

Evolutionary dynamics of the cryptocurrency market

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Abstract

The cryptocurrency market surpassed the barrier of \$100 billion market capitalization in June 2017, after months of steady growth. Despite its increasing relevance in the financial world, however, a comprehensive analysis of the whole system is still lacking, as most studies have focused exclusively on the behaviour of one (Bitcoin) or few cryptocurrencies. Here, we consider the history of the entire market and analyse the behaviour of 1,469 cryptocurrencies introduced between April 2013 and June 2017. We reveal that, while new cryptocurrencies appear and disappear continuously and their market capitalization is increasing (super-) exponentially, several statistical properties of the market have been stable for years. These include the number of active cryptocurrencies, the market share distribution and the turnover of cryptocurrencies. Adopting an ecological perspective, we show that the so-called neutral model of evolution is able to reproduce a number of key empirical observations, despite its simplicity and the assumption of no selective advantage of one cryptocurrency over another. Our results shed light on the properties of the cryptocurrency market and establish a first formal link between ecological modelling and the study of this growing system. We anticipate they will spark further research in this direction.

1 Introduction

Bitcoin is a digital asset designed to work as a medium of exchange [1, 2]. Users can send and receive native tokens - the “bitcoins” - while collectively validating the transactions in a decentralized and transparent way. The underlying technology is based on a public ledger - or blockchain - shared between participants and a reward mechanism in terms of bitcoins as an incentive for users to run the transaction network. It relies on cryptography to secure the transactions and to control the creation of additional units of the currency, hence the name of “cryptocurrency” [3, 4].

After Bitcoin appeared in 2009, approximately 1,500 other cryptocurrencies have been introduced, around 600 of which are actively traded today. All cryptocurrencies share the underlying blockchain technology and reward mechanism, but they typically live on isolated transaction networks. Many of them are basically clones of Bitcoin, although with different parameters such as different supplies, transaction

validation times, etc. Others have emerged from more significant innovations of the underlying blockchain technology [5] (see A.3).

Cryptocurrencies are nowadays used both as media of exchange for daily payments, the primary reason for which Bitcoin was introduced, and for speculation [6, 7]. Other uses include payment rail for non-expensive cross borders money transfer and various non-monetary uses such as time-stamping [2]. The self-organization of different usages both within a single cryptocurrency and as an element of differentiation between cryptocurrencies makes the market of cryptocurrencies unique, and their price extremely volatile [8–10].

Between 2.9 and 5.8 millions of private as well as institutional users actively exchange tokens and run the various transaction networks [5]. In May 2017, the market capitalization of active cryptocurrencies surpassed \$91 billion [11]. Bitcoin currently dominates the market but its leading position is challenged both by technical concerns [12–16] and by the technological improvements of other cryptocurrencies [17].

Despite the theoretical and economic interest of the cryptocurrency market [2, 4, 18, 19], however, a comprehensive analysis of its dynamics is still lacking. Existing studies have focused either on Bitcoin, analysing for example the transaction network [20–24] or the behaviour and destiny of its price [9, 25–30], or on a restricted group of cryptocurrencies (typically 5 or 10) of particular interest [5, 17, 31, 32]. But even in this case there is disagreement as to whether Bitcoin dominant position may be in peril [5] or its future dominance as leading cryptocurrency is out of discussion [31].

Here we present a first complete analysis of the cryptocurrency market, considering its evolution between April 2013 and June 2017. We focus on the market shares of the different cryptocurrencies (see 4) and find that Bitcoin has been steadily losing ground to the advantage of the immediate runners-up. We then show that several statistical properties of the system have been stable for the past few years, including the number of active cryptocurrencies, the market share distribution, the stability of the ranking, and the birth and death rate of new cryptocurrencies. We adopt an “ecological” perspective on the system of cryptocurrencies and notice that several observed distributions are well described by the so-called “neutral model” of evolution [33, 34], which also captures the decrease of Bitcoin market share. We believe that our findings represent a first step towards a better understanding and modelling of the cryptocurrency market.

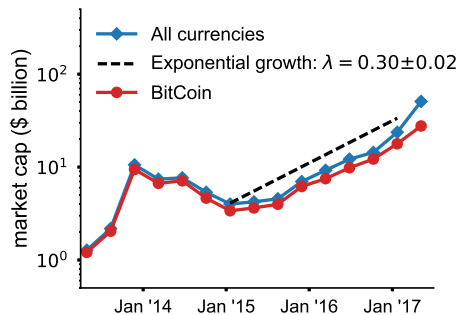


Figure 1: **Evolution of the market capitalization.** Evolution of the market capitalization over time (starting from April 2013), for all cryptocurrencies (blue line, diamonds) and for Bitcoin (red line, dots). The dashed line is an exponential curve $f(t) \sim e^{\lambda t}$, with $\lambda = 0.3$, shown as a guide for the eye. Data is averaged over a 15-week window.

