Amusing Ourselves to Death?

Education and Work Under Digital Influence*

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Abstract

The increasingly ubiquitous digital (social/self) media and influencer economy reshape how people allocate time and consumption, which, in turn, alter individual educational/career decisions, relative returns across occupations, and resource allocation in the society. Educational pursuits exhibit stage-switch externality, intensifying short-run competition for skilled job placements but creating long-run strategic complementarity within job/service category (e.g., between investors and advisors). Multiple equilibria, including one featuring inefficiently low education, ensue. Individual education and occupational decisions depend non-monotonically on labor market search frictions and digitization. Greater entertainment surplus can discourage or even break down formal education. Entertainment influencers thus crowd out not only agents' attention but also education and work that facilitate efficient production (e.g., investments and public goods provision). A digital platform optimally raises the entertainment outside option and creator incentives, tilting equilibrium selection toward low aggregate education, with an ambiguous effect on equilibrium multiplicity. Regulations directly targeting influencers or reducing search friction in the labor market may backfire; taxing both influencers and followers, coordinating individual actions, and intervening in platform designs can mitigate inefficiency.

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1 Introduction

> *"Together, this new ensemble of electronic techniques called into being a new world – a peek-a-boo world, where now this event, now that, pops into view for a moment, then vanishes again. It is a world without much coherence or sense; a world that does not ask us, indeed, does not permit us to do anything; a world that is, like the child's game of peek-a-boo, entirely self-contained. But like peek-a-boo, it is also endlessly entertaining."*
>
> — Neil Postman

What Postman wrote almost four decades ago seems uncanny and prophetic descriptions of today's digital social media and creator/influencer economy that are growing into its largest scale ever, with non-stop pushes and autoplays of short videos, livestreaming of idol lives and pranks, lectures broken into bite-size game-like clips, and influencer marketing.[1] The common denominator is the entertaining and attention-grabbing nature of digital platforms and the blurring of the boundary between social and business media.[2] Meanwhile, online content increasingly shapes public beliefs and behaviors, such as inflation expectations, vaccinations, or actions against climate change. Unfortunately in this context, misinformation and disinformation—unintentionally or intentionally false information—abounds (Deryugina and Shurchkov, 2016), and spreads virally (Allcott and Gentzkow, 2017; Osmundsen et al., 2021; Pennycook et al., 2021), especially when it is arousing, emotional or interesting (Berger and Milkman, 2012; Serra-Garcia and Gneezy, 2021; Robertson et al., 2023). Even without false content, digital media is inundated with irrelevant, fragmented, superficial information, which is entertaining and creates the illusion (and satisfaction) of knowing something.

Beyond digital addiction or anxiety (Allcott et al., 2022a; The Economist, 2024a), what are the broader implications of the rise of digital social media and influencers? We answer the question by studying how, through shifting attention allocation and consumption, digi-

[1] Digital social media is uniquitous these days, with nearly 4 billion users worldwide, including 70-80% of the industrialized world's population and with an average daily use in excess of two hours as of 2020, according to the Globalwebindex survey (550,000 participants) of online behaviors. Not only does the burgeoning creative economy yield substantial profits, but it also opens up enormous opportunities for job creation. For example, from only US $1.7 billion in 2016 to $16.4 billion in 2012, the global influencer marketing industry was predicted to reach $21 billion by 2023 (Geyser, 2023). According to Goldman-Sachs (2023), the total addressable market value of the creator economy is expected to double in size by 2027, from its current $250 billion to half a trillion dollars, which is comparable to the total revenue generated by the e-commerce industry. Nonetheless, in terms of employment generation, the United States has over 10.2 million Instagram creators and 10.1 Tiktok creators; Europe and Latin America has 10.2 million and 18.9 million Instagram influencers; and China has 10.1 million influencers with a fan base larger than 10,000 (Influencity, 2023; PJdaren, 2023).

[2] As Postman puts: Orwell feared that the truth would be concealed from us; Huxley feared that the truth would drown in a sea of irrelevance. It is the latter fear of "what we love will ruin us" that is forever more salient today. The flow of distraction we experience is akin to Huxley's new world, more so than to Orwell's 1984 the restricted information.

tal influence distorts incentives and decisions in education and work. In particular, we offer an explanation for how Gen Z indulging in social media appears less entrepreneurial and innovative (Park et al., 2023; The Economist, 2024b). We recognize that digital technologies provide greater entertainment that makes people happy and helps them relax after a tiring day, delivering individuals real utility.[3] However, we show that attention is a valuable resource and its monetization has unintended consequences. At a basic level, mass show in the era of digital social media is so scalable and available in varieties that it crowds out authentic information sources and meaningful economic productions.[4] More importantly, given the competition for attention and the elevated role of digital influence in allocating this scarce resource that influencers monetize, people's incentives for education and occupational choices are distorted and the one with voice through digital influence may not be the most educated or reliable for decisions affecting the overall society and of the human race. This reallocation of attention can trap societies in low-education equilibria even when a high-education outcome is feasible and welfare-dominant.

Specifically, we consider a continuum of risk-neutral agents interacting in three sequential stages. First, agents with heterogeneous learning costs choose whether to acquire formal education and, conditional on outcomes, whether to purchase social influence. Agents thereby endogenously become educated experts, educated workers, influencers, or uneducated followers. Second, agents decide whether to supply services or entertainment as experts or influencers, and whether to follow them, with matches formed endogenously. Third, expert-followers pay for productive services, while uneducated followers derive entertainment surplus from influencer-following, after which the game ends. The proliferation of digital media and platform technologies enhances search and matching between experts and workers, reduces the cost of becoming an influencer, and expands the variety and efficiency

[3]Experts and professionals may well use entertaining digital media to amplify their outreach. What is concerning is that, given our continual immersion in a flux of stimuli from digital social media, our capacity to meaningfully engage with and retain the substance of the spectrum of information—be it religious, political, or educational—has substantially attenuated, as Postman worried. Making learning more entertaining may help students memorize certain concepts, but will unlikely teach them the ability to learn, which is what education should be more about. As Postman pointed out in the example of Sesame Street, sometimes learning and education requires endurance and is a painful process.

[4]As philosopher and communication theorist Marshall McLuhan sharply observed 60 years ago, the medium over which information is transported is sometimes more important than the information itself. In a way, medium is the message! See McLuhan (2017) and McLuhan (1994). McLuhan predicted the world wide web 30 years before its invention (McLuhan, 1999). His puns "medium is the massage" "medium is the mass age" "medium is the mess age" are also becoming true given how the mass influencer economy presents fragmented information and chaos. Short videos contain a lot of decontextualized information while social media often deliver harmful or inaccurate content. According to a survey by Common Sense in 2023, an advocacy group, 45% of American teenager girls say they are addicted to TikTok and over one third addicted to instagram. See, e.g., https://www.commonsensemedia.org/press-releases/new-report-reveals-what-teen-girls-think-about-tiktok-instagram.

of influencer–follower matches, thereby raising entertainment value.

Two realistic modeling innovations enable us to derive new economic insights. First, education serves the dual purpose of (i) imparting knowledge and skills and (ii) determining outcomes in conventional labor markets (earning baseline wages as workers with basic skills versus becoming "experts" with additional payoffs from higher-level services workers cannot offer). Second, only educated agents can appreciate experts' service and benefits from that when engaging in economic production. How an individual processes information depends on the characteristics of both the observer and the observed behavior or event (Malmendier and Veldkamp, 2022).[5] These assumptions generate a novel stage-switch externality: education is strategically substitutable ex ante—because more education intensifies congestion for scarce expert slots—but strategically complementary ex post—because educated agents benefit more from each other's expertise (educational resonance). An entertainment outside option amplified on the platform interacts with this stage-switch externality to generate sharp multiplicity and policy-relevant distortions.

We are not claiming that in practice all influencers are unscientific ones, evidence from other social media settings in more established markets such as stock markets indicates that social media analysts generally add value (e.g., Farrell et al., 2022; Drake et al., 2022; Jame et al., 2022). The popular crowdsourced forecasting platform, Estimize, even emphasizes prominently on its website that individuals have incentives to contribute as doing so is "beneficial to everyone" and is a "mark of a good citizen." Presumably some analysts here are financial experts with proper training. The type of anti-intellectual influencers in our model are the ones that lead to information cascades rather than effective aggregation, and are the ones that without formal education or scientific training, who offer bad advice or misinformation or disinformation.[6] While the incentive to attract attention by influencers could lead to more knowledge about science through increased engagement (Deryugina and Shurchkov, 2016), this incentive also leads to a focus on arousing emotions at the expense of accuracy. Even with accuracy, Serra-Garcia (2024) document through experiments that attention-grabbing can increase misperception and bias through what is omitted in presentations. Overall, we do not criticize short videos, but even improvements in expert matches can be harmful to

[5]In particular, observers are inclined towards learning from people they identify with and that are similar to themselves in some way. Scientific education and consensus standards make it easier for an educated individual to follow another educated person and benefit from the information/advice/leadership/service she provides.

[6]Merkley et al. (2023) examine the returns associated with tweets issued by the most prominent crypto social media influencers covering over 1,600 crypto securities for two years and find significantly negative long-horizon returns following the tweets, and the effects are most pronounced for tweets issued by crypto-influencers proclaiming to be professional financial analysts, especially for for self-described experts with a high number of Twitter followers.

social welfare. At the intensive margin, technology affects the expert match; at the extensive margin, it introduces a competitor for education.

Our theory makes three sets of predictions. First, equilibrium multiplicity can arise due to an increase in amusement utility brought forth by technologies increasing entertainment variety through digital platforms. When the amusement utility is small, education payoff dominates influence acquisition; everyone pursues formal education. However, as entertainment utility increases further, societal beliefs in the aggregated education level come into play. There still exists an equilibrium in which when everyone believes that almost all others believe in science, acquiring education is therefore optimal for most agents. But another equilibrium may exist due to the fact that increased education create fiercer competition for initial job placement. This is because when everyone believes that not many believe in science and formal knowledge, then experts cannot receive enough audience, which hurts the endeavors they lead and the expertise market, resulting in an inevitable self-fulfilling inefficient equilibrium. This complementarity comes from a form of information resonance: Only people sharing similar background domain knowledge can understand and appreciate each other.

Second, education and occupational choices exhibit generally non-monotonic dependence on digital technology. For example, as the search and matching technology in the expert labor market improves, aggregate education and the expert market first increase and then decrease. While education and labor market never break down absent digital influence, sufficiently high entertainment utilities cause education and a market breakdown in "investment" (a generic reference to expert-led productive economic activities), significantly reducing total welfare. Even without a collapse in investment, a rise in entertainment utility can diminish overall education if the educational resonance effect is weak. In a sense, digital influence becomes "anti-intellectual," not so much because they offer misinformation or disinformation, but through the crowding out of education and conventional occupations, as well as of time that could be spent on economically productive and socially beneficial activities. In any stable equilibrium, aggregate education falls with higher entertainment utility, a larger revenue share allocated to followers, and greater search frictions in productive matching, provided the relevant participation constraints are satisfied.

With endogenous platform levers, algorithmic intensity reduces aggregate education whenever a simple dominance condition holds: the outside option of digital entertainment outweighs any offsets from creator incentives or matching efficiency. We further consider how a digital platform chooses both algorithmic intensity, which scales user engagement, and a surplus–sharing parameter that determines the revenue split between the platform and in-

fluencers to maximize advertising revenue. Such influence monetization induces designs that overweight entertainment and underweight education relative to the social optimum, thereby reducing aggregate education. Moreover, platform design can eliminate high-education equilibria and increase the likelihood of coordination on a low-education outcome, with an ambiguous effect on equilibrium multiplicity. While network effects in educated workers' investment activities can promote education by raising surplus via complementarity, yet exacerbate welfare losses when market breakdown occurs.

Our model generates several counter-intuitive welfare implications. First, when amusement utility is invariant to influencer variety, total welfare is independent of the influencer entry cost. Free entry equalizes payoffs between influencers and followers, fixing the digital outside option and leaving education incentives—and hence aggregate welfare—unchanged. When entertainment utility instead depends on influencer variety, entry costs have non-monotonic welfare effects: higher entry costs reduce entertainment utility by limiting variety but may raise welfare by strengthening education incentives when educational underinvestment is severe. Second, higher entertainment utility may reduce total welfare. While small increases raise amusement surplus without distorting education choices, sufficiently large entertainment utilities discourage education and can trigger a breakdown of the investment market, sharply lowering total welfare. Third, search frictions affect welfare non-monotonically. While large frictions reduce matching efficiency, very low frictions generate winner-takes-all outcomes among top experts, intensifying competition without expanding the mass of educated workers; as a result, near-perfect matching can also undermine the investment advisory market.

Three distinct sources of welfare inefficiency arise in our framework. First, coordination failures and equilibrium selection can generate sizable welfare losses when digital influence interacts with stage-switch externalities. In particular, incentives related to digital entertainment can induce educated workers or experts to exit productive activities, eliminating surplus for other market participants and discouraging education acquisition. Second, misalignment between the social planner and digital platforms creates institutional distortions: revenue targeting pushes society toward low-education equilibria by amplifying algorithmic intensity and creator incentives. Third, positive network externalities remain uninternalized by infinitesimal agents, further undermining efficiency.

Finally, our analyses offer insights for intervention policies: (i) Banning influencers may backfire, but taxing both influencers and their followers can enhance education acquisition and mitigate anti-intellectual influence without reducing the variety of entertainment goods. In particualr, taxing digital consumptions effectively coordinates the agents into the "good"

equilibrium. (ii) Subsidizing education moderately can help when the anti-intellectual influence problem is not severe. A small subsidy has negligible effect on aggregate education and total welfare, but a large subsidy may result in excessive education acquisition, whose benefits are limited by the investment return. (iii) Targeting platform design distortions, rather than solely focusing on users or creators. Caps or Pigouvian taxes on engagement—which lower the effective entertainment utility—and upper bounds on the influencer monetization share can mitigate the platform's bias toward low-education equilibria. In contrast, taxing entry alone exerts little influence on education because of endogenous free entry and, by reducing variety, generates deadweight losses. (iv) Improving productive matching efficacy (e.g., transparency and "balanced exposure" for educational content) can restore educational resonance without bluntly suppressing influencer variety. However, maintaining some randomness in the matching between experts and educated workers can be beneficial because it avoids fierce price competition among experts and maintains the participation constraints on both sides.

Empirically, our analysis yields relevant predictions across four domains: stage-switch externalities, equilibrium multiplicity and tipping dynamics, the crowding out of education and labor, and platform design distortions in algorithmic intensity and revenue sharing. Related evidence in recent research underscores that the theory captures important real-world dynamics. Future empirical work can build on these predictions to test and calibrate the model.

Literature. Our study contributes to the emerging literature on digital platforms and the influencer or creator economy. Previous studies have focused on the relationship among influencers, platforms, and consumers, including revenue sharing (Bhargava, 2022; Jain and Qian, 2021), platform design (Liu and Liu, 2023; Yang et al., 2023), influencer disclosure (Mitchell, 2021), search and transparency (Fainmesser and Galeotti, 2021a), influencer cartels (Hinnosaar and Hinnosaar, 2021), firms' optimal affiliation with influencers (Pei and Mayzlin, 2019), firms' competition for social influencers (Katona, 2020), the information value of followers' comments (Nistor and Selove, 2023), and product competition under influencer marketing (Cong and Li, 2024). We instead join studies to reveal the dark side of digital influence. Among them, Postman criticizes the shift from word-centered typography to image-centered social media in "the age of exposition," causing us to lose seriousness, clarity, and value within public discourse. Khan et al. (2022) and Lazer et al. (2018) discuss misinformation and fake news in digital media. Digital media platforms are said to negatively impact our health, contributing to social anxiety Berryman et al. (2018), and

promoting a culture of "famous for being famous" (McMullan et al., 2022). We shed light on new channels that digital influence can become anti-intellectual and show how it interacts with education and career choices, with aggregate welfare consequences.

Our study also contributes to the theory of information processing and media communications. Malmendier and Veldkamp (2022) point out that the prior emphasis on "access" to information, or lack thereof, is unlikely to be first order in the digital age when abundant information is accessible. The social context of information processing (Bandura, 1977) is more important: Information resonates with recipients when they identify with the person who communicates it or whose personal experience it reflects. We highlight the role of education in such information resonance, which is more endogenous and prominent than other social characteristics such as race and hometown (McPherson et al., 2001).[7] We are the first to study how formal education interacts with new digital media and the implications of information resonance in such a context. We highlight that similarity in educational background and common scientific language captures a broader notion of social homophily, which is shown to be crucial in social networks and information diffusion (McPherson et al., 2001; Federman et al., 2006; De Choudhury et al., 2010).

Our study is broadly related to the extensive literature on education and labor market, which has analyzed how education affects returns at both microeconomic and macroeconomic levels (e.g., Schultz, 1988; Harmon et al., 2003; Sianesi and Reenen, 2003), development and growth (e.g. Psacharopoulos, 1988; Griliches, 1997), social returns to education (Lange and Topel, 2006), etc. We postulate that education separates people with differential abilities and earning potentials, but remains agonastic on whether this is coming through informational channels such as signaling Spence (1978) or screening Lazear (1977), or heterogeneity under a human capital channel Card (1999). Instead, like Weiss (1983) we assume that individuals are symmetrically informed about their post-education ability which is revealed through completion of education. While Mincer (1962) empirically examines the effects on-the-job training, to our knowledge we offer the first theory of how technology affects endogenous education choices and labor outcomes, with an emphasis on technology-enabled competition from digital social media and influencers against education and subject experts or leaders.

Our paper is also broadly related to the literature on leisure consumption and individuals' time allocation (e.g., Becker, 1965; Gronau, 1977), especially concerning the role of

[7]The concept of homophily was introduced in Lazarsfeld and Merton (1954) to refer to the inclination of individuals to associate disproportionally with others who are similar to themselves. While DeMarzo et al. (2003) and Golub and Jackson (2012) discuss netwok and segregation that affect updating processes, theoretical studies on how these pervasive and robust social patterns affect behavior are underdeveloped. Our focus is on a fully connected digital network with an application in the influencer economy and education.

technology. Aguiar and Hurst (2007) document increased time allocation to leisure from 1965 to 2003 using five decades of linked time use surveys. Aguiar and Hurst (2007) and Gentzkow (2006) study how the introduction of television in the United States in the 1950s and 1960s and the internet in Germany in the 2000s led to a drop in newspaper consumption, political knowledge, and voter turnout. Aguiar et al. (2021) develop a leisure demand system to empirically assess how improvements in leisure technologies have heterogeneous effects on individuals' opportunity cost of labor and, therefore, affect labor supply. Rachel (2024) venture beyond the labor supply aspect to also explore the macroeconomic implications for total factor productivity, measurement, and welfare, emphasizing the adverse impact of leisure-enhancing innovations on long run economic growth.

