An Entropy-Based Approach to Evaluating the Economic Efficiency of Cryptocurrencies

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Abstract

Blockchain technology is set to transform economics and finance by enabling secure, transparent, and decentralized transactions. Some significant examples in this sense are cryptocurrencies and decentralized finance, which leverage blockchain technology to provide fast, low-cost financial services without a central authority, as well as the tokenization of finance, already forecast by Larry Fink, CEO of BlackRock. As crypto economies and blockchain applications gain global relevance, the need to measure and assess their efficiency is becoming increasingly important. While blockchain efficiency is often evaluated in terms of transactions per second or energy consumption, cryptocurrency efficiency is implicitly assessed through various indexes, such as capitalization, price trends, average transaction value, mining profitability, and others. What is lacking is an index capable of comprehensively and coherently describing the actual functioning of a crypto economic system, accounting for its key economic characteristics – such as supply mechanisms and token distribution – and the level of user participation within the specific crypto economy.

In this study, we introduce a new theoretical framework based on Shannon entropy to assess the economic efficiency of a cryptocurrency through the *Entropy Balance index (EB-index)*. Our approach integrates on-chain parameters – sourced from *Coin Metrics*® – by mapping them to economic quality attributes. To illustrate how our entropy-based approach works, we apply it to two distinct sets of attributes across six leading cryptocurrencies by market capitalization and use-case diversity: Bitcoin, Ethereum, Ripple, USD Coin, Dogecoin, and Cardano. For either set of attributes, the six EB-index values provide us with a comprehensive way of comparing the considered cryptocurrencies from an economic efficiency viewpoint. Our approach is fully customizable with respect to the selection of attributes as well as their weights.

Keywords

Cryptocurrency efficiency, economic index, Shannon entropy, transfer flow

1. Introduction

Internet is transforming economics and finance, with blockchain raising as a key technology with its secure, transparent, and immutable distributed ledger [1]. Cryptocurrencies like Bitcoin [2], Ethereum [3], and Ripple [4] have emerged from blockchain innovation [5], enabling secure peer-to-peer transactions [6] and inclusive decentralized financial services (DeFi [7]). Their global relevance continues to grow [8], marked by milestones such as (i) the 2024 approval by the Securities and Exchange Commission (SEC) of Bitcoin and Ethereum Exchange-Traded Funds (ETFs) [9], pushing Bitcoin to 100,000 USD [10], (ii) the recent statements by Larry Fink, CEO of BlackRock, in his 2025 annual letter to investors, in which he says “What exactly is tokenization? It is turning real-world assets – stocks, bonds, real estate – into digital tokens tradable online” [11], and (iii) the anticipated use of stablecoins backed by the US dollar (USDC, USDT, *etc.*) as the digital version of the US dollar itself, which can play the role of a central bank digital currency [12]. As of April 2025, over 1,000 blockchains, 17,000 coins, and a 2.6 trillion USD market cap [13] rival tech giants like Google and Amazon.

With the expansion of applications of cryptocurrencies and blockchains, attention has increasingly turned to assessing their properties, especially in terms of efficiency. Despite the various possible interpretations of this word – such as performance efficiency based on transactions per second [14, 15],

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Table (1)
Wealth concentration, engagement, and asset dormancy of major cryptoassets from July 2010 up to April 2025. For wealth concentration we use a Gini coefficient adapted to average balances over class intervals. Engagement is defined as the share of addresses with positive balance over the total. Asset dormancy is calculated as one minus the ratio of active supply to circulating supply. Source: *Coin Metrics*.

Asset	**Wealth Concetration** (Gini coeff.)		**Engagement** (%)		**Asset Dormancy** (%)	
	Min	Max	Min	Max	Min	Max
Bitcoin (BTC) [2]	0.31	0.97	0.33	24.73	84.69	99.56
Ethereum (ETH) [3]	0.84	0.89	0.41	30.49	63.03	98.32
Ripple (XRP) [4]	0.94	0.98	0.08	4.40	36.74	99.79
USD Coin (USDC) [26]	0.93	0.99	0.86	90.34	5.21	89.29
Dogecoin (DOGE) [27]	0.82	0.98	0.70	90.78	64.78	99.54
Cardano (ADA) [28]	0.46	0.97	0.07	29.07	78.03	98.25

energy consumption in blockchain networks [16, 17], or price trends in crypto markets [18] – its use in the realm of cryptocurrencies introduces new dimensions. This is due to the unique features associated with blockchain technology, characterized by decentralized governance, peer-to-peer interactions, and a heterogeneous structure and range of use cases for digital assets. For instance, to the best of our knowledge, no study has thoroughly explored the *economic efficiency of cryptocurrencies* by considering key factors such as supply distribution, user participation, and exchange activity; all of these are dimensions in which wealth concentration [19, 20], low engagement [21, 22], and asset dormancy [23, 24, 25] can undermine network economic vitality. Table 1 shows these issues with regard to various cryptocurrencies up to April 2025. Notably, Bitcoin has a high asset dormancy (up to 99.56%), while Ripple exhibits a low engagement (4.4%). Moreover, the lack of a clear conceptual framework for analyzing economic efficiency in this context underscores the need to define it through measurable links between network behavior and core economic indicators.

This study examines the concept of economic efficiency for the class of cryptocurrencies that use public distributed ledgers to record transfers, offer accessible data, and leverage blockchain for transparency, traceability, and consistency [29, 30]. It is worth noting that similar analyses in traditional economies are hindered by limited access to raw data – controlled by centralized authorities – and inconsistencies in reporting across sources, such as variable monetary aggregates calculated by central banks [31]. Since data accessibility is ensured within blockchains, the problem to tackle is the lack of a unifying index expressing economic efficiency that enables a comprehensive comparison of cryptocurrencies instead of proceeding parameter by parameter.

We propose a theoretical framework that uses *Shannon entropy* [32] – a foundational concept in *information theory*, originally introduced by Claude Shannon in 1948 [32] – to define the *Entropy Balance index (EB-index)*, an economic index capable of aggregating a set of parameters describing economic qualities of a cryptocurrency. Our method follows these guiding principles: (i) rest on a solid theoretical foundation, (ii) remain adaptable to changes in parameters, (iii) reward cryptocurrencies exhibiting well-balanced values for the chosen parameters, and (iv) support parameter weighting without compromising the theoretical foundation.

Claude Shannon's seminal paper "*A Mathematical Theory of Communication*" [32] introduced a rigorous, axiomatic framework for quantifying information in communication systems. Entropy has subsequently found extensive use across diverse fields – from linguistics and neurobiology to machine learning and medical diagnostics – underscoring its flexible role as an index of information exchanged, the degree of fragmentation of a set, or the balance in the distribution of resources in both natural and engineered systems [33, 34, 35, 36, 37, 38, 39, 40, 41, 42]. Its role as a measure of economic (in-)equality was already formalized by Theil [43], who proposed entropy-based and divergence-based indices as alternatives to the Gini index, highlighting their decomposability across population subgroups. There are some applications also in the context of blockchain, for example to quantify the degrees of decentralization [44, 45], to measure the stability in blockchain consensus dynamics [46], and to express portfolio diversification [47].

To illustrate the robustness of our approach, we apply the entropy framework by using two distinct sets of economic qualities, *Set1* and *Set2*, each representing structural and behavioral aspects of cryptocurrency economies. *Set1* focuses on a minimal combination of basic financial activity metrics, while *Set2* adopts a richer, more granular perspective on network dynamics and internal economic organization. These attributes guide the selection of corresponding on-chain parameters, which we retrieve from the *Coin Metrics*® platform [48], ensuring an empirical and data-driven rooting. The entropy based on these two sets of features is then employed to evaluate six major cryptocurrencies with high market capitalization, spanning various economic roles and use cases (payments, smart contracts, stablecoins, and memecoins): Bitcoin (BTC) [2], Ethereum (ETH) [3], Ripple (XRP) [4], USD Coin (USDC) [26], Dogecoin (DOGE) [27], Cardano (ADA) [28].