2 Results

2.1 Market Description

Our analysis focuses on the market share of the different cryptocurrencies and is based on the whole history of the cryptocurrency market between April 28, 2013 and May 13, 2017. Our dataset includes 1,469 cryptocurrencies, of which around 600 were active by that time (see 4).

The total market capitalization C of cryptocurrencies has been increasing since late 2015 after a period of relative tranquillity (Fig. 1). As of May 2017, the market capitalization is more than 4 times its value compared to May 2016 and it exhibits an exponential growth $C \sim \exp(\lambda t)$ with coefficient $\lambda = 0.30 \pm 0.02$, where t is measured in units of 15 weeks.

2.2 Decreasing Bitcoin Market Share

Bitcoin was introduced in 2009 and followed by a second cryptocurrency (Namecoin, see A.1) only in April 18, 2011. This first-mover advantage makes Bitcoin the most famous and dominant cryptocurrency to date. However, recent studies analysing the market shares of Bitcoin and other cryptocurrencies reached contrasting conclusions on its current state. While Gandal and Halaburdain in their 2016 study concluded that “Bitcoin seems to have emerged - at least in this stage - as the clear winner” [35], the 2017 report by Hileman and Rauchs noted that “Bitcoin has ceded significant market cap share to other cryptocurrencies” [5].

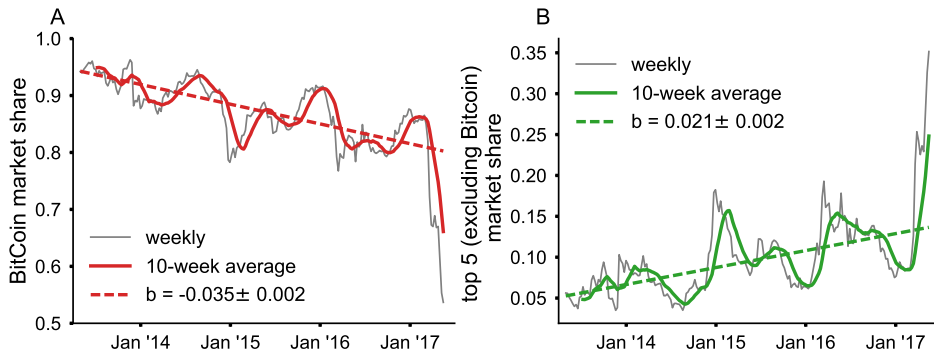


Figure 2: **Evolution of the market share of top-ranking cryptocurrencies.** (A) The market share of Bitcoin across time sampled weekly (gray line) and averaged over a rolling window of 10 weeks (red line). The dashed line is a linear fit with angular coefficient $b = -0.035 \pm 0.002$ (the rate of change in 1 year) and coefficient of determination $R^2 = 0.63$. The Spearman correlation coefficient is $\rho = -0.8$, revealing a significant negative correlation at significance level of 1%. (B) Total market share of the top 5 cryptocurrencies excluding Bitcoin sampled weekly (gray line) and averaged over a rolling window of 10 weeks (green line). The dashed line is a linear fit with angular coefficient $b = 0.021 \pm 0.002$ (the rate of change in 1 year) and coefficient of determination $R^2 = 0.45$. The Spearman correlation coefficient is $\rho = 0.67$, revealing a significant positive correlation at significance level of 1%.

To clarify the situation, we consider the whole evolution of the Bitcoin market share over the past 4 years. Fig. 2A shows that Bitcoin market share has been steadily decreasing for the past years, beyond oscillations that might mask this trend to short-term investigations. The decrease is well described by a linear fit $f(t) = a + bt$ with angular coefficient $b = -0.035 \pm 0.002$ representing the change in market share over $t = 1$ year. Neglecting the impact of non-linear effects and potential changes in the competition environment, the model indicates that Bitcoin market share can fluctuate around 50% by

2025. Conversely, Fig. 2B shows that the top 5 runners-up (see A.1) have gained significant market shares and now account for more than 20% of the market.

2.3 Stability of the Cryptocurrency Market

In order to characterize the cryptocurrencies dynamics better, we now focus on the statistical properties of the market. We find that while the relative evolution of Bitcoin and rival cryptocurrencies is tumultuous, many statistical properties of the market are stable.

