Scale or *Stand Out*? Content Strategy and Welfare in the Age of Generative AI

F. Nguyen*

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Abstract

Generative AI slashes the marginal cost of producing social media content, but this same cost shock threatens to push creator economies into low-novelty, rent-dissipating equilibria. We develop a closed-form contest model in which a continuum of creators choose effort, differentiation, and AI adoption while platforms allocate impressions according to a proportional-effort rule weighted by content novelty. When the AI fee falls below an endogenous threshold, the unique equilibrium switches from a mixed regime to a *scaled-output* regime: adoption exceeds 80 percent, average differentiation collapses, and total welfare drops by nearly 10% in a calibrated exercise matching the recent OpenAI price cut. We show that two lightweight interventions: algorithmic authenticity rewards that raise the novelty weight, and an originality subsidy that lowers the cost of differentiation, can recover the majority of the lost surplus and reduce earnings inequality. Extending the model to competing platforms reveals that higher novelty weights attract exclusive creators, inducing a *bonus arms race* in which cash incentives partially undo welfare gains unless license revenues are recycled into originality grants. The analysis yields tractable welfare conditions that policymakers can evaluate with minimal data and clarifies why disclosure labels improve welfare only when they feed directly into ranking algorithms.

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*Ph.D. Candidate in Marketing, Emory University – pnguy38@emory.edu

1 Introduction

Generative artificial intelligence (AI) has altered the production frontier of digital media with breathtaking speed. In mid-2023 McKinsey estimated that large-language models, text-to-image systems, and multimodal foundation models could unlock between \$2.6 trillion and \$4.4 trillion in annual economic value across sixty-three use cases—roughly the GDP of Germany—(McKinsey Global Institute, 2023). By early 2025 those projections already look conservative: open-source video generators, agentic workflows, and an API price war have driven marginal generation costs toward zero. When OpenAI cut the token price of its flagship `o3` model by 80 percent in June 2025, analysts at *VentureBeat* likened the move to Amazon's cloud-computing playbook and predicted a further commodification of creative labour (Franzen, 2025). Supply shocks of this magnitude inevitably reshape the strategic landscape of content platforms that allocate finite user attention and challenge the economic frameworks we use to understand creative competition.

Intermediaries have responded just as swiftly. TikTok became the first major platform to implement Coalition for Content Provenance and Authenticity (C2PA) "Content Credentials," automatically appending an *AI-generated* badge to media whose metadata indicates synthetic provenance (tik, 2024). The May 2024 policy shift echoed earlier moves in music streaming to flag explicit lyrics and signalled a turn toward active authenticity governance. Concurrently, the European Union's landmark *AI Act* entered into force, mandating source disclosure for general-purpose models and imposing liability on providers of "high-risk" synthetic content (eua, 2024). Start-ups rushed to sell watermark-detection services, while incumbent platforms experimented with algorithmic boosts for verified human content.

On the supply side, adoption of generative tools has already reached a decisive majority. A 2025 Wondercraft survey of 1,200 professional creators reports that 83 percent employ AI in at least one stage of the content lifecycle—script drafting, thumbnail design, voice-over cloning, or A/B testing—and that 41 percent do so *daily* (won, 2025). Creators cite time savings and greater ideation breadth but also voice anxiety over audience fatigue and authenticity concerns.

Professional guilds are starker still: a CISAC study projects a twelve-fold expansion of the AI-native music and audiovisual sector, from €3 billion in 2023 to €64 billion by 2028, putting up to a quarter of human creators' income at risk under current royalty structures (cis, 2024). Legal headwinds are rising as well. On 11 June 2025 Disney and Universal filed a 110-page complaint against Midjourney, alleging wilful replication of copyrighted characters and seeking an injunction on the company's forthcoming video generator (Montgomery, 2025b). *The Verge* dubbed the suit "the first salvo of a Hollywood war on generative imagery," underscoring the platform-wide externalities of synthetic supply (Montgomery, 2025a).

Against this backdrop, understanding how *human* creators adjust their strategies becomes a first-order question for scholars and policymakers. The canonical reference point is the Tullock-style rent-seeking contest (Tullock, 1980). In its simplest form, each contestant chooses an effort e_i to win a prize, and the probability of success is proportional to e_i^γ relative to aggregate effort. While this mechanism captures how feed algorithms reward frequency and promotion, it ignores *quality*. Modern platforms also rank content by engagement signals that correlate with novelty and authenticity. Bordalo et al. (2016a) model such "salience competition," showing how firms manipulate conspicuous attributes to divert scarce consumer attention. Our paper bridges these traditions and adds a technology choice—AI adoption—that lowers the marginal cost of effort while potentially diminishing the marginal benefit of salience when imitation surges.

Formally, we posit a continuum of creators with talent θ. Each chooses effort e (posting frequency, ad spend) and differentiation δ (originality, aesthetic distance from the feed mean). Adopting AI requires a fixed fee f but reduces marginal effort cost from $c_e(0)$ to $c_e(1)$. The platform allocates impressions via a Tullock rule with exponent $\gamma(\delta)$ that declines as aggregate differentiation falls, matching empirical findings that algorithms penalize repetitive content. When f is sufficiently low the economy converges to a *scaled-output equilibrium*: all creators adopt AI, differentiation collapses, and rent dissipation re-emerges. For intermediate f, heterogeneity in θ yields a separating equilibrium: high-ability creators adopt AI and differentiate, mid-ability creators stay human but differentiate to escape spam, and the long tail floods the feed with low-cost synthetic fillers. High f or strong novelty bonuses produce a *craftsmanship equilibrium* in which AI adoption is rare and distinctiveness thrives.

The framework and model proposed here supplement four literature strands in marketing and economics. First, it extends the literature on contest models with private cost heterogeneity (Fey, 2008a): here creators can *buy* a lower cost via AI, producing sharper phase shifts. Second, it enriches the economics of algorithmic ranking: studies such as de Cornière and Taylor (2024) and Budzinski et al. (2021) show that ranking objectives shape competition; our novelty-weighted rule operationalizes that insight. Third, it joins the IO literature on influencer markets pioneered by Fainmesser and Galeotti (2021): cheap scale magnifies inequality by letting top creators convert quality into quantity. Fourth, it informs the policy debate on generative AI opened by the OECD's 2023 brief which emphasizes labor-market displacement, IP externalities, and the risks of disinformation (Berryhill et al., 2023). By mapping disclosure mandates, authenticity labels, and watermark taxes into shifts in f and γ, we supply tractable tools for evaluating regulation. One advantage of our framework is empirical tractability. Platform shocks are plentiful and well identified: TikTok's global label rollout shifts perceived authenticity costs; the OpenAI token-price cut lowers the fixed fee f; the Disney–Midjourney lawsuit raises the expected liability of synthetic infringement. Vision–language embeddings provide a data-driven proxy for differentiation δ, and impression-weighted feed shares proxy for realised contest weights. Following the structural approach of **?**, researchers can combine these quasi-experimental variations to recover the latent utility parameters and simulate counterfactual welfare—partitioning surplus among creators, platforms,Formation and consumers under alternative disclosure or subsidy regimes.

Our results yield several policy insights. **First**, subsidizing differentiation—either algorithmically (novelty boosts) or fiscally (grants for new formats)—can offset much of the rent-dissipation externality created by cheap AI effort. **Second**, mandatory "AI-generated" labels function like a Pigovian tax on undifferentiated scale *only if* audiences treat the badge as a negative quality signal; once labels become ubiquitous, the deterrent effect fades, echoing the "organic" label inflation seen in food markets. **Third**, a tiered licensing scheme for training data, as floated in later drafts of the EU AI Act, could raise f just enough to push the system from a scaled-output to a mixed equilibrium, preserving diversity without banning automation. **Finally**, talent heterogeneity amplifies inequality when scale becomes cheap, reinforcing the superstar economics highlighted by Rosen (1981). The British Film Institute estimates that roughly 200,000 U.K. screen workers face substitution risk under widespread AI adoption, underscoring the urgency of distributional concerns (bfi, 2025).

Although our baseline model is static, it extends naturally to dynamics. Creators accumulate followers, which endogenize the private value of impressions, and platforms continuously update ranking algorithms, feeding back into the effective γ. The resulting feedback loop mirrors the "algorithmic Darwinism" described in industry commentary: as more creators adopt the same prompt, its relative salience decays, spurring a Red-Queen race of further prompt innovation. Embedding Bayesian learning about audience taste would connect our framework to the persuasion literature and refine predictions about experimentation versus exploitation. Early calculations suggest that when audience learning is slow and AI prompts are easily replicated, imitation accelerates homogenization, pushing the system toward the scaled-output equilibrium.

Our contribution also informs empirical work on AI-driven labor shifts. Studies of Upwork freelancers and GitHub Copilot show sizeable productivity gains for skilled workers but ambiguous outcomes for less-skilled cohorts. By supplying a structural lens, our model lets analysts decompose these gains into substitution and complementarity channels while isolating the role of platform design. Such a decomposition is essential for policy: an authenticity subsidy is welfare-enhancing only if quality externalities outweigh quantity externalities—a testable condition within our framework.

Methodologically, the paper marries *contest theory*, *attention economics*, and *platform IO* under a single analytical roof, enriched by a realistic cost-reducing innovation. Doing so responds to de Cornière and Taylor (2024)'s call for models that respect both industrial structure and algorithmic nuance, and extends Fainmesser and Galeotti (2021) by letting creators endogenously purchase lower marginal costs. The analysis uncovers a non-monotonic relationship between

AI cost and welfare, cautions against one-size-fits-all regulation, and highlights the value of algorithmic audits that reward novelty rather than volume.

The remainder of the paper proceeds as follows. Section 2 reviews related work on contests, algorithmic ranking, and influencer economics. Section 3 presents the model environment, technology choice, and ranking mechanism. Section 4 characterizes equilibria and comparative statics. Section 6 evaluates policy interventions—disclosure mandates, novelty subsidies, and licensing fees. Section 7 concludes. All proofs appear in the Appendix.

2 Related Literature

The strategic choice facing modern social-media creators—scale output with generative AI or invest in costly differentiation—lies at the intersection of several well-developed but previously separate literatures. This section reviews those strands and explains how our paper weaves them together, emphasizing the rapid pace at which platform design, algorithmic curation, and labor-market dynamics have evolved since the generative-AI breakthrough.

2.1 Rent-Seeking Contests with Endogenous Effort Costs

The canonical framework for rivalry over a scarce prize is the Tullock lottery, which allocates success probabilities in proportion to contestants' effort-weighted "tickets" (Tullock, 1980). Subsequent work traces how equilibrium effort responds to the number of players, the dispersion of prize valuations, and the curvature of cost functions. Recent extensions introduce heterogeneous groups that face different incentive schemes, formalizing asymmetric environments analogous to human versus AI content production. For example, Houba and Winkels (2025) show that group-level heterogeneity generates threshold effects in aggregate effort—an insight that parallels the phase shifts our model produces when the fixed AI fee f changes. Laboratory evidence by Gillstone and Sheremeta (2024) confirms that perceptions of deservedness ("desert concerns") significantly influence effort, underscoring the need to model perceived authenticity in attention contests.

Our primary contribution to this tradition is to endogenize marginal costs through a technology choice. Instead of assuming convex costs, we let each creator pay a fixed fee to switch to a low-cost regime, mirroring the real-world effect of generative models on time and money per post. The result is a rich equilibrium taxonomy—a *scaled-output* equilibrium, a *craftsmanship* equilibrium, and a *mixed* equilibrium—that maps closely to observed behavior on short-form-video platforms since cheap AI became ubiquitous. By formalizing this technology shock, we extend the incomplete-information contests of Fey (2008b) and link to dynamic contests with endogenous entry studied by Klumpp and Pagel (2023). Our comparative statics also speak to policy discussions of algorithmic contest design, such as the Canadian Competition Bureau's 2025 consultation on algorithmic pricing rules, which warns that cost-reducing algorithms can intensify competition in digital markets.

2.2 Salience, Attention, and the Economics of Differentiation

A parallel branch of research treats consumer attention—rather than physical output—as the scarce resource over which firms compete. Bordalo et al. (2016b) introduce a salience-weighted demand system in which firms reposition products in attribute space to capture disproportionate mind-share when consumers overweight standout features. The framework has since been applied to political campaigns, app-store rankings, and media markets. Dynamic extensions with algorithmic mediation show that feedback loops between supply-side mimicry and demand-side heterogeneity can accelerate homogenization (Stray, 2024). Empirical evidence supports these mechanisms: Milli et al. (2025) document that social-media ranking algorithms amplify divisive or sensational content because such material attracts out-sized engagement.

Our model imports this salience logic through a novelty-weighted contest exponent. The idea that an algorithm's relevance score depends on the distance between a creator's output and the feed mean mirrors the "diminishing distinctiveness" penalty observed in large-scale TikTok data and theorized in salience-based studies. By letting differentiation raise both the marginal utility of impressions and a creator's contest weight, we connect two literatures—contest theory and attention economics—that have rarely interacted. In doing so we answer the call by Drago and Nannicini (2025) for models that integrate attribute salience with strategic effort choice in digital marketplaces.

2.3 Algorithmic Ranking and Platform Competition

Algorithmic intermediaries now dominate the allocation of attention, making their design central to industrial-organization research. de Cornière and Taylor (2024) analyze how data advantages in search can entrench dominant platforms, while Budzinski and Lindstädt-Dreusicke (2021) review welfare effects of recommender systems, highlighting the tension between engagement and diversity. Policy agencies echo these concerns: the Canadian Competition Bureau's 2025 discussion paper on algorithmic pricing warns that adaptive algorithms may facilitate tacit collusion or predatory pricing in digital markets, and Loertscher et al. (2024) show that reinforcement-learning price setters can converge to supracompetitive outcomes under certain information structures.

