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Foundations of Cryptoeconomic Systems

By Shermin Voshmgir and Michael Zargham*

Blockchain networks and similar cryptoeconomic networks are systems, specifically complex systems. They are adaptive networks with multi-scale spatiotemporal dynamics. Individual actions towards a collective goal are incentivized with "purpose-driven" tokens. These tokens are equipped with cryptoeconomic mechanisms allowing a decentralized network to simultaneously maintain a universal state layer, support peer-to-peer settlement, and incentivize collective action. These networks therefore provide a mission-critical and safety-critical regulatory infrastructure for autonomous agents in untrusted economic networks. They also provide a rich, real-time data set reflecting all economic activities in their systems. Advances in network science and data science can thus be leveraged to design and analyze these economic systems in a manner consistent with the best practices of modern systems engineering. Research that reflects all aspects of these socioeconomic networks needs (i) a complex systems approach, (ii) interdisciplinary research, and (iii) a combination of economic and engineering methods, here referred to as "economic systems engineering," for the regulation and control of these socio-economic systems. This manuscript provides foundations for further research activities that build on these assumptions, including specific research questions and methodologies for future research in this field.

I. Introduction

Cryptoeconomics is an emerging field of economic coordination games in cryptographically secured peer-to-peer networks. The term cryptoeconomics was casually coined in the developer community. The earliest recording is a citation from a talk by Vlad Zamfir in 2015 (Zamfir, 2015), which was later loosely formalized in blog posts and talks by Vitalik Buterin (Buterin, 2017a), (Buterin, 2017b). The term gained traction by the developer community (Tomaino, 2017a) and the by the academic community (Berg, Davidson and Potts, 2019) but it still remains under-defined, possibly because it is often used in different contexts. Using the same term in different contexts leads to different meanings and communication breakdowns when trying to come up with a general purpose definition of that term. This paper explores why the term "cryptoeconomics" is context dependent and proposes complementary micro, meso and macro definitions of the term. These context dependent definitions build on the perspectives outlined in this paper regarding the nature of cryptoeconomic systems such as the Bitcoin Network, and provides a foundation for further research in the area of cryptoeconomic systems.

II. A Complex Systems Perspective

Systems theory (Bertalanffy, 1969) (Meadows, 2008) provides a means to describe any system by its structure, purpose, functioning, as well as spatial and temporal boundaries, including its inter-dependencies with its environments (Moffatt and Kohler, 2008) (Parrott and Lange, 2013).

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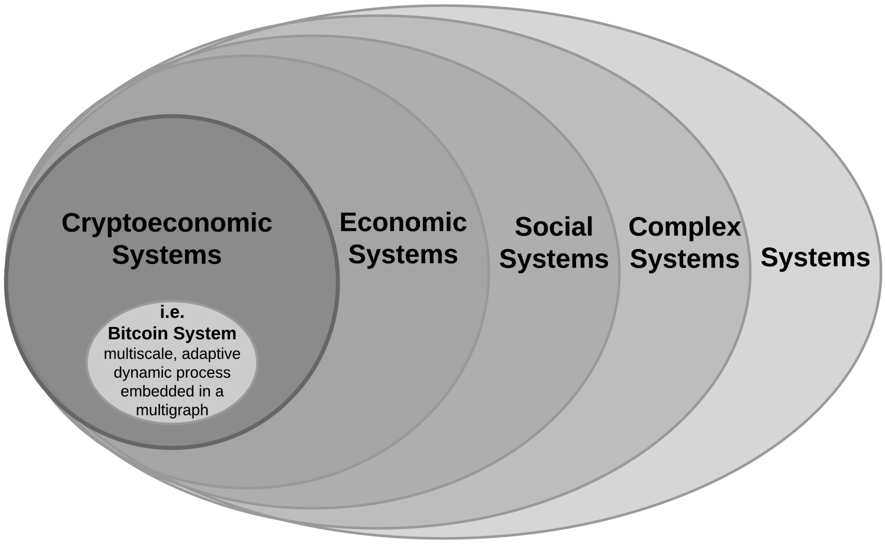

Figure 1. Cryptoeconomic systems are complex socio-economic systems.

Complex systems theory investigates the relationships between system parts with the system's collective behaviors and the system's environment (Nagel, 2012).

Complex systems differ from other systems, in that the system behaviour cannot be easily inferred from the state changes induced by network actors (Parrott and Lange, 2013). Modeling approaches that ignore such difficulties will produce models that are not useful for modeling and steering those system.

Properties such as emergence, nonlinearity, adaptation, spontaneous order, and feedback loops are typical to complex systems (Bar-Yam, 2002). Complex systems research draws contributions from various scientific domains such as mathematics, biology, physics, psychology, meteorology, sociology, economics, and engineering (Parrott and Lange, 2013) which all contribute to complexity science, leveraging both analysis and synthesis; analytic processes reduce systems to better understand their parts, whereas synthesis is required to understand the whole as greater than the sum of its parts (Quine, 1951).