Fig. 3A shows the evolution of the number of active cryptocurrencies across time, averaged over a 15-week window. The number of actively traded cryptocurrencies is stable due to similar birth and death rates since the end of 2014 (Fig. 3B). The average monthly birth and death rates since 2014 are 1.16% and 1.04%, respectively, corresponding to approximately 7 cryptocurrencies appearing every week while the same number is abandoned.

Interestingly, the market share distribution remains stable across time. Fig. 4A shows that curves obtained by considering different periods of time are indistinguishable. This is remarkable because the reported curves are obtained by considering data from different years as well as data aggregated on different time spans - from one week to the entire ~ 4 years of data. The obtained distribution exhibits a broad tail well described by a power law $P(x) \sim x^{-\alpha}$ with exponent $\alpha = 1.58 \pm 0.12$ (Fig.4A), where the fit coefficient is computed using the method detailed in [36]. The expected relationship between the probability distribution and the frequency rank distribution predicts the latter is a power-law function $P(r) \sim r^{-\beta}$ with exponent $\beta = 1/(\alpha - 1)$ [37], yielding in our case $\beta = 1.72$ Fig.4B. The empirical fit coefficient $\beta = 1.93 \pm 0.23$ is consistent with this prediction. (Fig. 4B). This was also verified for each year individually (see A.4).

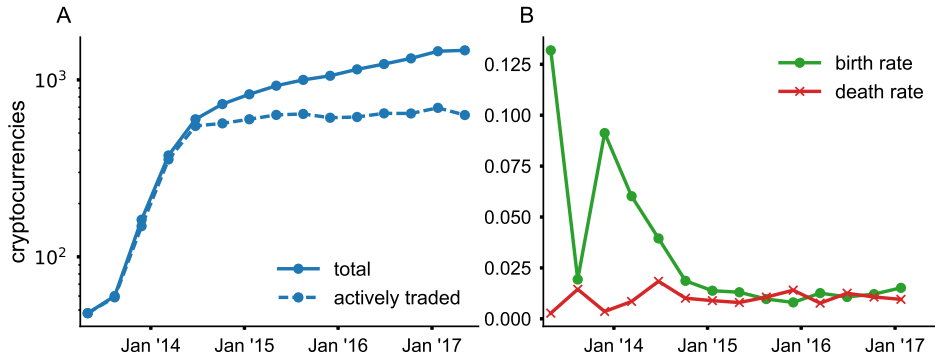


Figure 3: **Evolution of the number of cryptocurrencies.** (A) The number of cryptocurrencies that ever entered the market (filled line) since April 2013, and the number of actively traded cryptocurrencies (dashed line). (B) The birth and death rate computed across time. The birth (resp. death) rate is measured as the fraction of cryptocurrencies entering (resp. leaving) the market on a given week over the number of living cryptocurrencies at that point. Data is averaged over a 15 weeks window.

We further investigate the stability of the market by measuring the average rank occupation time (Fig. 4C), defined as the amount of time a cryptocurrency typically spends in a given rank before changing it. We find that the time spent in a top-rank position decays fast with the rank, while for low-rank positions such time approaches 1 week. Again, this behaviour is stable across years (Fig. 4C - inset). We also consider the turnover profile defined as the total number of cryptocurrencies ever occupying rank higher than a given rank in period t (see [38] for a similar definition). Fig. 4D shows that also this quantity is substantially stable across time.