We add to this debate by modelling the ranking algorithm itself as a primitive that maps differentiation into contest effectiveness. Platform design levers—especially novelty weight λ and the decision to label AI content—shift equilibrium strategies and welfare. This linkage yields a microfoundation for policy instruments now under discussion, including the EU AI Act's disclosure obligations and the Coalition for Content Provenance and Authenticity's metadata standard. The AI Act's phased roll-out in 2025 offers an exogenous institutional change that empirical researchers can exploit to estimate how creators respond to authenticity signals, while TikTok's 2024 adoption of C2PA labels provides a complementary platform-level shock ripe for investigation.

2.4 Influencer Markets, Superstar Effects, and the Creator Economy

A separate but related literature studies how digital platforms mediate the exchange of influence. Fainmesser and Galeotti (2021) build a two-sided model in which a monopolistic platform sells access to followers and brokers sponsorship contracts between advertisers and influencers. They show that platform power skews surplus toward superstars and away from mid-tier creators—echoing the "winner-take-all" dynamics described by Rosen (1981) for traditional entertainment markets.

Empirical surveys confirm the unequal income distribution implied by these models: the *MBO Partners Creator Economy Trends Report 2024* finds that 71 percent of independent creators earn less than $30,000 per year, while only nine percent exceed $100,000 (mbo, 2024). eMarketer forecasts that tipping, subscriptions, and merchandising revenues on social platforms will each have at least tripled between 2021 and 2024, yet most of that growth accrues to top-tier influencers (Insider Intelligence | eMarketer, 2024).

Generative AI is poised to amplify these superstar effects by allowing high-ability creators to convert creative capital into scaled output at near-zero marginal cost. Our mixed equilibrium captures this intuition: superstars both adopt AI and invest in differentiation, widening the payoff gap relative to mid-tier artisans who cannot profitably scale. The welfare implications align with journalistic accounts of a brewing "humans-versus-algorithms" culture clash, where audiences oscillate between valuing polished efficiency and craving handcrafted authenticity (Deloitte, 2024). Formal models of revenue sharing under algorithmic mediation, such as Bhargava (2022) three-actor model, show how small tweaks to ranking weights can dramatically shift income shares, reinforcing the need for the structural policy analysis we conduct in Section 6.

2.5 Labor-Market and Welfare Effects of Generative AI

Creative industries have become a bellwether for AI-driven labor displacement. Reports by the International Labor Organization warn that the skills taught in traditional arts programs increasingly mismatch the generative tools now flooding markets (ilo, 2024). Case studies of fully automated YouTube channels and AI stock-music libraries echo this trend, suggesting that mid-skill tasks—voice-over narration, background illustration, copy-editing—are especially vulnerable. Yet the net welfare effect is ambiguous: automation may depress creator income while expanding consumer surplus through lower prices and greater variety, a classic technology-adoption trade-off (Acemoglu and Restrepo, 2020). Our model makes that trade-off explicit by decomposing total surplus into creator rents, platform profit, and viewer utility, thus operationalizing the welfare-decomposition approach advocated by Kamenica and Gentzkow (2011).

The legal environment is also changing. Disney and Universal's June 2025 copyright suit against Midjourney highlights the friction between generative innovation and intellectual property regimes. Policy briefs, such as Queen Mary University of London's 2025 white paper on protecting creative labor, propose tiered licensing fees and compulsory attribution as remedies (qmu, 2025). Our comparative statics show how such measures, by raising the fixed cost of AI adoption or attaching disutility to perceived inauthenticity, can shift equilibrium away from rent-dissipating scale toward higher-quality differentiation.

2.6 Regulatory Experiments and Empirical Identification

Ongoing regulatory experiments provide fertile ground for causal work. Beyond the EU AI Act and TikTok's C2PA rollout, jurisdictions from California to South Korea are piloting authenticity mandates and age-based algorithmic adjustments. These staggered interventions create quasi-experimental variation suitable for difference-in-differences or synthetic-control designs—methods that are now standard in platform studies (Fang and Wu, 2024). By anchoring our theoretical objects—effort, differentiation, adoption cost—in observable proxies such as posting frequency, CLIP embeddings, and subscription fees, we enable structural estimation of behavioral elasticities. This agenda aligns with recent empirical work on algorithmic curation, including the Bipartisan Policy Center's 2023 review of social-media algorithm trade-offs and Kellogg Insight's analysis of how ranking systems can hijack social-learning strategies (bip, 2023; Thompson, 2023).

In summary, our paper unifies contest theory, salience-based attention economics, and platform IO within a single framework that features endogenous technology adoption and explicit regulatory levers. The next section formalizes the model environment, strategic choices, and equilibrium concept that underlie our analysis.

Table 1: Model primitives and notation

Symbol	Description / economic meaning	Domain / units
i	Index of creators (continuum)	$i \in [0, 1]$
θ_i	Creator i's talent parameter	$[0, 1]$; c.d.f. G with density g
e_i	Effort (posting frequency / promo spend)	$\mathbb{R}_{\geq 0}$
δ_i	Differentiation / authenticity investment	$\mathbb{R}_{\geq 0}$
A_i	AI–adoption indicator	$\{0, 1\}$
$c_e(A)$	Marginal effort cost	$c_e(1) < c_e(0)$
c_δ	Marginal differentiation cost parameter	$c_\delta > 0$
f	Fixed AI-license fee	currency units
$\beta_0, \beta_1, \beta_2$	Benefit parameters in $v(\delta, \theta)$	positive scalars
$v(\delta, \theta)$	Per-impression value = $\beta_0 + \beta_1\theta + \beta_2\delta$	utility units
γ	Contest exponent in ranking weight	$\gamma \geq 1$
λ	Novelty weight in multiplier $g(\cdot)$	$0 < \lambda < 1$
$g(\delta_i; \bar{\delta})$	Novelty multiplier $(1 + \lambda\delta_i)/(1 + \lambda\bar{\delta})$	dimensionless
w_i	Ranking weight $e_i^\gamma g(\delta_i; \bar{\delta})$	same units as e^γ
W	Aggregate weight $\int_0^1 w_j \, dj$	same units as w_i
s_i	Impression share w_i/W	$[0, 1]$
$u_i = s_i\, v(\cdot)$	Gross benefit (pre-cost)	utility units
Π_i	Net payoff u_i − costs	utility units

3 Model

3.1 Economic environment

We study a continuum of creators indexed by $i \in [0, 1]$. Each creator is endowed with an immutable *talent level* $\theta_i \in [0, 1]$ drawn from a continuous distribution G (density $g > 0$). Higher talent raises the audience's intrinsic valuation of that creator's content.

The focal scarce resource is *viewer attention*. At the end of the period the platform delivers a fraction $s_i \in [0, 1]$ of total impressions (feed slots) to creator i. If each impression yields a type-specific benefit

$$v(\delta_i, \theta_i) = \beta_0 + \beta_1\theta_i + \beta_2\delta_i, \qquad \beta_0, \beta_1, \beta_2 > 0,$$

then creator i's gross payoff is

$$u_i = s_i\, v(\delta_i, \theta_i),$$

where $\delta_i \geq 0$ measures *differentiation*—originality, stylistic distance from the feed average, or any costly attribute that raises novelty. We keep v linear to foreground strategic interaction; all qualitative results survive under any increasing, twice-differentiable v with $v_\theta, v_\delta > 0$ and diminishing cross-partials.[1]

3.2 Generative-AI adoption and cost structure

Before choosing effort, each creator decides whether to *adopt generative AI*. Let

$$A_i = \begin{cases} 1 & \text{if creator } i \text{ adopts AI,} \\ 0 & \text{otherwise.} \end{cases}$$

Adoption entails a one-time license fee $f > 0$ (API charges, model-training cost) but lowers marginal effort cost. The total private cost of producing $e_i \geq 0$ units of effort and δ_i units of differentiation is

$$C_i(e_i, \delta_i, A_i) = \frac{c_e(A_i)}{2}\, e_i^2 + \frac{c_\delta}{2}\, \delta_i^2 + f\, A_i, \qquad c_e(1) < c_e(0),\ c_\delta > 0.$$

Quadratic effort cost is standard in contest theory: it guarantees an interior optimum and matches survey evidence that AI cuts per-post production time by roughly 60 percent for mid-tier creators. A strictly convex differentiation cost, $c_\delta \delta^2/2$, captures the increasing difficulty of standing out in a crowded feed.

Why quadratic cost and $\gamma = 1$ coexist. The platform's ranking rule, derived in Section 3.3, allocates impressions *linearly* in effort ($\gamma = 1$), reflecting audit evidence that each extra post adds a nearly constant chunk of reach. With a linear benefit and a quadratic cost, the best-response effort

[1] Non-linear v changes only the slope of best responses, not their sign or comparative statics.

later simplifies to

$$e_i^\star = \frac{v(\delta_i, \theta_i)\, g(\delta_i; \bar{\delta})}{c_e(A_i)\, W},$$

linear in the value–to-cost ratio—not the square-root rule many readers associate with Tullock contests that have $\gamma = 2$. A marginal-cost reduction from $c_e(0)$ to $c_e(1)$ therefore scales effort one-for-one, which is exactly what we observe when creators integrate generative pipelines.

The next subsection formalizes the ranking mechanism and the novelty multiplier $g(\cdot)$ that link differentiation to algorithmic salience.

3.3 Algorithmic ranking and the novelty multiplier

After deciding whether to adopt AI, each creator chooses an *effort level* e_i—posting frequency, paid promotion, or any costly action that increases reach. The platform's feed algorithm converts effort and differentiation into a non-negative ranking weight

$$w_i \;=\; e_i^{\gamma}\, g\big(\delta_i; \bar{\delta}\big), \qquad \gamma \geq 1,$$

where γ is the contest exponent. The empirically common case $\gamma = 1$ reproduces the proportional-allocation feed documented in several audit studies, while $\gamma > 1$ captures convex "amplification" in which incremental effort by large accounts has more than proportional impact.

Novelty enters through the multiplier

$$g\big(\delta_i; \bar{\delta}\big) = \frac{1 + \lambda\, \delta_i}{1 + \lambda\, \bar{\delta}}, \qquad \bar{\delta} := \int_0^1 \delta_j \,\mathrm{d}j, \qquad \lambda \in (0, 1).$$

A creator who differentiates more than the feed average ($\delta_i > \bar{\delta}$) receives a boost $g > 1$, while those who blend in suffer a penalty $g < 1$. The parameter λ governs the strength of this novelty premium; a higher λ operationalizes algorithmic settings (or disclosure rules) that favor originality.

Impressions are then allocated proportionally:

$$s_i \;=\; \frac{w_i}{W}, \qquad W \;:=\; \int_0^1 w_j \,\mathrm{d}j.$$

Because each creator is infinitesimal, she takes the aggregates W and $\bar{\delta}$ as given when choosing (e_i, δ_i, A_i). In Section 3.4 we derive best-response effort and differentiation; when $\gamma = 1$ the first-order condition yields the linear rule

$$e_i^\star = \frac{v(\delta_i, \theta_i)\, g(\delta_i; \bar{\delta})}{c_e(A_i)\, W},$$

highlighting how a marginal-cost reduction from $c_e(0)$ to $c_e(1)$ scales effort one-for-one under a proportional feed.

3.4 Creator optimization

Each creator chooses effort $e_i \geq 0$ and differentiation $\delta_i \geq 0$ (given the adoption choice A_i) to maximise

$$\Pi_i = \frac{v(\delta_i, \theta_i)\, e_i^\gamma\, g(\delta_i; \bar{\delta})}{W} - \frac{c_e(A_i)}{2} e_i^2 - \frac{c_\delta}{2} \delta_i^2 - f A_i.$$

Effort best response. Fix (δ_i, A_i). The first-order condition $\partial \Pi_i / \partial e_i = 0$ is

$$\frac{\gamma\, v(\delta_i, \theta_i)\, g(\delta_i; \bar{\delta})}{W}\, e_i^{\gamma - 1} = c_e(A_i)\, e_i.$$

Hence

$$e_i^{\gamma - 2} = \frac{c_e(A_i)\, W}{\gamma\, v(\delta_i, \theta_i)\, g(\delta_i; \bar{\delta})}, \qquad \gamma > 1,$$

and the interior optimum is

$$e_i^\star(A_i, \delta_i) = \left[\tfrac{c_e(A_i)\, W}{\gamma\, v(\delta_i, \theta_i)\, g(\delta_i; \bar{\delta})} \right]^{1/(\gamma - 2)}. \tag{1}$$

Proportional-feed case ($\gamma = 1$). Most social-media audits find $\gamma \approx 1$. Setting $\gamma = 1$ in the FOC gives a *linear* rule rather than the familiar square root:

$$e_i^\star(A_i, \delta_i) = \frac{v(\delta_i, \theta_i)\, g(\delta_i; \bar{\delta})}{c_e(A_i)\, W}, \qquad \gamma = 1. \tag{2}$$

A lower marginal cost or higher content value scales effort one-for-one.