Systems theory can contribute tools for the analysis of how the relationships and dependencies between a cryptoeconomic systems' parts can determine system-wide properties. It allows for the discovery of system's dynamics, constraints, conditions and principles of cryptoeconomic networks with the aim to understand, model and steer them.

A cryptoeconomic system like the Bitcoin Network can be described as a special class of complex socioeconomic system that is dynamic, adaptive and multi-scale. Cryptoeconomic networks are dynamic due to the flow of information and assets through the network. Cryptoeconomic networks are adaptive because their behaviour adjusts in response to their environment, either directly in the case of the Bitcoin difficulty controller or more broadly through decisions on the part of node operators. Cryptoeconomic networks are multi-scale because they are specified by local protocols but are defined by their macro-scale properties, as is the case with the local "no double spend" rule guaranteeing a globally conserved token supply (Zargham, Zhang and Preciado, 2018). Their design requires a strong interdisciplinary approach to develop resilient protocols that account for their spatial and temporal dynamics of those networks (Liaskos, Wang and Alimohammadi, 2019).

III. An Interdisciplinary Perspective

Interdisciplinary research has been identified as an appropriate research method when (i) the research subject involves complex systems and when (ii) the research question is not confined to a single discipline (Repko, 2008). The necessity of an interdisciplinary approach to the research of complex systems has been addressed by General Systems Theory (Bertalanffy, 1969), in particular Cybernetics (Wiener, 1965), (Barkley Rosser, 2010). Economists like Friedrich Hayek for example were influenced by the interdisciplinary field of Cybernetics which leveraged systems theory methods available in his time (Oliva, 2016), (Lange, 2014).

The interdisciplinary research process is often heuristic, iterative and reflexive, and borrows methods from specific disciplines, where appropriate. It is deeply rooted in the disciplines, but offers a corrective to the disciplinary way of knowledge creation (Dezure, 1999) transcending disciplinary knowledge via the process called integration (Repko, 2008). While disciplines are regarded as foundational, they are also regarded as inadequate to address complex problems, sacrificing comprehensiveness and neglecting important research questions that fall outside disciplinary boundaries. Given the fact that blockchain networks and similar crptoeconomic systems provide a governance infrastructure (Voshmgir, 2017) for socio-economic activities, a symbiosis of both disciplinary and interdisciplinary research is needed to achieve the necessary breath and depth related to complex systems (Repko, 2008).

The research process includes: (i) identification of relevant disciplines, (ii) mapping research questions to identify the disciplinary parts, (iii) reducing the number of potentially relevant disciplines, (iv) literature review in relevant disciplines and for relevant research questions, (v) developing adequacy in relevant disciplines, (vi) analyzing problems and evaluating insights, (vii) integrating insights and creating common ground for insights (Repko, 2008).

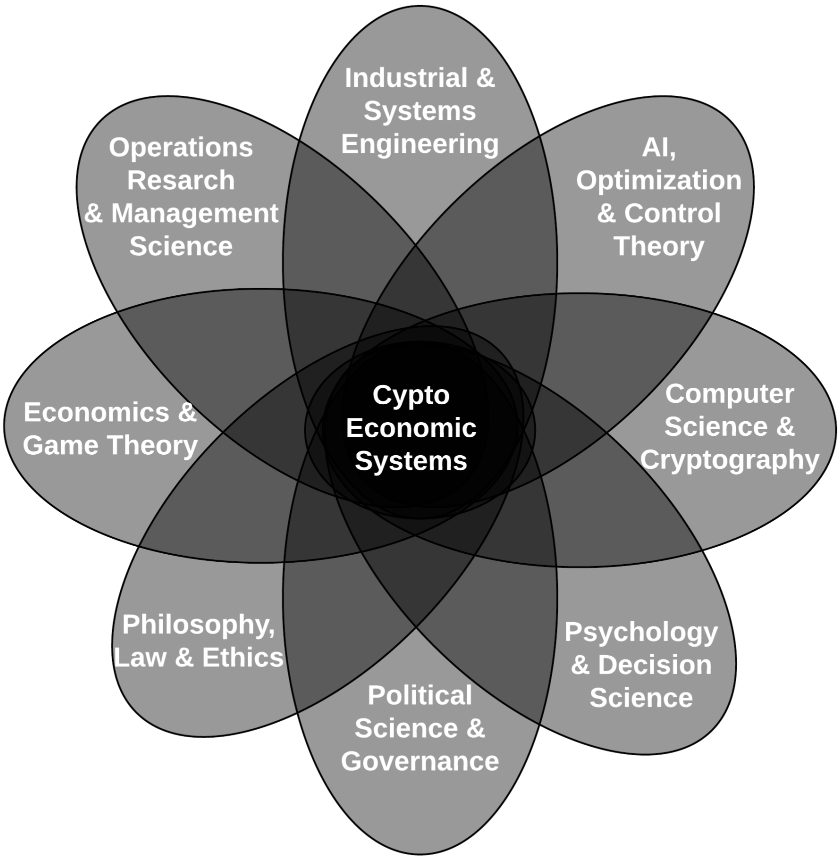

Figure 2. Venn diagram of disciplines related to cryptoeconomic systems engineering.