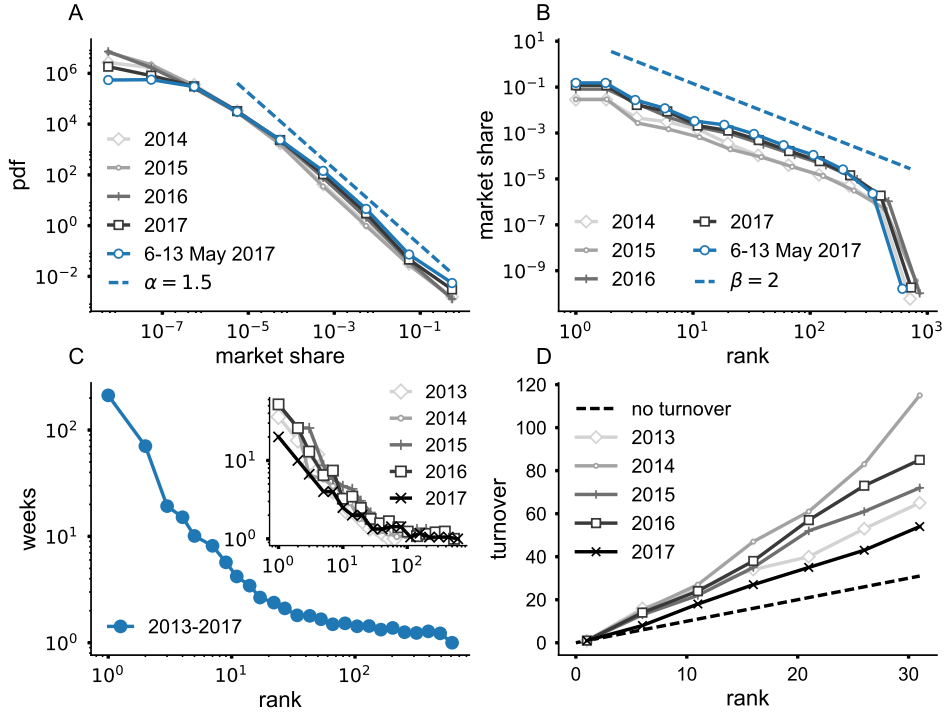


Figure 4: **Stable properties of the cryptocurrency market.** (A) Distribution of market share computed aggregating across a given year (gray filled lines), and over the week 6-13 May 2017 (blue thick line). The dashed line is a power law $P(x) \sim x^{-\alpha}$ curve with exponent $\alpha = 1.5$. (B) Frequency-rank distribution of cryptocurrencies, computed aggregating across a given year (gray filled lines), and over the week 6-13 May 2017 (blue thick line). The dashed line is a power law curve $P(r) \sim r^{-\beta}$ with exponent $\beta = 2$. (C) Average amount of time (in weeks) a cryptocurrency occupies a given rank computed averaging across all years (blue line), and across given years (gray lines, inset). (D) Turnover of the ranking distribution, defined as the total number of cryptocurrencies ever occupying rank higher than a given rank. The measure is computed averaging across given years (gray filled lines). The 2013 and 2017 curves must be taken purely as an indication as they are computed on less than 12 months (approximately 8 and 4 months, respectively). The dashed line has angular coefficient 1, and corresponds to the case in which the ranking of cryptocurrencies is fixed (i.e., the variable turnover captures only the initial size of the toplist).

The first rank has been always occupied and continues to be occupied by Bitcoin, while the subsequent 5 ranks (i.e., ranks 2 to 6) have been populated by a total of 33 cryptocurrencies with an average life time of 12.6 weeks. These values change rapidly when we consider the next set of ranks from 7 to 12 to reach 70 cryptocurrencies and an average life time of 3.6 weeks. At higher ranks, the mobility increases and cryptocurrencies continuously change position.

2.4 A Simple Model for the Cryptocurrency Ecology

In order to account for the empirical properties of the dynamics of cryptocurrencies we have discussed above, we adopt the view of a “cryptocurrency ecology” and consider the neutral model of evolution, a prototypical model in population-genetics and ecology [33, 34].

The Wright-Fisher model of neutral evolution describes a fixed size population of N individuals where each individual belongs to one of m species. At each generation, the N individuals are replaced by N new individuals. Each new individual belongs to a species copied at random from the previous generation,

with probability $1 - \mu$, or to a species not previously seen, with probability μ , where μ is a mutation parameter that does not change over time [39]. Despite its simplicity, the neutral model is able to reproduce the static patterns of the competition dynamics of many systems including ecological [40] and genetics [41] systems, cultural change [42], English words usage [43] and technology patents citations [44].

In our mapping of the ecological model to the cryptocurrency market, each individual corresponds to a certain amount of dollars, while species correspond to different cryptocurrencies (see A.2). The copying mechanism represents trading, with μ denoting the probability that a new cryptocurrency is introduced. Our choice of μ is informed by the data to yield a number of new cryptocurrencies per unit time corresponding to the empirical observation. We thus fix $\mu = \frac{7}{N}$, where N is the population size in the model. Thus, one model generation corresponds to 1 week of observations, the choice of μ guaranteeing an average of 7 new cryptocurrencies entering the system every week, as empirically observed. Finally, in contrast to most neutral models, we assume that a new species does not enter the system with a single individual but with a size proportional to the empirical average market share of new cryptocurrency (see A.2).