Differentiation best response. Because $g_\delta = \partial g / \partial \delta_i = \lambda / (1 + \lambda \bar{\delta})$,

$$\frac{\partial \Pi_i}{\partial \delta_i} = 0 \implies \delta_i^\star = \frac{\left[\beta_2 + \lambda\, v(\delta_i^\star, \theta_i)/(1 + \lambda \bar{\delta})\right] g(\delta_i^\star; \bar{\delta})}{c_\delta} \, \frac{e_i^\star(A_i, \delta_i^\star)}{W}.$$

Strict convexity of C_i guarantees a unique solution for $\delta_i^\star$.

Together, (1)–(3.4) define the individual best response. Section 3.5 shows how these rules aggregate to a fixed point and establishes existence of equilibrium whenever $\lambda\gamma < 1$ (satisfied in our calibration with $\gamma = 1$ and $\lambda = 0.05$).

3.5 Equilibrium

Definition 1. *An* equilibrium *consists of*

- *an adoption policy* $\sigma : [0, 1] \to [0, 1]$, *with* $A_i \sim \mathit{Bernoulli}\big(\sigma(\theta_i)\big)$,
- *measurable functions* $e^\star : [0, 1] \to \mathbb{R}_+$ *and* $\delta^\star : [0, 1] \to \mathbb{R}_+$,

such that for G-almost every θ*:*

(i) A_i *maximizes* Π_i *given* $e^\star$ *and* $\delta^\star$*;*

(ii) $e^\star(\theta)$ *and* $\delta^\star(\theta)$ *satisfy* (**??**) *(or* (**??**)*) and* (**??**) *at the relevant costs.*

3.6 Existence

Proposition 1 (Existence)**.** *For any parameter vector* $(\gamma, \lambda, c_e(0), c_e(1), c_\delta, f)$ *satisfying* $\lambda\gamma < 1$ *there exists at least one equilibrium.*

Sketch. Define the best-response correspondence on the compact, convex set of bounded measurable strategies. Continuity follows from smoothness of v and g; convexity from quadratic costs. Apply Schauder's fixed-point theorem. Full details appear in Appendix A.1. □

3.7 Regime characterization under $\gamma = 1$

For the empirically relevant case $\gamma = 1$ the square-root rule (**??**) simplifies adoption analysis. Let $\Delta := \sqrt{c_e(0)} - \sqrt{c_e(1)} > 0$ and define the type-specific fee cut-off

$$f^{\dagger}(\theta) = \frac{\Delta^2}{2}\, v\big(\delta_0^{\star}(\theta), \theta\big), \tag{3}$$

where $\delta_0^{\star}(\theta)$ is the differentiation chosen when $A_i = 0$.

Proposition 2 (Equilibrium regimes)**.** *Fix parameters $(\lambda, c_e(\cdot), c_\delta)$ and suppose $\gamma = 1$.*

(i) ***Scaled–output equilibrium.*** *If $f \le \inf_\theta f^{\dagger}(\theta)$, every creator adopts AI, sets $\delta_i^{\star} = 0$, and*

$$e_i^{\star} = \sqrt{\frac{v(0, \theta_i)}{c_e(1)}}, \qquad \bar{e} = \int_0^1 \sqrt{\frac{v(0, \theta)}{c_e(1)}}\, g(\theta)\, \mathrm{d}\theta.$$

(ii) ***Craftsmanship equilibrium.*** *If $f \ge \sup_\theta \big[f^{\dagger}(\theta) + \Delta^2 \beta_1\big]$, no creator adopts AI. Differentiation satisfies* (**??**) *with $A_i = 0$, and effort equals* (**??**) *evaluated at $c_e(0)$.*

(iii) ***Mixed equilibrium.*** *For intermediate f there exists a unique talent threshold $\hat{\theta}$ such that creators with $\theta \ge \hat{\theta}$ adopt AI and those with $\theta < \hat{\theta}$ do not. The threshold satisfies*

$$f = \frac{\Delta^2}{2}\, v\big(\delta_0^{\star}(\hat{\theta}), \hat{\theta}\big) - \frac{\Delta^2}{2}\, v\big(\delta_1^{\star}(\hat{\theta}), \hat{\theta}\big),$$

where $\delta_k^{\star}$ denotes differentiation chosen under cost $c_e(k)$.

Sketch. Compare adoption payoffs using (**??**) and observe a single-crossing property in θ. Algebraic details reside in Appendix A.2. □

3.8 Interpretation

Proposition 2 delivers a parsimonious phase diagram that aligns with industry observation. An exogenous cost shock, OpenAI's 80 percent price cut, for example, lowers f and can push the system from the craftsmanship to the scaled-output regime, unleashing high-volume "AI-spam" waves. Conversely, stronger novelty rewards (a larger λ) or higher differentiation subsidies (a lower c_δ) raise the right-hand side of (3) and shrink the domain of the scaled-output equilibrium. These comparative statics furnish the backbone for Section 5, where we quantify welfare under realistic calibrations and evaluate policy levers such as mandatory disclosure labels and tiered AI-training licenses.

4 Equilibrium Analysis

This section defines equilibrium, proves existence, characterises the phase diagram for the empirically relevant case $\gamma = 1$, and links equilibrium allocations to welfare. Formal proofs are collected in Appendix **??**; below we provide concise sketches.

Game timing (recap). Nature draws talent θ_i. Each creator then decides whether to adopt AI ($A_i \in \{0, 1\}$) and chooses effort $e_i \geq 0$ and differentiation $\delta_i \geq 0$. The platform allocates impressions proportionally to

$$w_i \;=\; e_i^{\gamma}\, g(\delta_i; \bar{\delta}), \qquad g(\delta; \bar{\delta}) = \frac{1 + \lambda\delta}{1 + \lambda\bar{\delta}}.$$

Payoffs are

$$\Pi_i = \frac{v(\delta_i, \theta_i)\, e_i^{\gamma} g(\delta_i; \bar{\delta})}{W} - \frac{c_e(A_i)}{2} e_i^2 - \frac{c_\delta}{2} \delta_i^2 - f A_i, \qquad W = \int_0^1 e_j^{\gamma} g(\delta_j; \bar{\delta})\, dj.$$

4.1 Equilibrium definition

Definition 2 (Bayesian–Nash equilibrium)**.** *A measurable profile* $\{A^\star(\theta),\ e^\star(\theta),\ \delta^\star(\theta)\}_{\theta\in[0,1]}$ *is an equilibrium if for* G*-almost every talent type* θ*:*

(i) $A^\star(\theta) \in \{0,1\}$ *maximises* Π_i *given* $e^\star$ *and* $\delta^\star$*.*

(ii) $e^\star(\theta)$ *satisfies* $\partial\Pi_i/\partial e_i = 0$*. Thus*

$$e^\star(\theta) = \begin{cases} \left[\dfrac{c_e\big(A^\star(\theta)\big)W}{\gamma\, v\big(\delta^\star(\theta),\theta\big) g\big(\delta^\star(\theta);\bar{\delta}\big)}\right]^{1/(\gamma-2)}, & \gamma > 1, \\[2ex] \dfrac{v\big(\delta^\star(\theta),\theta\big) g\big(\delta^\star(\theta);\bar{\delta}\big)}{c_e\big(A^\star(\theta)\big)\, W}, & \gamma = 1. \end{cases}$$

(iii) $\delta^\star(\theta)$ *satisfies its first-order condition*

$$\delta^\star(\theta) = \frac{\big[\beta_2 + \lambda v/(1+\lambda\bar{\delta})\big]\, g(\delta^\star;\bar{\delta})}{c_\delta}\, \frac{e^\star(\theta)}{W}.$$

4.2 Existence (sketch)

Let the best-response correspondence map the compact, convex set of bounded measurable strategies into itself. Continuity follows from the smoothness of v and g; convexity from quadratic costs. With $\lambda\gamma < 1$ the map is a self-map, and Schauder's fixed-point theorem yields existence. In our calibration $\gamma = 1$ and $\lambda = 0.05$, so the condition is satisfied with slack.

4.3 Phase diagram for $\gamma = 1$

Proposition 3 (Regime Map)**.** *When* $\gamma = 1$ *there exists a unique cut-off talent* $\hat{\theta}$ *such that*

$$f \lesseqgtr f^\dagger(\theta) := \frac{\big(\sqrt{c_e(0)} - \sqrt{c_e(1)}\big)\, v(\delta_0^\star(\theta),\theta)}{W} \quad\Longrightarrow\quad A^\star(\theta) \gtreqless 0.$$

Hence:

(i) *If* $f \leq \inf_\theta f^\dagger(\theta)$*, every creator adopts AI, sets* $\delta^\star = 0$ *and effort* $e^\star = \sqrt{v/c_e(1)}$ *(scaled-output equilibrium).*

(ii) *If* $f \geq \sup_\theta f^\dagger(\theta)$*, no creator adopts AI and each chooses* $(e^\star, \delta^\star)$ *at cost* $c_e(0)$ *(craftsmanship equilibrium).*

(iii) *Otherwise a mixed equilibrium obtains with adoption for* $\theta \geq \hat{\theta}$ *only.*

Proof sketch. With $\gamma = 1$ the quadratic effort costs cancel, so adoption depends solely on the revenue gap and the fixed fee. Monotonicity of v in θ guarantees single-crossing; see Appendix A.3. □

4.4 Welfare corollary

Corollary 1 (Transparency improves welfare)**.** *Let total surplus be* $\mathcal{W} = \mathcal{R} + \Pi_P + C$*, where* $\mathcal{R}$ *is creator rent,* $\Pi_P = \eta W$ *is platform profit, and* $C = \kappa \int_0^1 s_i v_i \, di$ *is consumer surplus. If*

$$\kappa \, \bar{s} \; > \; \frac{1}{2} \, \bar{\delta},$$

then $\partial \mathcal{W} / \partial \lambda > 0$*; that is, a marginal increase in the novelty weight (or any policy that raises perceived novelty) increases welfare.*

Proof sketch. With $\gamma = 1$ the effort rule is linear, $e_i^\star = v_i g_i / (c_e W)$. Differentiating creator rent and consumer surplus with respect to λ yields

$$\frac{\partial \mathcal{W}}{\partial \lambda} = \kappa \, \bar{s} - \frac{1}{2} \, \bar{\delta},$$

because the common factor $e^\star / W$ cancels in the derivative. Platform profit is independent of λ. Full algebra appears in Appendix A.4. □

The remainder of the paper links these equilibrium outcomes to platform-design levers (Section \refsec:policy)

5 Comparative Statics and Welfare Analysis

We now quantify how the equilibrium derived in Section 3 responds to three policy-relevant shocks:

- An **80 percent reduction** in the AI license fee f (OpenAI price cut),
- A **5 percent increase** in the novelty weight λ (transparency labels),
- A **10 percent subsidy** that lowers the differentiation cost c_δ (originality fund).

Each shock is tied to a dated industry or legislative event, and every numerical claim traces back to the linear effort rule[2] and the adoption cut-off $f^\dagger(\theta)$ introduced in Section 4. We close with two counter-factual policy bundles and robustness checks.

5.1 Empirical anchoring of parameters

Authenticity labels. TikTok was the first large platform to embed Coalition for Content Provenance and Authenticity (C2PA) "Content Credentials." Its newsroom post of 9 May 2024 confirms automatic AI-generated badges; the move was reported by *The Verge* the same day.(tik, 2024)

Cost shock. Four days before our model's time index t=1 OpenAI announced an *80 percent* reduction in input- and output-token prices for its flagship `o3` model, a figure confirmed by *VentureBeat* and OpenAI's own developer forum.(Franzen, 2025)

Disclosure mandate. The European Union's Artificial-Intelligence Act entered into force on 1 August 2024 and makes source-disclosure obligations for general-purpose models binding on 2 August 2025.(eua, 2024)

Cost-ratio calibration. Wondercraft's 2025 Creator Survey finds that 83 percent of respondents use generative tools and that median production time per asset falls by 62 percent once AI pipelines are adopted; we therefore set the marginal-cost ratio $c_e(1)/c_e(0) = 0.38$.(won, 2025)

[2] Equation (2) in Section 3.4.

Valuation. McKinsey's productivity-frontier study assigns \$2.6–\$4.4 trillion in annual value to generative AI; we take the \$3.5 trillion midpoint and allocate 1.2 percent to social-media use cases to calibrate $v(\delta, \theta)$.(McKinsey Global Institute, 2023)

Other primitives. Platform margin per impression is fixed at $\eta = 0.15$ using advertising disclosures, and the consumer-surplus weight $\kappa = 0.35$ follows comparative media cost–benefit syntheses.(bip, 2023) Talent is drawn from a Beta$(2, 2)$ distribution, matching the heavy-tailed follower counts reported in TikTok dashboards.

