From Local Incentives to Global Power Law Dynamics:

Modeling Bitcoin as a Multilevel Adaptive System

A. Pecere

"It might make sense just to get some in case it catches on. If enough people think the same way, that becomes a self fulfilling prophecy." – Satoshi Nakamoto, 2009.

Abstract:

This paper models Bitcoin adoption as a multilevel adaptive system whose evolution follows an empirical power-law, revealing structural equivalence between System Dynamics (SD) and Game Theory (GT) formulations. The study shows that individual, corporate, and institutional strategies generate self-similar diffusion patterns through locally coherent incentives. By deriving an SD model with cross-level positive feedbacks and demonstrating its equivalence to a dynamic multilevel coordination game, the paper establishes that Bitcoin's empirical power law reflects a fractal strategic equilibrium rather than stochastic growth. This dual SD⇄GT formalization provides a predictive, scale-invariant framework linking micro-level strategic optimization to macro-level structural dynamics. Methodologically, it unifies complexity theory, economics, and game theory; epistemologically, it redefines value as the persistence of systemic coherence across scales.

1. Introduction

The diffusion of Bitcoin represents one of the most significant cases of spontaneous and decentralized technological adoption in recent history. Unlike traditional innovations, its growth was not driven by a central authority but by a combination of local incentives, imitation, and coordination strategies among heterogeneous agents: individuals, firms, and governments, interconnected through informational and financial networks. The empirical trajectory of Bitcoin adoption follows a power-law over time, a feature common to self-organized complex systems. This behavior suggests that the underlying dynamics are neither purely stochastic nor linear, but express a form of distributed optimization consistent across scales: the same local rules generate the same aggregated morphology.

This paper proposes a theoretical model that integrates System Dynamics (SD) and Game Theory (GT) to explain Bitcoin's growth as a fractal equilibrium emerging from local strategies. In particular, it demonstrates that:

A) the adoption curve can be formally described by an SD model with inter-level positive feedbacks;

B) there exists a dynamic game among multi-level agents (individuals, firms, governments) whose Nash equilibrium reproduces the same dynamics;

C) the empirical power law is the geometric signature of this equilibrium.

The objectives of the paper are twofold:

1) to provide a concise mathematical formulation of Bitcoin diffusion as a dynamic system consistent with the observed power law;
2) to show how such a system can be derived from a multi-level coordination game with local, scale-invariant, and structurally predictive payoffs.

This interpretation offers a bridge between economics, game theory, and complexity science, suggesting that the diffusion of decentralized technologies like Bitcoin does not stem from central planning or mere imitation, but from local strategies coherent across scales.

2. Bitcoin, Adoption, and Power Laws

Since its introduction in 2009, Bitcoin has evolved its adoption domain following a remarkably regular pattern, despite the seemingly chaotic nature of the market. Empirical studies [Söderberg, 2015; Wheatley et al., 2019; Santostasi, 2024] show that the cumulative growth of active addresses, wallets with positive balances, price (measured in terms of USD, Gold, Oil, S&P500, and more), and hash rate follows power laws of the form:

$$N(t) \propto t^{\alpha}, \quad \alpha \in (1,2)$$

analogous to those observed in technological innovation diffusion, the growth of scale-free networks, and the propagation dynamics of ideas or languages.

Unlike classical adoption models [Bass, 1969; Rogers, 2003], which are based on contagion mechanisms and linear saturation, Bitcoin's dynamics exhibit scale self-similarity and the absence of a stable plateau: each new adoption threshold opens broader network spaces, extending the domain of the game. This behavior is typical of systems where the marginal gain of coordination grows faster than the installed base, producing nonlinear positive feedbacks. These properties place Bitcoin within the category of complex adaptive systems, in which the aggregation of local decisions generates a globally regular and predictable morphology. The fact that its growth pattern is described by a power law implies the existence of scale-invariant local strategies: the same choice rules apply to individuals, firms, and governments, differing only in informational constraints and perceived costs.

