Consequence Minimization: A Cross-Disciplinary Principle of Adaptive Order

Abstract.

This paper proposes Consequence Minimization (CM) as a unifying principle linking evolutionary transitions, neural computation, social cooperation, strategy, and international politics. The semantic definition is compact: any adaptive agent will first seek to constrain catastrophic outcomes or premature exits before maximizing exploitation or gains. The concept is descriptive rather than moral; it explains observed behavior under selection and constraint. Philosophically, it refines older "grand struggle" narratives—Heraclitus' agon, Hobbes' state of nature, Nietzsche's will to power—by grounding them in enforceable consequence structures rather than in metaphysical drives. In international relations, it extends Mearsheimer's offensive realism by treating institutions and deterrence as consequence compilers that reshape the effective payoff landscape. We formalize CM with lexicographic preferences over (i) a catastrophe functional and (ii) a performance functional; define a Consequence-Lexicographic Equilibrium (CLE); derive comparative statics for certainty, celerity, and proportionality of enforcement; and show how the same mathematics explains: (1) organelles joining cells, cells joining organisms, and organisms coordinating in tribes; (2) neural learning as consequence-biased control, contrasting CM with the free energy program; (3) deterrence and war across polities of varying scale; and (4) competitive dynamics such as chess, markets, and platform governance. The maxim "take the action you'll regret least" falls out as the one-agent corollary.

1. Introduction

The narrative of human affairs as a **grand struggle** is perennial. What such narratives lack is an operational account of how struggle is stabilized into order. Realist international relations theory, epitomized by Mearsheimer, begins with anarchy and explains power-seeking under the absence of a world police. Game theory shows how cooperation can emerge under repeated interaction. Evolutionary biology explains how policing and punishment stabilize multicellular cooperation. Neuroscience shows that organisms overweight pain and losses. Complexity theory insists that stability is a property of feedback.

Consequence Minimization (CM) synthesizes these strands. The claim is not that agents maximize expected utility over all outcomes, but that they **lexicographically** prioritize avoiding catastrophic outcomes ("premature exit from the game") and only then optimize gains. This priority ordering is both adaptive and measurable. It predicts when cooperation is stable, why institutions matter, and how systems fail when feedback is weak, delayed, or mis-calibrated.

Our contributions are threefold. First, we provide a formal framework: catastrophe sets, hazard functionals, lexicographic preferences, a limit construction that yields a fixed-point equilibrium, and comparative statics for enforcement. Second, we instantiate the framework across levels—from endosymbiosis to NATO, from nociception to safe exploration in learning. Third, we derive practical handles: increase certainty of detection, shorten enforcement delay, and calibrate sanction; otherwise expect reversion to high-conflict attractors.

2. Background and Related Work

Philosophy. Heraclitus, Hobbes, and Nietzsche describe agonistic worlds but do not specify the regulator. CM treats order as an emergent property of **credible consequences**. Rawlsian maximin and Savage's minimax regret anticipate CM's lexical priority of worst-case avoidance, but CM is multi-agent and dynamical rather than single-agent and static.

International relations. Mearsheimer's offensive realism starts from anarchy and rational power maximization. Deterrence theory (Schelling) and alliance theory supply the tools of credibility. CM recasts these as *parameterized feedbacks*—certainty, celerity, and proportionality.

Game theory. Folk theorems show cooperation under sufficient patience. CM adds **external consequence fields** that alter incentives when patience or monitoring alone is insufficient. The formalism fits repeated games, stochastic games, and evolutionary games with punishment.

Evolution. The evolution of multicellularity and sociality depends on policing and sanction; cancer is the canonical failure mode. CM packages these as changes in detection, delay, and sanction within a shared inequality.

Neuroscience. Pain and aversion systems bias action selection away from high-cost outcomes; reinforcement learning updates are typically more sensitive to negative

prediction errors. CM positions this asymmetry as lexicographically prior: avoid catastrophic branches, then exploit.