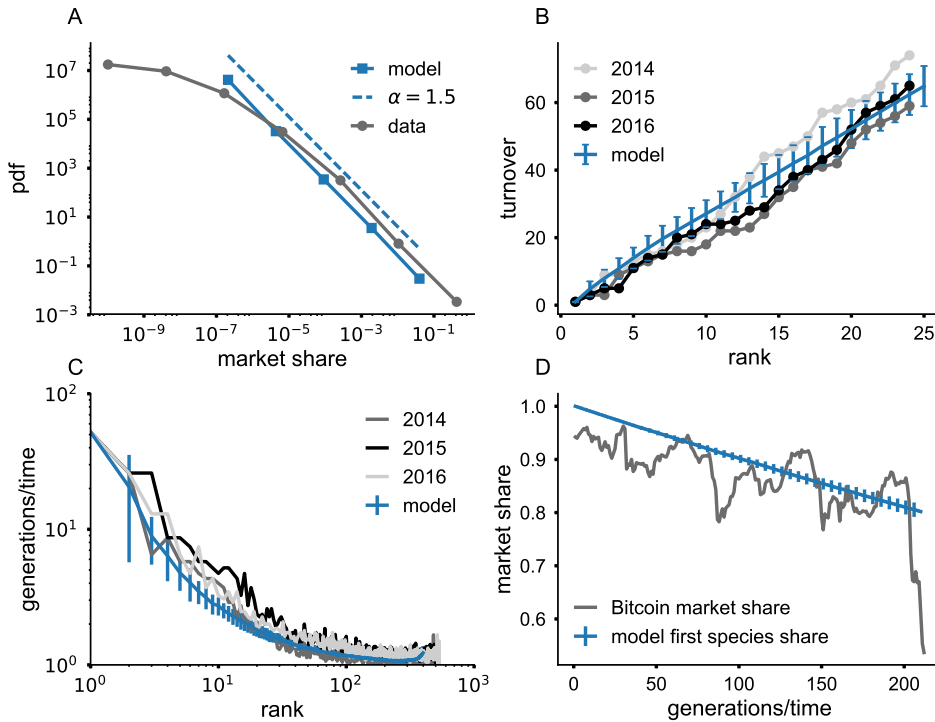


Figure 5: **Neutral model for evolution and empirical observations.** (A) Distribution of cryptocurrencies market shares aggregated over all years (gray line, dots) and the equilibrium distribution resulting from numerical simulations (blue line, squares) aggregated over 210 generations. The dashed line is the power law curve $P(x) \sim x^{-\alpha}$ predicted analytically with exponent $\alpha = 1.5$ [45]. (B) Turnover of the ranking distribution computed considering 52 generations for the cryptocurrencies data (gray lines, dots) and for numerical simulations (blue line), (C) Average number of generations a cryptocurrency (gray lines) and a species in the neutral model (blue line) occupies a given rank. Averages are computed across 52 generations. (D) Evolution of the market share of Bitcoin (gray line) and the expected market share of the first species in numerical simulations (blue line). All simulations are run for $N = 10^5$ and $\mu = 7/N$ starting from 1 species in the initial state. The size of entering species m , whose average $m = 15$ is informed by the data, is taken at random in the interval $m = [10, 20]$. Error bars are standard deviations, computed across 100 simulations. For panels (B) and (C) measures start at generation $g_1 = 105$ (see A.2 for variations of this parameter).

The neutral model translates in the simplest way three main assumptions [46]: (i) interactions between cryptocurrencies are equivalent on an individual per capita basis (i.e., per US dollar); (ii) the process is stochastic; and (iii) it is a sampling theory, where the new generation is the basis to build the following one. In other words, the neutral model assumes that all species/cryptocurrencies are equivalent and that all individuals/US dollars are equivalent.

Testing the consistency between observed patterns of the cryptocurrency market and theoretical expectations of neutral theory revealed that neutrality captures well at least four features of the cryptocurrency ecology, namely:

1. The exponent of the market share distribution (Fig 5A);
2. The linear behavior of the turnover profile of the dominant cryptocurrencies (Fig 5B);
3. The average occupancy time of any given rank (Fig 5C);
4. The linear decrease of the dominant cryptocurrency (Fig 5D).

The neutral model generates in fact an aggregated species distribution (i.e., obtained when all generations up to the i^{th} are combined together and analysed as a single population of size $N * i$ [44,47]) that, at equilibrium, can be described by a power law distribution $P(x) \sim x^{-\alpha}$ with $\alpha = 1.5$ [45], in agreement with the empirical value $\alpha = 1.58 \pm 0.12$ obtained by the fitting procedure described in [36]. Fig. 5A shows the agreement between simulations and data (same behaviour of the long tail), where simulations results are aggregated over $i = 210$ generations, corresponding to 4 years of empirical observations under our choice of μ . The existence of a power law phase with exponent 1.5 in the model is independent of μ (see A.2) [45].

