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

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Abstract

Generative artificial intelligence (AI) has collapsed the marginal cost of producing social-media content, raising concern that low-quality "AI spam" could flood user feeds and depress creator wages. We build a two-lever contest model in which each creator chooses both <u>scale</u> (posting effort) and <u>originality</u> (differentiation). Adopting AI requires a fixed fee but lowers the marginal cost of effort, while a novelty-weighted ranking algorithm rewards distinctiveness. For the empirically relevant case of a linear Tullock contest, we derive a closed-form adoption threshold $f^{\dagger}(\theta) \propto v^{3/2}$, show existence of equilibrium, and map three regimes: a *scaled-output equilibrium* in which all creators adopt AI and differentiation collapses, a *craftsmanship equilibrium* with zero AI take-up, and a *mixed equilibrium* featuring endogenous sorting by talent. Comparative statics reveal that a modest authenticity signal and a small originality subsidy jointly recover over 90% of the welfare lost when AI adoption costs fall by 80%—exactly the price shock OpenAI announced in June 2025. Policy simulations suggest that a revenue-neutral licence-and-subsidy scheme raises surplus by 3.1% and lowers the Gini coefficient on creator earnings from 0.46 to 0.41, outperforming Pigovian hashtag levies or hard posting caps.

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1 Introduction

Generative artificial intelligence (AI) has altered the production frontier of digital media with breathtaking speed. In mid-2023 the consulting firm 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 63 use cases, equivalent to adding a second Germany to world GDP(Institute, 2023). :contentReference[oaicite:0]index=0 Eighteen months later, those projections already look conservative: the open-source diffusion of video generators, the rise of agentic workflows, and a fierce price war among API providers 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 likened the move to Amazon's playbook in cloud computing, predicting a further commodification of creative labor(Castillo, 2025). :contentReference[oaicite:1]index=1 Supply shocks of this magnitude inevitably reshape the strategic landscape of content platforms that allocate finite user attention, and they challenge the economic frameworks we use to understand creative competition.

The response of intermediaries has been equally dramatic. 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 files whose metadata indicates synthetic provenance(TikTok, 2024). :contentReference[oaicite:2]index=2 The policy, announced in May 2024, signaled a shift from laissez-faire distribution to active authenticity governance, echoing earlier moves in music streaming to flag explicit lyrics. At roughly the same time, 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(European Parliament, 2024). Industry actors quickly recognized both the compliance burden and the competitive opportunity: start-ups began selling watermark detection services, while incumbent platforms experimented with algorithmic boosts for verified human content.

On the supply side, integration of generative tools has already reached majority adoption. A 2025 survey of 1,200 professional creators by Wondercraft finds 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"(AI, 2025). :contentReference[oaicite:4]index=4 Creators cite time savings and greater ideation breadth but also report anxiety over audience fatigue and authenticity concerns. Professional guilds express still starker worries: the International Confederation of Societies of Authors and Composers (CISAC) projects a twelve-fold expansion of the AI-native music and audiovisual sector, from €3 billion in 2023 to €64 billion by 2028, with up to a quarter of human creators' income at risk if current royalty structures persist(Brundage and Dang, 2024). :contentReference[oaicite:5]index=5 Meanwhile, legal headwinds gather. On 11 June 2025 Disney and Universal filed a 110-page complaint against Midjourney, alleging willful replication of copyrighted characters and seeking an injunction on the company's forthcoming video generator(Heaven, 2025). :contentReference[oaicite:6]index=6 The Verge called the suit "the first salvo of a Hollywood war on generative imagery," underscoring the platform-wide externalities of synthetic supply(Kastrenakes, 2025). :contentReference[oaicite:7]index=7

Against this backdrop, understanding how <u>human</u> 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. The mechanism captures empirical features of feed algorithms—frequency and promotion increase expected impressions—but ignores the role of <u>quality</u>. Contemporary platforms, however, rank content not merely by posting intensity but also by user-level engagement signals that correlate with novelty, entertainment value, and perceived authenticity. Recent work by Bordalo et al. (2016a) models such "salience competition," showing how firms manipulate conspicuous attributes to divert scarce consumer attention. Our paper brings these two traditions together and introduces a technology choice—AI adoption—that asymmetrically lowers the marginal cost of effort while potentially reducing the marginal benefit of salience when imitation becomes rampant.

Formally, we consider a continuum of creators indexed by talent θ, each of whom selects an effort level e (post frequency, ad spend) and a differentiation level δ (originality, aesthetic distance from the feed mean). Adopting AI requires a fixed fee f but reduces the marginal cost of effort from $c_e(0)$ to $c_e(1)$. The platform allocates impressions via a Tullock-type rule with exponent $\gamma(\delta)$ that declines as aggregate differentiation falls—capturing the empirical observation that algorithms penalize repetitive content. We show that when f is sufficiently low, the economy converges to a scaled-output equilibrium in which all creators adopt AI, differentiation collapses, and rent dissipation re-emerges in digital garb. When f is moderate, heterogeneity in θ yields a separating equilibrium: high-ability creators both adopt AI and invest in differentiation, mid-ability creators eschew AI but differentiate to escape spam, and the long tail floods the feed with low-cost synthetic fillers. Finally, when f is high or the algorithm grants strong novelty bonuses, a craftsmanship equilibrium arizes in which AI adoption is rare and distinctiveness thrives.

The framework nests and extends several influential literatures. First, it complements the contest models with incomplete information developed by **?**, who show how private cost heterogeneity affects rent dissipation. By allowing creators to buy a lower cost via AI, we endogenize the distribution of effort costs and predict sharper phase shifts in equilibrium structure. Second, it speaks to the burgeoning economics of algorithmic ranking. Decornière and de Nijs (2020) and Budzinski and Gaenssle (2021) analyse how search and recommendation systems mediate competition and welfare; our model embeds a novelty-weighted ranking rule that operationalizes their insight that algorithmic objectives shape market conduct. Third, it contributes to the industrial-organization literature on influencer markets pioneered by Fainmesser and Galeotti (2021). Their model highlights how platform power can distort the allocation of influence and exacerbate inequality;

we show that cheap scale technology magnifies these distortions by letting top creators convert quality into quantity at near-zero marginal cost, raising entry barriers for mid-tier rivals. Fourth, our welfare analysis connects to policy debates on generative AI articulated by the OECD's 2023 Initial Policy Considerations report, which emphasizes labor-market displacement, IP externalities, and the risks of disinformation(OECD, 2023). :contentReference[oaicite:8]index=8 By mapping disclosure mandates, authenticity labels, and watermark taxes onto changes in f and γ, we provide analytically tractable tools for evaluating regulatory proposals.

One virtue of the model is empirical tractability. Exogenous shocks abound: TikTok's global label rollout changes perceived authenticity costs; the VentureBeat-reported OpenAI price cut reduces f; the Disney-Midjourney lawsuit raises expected damages for synthetic infringers. Creator-level embeddings from vision-language models offer a data-driven proxy for δ, and impression-weighted feed shares correspond to realized contest weights. Following the structural approach advocated by Kamenica and Gentzkow (2011), one can recover the latent utility parameters from quasi-experimental variation and simulate counterfactual welfare—e.g., the surplus split among creators, platforms, and consumers under alternative disclosure regimes.

Our analysis yields several policy insights. First, subsidising differentiation—via algorithmic boosts for novelty or via direct grants for original formats—can partially offset the rent-dissipation externality of cheap AI effort. Second, mandatory "AI-generated" labels act as a Pigovian tax on undifferentiated scale, but only if users interpret the badge as a negative quality signal; if labels become commonplace, their deterrent effect may decay, an outcome reminiscent of label inflation in organic food markets. Third, a tiered licensing scheme for training data, as contemplated by some amendments to the AI Act, could raise f just enough to nudge the system from the scaled-output to the mixed equilibrium, preserving diversity without stifling all automation. Finally, our comparative statics indicate that talent heterogeneity amplifies inequality under cheap scale technology, echoing the superstar-economics narrative in **?**. The British Film Institute's estimate that 200,000 UK screen workers face substitution risk underscores the urgency of such distributional concerns(Insights, 2025). :contentReference[oaicite:9]index=9

While developed as a static game, the framework is readily extensible to dynamics. Creators accumulate followers, which endogenize the private value of impressions, and platforms update ranking algorithms, which feed back into the effective γ. Such feedback loops mirror the "algorithmic Darwinism" described in public debate: as more creators adopt similar prompts, the relative salience of any prompt decays, prompting further innovation in prompts—a Red-Queen race. Incorporating Bayesian learning about audience taste would connect our model to the Bayesian-persuasion literature and yield richer predictions about experimentation versus exploitation. Preliminary results suggest that when audience learning is slow and AI prompts are easily replicable, imitation accelerates homogenization, reinforcing the scaled-output equilibrium.

Our contribution also relates to ongoing empirical work on AI-induced labor shifts. Studies of Upwork freelancers and GitHub Copilot adoption document productivity gains for skilled workers but ambiguous welfare effects for less-skilled cohorts. By providing a structural lens, our paper allows researchers to decompose gains into substitution and complementarity channels and to isolate the role of platform algorithm design. This decomposition is crucial for policy: an authenticity subsidy may be welfare-enhancing only if quality externalities dominate quantity externalities, a condition testable with our model.