Complexity and control. Stability requires timely, reliable negative feedback; Ashby's law demands regulators match the variety of disturbances; Goodhart's law warns against proxy gaming. CM quantifies regulator effectiveness with three levers.

3. Formal Framework

3.1 Basic objects

Let agents i=1,...,ni=1,\dots,n interact in a Markovian environment with state space SS, joint action space $A=\prod iAiA=\pmod iA_i$, transition kernel $P(\cdot|s,a)P(\cdot t)$, and discount $\gamma \in (0,1) \cdot t$. Let $F \subseteq SF(\cdot t)$ be the **catastrophe set** (absorbing "premature exit" states). Let $F \subseteq SF(\cdot t)$ be the first hitting time of $FF(\cdot t)$.

For agent ii:

Catastrophe functional

with $\lambda \in (0,1) \setminus (0,1) \in \mathbb{R}$ with $\lambda \in (0,1) \setminus (0,1) \in \mathbb{R}$

Performance functional

 $\label{limit} Ji(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(st,at)]. \\ J_i(\pi):= \mathbb{E}_{\pi}[\pi]. \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\ \forall \ r_i(s_t,a_t) \\ I_i(\pi):=E\pi\ \square[\sum t\geq 0 \\$

Define Consequence-Lexicographic Preference (CLP): for profiles $\pi, \pi' \neq 0$, $\pi \neq 0$

 $\pi > iCLP\pi' \iff (\phi_i(\pi) < \phi_i(\pi')) \text{ or } (\phi_i(\pi) = \phi_i(\pi')) \text{ and } J_i(\pi) > J_i(\pi')). \phi_i(\pi') \text{ or } (\phi_i(\pi) < \phi_i(\pi')) \text{ or } (\phi_i(\pi) < \phi_i(\pi')) \text{ or } (\phi_i(\pi) < \phi_i(\pi)) \text{ or } (\phi_i(\pi) < \phi_i(\pi$

This is the formal content of "constrain catastrophe first; then maximize gains."

Two equivalent optimization forms:

· Lexicographic program

Constrained program (safety-first)

 $\max_{\pi} Ji(\pi)s.t.\phi i(\pi) \le \epsilon.\max_{\pi} Ji(\pi)s.t.\phi i(\pi) \le \epsilon.\max_{\pi} Ji(\pi)s.t.\phi i(\pi) \le \epsilon.\max_{\pi} Ji(\pi)s.t.\phi i(\pi) \le \epsilon.\min_{\pi} Ji(\pi)s.t.\phi i(\pi)s.t.\phi i(\pi) \le \epsilon.\min_{\pi} Ji(\pi)s.t.\phi i(\pi)s.t.\phi i(\pi)s.t$

As $\epsilon \vee \epsilon \star := \inf_{\pi \to \pi} (\pi) \cdot (\pi)$

3.2 Equilibrium

A strategy $\pi i \pi_i = \mathbf{Consequence-Lexicographic Best Response}$ (CLBR) to $\pi_i = \mathbf{conseque$

A profile $\pi*\pi$ is a **Consequence-Lexicographic Equilibrium (CLE)** if each $\pi i*\pi i$ a CLBR to $\pi - i*\pi i$.

Existence via penalty limits. For M>0M>0 define the penalized utility

 $U\sim i(M)(\pi):=Ji(\pi)-M \phi i(\pi).\tilde U_i^{(M)}(\pi):=J_i(\pi)-M\,\phi i(\pi).$

Let $\Pi(M)\Pi^{(M)}$ be the set of Nash equilibria under U~(M)\tilde U^{(M)}. Under standard compactness and continuity assumptions, $\Pi(M)\Pi^{(M)}$ is nonempty; any accumulation point of $\{\Pi(M)\}M\to\infty\{\Pi^{(M)}\}\$ is a CLE. This "large-penalty limit" provides both existence and computation.