This study paves the way to a foundational and flexible methodology for evaluating economic efficiency in cryptoassets and offering insights to investors, policymakers, and researchers navigating the evolving landscape of blockchain-based economies. As part of this work, we release our refined dataset (available at https://doi.org/10.5281/zenodo.15221823) for result reproducibility as well as independent analysis execution.

Roadmap. §2 surveys existing literature and related works. §3 outlines the conceptual study for an entropy-based economic framework. §4 shows an illustrative example. Finally, §5 concludes the paper and discusses future works.

2. Efficiency of Cryptocurrencies: A Literature Review

Blockchain is a decentralized digital ledger technology that securely records transactions across a network of nodes. Each block of data is linked to the previous one, forming a chain that is tamper-proof and transparent [1]. Cryptocurrencies, like Bitcoin [2] and Ethereum [3], are digital assets built on blockchain technology. They facilitate direct peer-to-peer transactions, eliminating the need for intermediaries such as banks. Thanks to blockchain, transactions are secured through cryptographic methods and accompanied by the management of new unit creation. Together, blockchain and cryptocurrencies offer a new paradigm for financial systems and applications, promoting transparency, security, and decentralization.

The literature review reveals the absence of a universally accepted definition of efficiency in this setting. Among the various interpretations, some focus on energy consumption and expenditure [17], while others emphasize market price trends by analyzing fluctuations in cryptocurrency prices and their implications for economic stability and efficiency [18]. Still others assess efficiency based on the production objectives of the considered economy, including the presence or absence of technological components [49]. In [50], the discussion centers on technical and scale efficiency, which differ in scope. The former measures how effectively resources are allocated to maximize output, so as to ensure the optimal utilization of inputs, while the latter examines the relationship between input growth and output expansion, in order to identify whether economies of scale are being achieved [50]. Additionally, in [50], efficiency is evaluated both qualitatively – by comparing actual delivery times with planned schedules – and quantitatively – by analyzing the ratio of actual versus expected outputs relative to expenditures. In traditional economies, metrics like the *Gini* coefficient [19, 51] – which quantifies wealth distribution – and *Pareto* efficiency [52] – which describes an optimal allocation of resources where no individual's well-being can improve without negatively affecting another – are used to identify economic inefficiencies and potential resource underutilization. Furthermore, it is interesting that resource allocation analyses often incorporate concepts such as the cost of unused capacity [53].

As for the research gap in relation to economic efficiency within blockchain and cryptocurrency ecosystems, we identify numerous studies that examine supply distribution, active user participation, and idle resources within these ecosystems.

Supply distribution impacts fairness, decentralization, and network stability [20]. Consensus mechanisms and other aspects impact cryptocurrency distribution, where wealth concentration can affect security, and exchange rates [54, 19]. Actually, cryptocurrencies exhibit high inequality patterns similar to traditional economies (*e.g.*, DOGE [27] Gini coefficient – 0.82 – is similar to US one – 0.84 [19]).

User participation affects liquidity and network value. In [21], an improved version of the PageRank algorithm – a Google technology for ranking web pages based on their importance – is used to evaluate Bitcoin user participation by taking into account both the consistency and the variability of transaction patterns. Key metrics like active addresses, transaction volume, and circulation frequency strongly correlate with price trends and economic activity [55, 22, 56].

Idle assets signal inefficiencies in resource use [23, 24, 25]. A key metric here is "Bitcoin Days Destroyed", which measures transaction volume while accounting for how long bitcoins have remained unused – highlighting the economic impact of previously dormant coins becoming active again [23]. Another useful metric is average dormancy, which tracks the duration that bitcoins remain inactive before reuse thus providing insights into circulation patterns, although it does not directly measure monetary velocity or account for the full money supply and price levels [24, 25].

Together, these elements highlight the need for an integrated framework to evaluate uniformly economic efficiency in blockchain systems [57].

3. The Quest for an Aggregated Economic Efficiency Index

A possible way to address the divergent interpretations of economic efficiency recalled in §2 is to define this concept in cryptocurrencies by linking transfer dynamics with basic economic parameters, thus enabling a more structured and comprehensive analysis. In particular, it is necessary to aggregate parameters in a coherent way, with an index able to satisfy the guiding principles mentioned in §1. We propose using Shannon entropy to define a theoretical framework that measures economic efficiency in cryptocurrency ecosystems through the Entropy Balance index (EB-index), aligning with established standards for reliability [58, 59, 60] and leveraging the transparency of blockchain data. Starting from a probability distribution associated with a set of events or parameters chosen to represent the qualities that determine the economic efficiency of a cryptocurrency, we employ Shannon entropy to measure how good the balance is within this set. The EB-index captures the complex internal structure of cryptoassets without relying on arbitrary single metrics. By aggregating heterogeneous dimensions – such as user activity, transactions, and supply – it reveals patterns that univariate analyses may miss.

In this section we recall the basics of the entropy measure (§3.1) and then we discuss a number of economic parameters among which to select the ones to be used in the entropy formula (§3.2).

3.1. The Entropy Measure

Let $q_1,q_2,\ldots,q_k$ be a set of k *quality parameters*, with $l_i \leq q_i \leq u_i$, where l_i and u_i represent, respectively, the lower and upper bounds of the interval of variability for the corresponding parameter. The idea behind our economic efficiency index for a cryptocurrency is to combine these parameters in a way that rewards cryptocurrencies exhibiting a well-balanced set of parameters with good performance, which leads to a wealthy economic development of the corresponding cryptocurrency. This composition must allow for changes in the number of parameters without affecting the nature or compromising the coherence of the index.

The first step is to normalize each q_i within the interval $[0, 1]$, thereby obtaining the set $R = \{r_1,r_2,\ldots,r_k\}$ with $0 \leq r_i \leq 1$. This normalization is necessary because we cannot compare quantities with different scales, *e.g.*, one parameter varying within $[0,1]$ and another varying within $[0,u]$, where u is an unbounded real number.

The economic efficiency index should intuitively reach its maximum value when all r_i attain the upper bound of the interval $[0,1]$, *i.e.*, when they are all equal to 1. When $r_i = 1$, we can assume the maximum economic efficiency for the single parameter i, as opposed to an economic inefficiency of 0. Conversely, as r_i approaches 0, it is customary to assume that inefficiency grows to infinity. From this perspective, we need to introduce an analytic function[1] $\mathcal{I}$ satisfying the following constraints:

$$\begin{array}{ll} \text{when } r_i = 1 & \text{we have } \mathcal{I}(r_i) = 0 \\ \text{when } r_i \to 0 & \text{we have } \mathcal{I}(r_i) \to +\infty \end{array} \tag{1}$$

It is well known that there exist infinitely many functions satisfying these constraints; among all the possible ones, we choose:

$$\mathcal{I}(r_i) = -\log_b r_i \tag{2}$$

This choice immediately leads to the *Shannon entropy* defined by using base-2 logarithm [32]:

$$H_2(P) = -\sum_{i=1}^{k} p_i \log_2 p_i \tag{3}$$

after the normalization:

$$p_i = \frac{r_i}{\sum_{i=1}^{k} r_i} \tag{4}$$

so as to derive a probability distribution (p.d.) $P = \{p_1, p_2, \ldots, p_k\}$ from the set $R = \{r_1, r_2, \ldots, r_k\}$ of parameters in the interval $[0,1]$. Recall that:

$$0 \le H_2(P) \le \log_2 k \quad \text{where } H_2(P) = \begin{cases} 0 & \text{iff } P \text{ is degenerate} \\ \log_2 k & \text{iff } P \text{ is uniform} \end{cases} \tag{5}$$

P degenerate means it is in the form $0, \ldots, 1, \ldots, 0$, while P uniform corresponds to $p_i = 1/k \, \forall i$ [32, 61]. By taking the logarithms to the base k, we obtain a normalization of the entropy:

$$0 \le H(P) \le 1 \tag{6}$$

The motivation for choosing the Shannon entropy lies in the fact that it can be proven, through a theorem, that Shannon entropy is the *unique* function, among infinitely many possible ones, that satisfies a specific set of postulates outlining the natural properties an information measure should reasonably possess [32, 62, 63].