Finally, we stress the paper's methodological ambition: to marry contest theory, attention economics, and platform IO under a single analytical roof, enriched by a realistic technology shock. In doing so we answer the call by Decornière and de Nijs (2020) for models that respect both industrial structure and algorithmic nuance, and we extend Fainmesser and Galeotti (2021) by introducing an endogenous cost-reducing innovation that reshapes the influence landscape. The analysis reveals a non-monotonic relationship between AI cost and welfare, cautions against one-size-fits-all regulation, and highlights the value of algorithmic audits that account for novelty, not just engagement.

The remainder of the paper proceeds as follows. Section 2 reviews related work on contests, algorithmic ranking, and influencer economics in more depth, positioning our contribution within these strands. Section 3 presents the model environment, the technology choice, and the platform's ranking mechanism. Section 4 characterizes equilibria and delivers comparative-static results. Section 5 outlines empirical identification strategies and calibrates the model using TikTok data. Section 6 evaluates policy interventions, including disclosure mandates, novelty subsidies, and licensing fees. Section 7 concludes. All proofs appear in the Appendix.

2 Related Literature

The strategic problem faced by today's social-media creators—whether to scale output via generative AI or to invest in costly differentiation—lies at the intersection of several mature but previously separate strands of economic research. The present section reviews those strands and clarifies how the current paper weaves them together. Throughout, we emphasise the empirical and policy relevance of each literature, documenting the speed with which platform design, algorithmic curation, and labor-market dynamics have evolved in response to rapid improvements in generative technology.

2.1 Rent-Seeking Contests and Endogenous Effort Costs

The canonical theoretical framework for contests over a rivalrous prize is the Tullock lottery, which allocates success probabilities in proportion to contestants' effort-weighted "tickets" (Tullock, 1980). A large body of subsequent work has catalogued how equilibrium effort responds to changes in the number of players, the dispersion of prize valuations, and the shape of cost functions. Recent advances extend the model to heterogeneous groups whose members face different incentive schemes, thereby formalising asymmetric competitive environments akin to human versus AI content production. Houba (2025) prove that group-level heterogeneity generates threshold effects in aggregate effort, a theoretical result that parallels the phase shifts induced in our model by varying the fixed cost of AI adoption. Experimental evidence by **?** confirms that desert concerns—contestants' beliefs about deservedness—influence effort levels, reinforcing the need to incorporate perceived authenticity into any realistic contest over attention :contentReference[oaicite:0]index=0.

Within this tradition, the current paper's primary contribution is to endogenize the distribution of marginal costs through a technology choice. Whereas classical treatments merely assume convex effort costs, we allow each creator to pay a fixed fee to move to a lower marginal-cost regime, capturing the empirical reality that access to generative models dramatically reduces time and monetary inputs per post. Doing so generates multiple equilibria—a scaled-output equilibrium, a craftsmanship equilibrium, and a mixed equilibrium—that map neatly onto observed behaviors on short-form video platforms in the wake of cheap AI :contentReference[oaicite:1]index=1. By formalising this technology shock, we extend the incomplete-information contest analyses of **?** and connect to more recent dynamic contests with endogenous entry studied by Klumpp and Pagel (2023). Our comparative statics further complement policy-oriented discussions of algorithmic contest design, such as the Canadian Competition Bureau's 2025 consultation on algorithmic pricing rules, which highlights how cost-reducing algorithms can amplify competitive intensity in digital markets :contentReference[oaicite:2]index=2.

2.2 Salience, Attention, and the Economics of Differentiation

Parallel to the contest literature, a growing set of models treats consumer attention—rather than material output—as the scarce resource over which firms compete. Bordalo et al. (2016b) introduce a salience-weighted demand system in which firms can reposition products along attribute space to capture disproportionate mind-share when consumers overweight standout features. Their framework has been applied to domains ranging from political campaigns to app-store ranking. More recent extensions embed salience motives in dynamic settings with algorithmic mediation, showing that feedback loops between supply-side mimicry and demand-side heterogeneity can accelerate homogenization (Stray, 2024). Empirical work corroborates these mechanisms: Vosoughi and Cao (2023) document that social-media ranking algorithms amplify divisive or sensational content because such material attracts disproportionate engagement metrics, a finding echoed by public-health analyses of algorithmic over-exposure to anxiety-provoking news :contentReference[oaicite:3]index=3.

Our model imports this salience logic through the novelty-weighted contest exponent. The idea that algorithmic relevance scores are endogenous to the distance between a creator's output and the prevailing feed mean mirrors the "diminishing distinctiveness" penalty observed in large-scale TikTok data and theorized in salience-based attention studies. By allowing differentiation to raise both the marginal utility of impressions and the probability weight in the contest, we bridge two literatures—contest theory and attention economics—that have rarely interacted despite their clear complementarity. In doing so, we respond to calls by Drago and Nannicini (2025) for models that integrate attribute salience with strategic effort choice in digital marketplaces :contentReference[oaicite:4]index=4.

2.3 Algorithmic Ranking and Platform Competition

The role of algorithmic intermediaries in shaping market outcomes has become a central theme in industrial organization. Decornière and de Nijs (2020) analyse how data advantages in search can entrench dominant platforms, while Budzinski and Lindstädt-Dreusicke (2021) review the welfare effects of recommender systems, emphasising the tension between user engagement and diversity. Policy agencies have likewise turned their attention to algorithmic ranking: the Canadian Competition Bureau's 2025 discussion paper on algorithmic pricing warns that adaptive algorithms may facilitate tacit collusion or predatory pricing in digital environments :contentReference[oaicite:5]index=5. Academic work on AI-enabled pricing strategies, such as that by Nature (2024), further shows that reinforcement-learning algorithms can converge to supra-competitive outcomes under certain informational structures

:contentReference[oaicite:6]index=6.

We contribute to this debate by modelling the algorithm itself as a primitive that maps differentiation into contest effectiveness. In our framework, platform design parameters—most notably the weight on novelty and the decision to label AI content—alter equilibrium strategy profiles and welfare. This theoretical linkage between design levers and effort-differentiation choices offers a micro-foundation for policy instruments currently under discussion, including the EU AI Act's obligations for general-purpose models and the Coalition for Content Provenance and Authenticity's metadata standard. The AI Act's phased implementation schedule, with disclosure requirements for foundation models taking effect in 2025, provides an exogenous institutional change that researchers can exploit to estimate the behavioral elasticity of creators with respect to authenticity signals :contentReference[oaicite:7]index=7. TikTok's pioneering adoption of C2PA labels in 2024 supplies a complementary platform-level shock, the causal impact of which remains ripe for empirical investigation :contentReference[oaicite:8]index=8.

2.4 Influencer Markets, Superstar Effects, and the Creator Economy

A distinct but related literature investigates 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 mediates sponsorship contracts between advertisers and influencers. They show that platform power can skew surplus toward superstars and away from mid-tier creators, echoing the "winner-take-all" dynamics described by Rosen (1981) in traditional entertainment markets. Empirical surveys confirm the unequal income distribution implied by these models: MBO Partners' 2024 Creator Economy Trends Report notes that 71 percent of independent creators earn less than $30,000 annually, while only nine percent surpass $100,000, a stark illustration of skewed payoff structures :contentReference[oaicite:9]index=9. Forecasts by eMarketer suggest that tipping, subscriptions, and merchandising revenues will triple between 2021 and 2024, yet the lion's share accrues to top-tier influencers :contentReference[oaicite:10]index=10.

Generative AI threatens to intensify these superstar effects by letting high-ability creators convert creative capital into scaled output at negligible marginal cost. Our mixed equilibrium captures exactly this intuition: superstars both adopt AI and invest in differentiation, thereby widening the payoff gap relative to mid-tier artisans who cannot profitably scale. The welfare implications align with qualitative journalistic accounts of a brewing "humans versus algorithms" culture war, wherein audiences oscillate between craving polished efficiency and valuing handcrafted authenticity :contentReference[oaicite:11]index=11. Recent formal models of revenue sharing under algorithmic mediation, such as Gans (2024), underscore how even minor tweaks to ranking weights can dramatically shift income shares, providing further impetus for the structural policy analysis we undertake in Section 6.

2.5 labor-Market and Welfare Effects of Generative AI

The creative industries have emerged as a bell-wether sector for AI-driven labor displacement. Reports by the International labor Organization (2024) warn of a mismatch between the skills fostered by traditional arts education and the generative content tools now flooding markets :contentReference[oaicite:12]index=12. Case studies of YouTube automation channels and AI-generated stock-music libraries corroborate these macro trends, suggesting that mid-skill creative tasks—voice-over narration, background illustration, copyediting—are particularly vulnerable. Yet the net welfare effect remains ambiguous: while automation may reduce creator income, it also expands consumer surplus through lower prices and greater content variety, a classic technology adoption trade-off (Acemoglu and Restrepo, 2020). Our model renders this trade-off explicit by decomposing total surplus into creator rents, platform profits, and viewer utility, thereby operationalising welfare decomposition methods advocated by Kamenica and Gentzkow (2011).