3.3 Enforcement as consequence engineering

Let p(s,a)p(s,a) denote **certainty of detection**, $\Delta(s,a)$ Delta(s,a) **sanction severity**, and $\tau(s,a)$ tau(s,a) **enforcement delay**. The **effective expected penalty** of an act under discount γ amma is

 $E(s,a):=p(s,a) \Delta(s,a) \gamma \tau(s,a).E(s,a):=p(s,a) \setminus Delta(s,a) \setminus gamma^{\lambda(s,a)}.$

Institutions and controllers operate by shaping EE; comparative statics predict that increasing pp and decreasing τ and the cooperation region more efficiently than increasing Δ Delta alone.

3.4 The repeated Prisoner's Dilemma inequality

With stage payoffs T>R>P>ST>R>P>S, suppose a defection triggers (i) a strategic loss from future play under grim trigger and (ii) an external sanction after delay τ with probability pp and magnitude Δ Delta. Unilateral defection is unprofitable iff

 $(T-R) \le \gamma 1 - \gamma (R-P) + p \Delta \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) \setminus \frac{\gamma - R}{1 - \gamma} (R-P) + p \lambda \gamma \tau. (T-R) + p \lambda \gamma \tau. (T-R$

The three enforcement levers appear explicitly; the inequality generalizes to partial monitoring and networked enforcement by taking expectations over pp and τ

3.5 Population dynamics with punishment

Let xx be the share of cooperators in a population; baseline payoffs $\pi C(x), \pi D(x) \setminus pi_C(x), \forall pi_D(x). \text{ With punishment intensity } \kappa \setminus px, \text{ certainty } p(x)p(x), \text{ severity } \Delta \setminus pi_D(x) \setminus px, \text{ certainty } p(x)p(x), \text{ severity } \Delta \setminus pi_D(x) \setminus px, \text{ certainty } p(x) \setminus px, \text{ severity } \Delta \setminus px, \text{ certainty } p(x) \setminus px, \text{ severity } \Delta \setminus px, \text{ certainty } p(x) \setminus px, \text{ severity } \Delta \setminus px, \text{ certainty } p(x) \setminus px, \text{ severity } \Delta \setminus px, \text{ certainty } p(x) \setminus px, \text{ severity } \Delta \setminus px, \text{ certainty } p(x) \setminus px, \text{ severity } p(x) \setminus px, \text{ certainty } p(x) \setminus px, \text{ certainty$

4. Evolutionary Transitions: Organelles → Cells → Organisms → Tribes

CM interprets major transitions as the tightening of consequence webs.

Endosymbiosis and organelle domestication. Let bb be the short-run benefit to an organelle lineage from selfish replication or resource hoarding. Host control—gene transfer to the nucleus, targeted degradation—raises detection and sanction and lowers delay. Stability is achieved when

b≤p $\Delta \gamma \tau$.b \le p\,\Delta\,\gamma^{\tau}.

Uniparental inheritance also depresses bb by aligning organelle and host fitness.

Multicellularity. With germ–soma separation, somatic defection has negligible heritable payoff but a high sanction: surveillance (DNA damage checkpoints), fast apoptosis, immune clearance. Cancer illustrates failure: mutations reduce detection and sanction or extend delay, flipping the inequality.

Social animals and tribes. Individual defection yields a gain gg. Repeated interaction and reputational monitoring increase pp; swift, proportionate punishment compresses τ and tunes Δ Delta. Ritualized dominance and prosocial norms are institutionalized controllers that preserve cooperation while avoiding costly spirals. Kinship and identifiability are not sentimental—they are detection technologies.

The same replicator account explains policing in eusocial insects and punishment-backed cooperation in primate groups; cooperative equilibria disappear when group size, anonymity, or mobility collapses pp or stretches thau.

