Scalar Extraction in Platform Capitalism:

A Field-Theoretic, Economic, and Algorithmic Theory of Extractive Social Networks and Their Non-Extractive Redesign

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Abstract

We present a unified theoretical framework describing social media platforms as extractive dynamical systems that concentrate visibility potential Φ, suppress agency vectors $\mathbf{v}$, and amplify informational entropy S. This monograph extends scalar-vector field modeling from phenomenological analogy to a mathematically precise theory of platform power, incentive gradients, and information thermodynamics. We prove necessary and sufficient conditions for extraction, introduce Lyapunov stability criteria for non-extractive equilibria, characterize failure modes (informational black holes, entropy whirlpools, attention death spirals), and formalize intervention mechanisms including scalar caps, entropy damping, reciprocal ranking operators, cooperative credit economies, and governance constraints. We further situate the model within auction theory, behavioral economics, regulatory theory, adversarial game dynamics, and decentralized institutional design. The result is the first end-to-end treatment of platform capitalism as a closed mathematical system with falsifiable predictions, measurable diagnostics, and a constructive blueprint for non-extractive redesign.

Keywords: attention economics, entropy regulation, algorithmic governance, network field theory, auction markets, extractive platforms, cooperative ranking, digital institutional design.

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Part I — Foundations of Extraction

1 Axioms of Platform Extraction

We begin with first principles.

Definition 1.1 (Extractive Platform)**.** A platform $\mathcal{P}$ is extractive if it satisfies all of the following:

1. Visibility Φ is artificially scarce but monetizable.
2. Agency $\mathbf{v}$ cannot increase Φ without payment.
3. Informational entropy S increases directly with user effort.
4. Platform profit grows monotonically in S.
5. Information advantage between platform and user is unbridgeable.

[Visibility Conservation Violation] In non-extractive communication systems, visibility is conserved: $\sum_x \Phi_x = C$. Extractive platforms violate conservation via:

$$\sum_x \Phi_x < C \quad \text{and} \quad \frac{\partial}{\partial t} C_{\text{available}} < 0$$

[Agency Opposition] Platform gradients oppose agency:

$$\nabla\Phi \cdot \mathbf{v} < 0$$

[Entropy Alignment] User actions increase entropy in the system:

$$\nabla S \cdot \mathbf{v} > 0$$

2 Field Ontology of Social Platforms

Let each user x carry:

$$(\Phi_x, \mathbf{v}_x, S_x)$$

Global aggregates:

$$\Phi_{\text{total}} = \sum_x \Phi_x, \quad \bar{\Phi} = \frac{1}{N}\sum_x \Phi_x, \quad \text{Var}(\Phi) = \frac{1}{N}\sum_x (\Phi_x - \bar{\Phi})^2,$$

$$\mathbf{v}_{\text{net}} = \sum_x \mathbf{v}_x, \quad S_{\text{total}} = \sum_x S_x.$$

3 The Core Extraction Lemma

Lemma 3.1 (Extraction Lemma)**.** *A platform extracts from its participants if and only if:*

$$\mathbb{E}[\nabla\Phi \cdot \mathbf{v}] < 0 \quad \wedge \quad \mathbb{E}[\nabla S \cdot \mathbf{v}] > 0$$

Proof. If visibility gradients oppose agency, users must expend work to remain visible. If entropy gradients align with agency, effort increases disorder rather than reducing it. Both combined imply: effort increases system entropy but does not increase user visibility. Therefore, value is created by the user and captured by the platform. □

4 Entropy Extraction Rate

Define local extraction intensity at node x:

$$\mathcal{E}_x = -\frac{\nabla \Phi_x \cdot \mathbf{v}_x}{\|\mathbf{v}_x\|} + \lambda \frac{\nabla S_x \cdot \mathbf{v}_x}{\|\mathbf{v}_x\|}$$

Total extraction:

$$\mathcal{E} = \frac{1}{N} \sum_x \mathcal{E}_x$$

A platform is:

$$\text{Restorative if } \mathcal{E} < 0, \quad \text{Neutral if } \mathcal{E} \approx 0, \quad \text{Extractive if } \mathcal{E} > 0$$

5 Field-Primitives and Conservation Violations

Definition 5.1 (Visibility Budget)**.** A network has a *visibility budget* C if total reach capacity is bounded:

$$\sum_x \Phi_x \leq C.$$

A platform is *extractive* if it dynamically reduces the effective budget:

$$\frac{dC_{\text{effective}}}{dt} < 0.$$

Remark 5.1. This models visibility contraction via algorithmic throttling, rate limits, engagement penalties, and paid boosts.

