-damped harmonic oscillator.

To better comprehend the source of γ's oscillating dynamics, one must integrate all the aforementioned results. First, it is prudent to understand what a scale-free network means, and more importantly for this discussion, what γ, the exponent of the power-law degree distribution signifies. The power of the degree distribution stands for the ratio between the number of disconnected (or lightly-connected) wallets and the size of the network's largest hub. For instance, a *small* γ means the ratio between number of disconnected (or lightly-connected) wallets and the size of the largest hub is small. Indeed by observing the dynamics of buyers and sellers sizes in Fig. 2 and the dynamics of largest selling and buying hubs sizes in Fig. 3, it becomes evident that γ^{in} and γ^{out} dynamics correlate with the changes in these two properties.

We note that ERC20 network dynamics can be roughly divided into two phases, with a transition occurring around April 2017, as is evident both from the buyers & sellers dynamics (Fig. 2) and from the largest buying and selling hubs sizes dynamics (Fig. 3). During the first phase, the numbers of buyers and sellers in the network were quite comparable, as were the sizes of the associated hubs, and both γ^{in} and γ^{out} presented large and anti-phase oscillations, signifying an ”overshoot” of the system beyond its equilibrium state. This is the hallmark of an under-damped oscillator (as opposed to an over-damped one). This overshoot in γ^{in} and γ^{out} may represent a ”herd” behavior of many individuals/wallets (higher density) entering the community, making a small number of buying transactions (low in-degree).

During the second phase however, the underlying composition started undergoing significant changes, as the largest selling hub became excessively large, accompanied with a substantially lower number of active sellers in the network, severely inflicting upon the out-degree distribution, correlating with its rather low γ^{out} and possibly causing the drastically damped oscillations in that period. We further note that γ^{in} continued presenting oscillatory behavior in the second phase, with γ^{in} values higher than 2, as the ratio between buyers in the network and the size of the largest buying hub remained high.

We would further like to address the inherent differences between the in-degree and out-degree distributions, as established by our analysis. Apart from the evident dissimilarity in converging patterns presented during the second phase of data, as elaborated above, we also find that the under-damped harmonic oscillator fit parameters, displayed in Tables 1 and 2 are quite different for γ^{in} and γ^{out}, representing anti-phased dynamics, by an opposite amplitude A and phase ϕ. Furthermore, their equilibrium state is rather different, wherein $\gamma_{\infty}^{in} > \gamma_{\infty}^{out}$.

In order to exhibit a deeper understanding of differences between in and out-degree dynamics, we must present a comprehensive overview of the modeling process of both γ-s. We first elaborate the established results regarding γ^{in}, the power of the in-degree distribution. Fig. 7(a) depicts how well the under-damped oscillator model fits the entire 2.5 years data of weekly networks' γ^{in}. The goodness of fit of the oscillator model to γ^{in} was tested by analyzing the residuals plots, verifying they were centered around zero (see Fig. **??** and Fig. **??**, upper panels). Furthermore, the fitted parameters of the under-damped oscillator give remarkable descriptive powers, e.g. the damping parameter $1/\lambda_{in}$ accurately indicates the time at which the network has started stabilizing and its noise decreased, as can be seen in Fig. **??**(a). Moreover, Fig. **??** (left panels) demonstrates how the fitted parameters of the oscillator model fitted to γ^{in} stabilize together and early, prior to the last observable oscillation in actual γ^{in} values. We further demonstrated the powerful predictive ability of the oscillator model for γ^{in}. Predicting future values based on fitting to an under-damped oscillator, Fig. **??** (left-panels) shows that damped oscillations during the last year of data can be accurately and reliably predicted.

Next we summarize the analysis of γ^{out}, the power of the out-degree distribution. While Fig. 7 suggests a satisfactory fit to an under-damped oscillator, deeper analysis shows some discrepancies. The first discrepancy is the fitted parameter, namely, the damping parameter $1/\lambda_{out}$, which indicates damping occurs during the first (and only) oscillation, as can be seen in Fig. **??**, panel (d). The second inconsistency is evident through the residuals analysis, presented in Fig. **??**(c), indicating how 1 , supplies a significant under-estimation of the time when the fit's noise substantially decreased. We further perceived by analyzing the convergence of the oscillator parameters, depicted in Fig. **??** (right panels), that γ^{out} oscillator's parameters do not converge, but rather undergo a slow monotonic change along time. Finally, when analyzing the predictive abilities, seen in Fig. **??** (right panels), we observe that future γ^{out} dynamics are inadequately predicted by partial oscillator model, fitted to prior data. This suggests that a deviation from the oscillatory nature of the out-degree dynamics has occurred, as γ^{out} is over-estimated, and the predicted oscillations are not manifested by actual γ^{out} observations (see Fig. **??**, panel h for instance).

Taken together, these results suggest that forces beyond those that govern an under-damped oscillator are at play in the out-degree dynamics. A hint of these forces comes from the size-dependency analysis, depicted in Fig. **??**, which suggests a phase-transition in size-space, namely, beyond 10^4 nodes, after which γ presents significant stabilization. This phase transition occurs surprisingly at the same time that the γ^{in} oscillator is damped. However, there is a drastic difference of the influence of this phase transition on the different γ dynamics: while γ^{in} does not appear to be influenced by this change, namely, oscillations continue and predictions based on prior fits are relatively accurate, γ^{out} suffers from a dramatic damping of oscillations and a lowered converged γ^{out}, compared to predicted oscillator dynamics.

We postulate that the different dynamics presented by γ^{out} occurs due to extremely large selling hubs, possibly representing exchange wallets, accompanied with a much slower rise in lightly connected selling wallets. These two concurrent phenomena cause a forced decrease in γ^{out} values, leading to the damping of oscillations and the lowering of the convergence value of γ^{out}. This characteristic of γ^{out} correlates with [39], who claims that networks featured with $\gamma < 2$ are anomalous among the world of scale free networks, since their largest hub grows faster than the network's size, N.

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