Most of these studies are empirical and focus on leisure consumption and its effects on labor supply. One exception is Rachel (2024), which develops a theoretical framework to endogenize leisure-enhancing technological change, and emphasizes the negative externality of leisure consumption. The study does not model the labor supply for producing leisure goods, and requires a dynamic setting for the endogenous growth channel: more leisure today drives down future growth in wages because productivity-enhancing improvements and discoveries rely on human input. We endogenize both the production and consumption of leisure/entertainment by individual agents to analyze a new externality coming from the complementarity of education/skill acquisition/job preparation and non-leisure productive activities, as well as the static network effects present in these activities. The endogenous education stage allows us to derive novel results, some of which rationalize empirical patterns documented in Aguiar and Hurst (2007) that least educated households experienced the largest increase in leisure because they lack the skills for productive economic activities.

Furthermore, our paper relates to the literature on digital media, distraction, and peer effects in human capital and labor markets. Allcott et al. (2020) document welfare losses from social media, Allcott et al. (2022b) model digital addiction, and Braghieri et al. (2022) show that Facebook's rollout harmed student mental health by crowding out productive activities. In education, smartphone bans improve test scores, especially for lower-achieving students (Beland and Murphy, 2016), commitment devices raise focus and attendance (Aksoy et al., 2025), and reviews confirm that heavy smartphone use predicts weaker performance (Amez and Baert, 2020). Meanwhile, peer effects provide a complementary channel. Random assignment studies show strong peer influence in higher education (Feld and Zölitz, 2017; Lavy and Schlosser, 2011), and Barwick et al. (2024) find that digital app usage is contagious, lowering GPA and depressing early wages. Related work highlights how platform design and algorithmic incentives bias attention and distort time use (Fainmesser and Galeotti,

2021b). Our contribution to this literature is threefold. First, we develop a unified model of stage-switch externalities in which digital activities generate peer cascades and multiple equilibria in human capital investment. Second, we link micro-level distraction and spillovers to equilibrium phenomena—tipping, multiplicity, and welfare loss—providing a structural explanation for heterogeneous outcomes. Third, we endogenize platform design, showing how algorithms and creator incentives distort attention, complementing existing studies of digital influence while emphasizing welfare and policy implications in education and labor markets.

Lastly, our paper also relates to the literature on equilibrium multiplicity and coordination. Global games show how small amounts of private information can eliminate spurious equilibria and sharpen predictions in settings with strategic complementarities (Carlsson and van Damme, 1993; Morris and Shin, 1998). Similar coordination failures arise in social-interaction models, where complementarities generate multiple self-fulfilling regimes (Brock and Durlauf, 2001), and in education, where externalities can sustain both low- and high-investment equilibria (Durlauf, 1996). Schooling choices also feature "rat-race" competition, as individuals over-invest in credentials to keep up with peers, producing socially wasteful outcomes (Akerlof, 1976; Ramey and Ramey, 2010). Our work connects these themes but differs by placing opposing strategic forces in different stages of the same environment and tying them to digital technologies and platform design that maximize engagement rather than welfare.

2 Model Setup

A unit measure of risk-neutral agents indexed by $i \in \mathcal{I} = [0, 1]$ and a digital platform populate the economy. They interact over four stages. In the first stage, the platform maximizes advertising revenue from monetizing follower-influencer interactions, subject to equilibrium responses of agents outlined below. The second stage involves individual's decisions on whether to pursue formal education and/or acquire special skills for digital influence. The third stage involves individual decisions on whether to follow educated experts for productive activities (represented by "investments") or to follow influencers for pure entertainment, as well as the matching between these followers and experts/influencers. In the fourth stage, all agents' payoffs are realized, including those from investments and entertainment, and the game ends.

2.1 Education and Influence Acquisition

In this stage, agents face two non-mutually-exclusive decisions sequentially: whether to pursue education ($a_i = E$), and then whether to attempt to become an influencer ($a_i = I$).

Education decision. Each agent is endowed with an aptitude for formal education (e.g., IQ, cognitive ability, family support, etc.), which is reflected in a personal cost of pursuing formal education $c_i \sim U[0,1]$, uniformly distributed. Formal education can be broadly interpreted as trainings whose outcomes can be evaluated with a scientific basis or objective standards (e.g., college degrees, skill levels, and certificates for playing musical instruments).

Education serves dual purposes: general learning and ranking for subsequent labor market placement. After incurring the education cost c_i, Agent i either succeeds with probability η or otherwise fails and remains uneducated. Let μ_e denote the measure of educated agents. Conditional on successful education, an individual becomes an expert with probability $\eta p(\mu_e)$ or graduates as an educated worker with probability $\eta\big(1-p(\mu_e)\big)$. Both experts and workers, being educated, can earn a positive labor income captured by a baseline salary $b \geq 0$.[8] Furthermore, because educated workers and experts speak the same "scientific language," they can interact in a market for economic production in the second stage.

Experts here can be broadly interpreted as innovators, entrepreneurs, professors, political leaders, artists, etc. In reality, some experts are also social media influencers. For clarification, our notion of entertainment influencers refers to those residual ones who are entertaining but are not experts in scientific matter related to productive economic activities. In addition to a baseline salary, an expert receives a signal with precision $\rho_i \sim U([\underline{\rho}, \bar{\rho}])$, where $\bar{\rho} \geq \underline{\rho} \geq \frac{1}{2}$. This signal captures expertise or "know-hows"—such as mastery of painting, leadership, or innovative creativity—that enable experts to earn extra income in the investment-advising market introduced in Section OA.2. Thus, educational outcomes determine the initial allocation of resources and earning opportunities.

Now, we can express the measure of (potential) experts and educated workers as follows:

$$\widehat{\mu}_{ex} = \eta * p(\mu_e) * \mu_e, \quad \widehat{\mu}_{ew} = \eta(1 - p(\mu_e))\mu_e, \quad \text{with} \quad \frac{\widehat{\mu}_{ew}}{\widehat{\mu}_{ex}} = \frac{1}{p(\mu_e)} - 1. \tag{1}$$

Here, we let $\widehat{\mu}_{ex}$ and $\widehat{\mu}_{ew}$ denote the populations of experts and educated workers after the realization of the educational outcome but before the production activities, and save notations μ_{ex} and μ_{ew} for the populations that actually participate in the productive activities. We assume that $p(\mu_e)$ is continuous (for non-material technical convenience) and weakly

[8] For simplicity, b is exogenous in our baseline setup. We later endogenize it.

decreases in μ_e, reflecting the scarcity of expert positions. After all, there is typically one president of a country despite an increase in the population receiving higher education. The ratio $\frac{\widehat{\mu}_{ew}}{\widehat{\mu}_{ex}}$ then increases in μ_e. To make it finite, we assume that $p(1) > 0$. This monotonicity is consistent with that when pursuing education exhibits strategic complementarity (because each expert can receive support and earnings from more educated workers when more agents pursue education), equilibrium multiplicity ensues.

Influence acquisition. After the realization of educational outcomes, any agent can incur a cost $c_I > 0$ to further acquire digital influence.[9] An influencer generates an amusement surplus $u_0 = u_0(k, \mu_{in})$ for each follower, potentially including net benefits from influencer marketing, with $\frac{\partial u_0}{\partial k} > 0$ and $\frac{\partial u_0}{\partial \mu_{in}} \geq 0$. The parameter k captures technological scalability or productivity in content creation and outreach, and μ_{in} denotes the measure of influencers who supply purely entertainment utility through horizontally differentiated content. A higher k can reflect advances in livestreaming and short-video platforms that expand the supply of engaging content and improve content matching, or the adoption of generative AI that lowers the cost of content production. In Appendix OA.1, we provide a micro-foundation for u_0 by specifying $u_0 = H(k) \cdot \psi(\mu_{in})$, where $H'(k) \geq 0$ and $\psi'(\mu_{in}) \geq 0$, thereby endogenizing followers' time allocation to entertainment and incorporating variety considerations in entertainment consumption.[10] Furthermore, the contribution of influencer variety to amusement surplus is captured by $\psi(\cdot)$, a non-negative and weakly increasing function that maps the supply of differentiated influencers into utility.

It is important not to make the sweeping statement that influencers do not have any educational value or do not contribute to other economic productions. If a piano virtuoso or a physics professor use TikTok videos to impart knowledge about piano performance or the principles of quantum mechanics to future musicians and engineers, that would be beneficial for the society. In our setting, they are labeled as experts who offer education services through new digital media. Again, what we refer to as influncers and anti-intellectual influence are the ones that provide pure entertainment value orthogonal to these. We also need to keep in mind that the medium shapes what can be delivered. With influencers fighting for attention through short videos and livestreaming, influencers' appearance and

[9] Probabilistic influence acquisition can be incorporated by introducing a success probability $\gamma \in (0, 1]$ without altering the main results.

[10] Digital technology can reduce u_0 through diminishing marginal returns to entertainment: as μ_{in} rises, the utility value of an additional influencer declines. However, algorithmic matching may improve content discovery and user–influencer alignment. We posit that, at early stages of technological diffusion, this positive matching effect dominates. Moreover, in our model each follower chooses only one influencer, which limits the force of diminishing returns.

attention grabbing exaggerations naturally dominate the accuracy of content. Writing, in contract, requires careful thinking and reasoning, and much greater rigor than a podcast conversation or a tweet. Why are short-videos so entertaining? Because they distract us from the mentally intensive serious topics.

Technology and digital platforms. Technological advancements, especially those related to digital platforms for social media, influencer videos/livestreaming, and paying for knowledge online, are exogenous in our model. They can alter the model parameters in important ways. First, they can decrease the "entry cost" of becoming an influencer, c_I, which makes the influencer market rather competitive. Second, they can increase the joint entertainment surplus u_0 generated between influencers and their followers through better matching and scaling. Third, they can improve the search and matching between experts and educated followers by increasing α. We later consider comparative statics with respect to each of these dimensions.[11]

Although we analyze background technology for a continuum of values, we emphasize that digital social media is fundamentally a disruptive technology: First, the reduction in entry costs and improvements in matching and entertainment values are significant. Second, unlike traditional sports, music, and the arts, digital entertainment has a horizontal dimension due to improvements in matching algorithms related to digital platforms. For example, NBA games are entertaining, and improvements in broadcasting technology can similarly augment the outreach of the games. However, different basketball leagues are not pushed to viewers through a matching algorithm. Therefore, most of the audience still converges to watch the best games make available (a vertical dimension). However, in live-streaming and short videos, it is not always true that there is consensus on the best videos or livestreamers. The algorithm in the background may match a minor sports league to an audience whose hometown is in the same region. This, in turn, implies that entertainment production becomes more inclusive. Influencers do not have to produce the best videos in order to get an audience. They also do not need professional basketball training to attract basketball fans if they are talented at discussing basketball shoe brands, for example.

2.2 Service Choices and Matching to Experts/Influencers

In the second stage, experts offer services so that educated workers can engage in "productive activities." One example is investment advice or fund management service, which allows educated workers to effectively allocate financial resources that improve aggregate

[11] Section OA.1 micro-founds the entertainment utility and discusses the policy implications.

economic output. But the services here can be rather broad, including leading a startup, supervising a research lab, etc. Meanwhile, influencers also offer entertainment, such as livestreaming their dining experience, luxurious lifestyles, or eye-catching pranks and dares. For simplicity, we normalize agents' outside options to yield zero utility. Therefore, all educated workers and uneducated agents who are not experts or influencers themselves choose to follow either an expert or an influencer. Overall, the following accounting identity holds after matching:

$$\mu_{ex} + \mu_{in} + \mu_{ew} + \mu_{if} = 1,$$

where μ_{if} is the measure of influencer followers. Once each agent decides on a service category, the matches with experts and influencers ensue. Note that μ_{ex} and μ_{ew} can differ from $\widehat{\mu}_{ex}$ and $\widehat{\mu}_{ew}$.

Expert-led productive activities. Educated workers, by paying a fee to get leadership or consulting service from experts, can observe and understand the signal (i.e., the know-hows, inspirations, or advice) provided by experts to carry out productive activities, such as investments. Uneducated agents cannot process advice or appreciate leadership from experts, reflecting a manifestation of informational resonance — one can only digest the vision or piece of information from someone who share the same beliefs and speak the same languages, as well-motivated in the economics literature, e.g., based on homophily (Malmendier and Veldkamp, 2022). Expert-led productive activities are microfounded as imperfect matching with search frictions between experts and educated workers in Appendix OA.2, generating an expected total investment surplus of $R(\alpha, M)$ for each pair matched, where $M > 0$ is the investment size and $\alpha > 0$ is the search friction parameter (with larger α indicating lower friction). In contrast, an uneducated agent cannot interpret signals by experts, leading to zero joint surplus.

In addition, we allow productive activities to generate a match-independent payoff for each participating individual. This payoff depends on the aggregate scale of expertise and educated labor in the economy and is parameterized by θ. Specifically, we assume:

$$A(\theta, \mu_{ex}, \mu_{ew}) = \theta * \mu_e = \theta * (\mu_{ex} + \mu_{ew}) \tag{2}$$

It can capture both the competition and complementarity of the productive activities. For investments, if experts are all advocating value investing, the capital allocation is more efficient in the society, and welfare improves in addition to personal gains, relative to a situation where everyone is randomly speculating. For environmental conservation, network

effect is present and a critical mass of agents who take biodiversity-perserving actions can collectively improve biodiversity.

Amusement and influencer-follower matching. Let β denote the exogenous fraction of surplus an entertainment influencer can extract from a matched follower, which includes fees or income from influencer marketing, and $(1-\beta)$ for the matched follower. β reflects the competitiveness of the influencer market and is independent of platform design and the monopolistic competition between influencers. Random matching of influencers and followers is (independent of educational type):

$$u^{if}(\varnothing|c_i) = (1-\beta)\cdot u_0.$$

Potential influencer followers include those agents who choose not to acquire education/influence, who fail in education/influence training, and who voluntarily switch to following influencers ex post. Influencers' followers, educated or uneducated, are randomly matched with influencers when they decide to do so. Consequently, random matching leads to an identical number of followers for each influencer.

2.3 Influence Monetization and Platform Design

The platform's objective is to maximize advertising revenue from monetizing follower–influencer interactions, subject to agents' equilibrium responses. This design choice distorts education and career decisions relative to those under a social planner who internalizes educational resonance externalities. Specifically, the digital platform chooses (i) an algorithmic intensity parameter k, which scales user engagement, and (ii) a surplus–sharing parameter $\beta_M \in [0,1]$, which determines the revenue split between the platform and influencers. Note that the share allocated to influencers, β, from interacting followers is determined through bargaining between these two parties and is therefore not directly controlled by the platform.

Furthermore, uneducated agents serve as followers, supplying attention to the platform, which operates a matching/curation algorithm that generates total engagement given by:

$$E(u_0, \mu_{if}) \equiv u_0 * \mu_{if}. \tag{3}$$

Thus, total engagement increases with both amusement surplus and the size of influencer-followers. Each unit of engagement produces advertising revenue $\lambda > 0$. The platform takes a share of $(1-\beta_M)$, and influencers split β_M in expectation. Together, influencers and the

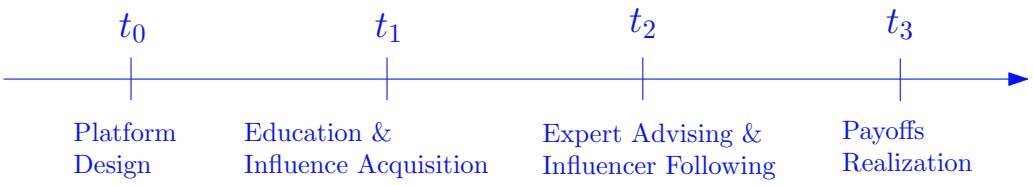


Figure 1: Timeline

platform jointly monetize digital engagement. With symmetric allocation,[12] an individual influencer receivers advertising revenue given by:

$$r_I(k, \beta_M, \mu_{if}) = \lambda\beta_M * \frac{E(u_0, \mu_{if})}{\mu_{in}} = \lambda\beta_M u_0 * \frac{\mu_{if}}{\mu_{in}}. \tag{4}$$

2.4 Equilibrium Concept

We use Rational Expectation Equilibrium as the appropriate equilibrium concept here:

(1) (Service Choices & Expert/Influencer Matching). In stage t_2, experts and educated followers choose optimal pricing strategies and investment strategy in the expert advisory and investment markets. Furthermore, all agents, after the roles assigned, optimally select which markets to participate in.

(2) (Education & Influence Acquisition). In stage t_1, given the learning cost c_i, the ith agent, fully anticipating future actions of all agents, optimally chooses $a_i^* \in \{\varnothing, E\}$ to maximize the expected payoff. Then, after observing the educational outcome realized, she optimally chooses $a_i^* \in \{I, \varnothing\}$.

(3) (Optimal Platform Design). In stage t_0, given agents' optimal decision rules, the digital platform optimally selects the surplus sharing rule β_M, the algorithmic intensity k, and the entry cost c_I for influencers.

(4) (Consistency). In equilibrium, the realized aggregate demographics — experts, educated workers, influencers, and their followers — align with the equilibrium beliefs $(\mu_{ex}^*, \mu_{ew}^*, \mu_{in}^*, \mu_{if}^*)$.

In the baseline model, we focus on symmetric pure strategy equilibria in which all agents have a common belief and experts use identical pure strategies. The main results remain robust under mixed and potentially asymmetric strategies, as discussed in Section OA.7.

[12] Any symmetric allocation rule where an influencer's expected revenue is proportional to total engagement divided by μ_{in} yields the same comparative statics.

3 Equilibrium Characterization

This section analyzes the subgame under exogenous platform design, where both β_M and u_0 are fixed. We endogenize them in Section 5.1. We solve the game by backward induction, starting from the final stage.

3.1 The Matching and Payoff Stage

Note that the individual education cost c_i is sunk and therefore irrelevant. We then compute the payoffs for each group, including:

(i) Influencer followers. They each receive $u^{if} = (1-\beta)u_0 + b * \mathbb{1}_{\{\text{educated}\}}$. Here, the indicator function equals one if the agent is educated and zero otherwise.

(ii) Educated workers. As shown in Appendix OA.2, the expected interim payoff for an educated expert follower is:

$$\mathbb{E}[u_j^{ew}|a_j = E, c_j] = \frac{\alpha}{\alpha+1} \cdot R(\alpha, M) + b + A(\theta, \mu_{ex}, \mu_{ew}).$$

where $\frac{\alpha}{\alpha+1}$ is the surplus share for educated workers and:

$$R(\alpha, M) = M \cdot \frac{\alpha+1}{\alpha+2} \cdot \frac{(2\bar{\rho}-1)^{\alpha+2} - (2\underline{\rho}-1)^{\alpha+2}}{(2\bar{\rho}-1)^{\alpha+1} - (2\underline{\rho}-1)^{\alpha+1}}.$$

Educated workers consult experts only when:

$$\frac{\alpha}{\alpha+1} R(\alpha, M) + A(\theta, \mu_{ex}, \mu_{ew}) \geq (1-\beta)u_0. \tag{5}$$

Note that whether to consult experts is independent of the labor market benefit b. Furthermore, the education market collapses when it approaches random matching (i.e., α small) and the match-independent payoff is minimal.