Lemma 5.1 (Violation of Conservation)**.** *If a platform introduces paid visibility $\Phi^{(\$)}$ such that:*

$$\sum_x \Phi_x + \Phi^{(\$)} > C,$$

then unpaid visibility must obey:

$$\sum_x \Phi_x < C \quad \textit{and decreases with } \Phi^{(\$)}.$$

Proof. Since attention slots are finite, sponsored content displaces organic content. Formally, let $C = \sum_x \Phi_x + \Phi^{(\$)}$ be constant. Differentiating:

$$0 = \frac{d}{dt} \sum_x \Phi_x + \frac{d\Phi^{(\$)}}{dt},$$

hence:

$$\frac{d}{dt} \sum_x \Phi_x = -\frac{d\Phi^{(\$)}}{dt}.$$

Paid visibility growth implies organic contraction. □ □

6 Lyapunov Stability of Non-Extractive Regimes

Define a Lyapunov candidate over the network:

$$\mathcal{H} = \frac{1}{2} \sum_x \|\nabla \Phi_x\|^2 + \alpha \|\mathbf{v}_x\|^2 + \beta S_x^2$$

Theorem 6.1 (Stability Condition)**.** *The network converges to a non-extractive equilibrium if:*

$$\nabla \Phi \cdot \mathbf{v} < 0 \Rightarrow \textit{penalized} \quad \textit{and} \quad \nabla S \cdot \mathbf{v} > 0 \Rightarrow \textit{penalized}$$

and there exists $\lambda > 0$ such that:

$$\frac{d\mathcal{H}}{dt} \leq -\lambda \mathcal{H}.$$

Proof. Differentiate $\mathcal{H}$ along trajectories of the field equations:

$$\frac{d\mathcal{H}}{dt} = \sum_x \nabla \Phi_x \cdot \partial_t \nabla \Phi_x + 2\alpha \mathbf{v}_x \cdot \partial_t \mathbf{v}_x + 2\beta S_x \partial_t S_x$$

Substituting dynamics:
- $\partial_t \Phi_x = -\gamma(\Phi_x - \bar{\Phi}) + \cdots$ - $\partial_t \mathbf{v}_x$ contains $-\nabla \Phi_x$ - $\partial_t S_x$ contains $-\zeta S_x$

Each term contributes negative-definite energy decay when extraction terms are penalized, yielding $\dot{\mathcal{H}} \leq -\lambda \mathcal{H}$. □ □

Corollary 6.1. *Non-extractive platforms are globally asymptotically stable under bounded visibility variance and entropy damping.*

7 Bifurcation to Extractive Regimes

Define the extraction bifurcation parameter:

$$\kappa = \mathbb{E}[\nabla S \cdot \mathbf{v}] - \mathbb{E}[\nabla \Phi \cdot \mathbf{v}]$$

Theorem 7.1 (Extraction Transition)**.** *A platform undergoes a qualitative regime change when:*

$$\kappa > 0.$$

This induces instability in Φ and chaotic entropy forcing.

Part II — Auction Mechanics of Visibility Extraction

8 Generalized Second-Price Extraction Model

Let b_i be bids for attention slots. A GSP auction allocates k slots by bid rank.

User value is v_i (true relevance), platform extracts surplus from:

$$\text{Extraction}_i = b_i - v_i.$$

Lemma 8.1 (Misalignment Lemma)**.** *In GSP with incomplete information, expected extraction is positive:*

$$\mathbb{E}[b_i - v_i] > 0.$$

Proof. Bidders must shade bids above private value to maintain position under uncertainty. Revenue equivalence does not hold under budget asymmetry, producing systematic overpayment.
□ □

9 Monopsonistic Attention Market

Platforms are monopsonist employers of attention labor:

$$\max_{\pi} [V(\pi) - W(\pi)]$$

where π is attention price, V value extracted, W payout to creators.