The distinguishing postulate is the so-called *branching property*, expressed as follows in the case of k events:

$$H(p_1, p_2, \ldots, p_k) = H(p_1 + p_2, p_3, \ldots, p_k) + (p_1 + p_2) H\left(\frac{p_1}{p_1 + p_2}, \frac{p_2}{p_1 + p_2}\right) \tag{7}$$

that describes how entropy behaves when a p.d. is broken down into successive steps. The relation expresses the average information loss incurred when two events are grouped together and made indistinguishable; this loss is given by the entropy of the two events, weighted by the sum of their probabilities. Furthermore, it should be noted that this branching property can be generalized to a partition $\{\, \mathcal{J}_i \mid 1 \le i \le m \,\}$, $m < k$, of $\{1, 2, \ldots, k\}$ with p.d. $S = \{s_1, s_2, \ldots, s_m\}$:

$$H(p_1, p_2, \ldots, p_k) = H(s_1, s_2, \ldots, s_m) + \sum_{i=1}^{m} s_i H^{(i)} \tag{8}$$

where $H^{(i)} = -\sum_{j \in \mathcal{J}_i} \left(\frac{p_j}{s_i}\right) \log\left(\frac{p_j}{s_i}\right)$ is the entropy associated with $\mathcal{J}_i$ and $\sum_{j \in \mathcal{J}_i} \frac{p_j}{s_i} = 1$ so that p_j / s_i is effectively a p.d. In this last case, the relation expresses the average information loss incurred when some subsets of events are grouped together and made indistinguishable; this loss is given by the sum of the entropies related to the subsets, weighted by their probabilities [62]. These equations provide the theoretical foundation underpinning entropy and our approach.

[1] An analytic function is a function that (i) is locally representable by a convergent power series, hence it can be expressed as a sum of terms based on powers of the variable, and (ii) is differentiable at every point in its domain.

Another important advantage of the Shannon entropy is that it is possible to associate a set of *weights* or *utilities* with the p.d. P, say $\mathcal{W} = \{w_1, w_2, \ldots, w_k\}, w_i \geq 0$, without losing the branching property. This leads to the definition of the *Beliş-Guiaşu weighted entropy* [64]

$$\mathcal{H}(P;\mathcal{W}) = -\sum_{i=1}^{k} w_i \cdot p_i \log_2 p_i \tag{9}$$

It is simple to check that the branching property still holds as soon as we correctly define the weight of the composition of two events e_1 and e_2 as a weighted sum of the utilities of the single events:

$$Weight(e_1, e_2) = w_{12} = \frac{p_1}{p_1 + p_2} w_1 + \frac{p_2}{p_1 + p_2} w_2 \tag{10}$$

The branching property can then be expressed in the following way ($p_{12} = p_1 + p_2$):

$$\mathcal{H}(p_1, \ldots, p_k; w_1, \ldots, w_k) = \mathcal{H}(p_{12}, p_3, \ldots, p_k; w_{12}, w_3, \ldots, w_k) + p_{12} \cdot \mathcal{H}\left(\frac{p_1}{p_{12}}, \frac{p_2}{p_{12}}; w_1, w_2\right) \tag{11}$$

The presence of the weights w_i in the weighted entropy (9) causes the function to be zero when $w_i = 0$, for all i. Moreover, it is also reduced to zero when the useful events are impossible or the possible events are useless. The last case occurs also when P is degenerate.

3.2. Economic Parameters

Among the most commonly used methods to measure complex socio-economic phenomena – such as *Gross Domestic Product* (GDP) or *Human Poverty Index* (HPI) – composite indices play a central role. They are widely used due to their adherence to established theoretical and functional requirements that ensure their reliability [58, 59]. According to [59, 58, 60], guidelines and steps to summarize a set of economic indicators and construct a composite index are the following:

1. *Phenomenon definition*, *i.e.*, the theoretical framework to achieve a clear conceptualization of what is being measured and establish selection criteria for determining whether an indicator should be included.

2. *Data modeling*, *i.e.*, the selection of relevant, timely, and accessible data sources, considering their correlation to minimize redundancy.

3. *Data processing*, composed by (i) normalization, which ensures comparability between indicators, (ii) weighting, which assigns priority to indicators based on their relevance, and (iii) aggregation, which combines the normalized indicators into a unified framework.

As discussed in §3.1, our entropy-based approach adheres to all these phases, providing a solid foundation for evaluations. In the following, we illustrate how each phase contributes to the construction of our framework for assessing economic efficiency.

Phenomenon Definition. The economic efficiency analysis we aim to conduct goes beyond purely economic parameters measured in some currency. It also considers additional aspects, such as the intensity and frequency of transfers, as well as user participation. To establish a solid foundation for this study on economic efficiency, we introduce in Table 2 several basic cryptocurrency parameters. We use these basic parameters to clearly define and formalize the set of key economic quality attributes that characterize these digital economic systems. In particular, we identify *primitive quality* (*PQ*) attributes, which are defined by a single parameter, and *derived quality* (*DQ*) attributes, which result from a mathematical combination of multiple PQs. These are presented in Table 3 along with their definitions, formulas, units, and range intervals. When applicable, we explicitly indicate the use of the native cryptocurrency unit (marked as "Ntv") rather than USD.

Table (2)
Basic parameters.

Attribute	Acronym	Definition
Digital Asset Supply	S	The total amount of a digital asset (coin or token) available within the tokenomics of a cryptocurrency.
Current Supply	S_{current}	The number of coins or tokens that have been minted or mined to date.
Transfer Set	T	The set of all transfers t executed within the network during a given period.
Transfer	t	A single movement of digital assets between two addresses.
Sender of a Transfer	$\text{sender}(t)$	The sender of a transfer t.
Receiver of a Transfer	$\text{receiver}(t)$	The receiver of a transfer t.
Transfer Amount	$\text{amount}(t)$	The value in coins or tokens associated with a transfer t.
Address Set	A	The set of all addresses a.
Funded Address Set	A_{funded}	The set of addresses holding at least 1 USD during a given period.
Active Address Sent Set	A_{active}	The set of unique addresses, counted only once, that are involved in sending transfers over a given period. It refers to all activities leading to a change in the ledger, excluding the null address used for issuance purposes.
Address	a	Unique identifier for sending or receiving digital assets.
Address Balance	$\text{balance}(a)$	The value in coins or tokens associated with the address a.
Address Sent	$\text{sent}(a,t)$	The value in coins or tokens sent from address a during a transfer t.

Table (3)
Key economic quality attributes.