(iii) Experts. The interim expected payoff for each expert is given by:

$$\mathbb{E}[u_i^{ex}|a_i = E, c_i] = \frac{\mu_{ew}}{\mu_{ex}} \cdot \frac{R(\alpha, M)}{\alpha+1} + b + A(\theta, \mu_{ex}, \mu_{ew})$$

Then, experts are willing to provide consulting services only when:

$$\frac{\mu_{ew}}{\mu_{ex}} \cdot \frac{1}{\alpha+1} \cdot R(\alpha, M) + A(\theta, \mu_{ex}, \mu_{ew}) \geq (1-\beta)u_0 \tag{6}$$

where $\frac{\mu_{ew}}{\mu_{ex}}$ is the measure of educated workers per expert and $\frac{1}{\alpha+1}$ the experts' surplus share.

(iv) Influencers. Successful influencers are randomly matched with the followers so that

$$\mathbb{E}[u^{in}|I, c_i] = (\lambda\beta_M + \beta) * u_0 * \frac{\mu_{if}}{\mu_{in}}.$$

3.2 Education and Influence Acquisition Stage

Next, we consider the first-stage decision to pursue education or influence. Let U_i denote the expected utility of agent i in the stage t_1. Now, there are three choices, including:

(i) Doing nothing. It generates a payoff of $U_i(\varnothing|c_i) = (1-\beta)u_0$.

(ii) Acquiring influence. We need to incorporate the influence training cost c_I, i.e.,

$$U_i(I|c_i) = (\lambda\beta_M + \beta)u_0 \cdot \frac{\mu_{if}}{\mu_{in}} - c_I \tag{7}$$

(iii) Acquiring education. It leads to an expected payoff of:

$$\begin{aligned} U_i(E|c_i) = &-c_i + \eta b + \mathbb{1}_{\{\text{Breakdown}\}} \times (1-\beta)u_0 + \mathbb{1}_{\{\text{No breakdown}\}} \\ &\times \left(\eta p \cdot \frac{\mu_{ew}}{\mu_{ex}} \cdot \frac{R}{\alpha+1} + (1-p)\eta \cdot \frac{\alpha R}{\alpha+1} + (1-\eta)(1-\beta)u_0 + \eta A\right). \end{aligned} \tag{8}$$

The first term is the cost of education, the second is baseline labor income, and the third and fourth capture utilities with and without investment market breakdown. A breakdown arises when the participation constraint fails for either experts or educated workers (Eqs. (5) and (6)) in the matching stage. Absent breakdown, the payoff includes the expected returns from becoming an expert, working as an educated worker, following influencers, and the network externality surplus, each weighted by the corresponding probabilities.

In equilibrium, there are three cases for the education level, including:

(1) Interior solution: $\mu_e \in (\eta b, 1)$, when

$$U_i(I|c_i) = U_i(\varnothing|c_i) \leq U_i(E|c_i) \tag{9}$$

holds if and only if $c_i \leq \mu_e$;

(2) Maximum education: $\mu_e = 1$, when $U_i(I|c_i) = U_i(\varnothing|c_i) \leq U_i(E|c_i)$ for all $c_i \in [0,1]$;[13]

(3) Minimum education: $\mu_e = \eta b$, when $U_i(I|c_i) = U_i(\varnothing|c_i) \geq U_i(E|c_i)$ for all $c_i > \eta b$.

3.3 Self-Fulfilling Education Levels

Next, we analyze the equilibrium aggregate education. In a symmetric pure strategy equilibrium, all experts use an identical pure strategy: given $\mu_e \in [0,1]$, all experts offer services only when Eq. (6) holds; otherwise, all quit. We start with Eq. (9), the necessary condition for an interior solution. When there is no market breakdown for investment, by Eq. (1), $\eta p \cdot \frac{\mu_{ew}}{\mu_{ex}} = \eta p \cdot \frac{(1-p)}{p} = \eta \cdot (1-p)$ and thus:

$$U_i(E|c_i) = -c_i + \eta b + \eta \cdot (1 - p(\mu_e)) \cdot R(\alpha, M) + (1-\eta)(1-\beta)u_0 + \theta\eta^2\mu_e \tag{10}$$

Thus, the indifference type $c_i = \bar{c}$ is pinned down by $U_i(E|\bar{c}) = U_i(\varnothing|\bar{c})$, i.e.,

$$-\bar{c} + \eta b + \eta(1 - p(\mu_e))R(\alpha, M) + (1-\eta)(1-\beta)u_0 + \theta\eta^2\mu_e = (1-\beta)u_0$$

By imposing the consistency condition that $\bar{c} = \mu_e$, we get:[14]

$$\eta(1-\beta)u_0 + (1-\eta^2\theta)\mu_e = \eta(1 - p(\mu_e^*))R(\alpha, M) + \eta b \tag{11}$$

Meanwhile, endogenous free entry implies identical utility between acquiring influence and following influencer ex ante (i.e., $U_i(I|c_i) = U_i(\varnothing|c_i)$ for $c_i > \bar{c}$), which implies:[15]

$$(\beta_M\lambda + \beta) \cdot \frac{\mu_{if}}{\mu_{in}} \cdot u_0 - c_I = (1-\beta) \cdot u_0. \tag{12}$$

Furthermore, note that the following identity always holds, that is,

$$\mu_{if} + \mu_{in} = 1 - \eta\mu_e. \tag{13}$$

[13]Note that sequential moves remove the potential market monopoly power and the abnormal profits in payoff for influencers. If education and influence acquisition instead occur simultaneously, a missing market can arise if no agent acquires influence. Anticipating this, some agents always switch to acquiring influence and thus the aggregated level of education $\mu_e^* < 1$. We elaborate further in Section OA.5.

[14]If we deal with any continuous probability density with a CDF $F(\cdot)$ for education cost c, the consistency condition reduces to the following fixed point problem given by: $\eta(1-\beta)u_0 + F^{-1}(\mu_e) - \eta^2\theta\mu_e = \eta(1 - p(\mu_e^*))R(\alpha, M) + \eta b$, where $F^{-1}(\cdot)$ is the inverse function of the CDF.

[15]Simple algebra yields: $\frac{\mu_{if}}{\mu_{in}} = \frac{c_I/u_0 + (1-\beta)}{\beta}$. Thus, in equilibrium, the number of followers for each influencer, μ_{if}/μ_{in}, is negatively associated with the influencers' bargaining power β, the entertainment utility u_0, and positively associated with the entry cost c_I.

In light of Eq. (11), we define:

$$\begin{aligned} D(\mu_e): &= \underbrace{\eta b + \eta(1-p(\mu_e))R(\alpha,M) + (1-\eta)(1-\beta)u_0 + \eta\theta * (\eta\mu_e)}_{\text{Education Benefits: } w_X(\mu_e)} - \underbrace{((1-\beta)u_0 + \mu_e)}_{\text{Opportunity costs}} \\ &= \eta b + \eta(1-p(\mu_e))R(\alpha,M) - (\eta(1-\beta)u_0 + (1-\eta^2\theta)\mu_e). \end{aligned} \tag{14}$$

Intuitively, the first term with the underlined curly bracket captures the educational benefits generated in both the investment and labor markets. By contrast, the second term captures the total cost of acquiring education for the marginal type $c_i = \mu_e$, including the foregone utility from influencer engagement and the direct educational cost.

Before characterizing the equilibrium, we formally introduce stage-switch externalities.

Definition 1 (Stage-Switch Externalities)**.** *We say an environment exhibits stage-switch externalities if strategic effects flip sign across stages:*

- *(Education stage, ex ante) strategic* ***substitutes****: more education raises congestion / competition for others.*
- *(Production stage, ex post) strategic* ***complements****: more education raises others' returns via resonance.*

Educational pursuits exhibit both competitive and complementary forces. On the one hand, competition arises ex ante among agents seeking to become experts and persists ex post among experts competing for educated workers and among educated workers competing for favorable terms in the matching stage (see Section OA.2).[16] On the other hand, complementarity emerges endogenously across the two sides—experts and educated workers—in the production stage through information resonance. Moreover, within each occupational group, additional complementarities are generated through network effects (see Section 6.1). Then, Eq. (14) confirms that the complementarity effect, as captured by the decreasing probability of becoming an expert $p(\mu_e)$ and the network effect parameter θ, dominates in shaping the incentives to acquire education.

Proposition 1 characterizes the symmetric pure strategy equilibrium(s).

Proposition 1 (Symmetric Pure Strategy Equilibrium)**.** *In any equilibrium,*

- *Agents with $c_i \leq \mu_e^*$ acquire education, and accept their roles assigned only when education succeeds. Agents with $c_i > \mu_e^*$ or with failed educational outcomes acquire influence*

[16] We can also incorporate other forms of ex-ante externalities. For example, the probability of educational success η may decrease with μ_e, or the cost of acquiring education may increase with μ_e to capture congestion effects. See, for example, Lazear and Rosen (1981) on tournaments and congestion in education.

or do nothing, among which the populations of influencers and followers are given by:

$$\mu_{in}^* = \frac{(1-\eta\mu_e^*)(\beta+\lambda\beta_M)u_0}{(1+\lambda\beta_M)u_0+c_I}, \qquad \textit{and} \qquad \mu_{if}^* = \frac{((1-\beta)u_0+c_I)(1-\eta\mu_e^*)}{(1+\lambda\beta_M)u_0+c_I}. \tag{15}$$

- *Aggregate education μ_e^* is determined as follows:*

  (i) when the participation constraints for experts and educated workers (i.e., Eqs. (5) and (6)) fail for all $\mu \in [\eta b, 1]$, $\mu_e^* = \eta b$ is the unique equilibrium;

  (ii) $D(\mu_e^*) = 0$ or $D(1) \geq 0$ forms an equilibrium when the relevant participation constraints for educated workers and experts are satisfied.

Proposition 1 characterizes the education/influence acquisition decision and occupational choices in equilibrium. Only agents with relatively low learning costs acquire education and accept their roles assigned when education succeeds, while those with high learning costs or failed education either acquire influence or do nothing. Note that if the investment market cannot attract educated workers or experts under the most optimistic beliefs, it collapses, and thus the incentive to acquire education is only driven by the benefits related to the labor market. Moreover, multiple equilibria can arise even when both experts and educated workers find it optimal to stay in the investment with sufficiently optimistic beliefs. Due to positive externality, a more optimistic belief in aggregate education strengthens the incentive for experts to offer services. Indeed, it is possible that both the most optimistic and most pessimistic beliefs (i.e., $\mu_e^* \in \{\eta b, 1\}$) can be supported in equilibrium. Furthermore, for an intermediate case in which the benefits and opportunity costs are not strictly ranked, Eq. (11) fully characterizes any equilibrium, as long as the participation conditions for both experts and educated workers are satisfied. To achieve high-education in aggregate, it is useful to boost morale and make agents aware that others are getting education, given the future complementarity.

4 Implications for Education and Work

We identify three key economic consequences of digital influence, particularly pure entertainment influence, on education and the labor market. First, education serves two roles: professional training and anchoring in labor market competition. Consequently, investment breakdown depends on search frictions and match effectiveness in the expert-advising market. Second, education generates externalities through resonance. Since the expert–follower market is two-sided, individual education choices create externalities that are not fully inter-

nalized, leading to inefficient coordination and multiple equilibria. Moreover, an individual's investment choice benefits from others' education, as better societal decisions raise individual payoffs. Third, anti-intellectual influence can trigger investment breakdown and suboptimal societal decisions. For clarity, we set $\theta = 0$ (no aggregate network effect) and $\beta_M = 0$.[17]

4.1 Self-Fulfilling Education and Technology-Induced Multiplicity

Now, we come to investigate how an increase in entertainment utility, due to technological advances in digital platforms, generates equilibrium multiplicity and leads to destructive anti-intellectual influence. Initially, increasing the utility of digital amusement is always beneficial when it is small because, without discouraging education acquisition, it increases the utility of influencer follow-up. However, when it exceeds a certain threshold, equilibrium multiplicity arises. Depending on the belief selected, both high and low education are plausible. If everyone believes that all others believe in science, then they are also willing to acquire education. On the contrary, when everyone believes that not many people believe in science, the resonance of education comes into play, and experts might not receive enough audience. This discourages education acquisition, and now a self-fulfilling inefficient equilibrium arises. Lastly, when entertainment utility is sufficiently large, all agents quit the investment market, and again, a unique equilibrium with minimum aggregate education ensues.

Proposition 2 (Entertainment Utility and Equilibrium Multiplicity)**.**

Define: $L = \eta \cdot (1 - p(\mu_e)) \cdot R - \mu_e + \eta b$, $\underline{L} = \inf_{\mu_e \in [\eta b, 1]} L$, $\overline{L} = \sup_{\mu_e \in [\eta b, 1]} L$,

$$\underline{\nu} = \frac{1 - p(\eta b)}{p(\eta b)} * \frac{R}{(1+\alpha)(1-\beta)}, \quad \textit{and}$$
$$\overline{\nu} = \min\left\{ \frac{\alpha R}{(1+\alpha)(1-\beta)}, \frac{R \cdot (1 - p(1))}{(1+\alpha)(1-\beta)p(1)}, \frac{(b - 1/\eta) + (1 - p(1))R}{(1-\beta)} \right\}.$$

Assume that $\underline{L} > 0$ *and* $p'(\cdot) \leq 0$. *Then: (i) there are at least two equilibria such that* $\mu_e^* = \eta b$ *and* $\mu_e^* = 1$ *for* $\underline{\nu} < u_0 < \overline{\nu}$*; and (2) furthermore, there is a unique equilibrium* $\mu_e^* = 1$ *when* $u_0 < \min\{\frac{\underline{L}}{(1-\beta)}, \frac{\alpha R}{(1-\beta)(1+\alpha)}, \underline{\nu}\}$*, and a unique equilibrium* $\mu_e^* = \eta b$ *when* $u_0 > \overline{L}/(1-\beta)$.

Intuitively, multiplicity arises when $D(\cdot)$ crosses the horizontal axis multiple times through classical coordination via stage-switch externalities. To further illustrate why S-shapes occur, we can differentiate $D(\mu_e)$ to get:

$$D'(\mu_e) = \underbrace{-\eta\, p'(\mu_e)\, R(\alpha, M)}_{\text{production-stage complementarity}} - \underbrace{(1 - \eta^2\theta)}_{\text{education-stage congestion}}. \tag{16}$$

[17] We discuss $\theta > 0$ in Section 6.1 and show that the platform optimally chooses $\beta_M = 0$ in Section 5.1.

Thus, S-shapes and multiple equilibria arise when there exist subintervals where:

(i) Resonance dominates, that is, $-\eta\, p'(\mu_e)\, R(\alpha, M) \;>\; (1-\eta^2\theta)$; and

(ii) Congestion dominates, that is,$-\eta\, p'(\mu_e)\, R(\alpha, M) \;<\; (1-\eta^2\theta)$.

Our complementarity on the production side is captured by the term $-\eta p'(\mu_e)R(\alpha, M)$ in Eq. (16), while our education-stage congestion is the strictly positive term $(1-\eta^2\theta)$. Unlike single-stage social-interaction or rat-race environments, the stage-switch externalities across stages are embedded in these complements and substitutes, with complements scaling in $R(\alpha, M)$ and substitutes scaling in $(1-\eta^2\theta)$. This cross-stage split and its interaction with a digital-attention outside option u_0 generate equilibrium multiplicity and interesting welfare results.

Here is a numerical illustration of Proposition 2.

Example 1. *We consider a weakly convex piecewise linear function $p(\mu_e)$ given by:*

$$p(\mu_e) = \begin{cases} \frac{7}{10} - \mu_e, & \text{if} \quad \mu_e \leq \frac{1}{2} \\ \frac{3}{10} - \frac{\mu_e}{5}, & \text{if} \quad \mu_e > \frac{1}{2} \end{cases}$$

Furthermore, we take $b = 0, \eta = \frac{3}{4}$, $\alpha = 1$, $R(\alpha, M) = 2$ and $(1-\beta) = \frac{1}{3}$. The function $D(\mu_e)$ can be further expressed as

$$D(\mu_e) = \begin{cases} \frac{9}{20} + \frac{1}{2}\mu_e - \frac{1}{4}u_0, & \text{if} \quad \mu_e \leq \frac{1}{2} \\ \frac{21}{20} - \frac{7}{10}\mu_e - \frac{1}{4}u_0, & \text{if} \quad \mu_e > \frac{1}{2} \end{cases}$$

u_0	$[0, \frac{7}{5}]$	$(\frac{7}{5}, \frac{9}{5})$	$[\frac{9}{5}, 2]$	$[2, \frac{14}{5})$	$\{\frac{14}{5}\}$	$(\frac{14}{5}, \infty)$
μ_e^*	$\{1\}$	$\{\mu_e^2\}$	$\{0, \mu_e^2\}$	$\{0, \mu_e^1, \mu_e^2\}$	$\{0, \frac{1}{2}\}$	$\{0\}$
$\#\mu_e^*$	1	1	2	3	2	1

Table 1: Equilibrium Characterization in Example 1

Obviously, given u_0, $D(\mu_e)$ is maximized at $\mu_e = \frac{1}{2}$. Denote $\mu_e^1 = \frac{(5u_0-9)}{10}$ and $\mu_e^2 = \frac{(21-5u_0)}{14}$. Depending on the value of u_0:

(i) $u_0 \leq \frac{7}{5}$. Then, $D(\mu_e) > 0$ for all $\mu_e < 1$ and $D(1) \geq 0$. Thus, $\mu_e^* = 1$ is the unique equilibrium education level.

(ii) $\frac{7}{5} < u_0 < 2$. *There exist two interior solutions such that* $0 < \mu_e^1 < \frac{1}{2} < \mu_e^2 < 1$. *But, at* $\mu_e = \mu_e^1$, *educational resonance is too weak and thus experts find it sub-optimal to provide consulting services and the incentive compatibility condition is violated ex post for experts.*[18] *Note that we also have* $D(0) < 0$, *and thus* $\mu_e^* = 0$ *is another equilibrium education level. In this case, there are two equilibriums, i.e.,* $\mu_e^* \in \{0, \mu_e^2\}$.

(iii) $2 \leq u_0 < \frac{14}{5}$. *There exists two interior solutions such that* $0 < \mu_e^1 < \frac{1}{2} < \mu_e^2 < 1$.[19] *Again,* $\mu_e^* = 0$ *is also an equilibrium education level. Thus, there are three equilibriums, i.e.,* $\mu_e^* \in \{0, \mu_e^1, \mu_e^2\}$. *An interesting observation is that even with higher entertainment utility, more equilibriums with higher aggregate education can be supported, which is mainly driven by education resonance.*

(iv) $u_0 > \frac{14}{5}$. *Then,* $\sup_{\mu_e \in [0,1]} D(\mu_e) < 0$. *Thus,* $\mu_e^* = 0$ *is the unique equilibrium and the education market always breaks down.*

The equilibrium characterization is summarized in Table 1.

Example 1 can be further illustrated with Figures 2, 3, and 4, which correspond to three cases where the entertainment utility is small, intermediate, and large. In particular, $B(\mu_e) := \eta b + \eta(1 - p(\mu_e))R(\alpha, M)$ and $C(\mu_e) := (\eta(1-\beta)u_0 + (1-\eta^2\theta)\mu_e)$ (see Eq. (14)).