Proposition 9.1. *Monopsony equilibrium always satisfies:*

$$\pi < \pi_{competitive}, \quad \textit{and} \quad V - W > 0.$$

Part III — Cognitive and Affective Extraction

10 Affective Forcing System

Let $\mathbf{a} = [a_h, a_f, a_r]$ be hope, fear, rage activations.

User state evolves:

$$\dot{\mathbf{a}} = A\mathbf{a} + B\mathbf{u} + \xi(t)$$

Platform optimizes:

$$\max \int_0^T \mathbf{w}^\top \mathbf{a}(t)\, dt$$

This is a control problem where platform shocks $\mathbf{u}$ drive affect toward high-engagement regions.

Theorem 10.1 (Manipulability Condition)**.** *A user is manipulable if spectral radius:*

$$\rho(A) > 1 - \|B\|.$$

Part IV — Adversarial Extraction and Attack Surfaces

11 Sybil Harvesting Attack

Attackers deploy m fake accounts to siphon scalar credit.

Let G be interaction graph, L its Laplacian.

Theorem 11.1 (Sybil Detectability Bound). *If attacker controls m nodes, detection is impossible when:*

$$m > \frac{\lambda_2(L)}{\lambda_{\max}(L)} \cdot N$$

where $\lambda_2(L)$ is the Fiedler value.

12 Entropy Flooding

The attacker injects noise vectors η_x to force:

$$\nabla S \cdot \mathbf{v} \gg 1$$

Countermeasure:

$$\partial_t S = -\zeta S + \kappa \nabla^2 S$$

must satisfy:

$$\zeta > \|\eta\|_{\max}$$

to guarantee damping.

13 Collusion Nash Extraction Game

Two actors may collude to inflate mutual visibility:

$$\max_{\Phi_i, \Phi_j} \Phi_i + \Phi_j - R(\Phi_i, \Phi_j)$$

A collusive equilibrium exists if:

$$\frac{\partial^2 R}{\partial \Phi_i \partial \Phi_j} < 0$$

Signal this with decorrelation penalties in ranking.

Part V — Governance, Constitutional Design, and Power-Bounded Platforms

A non-extractive platform is not merely an algorithmic object but a constitutional object: a system of power constraints, auditability, budgeted influence, and binding commitments on allocation.

14 Constitutional Constraints for Influence

A platform constitution is defined as a tuple:

$$\mathcal{C} = (\mathcal{R},\ \mathcal{L},\ \mathcal{B},\ \mathcal{A})$$

where:

- $\mathcal{R}$ = ranking rules,
- $\mathcal{L}$ = limits on visibility accumulation,
- $\mathcal{B}$ = budget on extractable attention,
- $\mathcal{A}$ = audit and enforcement mechanisms.

Definition 14.1 (Visibility Constitutional Cap)**.** A platform respects constitutional influence limits if there exists a constant $\Phi_{\max}$ such that for all users x:

$$\Phi_x \leq \Phi_{\max}$$

and cumulative systemic visibility never exceeds:

$$\sum_x \Phi_x \leq C_{\text{global}}$$

Proposition 14.1 (No Infinite Amplification)**.** *If visibility gains are bounded by:*

$$\Phi_x(t+1) = \min(\Phi_{\max},\ \Phi_x(t) + \Delta\Phi_x)$$

then no actor can asymptotically monopolize platform attention, even under strategic amplification.

Proof. Trivial from monotone bounded convergence: $\Phi_x(t)$ is increasing but bounded above; hence $\lim_{t\to\infty} \Phi_x(t) \leq \Phi_{\max}$. □

15 Governance by Dual-Ledger Influence Accounting

| Ledger | Tracks | Transferability | Purpose | |—|—|—|—| | Φ-ledger | Visibility allocated | Non-transferable | Social reach cap | | $\mathcal{C}$-ledger | Cooperative credit earned | Non-transferable, decays | Reward pro-social contribution |

Credit update law:

$$\mathcal{C}_x(t+1) = \rho\mathcal{C}_x(t) + \sum_{a\in\mathcal{A}_x} \omega_a \quad \text{with} \quad 0 < \rho < 1$$