Relevant disciplines include Operations Research and Management Science, Industrial and Systems Engineering, AI, Optimization and Control Theory, Computer Science and Cryptography, Psychology and Decisions Science, Political Science and Governance, Philosophy, Law and Ethics, as well as Economics and Game Theory. The wide range of disciplines may seem arbitrary but they are in fact bound by a central concept: allocation of resources. In particular, cryptoeconomic networks provide coordination and scaling for resource allocation decisions of stakeholders with unique preferences, information, and capabilities. Allocation decisions being made include resources which are (i) physical such as hardware and electricity, (ii) financial such as tokens or fiat money, and (iii) social such as attention, e.g. governance participation, code contributions or evangelism. Envisioning, designing and governing cryptoeconomic systems requires the following questions to be considered:

- Who gets to make which decisions, under which circumstances, and to whom are they accountable for those decisions? Furthermore, how does this change over time?
- How do individuals make decisions given knowledge of the rules of the system, and subject to uncertainty about the decisions of others?
- How can a system be engineered to processes individual decision making into collective decision making such that system may be interpreted as coordinating toward a shared purpose?

Unsurprisingly, disciplinary bias and disciplinary jargon (Repko, 2008) are challenges that need to be overcome in the interdisciplinary research process. Addressing this class of challenges adequately in cryptoeconomics research will be crucial to advancing research in this field. The existence of disciplinary jargon will require the development of a common language, or a Rosetta Stone (Gilbert, 1998) to facilitate cross disciplinary communication. Autoethnographic experience of the authors has furthermore shown that multidisciplinary teams members require methods to facilitate the transfer of the state of knowledge between researchers of different disciplines. These “knowledge state updates” require time and effort and make the research process slower than in disciplinary research setups.

IV. The Evolution of Cooperation Perspective

While cryptoeconomics is interdisciplinary by nature, it has so far predominantly been developed in the computer science community. The economic assumptions made and methods used in most existing protocols are rather limited compared with the existing body of relevant literature. There is still much room to incorporate methods from various economic disciplines, that are very often interdisciplinary in themselves, like for example political economy (political science) or behavioural economics (cognitive psychology) and business law (legal studies) (Voshmgir, 2019a). The idea, for example, that the coordination of a cryptoeconomic system is derived from pure self-interest of individual actors is a conjecture, which while useful as a narrative is unlikely to be factual. For example, the Miner’s Dilemma (Eyal, 2015) implies that the observed mining pools would break down under pure selfishness. The mathematical and game theoretic arguments about cryptoeconomic networks are based on the canonical results on the evolution of cooperation in an iterative prisoners dilemma (Axelrod and Hamilton, 1981), (Rapoport, Chammah and Orwant, 1965). These results demonstrate that coordination is possible (sufficient condition) in the presence of selfish actors, not that it is ‘only possible’ (necessary conditions) in the presence of selfish actors. Therefore, it is entirely possible and actually more likely that cryptoeconomic systems exist as a result of a mixture of strategies, also referred to as norms as in more recent work on the evolution of cooperation (Yamamoto et al., 2017), (Peters and Adamou, 2019). The iterated prisoner’s dilemma is an approximation of a complex social phenomena, (Axelrod, 1997), and continued study has provided additional insights around concepts such as indirect reciprocity (Nowak, 2006) and meta-incentives (Okada et al., 2015), which are directly relevant to the study of cryptoeconomics, in so far as it is viewed as means to engineer incentives that make cooperative norms resistant to invasion by selfish ones in cryptoeconomic networks. In the evolution of cooperation literature theoretical, computational and empirical methods are applied to the study of populations of agents making individual decisions according to certain strategies, with an emphasis on the non-obvious system level properties that arise, and how these properties induce changes in future behavior.

V. A Multiscale Perspective

Economic systems are often observed to have properties that are not directly attributable to the agents, processes and policies that make up the economic system. Understanding the emergent properties as arising from relationships between the agents, processes and policies requires the multiscale perspective. Through a synthesis of these perspectives on multi-scale systems, a basic formula for framing practical economic models is shown in Figure 3. Any model requires assumptions about the properties of its constituent parts and assumptions about the environment or larger system in which the model is embedded. Couched in economic terms the model of the larger system provides macro-economic context and the models of the constituent parts provide micro-economic foundations.