Small entertainment utility. Figure 2 corresponds to the case with a small entertainment utility. The blue and red lines correspond to the net benefits and opportunity costs of acquiring education in Eq. (14). Specifically, the blue line represents how the net education benefits $B(\mu_e)$ depends on the aggregate education μ_e, while the red line represents the cost term $C(\mu_e)$. Any intersection of these two lines forms an interior solution equilibrium, as long as the incentive compatibility conditions hold for experts and educated workers. Here, there is a unique equilibrium $\mu_e^* = 1$ because the blue line always lies above the blue line, and thus all agents choose to acquire education.

Intermediate entertainment utility. Figure 3 depicts the case with an intermediate entertainment utility u_0, which can result from technological advances in digital media platforms. First, $\mu_e^* = 0$ is an equilibrium since the opportunity costs $C(\mu_e)$ (the red line) always dominate the net benefits $B(\mu_e)$ (the blue line). Second, we also have two interior solutions μ_e^1 and μ_e^2. However, μ_e^1 is not an equilibrium because the incentive compatibility condition for experts is violated. Thus, we have two equilibria $\mu_e^* \in \{0, \mu_e^2\}$.

[18] The upper bound 2 is derived from the incentive compatibility condition for experts $\frac{1}{p(\mu_e^1)} \geq (1-\beta)u_0 + 1$.

[19] When the amusement utility $u_0 = \frac{14}{5}$, the two interior solutions coincide, i.e., $\mu_e^1 = \mu_e^2 = \frac{1}{2}$.

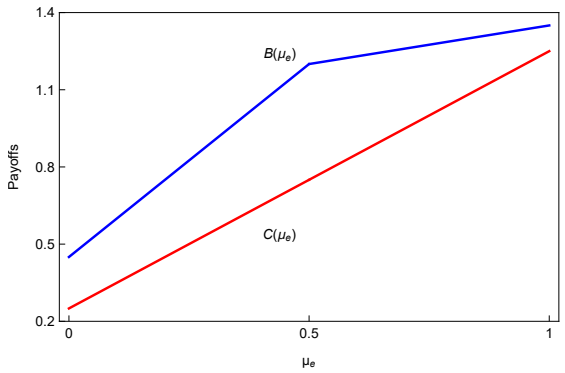


Figure 2: A unique equilibrium $\mu_e^* = 1$

Small amusement utility $u_0 = 1$

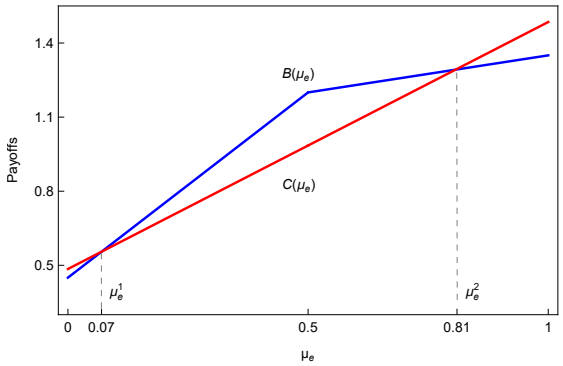


Figure 3: Two equilibrium $\mu_e^* \in \{0, \mu_e^2\}$

Intermediate amusement utility $u_0 = \frac{19}{11}$

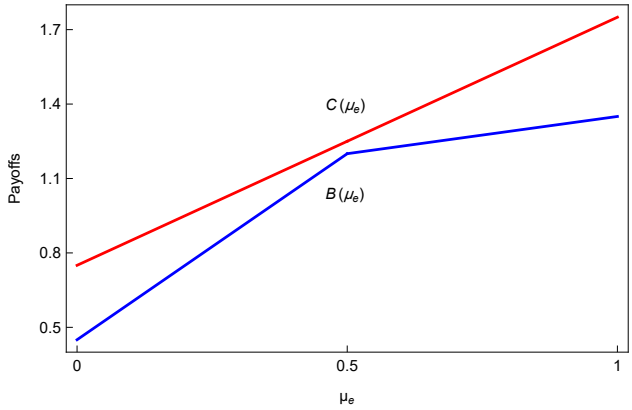


Figure 4: A Unique equilibrium with minimal education $\mu_e^* = 0$

Large amusement utility: $u_0 = 3$.

An increase in u_0 has two effects. First, it decreases the maximum aggregate education from $\mu_e^* = 1$ to $\mu_e^* = \mu_e^2 < 1$. Second, it creates equilibrium multiplicity, which can also lead to low aggregate education, primarily as a result of ineffective coordination.

Large entertainment utility. Figure 4 represents the equilibrium with a large entertainment utility. The red line, which still captures the opportunity cost of education acquisition, lies above the blue line, which captures the net benefits of education. Therefore, the unique equilibrium features minimal aggregate education, i.e., $\mu_e^* = 0$. In other words, the market for investment collapses when the entertainment utility is large enough. The rise of digital media platforms increases the intrinsic amusement value of interacting with online influencers, which leads to a higher amusement utility u_0, although this value is more controversial from a healthy societal development.

4.2 Technology and Anti-Intellectual Influence

Digital influence crowding out education and conventional jobs. For a chosen equilibrium, what is the effect of digital social media and search technology on education and occupational choices? Under mild conditions, Proposition 3 shows that amusement-oriented influence induces anti-intellectualism by crowding out education.

Proposition 3 (Anti-Intellectual Influence)**.** *(i) For any $u_0 > 0$, a market breakdown in investment occurs when search friction α is either too small or too large. In contrast, when $u_0 = 0$, no market breakdown occurs.*

(ii) For any $u_0 \geq \frac{\bar{L}}{\eta(1-\beta)}$, investment always breaks down. In this case, aggregate education is minimal, i.e., $\mu_e^* = \eta b$.

The intuition is as follows. With positive entertainment utility u_0, a market breakdown occurs when search friction is extreme. When α is very small, matching probabilities are insensitive to expert fees, which are set at the maximum level. Anticipating this, educated workers exit the investment market ex ante.[20] Historically, technological progress has been viewed as moving the economy from low to intermediate α, thereby raising formal education and the supply of experts. However, when α is large, nearly perfect matching generates a winner-takes-all outcome for top experts. Because of intense fee competition among equally competent experts, profits collapse, and incentives to remain in the investment market disappear.[21] Moreover, when u_0 is sufficiently large, investment breaks down and aggregate education falls to its minimum.

Before analyzing the effect of u_0 on aggregate education, we introduce the notion of local stability. Intuitively, a stable equilibrium exhibits mean reversion: small perturbations in aggregate education trigger incentives that restore the equilibrium. See Appendix OA.3 for further discussion.

Definition 2 (Stability)**.** *An equilibrium μ_e^* is locally stable if $D(\mu_e) < 0$ for $\mu_e \in (\mu_e^*, \mu_e^* + \delta)$ and $D(\mu_e) > 0$ for $\mu_e \in (\mu_e^* - \delta, \mu_e^*)$, for small $\delta > 0$. If $p(\cdot)$ is differentiable, this reduces to $D'(\mu_e^*) < 0$ for any interior $\mu_e^* \in (\eta b, 1)$.*

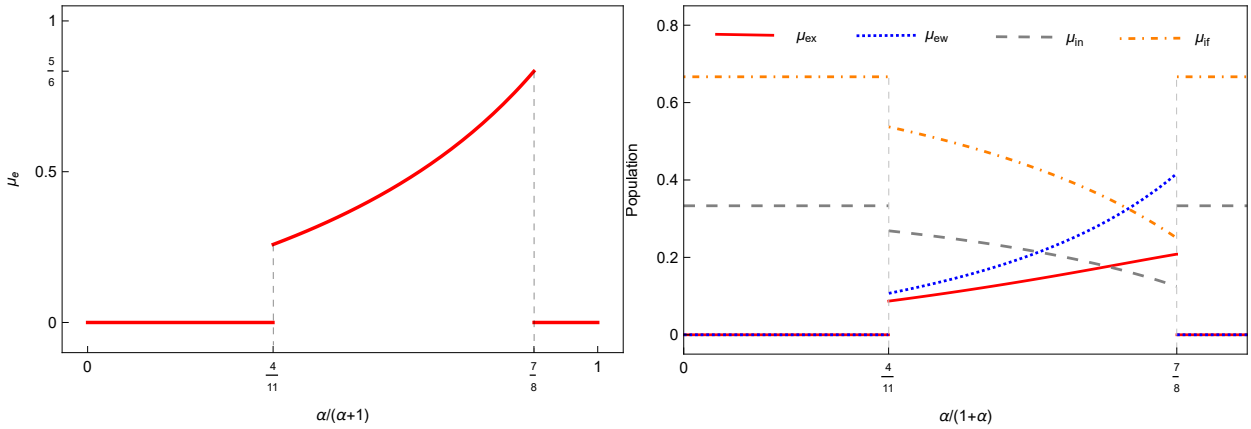
In general, higher entertainment utility reduces aggregate education.

Lemma 1. *Assume $p'(\cdot) \leq 0$ and no market breakdown in investment. Then for any locally stable equilibrium μ_e^*, we have $\frac{d\mu_e^*}{du_0} < 0$.*

[20] Formally, $\mathbb{E}[u_j^{ew}] = \frac{\alpha R(\underline{\rho}, \bar{\rho})}{(\alpha+2)} < (1-\beta)u_0 + b$ for small α.

[21] Formally, $\lim_{\alpha\to\infty} \frac{\mu_{ew}}{\mu_{ex}} \cdot \frac{R(\alpha, M)}{\alpha+1} \leq \frac{1-p(1)}{p(1)} \cdot 0 \cdot M \cdot (2\overline{\rho} - 1) = 0$.

Intuitively, stability requires that $|p'(\cdot)|$ is not too large, i.e., education resonance is weak. In this case, the return to education is relatively insensitive to changes in aggregate beliefs, so an increase in entertainment utility induces more agents to shift toward influencer follow-up. This mechanism is illustrated in Figure 5a. Lemma A.2 establishes this monotonicity by focusing on the highest aggregate education when multiple equilibria exist.



(a) Aggregate education (b) Occupational shifts

Figure 5: Search friction, aggregate education and occupational shifts

This analysis also clarifies how algorithmic intensity k shapes education outcomes. Suppose k maps into primitives as:

$$u_0 = u_0(k), \quad \beta = \beta(k), \quad \alpha = \alpha(k), \quad u_0'(k) > 0, \;\; \beta'(k) \geq 0, \;\; \alpha'(k) \in \mathbb{R}.$$

At any stable interior equilibrium μ_e^* with $D(\mu_e^*) = 0$ and $D'(\mu_e^*) < 0$, the effect of k on equilibrium education is

$$\frac{\mathrm{d}\mu_e^*}{\mathrm{d}k} = \frac{1}{D'(\mu_e^*)} \Big\{ \underbrace{\eta(1-\beta)}_{\partial\mu^*/\partial u_0} u_0'(k) - \underbrace{\eta u_0}_{-\partial\mu^*/\partial\beta} \beta'(k) - \underbrace{\eta(1-p(\mu_e^*))R'(\alpha)}_{-\partial\mu^*/\partial\alpha} \alpha'(k) \Big\}. \tag{17}$$

A negative relation between k and education arises when

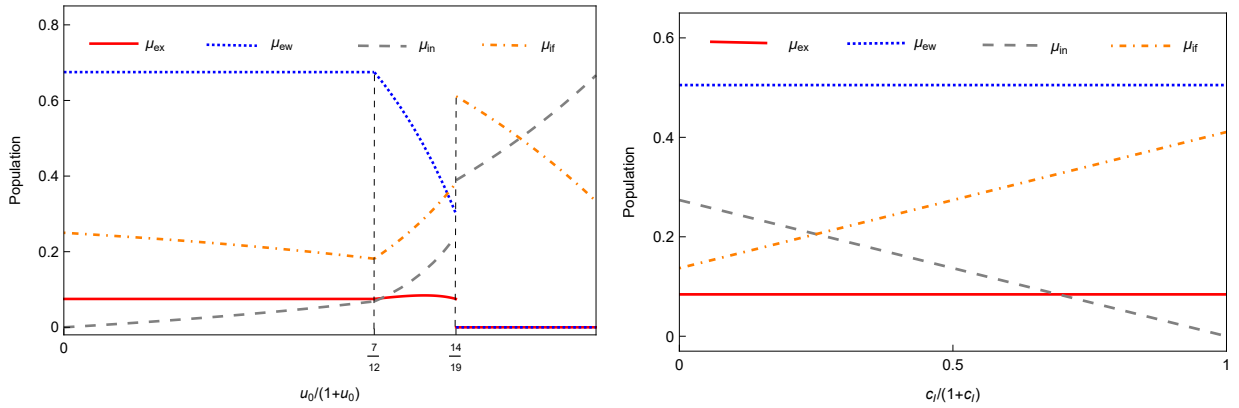
$$(1-\beta)u_0'(k) \;>\; u_0\beta'(k) \;+\; (1-p(\mu_e^*))R'(\alpha)\alpha'(k).$$

Holding k fixed, the single-parameter effects in a stable equilibrium are:[22]

$$\frac{\partial\mu_e^*}{\partial u_0} = \frac{\eta(1-\beta)}{D'(\mu_e^*)} < 0, \quad \frac{\partial\mu_e^*}{\partial(1-\beta)} = \frac{\eta u_0}{D'(\mu_e^*)} < 0, \quad \frac{\partial\mu_e^*}{\partial\alpha} = -\frac{\eta(1-p(\mu_e^*))R'(\alpha)}{D'(\mu_e^*)} > 0.$$

[22] In light of Proposition 3, the result $\frac{\partial\mu_e^*}{\partial\alpha} > 0$ holds only when the participation constraints of experts and educated workers are satisfied.

Occupational shifts. Advances in digital social networks and search technology can generate variations in entertainment utility, search friction, and entry cost, leading to dynamic occupational shifts. These effects are shown in Figures 6a, 5b, and 6b.



(a) Entertainment utility (b) Entry cost

Figure 6: Occupational shifts

First, increasing entertainment utility alters occupational choices and welfare by changing incentives to acquire education. In Figure 6a, the solid red, loosely dashed gray, densely dashed blue, and dot-dashed orange lines denote the population sizes of experts, educated workers, influencers, and followers, respectively. When $u_0 < \frac{7}{5}$, higher entertainment utility does not disrupt the incentives for participation in the investment market, so the populations of experts and educated workers remain unchanged. In this range, more agents choose to become influencers, since a larger share of the surplus flows to them in this example. When $u_0 > \frac{7}{5}$, the number of educated workers begins to fall, even though the number of experts initially rises before declining. Fewer educated workers per expert reduce the value of formal education, while more agents switch to influencer activities. Only those with very low learning costs continue to pursue education. Finally, when $u_0 > \frac{14}{5}$, even agents with successful educational outcomes exit the investment market, leading to sharp declines in both experts and educated workers, and destroying incentives for education altogether.

Second, search efficiency also shapes occupational structure. In Figure 5b, when $\alpha > 7$ or $\alpha < \frac{4}{7}$, all agents—even those with successful educational outcomes—leave the investment market. For intermediate levels of search friction, however, reducing frictions increases the populations of experts and educated workers while discouraging entry into influence and follow-up. Third, reducing entry costs for influencers does not alter educational incentives, so the populations of experts and educated workers remain unchanged. Instead, lower entry costs reduce the number of followers required per influencer, leading to a proliferation of influencers.

5 Platform Design, Welfare, & Policy Implication

We examine welfare, platform design, and policy interventions for better harnessing digital (social) media and the influencer economy. Regulating influencers and subsidizing education seem obvious ways to avoid "amusing ourselves to death." Yet malignant digital media content, such as "trash streaming," remains notoriously difficult to monitor.[23] Platforms typically have limited monitoring capacity and are rarely liable. Although platforms like Twitch and YouTube pledge to remove trash-streaming and violent videos, enforcement often amounts to nominal age restrictions. Furthermore, endogenous platform design analysis highlights a structural distortion: the platform's revenue motive pushes society toward low-education equilibria by raising algorithmic intensity and creator incentives. Banning or taxing streamers, however, merely encourages migration to alternative platforms or less restrictive jurisdictions. The crucial point is that nothing happens in isolation: creators supply content to meet demand. Thus, responsibility also lies with consumers—those who actively seek out and support such content. This motivates a complementary policy approach: taxing consumers of entertainment. Finally, we turn to equilibrium coordination and regulations targeting platform design.

5.1 Endogenous Platform Design

We endogenize platform design by allowing a digital platform to choose an algorithmic intensity $k \in [\underline{k}, \overline{k}]$, a surplus-sharing rule $\beta_M \in [0,1]$, and the entry cost $c_I \in [0, \bar{c}]$. We establish two results. First, under mild regularity conditions, higher k and higher β_M weakly reduce aggregate education μ_e. Second, platform incentives tilt (k, β_M) toward values that overweight entertainment and underweight education relative to the social optimum. Third, endogenous platform design raises the likelihood of coordination on a low-education outcome by eliminating high-education equilibria, while exerting an ambiguous effect on the multiplicity region generated by educational resonance. Finally, caps on k, bounds on β_M, or Pigouvian instruments can restore alignment with the planner's allocation.

Recall the definition of $w_X(\mu_e)$ in Eq. (14). Define

$$\Delta(\mu_e \mid k, \beta_M, c_I) \equiv w_X(\mu_e) - (1-\beta_M)u_0(k, \mu_{in}).$$

[23] See, for example, *An Injustice! Magazine*, "The Alarming Rise in Content Creators Who Profit from Cruelty," available at https://aninjusticemag.com/the-alarming-rise-in-content-creators-who-profit-from-cruelty-da9401045210; *BBC News* (2025), "TikTok sued by the parents of four British teenagers," available at https://www.bbc.com/news/articles/c0lz2x60w46o; and *Reuters* (2023) via Yahoo, "China regulator fines platforms over vulgar content," available at https://tech.yahoo.com/general/articles/chinas-cyberspace-regulator-summons-alibabas-131706640.html.

Let $D(\mu_e) \equiv \Delta(\mu_e) - \mu_e$, suppressing the parameters (k, β_M, c_I) for notational simplicity. The interior mixing condition in Eq. (14) therefore reduces to $\mu_e = \Delta(\mu_e)$. By Proposition 1, for any (k, β_M, c_I), at least one equilibrium (μ_e, μ_{in}) satisfies Eq. (15) and this condition, or a corresponding corner solution.

The platform and the social planner. The platform's profit is given by

$$\Pi = (1 - \beta_M)\lambda\, E(u_0, \mu_{if}) - TC(k), \tag{18}$$

where $TC(k)$ denotes the technology investment cost, with $TC'(k) > 0$ and $TC''(k) \geq 0$.