5. Neuroscience and Intelligence: Learning from Consequences

Neural systems allocate computational resources to **avoid catastrophic branches**. Nociception and aversive learning weight negative prediction errors; the basal ganglia gate action selection based on reinforcement contingencies; prefrontal circuits simulate counterfactuals to prune risk.

CM offers a crisp decision rule for a single agent:

Choose the action you will regret least \Leftrightarrow min $\[]$ a $\rho(L(a))$ subject to L(a) capturing catastrophic loss; tie-break by max $\[]$ $\[$

with ρ ho a risk functional (probability of ruin, CVaR of tail loss, or hazard). This is not timidness; it is a **lexicographic guardrail** before exploitation. In learning terms, fit a **safety critic** ϕ hat his and a **reward critic** J hat J; optimize on two timescales: constrain ϕ hat his first, then maximize J hat J. This framework explains why biological agents exhibit strong avoidance learning and why engineered agents trained with safe-exploration constraints behave more robustly.

Relation to the Free Energy Principle (FEP). FEP minimizes expected surprise under a generative model. CM is compatible but sharper about asymmetry: it insists that the cost of "bad surprises" dominates policy shaping and is **ordered before** average surprise reduction. Expected free energy includes risk terms; CM asserts those terms are lexically prior when they correspond to catastrophic outcomes.

6. Polities: From Clans to City-States to Nuclear Powers

Scale modulates the enforceability of consequences.

Small polities. In Greek and Italian city-states, monitoring was local, alliances brittle, and retaliation logistically slow. Attribution noise lowers pp; mobilization lags lengthen τ severity Δ Delta is uncertain ex ante. The temptation to predate exceeds the shadow of the future plus external consequence, and conflict rates are high.

Modern deterrence. Intelligence, surveillance, and reconnaissance increase pp; forward-deployed and automated responses shorten τ \tau; credible alliances and second-strike capabilities raise Δ \Delta. The inequality supporting peace becomes easier to satisfy. Institutions—NATO, mutual defense treaties, trade law—function as compiled consequence maps.

Contemporary erosion. Deniable cyber and proxy operations depress pp and extend τ tau, reopening windows for opportunism despite nominally high severity. Sanctions that are draconian but leaky perform worse than sanctions that are moderate but certain and rapid. Audience costs and public commitments deliberately increase the consequence of backing down to enhance the credibility of threats.

This is control theory: institutions are controllers; when latency is high or observability low, overshoot and oscillation follow—arms races, sanction spirals, and accidental escalation.

7. Other Competitive Dynamics

Chess. Strong play begins with king safety and material non-loss, then transitions to exploitation. Sacrifices are rational only when the downstream consequence budget is bounded. CM explains why "don't make moves you'll regret" is a first principle rather than a platitude.

Markets and finance. Circuit breakers, margin requirements, and risk limits engineer certainty and celerity; violations are detected, halted, and liquidated automatically. Remove these and systems exhibit bubbles and crashes; the catastrophe functional (ruin probability) rises sharply.

Platforms and governance. Identity, logging, and reputation raise pp; prompt moderation shrinks τ \tau; proportional sanctions Δ \Delta preserve participation while deterring defection. Anonymous spaces predictably drift toward predation; safety theater that raises perceived Δ \Delta without changing pp or τ \tau is ineffective.

Immunity. Vaccination and immune memory raise pp, effectors increase Δ\Delta, primed responses reduce τ\tau. Pathogens evolve around these levers; hosts update controllers. CM reads host–pathogen dynamics as an arms race in consequence engineering.

8. Design Principles and Predictions

The model yields operational guidelines.

- Prioritize certainty and celerity. For fixed cost, increasing pp and decreasing τ\tau
 suppress defection more efficiently than raising Δ\Delta. This is visible in criminal
 justice, regulatory policy, and sanctions.
- 2. **Tune proportionality.** Sanctions should be predictable and calibrated to avoid rebellion, displacement, and Goodharting. Over-severe penalties with low certainty invite gaming; under-severe penalties invite opportunism.
- 3. **Maintain exploration with guardrails.** CM is not anti-innovation. It prescribes **bounded exploration**: enforce hard constraints on catastrophic outcomes, preserve slack for variance-seeking within the safe set.
- 4. **Beware enforcement elasticity.** If powerful actors can buy down penalties, the effective E(s,a)E(s,a) shrinks and cooperation collapses at the margin.