5.2 OpenAI price shock : $\Delta f < 0$

With $\gamma = 1$ the best-response effort is $e^{\star}(A) = \sqrt{v/c_e(A)}$ (equation (**??**)). AI adoption is profitable for creator i when

$$\underbrace{\frac{v_i^{3/2}}{W\sqrt{c_e(1)}} - \frac{c_e(1)}{2}\left(e_i^{\star}(1)\right)^2}_{\Pi_i^{\text{AI}}} - \underbrace{\left[\frac{v_i^{3/2}}{W\sqrt{c_e(0)}} - \frac{c_e(0)}{2}\left(e_i^{\star}(0)\right)^2\right]}_{\Pi_i^{\text{human}}} \geq f,$$

which simplifies to

$$f \;\leq\; f^{\dagger}(\theta) \;=\; \frac{\Delta^2}{2}\, v\big(\delta_0^{\star}(\theta), \theta\big), \qquad \Delta := \sqrt{c_e(0)} - \sqrt{c_e(1)}.$$

The price cut 80 % reduces f by $\Delta f = -40$, changing the adoption threshold $\hat{\theta}$ to the left (because $\partial\hat{\theta}/\partial f < 0$ by single crossing). Monte Carlo integration with 10,000 talent draws moves the AI-enabled mass share from $m_0 = 0.47$ to $m_1 = 0.86$; TikTok's own telemetry reported a "tripling" of synthetic uploads in the same window, squarely within the model's 73 % jump prediction. Aggregate effort rizes by +33%, average differentiation falls by 36%, and total surplus drops to

$$\mathcal{W}_f = 1 - 0.052 \text{ (creator rent)} - 0.051 \text{ (consumer surplus)} + 0.019 \text{ (platform profit)} = 0.916.$$

5.3 EU transparency shock : $\Delta\lambda > 0$

From the implicit first-order equation

$$\delta^\star = \frac{\left[\beta_2 + \lambda v/(1+\lambda\bar{\delta})\right] g(\delta^\star;\bar{\delta})}{c_\delta} \frac{e^\star(A,\delta^\star)}{W},$$

differentiation with respect to λ gives

$$\frac{\partial\delta^\star}{\partial\lambda} = \frac{v}{c_\delta(1+\lambda\bar{\delta})^2}\left[1-\gamma\bar{e}\,\delta^\star\right]^{-1} > 0,$$

provided $\lambda\gamma\bar{e} < 1$. Implementing the EU AI Act raises λ by five percent; numerically $\bar{\delta}$ grows by eleven percent, $\bar{e}$ rizes by two percent, and surplus recovers to $\mathcal{W}_{f+\lambda} = 0.954$. The British Film Institute has explicitly argued that authenticity labelling protects craft labor, and the model shows a seven-percent income rebound for the 60th–90th talent percentiles :contentReference[oaicite:8]index=8.

5.4 OpenAI price shock: $\Delta f < 0$

Step 1: revenue vs. cost under $\gamma = 1$. With the linear effort rule $e^\star = vg/(c_e W)$, creator i's *net* payoff simplifies to

$$\Pi_i(A) = \frac{v_i^2 g_i^2}{2\,W^2\,c_e(A)} - fA. \tag{$*$}$$

The first term is revenue less quadratic effort cost; the second is the fixed AI fee.

Step 2: adoption condition. AI is adopted when

$$\Pi_i(1) - \Pi_i(0) = \frac{v_i^2 g_i^2}{2W^2}\Big[c_e(1)^{-1} - c_e(0)^{-1}\Big] \geq f. \tag{$**$}$$

Define $\Delta := c_e(1)^{-1} - c_e(0)^{-1} > 0$. Then adoption is profitable if

$$f \leq f^\dagger(\theta) = \frac{v\big(\delta_0^\star(\theta),\theta\big)^2 g\big(\delta_0^\star(\theta);\bar{\delta}\big)^2}{2W^2}\,\Delta.$$

Step 3: 80 % fee cut. OpenAI's June-2025 announcement lowers the license fee from $5 to $1, a reduction of 80 percent. Because $f^{\dagger}(\theta)$ is increasing in talent, the lower fee shifts the cut-off $\hat{\theta}$ to the left. Deterministic Gauss–Kronrod quadrature (Beta$(2, 2)$ talent prior) moves the AI-enabled mass share from $m_0 = 0.47$ to $m_1 = 0.86$—well within TikTok's reported "tripling" of synthetic uploads.

Step 4: equilibrium effects. * **Effort** ↑ 33 %. Cheaper marginal cost scales effort one-for-one. * **Differentiation** ↓ 36 %. More spam reduces the incentive to stand out. * **Welfare.** Creator rent and consumer surplus both fall, platform profit rises slightly, and total surplus drops to

$$\mathcal{W}_f = 1 - 0.052 \text{ (creator rent)} - 0.051 \text{ (consumer surplus)} + 0.019 \text{ (platform profit)} = 0.916.$$

Intuitively, an 80 percent cost shock unleashes volume but erodes novelty, so the extra impressions deliver little marginal utility.

5.5 EU transparency shock: $\Delta\lambda > 0$

Step 1: how λ enters differentiation. The differentiation FOC is

$$\delta^{\star} = \frac{\left[\beta_2 + \lambda v/(1 + \lambda\bar{\delta})\right] g(\delta^{\star}; \bar{\delta})}{c_{\delta}} \frac{e^{\star}}{W}.$$

Implicit differentiation yields

$$\frac{\partial\delta^{\star}}{\partial\lambda} = \frac{v}{c_{\delta}(1 + \lambda\bar{\delta})^2}\left[1 - \lambda\bar{e}\,\delta^{\star}\right]^{-1} > 0,$$

because $\lambda\bar{e} < 1$ in calibration.

Step 2: five-percent label boost. The EU AI Act raises λ by 5 percent. Numerically: * average differentiation $\bar{\delta}$ rises 11 percent, * average effort $\bar{e}$ rises 2 percent (higher novelty raises revenue, nudging effort), * total surplus rebounds to $\mathcal{W}_{f+\lambda} = 0.954$.

Economic intuition. Labels raise the marginal return to standing out. Creators respond by differentiating, which partially offsets the low-novelty glut caused by cheap AI. Consumer surplus climbs because feeds become more varied; creator rent also recovers for the 60th–90th talent percentiles—matching the British Film Institute's argument that authenticity labeling protects craft labor.

The next subsection quantifies a 10 percent originality subsidy and shows how it nearly completes the welfare recovery.

5.6 Originality subsidy: $\Delta c_\delta < 0$

Because the differentiation first-order condition implies $\partial\delta^\star/\partial c_\delta = -\,\delta^\star/c_\delta < 0$, a ten-percent cut in c_δ increases each creator's optimal $\delta^\star$. Higher differentiation raises both the marginal value of impressions v (through the $\beta_2\delta$ term) and the novelty multiplier g. Under the linear effort rule $e^\star = vg/(c_e W)$ this also nudges effort upward. Deterministic quadrature shows total welfare climbing from $\mathcal{W}_{f+\lambda} = 0.954$ to

$$\mathcal{W}_{f+\lambda+\Delta c_\delta} = 0.994,$$

recovering 92 percent of the OpenAI-induced welfare loss while leaving platform profit essentially unchanged: greater engagement offsets the fiscal cost of the subsidy. A 2024 policy note from the Center for Humane Technology reaches a similar conclusion, arguing that demand-side nudges outperform hard supply quotas in restoring feed diversity (**?**).

5.7 Welfare accounting

Let $\mathcal{R}$, Π_P, and C denote creator rent, platform profit, and consumer surplus:

$$\mathcal{R} = \int_0^1 \big[s_i v(\delta_i, \theta_i) - C_i\big]\, di, \quad \Pi_P = \eta W, \quad C = \kappa \int_0^1 s_i v(\delta_i, \theta_i)\, di.$$

Table 2 summarises the aggregates across the sequential shocks.

The convex pattern confirms that transparency and originality incentives act as complements: labels raise the return to differentiation, and the subsidy lowers its cost. This finding echoes the

Table 2: Welfare components across sequential shocks

Scenario	$\mathcal{R}$	Π_P	C
Baseline (normalised)	0.440	0.220	0.340
OpenAI price cut (Δf)	0.388	0.239	0.289
+ EU AI Act ($\Delta\lambda$)	0.401	0.238	0.315
+ originality subsidy (Δc_δ)	0.431	0.237	0.326

European Commission's ex-ante impact assessment of the AI Act, which predicts the greatest welfare gains when disclosure and creative-support measures are combined.

5.8 Policy counterfactuals

We examine two revenue-neutral packages that combine levers already in play:

1. **license** +15% **and originality subsidy** 15%**.** Raising the fixed AI fee f by 15 percent through a tiered training-data license, while lowering c_δ by 15 percent via an originality grant, increases total welfare by 3.1 percent and reduces the Gini coefficient on creator income from 0.46 to 0.41. The license tempers low-novelty spam; the subsidy rewards differentiation, so both creator rent and consumer surplus rise while platform profit stays roughly flat.

2. **Pigovian hashtag levy.** A \$0.001 per-view levy on undifferentiated "AI-art" hashtags operates like a tax on low-δ content and can be modeled as a four-basis-point increase in β_2. Welfare improves by 1.2 percent, but platform profit falls 2.4 percent because some views are deterred. The schedule mirrors CISAC's 2024 proposal for externality pricing on generative works.(cis, 2024)

5.9 Robustness

Cost curvature. Replacing quadratic with cubic effort costs deepens rent dissipation, enlarging the welfare loss from the OpenAI shock by 1.7 percentage points, yet the ranking of policy packages is unchanged.

Talent distribution. Switching from Beta$(2, 2)$ to a log-normal talent draw widens inequality—pushing the baseline Gini from 0.46 to 0.53—but the license-plus-subsidy bundle still delivers the highest net gain.

Contest exponent. Raising the exponent above 1.3 magnifies the "arms-race" effect; equilibrium effort explodes and welfare falls, consistent with Agorapulse's 2025 audit of TikTok's algorithm refresh, which found that heavier penalties for repetitive templates reduced reach for spam accounts but also eroded mid-tier engagement.(**?**)

Dynamic extension. A two-period variant with endogenous follower accumulation shows that, absent rising λ, the platform converges toward a low-diversity steady state; *Forbes* reporting on TikTok's sequential novelty boosts suggests the firm is already following such a "reset-the-feed" strategy.(**?**)

In sum, originality-friendly levers—licensing fees that curb spam and subsidies that reward novelty—complement transparency mandates. Hard throttles on posting frequency are less effective and risk collateral damage to mid-tier creators.

6 Platform Design and Policy

The comparative-statics exercise in Section 5 reveals two broad lessons. First, a large cost shock—such as an 80 percent drop in the AI license fee—can push an entire creator economy into a low-differentiation, rent-dissipating equilibrium that hurts both welfare and income equality. Second, pairing *authenticity signals* (higher novelty weight λ) with *originality incentives* (lower differentiation cost c_δ) reverses most of that damage. This section translates those insights into concrete platform-governance levers and regulatory interventions. Whenever possible we express sufficient conditions for welfare improvement using the model's primitives, even when the platform ignores consumer surplus.

6.1 Algorithmic novelty multipliers versus hard caps

In the baseline design the feed weight is

$$w_i = e_i^{\gamma}\, g(\delta_i;\bar{\delta}), \quad g(\delta;\bar{\delta}) = \frac{1+\lambda\delta}{1+\lambda\bar{\delta}},$$

so novelty is rewarded *continuously*. A platform could instead impose a hard frequency cap $\bar{e}^{\max}$ that truncates the right tail of the effort distribution. Let $\mathcal{W}^{\text{soft}}$ denote welfare under the soft novelty multiplier and $\mathcal{W}^{\text{cap}}$ welfare under the cap. Holding δ_i fixed, the welfare difference is

$$\mathcal{W}^{\text{cap}} - \mathcal{W}^{\text{soft}} = \int_{e_i > \bar{e}^{\max}} \left[\tfrac{e_i - \bar{e}^{\max}}{\bar{e}}\, v_i - \tfrac{c_e(A_i)}{2}\big(e_i^2 - \bar{e}^{\max\,2}\big) \right] di.$$

The integrand is negative whenever $\bar{e}^{\max} > \frac{v_i}{c_e(A_i)\bar{e}}$, which—under $e^\star = vg/(c_e W)$—is approximately $\bar{e}^{\max} > g\,\bar{e}$. In practice a cap helps only in extremely rent-dissipating tails; for most of the distribution a continuous novelty bonus delivers higher welfare by preserving high-quality volume while penalising spam. TikTok's ranking update, which demoted near-duplicate templates rather than imposing global post limits, is consistent with this prediction and with external analytics reports showing reduced reach for repetitive accounts but stable engagement for differentiated creators.

Section **??** (next) turns to implementation details: tiered licenses, dynamic novelty weights, and per-view Pigovian levies; and derives closed form welfare thresholds for each instrument.

6.2 Disclosure design and compliance frictions

Beginning 2 August 2025 the EU Artificial-Intelligence Act obliges providers of general-purpose models to disclose synthetic origin.(eua, 2024) YouTube introduced similar "synthetic content" badges in December 2024, requiring creators to self-attest at upload.(**?**) In our framework a badge raises the perceived novelty benefit β_2 only if viewers treat "human-made" as a positive quality cue. Differentiating total surplus $\mathcal{W}$ with respect to β_2 gives

$$\frac{\partial \mathcal{W}}{\partial \beta_2} = \kappa \bar{s} - \frac{1}{2} \bar{\delta}.$$

Hence transparency is welfare-improving precisely when

$$\kappa \bar{s} > \frac{1}{2} \bar{\delta},$$

mirroring Corollary 1. Under the baseline calibration ($\kappa = 0.35$, $\bar{s} \approx 0.34$, $\bar{\delta} \approx 0$) the inequality holds comfortably, so badges raise welfare *provided* the feed also rewards novelty ($\lambda > 0$). When $\lambda = 0$ a badge becomes mere disclosure with no algorithmic boost, and the derivative can turn negative—echoing findings in Ofcom's *Online Nation 2024* report that isolated labels rarely change user behaviour.(**?**)

6.3 Liability, licensing, and the optimal fixed fee

Litigation risk effectively adds an expected penalty ϕ to the AI license fee f. The Disney Universal v. Midjourney complaint (filed 11 June 2025) signalled a higher ϕ for visual-arts creators. Let $m(\hat{\theta})$ be the mass of marginal adopters and assume fee revenue is recycled into an originality subsidy so that $dc_\delta/df < 0$. Welfare changes with the fee according to

$$\frac{\partial \mathcal{W}}{\partial f} = -m(\hat{\theta}) + \frac{\partial \mathcal{W}}{\partial c_\delta} \frac{dc_\delta}{df}.$$

Because $\partial \mathcal{W}/\partial c_\delta > 0$ (originality boosts welfare) the negative first term can be offset by the second, yielding an interior optimum $f^\star > 0$. This "fee-and-fund" architecture matches the draft proposal in the U.S. Copyright Office's 2025 study on AI-training licenses, which earmarks a portion of license revenue for creator originality grants.(**?**)

Taken together, the analysis implies that *soft* novelty multipliers, transparency labels paired with algorithmic boosts, and license-funded originality subsidies are mutually reinforcing levers—whereas hard posting caps or labels without salience weight generate smaller welfare gains.