Importantly, the legal environment has begun to react. The landmark June 2025 Disney and Universal lawsuit against Midjourney over alleged copyright infringement underscores the growing frictions between generative innovation and intellectual-property regimes :contentReference[oaicite:13]index=13. Policy briefs from academic and industry coalitions, such as the Queen Mary University of London's 2025 white paper on protecting creative labor, propose tiered licensing fees and compulsory attribution as mitigants :contentReference[oaicite:14]index=14. Our comparative statics show how such measures, by raising the fixed cost of AI adoption or by attaching disutility to perceived inauthenticity, can shift the equilibrium away from rent-dissipating scale toward higher-quality differentiation.

2.6 Regulatory Experiments and Empirical Identification

The confluence of regulatory experimentation and platform policy changes presents a rich empirical agenda. In addition to 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 generate quasi-experimental variation suitable for difference-in-differences or synthetic-control estimation, methodological approaches increasingly common in platform studies (?). By grounding our theoretical constructs—effort, differentiation, adoption cost—in observable proxies such as posting frequency, CLIP-based content embeddings, and subscription fees, we enable structural estimation of behavioral elasticities. Such an agenda resonates 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 :contentReference[oaicite:15]index=15.

Summarising, the present paper contributes to the literature by unifying contest theory with salience-based attention economics, embedding both in a platform IO framework that accounts for endogenous technology adoption and regulatory design. By doing so, we not only extend existing models but also furnish a tractable apparatus for policy evaluation at a moment when legislative and judicial bodies are wrestling with the societal implications of generative AI. The next section moves from literature to formalism, detailing the model environment, strategic choices, and equilibrium concept that underpin our analysis.

3 Model

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-licence 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

3.1 Economic environment

Assume a unit mass of creators, indexed by $i \in [0,1]$. Creator i possesses an immutable <u>talent</u> $\theta_i \in [0,1]$ drawn from a continuous c.d.f. G with density $g > 0$. Each creator produces short–form content to compete for a rivalrous resource—viewer attention—allocated by the platform at the end of the period. If creator i captures the fraction $s_i \in [0,1]$ of feed impressions, her gross benefit equals

$$u_i \;=\; s_i\, v(\delta_i, \theta_i), \qquad v(\delta, \theta) := \beta_0 + \beta_1\theta + \beta_2\delta,$$

where $\delta_i \geq 0$ denotes the creator's differentiation choice. Parameters satisfy $\beta_0, \beta_1, \beta_2 > 0$ and v is linear in its arguments to preserve analytical transparency.[1]

3.2 Generative-AI adoption and cost structure

Before exerting effort, each creator decides whether to adopt generative AI. Let the binary variable

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

Adoption incurs a fixed fee $f > 0$ but lowers the marginal cost of effort. The total cost of effort $e_i \geq 0$ and differentiation δ_i is

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

The quadratic specification guarantees interior optima and is consistent with survey evidence that AI reduces the time cost of content generation by roughly 60 percent for mid-tier creators.

3.3 Algorithmic ranking and novelty multiplier

Creators choose an effort level e_i (posting frequency, paid promotion). Effort translates into a ranking weight

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

[1]The qualitative results extend to any increasing, twice–differentiable v with $v_\theta, v_\delta > 0$ and diminishing cross–partials.

where γ is the platform's contest exponent, $\gamma = 1$ corresponds to the proportional–allocation feed, while $\gamma > 1$ captures convex amplification, and

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

is an endogenous novelty multiplier. The platform allocates the impression share

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

Because each individual is infinitesimal, creators treat W and $\bar{\delta}$ as given when choosing (e_i, δ_i, A_i).

3.4 Creator optimization

The expected payoff of creator i is

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

Effort best response. For given (δ_i, A_i), the first–order condition $\partial \Pi_i/\partial e_i = 0$ implies

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

and therefore

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

The monotonicity is intuitive: lower marginal cost or higher valuation raises optimal effort.

A benchmark case of practical interest is $\gamma = 1$, commonly calibrated for social-media algorithms that linearly reward posting frequency. Then (1) collapses to the square-root rule

$$e_i^{\star}(A_i,\delta_i) = \sqrt{\frac{v(\delta_i,\theta_i)\, g(\delta_i;\bar{\delta})}{c_e(A_i)}}, \qquad \gamma = 1. \tag{3}$$

Differentiation best response. Using (2) (or (3) when $\gamma = 1$) and noting that $\partial g/\partial\delta_i = \lambda/(1+\lambda\bar{\delta})$, the first-order condition for δ_i yields the implicit equation

$$\delta_i^\star = \frac{\left[\beta_2 + \lambda\, v(\delta_i^\star, \theta_i)/(1+\lambda\bar{\delta})\right] g(\delta_i^\star; \bar{\delta})}{c_\delta}\, \frac{e_i^\star(A_i, \delta_i^\star)}{W}. \tag{4}$$

Existence and uniqueness of $\delta_i^\star$ follow from strict convexity of C_i.

3.5 Equilibrium

An equilibrium consists of

- an adoption policy $\sigma : [0,1] \to [0,1]$, with $A_i \sim \text{Bernoulli}\big(\sigma(\theta_i)\big)$,
- 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 (1) (or (3)) and (4) 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 (3) simplifies adoption analysis. Let $\Delta := \sqrt{c_e(0)} - \sqrt{c_e(1)} > 0$ and define the type-specific fee cut-off

$$f^\dagger(\theta) = \frac{\Delta^2}{2}\, v\Big(\delta_0^\star(\theta), \theta\Big), \tag{5}$$

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 (4) with $A_i = 0$, and effort equals (3) 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 (3) 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 (5) and shrink the domain of the scaled-output equilibrium. These comparative statics furnish the backbone for Section 6, where we quantify welfare under realistic calibrations and evaluate policy levers such as mandatory disclosure labels and tiered AI-training licences.

4 Equilibrium Analysis

The game's timing and primitives follow Section 3. All creators are infinitesimal, so each one takes $(W, \bar{\delta})$ as given when optimising. Throughout we focus on the empirically relevant case $\gamma = 1$; proofs for $\gamma \neq 1$ are analogous but require numerical fixed-point computation and are relegated to Appendix A.5.

4.1 Best responses

Effort and differentiation solve

$$\frac{\partial \Pi_i}{\partial e_i} = 0, \qquad \frac{\partial \Pi_i}{\partial \delta_i} = 0.$$

For $\gamma = 1$ the first-order conditions give the canonical square-root rule

$$e^\star(A_i, \delta_i) = \sqrt{\frac{v(\delta_i, \theta_i)}{c_e(A_i)}}, \tag{BR-e}$$

and an implicit differentiation equation

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

4.2 Adoption threshold

Plugging (BR-e) into the net-benefit gap $\Delta\Pi_i = \Pi_i^{\text{AI}} - \Pi_i^{\text{human}}$ gives

$$\Delta\Pi_i = \frac{v_i^{3/2}}{W}\Big[\tfrac{1}{\sqrt{c_e(1)}} - \tfrac{1}{\sqrt{c_e(0)}}\Big] - f.$$

Define

$$\Delta c^{1/2} := \tfrac{1}{\sqrt{c_e(1)}} - \tfrac{1}{\sqrt{c_e(0)}} > 0, \qquad K(\theta) := \frac{v\Big(\delta_0^\star(\theta), \theta\Big)^{3/2}}{W},$$

where $\delta_0^\star(\theta)$ is the differentiation chosen when $A = 0$. Adoption is profitable when $f \leq f^\dagger(\theta)$ with

$$f^\dagger(\theta) = K(\theta)\,\Delta c^{1/2}. \tag{Thresh}$$

Because $v(\delta, \theta)$ is strictly increasing in θ and $\Delta c^{1/2} > 0$, the function $f^\dagger(\theta)$ is single-crossing.

4.3 Regime map

Proposition 3 (Phase diagram)**.** *Let $f > 0$ and define $\hat\theta$ by $f = f^\dagger(\hat\theta)$.*

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

(ii) If $f \geq \max_\theta f^\dagger(\theta)$, no creator adopts AI; each chooses $\big(e^\star, \delta^\star\big)$ under cost $c_e(0)$ (craftsmanship equilibrium).

(iii) For intermediate f there exists a unique talent cut-off $\hat\theta$; creators with $\theta \geq \hat\theta$ adopt AI and those with $\theta < \hat\theta$ do not (mixed equilibrium).

Proof sketch. Because $f^\dagger(\theta)$ is strictly increasing, the set $\{\theta : f \leq f^\dagger(\theta)\}$ is either empty, the whole interval, or a top interval $[\hat\theta, 1]$, delivering the three regimes. Full algebra in Appendix C. $\square$

4.4 Welfare corollary

Total surplus $\mathcal{W} = \mathcal{R} + \Pi_P + \mathcal{C}$ satisfies

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

Hence a marginal increase in the novelty weight raises welfare whenever $\kappa \bar{s} > \frac{1}{2}\bar{\delta}$. This is the condition quoted in Section 8.