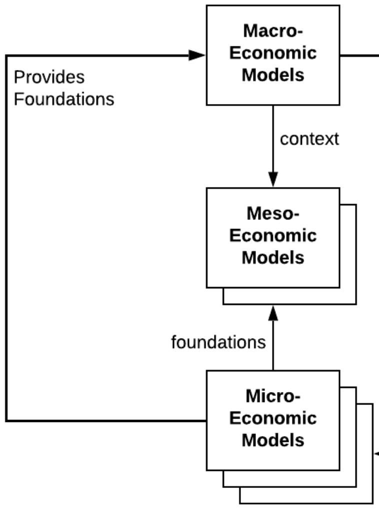

Figure 3. Micro-Economic foundations and Macro-Economic context together form the basis of a multi-scale model required to capture interscale effects common in complex systems.

Applying a multiscale perspective to economic systems is not a new idea. It has been addressed implicitly by representatives of the Austrian School of Economics, and also other heterodox economic schools including Complexity Economics (Foster, 2005), (Montuori, 2005), (Bateson et al., 1989) and Ecological Economics (Common and Stagl, 2005), (Schumacher, 2011). While Ecological Economics was originally motivated by ecology rather than systems theory, it also criticized the failings of the orthodox economic canon in addressing the complex dynamics that arise when there are interaction effects between parts and wholes with special attention to human activity as being a part of the natural world. A recently yet widely accepted idea in macroeconomics, the Lucas Critique (Lucas, 1976) explicitly addresses feedback effects between micro and macro scale behavior. The need for multiscale representations is further borne out in Evolutionary Economics (Dopfer, Foster and Potts, 2004) and in the standard practice of systems engineering (Hamelin, Walden and Krueger, 2010).

Through the multiscale perspective, it is possible to study interscale phenomena such as *emergence* as shown in Figure 4. "Emergence (...) refers to the arising of novel and coherent structures, patterns and properties during the process of self organization in complex systems. Emergent phenomena are conceptualized as occurring on the macro level in contrast to the micro level components and processes out of which they arise." (Goldstein, 1999).

Emergence closes the feedback loop of the macro, meso and micro level activities where policy makers measure phenomena on a macro level, decide over new policies on a meso level, and implement these policies impacting agent behavior a micro level, which in turn result in systemic effects that can only be measured on a macro level. An example of *Multi-scale feedback* in the Bitcoin Network is the interaction between the proof-of-work game being played between

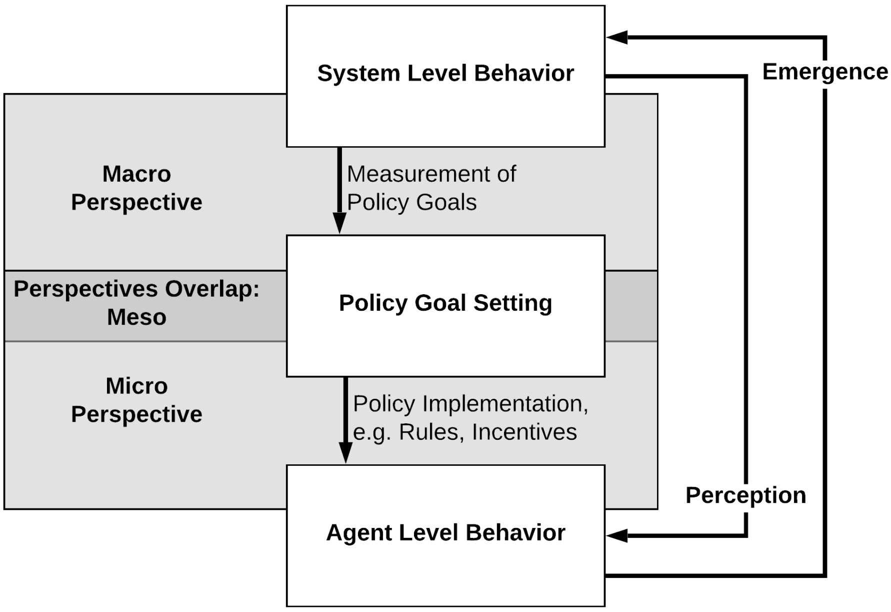

Figure 4. Multi-Scale Feedback: In cryptoeconomic networks the system level behavior emerges from the agent level behavior responding to rules and incentives implemented as part of cryptoeconomic policy design.

the agents (miners), and the Bitcoin Network itself. By introducing a feedback loop to correct the difficulty[1] and maintain the ten minute block time, the system itself becomes part of the game. One way of viewing this macro-scale game is as a two player game between the miners as a population and the network itself. The miners as a collective have their action space defined by the total hashpower provided and the network's action space is to set the difficulty. Even though all of the miners know what strategy the network is playing, the fact that they are still playing a micro-scale game with each other leads to increases in hashpower despite the fact that this is objectively more expensive than providing less hashpower for the same predetermined block rewards. This example shows the necessity of multi-scale models for cryptoeconomic systems because neither the micro-scale game played between the entities running nodes, nor the macro-scale game between the Bitcoin Network and miners is sufficient to characterize the system dynamics.