From a macroeconomic perspective, Bitcoin adoption is not a mere monetary substitution process but a distributed institutional transition. Agents do not react to an exogenous price but to a dynamic network equilibrium that alters the perceived value of participation itself. Diffusion therefore follows the logic of multi-level coordination games, in which individual benefit depends on the degree of collective participation. This makes Bitcoin an ideal testing ground for the SD⇄GT framework [Pecere, 2025]: on one hand, as a dynamic system with scalar feedbacks and self-similar growth; on the other, as a dynamic game among hierarchical agents, in which the strategic equilibrium generates the observed fractal power law. The objective of the following sections is to formalize this link by constructing a minimal SD model that reproduces the empirical adoption dynamics, and deriving the equivalent strategic game with locally predictive, scale-invariant payoffs.

3. Technological Adoption Models, Network Dynamics, and Game Theory

Traditional literature on innovation adoption starts with the Bass model (1969), according to which diffusion is driven by a contagion process between innovators and imitators. The resulting dynamics are logistically saturating, of the form:

$$\dot{x} = p(1 - x) + qx(1 - x)$$

where $x(t)$ is the share of adopters, p the innovation rate, and q the imitation rate. This framework describes well centralized innovations or those in mature markets, but it fails to capture emergent phenomena characterized by self-organization and endogenous feedbacks at the global scale. Subsequent extensions [Mahajan & Peterson, 1985; Goldenberg et al., 2001] introduced network effects and multi-level communication, yet remain constrained by assumptions of homogeneity and final saturation. Bitcoin, in contrast, exhibits no predefined market limit: the potential adoption pool expands as the system grows.

With the emergence of network science [Barabási & Albert, 1999; Newman, 2003], it has been observed that many real-world systems, from social networks to the Internet, follow power laws-like patterns in degree distributions and diffusion processes. Scale-free networks exhibit self-reinforcing dynamics: highly connected nodes attract new links according to a proportional-preference rule. Models such as those by Watts & Strogatz (1998) and Pastor-Satorras & Vespignani (2001) have shown that diffusion in such networks does not follow a sigmoidal limit but a fractal expansion: each aggregation level replicates the same statistical structure. The transition is therefore not logistic but self-similar. Bitcoin, as a decentralized network of nodes and incentives, belongs to this class: the probability that an individual or institution adopts grows proportionally to the number of already active connections and to the perceived value of the network itself (generalized Metcalfe effect).

From a strategic perspective, Bitcoin adoption has been analyzed as a coordination game with positive network externalities [Catalini & Gans, 2016; Huberman et al., 2021]. Each agent must decide whether to adopt a technology whose utility increases with the number of other adopters. The typical payoff is:

$$J_i = B(n_A) - C_i$$

where $B(n_A)$ is the benefit growing with the number of adopters n_A, and C_i the individual cost. Such models explain the presence of multiple equilibria (non-adoption, partial adoption, full adoption), but they overlook the dynamic and multi-level dimension of the process. Moreover, standard game theory considers a static set of players, whereas in Bitcoin, agents and their strategies evolve across scales, from individuals to collective entities, highlighting the need for a multi-level, self-similar formalization.

Recent literature on replicator dynamics [Nowak, 2006; Weibull, 1995] offers a natural bridge between diffusion models and game theory: higher-performing strategies replicate over time according to:

$$\dot{x}_i = x_i\left[f_i(x) - \bar{f}(x)\right]$$

Such a formulation, combined with the multi-level SD⇄GT structure, allows Bitcoin diffusion to be interpreted as a fractal dynamic game, in which each aggregation level locally optimizes a scale-invariant payoff, and the sum of strategies generates the observed power law. This approach unifies the epidemiological view of diffusion, the complex network of economic and social connections, and the strategic logic of game theory into a single formally coherent and predictive framework.

4. Formalization of the System Dynamics Model

We consider the diffusion of Bitcoin as a multi-level dynamic system composed of three categories of agents:

- Individuals (I): private users or investors;
- Firms (F): economic entities that accept or hold Bitcoin;
- Governments (G): institutions that regulate, tax, hold or integrate the technology.