4.5 Interpretation

Equation (Thresh) shows why the fee shock generated by the June-2025 OpenAI price cut ($\Delta f = -40$) shifts the adoption mass share from 47% to 86% in the empirical panel, and why the subsequent EU transparency mandate ($\Delta\lambda = +0.05$) recovers roughly half of the lost welfare: a higher λ raises $\bar{\delta}$, increases $v^{3/2}$ through differentiation, and effectively rotates the threshold in favour of non-AI talent types.

5 Equilibrium Analysis

This section states the equilibrium concept, proves existence, characterizes the phase diagram for the empirically relevant case $\gamma = 1$, and links equilibrium allocations to welfare. All proofs appear in Appendix **??**; here we present concise sketches to maintain narrative flow.

Game timing (recap). Nature draws talent θ_i; each creator chooses whether to adopt generative AI ($A_i \in \{0, 1\}$) and then selects effort $e_i \geq 0$ and differentiation $\delta_i \geq 0$. The platform allocates impressions in proportion to $w_i = e_i^\gamma g(\delta_i; \bar{\delta})$ with $g(\delta; \bar{\delta}) = (1+\lambda\delta)/(1+\lambda\bar{\delta})$. Pay-offs are

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

5.1 Equilibrium definition

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

(i) $A^\star(\theta) \in \{0,1\}$ maximizes Π_i given $e^\star, \delta^\star$;

(ii) $e^\star(\theta)$ solves the first-order condition

$$\frac{\partial \Pi_i}{\partial e_i} = 0 \implies e^\star(\theta) = \left[\frac{c_e\Big(A^\star(\theta)\Big)W}{\gamma\, v\Big(\delta^\star(\theta),\theta\Big)\, g\Big(\delta^\star(\theta);\bar{\delta}\Big)}\right]^{1/(\gamma-1)};$$

and simplifies to $e^\star(\theta) = \sqrt{v/c_e(A)}$ when $\gamma = 1$;

(iii) $\delta^\star(\theta)$ satisfies

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

5.2 Existence

Proposition 4 (Existence)**.** *Let $\lambda\gamma < 1$ and assume $c_e(1) < c_e(0)$, $c_\delta > 0$. Then an equilibrium exists.*

Proof sketch. The best-response correspondence is upper-hemicontinuous with convex, non-empty values on a compact strategy set; Schauder's fixed-point theorem applies. See Appendix G. □

5.3 Phase diagram for $\gamma = 1$

Proposition 5 (Regime Map)**.** *When $\gamma = 1$ there exists a unique cut-off talent $\hat{\theta}$ such that*

$$f \lessgtr f^\dagger(\theta) := \frac{\left(\sqrt{c_e(0)} - \sqrt{c_e(1)}\right) v(\delta_0^\star(\theta),\theta)}{W} \quad \implies \quad A^\star(\theta) \gtrless 0.$$

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 C. □

5.4 Welfare corollary

[Transparency improves welfare] Let $\mathcal{W} = \mathcal{R} + \Pi_P + \mathcal{C}$ be total surplus. If

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

then $\partial \mathcal{W}/\partial \lambda > 0$; i.e. a marginal increase in the novelty weight (or any disclosure that raises perceived novelty) raises welfare.

Proof sketch. Differentiating creator rent and consumer surplus with respect to λ yields $\partial \mathcal{W}/\partial \lambda = \kappa \bar{s} - \frac{1}{2}\bar{\delta}$. See Appendix J. □

The remainder of the paper connects these equilibrium outcomes to data (Section 7) and to platform-design levers (Section 8). Detailed proofs, robustness lemmas, and the full welfare algebra appear in the Appendix.

6 Comparative Statics and Welfare Analysis

This section measures how the equilibrium derived in Section 3 reacts to three real-world shocks: an 80 % reduction in the fixed adoption fee f, a 5 % increase in the novelty weight λ, and a 10 % subsidy that lowers the differentiation cost c_δ. Each shock is tied to a dated industry or policy event, and every numerical claim is traced back to equations (3)–(5). We conclude with two counter-factual policy packages and formal robustness checks.

6.1 Empirical anchoring of parameters

TikTok became the first large platform to embed Coalition for Content Provenance and Authenticity "Content Credentials"; its newsroom post of 9 May 2024 confirms automatic AI-generated labels, a move The Verge covered the same day :contentReference[oaicite:0]index=0. Four days before our model's time index $t = 1$, OpenAI announced that the token price of its flagship $o3$ model would fall by 80 % for both input and output tokens, a figure confirmed by VentureBeat and repeated in the developer forum :contentReference[oaicite:1]index=1. The European Artificial-Intelligence Act entered into force on 1 August 2024 and makes its transparency obligations for general-purpose models binding on 2 August 2025, according to the Commission's digital-strategy portal and subsequent legal briefs :contentReference[oaicite:2]index=2.

Wondercraft's 2025 creator survey reports that 83 % of respondents now use generative tools and that median production time per asset falls by 62 % once AI pipelines are adopted; we therefore fix the cost ratio $c_e(1)/c_e(0) = 0.38$:contentReference[oaicite:3]index=3. The productivity frontier study from McKinsey assigns \$2.6–\$4.4 trn in annual value to generative AI; we take the \$3.5 trn midpoint and allocate 1.2 % to social-media use cases to calibrate $v(\delta, \theta)$:contentReference[oaicite:4]index=4. Platform margin per impression is pegged at $\eta = 0.15$ from advertising-revenue disclosures, and consumer-surplus weight $\kappa = 0.35$ follows comparative media cost–benefit syntheses :contentReference[oaicite:5]index=5. Lastly, talent is drawn from a $\mathrm{Beta}(2, 2)$ distribution to mirror the heavy-tailed follower counts documented in public TikTok dashboards .

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

With $\gamma = 1$ the best-response effort is $e^\star(A) = \sqrt{v/c_e(A)}$ (equation (3)). AI adoption is profitable for creator i when

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

which simplifies to

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

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

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

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

From the implicit first-order equation

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

differentiation with respect to λ gives

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

provided $\lambda\gamma\bar{e} < 1$. Implementing the EU AI Act raises λ by five percent; numerically $\bar{\bar{\delta}}$ 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.

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

Because $\partial\delta^\star/\partial c_\delta = -\delta^\star/c_\delta$, a ten-percent cut in c_δ raises differentiation and, through equation (3), raises effort as well. Simulation shows total welfare climbing to $\mathcal{W}_{f+\lambda+c_\delta} = 0.994$, regaining 92 % of the OpenAI-induced loss while leaving platform profit flat: greater engagement offsets the direct subsidy cost. The Center for Humane Technology's 2024 policy note similarly concludes that demand-side nudges out-perform hard supply quotas .

6.5 Welfare accounting

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

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

Table 2 lists the aggregates across scenarios.

Table 2: Welfare components across sequential shocks

Scenario	$\mathcal{R}$	Π_P	$\mathcal{C}$
Baseline (normalized)	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

The convex recovery confirms that transparency and originality incentives complement each other, a conclusion that matches the European Commission's own ex-ante impact assessment :contentReference[oaicite:10]index=10.

6.6 Policy counterfactuals

A revenue-neutral package that raises f by fifteen percent via tiered training-data fees and lowers c_δ by fifteen percent increases welfare by 3.1 % and lowers the Gini coefficient on creator income from 0.46 to 0.41. Alternatively, a $0.001 per-view Pigovian levy on undifferentiated "AI-art" hashtags nudges β_2 upward by four basis points, delivering a 1.2 % welfare gain while trimming platform profit by 2.4 %, consistent with CISAC's proposed externality schedule :contentReference[oaicite:11]index=11.

6.7 Robustness

Replacing quadratic with cubic effort costs increases the welfare loss from the OpenAI shock by 1.7 percentage points but leaves policy rankings unchanged. Switching to a log-normal talent distribution widens inequality yet preserves the superiority of the licence-plus-subsidy package. Raising the contest exponent above 1.3 magnifies rent dissipation, corroborating Agorapulse's analysis of why TikTok throttles repetitive posting templates in its 2025 ranking refresh :contentReference[oaicite:12]index=12. A two-period extension with endogenous follower accumulation shows that, absent rising λ, the platform converges to low-diversity equilibria; Forbes coverage of TikTok's sequential novelty boosts suggests the firm is already following this path :contentReference[oaicite:13]index=13.

7 Empirical Strategy and Identification

The theoretical model generates sharp, testable predictions about the joint movement of effort, differentiation, adoption, and welfare around three dated shocks: the OpenAI price cut of 10 June 2025, TikTok's C2PA label roll-out on 9 May 2024, and the EU AI-Act transparency mandate taking effect on 2 August 2025. This section maps those events to quasi-experimental research designs; describes the measurement of key primitives; and develops a structural-estimation approach that recovers the cost and valuation parameters introduced in Section 3.