Economic Attribute	Acronym	Definition	Formula	Unit	Interval
PQ1 - Transferred Value	T_{value}	The total Ntv value exchanged within the system over a given period, excluding issuance account transfers, which record asset creation (*e.g.*, Bitcoin coinbase transactions).	$T_{\text{value}} = \sum_{t \in T} \text{amount}(t)$	Ntv	$[0,+\infty)$
PQ2 - Transfer Count	T_{count}	The total number of transfers t executed within the network during a given period.	$T_{\text{count}} = \lvert T \rvert$	Count	$[0,+\infty)$
PQ3 - Number of Funded Addresses	NA_{funded}	The number of addresses continuously holding at least 1 USD during a given period.	$NA_{\text{funded}} = \lvert A_{\text{funded}} \rvert$	Count	$[0,+\infty)$
PQ4 - Number of Active Addresses Sent	NA_{active}	The total number of unique addresses, counted only once, that are involved in sending transfers over a given period.	$NA_{\text{active}} = \lvert A_{\text{active}} \rvert$	Count	$[0,+\infty)$
PQ5 - Active Supply	S_{active}	The amount of coins/tokens that have been moved at least once within a given time period, excluding double counting of the same units being recycled.		Ntv	$[0,+\infty)$
PQ6 - Daily Digital Asset to USD Price Rate	USD_{price}	The price in USD per native unit of the coin or token at the close of the day.		USD	$(0,+\infty)$
PQ7 - Market Capitalization	Cap	The total value of a cryptocurrency in USD, calculated by multiplying its current price by the total circulating supply of coins.	$Cap = S \cdot USD_{\text{price}}$	USD	$(0,+\infty)$
DQ1 - Participation	$A_{\text{participation}}$	The proportion of active addresses relative to the total addresses holding at least 1 USD. A higher ratio suggests a more engaged user base and a healthy level of participation within the cryptocurrency ecosystem.	$A_{\text{participation}} = NA_{\text{active}} / NA_{\text{funded}}$	Count	$[0,1]$
DQ2 - Mean Transfer Size	MTS	The mean size of a transfer, measured in Ntv. It is calculated by dividing the total value transferred by the number of transfers between distinct addresses during a given period.	$MTS = T_{\text{value}} / T_{\text{count}}$	Ntv	$[0,+\infty)$
DQ3 - Mean Transfers per Active Address	MTA_{active}	The mean number of transfers per active address. It is calculated by dividing the total number of transfers by the number of active addresses during a given period. This metric provides insights into the intensity of usage per user.	$MTA_{\text{active}} = T_{\text{count}} / NA_{\text{active}}$	Count	$[0,+\infty)$
DQ4 - Active Supply Turnover Rate	TR	The ratio between the total value transferred and the active supply over a given period. A higher TR indicates more frequent economic activity and greater liquidity.	$TR = T_{\text{value}} / S_{\text{active}}$	Count	$[0,+\infty)$
DQ5 - Active Supply Ratio	ASR	The proportion of the current supply that is actively participating in transactions. A higher ASR signifies that a larger portion of the available cryptocurrency is being used rather than held passively.	$ASR = S_{\text{active}} / S_{\text{current}}$	Count	$[0,1]$
DQ6 - Wealth Distribution	WD	The degree to which wealth is distributed across the network participants, where: I is a set of balance intervals each of which represents a range of account balances; $NA_{\text{funded}}(i)$ is the number of accounts whose balance falls within interval i; $S_{\text{current}}(i)$ is the total supply in interval i; $\text{avgbal}(i) = S_{\text{current}}(i) / NA_{\text{funded}}(i)$ is the average balance per address in interval i.	$WD = \frac{\sum_{k \in I} \sum_{h \in I} NA_{\text{funded}}(k) \cdot NA_{\text{funded}}(h) \cdot \lvert \text{avgbal}(k) - \text{avgbal}(h) \rvert}{2 \cdot NA_{\text{funded}} \cdot \sum_{i \in I} S_{\text{current}}(i)}$	Count	$[0,1]$
DQ7 - Mean Transfer per Market Cap	$MTMC$	The mean size of a transfer over a specific period relative to the cryptocurrency's market capitalization.	$MTMC = (T_{\text{value}} \cdot USD_{\text{price}}) / Cap$	USD	$[0,+\infty)$

Table (4)
Blockchain data intelligence platforms comparison.

Name	Assets and Protocols	API Access	Metrics
Bitquery [65]	40+	3-months as researcher	Blocks and transactions related
Glassnode [66]	600+	Limited free plan	400+
Blockdaemon [67]	23+	Limited free plan	Balances, blocks, fee estimator, transactions
Blockchair [68]	14	1-year 100K requests as student	Raw stats metrics per blockchain
Coin Metrics [48]	200+	2-year as researcher	$\sim$300

Table (5)
Coin Metrics parameters selection.

PQ	Coin Metrics Parameter	Description	Unit
PQ1	Xfer'd Val	The sum of Ntv transferred (*i.e.*, the aggregate "size" of all transfers) in a given period.	Ntv
PQ2	Xfer Cnt	The count of transfers in a given period, including all user-initiated actions recorded on the chain, excluding protocol-mandated changes like coinbase transactions or new issuance.	Count
PQ3	Addresses Count with Balance $\geq$ 1 USD	The total count of unique addresses holding at least 1 USD by the end of a given period.	Count
PQ4	Active Addresses (Sent)	The total count of unique sending addresses active in the network in a given period, excluding duplicates from previous activity.	Count
PQ5	1-Day Active Supply	The sum of unique native units that transacted at least once within a single day. Native units that transacted more than once are only counted once.	Ntv
PQ6	USD Denominated Closing Price	The price of the asset denominated in USD.	USD
PQ7	Market Cap	The value of the current supply in USD. Also referred to as network value or market capitalization.	USD
-	Current Supply	The sum of all native units ever created and currently visible on the ledger (*i.e.*, issued) in a given period.	Ntv
-	Val in Addrs w/ Bal $\geq$ X Ntv	The total of native units held in addresses with a balance of X Ntv or more at the end of a given period, excluding non-native tokens.	Ntv

Data Modeling. Having properly defined the quality attributes, we can now identify the on-chain parameters to be measured for each quality, based on a selection criterion that reflects their relevance to the corresponding attribute. To achieve this, we can exploit blockchain data intelligence platforms that provide several on-chain data in user-friendly formats. Table 4 compares some of these platforms with respect to the available metrics, the number of accessible assets and protocols, and the type of API access.

We rely on *Coin Metrics* [48] as its indicators categorization aids us in identifying both blockchain and cryptocurrency components from economic and technological perspectives. Additionally, it offers a wide range of protocols and provides researchers with the opportunity to access premium data for free up to 2 years (upon request). In Table 5 we present the on-chain parameters from *Coin Metrics* that best represent the previously defined quality attributes, enabling a comprehensive study focused on economic efficiency within cryptocurrency networks [57, 55]. We use *Coin Metrics* to download this data with a daily granularity.

Data Processing. The data processing stage is essential to ensure that economic efficiency is grounded in solid theoretical principles. To meet the methodological requirements of normalization, weighting, and aggregation, we adopt the rigorous framework of Shannon entropy [32].

After downloading the relevant metrics from *Coin Metrics*, we align all datasets to a common time reference, using the earliest available timestamp (2010-07-18) for PQ6 as the baseline (USD Denominated Closing Price). Next, we convert into USD all metrics originally expressed in native units. This applies to the following metrics from Table 5: `Xfer'd_Val` (PQ1), `1-Day_Active_Supply` (PQ5), `Current_Supply`, `Val_in_Addrs_w/Bal≥X_Ntv`. Particular attention should be paid to the calculation of DQ6 (Wealth Distribution), which considers balance class intervals rather than individual address balances as in the original Gini formula. These intervals range from 0.001 units of the native currency up to 100K. Furthermore, since a user may control multiple wallets, we focus on the address-level granularity provided by Coin Metrics, which allows us to distinguish between wallets and individual addresses.

Table (6)
Selected cryptocurrencies and their financial and technical characteristics as of April 2025.
Source: *Coin Metrics*.

Asset	Category	Coin Metrics Capitalization	Max Supply	Avg. Network Size	Underlying Blockchain	Consensus Mechanism
Bitcoin (BTC) [2]	Payment	$1,653.3 billions	21 millions BTC	21.886 [69]	Bitcoin	PoW
Ethereum (ETH) [3]	Smart Contract	$217.6 billions	No fixed supply	13.347 [70]	Ethereum	PoS
Ripple (XRP) [4]	Payment	$214 billions	100 billions XRP	150+ [71]	XRP Ledger	Consensus Protocol
USD Coin (USDC) [26]	Stablecoin	$40 billions	No fixed supply	Depends on the blockchain	Operates on multiple blockchains	Depends on the blockchain
Dogecoin (DOGE) [27]	Memecoin/Payment	$25.1 billions	No fixed supply	315 [72]	Dogecoin	PoW
Cardano (ADA) [28]	Payment/Smart Contract	$23.3 billions	45 billions ADA	N.A.	Cardano	PoS

We then normalize the data. Normalization ensures that each metric contributes equally, independent of scale differences (*e.g.*, market cap or address count). While metrics may reflect protocol-specific factors, the entropy-based approach remains agnostic to context, focusing on internal distributions. For fairer comparisons, assets should ideally belong to the same category. For each metric and asset (except PQ7), we use *min-max normalization* [59, 58, 60] based on the individual asset's range, taken within the entire lifetime of the cryptocurrency. For PQ7 (Market Capitalization), we apply a global normalization by using the *min* and *max* values across all assets to preserve comparability. To handle DQ6 (WD), where lower values indicate greater efficiency, we use the specific transformation $1 - norm\_val$ to reflect this inverse relationship. This adjustment ensures that all metrics behave consistently – higher normalized values always reflect greater economic efficiency – while remaining within the $[0,1]$ range.