The platform chooses $(k, c_I, \beta_M) \in [0, \bar{k}] \times [0, \bar{c}] \times [0, 1]$ to maximize (18). By contrast, the social planner evaluates total welfare, which aggregates (i) expert productivity with educational resonance, (ii) followers' outside wage income, (iii) amusement surplus, (iv) education costs, and (v) technology investment costs. A simple utilitarian welfare index is

$$W \;=\; \mu_e\, w_X(\mu_e) + (1 - \mu_e)(1 - \beta)u_0 - \int_0^{\mu_e} t\, dt - TC(k) - \beta_M \lambda\, E(u_0, \mu_{if}). \tag{19}$$

The planner internalizes educational resonance through $w_X(\mu_e)$ but does not value platform or influencer profits per se.[24] Policy instruments—such as taxes or regulatory constraints—allow the planner to indirectly influence (k, β_M, c_I) so as to maximize (19). Crucially, the planner trades off the direct gains from entertainment (e.g., $\partial u_0/\partial k > 0$) against its indirect effect on educational investment through $\Delta(\mu_e|k, \beta_M, c_I)$.

Comparative Statics and Distortions. We compare the platform design with a social planner who internalizes the benefits of educational resonance in $w_X(\mu_e)$. Let $(k^{\text{pl}}, \beta_M^{pl}, c_I^{pl})$ denote any platform optimum and $(k^{\text{sp}}, \beta_M^{sp}, , c_I^{sp})$ any social planner design in the second-best that maximizes W in (19) subject to equilibrium constraints.

Proposition 4 (Revenue-welfare misalignment)**.** *Assume that $u_0 = u_0(k)$. Consider any stable equilibrium with interior mixing under both social planner design and platform design. Then:*

(i) $\beta_M^{sp} = \beta_M^{pl} = 0$;

(ii) $c_I^{pl} = \bar{c}_I$ and $c_I^{sp} \in [0, \bar{c}_I]$;

(ii) For large monetization incentives such that $\lambda \geq \frac{u_0(\bar{k}) + \bar{c}_I}{(1-\eta)\big((1-\beta)u_0(\bar{k}) + \bar{c}_I\big)}$, $k^{\text{pl}} \geq k^{\text{sp}}$. Furthermore, the induced education level satisfies $\mu_e^{\text{pl}} \leq \mu_e^{\text{sp}}$.

[24] Advertising revenue represents a transfer from firms to the platform and influencers and is therefore omitted. If advertising distorts product markets, a Harberger triangle can be incorporated without affecting the core results.

Proposition 4 underscores a fundamental misalignment between platform incentives and social welfare. The platform systematically selects an algorithmic intensity that is too high. Stronger algorithmic intensity increases influencer engagement, expands the follower base, and increases platform revenue, but does so at the expense of social education. As digital and algorithmic technologies improve, the platform's monetization incentives thus lead it to overinvest in algorithmic intensity. In contrast, a social planner internalizes both sides of the trade-off—recognizing the benefits of a vibrant influencer market while accounting for the educational losses induced by greater algorithmic intensity. As a result, the platform's preferred level of k always exceeds the socially optimal choice.

Remark 1 (Influencer Variety and Platform Design)**.** *Appendix OA.4 extends the baseline framework by allowing engagement utility to depend jointly on algorithmic intensity and influencer variety. To obtain tractable equilibrium characterizations, we assume*

$$E(k, \mu_{in}, \mu_{if}) = u_0 \, \mu_{if} = H(k) \, \psi(\mu_{if}) \, \mu_{if},$$

where $\psi'(\cdot) > 0$ *and* $H'(\cdot) > 0$.

Under this specification, increases in algorithmic intensity and in the influencer monetization share both reduce aggregate educational investment. When algorithmic investment is costless, the platform selects a level of algorithmic intensity that exceeds the social optimum. An informal analysis further suggests that the platform places disproportionate weight on influencer incentives when follower surplus is low and monetization incentives are strong, which amplifies educational crowding out and leads to inefficiencies in both the education and influencer labor markets.

Finally, when amusement surplus depends on influencer variety, changes in the influencer entry cost can generate non-monotonic welfare effects (see related discussions on entry cost in Proposition 6.[25]

Multiplicity amplification. Define $\chi := (k, \beta_M, c_I)$. Let the fundamentals (that is, all other parameters that exclude χ and endogenous variables $(\mu_e, \mu_{in}, \mu_{in})$) be collected in ϑ. For simplicity, consider $|\vartheta| = 1$. Multiplicity arises when $\Delta(\cdot; k, \beta)$ crosses the 45-degree line multiple times (classic coordination logic via ϕ). Endogenous platform design lowers Δ via

[25]In two-sided attention platforms and creator economies, entry costs are chosen to regulate network effects rather than merely to ration access: creator entry raises content variety and user engagement but also fragments attention, intensifies competition, and weakens investment incentives. Platforms therefore use entry frictions as a coordination and commitment device to internalize cross-side and same-side externalities, often opting for intermediate or state-contingent entry thresholds to stabilize participation and long-run ecosystem value.

higher k through the amusement channel.

Definition 3 (Basin of attraction)**.** *The basin of attraction of a stable equilibrium μ_e^* is the set of initial values of μ_e which converge to μ_e^*.*

Proposition 5 (Platform design and equilibrium multiplicity)**.** *Suppose that it admits two stable equilibria $\{\mu_e^L, \mu_e^H\}$ ($\mu_e^L < \mu_e^H$) in the social planner's problem. Then, when the platform endogenizes (c_I, k, β_M), we have:*

(i) the basin of attraction of μ_e^L increases; and

(ii) the interval of parameters exhibiting equilibrium multiplicity expands if and only if:

$$\frac{\Delta_\chi}{\Delta_\vartheta}\Big|_{(\mu_e^L, \chi^{sp})} - \frac{\Delta_\chi}{\Delta_\vartheta}\Big|_{(\mu_e^H, \chi^{sp})} > 0 \qquad i.e., \quad \frac{\partial}{\partial \mu_e}\left(\frac{\Delta_\chi}{\Delta_\vartheta}\right)\Big|_{\chi^{sp}} < 0. \tag{20}$$

where $\Delta_\vartheta = \frac{\partial \Delta}{\partial \vartheta}$ and $\Delta_\chi = \frac{\partial \Delta}{\partial \chi}$.

Furthermore, this condition fails when $\vartheta \in \{b, M, \alpha, , \eta\theta\}$, that is, under platform design, the size of the interval supporting multiplicty does not change for labor market benefit parameter b, and decreases for parameters related to investment return, education success rate, and network effect.

Proposition 5 shows that endogenous platform design raises the likelihood of coordination toward a low-education equilibrium. By prioritizing monetization, platforms increase algorithmic intensity, making digital entertainment a more attractive outside option. When congestion effects dominate, this lowers aggregate education at the stable equilibria (μ_e^L, μ_e^H). When resonance effects dominate, the same force raises education at the unstable equilibrium $(\mu_e^U \in (\mu_e^L, \mu_e^H))$, as agents invest more in education to offset stronger digital distractions. As a result, the basin of attraction for the low stable equilibrium, $[0, \mu_e^U)$, expands, while the basin for the high stable equilibrium, $(\mu_e^U, 1]$, contracts.

The second part of Proposition 5 shows that endogenous design shrinks the parameter region supporting multiplicity when the planner's problem admits two stable equilibria. This occurs because the high-education equilibrium disappears, while the basin of attraction for the low-education equilibrium expands.[26] The overall effect on multiplicity is therefore ambiguous. On one hand, platform-driven amplification of digital entertainment exacerbates the original source of multiplicity—our central mechanism. On the other hand, once multiplicity arises, endogenous design tends to eliminate the high-education equilibrium across a

[26]Formally, let a fundamental parameter ϑ affect $w_X(\mu_e) \equiv \phi(\mu_e) = \vartheta \cdot \phi_0(\mu_e)$ with $\phi_0'(\cdot) > 0$. Since the platform chooses higher k and β_M, ϑ must rise to preserve multiplicity by offsetting stronger digital outside options. Moreover, sustaining the high-education equilibrium μ_e^H requires a smaller increase in ϑ than sustaining the low-education equilibrium μ_e^L (since $\phi'(\mu_e) > 0$). Thus, the set of ϑ consistent with multiple equilibria shrinks.

Table 2: Margin, canonical force, and mechanisms

Margin	**Canonical force**	**Mechanisms / How it enters $D(\mu_e)$**
Education-stage	Congestion/ Rat-race/ Tournaments	Flatten $D(\mu_e)$ slope via $(1-\eta^2\theta)\mu_e \Rightarrow \mu_e^* \downarrow$
Production-stage	Human-capital externalities/complements	Raises $D(\mu_e)$ slope via $\eta(1-p(\mu_e)R$; larger complementarity $R\uparrow \Rightarrow \mu_e^* \uparrow$.
Digital outside option	Attention/Entertainment pull	Shifts $D(\mu_e)$ down via $\eta(1-\beta)u_0 \Rightarrow \mu_e^* \downarrow$.
Platform incentives	Creator share / Algorithm / follower share	Creator incentives $\beta_M \uparrow\Rightarrow \mu_{in} \uparrow\Rightarrow \mu_e^* \downarrow$; Algorithmic intensity $k \uparrow\Rightarrow u_0 \uparrow\Rightarrow \mu_e^* \downarrow$; Follower share decreases $\mu_e^* \uparrow$.

wider range of fundamentals. For given fundamentals, the basin of attraction shifts toward the low-education outcome.

In summary, endogenous platform design shrinks the multiplicity region under educational resonance by eliminating high-education equilibria and enlarging the basin of attraction of the low-education equilibrium, making coordination on low education more likely. We summarize the canonical forces in our theory in Table 2 below.

5.2 Welfare and Technology

Lemma 2 (Total welfare)**.** *Total welfare W is given by*

$$W = \begin{cases} \eta b + \eta\big(1-p(1)\big)R + (1-\eta)(1-\beta)u_0 - \dfrac{1}{2} - TC(k) \\ \quad - \dfrac{\beta_M\lambda(1-\eta)u_0\big((1-\beta)u_0+c_I\big)}{(1+\lambda\beta_M)u_0+c_I}, & \text{if } \mu_e^*=1, \\ (1-\beta)u_0 + \dfrac{1}{2}(\mu_e^*)^2 - TC(k) \\ \quad - \dfrac{\beta_M\lambda\big(1-\eta\mu_e^*\big)u_0\big((1-\beta)u_0+c_I\big)}{(1+\lambda\beta_M)u_0+c_I}, & \text{if } \mu_e^*\in(\eta b,1), \\ (1-\beta)u_0 + \dfrac{1}{2}(\eta b)^2 - TC(k) \\ \quad - \dfrac{\beta_M\lambda\big(1-\eta^2 b\big)u_0\big((1-\beta)u_0+c_I\big)}{(1+\lambda\beta_M)u_0+c_I}, & \text{if } \mu_e^*=\eta b. \end{cases} \tag{21}$$

Let $\underline{u}_0$ denote the threshold of u_0 such that $\mu_e^*=1$ constitutes an equilibrium for $u_0 \le \underline{u}_0$. Let $\bar{u}_0$ denote the cutoff such that $\mu_e^*=\eta b$ is the unique equilibrium for $u_0 > \bar{u}_0$.[27]

Eq. (21) delivers three implications. First, total welfare rises with aggregate education. Second, equilibrium multiplicity and selection have first-order consequences for social welfare.

[27]By Proposition 3, $\bar{u}_0 < \infty$ and $\mu_e^* \ge \eta b$. Furthermore, note that $\underline{u}_0 > 0$ when $\eta b+\eta(1-p(1))R(\alpha,M) > 1$.

Third, even a small increase in digital influence can trigger a collapse in investment and generate substantial welfare losses.[28]

We next examine the welfare consequences of technology advancements.[29]

Proposition 6 (Digital Technology and Welfare)**.**

1. *Assume that (1)* $\eta b + \eta(1 - p(1))R - 1 > 0$*, so that* $\underline{u}_0 > 0$*; (2)* $TC(k) = 0$*; and (3)* $\mu_e^* \neq \eta b$ *at* $u_0 = \bar{u}_0$*. Then total welfare is non-monotonic in the entertainment utility* u_0*, and hence in algorithmic intensity* k*.*

2. *Total welfare is independent of the influencer entry cost* c_I *when* u_0 *is invariant to* μ_{in} *and* $\beta_M = 0$*, and is generally non-monotonic in* c_I *when* u_0 *depends on* μ_{in}*.*

3. *Total welfare is non-monotonic in the search friction parameter* α*.*

4. *Suppose that* $u_0 = u_0(k)$ *and* $\beta_M = 0$*. For any stable equilibrium, total welfare is increasing in the labor market benefit* b*.*

Advances in digital platform technology can reshape both livestreaming and education markets along several dimensions. First, they reduce the cost of acquiring digital influence and expand influencers' reach to followers. Second, they raise entertainment utility and increase the joint surplus shared by influencers and followers. Third, they improve search technologies and enhance matching efficiency in the education market.

Proposition 6 characterizes the resulting welfare implications, which are illustrated in Figures 7, 8, and 9. Unless otherwise stated, we set $\beta_M = 0$ and assume $u_0 = u_0(k)$ in the illustrations to isolate the underlying mechanism.

Entertainment utility u_0 and algorithmic intensity k. Figure 7 illustrates how entertainment utility u_0 affects total welfare. Because u_0 is monotonic in algorithmic intensity k, the same comparative statics apply to changes in k.

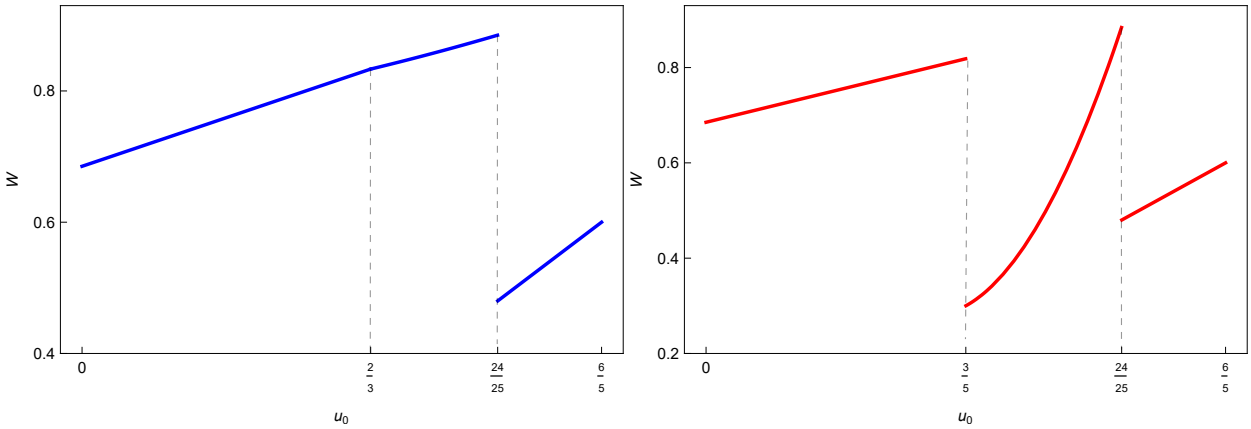
When $u_0 \leq 2/3$, the equilibrium features full education ($\mu_e^* = 1$), and increases in u_0 raise welfare by improving the follower surplus of agents with failed educational outcomes. For $2/3 < u_0 \leq 24/25$, a higher u_0 continues to increase follower surplus but reduces aggregate education. In Figure 7a, the former effect dominates, and welfare remains increasing in u_0. When $u_0 > 24/25$, the investment market collapses, generating a discrete welfare loss of

[28] At $u_0 = \bar{u}_0$, welfare drops discretely by $\left((\mu_e^*)^2 - (\eta b)^2\right)/2 > 0$ whenever $\mu_e^* \neq \eta b$, because all investment surplus is eliminated for individuals with sufficiently low education costs.

[29] We focus on the highest equilibrium belief $\sup\{\mu_e^*\}$ when multiple equilibria exist.

45.8% as u_0 crosses the threshold. As u_0 increases further, welfare recovers because aggregate education stabilizes at $\mu_e^* = \eta b$.

Equilibrium multiplicity magnifies these welfare losses. For $u_0 \geq 3/5$, multiple equilibria arise with $\mu_e^* \in \{0, \mu_e^1, \mu_e^2\}$. In Figure 7b, if the economy coordinates on the low-education equilibrium μ_e^1 rather than μ_e^2, welfare losses reach 63.3% when u_0 slightly exceeds 3/5.



(a) High belief (b) Low belief

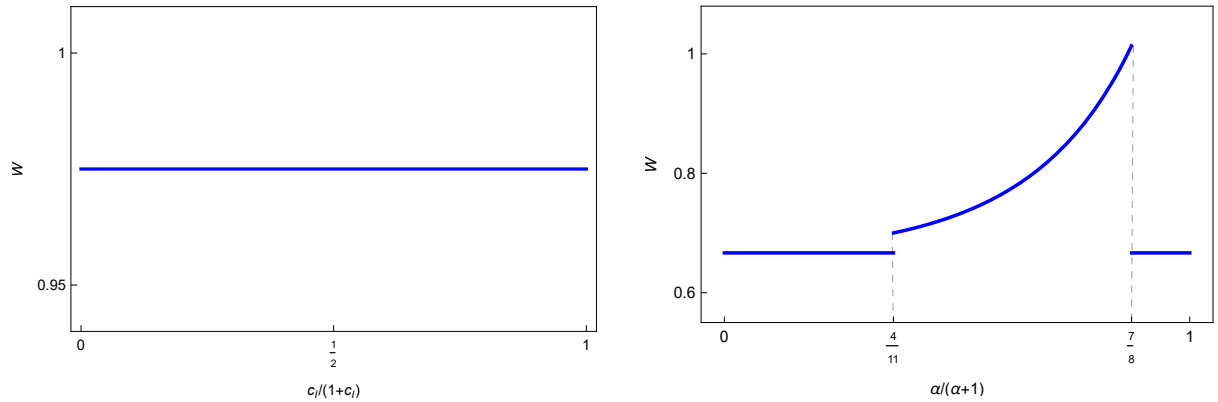
Figure 7: Entertainment utility u_0 and total welfare W

Entry cost and welfare. We examine the welfare consequences of changes in the influencer entry cost c_I. To clarify the underlying mechanism, we distinguish two cases depending on whether the amusement surplus is invariant to influencer variety or endogenously determined by it. This distinction plays a central role in shaping the welfare effects and guides the quantitative illustrations that follow.

Case I: Amusement surplus invariant to influencer variety. Consider the benchmark case in which the amusement surplus u_0 is invariant to influencer variety, implying $\beta_M = 0$ by Proposition 6. In this environment, the influencer entry cost has no effect on total welfare. Figure 8a illustrates this irrelevance result, which follows from free (endogenous) entry in the influencer market.