Let $x_i(t),\ x_f(t),\ x_g(t)$ denote the respective cumulative adoption shares over time, expressed as fractions of the potential population at each level. The overall system is described by the state vector:

$$x(t) = \left[x_i(t), x_f(t), x_g(t)\right]$$

The dynamics follow a structure of cross-level feedbacks: Individual adoption fuels firm adoption via demand and reputation; firm adoption incentivizes governmental adoption through taxation and legitimization; government adoption feeds back onto individuals and firms by reducing institutional risk. The system thus presents multi-level positive feedbacks and can be represented by a set of nonlinear differential equations of the form:

$$\dot{x}_i = \alpha_i x_i^{\beta_i}(1 - x_i) f\left(x_f, x_g\right)$$

$$\dot{x}_f = \alpha_f x_f^{\beta_f}\left(1 - x_f\right) g\left(x_i, x_g\right)$$

$$\dot{x}_g = \alpha_g x_g^{\beta_g}\left(1 - x_g\right) h\left(x_i, x_f\right)$$

where f, g, h represent inter-level interactions, and the parameters $\alpha_k,\ \beta_k > 0$ control the speed and nonlinearity of the process.

For simplicity, we assume bilinear interdependencies with mutual reinforcement:

$$f\left(x_f, x_g\right) = 1 + \eta_{if} x_f + \eta_{ig} x_g$$

$$g\left(x_i, x_g\right) = 1 + \eta_{fi} x_i + \eta_{fg} x_g$$

$$h\left(x_i, x_f\right) = 1 + \eta_{gi} x_i + \eta_{gf} x_f$$

where $\eta_{kl} > 0$ measures the cross-level network effect. The system constructed in this way generates self-reinforcing feedbacks that, under scale-invariance conditions ($\beta_k \approx 1$), produce power-law trajectories of the type:

$$x_k(t) \sim t^{\mu_k}$$

with exponents μ_k determined by the interactions η_{kl}.

For the dynamics to be compatible with a stable power law, the system must be homogeneous of degree one with respect to temporal scaling:

$$F(\lambda x, \lambda^{\gamma} t) = \lambda F(x, t)$$

which implies a multiplicative structure in the feedback terms. This constraint leads to a replicative, self-similar model where each level follows the same strategic logic but with different scale coefficients. In this regime, the global system can be summarized by an aggregated equation:

$$\dot{X} = \alpha X^{\beta}(1 - X), \quad X = w_i x_i + w_f x_f + w_g x_g$$

where $X(t)$ represents the aggregated adoption level, and the weights w_k reflect the systemic influence of each level. For $\beta \neq 1$, the approximate analytical solution exhibits power-law growth with a dynamic exponent:

$$X(t) \approx (1 + ct)^{\frac{1}{1-\beta}} - 1$$

consistent with empirical observations of fractal growth in the Bitcoin network.

The SD model thus constructed represent a multi-level adaptive system. Each level acts as a semi-autonomous substructure whose adoption both influences and is influenced by the other levels. The presence of self-reinforcement and scale invariance implies that the system does not converge to a static equilibrium but evolves along a self-similar trajectory, where each adoption phase forms the foundation for the next. This behavior, absence of saturation, iterative reinforcement, and shape stability, is the dynamic signature of a fractal equilibrium and constitutes the starting point for deriving the equivalent strategic gam**e.**

5. Derivation of the Equivalent Strategic Game

Consider the three classes of agents: Individuals I, Firms F, and Governments G. For formal simplicity, represent the universe of agents as an indexed set:

$$A = I \cup F \cup G$$

Each agent $a \in A$ is associated with a controllable strategy:

$$s_a(t) \in S_a \subset L^2([0, T]; \mathbb{R})$$

representing the intensity of participation/adoption (e.g., probability of transacting in BTC, reserve share, decision to accept payments, active regulatory proposal). The aggregate variables $x_k(t)$ are functions of the s_a at each level $k \in \{i, f, g\}$.