Furthermore, when we account for the fact that Bitcoin was originally the only cryptocurrency by setting 1 species in the initial state, the model captures also the remaining properties. In Fig. 5B and 5C, we compare the turnover profile and the ranking occupation times with the corresponding simulation results. We compute these quantities over a period of 52 generations, corresponding to one year of observations. The curves reported in Figs. 5B and 5C correspond to measures performed between generation $g_1 = 105$ and $g_2 = 156$, corresponding to year 3 (2015) in the data. Crucially, however, both measures are stable in time, i.e. they do not depend on the choice of g_1 (but for an initial period of high rank variability for the very first generations, see A.2). It is worth noting that the linearity of the turnover profile in Fig. 5B corresponds to a similar behaviour observed in [38] when the measure is performed between two consecutive generations. Fig. 5D shows the observed linear decrease of the leading cryptocurrency market share (Fig. 5C), indicating that newborn cryptocurrencies mostly damage the dominating one.

3 Discussion and Outlook

In this paper we have investigated the whole cryptocurrency market between April 2013 and June 2017. We have shown that the total market capitalization has entered a phase of exponential growth one year ago, while the market share of Bitcoin has been steadily decreasing. We have identified several observables that have been stable since the beginning of our time series, including the number of active cryptocurrencies, the market-share distribution and the rank turnover. By adopting an ecological perspective, we have pointed out that the neutral model of evolution captures several of the observed properties of the market.

The model is simple and does not capture the full complexity of the cryptocurrency ecology. However, the good match with at least part of the picture emerging from the data does suggest that some of the long-term properties of the cryptocurrency market can be accounted for based on simple hypotheses. In particular, since the model assumes no selective advantage of one cryptocurrency over the other, the fit with the data shows that there is no detectable population-level consensus on what is the “best” currency or that different currencies are advantageous for different uses. Furthermore, the matching between the neutral model and the data implies that the observed patterns of the cryptocurrency market are compatible with a scenario where technological advancements have not been key so far (see A.3) and where users and/or investors allocate each packet of money independently. Future work will need to consider the role of an expanding overall market capitalization and, more importantly, try to include the information about single transactions, where available, in the modelling picture.

In the immediate and mid-term future, legislative, technical and social advancements will most likely impact the cryptocurrency market seriously and our approach, together with recent results in computational social science dealing with the quantification of financial trading and bubble formation [48–51], could help make sense of the market evolution. In April 2017, for example, Japan started treating Bitcoin as a legal form of payment driving a sudden increase in the Bitcoin price in US dollars [52] while in February 2017 a change of regulation in China resulted to a \$100 price drop [53]. Similarly, the exponential increase in the market capitalization (Fig. 1) will likely attract further speculative attention towards this market while at the same time increasing the usability of cryptocurrencies as a payment method. While the use of cryptocurrencies as speculative assets should promote diversification [31], their adoption as payment method (i.e., the conventional use of a shared medium of payment) should promote a winner-take-all regime [54, 55]. How the self-organized use of cryptocurrencies will deal with this tension is an interesting question do be addressed in future studies.

4 Material and methods

4.1 Data

Cryptocurrency data was extracted from the website Coin Market Cap [11], collecting weekly data from 157 exchange markets platforms starting from April 28, 2013 up to May 13, 2017. For all living cryptocurrencies, the website provides the market capitalization, the price in U.S. dollars and the volume of trading in the preceding 24 hours. Data on trading volume was collected starting from December 29, 2013.

The website lists cryptocurrencies traded on public exchange markets that are older than 30 days and for which an API as well as a public URL showing the total mined supply are available. Information on the market capitalization of cryptocurrencies that are not traded in the 6 hours preceding the weekly release of data is not included on the website. Cryptocurrencies inactive for 7 days are not included in the list released. These measures imply that some cryptocurrencies can disappear from the list to reappear later on.

4.2 Analysis

The following quantities characterize individual cryptocurrencies: The *circulating supply* is the number of coins available to users. The *price* is the exchange rate, determined by supply and demand dynamics. The *market capitalization* is the product of the circulating supply and the price. The *market share* is

the market capitalization of a currency normalized by the total market capitalization.

Most of our analyses consider the market capitalization and market share of cryptocurrencies. These quantities neglect the destroyed or dormant coins, accounting for example to 51% of mined Bitcoins based on data from the period July 18, 2010 to May 13, 2012 [20].

Data accessibility

Dataset used in this study is public and can be found in Coin Market Cap [11].

Competing interests

The authors declare no competing financial interests.

Authors' contributions

Study conception: AB; Study design: AE, LA, AK, RPS, AB; Acquisition of data and pre-processing: AE; Analysis and interpretation of data: AE, LA, AK, RPS, AB; Drafting of manuscript: AE, LA, AK, RPS, AB;

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A Appendix

A.1 some relevant cryptocurrencies

Table 1 provides information on some relevant cryptocurrencies, either occupying high-rank positions or early introduced in the market. Data was collected in May 2017, see below for details on the Technology column.