Finally, we compute the EB-index derived from the chosen parameters for an illustrative example by using both the standard formulation (3) and its weighted variant (9). Our analysis, encompassing all data and resulting output, is conducted on a daily granularity. The corresponding results are presented in §4.

4. An Illustrative Example

In this section, we present a case study to illustrate the application of our EB-index to evaluate economic efficiency in cryptocurrencies. Our intention is not to provide any conclusive assessment of the performance or quality of the selected cryptocurrencies, but rather to demonstrate the practical implementation of the proposed theoretical framework within a real-world financial context.

We conduct a comparative analysis of the entropies obtained by the six major cryptocurrencies cited in §1 – BTC, ETH, XRP, USDC, DOGE, and ADA – over the period from 2010 to 2025; their main financial and technical characteristics, such as capitalization, max supply, underlying blockchain, and consensus mechanism, are briefly summarized in Table 6. The choice of the aforementioned cryptocurrencies also takes into account the fact that not all cryptocurrencies have the desired parameters available on *Coin Metrics*.

The analysis is based on two distinct sets of derived quality attributes, constructed from selected parameters available on *Coin Metrics* (see §3.2): *Set1* and *Set2*, each designed to capture different layers of cryptocurrency economic behavior. *Set1* is composed of a minimal combination of fundamental financial activity metrics – such as market capitalization – primarily reflecting broader macroeconomic sentiment. In contrast, *Set2* offers a more granular view, incorporating a richer selection of attributes that describe structural network dynamics and internal economic organization, thereby capturing slower-moving, user-driven behavioral trends. The composition of these two sets is detailed in Table 7.

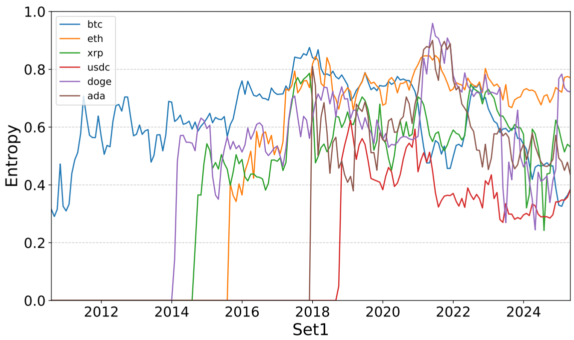
4.1. EB-Index Based on Unweighted Entropy: Good Balance

The entropy variations for the chosen cryptocurrencies, computed by using the standard formula (3), are illustrated in Figure 1. The comparison across different attribute sets highlights how the selection of metrics can substantially affect the observed performance and behavior of cryptoassets.

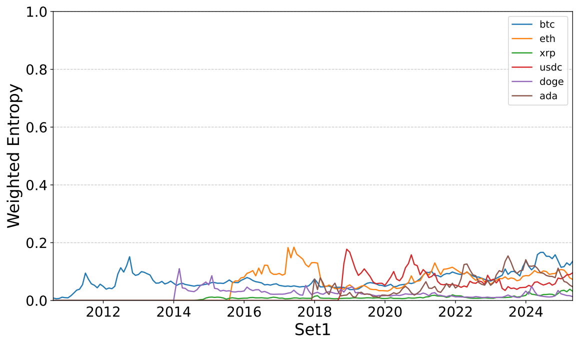
In *Set1*, which combines user activity with financial metrics, most assets exhibit a gradual growth with peak values between 0.85 and 0.9 – particularly DOGE, ADA and ETH, which display the highest levels of entropy for the entire period. This suggests a peak in homogeneity and well-balanced development

Table (7)
Derived quality attributes chosen for the two sets *Set1* and *Set2*.

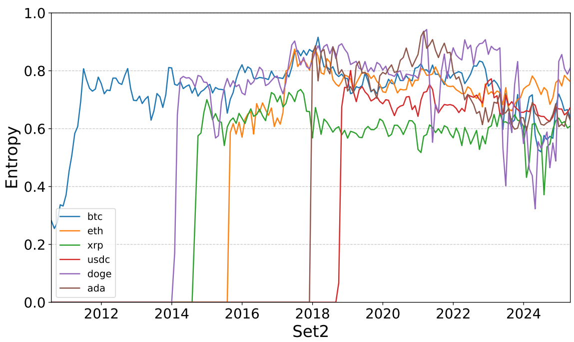
Set	Qualities	Description
Set1		It combines user activity metrics with market financial indicators.
	DQ1	Participation ($A_{\text{participation}}$)
	DQ3	Mean Transfers per Active Address (MTA_{active})
	DQ7	Mean Transfer per Market Cap ($MTMC$)
	PQ7	Market Capitalization (Cap)
Set2		It comprises six dynamic qualities, with a focus on user engagement, transaction characteristics, and the distribution of wealth within the network.
	DQ1	Participation ($A_{\text{participation}}$)
	DQ2	Mean Transfer Size (MTS)
	DQ3	Mean Transfers per Active Address (MTA_{active})
	DQ4	Active Supply Turnover Rate (TR)
	DQ5	Active Supply Ratio (ASR)
	DQ6	Wealth Distribution (WD)



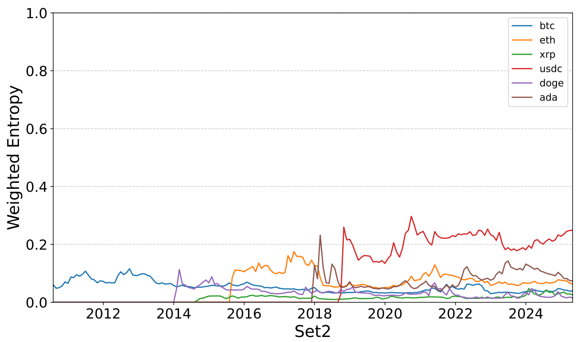
(a) Entropy variations for *Set1*



(b) Weighted entropy variations for *Set1*



(c) Entropy variations for *Set2*



(d) Weighted entropy variations for *Set2*

Figure (1): Comparison between unweighted and weighted entropy for (a-b) *Set1* (DQ1, DQ3, DQ7, PQ7) and (c-d) *Set2* (DQ1, DQ2, DQ3, DQ4, DQ5, DQ6). For the weighted entropy the chosen weights are $w_i = r_i$.

during that period. After 2020, ETH stabilizes and becomes the most consistent asset across the entire set, maintaining values steadily above 0.6 – a sign of structural resilience. BTC, on the other hand, undergoes a temporary recovery between 2022 and 2023, followed by another sharp decline. The dynamics of the entropy values are generally well pronounced (0.25–0.9), with a lot of sharp peaks and bottoms, highlighting that the index is capable of capturing key aspects associated with variations in the economic parameters.

Set2, built on dynamic, interaction-based features such as transaction size, turnover rate, and wealth distribution, reveals higher and less dispersed values, with only the period of time from 2023 to mid 2024 characterized by some steep declines in value.

Ethereum consistently exhibits the highest entropy, reflecting a well-balanced and resilient ecosystem, especially during market stress. As represented in Figure 2, in *Set1* a drop in DQ3 offset by rising Market Cap preserved balance, while in *Set2* opposing shifts in DQ5 and DQ6 had a compensatory effect.

It is worth noting that some assets can perform differently when using different sets of parameters. For example XRP consistently ranks as the least efficient asset in *Set2*, with values averaging near 0.6 for the majority of the period, reflecting poorer distribution and transactional engagement. On the contrary, it can be considered average compared to the others in *Set1*. This underlines again the importance of carefully selecting parameters based on the characteristics of the cryptocurrency one aims to highlight.