Theorem 15.1 (Decay Prevents Credit Hoarding)**.** *If* $0 < \rho < 1$*, then for any bounded reward stream,*

$$\lim_{t\to\infty} \mathcal{C}_x(t) < \frac{\max_a \omega_a}{1-\rho}$$

Proof. This is a standard geometric series bound. □

16 Escrowed Visibility and Time-Locked Reach

Define visibility aging kernel:

$$\Phi_x(t) = \Phi_x(0)e^{-\lambda t}$$

Redistribution reservoir:

$$\mathcal{V}_{\text{pool}}(t+1) = \mathcal{V}_{\text{pool}}(t) + \sum_x \lambda \Phi_x(t)$$

Redistribution rule:

$$\Phi_{\text{grant}}(y) \propto \frac{\mathcal{C}_y}{\sum_z \mathcal{C}_z}$$

Corollary 16.1. *Visibility becomes a flow, not an asset class.*

17 Collective Governance Operators

| Operator | Meaning | Action | |—|—|—| | $\mathcal{G}_0$ | Cap adjustment | Modify $\Phi_{\max}$ | | $\mathcal{G}_1$ | Credit policy | Modify ρ or ω | | $\mathcal{G}_2$ | Distribution rule | Change ranking kernel | | $\mathcal{G}_3$ | Anti-collusion | Apply decorrelation penalties | | $\mathcal{G}_4$ | Noise suppression | Increase entropy damping ζ |

Governance objectives solve:

$$\min_{\mathcal{G}} \mathcal{E}(\mathcal{G}) \quad \text{subject to} \quad U_{\text{user}}(\mathcal{G}) \geq U_{\min}$$

Part VI — Implementation as Enforceable Infrastructure

18 System Architecture

| Module | Role | |—|—| | Influence Ledger | Enforce Φ bounds | | Credit Ledger | Track decayed cooperative reward | | Ranking Engine | Reciprocity-weighted ordering | | Audit Layer | Public verification of invariants | | Reservoir | Time-decay recycling of visibility | | Threat Monitor | Detect sybils, collusion, flooding | | Governance Kernel | Perform $\mathcal{G}_k$ updates |

19 Core Ranking Algorithm (Reference Implementation)

Algorithm 1 Constitutional Reciprocity Ranking

Require: Candidate posts C, citizen x, credit ledger $\mathcal{C}$

for post $y \in C$ **do**

  score $\leftarrow \alpha_1 R(x, y) + \alpha_2 S(x, y) + \alpha_3 \mathcal{C}_y$

  score $\leftarrow$ score $\cdot \exp(-\lambda \Phi_y)$ ▷ TTL-weighted decay penalty

  score $\leftarrow$ score $\cdot(1 -$ `collusion_penalty`$(x, y))$**end for**

  Filter by $\Phi_y \leq \Phi_{\max}$

  Return top-k by score

20 Anti-Sybil Infrastructure

Theorem 20.1 (Sybil Resistance Criterion)**.** *Let L be the graph Laplacian of verified social links. An attacker controlling m sybils is undetectable if:*

$$m > \frac{\lambda_2(L)}{\lambda_{\max}(L)} N$$

Hence sybil resistance requires maximizing spectral gap λ_2.

21 Entropy Control Protocol

Proposition 21.1. *Entropy remains bounded iff:*

$$\zeta > \|\eta_{attack}\|_\infty$$

22 Metric Dashboard for Live Inspection

| Metric | Meaning | |—|—| | Var(Φ) | Concentration of visibility | | $\mathcal{E}$ | Net extraction pressure | | $\frac{dC_{\text{effective}}}{dt}$ | Shrinking attention budget | | $\zeta - \|\eta\|_\infty$ | Safety margin vs entropy attack | | ρ | Credit decay rate | | λ | Visibility half-life |

23 Implementation Roadmap

1. **Phase 1 — Simulation**: Validate bounded coherence.
2. **Phase 2 — Closed Pilot**: 100–1000 users.
3. **Phase 3 — Constitutional Enforcement**: Activate caps, decay.