Table 1: **Details on the top runner cryptocurrencies in the market.** The table is generated using data collected on May 28, 2013

Name	Year	Technology	Market Cap (\$)	Rank	Additional Info
Bitcoin	2009	Proof-of-work	35B	1	
Ethereum	2015	Proof-of-work	15B	2	Smart contracts
Ripple	2013	Distributed open source consensus ledger	8B	3	Widely adopted by companies and banks.
NEM	2015	Proof-of-importance	1B	4	
Ethereum Classic	2015	Proof-of-work	1B	5	DAO Hard-fork
Litecoin	2011	Proof-of-work	1B	6	
Dash	2014	Proof-of-work	809M	7	Gained market since early 2017. Privacy focused.
Monero	2014	Proof-of-work	535M	8	Gained momentum in late 2016. Privacy focused
NameCoin	2015	Proof-of-work	21M	58	

A.2 Simulations

Our choice of the mutation parameter μ is informed by the data to yield a number of new cryptocurrencies per unit time corresponding to the empirical observation. By choosing $\mu = \frac{7}{N}$, where N is the population size in the model it holds that 1 model generation corresponds to 1 week of observation (since on average 7 new cryptocurrencies enter the system every week, see Sec. 2.3). In Fig. A1 we show that the distribution of species sizes (see Fig. 5A) has a very similar shape for a broad range of choices of μ [45].

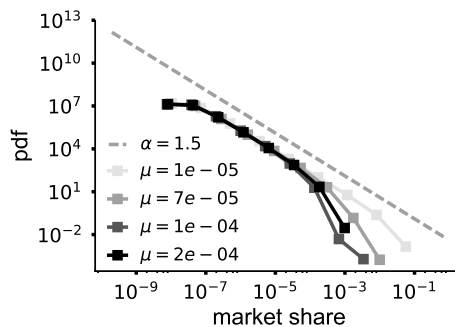


Figure A1: **Distribution of species sizes for different values of μ .** Distribution of the species sizes resulted from numerical simulations given different values of μ .

All simulations are run starting with one species in order to capture the initial dominance of Bitcoin in the cryptocurrency market. This reflects the initial state of the cryptocurrencies market, when Bitcoin was the only existing cryptocurrency. Simulations are run using $N = 10^5$, implying that an individual in the model maps to $\sim \$100,000$ (We verified that results do not depend on the choice of N , as long as N is large enough).

While in the neutral model a new species enters the system as a new individual, we further inform the model with the average size of a new cryptocurrency ($\sim \$1.5$ million), corresponding to $m = 15$ individuals in the model when $N = 10^5$ as in our case. To consider the fact that new cryptocurrencies do not enter the market with exactly the same size, in our simulations, when a mutation occurs, the new species enters with a number m of individuals randomly extracted from the interval $[10, 20]$.

The exponent $\alpha = 1.5$ exhibited by the data and the simulations (see Fig.5A) are equilibrium properties of the neutral model, and hence obtained under a broad range of conditions (e.g., initial condition, time of start of measure and aggregation window) and robust to changes in the value of μ [45], Fig. A1). Fig.5B and C are obtained starting from generation 104 and aggregating over 52 generations (i.e. performing the analysis over the single population obtained by aggregating the $N * 52$ individuals [44,47]). Fig. A2 shows the turnover profile (A) and average life time of a rank (B) when the measure is performed over 52 generations starting from different generations g_1 corresponding to the first year (measures start at generation $g_1 = 1$), second year (measures start at generation $g_1 = 53$), etc. It is clear that, with the exception of a high rank mobility characterizing the very first generations, the choice of g_1 has little effect on the curves produced by the model. Fig.5D is measured from generation 1 up to generation 210, corresponding to 4 years. Each point of the simulation curve corresponds to the instantaneous market share of the dominating cryptocurrency at that generation.