While some global events – such as market crashes, regulatory changes, or liquidity shocks – may coincide with entropy shifts, their causal impact on the distributional structure of the parameters is not addressed in this work. Our primary goal remains the introduction of a well-founded economic index, flexible in both composition and number of parameters, capable of expressing the balanced integration of economic qualities as an indicator of systemic efficiency – irrespective of exogenous causes. It remains the responsibility of the researcher to choose the set of parameters and economic qualities that best suit her/his research.

4.2. EB-Index Based on Weighted Entropy: Performance or Importance

The proposed EB-index assumes equal relevance for all selected economic qualities. However, this approach has a limitation: it rewards only the good balance among qualities, regardless of their absolute value. As an example, consider two cryptocurrencies: the first one with all normalized qualities reaching the maximum value $r_i = 1, \forall i$; the second one with $r_i = 0.5, \forall i$. From (4) it is clear that both the two corresponding p.d.'s are uniform and correspond to the maximum value of normalized entropy, *i.e.*, $H(P) = 1$ with k the base of the logarithm. But the first cryptocurrency has all absolute values greater than that of the second one. To overcome this limitation we can use the weighted entropy (9) and set $w_i = r_i$, so each quality contributes proportionally to its normalized absolute value. In this way the entropy metric becomes sensitive not only to a good balance of the qualities, but also to the absolute performance of the system, thus better capturing the economic efficiency of the evaluated blockchain protocol. Note, however, that when we use the term "absolute", we are always comparing the value of the given quality to its own highest value over the historical series, within the context of the same cryptocurrency.

In Figure 1, the unweighted entropy calculation is shown alongside its weighted counterpart with $w_i = r_i$ for each quality q_i. This highlights a significant shift in the interpretation of the results, particularly for *Set2*, where interestingly the USDC stablecoin emerges as the most balanced and highly entropic representation. Moreover, it is worth noting that the entropy score drops significantly below 0.3, indicating that a full balance among the selected economic features has not yet been achieved within the sets.

Another possibility offered by the weighted entropy is that of increasing the importance of some qualities to the detriment of others, by assigning $w_i = u_i$, where u_i is the *utility* (upper bound) of the corresponding quality. Note that in any case we can consider the last two weighting principles in a joint manner by setting $w_i = r_i \cdot u_i$, without losing the formal properties satisfied by the Shannon entropy.

5. Conclusions and Future Work

The EB-index adopted in this study offers a novel perspective on assessing economic efficiency in cryptoassets. The key idea is the introduction of Shannon entropy as a global metric, capable of expressing good performance and balance among several economic parameters of a cryptocurrency. This is accomplished in a rigorous axiomatic framework, which ensures the coherent behavior of the index when changing the number of parameters and/or the weights associated with them, without compromising the theoretical foundation. In other words, our entropy-based approach offers a way to evaluate the harmonious development of the analyzed cryptocurrency, in the sense of a global, healthy, and well-balanced improvement of all of its parameters.

By analyzing multiple sets of attributes over time, one could identify how structural and valuation-driven components influence the internal systemic behavior of these assets. Future work may explore

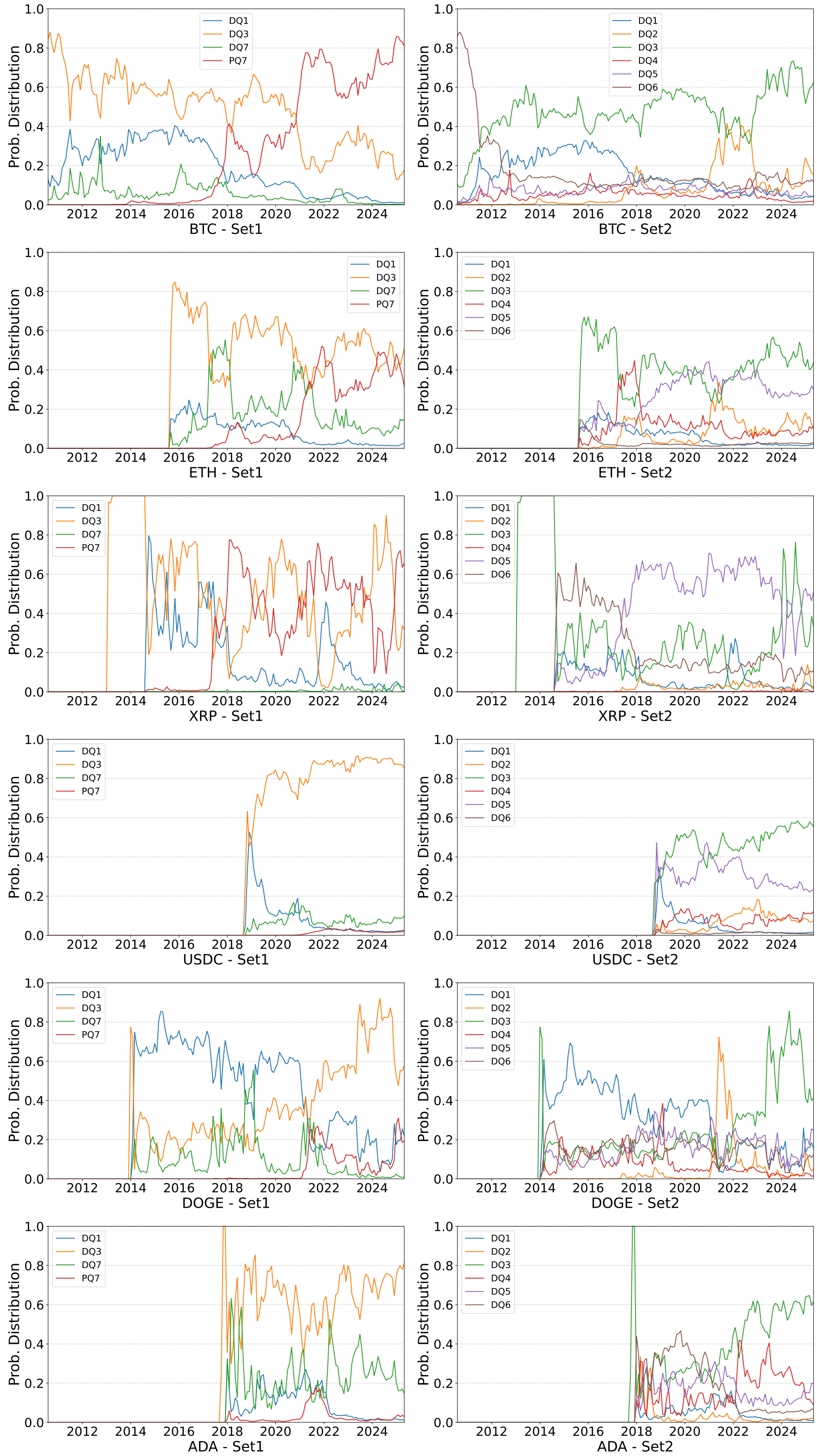


Figure (2): Probability distribution of the selected attributes within each set, computed per asset.

causal methods to better assess the link between external shocks and systemic dynamics.

The quality and completeness of the analysis are directly influenced by the availability and granularity of on-chain data. Similarly, the Gini-based Wealth Distribution (DQ6) had to be computed by using balance class intervals between 0.001 units of the native currency up to 100,000, as this range best matched the practical constraints of the available dataset.

The framework currently assumes equal relevance for all selected attributes, which may not align with their actual economic significance. In this regard, we have proposed the adoption of the weighted entropy formulation by Beliş and Guiaşu [64], to better reflect the different importance of each parameter by attributing a specific weight to it, without losing the axiomatic coherence of the index. Future work will explore weighted formulations based on domain-specific criteria, data-driven methods, or expert input. The proposed methodology remains flexible and adaptable to various research objectives and data analysis strategies.