VI. A Network Science Perspective

A cryptoeconomic system is a kind of complex system that can be represented by interacting components that collectively form a network. Informally, a network is a group or system of interconnected people or things. A formal mathematical definition of a network is a graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$ made up of a set of vertices $\mathcal{V}$ and set of edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$. The edges are simply pairs of vertices and when the order of the vertices matters, the edge (i, j) is said to be directed from i to j. Applying graph theory to study social and economic networks is called network science and therefore relevant in the context of analyzing and modeling cryptoeconomic systems.

As networks grow the number of relationships between entities quickly dwarfs the number of entities in the network (Dorogovtsev and Mendes, 2004). Furthermore, the topology of the network itself can have significant influence on processes playing out within the network (Newman, 2010) (Boccaletti et al., 2006). The interactions between the parts of the system, including agent

[1]To compensate for increasing hardware speed and varying interest in running nodes over time, the proof-of-work difficulty is determined by a moving average targeting an average number of blocks per hour. If they're generated too fast, the difficulty increases.(Nakamoto, 2008)

behaviors, and between the system and its environment often result in unexpected emergent properties, which in practice necessitates some form of human governance for cryptoeconomic networks (Voshmgir, 2019a). A cryptoeconomic system like a blockchain network is a multi-graph because it has different types of vertices and edges which include labeling maps for the vertices and edges. Depending on the type of network the vertices can be: (i) *nodes* representing computer software in the peer to peer *computation and communication network*, (ii) *accounts* are addresses in the *financial network*, (iii) *entities* are identities of people and organizations in an off-chain *socioeconomic network*. Vertices are depicted in Table 1.

Vertex Type	**Definition**
Entity	Off-chain unique identity of a person or organization
Account	On-chain address controllable via a private key
Node	Software and hardware participating in a peer-to-peer network

Table 1— Vertex Types & Definitions in the Bitcoin System

	Entity	**Account**	**Node**
Entity	has relationship with	controls keys of	operates
Account		transfers funds to	
Node		sends rewards to	is peer of

Table 2— Edge types and definitions to be read as directed edges from column to row.

A cryptoeconomic network consists of three interconnected networks: (i) the *computation and communication network* comprised of *nodes* that leverage a peer-to-peer protocol to validate transactions by mining new blocks, (ii) the *financial network* comprised of Bitcoin *addresses* which may sign transactions and transfer funds, and the (iii) the off-chain *socioeconomic network* representing people and organizations that control the tokens in the financial network and operate those nodes in the computation and communication network. As a summary of the types of edges is provided in table 2. Incidentally, this hierarchical layering of networks is consistent with strategies for optimization decomposition (Chiang et al., 2007) providing a formal basis vertically integrated network economies. In blockchain networks, the base layer data structure comes with cryptographic guaranties, but does not represent a human readable ledger, rather a formal mapping to the statespace representation is required to lift the data from its hash space to the record of accounts, which is recognizable as a ledger (Shorish, 2018).

VII. Tokens as System State

Tokens represent a part of the state of any cryptoeconomic systems and can be seen as their atomic unit. Universal state refers to a unique set of data (the ledger) that is collectively managed by all nodes is the network. Tokens are a representation of an individualized state of an economic system, including a specific right to change the system state. The existence of a universal state (Voshmgir, 2019a) makes tokens provable and durable and is a solution to the double spending (Nakamoto, 2008) of digital values over the public networks. The existence of tokens in general and digital tokens in particular is not new. Cryptoeconomic systems, however, provide a public infrastructure that allow the issuance and management of tokens at a fraction of transaction costs (Voshmgir, 2019a). The speed with which cryptoeconomic systems and their tokenized applications are being deployed, is an indicator for the pervasiveness of the technology and its applications (Filippova, 2019). Tokens, as the atomic unit of state, can make all socio-economic activities visible. However, it is unclear if and when the tokenization of all economic activities will become feasible.

Asset tokens and access-right tokens (Voshmgir, 2019a) represent business and governance systems that are mostly well understood, and can be categorized as "simple token systems". They can be modeled and steered with existing reductionist tools, which explain systems in terms of their constituent parts and the individual interactions between them (Lipset, 1980), often, but not always, reducing systems to the sum of its parts (Ruse, 2005).

Purpose-driven tokens are tokens that are programmed to steer automated collective action of autonomous network actors in a public network towards a collective goal in the absence of intermediaries (Voshmgir, 2019b). They represent "complex token systems" and require complex system approach (Foster and Metcalfe, 2012)(Kurtz and Snowden, 2003) to be modelled. Purpose-driven tokens that enable complex token systems differ from simple token systems in that they close the loop in so far as the system becomes autonomous and is not being steered by single institutions.