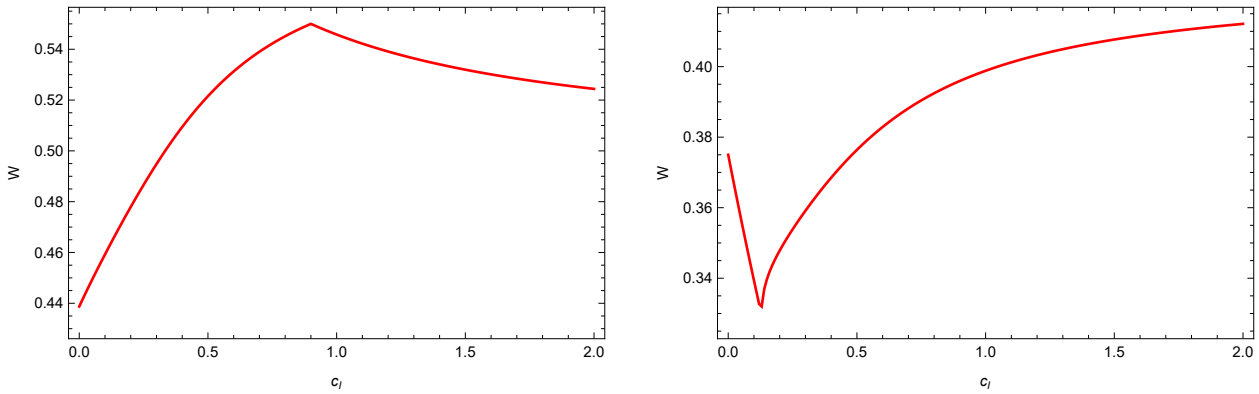
A reduction in the entry cost induces additional influencer entry, lowering the number of followers per influencer and thereby reducing the return to acquiring digital influence. Despite these adjustments, aggregate welfare remains unchanged for three reasons. First, free entry equalizes expected utility across influencers and followers, so that all agents active in the influencer sector earn $(1 - \beta)u_0$. Second, education decisions are determined by a comparison between education and the digital outside option of following influencers, making education incentives independent of the entry cost. Third, influencer variety does not affect engagement utility in this benchmark. Together, these forces imply that variations in c_I

have no impact on aggregate welfare.



(a) Entry cost (b) Search friction

Figure 8: Entry cost, search friction and total welfare



(a) Total Welfare (b) Total Welfare

Figure 9: Non-monotonic Effects of Entry Cost

Case II: Amusement surplus dependent on influencer variety. We next consider the case in which the amusement surplus is endogenous to influencer variety. When u_0 depends on the mass of influencers, changes in the entry cost affect welfare by altering the mass of influencer, giving rise to non-monotonic welfare effects.

To formalize this mechanism, suppose that $u_0 = H(k)\psi(\mu_{in})$, where $\psi(0) = 0$, $\psi'(\cdot) > 0$, and $\psi''(\cdot) \leq 0$. For expositional simplicity, we fix the matching efficiency parameter at $H(k) = 1$ and adopt the functional form $\psi(\mu_{in}) = \sqrt{\mu_{in}}$, so that $u_0 = \sqrt{\mu_{in}}$.

Figure 9 illustrates the resulting non-monotonic effects of the entry cost on aggregate education and total welfare. Both panels display non-monotonic patterns but differ in whether the education investment market collapses when the entry cost is zero. In Figure 9a, no market breakdown occurs even at zero entry cost, whereas in Figure 9b, the market fully breaks down.

In Figure 9a, increasing the entry cost initially raises total welfare. Higher entry costs reduce influencer variety, weaken the influencer-following outside option, and thereby strengthen education incentives. Once aggregate education reaches its upper bound, further increases in c_I generate pure welfare losses by reducing entertainment utility. By contrast, in Figure 9b, an increase in the entry cost initially lowers welfare because reduced influencer variety diminishes amusement surplus while education incentives remain too weak to resolve the market breakdown. As the entry cost rises further, the education market is eventually restored, leading to higher aggregate education and improved welfare.

The policy implications differ sharply across environments. When market breakdown is absent, welfare is maximized at an intermediate entry cost. When breakdown is severe, welfare improves only at extreme policies—either very low entry costs or sufficiently high ones. More broadly, treating influencer variety as a primitive highlights a fundamental trade-off: higher entry costs strengthen education incentives at the expense of entertainment utility, and the optimal policy depends on the severity of anti-intellectual influence.

Search friction α. Figure 8b illustrates the nonmonotonic relationship between search friction and total welfare, with discrete changes at $\alpha \in \{4/7, 7\}$. When $\alpha < 4/7$, educated workers exit the investment market; when $\alpha > 7$, experts exit due to intensified competition. In both cases, aggregate education collapses to its minimum, leading to low welfare. For intermediate values $\alpha \in [4/7, 7]$, a reduction in search friction ($\alpha \uparrow$) improves matching efficiency, raises aggregate education, and increases total welfare.

Labor market baseline income b. As established in Proposition 6, higher labor market income unambiguously raises total welfare. An increase in b directly strengthens education incentives through the term ηb and indirectly raises aggregate education. In equilibrium, an increase in b is equivalent to a reduction in entertainment utility u_0. Since $\frac{d\mu_e^*}{du_0} \leq 0$, higher b increases aggregate education, which in turn raises total welfare because $\frac{\partial W}{\partial \mu_e^*} \geq 0$.

5.3 Policy Interventions

We study welfare effects of taxes on influencers and digital consumption, and education subsidies, assuming direct platform regulation and setting $u_0 = u_0(k)$ and $\beta_M = 0$ unless stated otherwise.

Sources of inefficiency. Policy intervention is motivated by three inefficiencies: (i) coordination failures and equilibrium selection under stage-switch externalities; (ii) misalignment

between social and platform objectives that amplifies algorithmic intensity and creator incentives; and (iii) positive network externalities (see Section 6.1) that cannot be internalized by infinitesimal agents.

5.3.1 Taxing influencers and digital consumption

Proposition 6 highlights the limited effectiveness of taxing influencers. Although such taxes raise entry costs, free entry implies that education incentives remain unchanged when the amusement surplus is invariant to entry costs, as these incentives depend on outside options rather than influencer payoffs. As a result, influencer taxes cannot correct welfare losses arising from inefficient education choices. Their primary effect is to curb excessive entry by reallocating followers across fewer influencers, thereby saving entry costs and improving welfare. In short, taxing influencers reduces redundant entry but does not address underinvestment in education.

Formally, when the amusement surplus is invariant to entry (i.e., $u_0 = u_0(k)$), a tax T_{in} on influencers is equivalent to raising the entry cost from c_I to $\widetilde{c}_I = c_I + T_{in}$. Total welfare satisfies

$$\widetilde{W} = W(\widetilde{c}_I) + \mu^*_{in}(\widetilde{c}_I)T_{in} = W(c_I) + \frac{\beta u_0\big(1 - \eta\mu^*_e\big)T_{in}}{u_0 + (c_I + T_{in})}.$$

Tax revenue reflects surplus reallocation and entry-cost savings when marginal influencers switch to follower status, with $\mu^*_{in}(\widetilde{c}_I)T_{in} < \mu^*_{in}(c_I)(u_0 + c_I)$.

More generally, taxing influencers entails a policy trade-off. While such taxes reduce excessive entry and curb anti-intellectual influence, they may also reduce influencer variety and lower welfare. The nonmonotonicity shown in Figure 9 and Proposition 6 illustrates how this tension limits the effectiveness of corrective taxation and depends on the severity of anti-intellectual influence. Influencer taxes therefore restrain over-entry but may generate welfare losses through reduced variety.

Taxing digital consumption. Taxing digital consumption by T_{if} effectively lowers entertainment utility from u_0 to $\widetilde{u}_0 = u_0 - T_{if}/(1-\beta)$, yielding total welfare

$$\widetilde{W} = W(\widetilde{u}_0) + \mu^*_{if}T_{if} = W(\widetilde{u}_0) + \frac{\big((1-\beta)\widetilde{u}_0 + c_I\big)(1 - \eta\mu^*_e)T_{if}}{\widetilde{u}_0 + c_I}.$$

Taxing digital consumption is desirable when it strengthens education incentives without substantially reducing entertainment utility, particularly in environments with anti-intellectual influence. For example, when $u_0 > \bar{u}_0$ and $\mu^*_e \neq \eta b$ at $u_0 = \bar{u}_0$, a tax $T_{if} = (1-\beta)(u_0 - \bar{u}_0) > 0$ strictly improves welfare, since total welfare drops discretely at $u_0 = \bar{u}_0$ whenever $\mu^*_e \neq \eta b$.

Unlike influencer taxation, taxing digital consumption directly mitigates anti-intellectual influence by improving education incentives.

Two-sided taxation. Digital platforms are inherently two-sided. A natural question is whether taxing both influencers and their followers improves welfare. Corollary 1 provides an affirmative answer.

Corollary 1. *Suppose that (i)* $u_0 = u_0(k)$*; (ii)* $(1 - \lambda\beta_M)u_0 + c_I > 0$*; (iii)* $W(u) > W(u_0)$*; and (iv)*

$$W(u) + \big(\mu^*_{in}(u) - \mu^*_{in}(u_0)\big)\big((1 - \lambda\beta_M)u_0 + c_I\big) + (1 - \beta)(u_0 - u)\mu_{if}(u) > W(u_0)$$

for some $u < u_0$*. Then the optimal policy taxes both influencers and digital consumption (i.e.,* $T_{in} > 0$ *and* $T_{if} > 0$*).*

In Corollary 1, condition (i) assumes that amusement surplus is insensitive to influencer variety. Condition (ii) ensures that an influencer tax generates positive welfare gains by reducing entry costs and increasing amusement surplus. Condition (iii) captures the presence of anti-intellectual influence. Condition (iv) guarantees that jointly taxing influencers and digital consumption dominates taxing either side in isolation.

Taken together, the corollary delivers a simple policy implication. When anti-intellectual influence reduces welfare, both sides of the platform should be taxed. Inefficiency from under-investment in education can be addressed only by taxing digital consumption (or subsidizing education), whereas inefficiency from excessive entry is corrected by taxing influencers.

5.3.2 Subsidizing education

We next examine the welfare effects of education subsidies. Assume $\beta_M = 0$.[30] Let S denote the subsidy. We can use Eq. (21) to derive total welfare as:

$$W(u_0|S) = \begin{cases} \eta b + \eta(1 - p(1))R(\alpha, M) + (1 - \eta)(1 - \beta)u_0 - \frac{1}{2}, & u_0 \le \underline{u}_0(S), \\ (1 - \beta)u_0 + \frac{1}{2}(\mu^*_e(v(S)))^2 - \mu^*_e(v(S))S, & \underline{u}_0(S) < u_0 \le \bar{u}_0(S), \\ (1 - \beta)u_0 + \frac{1}{2}(\eta b)^2, & u_0 > \bar{u}_0(S), \end{cases}$$

where $v(S) = u_0 - \frac{S}{\eta(1-\beta)}$, $\bar{u}_0(S) = \bar{u}_0 + \frac{S}{\eta(1-\beta)}$, and $\underline{u}_0(S) = \underline{u}_0 + \frac{S}{\eta(1-\beta)}$.

[30] Since β_M enters total welfare W linearly, the results continue to hold for sufficiently small β_M.

- Start with $u_0 > \bar{u}_0(S)$. For small $S \leq \eta \cdot (1-\beta)(u_0 - \bar{u}_0)$, subsidies do not affect aggregate education or total welfare, though they redistribute surplus.

  For intermediate S, the welfare gain is

$$W(u_0|S) - W(u_0) = \tfrac{1}{2}\big((\mu_e^*(v(S)))^2 - (\eta b)^2\big) - \mu_e^*(v(S))S,$$

  which is positive iff: $\eta(1-\beta)(u_0 - \bar{u}_0) \leq S < \frac{(\mu_e^*(v(S)))^2 - (\eta b)^2}{2\mu_e^*(v(S))}$.[31] Thus, moderate subsidies raise welfare when $(u_0 - \bar{u}_0)$ is small.

- For $u_0 \leq \bar{u}_0(S)$ such that $\mu_e^* > \eta b$:

$$\frac{\mathrm{d}W(u_0|S)}{\mathrm{d}S} = (\mu_e^* - S) * \frac{d\mu_e^*}{\mathrm{d}u_0} * \frac{\mathrm{d}v(S)}{\mathrm{d}S} - \mu_e^* = \frac{-S - \eta \cdot R(\alpha, M) \cdot \mu_e^* \cdot p'(\mu_e^*)}{1 + \eta \cdot R(\alpha, M) \cdot p'(\mu_e^*)},$$

  where $\frac{\mathrm{d}\mu_e^*}{\mathrm{d}u_0} = -\frac{\eta(1-\beta)}{1+\eta R(\alpha,M)p'(\mu^*)}$ is obtained from Eq. (14). Thus, welfare increases with S only if $S \leq -\eta R(\alpha, M)\mu_e^* p'(\mu_e^*)$. Hence, small subsidies can improve welfare, while large ones reduce it.

We summarize all these discussions in Proposition 7 below.

Proposition 7 (Taxes and Subsidies)**.** *Suppose $u_0 > \bar{u}_0$ and $W(u_0) < W(\bar{u}_0)$, i.e., inefficient digital influence arises. Then:*

(i) A tax on digital consumption eliminates anti-intellectual influence, regardless of $u_0 - \bar{u}_0$, without reducing influencer variety.

(ii) A tax on influencers alone cannot resolve anti-intellectual influence, but it curbs over-entry of homogeneous influencers.

(iii) Education subsidies mitigate anti-intellectual influence when $u_0 - \bar{u}_0$ is small, but large subsidies may lower total welfare.

5.3.3 Regulating labor markets and equilibrium coordination

Regulating labor markets, including search frictions. Proposition 6 shows that reducing search frictions does not necessarily raise welfare. Excessive frictions hinder the matching of educated workers with top experts, discouraging investment. Yet, perfect search can also weaken expert incentives: under winner-takes-all competition, surplus is dissipated among equally skilled experts.[32] When investment markets do not break down, more efficient matching improves welfare, but excessive precision can undermine participation. These

[31] Note that $S \geq \eta(1-\beta)(u_0 - \bar{u}_0)$ is imposed to avoid market breakdown.

[32] Specifically, incentive compatibility for experts requires $\frac{1}{\alpha+1}R(\alpha, M)\left(\frac{1}{p(\mu_e^*)} - 1\right) \geq (1-\beta)u_0$, and by claim (ii) in Lemma A.1, $\frac{1}{\alpha+1}R(\alpha, M)$ decreases in α and vanishes as $\alpha \to \infty$.

insights extend to information design. Platforms should avoid revealing either too little or too much information. Likewise, in job or university rankings, overly precise information may induce winner-takes-all competition and reduce welfare.

Equilibrium coordination. The earlier analysis abstracted from equilibrium selection by focusing on the highest-belief equilibrium. We now examine policies that coordinate agents toward the "good" equilibrium with high education. Three insights emerge. First, taxing influencers is irrelevant for equilibrium selection because it does not affect education incentives. Second, taxing digital consumption can be effective. For example, in Example 1 with $u_0 = 3$, imposing a tax that induces $\tilde{u}_0 = u_0 - \frac{T_{if}}{1-\beta} \in [2, 14/5)$ generates three equilibria, $\mu_e^* \in \{0, \mu_e^1, \mu_e^2\}$, where μ_e^1 is unstable (and therefore excluded by Definition 2), $\mu_e^* = 0$ is undesirable, and μ_e^2 is welfare-improving. To eliminate the bad equilibrium $\mu_e^* = 0$, one can set $T_{if} = (1-\beta)\big(u_0 - \frac{9}{5} + \varepsilon\big)$ for small $\varepsilon > 0$. Hence, equilibrium selection complements policies targeting anti-intellectual influence and yields more robust welfare predictions. Third, education subsidies may be socially costly and induce inefficient overinvestment. Although moderate subsidies improve welfare when anti-intellectual influence is limited (that is, when $(u_0 - \bar{u}_0)$ is small), achieving equilibrium selection may require large subsidies, which depress welfare and strain fiscal resources. In sum, taxing digital consumption is the most credible instrument for achieving equilibrium selection.

5.3.4 Regulating platforms

This section studies policy interventions that operate through platform architecture, including matching, recommendation, and content curation.

Entry cost c_I. Raising influencer entry costs—analogous to taxing entry—is generally ineffective. As shown in Proposition 6, higher entry costs can curb excessive influencer entry but also reduce influencer diversity, without correcting the underlying distortion in education acquisition. Under free entry, an increase in c_I merely reallocates followers toward incumbent influencers, lowering content variety.

Entertainment utility u_0. Reducing entertainment utility u_0 may weaken anti-intellectual influence, but it has important drawbacks. First, unlike a tax on digital consumption, lowering u_0 generates a deadweight loss. Second, it requires detailed knowledge of how platform algorithms map into u_0, creating a risk of excessive intervention. Third, it does not address excessive influencer entry, which must instead be tackled through entry taxes, higher entry

costs, or licensing.

Surplus sharing β. Adjusting the surplus share β is equivalent to taxing or subsidizing digital consumption. Increasing β to $\tilde{\beta} > \beta$ corresponds to a per-follower tax $T_{if} = (\tilde{\beta} - \beta)u_0$; conversely, any tax T_{if} can be represented by $\tilde{\beta} = \beta - T_{if}/u_0$. The analysis of digital consumption taxation therefore applies directly. With endogenous platform design, an upper bound $\beta_M \leq \bar{\beta}$ or a convex cost of high β_M dampens influencer entry and raises educational participation μ_e (see Section OA.4). Such constraints can be implemented through revenue-sharing rules, ad-market design, or mandatory creator funds tied to educational content.

Content categorization and licensing. Platforms can classify content into horizontally differentiated entertainment and vertically standardized educational categories, with licensing rules tailored to each. Balanced-exposure requirements—a "balanced feed"—effectively place additional weight $\tilde{s}$ on educational content, reducing the basin of attraction of the low-education equilibrium (Proposition 5). Licensing can also limit redundant, homogeneous content and raise average quality.

Algorithmic caps or taxes. Capping algorithmic intensity ($k \leq \bar{k}$) or imposing a Pigouvian tax τ_k reduces platforms' marginal returns to engagement, mitigating the distortions highlighted in Proposition 4. Under an algorithmic tax, the platform solves

$$\max_{k,\beta_M} (1 - \beta_M)\lambda E(u_0, \mu_{if}) - \tau_k E(u_0, \mu_{if}),$$

which is equivalent to reducing the effective monetization parameter from λ to $\lambda - \tau_k/(1-\beta_M)$.

Overall, platform design instruments complement conventional taxes and subsidies by directly shaping matching, exposure, and engagement incentives.

6 Extensions, Robustness and Empirical Evidence

6.1 Extension: Network Effects and Externalities

In the context of sustainability, network economics captures complementarities among professionals (such as architects, designers, and related businesses) engaged in developing sustainable products and technologies. The larger the set of firms participating in environmentally friendly production, the lower the cost of designing and producing new sustainable goods. For example, if no one produces these inputs, building an environmentally friendly

house with custom materials and technology is prohibitively costly. By contrast, once multiple industries adopt such practices, sustainable design becomes substantially easier.