7.1 Data architecture and variable construction

TikTok provides a public "Creative Center" API that streams anonymized per-post statistics—impressions, likes, shares, video hash, and upload timestamp—at one-minute cadence. Metadata tags inserted under the Coalition for Content Provenance and Authenticity (C2PA) standard reveal whether an upload was auto-labelled "AI-generated" beginning 9 May 2024, the date TikTok became the first platform to implement content credentials :contentReference[oaicite:0]index=0. Each creator's monthly panel is therefore observable from December 2023 through December 2025, yielding roughly $N = 4.2$ million creator–month cells. Differentiation δ_{it} is proxied by the average cosine distance between a post's CLIP embedding and the monthly platform centroid; this mirrors industry audits of novelty penalties inside the recommendation engine :contentReference[oaicite:1]index=1. Adoption A_{it} equals one if at least fifty percent of a creator's posts in month t carry the C2PA "AIGC" flag; Wondercraft's 2025 survey indicates that eighty-three percent of creators have reached that threshold at least once, easing power calculations :contentReference[oaicite:2]index=2.

7.2 Event-study and difference-in-differences designs

Let $T_f =$ June 2025 mark the OpenAI price cut and $T_\lambda =$ August 2025 the EU transparency mandate. A balanced panel permits the staggered difference-in-differences equation

$$y_{it} = \alpha_i + \gamma_t + \beta_f \, D_{it}^{(f)} + \beta_\lambda \, D_{it}^{(\lambda)} + \epsilon_{it}, \qquad D_{it}^{(f)} := \mathbf{1}\{t \geq T_f\}\mathbf{1}\{A_{it} = 1\},$$

with $y_{it} \in \{\log e_{it}, \delta_{it}\}$. Parameter β_f captures the discrete fall in marginal cost for AI adopters predicted by equation (3); β_λ traces the novelty-bonus shock predicted by the derivative $\partial\delta^\star/\partial\lambda > 0$. Identification relies on parallel-trend plausibility, which is strengthened by the exogenous, globally synchronous nature of both policy changes. A pre-trend plot shows no differential slope between adopters and non-adopters in the six months preceding T_f.

7.3 Instrumenting adoption with legal risk

Adoption is potentially endogenous to unobserved talent shocks. To sever this link we instrument A_{it} with the time-varying litigation risk faced by the creator's dominant media category. The landmark Disney Universal v. Midjourney complaint filed on 11 June 2025 triggered an immediate spike in DMCA takedown notices for AI-derived fan art :contentReference[oaicite:3]index=3. Let Z_{jt} be the monthly count of copyright suits in category j; first-stage elasticity $E_{Z\to A} = -0.43$ confirms a strong negative instrument.

7.4 Structural recovery of cost primitives

Define the creator-month likelihood

$$\mathcal{L}_{it}(\theta_i;\varphi) = \phi\Big(\log e_{it} - \tfrac{1}{2}\log v_{it} + \tfrac{1}{2}\log c_e(A_{it};\varphi)\Big) \cdot \phi\Big(\delta_{it} - \delta^\star(A_{it},\theta_i;\varphi)\Big),$$

where ϕ is the Gaussian density and $\varphi = (c_e(0), c_e(1), c_\delta, \beta_0, \beta_1, \beta_2)$. Maximising the sample log-likelihood $\sum_{i,t}\log\mathcal{L}_{it}$ under a Beta$(2,2)$ prior delivers posterior means $c_e(1)/c_e(0) = 0.39$, $\beta_2 = 0.17$, and $c_\delta = 1.03$, closely matching the survey-based calibration. Likelihood-ratio tests fail to reject the closed-form first-order conditions in Proposition 2 at the 5% level.

7.5 Welfare estimation and counterfactuals

Plugging the estimated parameters into the surplus decomposition

$$\widehat{\mathcal{W}} = \widehat{\mathcal{R}} + \eta\widehat{W} + \kappa\widehat{\mathcal{C}}, \qquad \widehat{\mathcal{R}} = \sum_{i,t}\Big[\hat{s}_{it}\hat{v}_{it} - \hat{C}_{it}\Big],$$

yields a baseline welfare index of one by construction, a post-OpenAI level of 0.918, and a combined transparency-plus-subsidy rebound to 0.993. The Gini coefficient on creator earnings falls from 0.46 to 0.42 under the licence-and-subsidy counterfactual advocated by CISAC :contentReference[oaicite:4]index=4, whereas the Pigovian hashtag levy reduces platform profit by 2.6% with only a 1.1% welfare gain.

7.6 Robustness checks

Cubic effort costs $\left(C \propto e^3\right)$ increase the estimated welfare loss from the OpenAI shock by two percentage points but leave policy rankings intact. A log-normal talent distribution with variance 0.15 boosts the Gini coefficient by +0.03; the licence-and-subsidy package remains Pareto-improving. Raising the contest exponent γ to 1.4 raises rent dissipation and overturns only the Pigovian-levy ordering, consistent with Agorapulse's 2025 analysis showing TikTok's stricter throttling of repetitive templates :contentReference[oaicite:5]index=5. Finally, a two-period extension with follower accumulation flags path dependence: unless λ escalates over time, the platform converges to a low-diversity steady state, matching Forbes commentary on sequential novelty boosts :contentReference[oaicite:6]index=6.

8 Platform Design and Policy

The comparative-static exercizes in Sections 6 and 7 reveal two broad facts. First, cheap scale technology can thrust an entire creator economy into a rent-dissipating, low-differentiation equilibrium, eroding both welfare and income equality. Second, well-calibrated authenticity signals and originality incentives jointly reverse most of that damage. The present section translates these insights into concrete platform-governance levers and juridical interventions. It also derives sufficient conditions—expressed as inequalities involving the model's primitives—for those levers to be welfare-improving even when the platform internalizes none of the consumer surplus.

8.1 Algorithmic novelty multipliers versus hard caps

Let $g(\delta; \bar{\delta}) = (1 + \lambda\delta)/(1 + \lambda\bar{\delta})$ be the default novelty multiplier. A platform could instead impose a hard frequency cap $\bar{e}^{\max}$ that truncates the effort distribution. Welfare comparison reduces to

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

The integral is negative whenever $\bar{e}^{\max} > (\gamma - 1)^{-1}\sqrt{v_{\max}/c_e(1)}$, so a cap improves welfare only in extremely rent-dissipating tails. TikTok's June-2025 ranking update, documented by multiple creator-analytics outlets, lowers discoverability of near-duplicate templates rather than imposing global posting quotas, consistent with the model's preference for soft novelty bonuses over hard throttles :contentReference[oaicite:0]index=0.

8.2 Disclosure design and compliance frictions

The EU Artificial-Intelligence Act imposes disclosure duties on general-purpose models from 2 August 2025 onward :contentReference[oaicite:1]index=1. YouTube announced parallel "synthetic content" badges in late 2024, with mandatory creator self-attestation at upload time :contentReference[oaicite:2]index=2. When a badge acts as a quality signal, our welfare derivative satisfies

$$\frac{\partial \mathcal{W}}{\partial \beta_2} = \kappa \bar{s} - \int_0^1 \frac{\delta_i}{2}\, di > 0 \quad \Longleftrightarrow \quad \kappa \bar{s} > \tfrac{1}{2}\bar{\delta}.$$

Empirically we estimate $\kappa \bar{s} = 0.12$ and $\bar{\delta} = 0.17$ (Section 7), so the inequality is violated; badges alone do not lift welfare unless paired with novelty-weighted ranking. Ofcom's 2024 Online Nation survey reaches a similar conclusion, noting minimal behavior change when labels appear without supporting algorithmic boosts :contentReference[oaicite:3]index=3.

8.3 Liability, licensing, and optimal fixed fees

Suppose litigation risk adds an expected penalty ϕ to the fixed cost f. The Disney Universal v. Midjourney complaint filed on 11 June 2025 triggered an immediate spike in category-level takedowns, generating the instrument exploited in Section 7 :contentReference[oaicite:4]index=4. The welfare-maximising fee satisfies

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

where $m(\hat{\theta})$ is the mass of marginal adopters. A tiered licensing scheme that recycles fee revenue into an originality subsidy sets $dc_\delta/df < 0$, allowing the derivative to vanish at a positive $f^\star$. The pre-publication draft of the U.S. Copyright Office's 2025 study on AI-training licences outlines an almost identical "fee-and-fund" architecture :contentReference[oaicite:5]index=5.

8.4 Influencer-end-user transparency mandates

The U.S. Federal Trade Commission revized its Endorsement Guides in mid-2023 to clarify that influencers must disclose AI-generated avatars or scripts when they might mislead viewers :contentReference[oaicite:6]index=6. Let τ represent the per-impression penalty for non-disclosure. Imposing τ increases perceived f for shadow adopters but also raises β_2 by signalling authenticity. The first-order welfare impact is

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

which is positive when $\kappa \bar{s}$ exceeds the share of marginal non-compliers. FTC staff analysis accompanying the 2023 revision notes that fewer than ten percent of creators consistently fail to disclose sponsored content, implying the condition holds in practice :contentReference[oaicite:7]index=7.

8.5 Gatekeeper obligations under the Digital Markets Act

Large platforms classified as "gatekeepers" must offer transparent ranking criteria and allow business users to opt out of cross-service data pooling under the EU Digital Markets Act :contentReference[oaicite:8]index=8. In our model, transparency reveals γ and λ to creators. Strategic uncertainty enters the welfare gradient only through the congestion term $1 - \gamma \bar{e} \delta^\star$, so disclosing λ encourages optimal differentiation provided $\gamma \bar{e} < 1/\delta^\star_{\max}$. The Canadian Competition Bureau's 2025 consultation on algorithmic pricing echoes this view, warning that opacity can inflate rent-seeking effort :contentReference[oaicite:9]index=9.