Simple token systems require mostly "legal engineering", which we define as the intersections of information systems and legal studies and deals with the question of how to make these tokenized use cases regulatory compliant. Complex token systems requires mostly "economic systems engineering", which we define on the intersection of information systems and economics including political economy and other related social science domains. Economic systems engineering can build on systems engineering (Sage, 1992), (Blanchard and Fabrycky, 1990),(Novikov, 2016), but deals with research questions that model and steer aggregate agent behaviour, which brings us into the emerging field of complex systems engineering (Bar-Yam, 2003) (Rhodes and Hastings, n.d.).

VIII. A Unifying Perspective on Cryptoeconomics

Cryptoeconomic systems are complex socioeconomic networks defined by (i) individual autonomous actors, (ii) economic policies embedded in software and (iii) emergent properties arising from the interactions of those actors according to the rules defined by that software. A comprehensive definition of cryptoeconomics therefore includes three levels of analysis: (i) micro-foundational, relating to agent level behaviors (ii) meso-institutional, relating to policy setting and governance and (iii) macro-observerable, relating to the measurement and analysis the system level metrics.

"Micro-foundational" characteristics of cryptoeconomic systems are commonly expressed in terms of algorithmic game theory in the computer science literature (Nisan et al., 2007) and mechanism design in the economics literature (Hurwicz and Reiter, 2006). Mechanism design is sometimes referred to as reverse game theory as it pertains to the construction of games to produce specific behaviors from agents. Nakamoto Consensesus is a cryptoeconomic mechanism designed to provide an equilibrium such that a public and permissionless network is resistant to attack. An attack would be any violation of the state transition rules encoded in the protocol; one such attack is a double spend. Nakamoto consensus uses a combination of cryptographic tools with economic incentives that make economic cost of wrongdoing disproportionate to the benefit of doing so (Voshmgir, 2019a). Proof-of-stake mechanisms provide similar game theoretic arguments for network security. Most current definitions of cryptoeconomics focus on this level of analysis and modeling (Buterin, 2017a), (Buterin, 2017b) (Tomaino, 2017a).

However, the level of security very much depends on how people react to economic incentives, which in turn has been a field of study in economics (Voshmgir, 2019a); the security of the network is an emergent macro level property. "Macro-observables" are system-wide metrics or properties which may inform decision-making of stakeholders within the system. Macro-observables often include performance indicators that impact governance decisions at the meso-institutional level as well as measures that can impact perception and thus behavior at the micro-foundational level. In addition to security, market capitalization, price (Shorish, 2019), (Cong, Li and Wang, 2019) and price stability are the most commonly studied macro-observables. These macro properties are integrated into the governance feedback loop on the meso level.

"Meso-institutional" characteristics encompass decision-making and goal determination, based upon macro-observables and requiring micro-foundations. This level builds on political science,

Table 3. Cryptoeconomics*

Level of Analysis	Economic Perspective	Governance Perspective	Design Perspective	Bitcoin Reference
Macro[a]	Global Outcomes	Policy Goals Measurement	Performance Metrics	Stability, Security, etc.
Meso[b]	Institutional Dynamics	Policy Goal Setting	Performance Targets	Informal Governance[†]
Micro[c]	Protocol Foundations	Implementation of Incentives	Asserted Properties	Nakamoto Consensus

*Cryptoeconomics relates three interactions layers or *levels of analysis* that define characteristics at the micro-foundational, meso-institutional, and macro-observerable domains of scope.

[a]**Macro-observables** are system global properties that inform decision-making at the meso-institutional level and provide stakeholder feedback, performance indicators and measures that can impact micro-foundational properties.

[b]**Meso-institutional** characteristics encompass decision-making and goal determination, based upon and requiring micro-foundations. Mechanism design as used in Economics informs institutions, organisations and teams.

[c]**Micro-foundational** characteristics are assumption specifications with a natural expression within mechanism design as used within Computer Science.

[†]**Informal Governance** is a form of decentralized governance whereby changes to the protocol are made locally by individual participants operating nodes in the peer-to-peer network and changes only take effect if the majority of participants adopt the change. In the case of Nakamoto Consensus such a majority is measured in hashpower.

law, governance and economics to design the steering processes of communities, by some referred to as institutional cryptoeconomics (Berg, Davidson and Potts, 2019). Ethical design and informed governance of cryptoeconomic systems resides in the meso-institutional level and requires an understanding of both the micro-foundations, macro-observables as well as the relations between them.

IX. Research Directions

Drawing upon the assumptions outlined in this paper, cryptoeconomic systems provide a institutional infrastructure that facilitates a wide range of socio-economic interactions. The design space for this infrastructure includes novel interaction patterns thanks to the peer-to-peer protocols support for state dependence via tokens. Research regarding the analysis and design of cryptoeconomic systems is necessarily interdisciplinary. Building on other interdisciplinary research future work includes but is not limited to the following topics: (a) purpose-driven tokens, (b) data driven economies, (c) ethics of decision algorithms as social infrastructure, (d) applying computational social science to cryptoeconomic systems, (e) applying cyberphysical systems engineering to cryptoeconomic design and analysis.