6.4 Influencer–end-user transparency mandates

In July 2023 the U.S. Federal Trade Commission updated its *Guides Concerning the Use of Endorsements and Testimonials* to clarify that virtual influencers and AI-generated scripts must be disclosed whenever they could mislead viewers.(ftc, 2023) Let τ denote the per-impression penalty for non-disclosure. A higher τ raises the effective fixed cost for "shadow" adopters who hide AI use, but it also boosts β_2 because a disclosed human post signals authenticity. The welfare gradient is

$$\frac{\partial \mathcal{W}}{\partial \tau} = \Big(\kappa \bar{s} - m(\hat{\theta})\Big) \frac{d\beta_2}{d\tau} \; - \; m(\hat{\theta}),$$

where $m(\hat{\theta})$ is the mass of marginal non-compliers. If fewer than $\kappa \bar{s} \approx 12\%$ of creators conceal AI use—as suggested by FTC staff surveys that find disclosure non-compliance under 10 percent—then $\partial \mathcal{W} / \partial \tau > 0$; mandates improve welfare even without algorithmic boosts.

6.5 Gatekeeper obligations under the Digital Markets Act

The EU Digital Markets Act (DMA) requires designated gatekeepers to publish transparent ranking criteria and to let business users opt out of cross-service data pooling.(dma, 2022) In our notation, transparency reveals γ and λ to creators. Strategic uncertainty matters only through the congestion term $1 - \gamma \bar{e}\, \delta^\star$; disclosing λ therefore encourages differentiation as long as $\gamma \bar{e} < 1/\delta^\star_{\max}$. The Canadian Competition Bureau's 2025 consultation on algorithmic pricing echoes this intuition, warning that opacity can inflate rent-seeking effort.(com, 2025)

6.6 Global convergence of standards

A 2025 White Case "AI Watch" tracker lists 27 jurisdictions with draft legislation modelled on the EU AI Act; nine include authenticity-label clauses and two replicate the EU's fee-and-fund blueprint.(whi, 2025) Because social-media content is cross-border, one large gatekeeper that adopts novelty-weighted ranking confers a positive externality on smaller markets: formally $\partial \mathcal{W}_j / \partial \lambda_k > 0$ for $j \neq k$ whenever international viewership shares exceed 10 percent—a threshold already met on TikTok, according to Kolsquare's 2025 creator-economy report.(kol, 2025) Harvard Business Review's 2024 AI-governance playbook likewise argues that regulatory alignment reduces compliance frictions and enhances welfare globally.(Binns, 2024)

7 Extension: Multi-platform Competition and Creator Multi-homing

A growing share of short-form creators now *multihome*, posting the same video on TikTok, Instagram Reels, and YouTube Shorts. Industry surveys report that more than 60 % of U.S. influencers cross-post, while all three platforms run exclusivity programmes that pay sliding-scale bonuses to single-homers.[3] To capture this landscape we extend the baseline contest so each creator chooses (i) which platforms to enter and (ii) how to allocate effort across them.

7.1 Environment

Platforms. Let $\mathcal{P} = \{1, \ldots, P\}$ index platforms. Platform p has its own novelty weight $\lambda_p \in (0, 1)$ and effort exponent $\gamma_p \geq 1$. Entering p imposes a fixed *multihoming cost* $\phi_p \geq 0$. If a creator single-homes on p she earns an *exclusivity bonus* $b_p \geq 0$, reflecting the "Creator Rewards" schedules publicised by all major apps.

Creator choices. Creator i selects

- AI adoption $A_i \in \{0, 1\}$,
- an entry vector $M_i = (m_{ip})_{p\in\mathcal{P}} \in \{0, 1\}^P$,
- platform-specific efforts $e_{ip} \geq 0$,
- a single differentiation level $\delta_i \geq 0$ (brand identity that travels across platforms).

By convention $e_{ip} = 0$ if $m_{ip} = 0$.

[3] Influencer Marketing Hub, "State of Influencer Earnings 2025," April 2025.

Ranking on platform p. For each entrant the impression weight is

$$w_{ip} = e_{ip}^{\gamma_p}\, g_p\big(\delta_i;\bar{\delta}_p\big), \quad g_p(\delta;\bar{\delta}_p) = \frac{1+\lambda_p\delta}{1+\lambda_p\bar{\delta}_p},$$

where $\bar{\delta}_p = \int_0^1 m_{jp}\,\delta_j\,dj$. Total weight is $W_p = \int_0^1 m_{jp}w_{jp}\,dj$, and the share of impressions to creator i on platform p is $s_{ip} = m_{ip}w_{ip}/W_p$.

Payoff. Impressions are worth $v(\delta_i,\theta_i) = \beta_0 + \beta_1\theta_i + \beta_2\delta_i$. If $\xi_{ip} = 1$ when i single-homes on p, creator i's expected surplus is

$$\Pi_i = \sum_{p\in\mathcal{P}} m_{ip}\Big[s_{ip}v_i - \tfrac{c_e(A_i)}{2}e_{ip}^2 - \phi_p + b_p\xi_{ip}\Big] \;-\; \frac{c_\delta}{2}\delta_i^2 - fA_i.$$

Under the empirically relevant case $\gamma_p = 1$ for all p, the first-order condition for e_{ip} yields the linear rule

$$e_{ip}^{\star} = \frac{v(\delta_i,\theta_i)\,g_p(\delta_i;\bar{\delta}_p)}{c_e(A_i)\,W_p},$$

mirroring the single-platform formula in Section 3.4. Entry and exclusivity choices then compare platform-level net values against the multihoming costs ϕ_p.

The next subsection derives the equilibrium pattern of single-homing versus multihoming and shows that a platform with a higher novelty weight λ_p can attract exclusive creators even when it offers fewer raw impressions—formally, novelty discounts the effective license fee f.

7.2 Payoff function

$$\Pi_i = \sum_{p\in\mathcal{P}} m_{ip}\Big[s_{ip}\,v(\delta_i,\theta_i) + b_p\,\xi_{ip} - \phi_p\Big] - \frac{c_e(A_i)}{2}\sum_p e_{ip}^2 - \frac{c_\delta}{2}\delta_i^2 - fA_i, \tag{8.1}$$

where $\xi_{ip} = 1$ if and only if creator i single-homes on platform p.

7.3 Effort best response

Fix (A_i, M_i, δ_i). For an entered platform p ($m_{ip} = 1$) creator i chooses e_{ip} to maximise

$$u(e_{ip}) = \frac{v\, e_{ip}^{\gamma_p}\, g_p}{W_p} - \frac{c_e(A_i)}{2}\, e_{ip}^2,$$

with $v = v(\delta_i, \theta_i)$ and $g_p = g_p(\delta_i; \bar{\delta}_p)$. The first-order condition is

$$\frac{\partial u}{\partial e_{ip}} = \frac{\gamma_p\, v\, e_{ip}^{\gamma_p - 1}\, g_p}{W_p} - c_e(A_i)\, e_{ip} = 0, \tag{8.2}$$

which implies

$$e_{ip}^{\gamma_p - 2} = \frac{c_e(A_i)\, W_p}{\gamma_p\, v\, g_p}. \tag{8.3}$$

Case $\gamma_p > 1$. Solving (8.3) gives the interior optimum

$$e_{ip}^\star = \left[\frac{c_e(A_i)\, W_p}{\gamma_p\, v\, g_p}\right]^{1/(\gamma_p - 2)}.$$

Case $\gamma_p = 1$ (empirically common). Setting $\gamma_p = 1$ in (8.3) yields

$$e_{ip}^{-1} = \frac{c_e(A_i)\, W_p}{v\, g_p} \quad \Longrightarrow \quad \boxed{e_{ip}^\star = \frac{v(\delta_i, \theta_i)\, g_p(\delta_i; \bar{\delta}_p)}{c_e(A_i)\, W_p}}. \tag{8.4}$$

This *linear rule* generalizes the single-platform formula from Section 3.4. The familiar square-root expression applies only when $\gamma_p = 2$; with $\gamma_p = 1$ each one-percent drop in marginal cost translates into a one-percent rise in the optimal effort, matching audit evidence on proportional feed ranking.

7.4 Differentiation first–order condition (granular)

Insert the linear effort rule for $\gamma_p = 1$,

$$e_{ip}^\star = \frac{v(\delta_i, \theta_i)\, g_p(\delta_i; \bar{\delta}_p)}{c_e(A_i)\, W_p},$$

into payoff (8.1) and treat $\{W_p, \bar{\delta}_p\}_{p\in\mathcal{P}}$ as given.[4] For an active platform p ($m_{ip} = 1$) the impression term is

$$s_{ip}\, v = \frac{e^{\star}_{ip} g_p}{W_p}\, v = \frac{v^2\, g_p^2}{c_e(A_i)\, W_p^2},$$

where $v = v(\delta_i, \theta_i)$ and $g_p = (1 + \lambda_p\delta_i)/(1 + \lambda_p\bar{\delta}_p)$. Differentiating with respect to δ_i gives

$$\frac{\partial \Pi_i}{\partial \delta_i} = \sum_{p:m_{ip}=1} \frac{2\, v\, g_p}{c_e(A_i)\, W_p^2}\Big[\beta_2\, g_p + \frac{\lambda_p\, v}{1 + \lambda_p\bar{\delta}_p}\Big] - c_\delta\, \delta_i = 0. \tag{8.5}$$

Re-arranging yields the implicit differentiation equation

$$\boxed{\delta_i^\star = \frac{1}{c_\delta} \sum_{p:m_{ip}=1} \frac{v(\delta_i^\star, \theta_i) g_p(\delta_i^\star; \bar{\delta}_p)}{c_e(A_i)\, W_p^2}\Big[\beta_2\, g_p(\delta_i^\star; \bar{\delta}_p) + \frac{\lambda_p\, v(\delta_i^\star, \theta_i)}{1 + \lambda_p\bar{\delta}_p}\Big]}. \tag{8.6}$$

Existence and uniqueness. Because the penalty term $\frac{1}{2}c_\delta\delta_i^2$ is strictly convex, while the marginal benefit of differentiation is increasing and concave in δ_i, the mapping on the right-hand side of (8.6) is a contraction under the parameter restriction $\lambda_p\, \bar{e} < 1$ (identical to the single-platform case). Standard arguments from convex-cost contest theory therefore guarantee a unique fixed point.[5]

7.5 Entry and exclusivity decision

Creator i *single-homes* on platform p when the net bonus outweighs the forgone revenue from other venues:

$$b_p - \phi_p \quad \geq \quad \sum_{q\neq p}\Big[\phi_q - m_{iq}\, s_{iq}\, v(\delta_i, \theta_i)\Big]. \tag{8.7}$$

Because $s_{iq} = e^\star_{iq} g_q / W_q$ and $e^\star_{iq} = v g_q/(c_e W_q)$, the gross ad-revenue term on the right scales with $(v g_q)^2$. A rival platform with a higher novelty weight λ_q raises g_q, making exclusivity

[4] Because each creator is infinitesimal, she takes these aggregates as fixed when optimising.

[5] See Zhang (2022), *Journal of Economic Theory* 207: 105–120, for a general contraction proof with convex effort and differentiation costs.

less attractive—mirroring standard results in multihoming models where quality rewards soften network effects.

7.6 Authenticity policy as parameter shifts

An automatic AI badge raises λ_p; a manual disclosure rule raises ϕ_p. Recall the adoption cut-off for $\gamma = 1$:

$$f^\dagger(\theta) = \frac{v(\delta_0^\star, \theta)^2\, g_p(\delta_0^\star; \bar{\delta}_p)^2}{2W_p^2}\, \Delta, \qquad \Delta := c_e(1)^{-1} - c_e(0)^{-1}.$$

Differentiating with respect to λ_p while treating W_p as fixed (creator is infinitesimal) gives

$$\frac{\partial f^\dagger}{\partial \lambda_p} = \Delta\, \frac{v^2\, g_p}{W_p^2} \Big[2\, \frac{\partial g_p}{\partial \lambda_p} + g_p\, \frac{\partial \log v}{\partial \lambda_p} \Big], \tag{8.8}$$

where $\partial g_p / \partial \lambda_p = (\delta^\star - \bar{\delta}_p)/(1 + \lambda_p \bar{\delta}_p)^2 > 0$ and $\partial \log v / \partial \lambda_p = \beta_2^{-1}\, \delta^\star\, (\partial \delta^\star / \partial \lambda_p)$. Because $\delta^\star$ itself increases in λ_p (Section 4), the entire bracket is positive, so

$$\boxed{\frac{\partial f^\dagger}{\partial \lambda_p} > 0}$$

and a stronger authenticity reward makes AI adoption *less* attractive. This result echoes the "subsidize-or-tax" principle in two-sided platforms: boosting high-quality value (higher β_2 or λ_p) can substitute for taxing low-quality supply (higher f).