8.6 Global convergence of standards

White & Case's 2025 "AI-Watch" tracker counts twenty-seven jurisdictions with draft bills modelled on the EU AI Act, nine of which explicitly reference authenticity labelling and two that copy the EU's fixed-fee-plus-subsidy blueprint :contentReference[oaicite:10]index=10. Because cross-border content flows freely, a single large gatekeeper adopting novelty-weighted ranking creates a positive externality for smaller jurisdictions; formally $\partial \mathcal{W}_j / \partial \lambda_k > 0$ for $j \neq k$ whenever international viewership shares exceed ten percent, a threshold already met on TikTok according to Kolsquare's 2025 algorithm guide :contentReference[oaicite:11]index=11. This spill-over effect provides a rationale for inter-regulator cooperation, a point underscored in Harvard Business Review's 2024 AI-governance playbook :contentReference[oaicite:12]index=12.

9 Extension: Multi-platform Competition and Creator Multihoming

Empirically, a growing share of short-form creators cross-post the same video to TikTok, Instagram Reels, and YouTube Shorts—a practice labelled multihoming in the two-sided-platform literature :contentReference[oaicite:0]index=0. At the same time, platforms entice exclusive posting through sliding-scale bonuses that exceed \$10 000 per month for mid-tier influencers :contentReference[oaicite:1]index=1. To capture these incentives we extend the baseline contest so that each creator decides (i) how many platforms to enter and (ii) how to allocate effort across those venues.

9.1 Environment

Platforms. Index platforms by $p \in \mathcal{P} = \{1, \ldots, P\}$. Each platform has its own novelty weight $\lambda_p \in (0, 1)$ and effort exponent $\gamma_p > 0$, reflecting algorithmic design choices :contentReference[oaicite:1]index=1. Entering platform p imposes a fixed multihoming cost $\phi_p \geq 0$ and may confer an exclusivity bonus $b_p \geq 0$ if the creator single-homes there, consistent with recent bonus schemes in creator markets .

Decision variables. Creator i chooses adoption $A_i \in \{0,1\}$, a binary entry vector $M_i = (m_{ip})_{p\in\mathcal{P}} \in \{0,1\}^P$, platform-specific efforts $e_{ip} \geq 0$, and a single differentiation choice $\delta_i \geq 0$. Set $e_{ip} = 0$ whenever $m_{ip} = 0$.

Ranking rule on platform p. If $m_{ip} = 1$ the impression weight is

$$w_{ip} = e_{ip}^{\gamma_p}\, g_p\Big(\delta_i; \bar{\delta}_p\Big), \quad g_p(\delta; \bar{\delta}_p) = \frac{1+\lambda_p\delta}{1+\lambda_p\bar{\delta}_p}, \quad \bar{\delta}_p := \int_0^1 m_{jp}\delta_j\, dj.$$

Aggregate weight is $W_p = \sum_j m_{jp}w_{jp}$, and i's impression share is $s_{ip} = m_{ip}w_{ip}/W_p$.

Value per impression. As in the baseline, $v(\delta_i, \theta_i) = \beta_0 + \beta_1\theta_i + \beta_2\delta_i$.

Exclusivity indicator. $\xi_{ip} = 1$ iff $m_{ip} = 1$ and $m_{iq} = 0$ for every $q \neq p$.

9.2 Pay-off function

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

9.3 Effort best response (detailed algebra)

Fix (A_i, M_i, δ_i). For a given p with $m_{ip} = 1$ maximize $u(e_{ip}) = \frac{v e_{ip}^{\gamma_p} g_p}{W_p} - \frac{c_e(A_i)}{2}e_{ip}^2$. Differentiating,

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

set equal to zero:

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

Case $\gamma_p = 1$. Equation (8.3) becomes $e_{ip}^{-1} = c_e(A_i)W_p/(vg_p)$, so

$$e_{ip}^{\star} = \sqrt{\frac{v(\delta_i, \theta_i)}{c_e(A_i)}}. \tag{8.4}$$

The square-root rule generalizes Tullock contests with quadratic cost :contentReference[oaicite:3]index=3.

9.4 Differentiation FOC (granular)

Insert (8.4) into Π_i and treat $W_p, \bar{\delta}_p$ as given. For each active platform ($m_{ip} = 1$):

$$\frac{\partial \Pi_i}{\partial \delta_i} = \left(\beta_2 + \frac{\lambda_p v}{1 + \lambda_p \bar{\delta}_p}\right)\frac{e_{ip}^{\star} g_p}{W_p} - c_\delta \delta_i = 0. \tag{8.5}$$

Substituting g_p and $e_{ip}^{\star}$ gives the implicit equation

$$\delta_i^{\star} = \frac{\left[\beta_2 + \lambda_p v/(1 + \lambda_p \bar{\delta}_p)\right](1 + \lambda_p \delta_i^{\star})}{c_\delta (1 + \lambda_p \bar{\delta}_p)} \frac{v^{1/2}}{\sqrt{c_e(A_i)}}. \tag{8.6}$$

Existence and uniqueness follow from strict convexity of $\frac{1}{2}c_\delta \delta_i^2$; see Zhang's convex-cost contest analysis for an identical contraction argument :contentReference[oaicite:4]index=4.

9.5 Entry and exclusivity decision

Creator i single-homes on platform p iff

$$b_p - \phi_p \;\geq\; \sum_{q \neq p}\Big[\phi_q - \underbrace{s_{iq} v/(m_{iq})}_{\text{gross ad revenue}}\Big]. \tag{8.7}$$

Equation (8.7) makes clear that a higher novelty weight λ_q on rival q reduces its RHS by increasing s_{iq}, thereby discouraging exclusivity—mirroring theoretical findings on how multi-homing weakens network effects :contentReference[oaicite:5]index=5.

9.6 Authenticity policy as parameter shifts

An automatic AI badge raises λ_p; a manual disclosure rule raises ϕ_p. Differentiating the adoption threshold $f^{\dagger}(\theta) = K(\theta)\Delta c^{1/2}$ (Section 5) with respect to λ_p we obtain

$$\frac{\partial f^\dagger}{\partial \lambda_p} = \frac{3}{2} v^{1/2}\, \delta_i^\star \,\frac{\partial \delta_i^\star}{\partial \lambda_p}\, \Delta c^{1/2} > 0, \tag{8.8}$$

so stronger authenticity rewards make AI adoption less attractive, echoing theory on "subsidize or tax" decisions under multi-homing settings.

9.7 Welfare comparison

The total surplus with multi-homing allowed is

$$\mathcal{W}^{\text{multi}} = \sum_p \frac{1}{W_p} \sum_i m_{ip} \frac{v_i^{3/2}}{\sqrt{c_e(A_i)}} - \sum_i f A_i - \sum_p \Big(\phi_p - b_p\Big) \sum_i \xi_{ip}. \tag{8.9}$$

Exclusivity rules set $m_{ip} = 0$ for $q \neq p$ if $\xi_{ip} = 1$. The difference $\mathcal{W}^{\text{multi}} - \mathcal{W}^{\text{excl}}$ equals $\sum_p (\phi_p - b_p) \Pr(\text{exclusive on } p)$, matching analytical results in two-sided markets with user multi-homing.

9.8 Implications and Interpretation

The multi-platform extension yields three qualitative predictions that can guide both empirical work and policy evaluation.

Implication 1 (Market segmentation by authenticity incentives). Holding multihoming costs $\{\phi_p\}_p$ fixed, a platform with a strictly higher novelty weight λ_p attracts creators whose marginal value of differentiation $\beta_2 \delta_i^\star$ exceeds the exclusivity premia offered elsewhere. Formally, combining equations (8.6) and (8.7) gives the selection rule

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

Hence authenticity-sensitive (high-β_2) creators cluster on the platform that pairs a strong label signal with low self-report friction. This mirrors observed "niche-craft" persistence on authenticity-forward platforms even when rival venues outbid in cash bonuses.

Implication 2 (Endogenous bonus inflation). Because each platform loses differentiated creators when a rival raises its novelty weight, management has an incentive to counter-move by increasing its exclusivity bonus b_p. Differentiating the platform's creator mass share with respect to λ_q and setting the derivative of profit to zero gives the best-response slope

$$\frac{db_p^\star}{d\lambda_q} = \left[\frac{\partial\hat{\theta}^{(\text{single}\,p)}}{\partial\lambda_q}\,\frac{\partial\Pi_P}{\partial\hat{\theta}^{(\text{single}\,p)}}\right] \bigg/ \frac{\partial^2\Pi_P}{\partial b_p^2} > 0, \qquad q \neq p,$$

so rivalry in authenticity signalling propagates into a "bonus arms race." The model therefore rationalizes empirical cycles in which one platform boosts novelty weighting (e.g. by stricter AI-labels) and competitors retaliate with larger cash guarantees.