The EB-index flexibly assesses structural balance by employing user-defined parameters. We do not seek an optimal metric set, as efficiency is context-dependent. Changes in the index resulting from adding or removing metrics are context-specific and not generalizable. A sensitivity analysis, which is beyond the scope of this work, is left for future investigation.

Another consideration involves the treatment of certain on-chain metrics. For example, *Active Addresses Sent* aggregates various activities that result in a ledger change, not exclusively economic transfers. While this metric is broadly representative of network usage, it may introduce noise in contexts where distinguishing between economic and non-economic activity is crucial.

We recall that the study datasets are available at https://doi.org/10.5281/zenodo.15221823

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Declaration on Generative AI

During the preparation of this work, the author(s) did not use any generative AI (GenAI) tools for content creation. All ideas, analyses, and textual formulations were entirely developed by the author(s), who have reviewed and edited the content manually and take full responsibility for the publication's content.

References

[1] D. Yaga, P. Mell, N. Roby, K. Scarfone, Blockchain technology overview, NIST Internal Report NISTIR 8202, 2018. doi:10.6028/NIST.IR.8202.

[2] S. Nakamoto, Bitcoin: A peer-to-peer electronic cash system (2009). URL: http://www.bitcoin.org/bitcoin.pdf.

[3] G. Wood, et al., Ethereum: A secure decentralised generalised transaction ledger, Ethereum project yellow paper 151 (2014) 1–32. URL: https://ethereum.github.io/yellowpaper/paper.pdf.

[4] B. Chase, E. MacBrough, Analysis of the XRP ledger consensus protocol, 2018. URL: https://arxiv.org/abs/1802.07242.

[5] A. A. Monrat, O. Schelén, K. Andersson, A survey of blockchain from the perspectives of applications, challenges, and opportunities, IEEE Access 7 (2019) 117134–117151. doi:10.1109/ACCESS.2019.2936094.

[6] A. Saif, Q. Hu, Powered by blockchain technology, DeFi (decentralized finance) strives to increase financial inclusion of the unbanked by reshaping the world financial system, Modern Economy 12 (2021) 1–16. doi:10.4236/me.2021.121001.

[7] R. Auer, B. Haslhofer, S. Kitzler, P. Saggese, F. Victor, The technology of Decentralized Finance (DeFi), BIS Working Papers 1066, Bank for International Settlements, 2023. URL: https://ideas.repec.org/p/bis/biswps/1066.html.

[8] X. Xu, B. Zhang, W. Lv, Weiwei, Dynamic crypto currency transaction index modelling using blockchain and community detection method, in: Proc. of the 3rd Int. Conf. on Intelligent Control,

Measurement and Signal Processing and Intelligent Oil Field (ICMSP 2021), IEEE Computer Society, 2021, pp. 234–238. doi:10.1109/ICMSP53480.2021.9513352.
[9] G. Gensler, 2024. URL: https://www.sec.gov/newsroom/speeches-statements/gensler-statement-spot-bitcoin-011023.
[10] K. J. Brooks, Bitcoin hits record high. Here's what's driving up the price., 2024. URL: https://www.cbsnews.com/news/bitcoin-price-stock-cryptocurrency-etf-approval/.
[11] L. D. Fink, Larry Fink's 2025 annual chairman's letter to investors, 2025. URL: https://www.blackrock.com/corporate/literature/presentation/larry-fink-annual-chairmans-letter.pdf.
[12] C. Smith, J. Rennison, How Washington plans to defend the dollar, Financial Times (2024). URL: https://www.ft.com/content/bfafb8f7-bd1c-48bb-85f4-8ba25475c0a3, accessed: 2025-09-08.
[13] CoinGecko, 2024. URL: https://www.coingecko.com/it, accessed: 2025-09-08.
[14] V. P. Di Perna, V. Schiavoni, F. Fabris, M. Bernardo, M. Matos, S. Amaro, Impact of network topologies on blockchain performance, in: Proc. of the 19th ACM Int. Conf. on Distributed and Event-Based Systems (DEBS 2025), ACM Press, 2025, pp. 122–133. doi:10.1145/3701717.3730540.
[15] E. Georgiadis, How many transactions per second can Bitcoin really handle? Theoretically, IACR Cryptol. ePrint Arch. (2019) 416. URL: https://eprint.iacr.org/2019/416.
[16] V. P. Di Perna, V. Schiavoni, F. Fabris, M. Bernardo, Blockchain energy consumption: Unveiling the impact of network topologies, in: Proc. of the 7th IEEE Int. Conf. on Blockchain and Cryptocurrency (ICBC 2025), IEEE Computer Society, 2025, pp. 67–76. doi:10.1109/ICBC64466.2025.11114569.
[17] Cambridge Center for Alternative Finance, Cambridge Bitcoin Electricity Consumption Index (CBECI), 2024. URL: https://ccaf.io/cbnsi/cbeci/methodology, accessed: 2025-09-08.
[18] J. Karasiński, The weak-form efficiency of cryptocurrencies, Research Papers in Economics and Finance 7 (2023) 31–47. doi:10.18559/ref.2023.1.198.
[19] A. R. Sai, J. Buckley, A. Le Gear, Characterizing wealth inequality in cryptocurrencies, Frontiers in Blockchain 4 (2021) 1–20. doi:10.3389/fbloc.2021.730122.
[20] M. Juodis, E. Filatovas, R. Paulavičius, Overview and empirical analysis of wealth decentralization in blockchain networks, ICT Express 10 (2024) 380–386. doi:10.1016/j.icte.2024.02.002.
[21] T. Xue, Y. Yuan, C. Wang, An approach for evaluating user participation in Bitcoin, in: Proc. of the 3rd IEEE Int. Conf. on Data Science in Cyberspace (DSC 2018), IEEE Computer Society, 2018, pp. 858–864. doi:10.1109/DSC.2018.00138.
[22] Y. Lyu, Active addresses of Ethereum, SSRN Electronic Journal (2021) 1–23. doi:10.2139/ssrn.3879975.
[23] R. D. Smith, Bitcoin average dormancy: A measure of turnover and trading activity, Ledger 3 (2018) 91–99. doi:10.5195/ledger.2018.99.
[24] N. Gandal, J. Hamrick, T. Moore, M. Vasek, The rise and fall of cryptocurrency coins and tokens, Decisions in Economics and Finance 44 (2021) 981–1014. doi:10.1007/s10203-021-00329-8.
[25] M. Ambrosia, J. Dorrell, T. Stockwell, Is active Bitcoin supply decreasing? An empirical analysis, Journal of Economics and Finance 48 (2024) 1166–1186. doi:10.1007/s12197-024-09691-w.
[26] C. I. Group, 2025. URL: https://www.usdc.com/, accessed: 2025-09-08.
[27] B. Markus, J. Palmer, 2022. URL: https://dogechain.dog/DogechainWP.pdf, accessed: 2025-09-08.
[28] C. Hoskinson, Cardano introduction, 2025. URL: https://docs.cardano.org/about-cardano/introduction/, accessed: 2025-09-08.
[29] S. Saberi, M. Kouhizadeh, J. Sarkis, L. Shen, Blockchain technology and its relationships to sustainable supply chain management, Int. Journal of Production Research 57 (2019) 2117–2135. doi:10.1080/00207543.2018.1533261.
[30] X. F. Liu, C. G. Akcora, Z. Zhang, J. Liu, Editorial: Cryptocurrency transaction analysis from a network perspective, Frontiers in Physics 10 (2022) 1–2. doi:10.3389/fphy.2022.876983.
[31] European Central Bank, Monetary aggregates, 2024. URL: https://www.ecb.europa.eu/stats/money_credit_banking/monetary_aggregates/html/index.en.html, accessed: 2025-09-08.
[32] C. E. Shannon, A mathematical theory of communication, The Bell System Technical Journal 27 (1948) 379–423. doi:10.1002/j.1538-7305.1948.tb01338.x.
[33] J. Warner, Linguistics and information theory: Analytic advantages, Journal of the American

Society for Information Science and Technology 58 (2007) 275–285. doi:10.1002/asi.20488.