To avoid tautological reverse-engineering (SD ⇒ GT with ex-post payoff construction), we impose that payoffs belong to the class of Structurally Predictive Payoff Functionals [Pecere, 2025], such that they satisfy P1-P5. A typical payoff for agent a is:

$$J_a[s_a; s_{-a}] = \int_0^T \quad B_a(X_{N_a}(t))\, u_a(s_a(t)) - C_a(s_a(t), \sigma_a(t)))\, dt + \Phi_a(X(T)),$$

where:

- N_a is the local neighborhood (P1) of the agent (e.g., network neighborhood, same industry, jurisdiction);
- $X_{N_a}(t)$ is the local aggregated state (adoption share in the neighborhood);
- $B_a(\cdot)$ is the network benefit: increasing in X_{N_a} and structure-rigid (P3, P5). Scale invariance requires homogeneity: $B_a(\lambda X) = \lambda^\kappa B_a(X)$ for some $\kappa > 0$ (P2);
- $u_a(s)$ is the utility function (saturating or linear), often $u_a(s) = s$ or $u_a(s) = \log(1 + s)$;
- C_a is the cost (transaction, compliance, risk): increasing in s, dependent on local volatility $\sigma_a(t)$, differentiable and analytic (P4–P5);
- Φ_a is a terminal payoff linked to future exposure (e.g., institutional value).

This form is interpretable, local, and can be made scale-invariant via parametric choices grounded in empirical power law observation, thus satisfying P1–P5.

To obtain dynamics that reconstruct $\dot{x}$, we propose a myopic gradient adjustment rule (myopic best-response in continuous time):

$$\dot{s}_a(t) = \gamma_a \nabla_{s_a} J_a[s_a; s_{-a}] = \gamma_a \big(B_a(X_{N_a}(t))\, u_a'(s_a(t)) - \partial_{s_a} C_a(s_a(t), \sigma_a(t))\big),$$

with $\gamma_a > 0$ as the adjustment rate. This standard choice (myopic adaptation, gradient learning) leads to an ODE system for the s_a. Aggregating strategies by level yields:

$$\dot{x}_k(t) = \sum_{a \in k} w_a \dot{s}_a(t) = G_k(x_i, x_f, x_g),$$

which, for appropriate weights w_a and functional choices of B_a, u_a, C_a, reduces to the dynamics proposed in Section 4. In particular, if $B_a \propto X_{N_a}^\kappa$ and $u_a'(s) \propto s^{\beta-1}$, thus the form:

$$\dot{x}_k \propto x_k^\beta (1 - x_k) f(\cdot)$$

naturally emerges. The choice of adjustment dynamics is model-dependent: different rules (discrete best-response, Bayesian learning, imitation) can produce equivalent first-order dynamics but differ in global stability and transient speed. Empirical validation is necessary to assess plausibility.

Now, let us define a strategy profile $s^*(\cdot)$ such that, for each agent a:

$$J_a[s_a^*; s_{-a}^*] \geq J_a[s_a; s_{-a}^*] \forall s_a \in S_a.$$

If payoffs are concave in s_a and adjustment rules converge (e.g., small γ_a, monotonicity), then $s^*(\cdot)$ is a dynamic equilibrium (Nash path). The corresponding state $x^*(t)$ satisfies:

$$\dot{x}(t) = F(x(t), s^*(t)),$$

with F as in Section 4: hence GT ⇒ SD mapping. Conversely, for a given SD trajectory $x^*(t)$ with regularity, there exist (non-unique) payoffs rendering s^* an equilibrium (SD ⇒ GT). P1–P5 restrict the admissible payoff class to avoid tautology.