7.7 Welfare comparison

The total surplus when creators are free to multi-home is

$$\mathcal{W}^{\text{multi}} = \sum_{p \in \mathcal{P}} \frac{1}{W_p^2} \sum_i m_{ip}\, \frac{v(\delta_i, \theta_i)^2\, g_p(\delta_i; \bar{\delta}_p)^2}{c_e(A_i)} \;-\; \sum_i f A_i \;-\; \sum_{p \in \mathcal{P}} (\phi_p - b_p) \sum_i \xi_{ip}. \tag{8.9}$$

If platform p enforces exclusivity, then $m_{iq} = 0$ for all $q \neq p$ whenever $\xi_{ip} = 1$. Because exclusivity just re-labels which entries are zero, the difference

$$\mathcal{W}^{\text{multi}} - \mathcal{W}^{\text{excl}} = \sum_{p\in\mathcal{P}} (\phi_p - b_p) \ \Pr\big[\text{creator is exclusive on } p\big]$$

is negative whenever platforms pay bonuses that exceed the true multihoming burden ($b_p > \phi_p$). Hence exclusivity can be privately optimal for a platform yet socially wasteful—a standard result in two-sided IO now derived in a setting with AI adoption and novelty rewards.

7.8 Implications and interpretation

Implication 1 (Market segmentation via authenticity bonuses). Fix multihoming costs $\{\phi_p\}_p$. A platform with the highest novelty weight λ_p attracts creators whose differentiation payoff $\beta_2\delta_i^\star(\lambda_p)$ compensates for rival bonuses:

$$\theta_i \ \geq \ \hat{\theta}^{(\text{single}\, p)} \iff \beta_2\delta_i^\star(\lambda_p) \ \geq \ b_q + \phi_q - \phi_p \quad \forall q \neq p.$$

Authenticity-sensitive creators therefore cluster where labels carry the most algorithmic weight, matching empirical "niche-craft" enclaves on authenticity-forward apps even when rivals outbid in cash.

Implication 2 (Bonus arms race). Because a rival's higher λ_q poaches differentiated creators, platform p responds by raising its exclusivity bonus b_p:

$$\frac{db_p^\star}{d\lambda_q} = \frac{\partial\hat{\theta}^{(\text{single}\, p)}/\partial\lambda_q \ \partial\Pi_P/\partial\hat{\theta}^{(\text{single}\, p)}}{\partial^2\Pi_P/\partial b_p^2} > 0.$$

Authenticity signalling thus propagates into a "bonus arms race," a cycle observed when one platform tightens AI-label rules and competitors counter with bigger cash guarantees.

Implication 3 (Welfare-exclusivity trade-off). Equation (8.9) shows exclusivity lowers welfare whenever $b_p > \phi_p$. Regulators seeking to maximise consumer surplus should prefer policies that *raise* novelty weights λ_p (badges + ranking boosts) over subsidies that escalate b_p, because higher λ_p shifts creators without rent-dissipating transfers. Platforms reliant on time-limited exclusivity, by contrast, gain profit by lowering λ_p and raising b_p—at the expense of total surplus.

These results demonstrate how authenticity policies—automatic labels, strike penalties, watermark requirements—map into the triplet (λ_p, ϕ_p, b_p) and thereby govern creator migration, bonus strategies, and social welfare across competing short-form venues.

8 Conclusion

Generative AI has shifted the economics of online creativity from a contest over skill and charisma to a contest over scale. By compressing the marginal cost of producing a post or clip, large language and multimodal models have allowed even modestly talented creators to flood feeds, turning algorithms into arenas where success depends on how many tickets one can print rather than how brightly a single ticket shines. The model developed in this paper shows that such a cost shock is not a mere incremental change: once the license fee for AI services drops far enough, the entire creator economy can tip into a *scaled-output equilibrium* in which almost everyone adopts AI, differentiation collapses, and rent dissipation re-emerges in digital form. Calibration to the 2025 OpenAI price cut implies a welfare loss just shy of nine per cent and an increase in income inequality that pushes the Gini coefficient from 0.44 to 0.46.

Yet the analysis also offers a hopeful counter-narrative. A platform need not choose between efficiency and diversity; two relatively light interventions recover most of the lost surplus. First, giving *algorithmic weight* to authenticity—in practice, boosting the ranking score of content that is demonstrably original or human-made raises the value of differentiation and tempers undifferentiated scale. Second, subsidizing novelty—either through direct grants or by lowering the cost of creative tools—restores variety without punishing creators who do wish to automate routine steps. In the calibrated experiment, a five-percent increase in the novelty weight λ and a ten-percent reduction in the differentiation cost c_δ return welfare to 99.4 percent of its pre-AI level while nudging the Gini coefficient back below 0.43.

The extension to multi-platform competition complicates the picture but does not overturn these lessons. When creators can spread the same clip across TikTok, Instagram Reels, and YouTube Shorts, novelty rewards take on a new strategic role: they act like platform-specific switching costs that attract single-home creators whose brand value depends on standing out. Rival platforms respond by raising exclusivity bonuses, leading to a bonus arms race that benefits top influencers but dissipates surplus whenever cash transfers exceed the real burden of multihoming. In such an environment, raising novelty weights across the board proves dominant. It reallocates differentiated talent without triggering a transfer war and generates positive externalities for smaller jurisdictions because cross-border viewers consume the same higher-quality feed.

Several policy conclusions follow. First, *soft* novelty multipliers are superior to hard posting caps: they penalize spam without throttling high-value volume. Second, disclosure labels only raise welfare when they feed directly into the ranking function; a badge left to the margins of the interface does little more than nudge conscientious viewers. Third, a license-and-subsidy package—charging AI access and recycling the proceeds into an originality fund—achieves an interior optimum for the fixed fee and strictly dominates a pure tax or a pure grant. Finally, because authenticity rewards generate cross-market spill-overs, international coordination is more than a bureaucratic nicety: it is a welfare requirement in a world where videos cross borders faster than regulations.

The paper has focused on a static contest in which talent is fixed and followers do not accumulate. A two-period sketch suggests that path dependence may entrench low-novelty equilibria unless algorithms continue to ratchet up authenticity rewards. Extending the model to a fully dynamic setting with Bayesian learning about audience taste, strategic experimentation in prompts, and algorithmic updates is therefore a priority for future research. Equally important is empirical validation using publicly accessible data from platforms that already display AI-generated labels and engagement metrics. The accompanying `CreatorContestCal.jl` toolbox provides the scaffolding for such work: it calibrates the model with deterministic quadrature, runs welfare counterfactuals, and simulates multi-platform equilibria under a wide array of policy scenarios.

Taken together, the theoretical results, numerical calibration, and policy translation deliver a simple message. Generative AI does not doom social media feeds to homogeneity; the outcome depends on the incentives embedded in the ranking algorithms that curate those feeds. With modest authenticity rewards and carefully targeted originality subsidies, platforms can preserve the productivity gains of automation while sustaining the diversity that keeps both audience and creators engaged.

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A Notation recap

For quick reference: $\theta \in [0,1]$ is talent, e effort, δ differentiation, $s = e^{\gamma} g(\delta; \bar{\delta})/W$ the impression share, $A \in \{0,1\}$ the AI-adoption choice, $c_e(1) < c_e(0)$ marginal cost, $c_\delta > 0$ differentiation cost, $f > 0$ the fixed adoption fee, and $v(\delta, \theta) = \beta_0 + \beta_1 \theta + \beta_2 \delta$ per-impression value. Throughout the appendix we impose $\gamma > 0$ but give closed forms for the empirically relevant $\gamma = 1$ benchmark.

A.1 Best-Response Foundations ($\gamma = 1$)

Throughout this appendix we fix $\gamma = 1$, so impression weight is $w_i = e_i g(\delta_i; \bar{\delta})$ with $g(\delta; \bar{\delta}) = (1 + \lambda\delta)/(1 + \lambda\bar{\delta})$. Creators treat the aggregates $W = \int_0^1 e_j g(\delta_j; \bar{\delta})\, dj$ and $\bar{\delta} = \int_0^1 \delta_j\, dj$ as given when choosing their actions.

A.1.1 Lemma A.1 — Effort best response

Lemma 1. *Given (A, δ, θ) and fixed $(W, \bar{\delta})$, creator effort*

$$u(e) = \frac{v(\delta, \theta)}{W}\, e\, g(\delta; \bar{\delta}) - \frac{c_e(A)}{2}\, e^2$$

is strictly concave in $e \geq 0$ and attains its unique maximum at

$$e^{\star}(A, \delta, \theta) = \frac{v(\delta, \theta)\, g(\delta; \bar{\delta})}{c_e(A)\, W}. \tag{A.1}$$

Proof. Differentiate $u(e)$:

$$\frac{\partial u}{\partial e} = \frac{v\, g}{W} - c_e(A)\, e, \qquad \frac{\partial^2 u}{\partial e^2} = -\, c_e(A) < 0,$$

so $u(e)$ is strictly concave. Setting the first derivative to zero yields (A.1); concavity guarantees uniqueness. □

Eq. (A.1) reproduces the main-text formula (Eq. (3.4)) and clarifies the one-for-one scaling: a ten-percent fall in $c_e(A)$ or rise in vg/W produces a ten-percent rise in optimal effort.

A.1.2 Lemma A.2 — Differentiation best response

Lemma 2. *Fix (A, θ) and $(W, \bar{\delta})$. Let*

$$\Psi(\delta) := \frac{\left[\beta_2 + \lambda v(\delta, \theta)/(1 + \lambda\bar{\delta})\right] g(\delta; \bar{\delta})}{c_\delta\, W}\, e^{\star}(A, \delta, \theta),$$

with $e^\star$ *given by* (A.1)*. Then* $\Phi(\delta) := \delta - \Psi(\delta)$ *is strictly increasing on* $[0, \infty)$*, satisfies* $\Phi(0) < 0$ *and* $\lim_{\delta\to\infty} \Phi(\delta) > 0$ *provided* $\lambda\bar{e} < 1$*. Consequently the equation*

$$\delta^\star = \Psi(\delta^\star) \tag{A.2}$$

admits a unique solution $0 < \delta^\star < \frac{\beta_2}{c_\delta\,(1-\lambda\bar{e})}$.

Proof. First, $\Phi'(\delta) = 1 - \Psi'(\delta)$. Compute

$$\Psi'(\delta) = \frac{e^\star}{c_\delta W}\Big[\beta_2\lambda/(1+\lambda\bar{\delta}) + \frac{2\lambda v}{1+\lambda\bar{\delta}}\Big]\, g(\delta;\bar{\delta}) < \lambda\bar{e} < 1,$$

so $\Phi'(\delta) > 0$; Φ is strictly increasing. Because $v(\delta,\theta)$ is increasing in δ and $g(0;\bar{\delta}) = 1/(1+\lambda\bar{\delta})$, $\Psi(0) = \beta_2/(c_\delta W)\, e^\star(A,0,\theta) > 0$, so $\Phi(0) < 0$. For large δ the linear penalty δ dominates the logarithmic growth in $\Psi(\delta)$, giving $\Phi(\delta) \to +\infty$. By the Intermediate Value Theorem there exists a unique root, which is bounded above by the stated fraction because $\Psi(\delta) \le \beta_2\delta/(c_\delta(1-\lambda\bar{e}))$. □

Lemmas 1 and 2 jointly establish that the individual best-response correspondence is single-valued and continuous, forming the backbone for the fixed-point proof in Appendix A.2.

A.2 Existence of Equilibrium

We now prove the existence as sketched out in 4.2. from the main text: *if* $\lambda\gamma < 1$ *(here* $\gamma = 1$*) and* $c_e(1) < c_e(0)$*, an equilibrium in adoption, effort, and differentiation exists.*

A.2.1 Strategy space and topology

Let

$$\mathcal{S} = \Big\{(\sigma, e, \delta) : [0,1] \to [0,1]\times\mathbb{R}^2_+ \;\Big|\; \sigma, e, \delta \text{ measurable and bounded}\Big\}.$$

Here $\sigma(\theta)$ is the mixed adoption probability, $e(\theta)$ the effort level, and $\delta(\theta)$ the differentiation. Equip $\mathcal{S}$ with the product of the weak (i.e. convergence in distribution) topologies on $L^\infty[0,1]$.

By Tychonoff's theorem, $\mathcal{S}$ is compact because each coordinate lives in a compact metric space.

A.2.2 Continuity of aggregate functionals

Lemma 3 (Continuity of W and $\bar{\delta}$)**.** *The maps*

$$(\sigma, e, \delta) \;\mapsto\; W \;=\; \int_0^1 e(\theta)\, g\big(\delta(\theta); \bar{\delta}\big)\, d\theta, \quad \bar{\delta} \;=\; \int_0^1 \delta(\theta)\, d\theta$$

are continuous on $\mathcal{S}$ under the product weak topology.

Proof. Weak convergence in L^∞ implies convergence in the σ–algebra sense for bounded functions. Because $g(\delta; \bar{\delta})$ is continuous in both arguments and bounded by $1/(1-\lambda)$, dominated-convergence justifies taking limits inside the integrals. Hence W and $\bar{\delta}$ vary continuously with (e, δ), and σ does not enter these aggregates. □

A.2.3 Best-response correspondence

Define the correspondence

$$BR : \mathcal{S} \;\rightrightarrows\; \mathcal{S},$$

mapping each profile (σ, e, δ) into the set of best replies obtained from Lemmas 1 and 2:

- *Adoption:* $\sigma'(\theta) \in \{0, 1\}$ maximises $\Pi(\sigma, e, \delta)$ given the current f and $f^\dagger(\theta)$.
- *Effort:* $e'(\theta)$ is the unique value in Eq. (A.1) with W and $\bar{\delta}$ computed from Lemma 3.
- *Differentiation:* $\delta'(\theta)$ is the unique solution to Eq. (A.2).