Falsifiable predictions include: policy changes that increase detection certainty or shrink enforcement delay should measurably reduce defection rates more than equal-budget increases in severity; anonymity shocks should degrade cooperation; alliance credibility shocks should increase opportunistic aggression; in biology, weakening apoptotic pathways increases somatic defection rates even if downstream cytotoxic severity is unchanged.

9. Limitations and Failure Modes

CM assumes that catastrophe is lexically dispreferred. Martyrdom utilities or sacralized values violate this assumption; for such agents, the catastrophe set is inverted. Goodhart's law threatens measurement-based enforcement; controllers that optimize proxies will be gamed unless the proxies are tightly coupled to true defection. The Peltzman effect is real: perceived safety can increase risk-taking if it reduces subjective E(s,a)E(s,a) faster than it reduces objective harm. Finally, legitimacy matters: if sanctions are perceived as unfair, actors may increase willingness to accept catastrophic risk.

10. Conclusion

Consequence Minimization articulates a single, cross-scale generator for adaptive order: **bound tail risk first; compete second**. It reframes classical agonistic philosophy as a system of enforced constraints; it extends realist IR by putting institutional feedback at center stage; it aligns with evolutionary policing and neural aversion learning; it predicts comparative statics in games, markets, and governance. The mathematics is elementary

but general: catastrophe functionals, lexicographic preferences, penalty limits, and three enforcement levers.

The pragmatic upshot is equally simple. If you want peace, prosperity, and progress in any system, do not sermonize about virtue; **engineer the consequences**: make detection certain, make enforcement swift, and calibrate sanction. The rest—cooperation, trust, and growth—emerges as an equilibrium artifact.

Appendix A: Notation Summary

SS: state space. AiA_i: actions. PP: transition kernel. F⊂SF\subset S: catastrophe set.

TFT_F: first hitting time of FF.

 $\phi_i(\pi) \phi_i(\pi) = i(\pi) J_i(\pi) J_i(\pi)$

CLP: lexicographic preference minimizing φ\phi then maximizing JJ.

CLBR: best response under CLP. CLE: fixed point of CLBR.

 $p,\tau,\Delta p,\lambda u,\Delta u,\Delta u$

 $E(s,a)=p\Delta\gamma\tau E(s,a)=p\Delta\gamma^{\tau}: effective expected penalty.$

Repeated PD stability: $(T-R) \le \gamma 1 - \gamma (R-P) + p\Delta \gamma \tau (T-R) \le \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)} = \frac{1-\gamma(R-P) + p\Delta \gamma \tau (T-R)}{1-\gamma(R-P)} =$

Replicator with punishment: $x = x(1-x)(\pi C - \pi D + \kappa p \Delta) \cdot x = x(1-x) \cdot x = x(1-$

Appendix B: Sketch of Existence for CLE

For each MM, the penalized game with utilities $U\sim(M)=J-M\varphi\setminus U^{(M)}=J-M\varphi\cap h$ has a mixed-strategy Nash equilibrium by standard fixed-point results (compact, convex strategy sets; continuous payoffs; quasi-concavity if needed, or invoke Glicksberg's theorem). The equilibrium correspondence is upper hemicontinuous in MM. Any accumulation point as $M\to\infty M\setminus h$ yields a profile in which no unilateral deviation can reduce h phi; among equal-h deviations, none improves JJ. Hence the limit lies in CLE.

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One-sentence semantic definition (for emphasis)

Consequence Minimization: Any adaptive agent will first seek to constrain catastrophic outcomes or premature exits before maximizing exploitation or gains.