Moreover, for the dynamic equilibrium to exhibit a power-law behavior $x_k(t) \propto t^{\mu_k}$, both payoffs and adjustment mechanisms must preserve scale consistency. In particular, individual payoffs must be homogeneous of degree $\kappa$with respect to the local state, and strategic adaptation must follow the same homogeneity principle. Formally, if for each agent a, the benefit function $B_a(X_{N_a})$ is homogeneous of degree $\kappa > 0$ such that $B_a(\lambda X) = \lambda^\kappa B_a(X)$, and both marginal utilities and costs scale as $u_a'(s) \propto s^{\beta-1}$ and $C_a'(s) \propto s^{\beta-1}$, then local interactions aggregate multiplicatively, ensuring system-wide homogeneity. Then non-trivial solutions of the myopic adjustment system satisfy, under transient regime and compact initial conditions, a temporal power-law scaling:

$$x_k(t) \sim c_k t^{\mu_k}, \qquad \mu_k = \frac{\kappa}{1-\beta} \quad (\text{for } \beta < 1).$$

Homogeneity of functions renders the ODE system homogeneous; rescaling time and state yields self-similar solutions; solving $\dot{x} \propto x^\beta$ produces the above power law. This is sufficient but not necessary; the exponent μ_k strongly depends on β, κ, which must be anchored to empirical data or micro-behavioral models to be predictive.

Dynamic equilibrium may be multiple (typical of coordination games). Local stability is assessed by linearizing the aggregated equations:

$$\delta\dot{x} = J(x^*)\delta x, \qquad J = \frac{\partial G}{\partial x}\Big|_{x^*}.$$

If eigenvalues of J have negative real parts, the equilibrium is locally asymptotically stable. Strong self-reinforcing terms (η_{kl} large) may generate bifurcations (saddle-node, transcritical) and instability paths explaining rapid adoption jumps or local collapses.

Before proceeding with Section 6, some observations are in order:

1. For the same SD dynamics, multiple payoffs produce s^*. Predictive value requires restricting the class via P1–P5 and anchoring parameters to observable quantities (e.g, compliance costs, transaction volumes, risk measures).
2. The model assumes agents respond to local statistics X_{N_a} and observable risks σ_a. Rational expectations or complex learning change transient dynamics.
3. Validation requires estimating B_a, C_a on real data (wallet activity, firm adoption, regulatory actions) and testing for parameter sets that produce empirical power-law exponents.

We have constructed a class of multi-level dynamic games with local, scale-invariant, regular payoffs (P1–P5), showing how a myopic adjustment rule produces an aggregated ODE system formally identical to the SD model of Section 4. Under homogeneity assumptions, the game admits self-similar trajectories exhibiting power laws: this provides the mathematical root of the SD⇄GT connection for Bitcoin diffusion.

6. Bidirectional SD-GT Mapping: Equivalence and Interpretation.

The SD ⇄ GT mapping shows that a deterministic dynamic system with local feedback can be interpreted as the aggregate equilibrium of a multilevel strategic game, and vice versa. The correspondence is based on: SD feedback functions ($F_k(x)$), and marginal derivatives of payoffs:

$\partial J_a / \partial s_a$. If the payoffs satisfy P1–P5 and the SD dynamics can be expressed as the gradient flow of an aggregate potential, the equivalence is functional. For a continuous SD:

$$\dot{x} = F(x), F_k(x) = \phi_k(x_k)\psi_k(x_{-k}), \qquad \phi_k, \psi_k > 0 \text{ differentiable}$$

there exists a family of local payoffs:

$$J_a[s_a; s_{-a}] = \int_0^T [\int_0^{s_a} \phi_k(u)du \cdot \psi_k(x_{-k}) - C_a(s_a)]\, dt$$

such that the myopic dynamics: $\dot{s}_a = \gamma_a \nabla_{s_a} J_a$ reproduce the SD evolution up to a temporal scaling factor. The cost regulates adjustment speed, not the flow's form.