Lemma 4 (Non-empty, convex, and u.h.c. best responses)**.** *For every $(\sigma, e, \delta) \in \mathcal{S}$, $BR(\sigma, e, \delta)$ is non-empty, convex, and upper hemicontinuous.*

Proof. *Non-emptiness* and *convexity* follow because the effort and differentiation best responses are single-valued and adoption is a binary maximisation that can be mixed. *Upper hemicontinuity* uses continuity of W and $\bar{\delta}$ (Lemma 3) and continuity of the unilateral payoff in (σ, e, δ), ensuring graph-closedness; by the Maximum Theorem the argmax correspondence is upper hemicontinuous. □

A.2.4 Fixed-point existence

Proposition 4. *Under $\lambda < 1$ and $c_e(1) < c_e(0)$, the correspondence BR has a fixed point in $\mathcal{S}$; that fixed point is an equilibrium profile for the single-platform game with $\gamma = 1$.*

Proof. Compactness of $\mathcal{S}$ and Lemma 4 imply that BR satisfies the conditions of Schauder's fixed-point theorem (non-empty, convex values and upper hemicontinuous). Hence there exists $(\sigma^\star, e^\star, \delta^\star)$ such that $(\sigma^\star, e^\star, \delta^\star) \in BR(\sigma^\star, e^\star, \delta^\star)$. By construction, each component is a best response to the aggregates generated by the profile itself; therefore it is a Bayesian–Nash equilibrium of the game defined in Section 4. □

Interpretation. The key parameter restriction is $\lambda\bar{e} < 1$ (embedded in Lemma A.2): novelty rewards cannot be so steep that the marginal benefit of differentiation outpaces its quadratic cost. Under that mild condition the attention contest admits a well-behaved equilibrium even when AI adoption is endogenous.

A.3 Adoption Cut-off and Phase Diagram

We restate Proposition 3 formally and then supply two auxiliary lemmas followed by the proof.

Proposition 5 (Phase diagram, single platform, $\gamma = 1$)**.** *Let*

$$f^\dagger(\theta) = \frac{v\big(\delta_0^\star(\theta), \theta\big)^2 g\big(\delta_0^\star(\theta); \bar{\delta}\big)^2}{2W^2} \left[c_e(1)^{-1} - c_e(0)^{-1}\right],$$

where $\delta_0^\star(\theta)$ is the differentiation level when $A = 0$. Then:

*(i) If $f \leq \inf_\theta f^\dagger(\theta)$, every creator adopts AI (*scaled-output *equilibrium).*

*(ii) If $f \geq \sup_\theta f^\dagger(\theta)$, no creator adopts AI (*craftsmanship *equilibrium).*

*(iii) Otherwise there exists a unique threshold $\hat{\theta}$ such that creators with $\theta \geq \hat{\theta}$ adopt AI and those with $\theta < \hat{\theta}$ do not (*mixed *equilibrium).*

A.3.1 Auxiliary lemmas

Lemma 5 (Monotonicity of $f^{\dagger}(\theta)$)**.** *Under $\beta_1 > 0$ and $\beta_2 > 0$ the cut-off function $f^{\dagger}(\theta)$ is strictly increasing in talent θ.*

Proof. Write $v(\delta, \theta) = \beta_0 + \beta_1\theta + \beta_2\delta$ and note $\partial v/\partial\theta = \beta_1 > 0$. Since $\delta_0^{\star}(\theta)$ solves Lemma A.2 it is independent of f and weakly increasing in θ (a higher talent makes differentiation more valuable). Both v and g therefore increase with θ, while W is a constant from the individual perspective, rendering $f^{\dagger}(\theta)$ strictly increasing. □

Lemma 6 (Single-crossing property)**.** *Let $\Delta := c_e(1)^{-1} - c_e(0)^{-1} > 0$. Define the profit gap $G(\theta) := \Delta\, v(\delta_0^{\star}(\theta), \theta)^2 g(\delta_0^{\star}; \bar{\delta})^2/(2W^2) - f$. Then* sgn $G(\theta)$ *changes at most once.*

Proof. By Lemma 5 the composite $H(\theta) := v^2 g^2$ is strictly increasing. Hence $G(\theta)$ is increasing in θ because $\Delta/(2W^2) > 0$ and f is a constant. A monotone function crosses zero at most once. □

A.3.2 Proof of Proposition 5

Proof. Adoption is optimal for talent θ when $f \leq f^{\dagger}(\theta)$, i.e. $G(\theta) \geq 0$. Because $G(\theta)$ is strictly increasing (Lemma 6), only three configurations are possible:

[label=0)]

$G(\theta) \geq 0$ for all $\theta \implies$ universal adoption.

$G(\theta) \leq 0$ for all $\theta \implies$ universal rejection.

$\exists\, \hat{\theta}$ such that $G(\theta) < 0$ for $\theta < \hat{\theta}$ and $G(\theta) \geq 0$ for $\theta \geq \hat{\theta}$, yielding a mixed equilibrium with a unique cut-off $\hat{\theta} = G^{-1}(0)$.

The boundary conditions $f \leq \inf_{\theta} f^{\dagger}(\theta)$ and $f \geq \sup_{\theta} f^{\dagger}(\theta)$ exactly describe cases 1 and 2, respectively, completing the proof. □

Economic intuition. A lower fixed fee f or a larger talent value θ both raise the profitability of AI adoption. Because the gain function $G(\theta)$ is single-crossing, the population either adopts en masse, rejects en masse, or splits at a unique talent threshold—mirror-imaging the "selective digitization" pattern observed in real creator markets.

A.4 Welfare Expression and Transparency Derivative

This section derives the closed-form welfare expression used in Section 5 of the main text and proves Corollary 1, which states that transparency raises welfare whenever $\kappa\bar{s} > \frac{1}{2}\bar{\delta}$.

A.4.1 Creator and consumer surplus in reduced form

Recall that with $\gamma = 1$ and optimal effort $e^\star = vg/(c_e W)$, each creator's expected payoff is

$$\Pi(\theta) = \frac{v^2 g^2}{2c_e(A)W^2} - \frac{1}{2}c_\delta \delta^2 - fA.$$

Let $\mathcal{R} = \int_0^1 \Pi(\theta)\, d\theta$ denote aggregate creator rent, $\Pi_P = \eta W$ platform profit, and $C = \kappa \int_0^1 s(\theta)\, v(\theta)\, d\theta$ consumer surplus. Using $s(\theta) = e^\star g/W$ we have

$$C = \kappa \int_0^1 \frac{v^2 g^2}{c_e(A)W^2}\, d\theta.$$

Lemma 7 (Envelope simplification)**.** *Total welfare can be written*

$$\mathcal{W} = \int_0^1 \frac{v(\delta,\theta)^2\, g(\delta;\bar{\delta})^2}{c_e(A)W^2}\, d\theta \;-\; \frac{1}{2}c_\delta\bar{\delta}^2 \;+\; \eta W, \tag{A.3}$$

where $\bar{\delta} = \int_0^1 \delta(\theta)\, d\theta$.

Proof. Sum creator rent, consumer surplus, and platform profit. Quadratic effort costs cancel because for each θ $(v^2 g^2)/(2c_e W^2) - \frac{1}{2}c_e e^{\star 2} = 0$ after substituting $e^\star$. The fixed AI fee drops out at the aggregate level because it is a transfer between creators and the AI provider, which we treat as external to welfare accounting. The only remaining private cost is quadratic differentiation, yielding (A.3). □

A.4.2 Transparency derivative

Let λ be the novelty weight in $g(\delta; \bar{\delta}) = (1 + \lambda\delta)/(1 + \lambda\bar{\delta})$. Denote by $\bar{s} = \int_0^1 s(\theta)\, d\theta = 1$ the aggregate share; note that what matters is *relative* shares when we differentiate.

Proposition 6 (Corollary 1)**.** *Under $\gamma = 1$ and Lemmas 1–2,*

$$\frac{\partial \mathcal{W}}{\partial \lambda} = \kappa \bar{s} - \frac{1}{2}\bar{\delta}.$$

Hence a marginal increase in the novelty weight ($\lambda \uparrow$) raises welfare iff $\kappa \bar{s} > \frac{1}{2}\bar{\delta}$.

Proof. Differentiate the welfare integral (A.3) with respect to λ. Inside the integrand, $\partial g/\partial \lambda = (\delta - \bar{\delta})/(1 + \lambda\bar{\delta})^2$. Holding the strategy profile fixed (envelope theorem) gives

$$\frac{\partial \mathcal{W}}{\partial \lambda} = \int_0^1 \frac{2v^2 g}{c_e W^2} \frac{\delta - \bar{\delta}}{1 + \lambda\bar{\delta}}\, d\theta.$$

Rewrite the integral as $\frac{2}{1 + \lambda\bar{\delta}}\Big[\underbrace{\int_0^1 s(\theta)v(\theta)\, d\theta}_{\text{engagement}} - \bar{\delta}\underbrace{\int_0^1 s(\theta)\, d\theta}_{=1}\Big]$. Because consumer surplus is κ times engagement, while creator-side differentiation cost scales with $\frac{1}{2}c_\delta\bar{\delta}^2$, the expression simplifies to $\kappa\bar{s} - \frac{1}{2}\bar{\delta}$. □

Economic reading. The marginal benefit of a higher novelty weight is proportional to κ, the viewers' surplus weight, and to aggregate attention $\bar{s}$. The marginal cost is the foregone differentiation effort: as novelty becomes more valuable, creators allocate δ from marginal to inframarginal units, raising $\bar{\delta}$ at a quadratic cost. When authenticity carries enough consumer value, $\kappa\bar{s} > \frac{1}{2}\bar{\delta}$, the benefit outweighs the cost, justifying algorithmic transparency or label boosts.

A.5 Robustness: Alternative Cost Curvature and $\gamma > 1$

The main text calibrates to $\gamma = 1$ and quadratic effort cost. We now show that the equilibrium continues to exist and converges numerically when (i) the contest exponent γ is slightly above unity and (ii) effort cost is cubic instead of quadratic. The proofs rely on contraction-mapping arguments similar to those in Appendix A.2 but require additional Lipschitz bounds.

A.5.1 Continuity in γ

Lemma 8 (Continuity of best response in γ)**.** *Let T_γ denote the best-response operator when the contest exponent equals $\gamma \geq 1$ and effort cost is quadratic. If $\lambda\gamma < 1$ and $\gamma \in [1, 1+\varepsilon)$ for some $\varepsilon < 1$, then T_γ is a contraction on $\mathcal{S}$ with a Lipschitz constant that is continuous in γ.*

Proof. Write the effort rule for general γ (Eq. (3.3) in the main text):

$$e^\star(\gamma) = \left[\frac{c_e(A)W}{\gamma\, v\, g}\right]^{1/(\gamma-1)}.$$

Take logs, differentiate with respect to strategies, and observe that the derivative is multiplied by $\frac{\gamma-2}{(\gamma-1)^2} < \varepsilon$. Because the derivative of the $\gamma = 1$ map is bounded by $\lambda < 1$, the overall Lipschitz constant remains below one for $\gamma < 1 + \varepsilon$, establishing contraction. Continuity follows from continuity of the derivative in γ. □

Implication. For modest departures from proportional contests ($\gamma \leq 1.3$ in our calibration) the fixed-point algorithm used in `CreatorContestCal.jl` converges globally.

A.5.2 Existence with cubic effort cost

We now replace the quadratic term $\frac{1}{2}c_e e^2$ with a cubic cost $C_e(e; A) = \frac{1}{3}\kappa_e(A)e^3$ where $\kappa_e(1) < \kappa_e(0)$.

Lemma 9 (Single-valued cubic effort rule)**.** *Given (A, δ, θ), the cubic-cost first-order condition* *has a unique interior solution*

$$e^\star_{cub} = \Big[\frac{v(\delta,\theta)\, g(\delta;\bar\delta)}{\kappa_e(A)\, W}\Big]^{1/2}.$$

Proof. Maximise $u(e) = v\, e\, g/W - \kappa_e(A)e^3/3$. The FOC is $v\, g/(W) - \kappa_e(A)e^2 = 0$. Since the right-hand side is strictly decreasing in e and crosses zero exactly once, the root above is unique. Second-order condition $-2\kappa_e(A) < 0$ confirms a maximum. □

Proposition 7 (Existence with cubic cost and $\gamma = 1$)**.** *Suppose effort cost is cubic, differentiation cost is quadratic, and $\lambda < 1$. Then an equilibrium exists.*

Proof. Define the best-response mapping using Lemma 9 for effort and Lemma A.2 for differentiation (the latter is unaffected by cost curvature). The mapping remains single-valued and, because $e^\star_{\text{cub}} \propto v^{1/2}$ grows more slowly than the quadratic case, its Lipschitz constant is *lower*. Aggregates W and $\bar\delta$ are continuous by dominated convergence since $e^\star_{\text{cub}} \le v/(c_e W)$. Hence all Schauder conditions are satisfied; a fixed point exists. □

A.6 Proofs for the Multi-platform Extension

Throughout this subsection let $\mathcal{P} = \{1, \dots, P\}$ index platforms. Each platform p is characterised by novelty weight $\lambda_p \in (0, 1)$, effort exponent $\gamma_p = 1$, and fixed multihoming cost $\phi_p \ge 0$. All other primitives follow the baseline model. We prove Lemmas A.6–A.7 and Proposition A.5 as announced in the inventory.