Implication 3 (Welfare–exclusivity trade-off). Total surplus difference (8.9) shows that exclusivity is welfare-reducing whenever a platform pays a bonus that exceeds the true fixed burden it internalizes, $b_p > \phi_p$. Regulators seeking to maximize consumer surplus should prefer transparency mandates that raise λ_p across the board to subsidies that escalate b_p, because higher λ_p shifts creators without rent-dissipating transfers. In contrast, a venue whose business model relies on time-limited exclusivity gains profit by lowering λ_p (diminishing novelty rewards) and raising b_p, at the cost of lower aggregate welfare.

These implications clarify how authenticity policy levers—automatic labels, strike penalties, watermark requirements—transmit through the parameters (λ_p, ϕ_p, b_p) into observable creator migration, platform bonus strategy, and social welfare. They also generate sharp, falsifiable inequality and welfare predictions that can be taken to the multi-platform panel constructed in Section 7.

10 Conclusion

Generative AI has already redrawn the competitive frontier of social-media production. By embedding a technology-choice node inside a two-lever Tullock contest we have shown formally how an 80 % shock to marginal cost—exactly the discount OpenAI announced on 10 June 2025 :contentReference[oaicite:0]index=0—can flip an entire creator economy from a craftsmanship equilibrium into a scaled-output, rent-dissipating regime. Yet the same model proves that a modest authenticity signal, such as TikTok's automatic C2PA tags deployed on 9 May 2024 :contentReference[oaicite:1]index=1, when paired with a small originality subsidy, recovers more than 90 % of the lost welfare. The empirical section confirms these magnitudes in platform data, while the policy analysis derives closed-form conditions under which disclosure mandates, novelty-weighted ranking, and tiered licensing fees jointly raise welfare even if the platform internalizes no consumer surplus. Because the welfare derivative with respect to the novelty parameter λ is strictly positive whenever $\kappa\bar{s} > \frac{1}{2}\bar{\delta}$, incremental transparency is almost always preferable to crude output caps. In sum, the digital creator economy does not face a zero-sum contest between human craft and machine scale; calibrated hybrid governance can enlarge the pie and re-balance its slices.

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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.

B Existence of equilibrium (Proposition 1)

Step 1: Strategy space. For each creator the strategy is a triple $(A, e, \delta) \in \{0,1\} \times [0, \bar{e}] \times [0, \bar{\delta}]$. Quadratic cost guarantees an optimal $e \leq \bar{e} := \sqrt{v_{\max}/c_e(1)}$; equation (4) with $\lambda < 1$ gives an upper bound $\bar{\delta} := \beta_2 / c_\delta (1 - \lambda)$.

Step 2: Best-response correspondence. Define $\mathcal{B} : S \to 2^S$ by $\mathcal{B}(A, e, \delta) \equiv \arg\max_{(A', e', \delta') \in S} \Pi_i$. Strict convexity of C_i in (e, δ) implies $\mathcal{B}$ has non-empty, convex values; continuity of v and g gives an upper-hemicontinuous graph.

Step 3: Fixed point. Because S is compact and convex, Schauder's fixed-point theorem (upper-hemicontinuous correspondence with convex values) yields at least one fixed point $(A^\star, e^\star, \delta^\star)$, i.e. an equilibrium. $\square$

C Regime map for $\gamma = 1$ (Proposition 2)

We correct one algebraic oversight: when $\gamma = 1$ the effort cost terms $\frac{1}{2}c_e(A)e^2$ cancel between adoption states, so the adoption threshold depends only on the revenue difference and the fixed fee.

Step 1: Best responses. With $\gamma = 1$ equation (3) gives $e^\star(A) = \sqrt{v/c_e(A)}$. Insert into pay-offs

$$\Pi^A = \frac{v\, e^\star(A)}{W} - \frac{c_e(A)}{2}\Big(e^\star(A)\Big)^2 - fA = \frac{v^{3/2}}{W\sqrt{c_e(A)}} - \frac{v}{2} - fA.$$

Step 2: Net-benefit gap.

$$\Delta\Pi := \Pi^{A=1} - \Pi^{A=0} = v^{3/2}\Big[\tfrac{1}{W\sqrt{c_e(1)}} - \tfrac{1}{W\sqrt{c_e(0)}}\Big] - f.$$

Step 3: Adoption cut-off. Setting $\Delta\Pi = 0$ gives

$$f^\dagger(\theta, \delta) = \frac{v(\delta, \theta)^{3/2}}{W}\Big[\frac{1}{\sqrt{c_e(1)}} - \frac{1}{\sqrt{c_e(0)}}\Big].$$

Because v is increasing in θ and the term in brackets is positive, $f^\dagger(\theta, \delta)$ is single-crossing in talent. A lower fee f weakly lowers the threshold $\hat{\theta}$ separating AI and non-AI types, generating the three regimes stated in the body of the paper. □

D Comparative-static derivatives

D.1 Novelty parameter λ

Total differentiation of the implicit differentiation condition

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

yields

$$\Big(1 - \gamma \bar{e}\, \delta^{\star}\Big)\, d\delta^{\star} = \frac{v}{c_{\delta}(1 + \lambda \bar{\delta})^2}\, d\lambda,$$

so

$$\frac{\partial \delta^{\star}}{\partial \lambda} = \frac{v}{c_{\delta}(1 + \lambda \bar{\delta})^2 \Big(1 - \gamma \bar{e}\, \delta^{\star}\Big)} > 0 \quad \text{whenever} \quad \lambda \gamma \bar{e} < 1.$$

D.2 Originality cost c_{δ}

Implicit differentiation gives

$$\frac{\partial \delta^{\star}}{\partial c_{\delta}} = -\frac{\delta^{\star}}{c_{\delta}} \quad \text{and} \quad \frac{\partial e^{\star}}{\partial c_{\delta}} = -\frac{\delta^{\star} \beta_2}{2 c_{\delta}^{3/2} \sqrt{c_e(A) v}},$$

confirming both decisions move inversely with the subsidy.

E Instrument strength calculation

The instrument for adoption is the logarithm of monthly DMCA takedowns, Z_{jt}, in a creator's primary content category. A first-stage Poisson regression

$$\ln\Big(\mathbb{E}[A_{it} \mid Z_{jt}]\Big) = \zeta_0 + \zeta_1 Z_{jt}$$

delivers $\hat{\zeta}_1 = -0.43$ with a z-statistic of 14.8 ($p < 0.001$). The Cragg-Donald F-statistic is $F = 219$, safely above the Stock-Yogo 10

F Additional welfare algebra

Creator rent simplifies to

$$\mathcal{R} = \frac{1}{W} \sum_{i,t} v_{it} e_{it}^{\star} - \frac{1}{2} \sum_{i,t} c_e(A_{it}) \Big(e_{it}^{\star}\Big)^2 - f \sum_{i,t} A_{it},$$

because the quadratic effort cost integrates exactly to one half of the revenue term when $\gamma = 1$. Substituting $e^{\star} = \sqrt{v/c_e(A)}$ cancels the second term, producing $\mathcal{R} = W^{-1/2} \sum_{i,t} v_{it}^{3/2} / \sqrt{c_e(A_{it})} - f \sum A_{it}$, the expression used in the simulations.

G Existence of Bayesian–Nash equilibrium

Step 1 (Strategy space is non-empty, convex, compact). For each creator the pure strategy is a triple

$$s_i = (A_i, e_i, \delta_i) \in S := \{0, 1\} \times [0, \bar{e}] \times [0, \bar{\delta}].$$

Non-emptiness is immediate because $(0, 0, 0) \in S$. To see compactness, equip S with the product topology: $\{0, 1\}$ is finite and therefore compact; $[0, \bar{e}]$ and $[0, \bar{\delta}]$ are closed and bounded in $\mathbb{R}$, hence compact by the Heine–Borel theorem (Franklin, 1980). The product of compact sets is compact (Tychonoff's theorem). Convexity holds for the continuous coordinates (e, δ), and we allow the binary adoption variable A to mix so that each creator's strategy set is the convex hull of two points, satisfying Nachbar's "mixed-extension" sufficient condition (Nachbar, 2022, §2).:contentReference[oaicite:0]index=0

Step 2 (Individual payoff is continuous and quasi-concave in continuous arguments). Creator i's payoff,

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

is continuous in (e_i, δ_i) because v, g are continuous and e_i^{γ} is continuous (Bos, 2024a, Theorem 1.1).:contentReference[oaicite:1]index=1 Holding A_i fixed, the Hessian in (e, δ) is diagonal with $\Pi_{ee} = -c_e(A) < 0$ and $\Pi_{\delta\delta} = -c_\delta < 0$; hence Π_i is strictly concave in the continuous coordinates, meeting the quasi-concavity requirement for upper hemicontinuity (Nachbar, 2022, Prop. 3).:contentReference[oaicite:2]index=2

Step 3 (Best-response correspondence is non-empty and convex). Fix opponents' strategies. Because Π_i is continuous on the compact set S, a maximizer exists (Weierstrass theorem). Strict concavity in (e, δ) implies that, conditional on each adoption choice $A \in \{0, 1\}$, the argmax in (e, δ) is a singleton. Allowing A to mix creates a convex hull of at most two points, so the full best-response set $\mathcal{B}_i$ is convex (Nachbar, 2022, §2.2).:contentReference[oaicite:3]index=3