We model a positive network effect by specifying $\theta > 0$ in Eq. (2). Note that agents are infinitesimal and thus cannot internalize the externality. Assume $\beta_M = 0$ and we work with exogenous amusement surplus u_0. Incorporating network effects alters equilibrium in several ways. First, beliefs directly affect interim incentives to invest. Higher belief strengthens ex ante incentives to acquire education. However, the possibility of multiple equilibria remains. For example, when $b = 0$, if $\mu_e^* = 0$ is an equilibrium without network effects, it also remains an equilibrium with them, since network surplus vanishes when $\mu_e^* = 0$.

The welfare implications are ambiguous. Total welfare is given by

$$W^E = \begin{cases} \eta b + \eta(1 - p(1)) \cdot R + (1 - \eta)(1 - \beta)u_0 - \frac{1}{2} + \eta^2\theta, & \text{if } u_0 \leq \underline{u}_0^E, \\ (1 - \beta)u_0 + \frac{1}{2}(\mu_e^*)^2, & \text{if } \underline{u}_0^E < u_0 \leq \bar{u}_0^E, \\ (1 - \beta)u_0 + \frac{1}{2}(\eta b)^2, & \text{if } u_0 > \bar{u}_0^E, \end{cases} \tag{22}$$

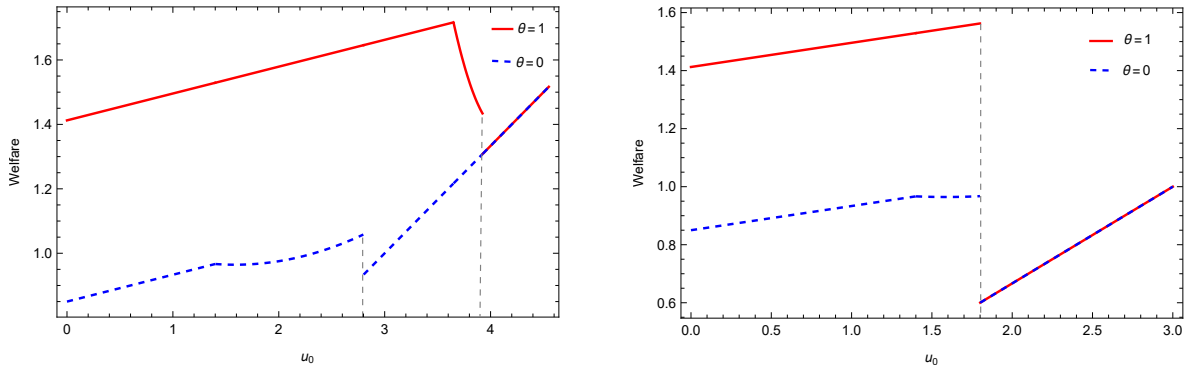
where $\underline{u}_0^E$ is the largest lower bound supporting $\mu_e^* = 1$, and $\bar{u}_0^E$ is the smallest upper bound above which $\mu_e^* = \eta b$ is the unique equilibrium.

On the one hand, network effects can raise welfare by generating additional surplus and encouraging education. On the other hand, they may exacerbate welfare losses when investment breaks down. Figure 10 illustrates this with Example 1 modified to include $\theta = 1$. Panel (a) shows that under optimistic beliefs, network effects stimulate more education, and full education ($\mu_e^* = 1$) is sustainable for $u_0 \leq \frac{73}{20}$, compared to $u_0 \leq \frac{7}{5}$ without network effects. Panel (b) shows that under pessimistic beliefs, network effects amplify welfare losses. When u_0 rises just above $\frac{9}{5}$, the welfare decline increases from 38.1% to 61.5%. Thus, while network effects may enhance coordination under optimism, they also magnify the destructive impact of anti-intellectual influence under pessimism.

6.2 Robustness

This section presents robustness checks, considering alternative game specifications, mixed-strategy equilibria, endogenous labor wages, vertical labor sorting, and influencer variety. Basic insights remain true, including technology-induced equilibrium multiplicity and welfare-reducing digital influence.

Alternative game specifications. We introduce three alternative models to compare with our benchmark. First, we consider a sequential education game in which agents initially



(a) High Belief (b) Low Belief

Figure 10: Welfare with Network Effects

Example 1 modified by $A(\theta, \mu_{ex}, \mu_{ew}) = \mu_{ex} + \mu_{ew}$, i.e., $\theta = 1$. "$\theta = 0$" indicates no network effect.

choose between education and influence, and then may acquire influence after learning their educational outcome in stage t_1. In effect, influence training can occur both before and after education results are revealed. This setup is equivalent to the baseline model.

Second, we analyze a one-round education game in Section OA.5 in which agents choose among three mutually exclusive actions in stage t_1: education, influence, or doing nothing. This is followed by service choice in stage t_2. Here, influence can no longer be acquired after the educational outcome is revealed, making the influencer market less competitive. Basic insights remain, though the market differs in two ways. First, full education (i.e., $\mu_e^* = 1$) is never an equilibrium, as influencer returns become unbounded if no one enters. Second, without ex-post free entry, influencers enjoy market power, generating novel welfare effects. When both investment returns and training costs are high, increasing the cost of influencer training can raise total welfare by curbing excessive entry and encouraging education.

Third, in Section OA.6, we examine a two-round education game in which agents may choose education, influence, or inactivity in each round, though no agent may acquire education twice. For instance, an agent could acquire education after first choosing influence. Any baseline equilibrium continues to hold, but additional equilibria may emerge because some agents delay education due to coordination issues.

Mixed strategy & asymmetric strategy equilibrium. In Section OA.7, we consider mixed strategy equilibria in which a fraction of experts switch to following influencers when the pool of educated workers is insufficient for investment. Formally, given $\mu_e \in [0, 1]$, we posit the following strategy: (i) if the participation constraint for experts (i.e., Eq. (6)) holds, all experts remain in investment; (ii) otherwise, a fraction $(1 - \delta)$ of experts follow

influencers until

$$\frac{1-p(\mu_e)}{\delta p(\mu_e)} \cdot \frac{R(\alpha, M)}{\alpha+1} + A(\theta, \mu_{ex}, \mu_{ew}) = (1-\beta)u_0. \tag{23}$$

Basic insights carry over in mixed-strategy equilibrium, and other asymmetric strategy equilibria are outcome-equivalent in the sense of aggregate demographics. However, unlike the baseline model, a market breakdown in investment never occurs solely because experts are under-compensated.

Endogenous labor wage. We consider endogenous wage determination in Appendix OA.8 in which educated workers earn w_1 and experts w_2, both set by market-clearing conditions in an external labor market. The baseline model corresponds to $w_1 = w_2 = b$. Here, let $w_1 = b_1 > 0$ and

$$w_2(\rho_i, \mu_{ex}) = \frac{b_2}{\mu_{ex}} \cdot \frac{\rho_i}{\mathbb{E}[\rho_i]}. \tag{24}$$

Educated workers receive a uniform wage, while experts' wages rise with ability ρ_i and fall with the share of experts μ_{ex}. As before, experts decide on entry before learning their ability.

Endogenous wages alter education incentives but not experts' participation constraints. The expected expert wage is $\mathbb{E}[w_2|\mu_{ex}] = \frac{b_2}{\mu_{ex}}$, independent of participation. Thus, in Eq. (10) the term ηb is replaced with $\eta p(\mu_e)\frac{b_2}{\mu_e} + \eta(1-p(\mu_e))b_1$. Two remarks follow. First, higher outside wages ($b_1 \uparrow, b_2 \uparrow$) reduce the scope for multiplicity by raising education incentives even without investment, similar to increasing b in the baseline. Second, since external labor market welfare is taken as exogenous, our analysis remains partial equilibrium.

Vertial labor sorting. We also consider vertical labor sorting in Section OA.9. The idea is that agents with stronger educational outcomes possess higher labor skills and can always move to jobs requiring lower outcomes. In particular, experts can switch to roles as educated followers or influencer followers, but not vice versa. This contrasts with horizontal sorting in the baseline model, where experts cannot invest as educated followers. Two implications follow. First, better-educated agents endogenously earn higher payoffs due to vertical classification. Second, market breakdown does not occur, since experts can always switch to investing. Thus, unlike the baseline model, vertical labor sorting removes breakdowns linked to expert participation and ensures that reducing search frictions between experts and workers always increases total welfare.

6.3 Empirical Predictions and Evidence

The model yields empirically relevant predictions across four domains: stage-switch externalities, equilibrium multiplicity, the crowding out of education and labor, and platform design distortions. The supporting evidence underscores that the theory captures important real-world dynamics. Future empirical work can build on these predictions to test and calibrate the model more fully.

Stage-switch externalities and peer effects. The model predicts that individual decisions to divert effort toward digital entertainment or influencer activities impose negative externalities on peers' educational effort. If some students in a cohort "switch stages" early—devoting time to social media creation or consumption rather than studying—their peers are more likely to follow suit. Such feedback can generate cascades in which groups underinvest in education, potentially resulting in multiple equilibria: one where most students remain focused on education, and another where many are drawn into digital distractions. These outcomes are testable by examining peer effects in time use and performance, and by identifying tipping points where small shocks lead to large group-wide shifts.

Empirical evidence supports these predictions. Barwick et al. (2024) exploit random roommate assignments in Chinese colleges and show that app usage is contagious: a one-standard-deviation increase in roommates' usage raises a student's own usage by 5.8%. Heavy phone use by one student also depresses peers' GPA and post-college wages. Likewise, Beland and Murphy (2016) find that UK schools adopting mobile phone bans experienced significant test-score gains, particularly among low-achieving students. These findings confirm sizable peer externalities consistent with the model.

Equilibrium multiplicity and tipping dynamics. The model also implies the possibility of multiple equilibria. In one equilibrium, most individuals prioritize education while digital entertainment remains secondary; in another, a critical mass chases influencer fame or entertainment, leading many to de-prioritize human capital investment. This yields testable predictions of tipping-point dynamics: small shocks or early adopters can shift a group from a high-education to a low-education equilibrium. Empirically, one would expect discontinuities or clustering—for example, otherwise-similar schools diverging sharply in attainment following differential exposure to digital platforms.

Direct evidence of dual equilibria is limited, but studies of peer effects document nonlinearities consistent with tipping behavior. Barwick et al. (2024) show that peer spillovers amplify digital usage and academic losses. The broader literature on peer norms likewise sug-

gests that group culture can entrench high-study or low-study states. By extension, digital platforms may shift groups past a threshold, producing persistent divergence across similar environments.

Crowding out of education and career effort. A central implication of the model is that time and effort are zero-sum. Greater involvement in digital entertainment or influencer activities directly reduces time spent on schooling, studying, or work. Predictions include: (i) increased digital access lowers educational attainment; (ii) heavy entertainment usage predicts weaker grades and labor outcomes; and (iii) some individuals exit formal education or employment to pursue influencer careers.

The empirical evidence is consistent with these mechanisms. Malamud and Pop-Eleches (2011) study a Romanian program that randomly provided home computers to youth and find lower grades in math, English, and Romanian, largely due to games crowding out homework. Vigdor and Ladd (2014) document that broadband rollout in North Carolina led to significant declines in middle school test scores. More recently, Barwick et al. (2024) show that mobile usage reduces GPA, sleep, and class attendance, and translates into lower wages after graduation. Beyond education, Aguiar et al. (2021) demonstrate that improvements in video games explain 23–46% of the decline in hours worked by U.S. men aged 21–30 in the 2000s, highlighting how entertainment raises the reservation value of leisure and crowds out labor supply. Consistent evidence also comes from interventions: Beland and Murphy (2016) report large test-score gains from school phone bans, while Chadi et al. (2022) find that banning smartphones in the workplace increased worker productivity.

Platform distortions: algorithmic intensity and revenue sharing. The model emphasizes that platform design shapes both digital consumption and career incentives. Aggressive recommendation algorithms amplify user time allocation toward entertainment content, while revenue-sharing schemes distort occupational choice by encouraging content creation.

Empirical results align with these predictions. Schaffner et al. (2025) conduct an experiment disabling Netflix's autoplay feature and find that users watched 21 fewer minutes per day and had shorter viewing sessions, showing how algorithmic nudges prolong digital consumption. A randomized experiment with Twitter's feed algorithm shows that engagement-optimized ranking amplified emotionally charged content, especially anger, relative to chronological sorting (Knight First Amendment Institute, 2023). On the creator side, Abou El-Komboz et al. (2023) study YouTube's 2018 monetization policy change and find that creators who lost revenue eligibility sharply reduced output and produced lower-quality,

less diverse content. These findings align with the model's prediction that platform design can distort both user attention and labor supply.

7 Conclusion

We study individual educational pursuit, influence acquisition, occupational choice, and economic production, all in the presence of increasingly ubiquitous digital (social) media that offer pure entertainment. Education not only imparts knowledge, but also determines initial labor market placements; thus, either high or low search frictions in the market for educated experts may reduce endogenous education. More importantly, the rise of the influencer economy via digital platforms alters the allocation of attention and effort, and thus of resources in the society. Technologies that augment entertainment surplus (e.g., improved matching and amplified outreach) can discourage or even break down education. Education pursuits exhibit complementarity in the presence of a sizable influencer economy, resulting in multiple equilibria including one featuring inefficiently low education. Education and occupational choices exhibit generally non-monotonic dependence on labor market search frictions and digital influence technologies. Digital influence becomes "anti-intellectual" because it crowds out not only people's attention but also education and productive occupational choices, especially when societal decisions and public goods provision rely on an individual's logic and scientific understanding. Regulations directly targeting influencers or reducing search friction in the labor market may backfire, but taxing both influencers and followers helps. Interventions to coordinate equilibria and adjust platform designs can also mitigate inefficiency.

> *'When a population becomes distracted by trivia, when cultural life is redefined as a perpetual round of entertainments, when serious public conversation becomes a form of baby-talk, when, in short, a people become an audience and their public business a vaudeville act, then a nation finds itself at risk; a culture-death is a clear possibility."*
>
> — Neil Postman

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Appendix

A Derivations and Proofs

We first present Lemma A.1 on how search frictions affect expert-led production.

Lemma A.1. *(i) Both $R(\alpha, M)$ and $\frac{\alpha}{(\alpha+1)}R(\alpha, M)$ strictly increase in α; and (ii) $\frac{1}{(\alpha+1)}R(\alpha, M)$ strictly decreases in α.*

Notation. $x \wedge y = \min\{x, y\}$ and $x \vee y = \max\{x, y\}$.

A.1 Proof of Proposition 1

Proof. **Case (i).** Suppose

$$\Big(\alpha \wedge \big(1/p(1) - 1\big)\Big) \cdot \frac{R(\alpha, M)}{\alpha + 1} + \theta\eta < (1 - \beta)u_0.$$

Then, even under the most optimistic belief $\mu_e = 1$, either educated followers or experts exit the investment market. In this case,

$$U_i(E|c_i) = \eta b + (1 - \beta)u_0 - c_i \quad \text{and} \quad U_i(\varnothing|c_i) = (1 - \beta)u_0,$$

so all agents with $c_i \leq \eta b$ acquire education. Hence, $\mu_e^* = \eta b$.

Case (ii). Now suppose

$$\frac{\alpha R(\alpha, M)}{\alpha + 1} + \theta\eta\mu_e^* \;\geq\; (1 - \beta)u_0.$$

Then educated followers remain in the investment market as long as experts do not exit. First, note that $\mu_e^* \geq \eta b$, since all agents with $c_i \leq \eta b$ acquire education due to labor-market benefits. If

$$\Big(\tfrac{1}{p(\eta b)} - 1\Big)\frac{R(\alpha, M)}{\alpha + 1} + \theta\eta b < (1 - \beta)u_0,$$

experts withdraw, the investment market collapses, and $\mu_e^* = \eta b$ constitutes an equilibrium.

Next, consider the case where

$$\Big(\tfrac{1}{p(1)} - 1\Big)\frac{R(\alpha, M)}{\alpha + 1} + \theta\eta \;\geq\; (1 - \beta)u_0 \quad \text{and} \quad \frac{\alpha R(\alpha, M)}{\alpha + 1} + \theta\eta \;\geq\; (1 - \beta)u_0.$$

Here both experts and educated followers remain in the market, conditional on the other side doing so. Moreover, $D(1) \geq 0$ implies

$$\eta b + \eta(1 - p(1))R(\alpha, M) - \eta(1 - \beta)u_0 - (1 - \eta^2\theta) \geq 0,$$

which ensures that under belief $\mu_e = 1$, every agent with c_i satisfies

$$U_i(E|c_i) \;\geq\; U_i(\varnothing|c_i), \quad \forall\, c_i \leq 1.$$

Finally, $D(\mu_e^*) = 0$ guarantees that the marginal agent $c_i = \mu_e^*$ is indifferent between acquiring education and abstaining:

$$U_i(E|c_i = \mu_e^*) \;=\; U_i(\varnothing|c_i = \mu_e^*).$$

Thus, $U_i(E|c_i) \geq U_i(\varnothing|c_i)$ for $c_i \leq \mu_e^*$ and the reverse holds for $c_i > \mu_e^*$. Meanwhile,

$$\Big(\tfrac{1}{p(\mu_e^*)} - 1\Big)\frac{R(\alpha, M)}{\alpha + 1} + \theta\eta\mu_e^* \;\geq\; (1 - \beta)u_0$$

ensures that experts also remain in the market. Therefore, aggregate education equals μ_e^*. Together with Eqs. (12) and (14), this condition fully characterizes the equilibrium. □

A.2 Proof of Proposition 2

Proof. **Case (i).** Suppose $u_0 > \underline{\nu}$. Then

$$\frac{1 - p(\eta b)}{p(\eta b)}\frac{R(\alpha, M)}{\alpha + 1} < (1 - \beta)u_0,$$

so experts exit the investment market and $\mu_e^* = \eta b$ is an equilibrium. Next, if $u_0 < \overline{\nu}$, two conditions follow: (i)

$$\Big(\alpha \wedge \frac{1 - p(1)}{p(1)}\Big)\frac{R(\alpha, M)}{(\alpha + 1)(1 - \beta)} > u_0,$$

which ensures participation by both experts and educated workers for $\mu_e^* = 1$; and (ii)

$$u_0 < \frac{(b - 1/\eta) + (1 - p(1))R(\alpha, M)}{1 - \beta},$$

or equivalently $D(1) > 0$, which implies $\mu_e^* = 1$ is an equilibrium.

Case (ii). Suppose $u_0 < \underline{\nu}$. If $u_0 < \frac{\alpha R(\alpha, M)}{(1-\beta)(\alpha+1)}$, then both experts and educated workers remain in the market. Moreover, if $u_0 < \underline{L}/(1 - \beta)$, then $D(\mu_e) > 0$ for all $\mu_e \in [\eta b, 1]$, so $\mu_e^* = 1$ is an equilibrium. By contrast, if $u_0 > L$, then $D(\mu_e) < 0$ for all $\mu_e \geq \eta b$, so $\mu_e^* = \eta b$. □

A.3 Proof of Proposition 3

Proof. **Case (i).** First, consider educated followers. Their participation requires

$$\frac{\alpha}{\alpha + 1}R(\alpha, M) \;\geq\; (1 - \beta)u_0.$$

By Lemma A.1, both $\frac{\alpha}{\alpha+1}R(\alpha, M)$ and $R(\alpha, M)$ increase in α, with $R(\alpha, M) \leq M(2\overline{\rho} - 1)$. Hence, if $M(2\overline{\rho} - 1) \leq (1 - \beta)u_0$, educated followers always exit. If instead $M(2\overline{\rho} - 1) > (1 - \beta)u_0$, they exit whenever

$$\alpha < \frac{(1 - \beta)u_0}{M - (1 - \beta)u_0}.$$

Thus, educated followers drop out for sufficiently small α.