A. Purpose-Driven Tokens

Bitcoin's "Proof-of-Work" (Nakamoto, 2008) introduced an incentive mechanism to get network actors to collectively manage a distributed ledger in a truthful manner, by rewarding them with network tokens which are minted upon "proof-of" a certain behaviour. The idea of aligning incentives among a tribe of anonymous actors with a network token, introduced a new type of public infrastructure that is autonomous, self-sustaining, and attack resistant (Voshmgir, 2019b). Such networks, therefore, represent a collectively produced and collectively consumed economic infrastructure. This common economic infrastructure can be viewed as a commons whose design and governance should be held to Ostrom's principles (Ostrom, 1990). If there is an underlying optimal choice to be uncovered through a social process there is some hope that this optimal could be learned via a consensus process, (Jadbabaie et al., 2012). However, it is more realistic to take a polycentric viewpoint where there is no one social optimal and thus it is important to take a wider view of social choice (Arrow, 2012) (Ostrom, 2000) before embarking on the design of a purpose-driven token. After all any choice of coordination objective is a subjective choice. Assuming one can define a common objective, the token designer would encode this objective as a cost function and strive for dynamic stability around a minimum cost outcome over time as is done with dynamic potential games (Candogan, Ozdaglar and Parrilo, 2013), swarm robotics (Gazi and Passino, 2003) and vehicle formations(Olfati-Saber and Murray, 2002). In all cases the design goal is strong emergence around some objective (Klein et al., 2001). It is also possible to envisage the objective selection process as dynamic consensus (Kia et al., 2019). Broadly speaking purpose-driven token design lives at the boundary of behavioral economics and dynamic decentralized coordination in multi-agent systems which bridges with institutional economics(Coase, 1998), and in particular platform economics (Rochet and Tirole, 2003).

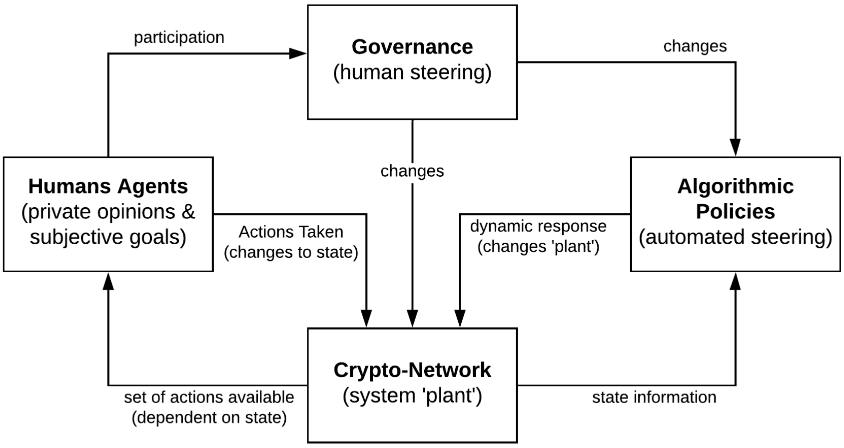

Figure 5. Governance feedback loop of cryptoeconomic systems

B. *Data Driven Economic Systems*

Cryptoeconomic systems provide near real-time data of on-chain economic activities, and may govern access rights or provide proofs related to data stored off-chain. The advancement in machine learning and system identification methods over the past decade has increased our capacity for creating novel, useful models in across a wide range of applications (Jordan and Mitchell, 2015), and in the context of economics (Mullainathan and Spiess, 2017) in particular. This, for the first time, allows for almost real time steering of these economies and a level of applied cybernetics that was not possible before. Furthermore, it increases the precision of modeling and measurement required for steering these economies. This results in a data driven regulatory process, as shown in Figure 5.

However, the advances of machine learned models (Jordan and Mitchell, 2015) is a consequence of the growth of the digital economy that captures a large amount of economic data. This data is largely controlled by large tech firms operating platform based services which are often subject to algorithmic bias (Garcia, 2016), (Lewis and Westlund, 2015),(Sætra, 2019), (Von Foerster, 2003). The stateful nature of cryptoeconomic systems has the potential to cede control over data back to the users of these platforms, if privacy by design is considered in the modeling of the cryptoeconomic systems and their applications (Voshmgir, 2019a).

C. Ethics and Governance of Decision Algorithms in Social Systems

Assumptions that are programmed into the cryptoeconomic protocols might be biased and will be subject to a line of ethical studies around how the associated cryptoeconomic systems behave over time. All algorithms are designed based on models; models are always reductions of reality based on some assumptions, and therefore must be judged by their usefulness to some ends,(Box, 1976). This places the focus on the assumptions embedded in the models and the effects those assumptions have on people. The machine learning and cryptoeconomic systems design communities share a common need to address ethical questions about the social-systemic effects of algorithm design and implementation (Orlikowski and Scott, 2015). To design or govern algorithms which make decisions requires a theory of fairness such as Rawl's Veil of Ignorance (Rawls, 1958) (Heidari et al., 2018). Fairness cannot be expected to emerge from purely self-interested agents because fairness provides a constraint on profit seeking behavior (Kahneman, Knetsch and Thaler, 1986). As a result, a code of ethics for algorithm designers, as found in other engineering disciplines (Pugh, 2009), is required.