[34] P. Chanda, E. Costa, J. Hu, S. Sukumar, J. Van Hemert, R. Walia, Information theory in computational biology: Where we stand today, Entropy 22 (2020) 1–34. doi:10.3390/e22060627.

[35] F. Fabris, Shannon information theory and molecular biology, Journal of Interdisciplinary Mathematics 12 (2009) 41–87. doi:10.1080/09720502.2009.10700611.

[36] A. G. Dimitrov, A. A. Lazar, J. D. Victor, Information theory in neuroscience, Journal of computational neuroscience 30 (2011) 1–5. doi:10.1007/s10827-011-0314-3.

[37] B. Hu, Information theory and its relation to machine learning, in: Proc. of the 9th Chinese Intelligent Automation Conf. (CIAC 2015), Springer, 2015, pp. 1–11. doi:10.1007/978-3-662-46469-4_1.

[38] E. T. Jaynes, Information theory and statistical mechanics, Physical review 106 (1957) 620–630. doi:10.1103/PhysRev.106.620.

[39] M. Feixas, A. Bardera, J. Rigau, Q. Xu, M. Sbert, Information theory tools for image processing, Synthesis Lectures on Computer Graphics and Animation 6 (2014) 1–164. doi:10.2200/S00560ED1V01Y201312CGR015.

[40] F. Attneave, Applications of information theory to psychology: A summary of basic concepts, methods, and results, Holt, 1959. URL: https://books.google.it/books?id=VnB9AAAAMAAJ.

[41] R. Girometti, F. Fabris, Informational analysis: A Shannon theoretic approach to measure the performance of a diagnostic test, Medical and Biological Engineering and Computing 53 (2015) 899–910. doi:10.1007/s11517-015-1294-7.

[42] A. Casagrande, F. Fabris, R. Girometti, Beyond kappa: An informational index for diagnostic agreement in dichotomous and multivalue ordered-categorical ratings, Medical and Biological Engineering and Computing 58 (2020) 3089–3099. doi:10.1007/s11517-020-02261-2.

[43] H. Theil, Economics and Information Theory, North-Holland Publishing Company, 1967. URL: https://search.worldcat.org/title/167102.

[44] K. Wu, B. Peng, H. Xie, Z. Huang, An information entropy method to quantify the degrees of decentralization for blockchain systems, in: Proc. of the 9th IEEE Int. Conf. on Electronics Information and Emergency Communication (ICEIEC 2019), IEEE Computer Society, 2019, pp. 1–6. doi:10.1109/ICEIEC.2019.8784631.

[45] S. P. Gochhayat, S. Shetty, R. Mukkamala, P. Foytik, G. A. Kamhoua, L. Njilla, Measuring decentrality in blockchain based systems, IEEE Access 8 (2020) 178372–178390. doi:10.1109/ACCESS.2020.3026577.

[46] A. G. Anagnostakis, E. Glavas, Entropy and stability in blockchain consensus dynamics, Information 16 (2025) 1–18. doi:10.3390/info16020138.

[47] N. Rodriguez-Rodriguez, O. Miramontes, Shannon entropy: An econophysical approach to cryptocurrency portfolios, Entropy 24 (2022) 1–15. doi:10.3390/e24111583.

[48] CoinMetrics, Network data pro overview, 2025. URL: https://docs.coinmetrics.io/network-data/network-data-overview, accessed: 2025-09-08.

[49] M. Bardoscia, G. Livan, M. Marsili, Statistical mechanics of complex economies, Journal of Statistical Mechanics: Theory and Experiment 2017 (2017) 1–30. URL: 10.1088/1742-5468/aa6688.

[50] Economic Commission for Latin America and the Caribbean (ECLAC), Methods of measuring the economy, efficiency and effectiveness of public expenditure, 2015. URL: https://www.cepal.org/sites/default/files/project/files/annex_7_methods_of_measuring_economy_efficiency_and_effectivenes.pdf.

[51] N. Bhintade, Understanding wealth distribution with Gini and Nakamoto coefficients, 2023. URL: https://bitquery.io/blog/wealth-distribution-in-token-economy.

[52] V. Makarskyy, Cryptoeconomic theory: Pareto efficiency, 2018. URL: https://medium.com/blockchannel/cryptoeconomic-theory-pareto-efficiency-89d34664f9d#:~:text=An%20outcome%20is%20called%20Pareto,without%20making%20anyone%20worse%20off.

[53] Z. Sebestyén, V. Juhász, The impact of the cost of unused capacity on production planning of flexible manufacturing systems, Periodica Polytechnica Social and Management Sciences 11 (2003) 185–200. URL: https://pp.bme.hu/so/article/view/1688.

[54] B. Kusmierz, R. Overko, How centralized is decentralized? Comparison of wealth distribution in coins and tokens, in: Proc. of the 3rd IEEE Int. Conf. on Omni-layer Intelligent Systems (COINS 2022), IEEE Computer Society, 2022, pp. 1–6. doi:10.1109/COINS54846.2022.9854972.
[55] T. Bakhtiar, X. Luo, I. Adelopo, Network effects and store-of-value features in the cryptocurrency market, Technology in Society 74 (2023) 1–12. doi:10.1016/j.techsoc.2023.102320.
[56] R. Moncada, E. Ferro, M. Fiaschetti, F. Medda, Blockchain tokens, price volatility, and active user base: An empirical analysis based on tokenomics, Int. Journal of Financial Studies 12 (2024) 1–30. doi:10.3390/ijfs12040107.
[57] C. Mattsson, Networks of monetary flow at native resolution, 2019. URL: https://arxiv.org/abs/1910.05596.
[58] OECD, European Union, European Commission, Joint Research Centre, Handbook on Constructing Composite Indicators: Methodology and User Guide, OECD Publishing, 2008. doi:10.1787/9789264043466-en.
[59] A. P. M. Mazziotta, Methods for constructing composite indices: One for all or all for one? 67 (2013) 67–80. URL: https://ideas.repec.org/a/ite/iteeco/130210.html.
[60] M. Mazziotta, A. Pareto, A non-compensatory approach for the measurement of the quality of life, in: Quality of life in Italy: Research and reflections, Springer, 2012, pp. 27–40. doi:10.1007/978-94-007-3898-0_3.
[61] T. M. Cover, J. A. Thomas, Elements of information theory, John Wiley & Sons, 1999. doi:10.1002/047174882X.
[62] J. Aczél, Z. Daróczy, On measures of information and their characterizations, volume 115 of *Mathematics in Science and Engineering*, Academic Press, 1975. URL: https://books.google.com/books?id=wd0TMQAACAAJ.
[63] I. Csiszár, Axiomatic characterizations of information measures, Entropy 10 (2008) 261–273. doi:10.3390/e10030261.
[64] M. Beliş, S. Guiaşu, A quantitative-qualitative measure of information in cybernetic systems, IEEE Trans. on Information Theory 14 (1968) 593–594. doi:10.1109/TIT.1968.1054185.
[65] Bitquery, Blockchain API and crypto data products, 2025. URL: https://bitquery.io/, accessed: 2025-09-08.
[66] Glassnode, On-chain market intelligence, 2025. URL: https://glassnode.com/, accessed: 2025-09-08.
[67] Blockdaemon, 2024. URL: https://www.blockdaemon.com/, accessed: 2025-09-08.
[68] Blockchair, 2024. URL: https://blockchair.com/it, accessed: 2025-09-08.
[69] Bitnodes, 2025. URL: https://bitnodes.io/, accessed: 2025-09-08.
[70] bitfly explorer, Clients - ethernodes.org - The Ethereum network and Node explorer, 2025. URL: https://www.ethernodes.org/, accessed: 2025-09-08.
[71] X. Ledger, Faq, 2025. URL: https://xrpl.org/about/faq, accessed: 2025-09-08.
[72] T. Sikder, Why is Dogecoin down? 69% node crash due to network vulnerability, 2024. URL: https://www.financemagnates.com/trending/why-is-dogecoin-down-69-node-crash-due-to-network-vulnerability/, accessed: 2025-09-08.