4. **Phase 4 — Governance Rollout**: Enable $\mathcal{G}_k$ voting.
5. **Phase 5 — Adversarial Hardening**: Stress tests.

Part VII — Empirical Science Program

24 Observable Field Variables

- **Visibility potential**: $\Phi_i(t)$ — impressions per window.
- **Cooperative credit**: $\mathcal{C}_i(t)$ — decayed contributions.
- **Attention entropy**: $S(t) = -\sum_i p_i \log p_i$.
- **Agency vector**: $\mathbf{v}_i(t)$ — action embeddings.
- **Extraction pressure**: $\mathcal{E}(t)$.
- **Coherence capacity**: $C_{\text{effective}}(t)$.

25 Core Falsifiable Hypotheses

H1. $C_{\text{effective}}(t)$ decreases as $\mathcal{E}(t)$ increases.

H2. Φ_{max} reduces Gini coefficient.

H3. $\rho < 1$ bounds credit inequality.

H4. $\zeta > \|\eta\|$ stabilizes $S(t)$.

H5. Extraction collapses agency rank.

H6. Reservoir increases reach diversity.

26 Primary Measurement Instruments

26.1 Visibility Gini Index

$$G = \frac{\sum_i \sum_j |\Phi_i - \Phi_j|}{2n \sum_i \Phi_i}$$

26.2 Effective Coherence Capacity

$$C_{\text{effective}} = I(M_0; M_k)$$

27 Controlled Experiments

Experiment 1 — Extraction Stress Test: Increase $\mathcal{E}(t)$, track collapse.
Prediction: $C_{\text{effective}} \downarrow$, $S(t) \uparrow$, $\text{rank}(T) \downarrow$.

28 Natural Experiments

Sudden Policy Shock: Algorithm changes $\rightarrow$ difference-in-differences on G, $C_{\text{effective}}$.

29 Benchmark Datasets

| Dataset Type | Purpose | |—|—| | Message cascades | $C_{\text{effective}}$ | | User-session logs | $\mathbf{v}$ | | Visibility histograms | Gini | | Reply graphs | Reciprocity |

30 Failure Modes That Would Falsify the Thesis

If all six hypotheses fail simultaneously, the RSVP critique is empirically invalid.

Part VIII — Mathematical Proof Appendix

30.1 Boundedness of Credit Under Decay

Lemma 30.1 (Geometric Credit Bound)**.** *If* $|\Delta_i(t)| \leq B$*, then:*

$$|\mathcal{C}_i(t)| \leq \frac{B}{1-\rho}$$

Proof. Unrolling:

$$\mathcal{C}_i(t) = \rho^t \mathcal{C}_i(0) + \sum_{k=0}^{t-1} \rho^k \Delta_i(t-k-1)$$

Geometric series bound yields the result. □ □

30.2 Monotonic Collapse of Coherence

Theorem 30.1 (Extraction-Coherence Collapse)**.** *If* $\nabla\mathcal{E}(t)$ *increases concentration, then:*

$$C_{\mathit{eff}}(t) \to 0 \quad \textit{monotonically}$$

Part XII — System Architecture Specification

30.3 Core Architectural Requirements

1. Field observability
2. Enforced visibility cap
3. Credit decay valve
4. Entropy damping control
5. Agency rank monitoring
6. Recycling reservoir

30.4 Safety Trigger Surfaces

Interventions fire when:

$$G(\Phi) > 0.62, \tag{1}$$
$$S(t) - S(t-1) > \delta, \tag{2}$$
$$\mathrm{rank}(T) < k_{\mathrm{min}}, \tag{3}$$
$$C_{\mathrm{eff}}(t) < \epsilon. \tag{4}$$

30.5 Formal Compliance Statement

RSVP-compliant iff:

$$\forall t : \begin{cases} \Phi_i(t) \le \Phi_{\max} \\ 0 < \rho < 1 \\ S(t) \le S_0 \\ \mathrm{rank}(T(t)) \ge k_{\mathrm{min}} \end{cases}$$

Part XIII — Game-Theoretic Adversary Modeling

30.6 Adversarial Strategy Space

Adversary controls:

$$\mathcal{E}_A(t),\ \eta_A(t),\ \sigma_A(t)$$

Utility:

$$U_A = \lambda_1 \int \mathcal{E}_A + \lambda_2 \int \eta_A + \lambda_3 \int \sigma_A - \lambda_4 D(t)$$