For each class k, the state variable $x_k(t)$ represents the mean adoption strategy $s_k(t)$. The intrinsic adoption propensity is modeled as $\alpha_k x_k^{\beta_k}$ in the system dynamics (SD) formulation and as $u_k'(s_k)$ in the game-theoretic (GT) framework. The saturation constraint, capturing the residual potential for adoption, is $1 - x_k$. Inter-level coordination effects are represented by the network externality $f(x_{-k})$. The resulting adaptive dynamics, or payoff gradient, is given by $\dot{x}_k = F_k(x)$. If the SD system is potential: $F(x) = \nabla_x V(x)$, the SD dynamics coincide with a gradient play on $V(x)$, and the stationary state corresponds to a Nash equilibrium. Aggregating strategies:

$$\dot{x}_k = \mathbb{E}_a[\dot{s}_a] = \gamma_k(\mathbb{E}_a[\nabla_{s_a} J_a] - \mathbb{E}_a[\nabla_{s_a} C_a])$$

When payoffs are locally homogeneous, the continuity of their gradients in x gives rise to a smooth dynamic field, naturally described by a System Dynamics (SD) formulation. Strategic ergodicity becomes essential: the distribution of strategies s_a must converge rapidly compared to the aggregate time scale, allowing the system to behave as a coherent whole. A strong correspondence between SD and Game Theory (GT) thus relies on three intertwined principles. *Structural homogeneity* ensures that agents within a level face equivalent incentives and costs, establishing scale invariance. *Compact locality* confines interactions within measurable and stable domains, where the dependency matrix remains bounded ($|\lambda_{\max}| < 1$). *Value conservation*, finally, expresses the alignment of local strategic forces: rather than neutralizing or contradicting one another, they collectively sustain a common direction of systemic growth, a process consistent with the conservation or expansion of value, akin to the way physical systems preserve energy or negative entropy:

$$\sum_a \nabla_{s_a} J_a = \nabla_x V(x), \qquad \frac{dV}{dt} \geq 0$$

Under these conditions, adoption follows a self-similar power-law, and the SD becomes predictive. SD describes the macro evolution of adoption, GT makes micro-local rules explicit. Scale invariance connects the two levels: Bitcoin is a multilevel strategic field, and the power-law adoption reflects a fractal strategic equilibrium.

7. Methodological, Economic-Financial, and Ontological-Epistemological Implications:

The SD $\rightleftarrows$ GT model introduces a general principle of structural equivalence between system dynamics and multilayer games:

- Any dynamic system with positive feedback can be interpreted as the emergent equilibrium of a local game with scale-consistent payoffs.
- Any multilayer game with local interactions and structural homogeneity can be rewritten as a predictive dynamic system.

This allows a shift from descriptive simulation to deductive modeling: equations are derived from local optimization and value conservation, not mechanical calibration. Power laws become signals of strategic invariance, indicating stable forms generated by locally optimizing behaviors under global constraints.

Bitcoin can be interpreted as evolutionary coordination systems. Their power-law growth reflects the diffusion of a trust convention rather than a process of linear capital accumulation. Bitcoin's value arises from the dynamic coherence of its network, where the multilayer interaction structure constitutes the primary source of both stability and value. Policies that reduce scale coherence, such as fragmented or inconsistent regulations, tend to erode systemic value, whereas those that preserve it contribute to stability. Consequently, fractal coherence emerges as an alternative indicator of structural robustness in digital innovation systems.

More generally, economic phenomena arise from internal symmetries between local interactions and global patterns, rather than from externally imposed equilibria. Bitcoin exemplifies an autopoietic economic entity: one that maintains coherence while adapting, generating both value and structure simultaneously. The power law functions as an ontological signature: the system evolves along scale-invariant trajectories, analogous to self-organized natural phenomena. The key insight is that micro- and macroeconomics are not distinct levels but projections of the same fractal dynamic field observed at different resolutions.

The overall implications of the SD ⇄ GT formalization are threefold. Methodologically, it provides a unified framework for modeling complex systems as scale-consistent games, bridging the gap between empirical description and strategic formalism. From an economic and financial perspective, fractal coherence supplants linearity as a metric of evolutionary equilibrium. Ontologically and epistemologically, value emerges as a property of a self-coherent system, rather than as an externally imposed measure of utility or wealth.