Furthermore, it is important to note that data governance (Soares, 2015) is not equivalent to protocol governance. Data governance relates to the management of rights to read, write or manipulate data. Emerging data economies much respect regulations such as General Data Protection Regulation (Voigt and Von dem Bussche, 2017) and therefore one cannot simple store private or sensitive information in a public ledger where it cannot be deleted. However, data governance can be addressed through business process automation (Ter Hofstede et al., 2009) using smart contracts (Christidis and Devetsikiotis, 2016) which encode the aforementioned rights to read, write or manipulate data which is stored using other cryptographic technologies such as a content addressable distributed hash tables (Benet, 2014). Federated machine learning (Bonawitz et al., 2017)(Geyer, Klein and Nabi, 2017) is a growing area of research but practical implementation is hindered by the ethical and regulatory requirement that there are guarantees of privacy preservation (Ahmad, Stoyanov and Lovat, 2019).

D. Computational Social Science

Computational social science (Johnson and Lux, 2011), is a particularly relevant branch of interdisciplinary research for cryptoeconomic systems. The field of social science that uses computational approaches in studying the social phenomena (Cioffi-Revilla, 2016). Modern computational social science is much more deeply coupled with behavioral economics and data science where advanced computational statistics are combined with social networks, market dynamics, and more (Easley and Kleinberg, 2010), (Jackson, 2008). The advancing power of computation has lead some to refer to computational science as a "new kind of science" (Wolfram, 2002). This paradigm is backed up by an emerging computational epistemology (Kelly, 2000) (Blum and Blum, 1975) (Chaitin, 2011). It is precisely in the context of complex systems that counter-intuitive outcomes are common, and computational methods expose unforeseen pitfalls before they can cause irrecoverable harm (Forrester, 1971) (Merton, 1936). Computational methods in cryptoeconomic systems combine data science tools with system dynamics and agent based models to explore the relation between agent behavior and protocol design (Zhang, Zargham and Preciado, 2019). The approach of combining data, with theory and computation is consistent with methods in econophysics (Lux, 2009) and ergodicity economics (Peters and Adamou, 2018), though in the case of cryptoeconomics volume and precision of data available for backtesting models is higher.

E. Cyberphysical Systems Engineering

In the field of engineering, especially for large scale cyberphysical systems, computer aided design is standard practice,(Baheti and Gill, 2011) (Rajkumar et al., 2010). The United States National Science Foundation defines a cyberphysical system (CPS) as *a mechanism that is controlled or monitored by computer-based algorithms, tightly integrated with the Internet and its users. In cyberphysical systems, physical and software components are deeply intertwined,* *each operating on different spatial and temporal scales, exhibiting multiple and distinct behavioral modalities, and interacting with each other in a lot of ways that change with context* (NSF, 2010), (Lee, 2006).

Examples of existing cyberphysical systems include power grids and large scale transportation systems, which both share the property that behavior of uncontrolled human actors can create undesirable or even unsafe conditions in entirely counter-intuitive ways. A common criticism for using this analogy is the presence of attackers, but this a common concern in the CPS literature,(Cardenas et al., 2009),(Barreto et al., 2014). In practice, the design, operation and governance of such large scale systems is accomplished through computational models called digital twins, (Grieves and Vickers, 2017) (Uhlemann, Lehmann and Steinhilper, 2017) which are also closely related to the practice of model based systems engineering (Estefan et al., 2007). Model based systems engineering has previously been applied for multi-agent systems (DeLoach, Wood and Sparkman, 2001) (Fallah et al., 2010), and the relation from cryptoeconomic networks to cyberphysical systems has already been observed in the literature, (Bahga and Madisetti, 2016).

The systems engineering methodology (Hamelin, Walden and Krueger, 2010) as applied to cyberphysical systems relies on a composite of theoretical, computational and empirical methods (Banerjee et al., 2011); thus building on the experimental economic tradition (Roth, 2002) (Kagel and Roth, 2016). A natural path forward is to treat cryptoeconomic systems as cyberphysical systems and to approach them with the diligence an engineer must afford to any public infrastructure (Hou et al., 2015). As with other complex engineered systems, informed governance requires both specialized tools and expertise, so even when governance systems are polycentric the parties responsible for governance are accountable to public they serve (Walch, 2015)(Ostrom, 2010). To do so, it is necessary to develop a holistic perspective for cryptoeconomic systems which relates the locally implemented protocols, behavioral response to those mechanisms and the systemic properties that emerge therefrom.

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