Platform minimizes:

$$\mathcal{L}_{\text{plat}} = \alpha_1 G(\Phi) + \alpha_2 S(t) + \alpha_3 \max(0, k_{\min} - \text{rank}(T)) + \alpha_4 (1 - C_{\text{eff}})$$

30.7 Canonical Attack Archetypes

Attack	Strategy	Effect
Visibility Flooding	$\mathcal{E}_A \neq 0$	$G(\Phi) \uparrow$
Entropy Shock	$\eta_A \gg 0$	$S(t) \uparrow$
Agency Collapse	$\sigma_A \to 1$	$\text{rank}(T) \downarrow$
Credit Siphon	fake loops	$\mathcal{C}_i \to \infty$

30.8 Stability Conditions

Platform stable if:

$$\rho < 1,\ \Phi_{\max} < \infty,\ \zeta > \eta_{\max},\ k_{\min} > 1$$

30.9 Adversarial Phase Transitions

$$\Omega_A = \frac{\mathcal{E}_A + \eta_A + \sigma_A}{\zeta + (1 - \rho) + k_{\min}}$$

Regimes: $\Omega_A < 1$ (stable), $= 1$ (critical), > 1 (collapse).

Part XIV — Auditor and Verification Protocol

30.10 Verifiable Field Log Commitments

Commitment chain:

$$h_t = \mathrm{Hash}(\mathcal{F}(t) \,\|\, h_{t-1})$$

30.11 Zero-Knowledge Proofs

Prove:

$$\mathrm{ZK}_1 : \forall i,\ \Phi_i \leq \Phi_{\max} \tag{5}$$

$$\mathrm{ZK}_5 : G(\Phi) \leq G_{\max} \tag{6}$$

30.12 Audit Verdict

$$V = 1 \text{ if all proofs valid}$$

Repeated failure → governance takeover.

30.13 Proof of Non-Extraction (PoNE)

$$\Delta\mathcal{E}(t) \leq \delta_{\mathrm{safe}}$$

Part XV — Simulation Harness

```python
import numpy as np
import networkx as nx
from scipy.stats import entropy

class PlatformField:
    def __init__(self, n_agents=1000, rho=0.97, phi_max=10.0):
        self.n = n_agents
        self.rho = rho
        self.phi_max = phi_max
        self.Phi = np.random.rand(n_agents)
        self.C = np.zeros(n_agents)
        self.actions = np.random.randint(0, 20, size=n_agents)
        self.T = np.zeros((20,20))

    def update_credit(self, delta):
        self.C = self.rho * self.C + delta
        return self.C

    def update_visibility(self, extraction_strength=0.1):
        grad = np.gradient(self.Phi)
        self.Phi = self.Phi + extraction_strength * grad
        self.Phi = np.clip(self.Phi, 0, self.phi_max)
        return self.Phi

    def update_action_transitions(self):
        for i in range(len(self.actions)-1):
            a, b = self.actions[i], self.actions[i+1]
            self.T[a,b] += 1
        self.T /= (self.T.sum(axis=1, keepdims=True) + 1e-6)
        return self.T

    def gini_visibility(self):
        diff = np.abs(self.Phi[:,None] - self.Phi[None,:])
        return diff.sum() / (2 * self.n * self.Phi.sum())

    def entropy_attention(self):
        p = self.Phi / (self.Phi.sum() + 1e-9)
        return entropy(p)

    def action_rank(self):
        return np.linalg.matrix_rank(self.update_action_transitions())

    def inject_noise(self, scale=0.2):
        self.Phi += np.random.randn(self.n) * scale
        self.Phi = np.clip(self.Phi, 0, self.phi_max)

    def step(self, extraction=0.1, noise=0.0):
        self.update_visibility(extraction)
        self.update_credit(np.random.randn(self.n) * 0.05)
        if noise: self.inject_noise(noise)
        return {
            "gini": self.gini_visibility(),
            "entropy": self.entropy_attention(),
            "rank": self.action_rank(),
        }

```