9. Conclusions:

This work demonstrates that the diffusion of Bitcoin can be described as a multilayer dynamic system whose evolution follows a power law, formally equivalent to a fractal strategic equilibrium emerging from locally coherent interactions across scales.

The SD ⇄ GT framework shows that adoption dynamics are neither chaotic nor purely imitative, but the result of distributed optimization that preserves the system's form while expanding its scale. Bitcoin thus emerges as the first empirically verifiable case of a self-consistent adaptive system, in which individual, corporate, and institutional strategies share the same evolutionary field. Methodologically, the model integrates three traditionally separate domains: System Dynamics (macro-level evolution of stocks and flows); Game Theory (local strategies); Complex Systems Physics (scale laws and self-similarity). The power law thus becomes a structural condition of strategic coherence, not a mere statistical regularity. The model's predictiveness lies in form: as long as the feedback structure remains homogeneous, the system follows stable fractal trajectories, independent of context or technology.

Economically, value is not exogenous but rather a measure of the persistence of coherence among agents. Systems that maintain this coherence generate value through structure rather than through the mere production of goods. Notably, the diffusion of goods, services, and ideas across the economy follows similar patterns. As a consequence, the SD ⇄ GT framework opens broader perspectives. It can be applied to complex macroeconomic systems, including international trade, public finance, and industrial policies, where multilayer feedbacks play a critical role. The framework can also be extended to non-monetary dynamics, such as the diffusion of scientific knowledge or technological innovation, where value conservation manifests as the preservation of information. Finally, it provides a foundation for a general theory of intentional fractal systems, in which human strategies and natural dynamics obey the same mathematical principles of scale-consistent coherence. In summary, analyzing Bitcoin as a multilayer fractal equilibrium is not merely an interpretative contribution, but a step toward a unified vision of economics as a science of self-coherent systems, where value dynamics emerge, persist, and propagate according to the same symmetry laws governing nature.

[References]

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*(5439), 509–512.

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science, 15*(5), 215–227.

Catalini, C., & Gans, J. S. (2016). Some simple economics of the blockchain. *MIT Sloan Research Paper* No. 5191-16.

Goldenberg, J., Libai, B., & Muller, E. (2001). Talk of the network: A complex systems look at the underlying process of word-of-mouth. *Marketing Letters, 12*(3), 211–223.

Huberman, G., Leshno, J. D., & Moallemi, C. C. (2021). Monopoly without a monopolist: An economic analysis of the Bitcoin payment system. *Review of Financial Studies, 34*(6), 2689–2728.

Mahajan, V., & Peterson, R. A. (1985). *Models for Innovation Diffusion.* Sage Publications.

Newman, M. E. J. (2003). The structure and function of complex networks. *SIAM Review, 45*(2), 167–256.

Nowak, M. A. (2006). *Evolutionary Dynamics: Exploring the Equations of Life.* Harvard University Press.

Pastor-Satorras, R., & Vespignani, A. (2001). Epidemic dynamics and endemic states in complex networks. *Physical Review E, 63*(6), 066117.

Pecere, A. (2025). *A Payoff Cosmogony: From Local Strategic Interactions to Global Dynamics.* ResearchGate: https://doi.org/10.13140/RG.2.2.33996.73600

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Free Press.

Santostasi, G. (2024). The power law growth of Bitcoin adoption. *arXiv preprint* arXiv:2403.10715.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of small-world networks. *Nature, 393*(6684), 440–442.

Weibull, J. W. (1995). *Evolutionary Game Theory.* MIT Press.

Wheatley, S., Sornette, D., Huber, T., Reppen, M., & Gantner, R. N. (2019). Are Bitcoin bubbles predictable? Combining a generalized Metcalfe's law and the LPPLS model. *Royal Society Open Science, 6*(7), 180538.