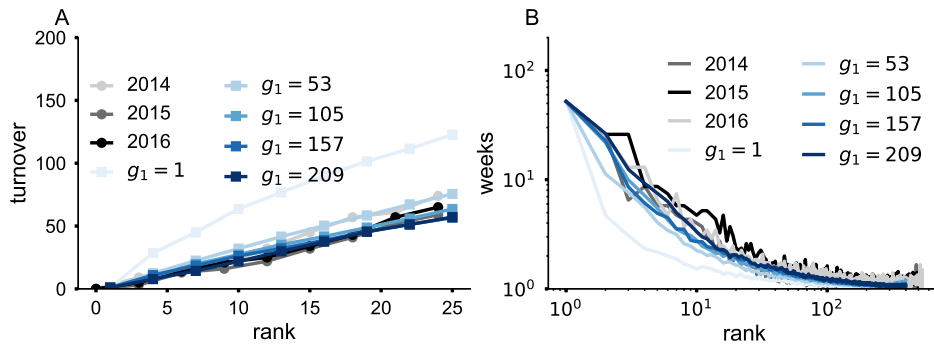


Figure A2: **Neutral model ranks dynamics.** (A) Turnover profile computed considering 52 for the cryptocurrencies data (gray lines, dots) and for numerical simulations (blue lines). (B) The Average life time a cryptocurrency/species stays in a given rank computed considering 52 generations for the cryptocurrencies data (gray lines, dots) and for numerical simulations (blue lines). Simulation parameters are $\mu = 7/N$, $N = 10^5$ and 1 species in the initial state.

A.3 technologies, same distribution

In order to check whether technical differences leave any detectable fingerprint at the level of statistical distributions, we look at cryptocurrencies adopting one of the two main blockchain algorithms for reaching consensus on what block represents recent transactions across the network: Proof-of-work (PoW) or the Proof-of-stake (PoS) consensus algorithms.

The PoW scheme was introduced as part of Bitcoin in 2009 [1]. To generate new blocks, participating users work with computational and electrical resources in order to complete “proof-of-works”, pieces of data that are difficult to produce but easy to verify. Block generation (also called “mining”) is rewarded with coins. To limit the rate at which new blocks are generated, every 2016 blocks the difficulty of the computational tasks changes [56].

While the PoW mechanism is relatively simple, there are concerns regarding its security and sustainability. First, severe implications could arise from the dominance of mining pools controlling more than 50% of the computational resources and who could in principle manipulate the blockchain transactions. This scenario is far from being unrealistic: in 2014, one mining pool (Ghash.io) [57] controlled 42% of the Bitcoin mining power. Also, the energy consumption of PoW based blockchain technologies has raised environmental concerns: it is estimated that Bitcoin consumes about 12.76 TWh per year [58].

The PoS scheme was introduced as an alternative to PoW. In this system, mining power is not attributed based on computational resources but on the proportion of coins held. Hence, the richer users are more likely to generate the next block. Miners are rewarded with the transactions fees. While proof-of-work relies heavily on energy, proof-of-stake doesn’t suffer from this issue. However, consensus is not guaranteed since miners sole interest is to increase their profit. Through the years both protocols have been altered to fix certain issues and continue to be improved.

Figure A3 shows that the market shares of the two groups of cryptocurrencies follow the same behavior. The figure is generated using data collected from [59] and [11].

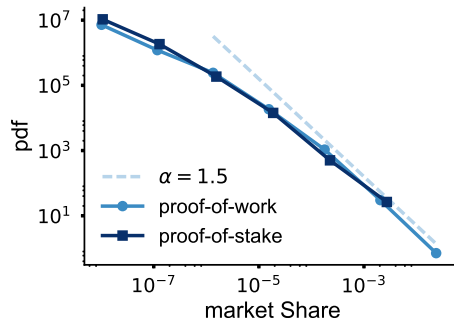


Figure A3: **Distribution of market share.** Distribution of the market share for proof-of-work cryptocurrencies (light blue filled line) and distribution of market share of (proof-of-stake or hybrid) cryptocurrencies (dark blue filled line). The dashed line is power law curve with exponent $\alpha = 1.5$.

A.4 share and frequency-rank distributions for individual years

The power-law fit for the distribution of market share (Table 2) and the frequency-rank distribution (Table 3) are consistent with the theoretical predictions of the neutral model [37] also for individual years. Fits coefficient for the distribution of market share are computed using the methodology described in [36] (errors are obtained by bootstrapping 1000 times). Fit coefficients with errors for frequency-rank distributions are computed with the least-square method.

Table 2: **Power-law fit coefficients of the market share distributions.**

Year	α
2013	1.37 ± 0.04
2014	1.54 ± 0.09
2015	1.62 ± 0.12
2016	1.59 ± 0.13
2017	1.60 ± 0.21
all years	1.58 ± 0.12

Table 3: **Power-law fit coefficients of the frequency-rank distributions.**

Year	β
2013	-1.98 ± 0.20
2014	-2.00 ± 0.13
2015	-1.83 ± 0.08
2016	-1.88 ± 0.08
2017	-1.86 ± 0.16
all years	-1.93 ± 0.23