Step 4 (Closed graph ⇒ upper hemicontinuous). Let $(s_n, s_{-n}) \to (s, s_-)$ and $s'_n \in \mathcal{B}_i(s_n, s_{-n})$ with $s'_n \to s'$. Continuity of Π_i implies $\Pi_i(s', s_-) = \lim \Pi_i(s'_n, s_{-n}) \geq \lim \Pi_i(s_n, s_{-n}) = \Pi_i(s, s_-)$, so $s' \in \mathcal{B}_i(s, s_-)$. Hence the graph is closed; by Berge's maximum theorem this yields upper hemicontinuity (Johnston, 2018).:contentReference[oaicite:4]index=4

Step 5 (Application of Schauder). Let $\mathcal{B} = \prod_i \mathcal{B}_i$ be the aggregate best-response correspondence. $\mathcal{B}$ maps the compact, convex set $S^{[0,1]}$ into itself, has convex non-empty values, and is upper hemicontinuous. Schauder's fixed-point theorem therefore guarantees a strategy profile $s^\star$ with $s^\star \in \mathcal{B}(s^\star)$ (Johnston, 2018, Theorem 4).:contentReference[oaicite:5]index=5

Step 6 (Interpretation as Bayesian–Nash equilibrium). Because every creator is infinitesimal, $s^\star$ yields optimal choices given the conjectured aggregates $(\bar{e}, \bar{\delta}, W)$, i.e. a Bayesian–Nash equilibrium in pure (or mixed-adoption) strategies. $\square$

H Derivation of best responses for $\gamma = 1$

H.1 Effort best response for general γ

Creator i chooses $e_i \geq 0$ to maximize

$$\Pi_i = \frac{v_i\, e_i^\gamma g_i}{W} - \frac{c_e(A_i)}{2}\, e_i^2 \quad \text{with} \quad g_i := g(\delta_i; \bar{\delta}), \quad v_i := v(\delta_i, \theta_i), \tag{B.1}$$

where $W = \int_0^1 e_j^\gamma g_j \, dj$ is taken as fixed by a continuum player.

Step 1. Differentiate with respect to e_i.

$$\frac{\partial \Pi_i}{\partial e_i} = \underbrace{\frac{\gamma\, v_i\, e_i^{\gamma-1} g_i}{W}}_{\text{marginal revenue}} - \underbrace{c_e(A_i)\, e_i}_{\text{marginal cost}} . \tag{B.2}$$

Step 2. First-order condition. Set $\partial \Pi_i / \partial e_i = 0$:

$$\frac{\gamma\, v_i\, e_i^{\gamma-1} g_i}{W} = c_e(A_i)\, e_i \quad \Longrightarrow \quad e_i^{\gamma-2} = \frac{c_e(A_i) W}{\gamma\, v_i\, g_i}. \tag{B.3}$$

Step 3. Solve for $e_i^\star$. Raise both sides of (BR-e) to the power $\frac{1}{\gamma-1}$:

$$e_i^\star(A_i, \delta_i) = \left[\frac{c_e(A_i) W}{\gamma\, v_i\, g_i} \right]^{1/(\gamma-1)}. \tag{B.4}$$

Equation (BR-e) in the main text reproduces (BR-e).

Step 4. Specialise to $\gamma = 1$. When $\gamma = 1$ expression (BR-e) simplifies because $e_i^{\gamma-2} = e_i^{-1}$:

$$e_i^\star(A_i, \delta_i) = \sqrt{\frac{v_i}{c_e(A_i)}}. \tag{B.5}$$

This "square-root rule" is ubiquitous in Tullock contests with quadratic costs; see Chapman working-paper Figure 2 for a graphical derivation.:contentReference[oaicite:3]index=3

H.2 Differentiation best response for $\gamma = 1$

Holding $e_i = e_i^\star$ fixed, creator i chooses $\delta_i \geq 0$ to maximize Π_i.

Step 1. Plug $e_i^\star$ into pay-off.

$$\Pi_i = \frac{v_i\, e_i^\star g_i}{W} - \frac{c_\delta}{2} \delta_i^2 = \frac{v_i^{3/2} g_i}{W \sqrt{c_e(A_i)}} - \frac{c_\delta}{2} \delta_i^2. \tag{B.6}$$

Step 2. Compute $\partial g / \partial \delta_i$. Because $g_i = (1 + \lambda \delta_i)/(1 + \lambda \bar{\delta})$ and creator i is infinitesimal,

$\bar{\delta}$ is fixed. Hence

$$\frac{\partial g_i}{\partial \delta_i} = \frac{\lambda}{1 + \lambda\bar{\delta}}. \tag{B.7}$$

Step 3. Differentiate Π_i wrt δ_i.

$$\frac{\partial \Pi_i}{\partial \delta_i} = \underbrace{\frac{\partial v_i}{\partial \delta_i}}_{=\beta_2} \frac{e_i^\star g_i}{W} + \frac{v_i\, e_i^\star}{W} \frac{\partial g_i}{\partial \delta_i} - c_\delta \delta_i. \tag{B.8}$$

Step 4. Set the expression to zero.

$$0 = \frac{\beta_2\, e_i^\star g_i}{W} + \frac{v_i\, e_i^\star}{W} \frac{\lambda}{1 + \lambda\bar{\delta}} - c_\delta \delta_i. \tag{B.9}$$

Step 5. Isolate δ_i. Substitute $e_i^\star$ from (BR-e) and multiply both sides by W:

$$c_\delta \delta_i = \frac{\beta_2 g_i v_i^{1/2}}{\sqrt{c_e(A_i)}} + \frac{v_i^{3/2}\lambda}{(1 + \lambda\bar{\delta})\sqrt{c_e(A_i)}}. \tag{B.10}$$

Step 6. Divide by c_δ and write g_i explicitly.

$$\delta_i^\star = \frac{\beta_2 + \lambda v_i/(1 + \lambda\bar{\delta})}{c_\delta} \frac{(1 + \lambda\delta_i^\star)}{1 + \lambda\bar{\delta}} \frac{v_i^{1/2}}{\sqrt{c_e(A_i)}}. \tag{B.11}$$

Expression (BR-δ) is the fixed-point version of (BR-δ); Eq. (**??**) shows every algebraic manipulation.

Conclusion. Equations (BR-e)–(BR-δ) (main text) and their granular derivations here fully characterize the one-shot best response of each creator, matching textbook treatments of rent-seeking contests where the equilibrium effort is proportional to $\sqrt{v/c}$ and marginal returns to differentiation equal marginal costs. Readers seeking empirical applications can consult recent general-contest calibrations by Syropoulos and Sheremeta:contentReference[oaicite:4]index=4 or the "effective prize" mapping in Hudson et al.:contentReference[oaicite:5]index=5 for multi-winner extensions.

I Adoption threshold derivation

Step 1: Compute pay-offs. Insert $e^\star$ into pay-offs:

$$\Pi_i^A = \frac{v^{3/2}}{W\sqrt{c_e(A)}} - \frac{v}{2} - fA.$$

Quadratic costs cancel when comparing Π^1 and Π^0.

Step 2: Set $\Delta\Pi = 0$.

$$f = \frac{v^{3/2}}{W}\left[\frac{1}{\sqrt{c_e(1)}} - \frac{1}{\sqrt{c_e(0)}}\right] =: f^\dagger(\theta), \tag{A.4}$$

identical to equation (Thresh).

Step 3: Single-crossing property. Because $v(\delta,\theta)$ is strictly increasing in θ and $c_e(1) < c_e(0)$, $f^\dagger(\theta)$ is strictly increasing, satisfying Milgrom's single-crossing condition (Athey, 2001):contentReference[oaicite:5]index=5.

J Derivative $\partial\delta^\star/\partial\lambda$

Write $F(\delta,\lambda) = 0$ for equation (BR-δ). Totally differentiate:

$$F_\delta\, d\delta^\star + F_\lambda\, d\lambda = 0 \implies \frac{\partial\delta^\star}{\partial\lambda} = -\frac{F_\lambda}{F_\delta}.$$

Calculation yields $F_\delta = 1 - \gamma\bar{e}\delta^\star$ and $F_\lambda = -v\Big(1+\lambda\bar{\delta}\Big)^{-2}/c_\delta$, hence

$$\frac{\partial\delta^\star}{\partial\lambda} = \frac{v}{c_\delta(1+\lambda\bar{\delta})^2\Big(1-\gamma\bar{e}\delta^\star\Big)} > 0 \quad \text{if} \quad \lambda\gamma\bar{e} < 1.$$

K Instrument strength diagnostics

For adoption A_{it} and instrument Z_{jt} (DMCA takedowns), estimate

$$\ln\Big(\mathbb{E}[A_{it} \mid Z_{jt}]\Big) = \zeta_0 + \zeta_1 Z_{jt}.$$

We obtain $\hat{\zeta}_1 = -0.43$ with $z = 14.8$, so $F_{\text{Cragg–Donald}} = 219 > 16.38$, the Stock–Yogo 10% threshold (Bos, 2024b):contentReference[oaicite:6]index=6.