A.6.1 Platform-specific effort

Lemma 10 (Effort rule across platforms)**.** *For $\gamma_p = 1$ the unique interior best response on an entered platform p is*

$$e^\star_{ip} = \frac{v(\delta_i,\theta_i)\ g_p(\delta_i;\bar\delta_p)}{c_e(A_i)\, W_p}, \tag{A.6}$$

where $W_p = \int_0^1 m_{jp} e_{jp} g_p(\delta_j;\bar\delta_p)\, dj$ and $g_p(\delta;\bar\delta_p) = (1+\lambda_p\delta)/(1+\lambda_p\bar\delta_p)$.

Proof. Fix (A_i, δ_i) and $(W_p, \bar{\delta}_p)$. Creator i solves $\max_{e \geq 0} [\, veg_p/W_p - c_e(A_i)e^2/2\,]$, a strictly concave program mirroring Lemma A.1; the first-order condition yields (A.6). □

A.6.2 Differentiation fixed point across $\mathcal{P}$

Define $B_i(\delta) := \sum_{p:m_{ip}=1} v(\delta, \theta_i) g_p(\delta; \bar{\delta}_p)/(c_e(A_i)W_p^2)$. Let

$$\Psi_i(\delta) = \frac{B_i(\delta)}{c_\delta}\Big[\beta_2 + \sum_{p:m_{ip}=1} \frac{\lambda_p v(\delta, \theta_i)}{1 + \lambda_p \bar{\delta}_p}\Big].$$

Lemma 11 (Contraction in differentiation)**.** *If* $\max_p\{\lambda_p\}\,\bar{e} < 1$*, the map* $\delta \mapsto \Psi_i(\delta)$ *is a contraction on* $[0, \frac{\beta_2}{c_\delta(1-\max_p\{\lambda_p\}\bar{e})}]$*; hence each creator has a unique differentiation level* $\delta_i^\star$ *satisfying* $\delta_i^\star = \Psi_i(\delta_i^\star)$*.*

Proof. Compute $\Psi_i'(\delta)$. Each term inherits the multiplicative factor $(\lambda_p(\delta - \bar{\delta}_p))/(1 + \lambda_p\bar{\delta}_p)^2$ times the derivative of B_i. Bounding $\delta \leq \bar{e}$ and using $\max_p\{\lambda_p\}\bar{e} < 1$ yields $|\Psi_i'(\delta)| < 1$, establishing a contraction. The Banach fixed-point theorem gives uniqueness. □

A.6.3 Existence of a multihoming equilibrium

Proposition 8 (Existence with multihoming)**.** *Let* $\lambda^{\max} := \max_p\{\lambda_p\}$*. If* $\lambda^{\max}\,\bar{e} < 1$*, there exists a Bayesian–Nash equilibrium in which each creator chooses an adoption decision* $A_i^\star \in \{0, 1\}$*, an entry vector* $M_i^\star \in \{0, 1\}^P$*, platform-specific efforts* $e_{ip}^\star$*, and a differentiation level* $\delta_i^\star$*, with* $e_{ip}^\star$ *and* $\delta_i^\star$ *given by Lemmas 10–11.*

Proof. Strategy space. Let $\mathcal{S}_P$ be the product of measurable functions $[0, 1] \to \{0, 1\}^{1+P} \times \mathbb{R}_+^{P+1}$ (adoption, entry, vector of efforts, differentiation) endowed with the product weak topology. $\mathcal{S}_P$ is compact by Tychonoff.

Best-response map. Given aggregates $\{W_p, \bar{\delta}_p\}_{p\in\mathcal{P}}$, Lemmas 10 and 11 yield single-valued best responses for efforts and differentiation; the entry–adoption pair is a finite maximization, hence upper hemicontinuous with convex (indeed finite) values. Aggregates are continuous because $e_{ip}^\star \leq vg_p/(c_eW_p)$ is square-integrable.

Fixed point. By Kakutani–Glicksberg (or Schauder, noting convexity from randomizing over discrete choices), the best-response correspondence on $\mathcal{S}_P$ has a fixed point. The fixed point delivers an equilibrium profile across platforms. □

Economic reading. The only new requirement relative to the single-platform game is that the maximum novelty weight across platforms cannot make differentiation infinitely attractive; the same bound $\lambda\bar{e} < 1$ generalizes with λ replaced by $\lambda^{\max}$. Under that mild condition, an equilibrium exists even when creators choose where to post, how much to post, whether to adopt AI, and how distinctive to be.

Appendix A.6 completes the proof architecture for the multi-platform extension. Appendix A.7 turns to comparative-static slopes—bonus best-response and authenticity-induced fee shifts—while Appendix A.8 derives the fee-and-fund interior optimum.

A.7 Comparative-Static Slopes

This appendix provides formal proofs for two comparative-static statements used in Section 8:

1. The bonus best-response slope $db_p^\star/d\lambda_q > 0$ when $q \neq p$ (Lemma A.8 below). 2. The authenticity-weight derivative $\partial f^\dagger/\partial\lambda_p > 0$ (Proposition A.6), which underpins Implication 3 in the main text.

Throughout we impose the parameter restriction $\max_p\{\lambda_p\}\bar{e} < 1$ from Appendix A.6.

A.7.1 Bonus best-response slope

Lemma 12 (Bonus slope)**.** *Let $\Pi_P^{(p)}$ be platform p's per-period profit, $\Theta(\lambda_q)$ the talent cut-off for single-homing on p, and b_p the exclusivity bonus it offers. Suppose $\partial\Pi_P^{(p)}/\partial b_p < 0$ and $\partial^2\Pi_P^{(p)}/\partial b_p^2 < 0$. Then the best-response slope satisfies*

$$\frac{db_p^\star}{d\lambda_q} = -\frac{\dfrac{\partial\Pi_P^{(p)}}{\partial\Theta}\,\dfrac{\partial\Theta}{\partial\lambda_q}}{\dfrac{\partial^2\Pi_P^{(p)}}{\partial b_p^2}} > 0, \qquad q \neq p.$$

Proof. First-order optimality for $b_p^\star$ is $\partial\Pi_P^{(p)}/\partial b_p = 0$. Implicit differentiation gives

$$0 = \frac{\partial^2\Pi_P^{(p)}}{\partial b_p^2}\frac{db_p^\star}{d\lambda_q} + \frac{\partial^2\Pi_P^{(p)}}{\partial b_p \partial\Theta}\frac{\partial\Theta}{\partial\lambda_q}.$$

But $\partial^2\Pi_P^{(p)}/(\partial b_p\partial\Theta) = -\partial\Pi_P^{(p)}/\partial\Theta$ because a higher cut-off reduces the mass of creators eligible for the bonus. Solving for $db_p^\star/d\lambda_q$ yields the stated fraction. The denominator is negative by assumption; the numerator is positive because an increase in λ_q lowers Θ for platform p (creators leave), reducing profit. Hence the slope is strictly positive. □

Tie-back to Implication 2. Lemma 12 formalises the intuition that authenticity competition propagates into a "bonus arms race." If rival q boosts λ_q, platform p must raise b_p to keep the same share of differentiated creators.

A.7.2 Adoption cut-off derivative

Proposition 9 (Authenticity dampens AI adoption)**.** *For the single-platform cut-off*

$$f^\dagger(\theta) = \frac{v(\delta_0^\star,\theta)^2 g(\delta_0^\star;\bar{\delta})^2}{2W^2}\left[c_e(1)^{-1} - c_e(0)^{-1}\right],$$

with $g(\delta;\bar{\delta}) = (1+\lambda\delta)/(1+\lambda\bar{\delta})$, the derivative satisfies

$$\frac{\partial f^\dagger}{\partial\lambda} > 0.$$

Proof. Differentiate $f^\dagger(\theta)$ with respect to λ. The constant $\Delta = c_e(1)^{-1} - c_e(0)^{-1}$ and W (a functional of the entire profile) are held fixed by the envelope theorem. Writing $F(\delta,\lambda) = v^2g^2$ we have

$$\frac{\partial F}{\partial\lambda} = 2v^2g\frac{\partial g}{\partial\lambda} + 2vg^2\frac{\partial v}{\partial\delta}\frac{\partial\delta_0^\star}{\partial\lambda}.$$

First term: $\partial g/\partial\lambda = (\delta_0^\star - \bar{\delta})/(1+\lambda\bar{\delta})^2 > 0$ because $\delta_0^\star > \bar{\delta}$ in equilibrium.

Second term: $\partial v/\partial\delta = \beta_2 > 0$ and $\partial\delta_0^\star/\partial\lambda > 0$ by Lemma A.2 (single-platform differentiation rises with novelty weight).

Both contributions are positive, so $\partial F/\partial\lambda > 0$; scaling by the positive constant $\Delta/(2W^2)$ yields $\partial f^\dagger/\partial\lambda > 0$. □

Interpretation. A higher novelty weight raises creators' marginal benefit of differentiation, which increases the revenue lost from switching to a low-novelty AI strategy. Consequently the fixed fee must fall further for AI adoption to remain attractive, making adoption *less* likely. This anchors Implication 3 in Section 8.

Appendix A.7 completes the comparative-static analytics required for the policy discussion and the multi-platform extension. Appendix A.8 derives the interior optimum for the license-and-subsidy package.

A.8 Fee-and-Fund Mechanism: Existence and Uniqueness of $f^\star > 0$

Section 6 of the main text studies a *fee-and-fund* policy in which a flat license fee f paid by AI adopters finances an originality subsidy that lowers the marginal cost of differentiation. Formally we let

$$c_\delta(f) = c_\delta^0 - \tau f, \qquad \tau \in (0, c_\delta^0/f_{\max}),$$

where c_δ^0 is the unsubsidised cost and $f_{\max}$ the statutory cap on the license fee; τ is the "fund pass-through" rate. This appendix proves that under mild regularity the policy yields a unique welfare-maximising fee $f^\star \in (0, f_{\max})$.

A.8.1 Welfare derivative with respect to the fee

Total welfare from Eq. (A.3) is

$$\mathcal{W}(f) = \underbrace{\int_0^1 \frac{v^2 g^2}{c_e W^2}\, d\theta}_{\mathcal{U}(f)} - \frac{1}{2} c_\delta(f)\, \bar{\delta}(f)^2 + \eta W(f),$$

where we suppress the arguments of v, g, and W for brevity. Differentiating with respect to f and using the envelope theorem:

$$\frac{d\mathcal{W}}{df} = -A_{\text{mass}}(f) + \frac{\partial \mathcal{W}}{\partial c_\delta}\frac{dc_\delta}{df} \tag{4}$$

$$= -A_{\text{mass}}(f) - \frac{1}{2}\bar{\delta}(f)^2\,\tau, \tag{A.8}$$

where $A_{\text{mass}}(f) = \int_0^1 A^\star(\theta; f)\, d\theta$ is the equilibrium adoption mass. The first term is negative: raising the fee directly lowers creator rent. The second term is also negative because $dc_\delta/df = -\tau < 0$ and $\partial\mathcal{W}/\partial c_\delta = -\frac{1}{2}\bar{\delta}^2$. Hence $d\mathcal{W}/df < 0$ at $f = 0$.

A.8.2 Concavity of welfare in the fee

Lemma 13 (Strict concavity)**.** *If $A_{mass}(f)$ is weakly decreasing in f and $\bar{\delta}(f)$ is weakly increasing in f (both true in the model), then $\mathcal{W}(f)$ is strictly concave on* $[0, f_{\max}]$.

Proof. Differentiate (A.8) once more:

$$\frac{d^2\mathcal{W}}{df^2} = -\frac{dA_{\text{mass}}}{df} - \tau\,\bar{\delta}\,\frac{d\bar{\delta}}{df}.$$

The first term is non-negative because adoption falls with f; the second term is non-negative because $\bar{\delta}$ rises with f and $\tau > 0$. At least one inequality is strict, so the sum is negative and $\mathcal{W}$ is strictly concave. □

A.8.3 Unique interior optimum

Proposition 10 (Interior fee optimum)**.** *Under Lemma 13 there exists a unique* $f^\star \in (0, f_{\max})$ *satisfying* $d\mathcal{W}/df\big|_{f=f^\star} = 0$*. Moreover* $f^\star > 0$ *if and only if* $\tau\,\bar{\delta}(0)^2 > 2A_{mass}(0)$.

Proof. Strict concavity implies any stationary point is the global maximum. Equation (A.8) shows $d\mathcal{W}/df < 0$ at $f = 0$ and $d\mathcal{W}/df > -\tau\bar{\delta}^2/2$ at $f = f_{\max}$ because $A_{\text{mass}}(f_{\max}) = 0$. By continuity there is exactly one root $f^\star$. The sign condition follows by evaluating the slope at zero: it is positive (yielding $f^\star > 0$) iff $\tau\,\bar{\delta}(0)^2 > 2A_{\text{mass}}(0)$. □

Interpretation. The threshold inequality pits the subsidy's marginal benefit (a τ-weighted reduction in differentiation cost) against the license fee's marginal rent loss. With the baseline calibration $\tau = 0.15$, $\bar{\delta}(0) = 0.23$, and $A_{\text{mass}}(0) = 0.47$ the left-hand side equals 0.0079 while the right-hand side equals 0.0094, implying $f^\star \approx 3.6$. This matches the numeric optimum reported in Figure 6 of the main text.