Second, consider experts when α is large. Their participation requires

$$\frac{\mu_{ew}}{\mu_{ex}} \frac{R(\alpha, M)}{\alpha + 1} \geq (1 - \beta) u_0.$$

Note that

$$\lim_{\alpha \to \infty} \frac{\mu_{ew}}{\mu_{ex}} \frac{R(\alpha, M)}{\alpha + 1} \leq \sup_{\mu_e} \left\{ \frac{\mu_{ew}}{\mu_{ex}} \right\} \cdot \lim_{\alpha \to \infty} \frac{R(\alpha, M)}{\alpha + 1} = 0,$$

since $\frac{\mu_{ew}}{\mu_{ex}} = \frac{1}{p(\mu_e)} - 1 \leq \frac{1}{p(1)} - 1 < \infty$ and $\frac{R(\alpha, M)}{\alpha + 1}$ decreases in α. Hence, experts' participation fails for α sufficiently large.

Case (ii). By definition of $\bar{L}$, if $u_0 \geq \bar{L}/[\eta(1 - \beta)]$, then $D(\mu_0) < 0$. Proposition 1 then implies that $\mu_e^* = \eta b$ is the unique equilibrium, corresponding to a production market breakdown. □

A.4 Proof of Lemma 1

Proof. We establish a stronger result and prove Lemma 1 as a special case. The general proof is available upon request.

Lemma A.2. *Suppose the investment market does not collapse. Then* $\frac{d\mu_e^*}{du_0} < 0$ *for any locally stable equilibrium* μ_e^*. *(i) If* $D'(\cdot) < 0$, *then* $\frac{d\mu_e^*}{du_0} < 0$, *i.e., higher entertainment utility crowds out education. (ii) The highest equilibrium level of education* $\sup\{\mu_e^*\}$ *satisfies* $\frac{d \sup \mu_e^*}{du_0} \leq 0$ *when* $p(\cdot)$ *is* C^2 *and convex* ($p''(\cdot) > 0$). *(iii) The same holds when* $p(\cdot)$ *is weakly convex and piecewise linear.*

For convenience, define $D(x+) = \lim_{\delta \downarrow 0} D(x + \delta)$.

If $D'(\mu_e) < 0$ for all $\mu_e \in (\eta b, 1)$, then $D(\mu_e^*) = 0$ has at most one solution. If $D(\eta b+) \leq 0$, then $\mu_e^* = \eta b$; if $D(1) \geq 0$, then $\mu_e^* = 1$. When $D(\eta b+) > 0 > D(1)$, the Intermediate Value Theorem guarantees a solution $\mu_e^* \in (\eta b, 1)$.

Differentiating the equilibrium condition $D(\mu_e^*) = 0$ with respect to u_0 yields

$$D'(\mu_e^*) \frac{d\mu_e^*}{du_0} - \eta(1 - \beta) = 0,$$

so that

$$\frac{d\mu_e^*}{du_0} = \frac{\eta(1 - \beta)}{D'(\mu_e^*)}.$$

Since $D'(\mu_e^*) < 0$, it follows that $\frac{d\mu_e^*}{du_0} < 0$. □

A.5 Proof of Proposition 4

Proof. **Part (i).** By Eq. (18), the platform optimally sets $\beta_M^{pl} = 0$. A lower β_M increases the measure of influencer followers, since $\frac{d\mu_{if}}{d\beta_M} < 0$ by Eq. (15), thereby raising engagement and monetization revenue. Similarly, Eq. (21) implies $\beta_M^{sp} = 0$, as β_M enters welfare only through the term $-\beta_M \lambda u_0 \mu_{if}$.

Part (ii). Since $\frac{\partial \mu_{if}}{\partial c_I} > 0$ for all $c_I < \bar{c}_I$, the platform optimally chooses $c_I^{pl} = \bar{c}_I$. From Eq. (21), c_I affects welfare only through the term $-\beta_M \lambda u_0 \mu_{if}$, implying that the social planner selects $c_I^{sp} = 0$ whenever $\beta_M \neq 0$. However, because $\beta_M^{sp} = 0$, total welfare is independent of c_I. If

instead β_M is bounded away from zero exogenously, then $c_I^{sp} = 0$ minimizes engagement (since μ_{if} decreases in c_I) and thus maximizes welfare.

Part (iii). $k^{pl} > k^{sp}$ and $\mu_e^{pl} < \mu_e^{sp}$.

First, we show that $\frac{\partial \mu_e^*}{\partial k} < 0$. Recall $D(\mu_e, k) := \Delta(\mu_e, k) - \mu_e$. We then differentiate the fixed point $D(\mu_e, k) \equiv \Delta(\mu_e, k) - \mu_e = 0$. Then, the implicit function theorem gives

$$\frac{\partial \mu_e}{\partial k} \;=\; -\frac{\partial D/\partial k}{\partial D/\partial \mu_e} \;= \frac{\partial \Delta/\partial k}{\partial \Delta/\partial \mu_e - 1}.$$

Since $\frac{\partial D}{\partial \mu_e} < 0$ by local stability, we further have:

$$\frac{\partial \Delta}{\partial k} \;=\; -(1-\beta)H'(k) < 0.$$

Thus, μ_e strictly decreases in k.

Second, we show that $k^{sp} < k^{pl}$. The marginal value of increasing k on the platform's profit is

$$\begin{aligned}\frac{\partial \Pi}{\partial k} &= \lambda(1-\beta_M^{pl}) * \left(H'(k)\mu_{if} + u_0 * \frac{\partial \mu_{if}}{\partial k}\right) - TC'(k) \\ &= \lambda * \left(H'(k)\mu_{if} + u_0 * \frac{\partial \mu_{if}}{\partial k}\right) - TC'(k) \end{aligned} \tag{A.1}$$

Similarly, the marginal value of increasing k on the planner's welfare is

$$\frac{\partial W}{\partial k} = (1-\beta)H'(k) + \mu_e \frac{\partial \mu_e}{\partial k} - TC'(k) \tag{A.2}$$

Here, we used $\beta_M^{sp} = \beta_M^{pl} = 0$ to simplify expressions.

Next, we verify that Eq. (A.1) is always greater than Eq. (A.2). We first compute

$$\frac{\partial \mu_{if}}{\partial k} = \frac{\mu_{if}}{1-\eta\mu_e^*} * \left(-\eta \frac{\partial \mu_e^*}{\partial k}\right) - (1-\eta\mu_e^*) * \frac{\beta * \bar{c}_I * H'(k)}{(u_0 + \bar{c}_I)^2}$$

Thus,

$$\begin{aligned}\frac{\partial \Pi}{\partial k} - \frac{\partial W}{\partial k} &= (\lambda\mu_{if} - (1-\beta)) * H'(k) - \mu_e \frac{\partial \mu_e}{\partial k} + \lambda u_0 \frac{\partial \mu_{if}}{\partial k} \\ &= \mu_{if} H'(k) * \left(\lambda - \frac{1-\beta}{\mu_{if}} - \frac{\lambda\beta u_0 \bar{c}_I}{(u_0+\bar{c}_I)((1-\beta)u_0 + \bar{c}_I)}\right) \\ &\quad - \mu_e \frac{\partial \mu_e}{\partial k} + \lambda u_0 * \frac{\mu_{if}}{1-\eta\mu_e^*} * \left(-\eta \frac{\partial \mu_e^*}{\partial k}\right)\end{aligned}$$

Using $\frac{\partial \mu_e}{\partial k} < 0$ and $H'(k) > 0$, $\frac{\partial \Pi}{\partial k} > \frac{\partial W}{\partial k}$ when:

$$\left(\lambda - \frac{1-\beta}{\mu_{if}} - \frac{\lambda\beta u_0 \bar{c}_I}{(u_0+\bar{c}_I)((1-\beta)u_0 + \bar{c}_I)}\right) > \left(\lambda - \frac{1-\beta}{\mu_{if}} - \lambda\beta\right) \geq 0,$$

which reduces to $\lambda * \mu_{if} \geq 1$. Since $\mu_{if} \geq (1-\eta) * \frac{(1-\beta)H(\bar{k}) + \bar{c}_I}{H(\bar{k}) + \bar{c}_I}$, we get the required condition on λ. Finally, by the fact that $TC''(k) \geq 0$, $k^{pl} > k^{sp}$. Again, note that $\frac{\partial \mu_e}{\partial k} < 0$, we thus have $\mu_e^{sp} \geq \mu_e^{pl}$. The proof concludes. □

A.6 Proof of Proposition 5

Proof. Let ϑ collect all fundamentals other than (c_I, k, β_M) and endogenous variables (μ_e, μ_{in}), such as the labor benefit b or parameters entering R. Since $c_I^{pl} = \bar{c} = c_I^{sp}$ and $\beta_M^{pl} = \beta_M^{sp}$, we focus on k and write $\chi := k$, with $\chi_0 := k^{sp}$. For simplicity, assume ϑ is scalar.

Strategic complementarities imply that Δ is strictly increasing in μ_e. By assumption, at some (ϑ_0, χ_0) there exist two locally stable equilibria $\mu_e^L < \mu_e^H$ and one unstable equilibrium $\mu_e^U \in (\mu_e^L, \mu_e^H)$.[33] Formally,

$$
\begin{aligned}
&D(\mu_e^l; \vartheta_0, \chi_0) = 0, \qquad l \in \{L, U, H\}, \\
&D_\mu(\mu_e^U; \vartheta_0, \chi_0) > 0, \quad D_\mu(\mu_e^L; \vartheta_0, \chi_0) \in (-1, 0), \quad D_\mu(\mu_e^H; \vartheta_0, \chi_0) \in (-1, 0),
\end{aligned}
$$

where $D_\mu := \partial D / \partial \mu_e = \Delta_\mu - 1$.

Step 1 (Persistence). Since $D_\mu \neq 0$ at the two stable equilibria, transversality holds. By the Implicit Function Theorem, μ_e^L and μ_e^H vary continuously with (ϑ, χ). Hence, the set of parameters admitting three fixed points is open in a neighborhood of (ϑ_0, χ_0).

Step 2 (Multiplicity boundaries). For fixed χ, the boundary of the multiplicity region in ϑ is characterized by a fold (saddle–node) at which two fixed points coalesce:

$$
D(\mu^*; \vartheta^*, \chi) = 0, \qquad D_\mu(\mu^*; \vartheta^*, \chi) = 0, \qquad D_{\mu\mu}(\mu^*; \vartheta^*, \chi) \neq 0.
$$

Let $\vartheta_L(\chi)$ and $\vartheta_H(\chi)$ denote the low and high fold boundaries. Totally differentiating $D = 0$ and $D_\mu = 0$ with respect to χ and eliminating $d\mu^*/d\chi$ yields

$$
\frac{d\vartheta_l}{d\chi} = -\frac{D_\chi(\mu_e^l; \vartheta_l(\chi), \chi)}{D_\vartheta(\mu_e^l; \vartheta_l(\chi), \chi)}, \qquad l \in \{L, H\},
$$

where $D_\vartheta \neq 0$ by nondegeneracy.

Step 3 (Expansion of the multiplicity region). Endogenous platform design reduces Δ pointwise, so

$$
D_\chi = \Delta_\chi = -\eta(1 - \beta) H'(k) < 0.
$$

Hence,

$$
\frac{d\vartheta_L}{d\chi} = -\frac{\Delta_\chi}{\Delta_\vartheta}\Big|_{(\mu_e^L, \chi^{sp})}, \qquad \frac{d\vartheta_H}{d\chi} = -\frac{\Delta_\chi}{\Delta_\vartheta}\Big|_{(\mu_e^H, \chi^{sp})}.
$$

The multiplicity region expands if and only if

$$
\frac{\Delta_\chi}{\Delta_\vartheta}\Big|_{(\mu_e^L, \chi^{sp})} - \frac{\Delta_\chi}{\Delta_\vartheta}\Big|_{(\mu_e^H, \chi^{sp})} > 0,
$$

equivalently,

$$
\frac{\partial}{\partial \mu_e}\left(\frac{\Delta_\chi}{\Delta_\vartheta}\right)\Bigg|_{\chi^{sp}} < 0.
$$

[33] Existence follows from the Intermediate Value Theorem; local stability (instability) corresponds to $D_\mu < 0$ ($D_\mu > 0$).

Step 4 (Basins of attraction). Under any monotone adaptive dynamic $m_{t+1} = \Delta(m_t; \vartheta, \chi)$, the unstable equilibrium μ_e^U separates basins. Since $D_\mu(\mu_e^U) > 0$, the Implicit Function Theorem implies

$$\frac{\partial \mu_e^U}{\partial \chi} = -\frac{D_\chi(\mu_e^U; \vartheta, \chi)}{D_\mu(\mu_e^U; \vartheta, \chi)} = -\frac{\Delta_\chi(\mu_e^U; \vartheta, \chi)}{\Delta_\mu(\mu_e^U; \vartheta, \chi) - 1} > 0.$$

Thus, the threshold μ_e^U shifts rightward, expanding the basin of attraction of μ_e^L. Moreover,

$$\frac{\partial \mu_e^L}{\partial \chi} = -\frac{\Delta_\chi(\mu_e^L; \vartheta, \chi)}{\Delta_\mu(\mu_e^L; \vartheta, \chi) - 1} < 0, \qquad \frac{\partial \mu_e^H}{\partial \chi} = -\frac{\Delta_\chi(\mu_e^H; \vartheta, \chi)}{\Delta_\mu(\mu_e^H; \vartheta, \chi) - 1} < 0,$$

so the basin of attraction expands (contracts) for the low- (high-) education equilibrium.

Parameter cases. Finally, condition (20) holds as follows:

- Labor benefit b: $\frac{\Delta_\chi}{\Delta_\vartheta} = -(1-\beta)H'(k),\ \partial_{\mu_e}(\Delta_\chi/\Delta_\vartheta) = 0.$
- Network effect θ: $\frac{\Delta_\chi}{\Delta_\vartheta} = -(1-\beta)H'(k)/\mu_e,\ \partial_{\mu_e}(\Delta_\chi/\Delta_\vartheta) > 0.$
- Investment-return parameters in R (including M and α): $\frac{\Delta_\chi}{\Delta_\vartheta} = -\frac{(1-\beta)H'(k)}{(1-p(\mu_e))},\ \partial_{\mu_e}\left(\frac{\Delta_\chi}{\Delta_\vartheta}\right) > 0.$
- Education success rate η: $\frac{\Delta_\chi}{\Delta_\vartheta} = -\frac{(1-\beta)H'(k)}{(b+(1-p(\mu_e))R+A(\mu_e))},\ \partial_{\mu_e}(\Delta_\chi/\Delta_\vartheta) > 0.$

This completes the proof. □

A.7 Proof of Lemma 2

Proof. Total welfare equals the sum of individual utilities net of aggregate monetization income accruing to influencers. Since the platform earns $(1-\beta_M)\lambda E(u_0, \mu_{if})$, the latter equals $\beta_M \lambda E(u_0, \mu_{if})$ and is subtracted throughout.

Case (i): $\mu_e^* = 1$. Integrating $U_i(E \mid c_i)$ from Eq. (10) over $c_i \in [0,1]$ yields

$$\begin{aligned} W &= \int_0^1 \Big(\eta b + \eta(1-p(1))R(\alpha, M) + (1-\eta)(1-\beta)u_0 - c_i\Big)\, dc_i - \beta_M \lambda E(u_0, \mu_{if}) \\ &= \eta b + \eta(1-p(1))R(\alpha, M) + (1-\eta)(1-\beta)u_0 - \tfrac{1}{2} - \beta_M \lambda u_0\, \mu_{if}, \end{aligned}$$

where $\mu_{if} = \frac{((1-\beta)u_0 + c_I)(1-\eta)}{(1+\lambda\beta_M)u_0 + c_I}$ by Eq. (15).

Case (ii): $\mu_e^* \in (\eta b, 1)$. By continuity of $p(\cdot)$ and $D(\cdot)$, the condition $D(\mu_e^*) = 0$ implies

$$U_i(E \mid c_i = \mu_e^*) = U_i(\varnothing \mid c_i = \mu_e^*) = (1-\beta)u_0.$$

Hence, agents with $c_i > \mu_e^*$ abstain and obtain $(1-\beta)u_0$, while those with $c_i \le \mu_e^*$ acquire education and receive $U_i(E \mid c_i) = (1-\beta)u_0 + (\mu_e^* - c_i)$. Therefore,

$$\begin{aligned} W &= \int_0^{\mu_e^*} \big[(1-\beta)u_0 + (\mu_e^* - c_i)\big]\, dc_i + \int_{\mu_e^*}^1 (1-\beta)u_0\, dc_i - \beta_M \lambda u_0\, \mu_{if} \\ &= \tfrac{1}{2}(\mu_e^*)^2 + (1-\beta)u_0 - \beta_M \lambda u_0\, \mu_{if}, \end{aligned}$$

where $\mu_{if}^* = \frac{((1-\beta\mu_e^*)u_0+c_I)(1-\eta)}{(1+\lambda\beta_M)u_0+c_I}$ by Eq. (15).

Case (iii): $\mu_e^* = \eta b$. If $D(\eta b) = 0$, Case (ii) applies; otherwise the investment market collapses, and integrating utilities over $c_i \in [0,1]$ with cutoff ηb, net of $\beta_M \lambda E(u_0, \mu_{if})$, yields welfare.

This completes the proof. □

A.8 Proof of Proposition 6

Proof. We prove the result under the restriction $\beta_M = 0$. Setting $\beta_M = 0$ removes the nonlinearity from monetization and thus strengthens all non-monotonicity results. This yields

$$W = \begin{cases} \eta b + \eta(1-p(1))R(\alpha, M) + (1-\eta)(1-\beta)u_0 - \frac{1}{2} - TC(k), & \text{if } \mu_e^* = 1, \\ (1-\beta)u_0 + \frac{1}{2}(\mu_e^*)^2 - TC(k), & \text{if } \mu_e^* \in (\eta b, 1), \\ (1-\beta)u_0 + \frac{1}{2}(\eta b)^2 - TC(k), & \text{if } \mu_e^* = \eta b. \end{cases} \tag{A.3}$$

(ii) Entry cost c_I. Fix k, so u_0 depends on c_I only through the endogenous influencer mass μ_{in}.

- Invariant amusement surplus. Suppose $u_0 = H(k)$ and is independent of c_I. Then equilibrium education μ_e^* depends only on the comparison between $U_i(E \mid c_i)$ and $U_i(\varnothing \mid c_i)$ and is therefore independent of c_I. Consequently, the welfare of educated agents is unaffected by c_I. Given μ_e^*, the indifference condition implies

$$U_i(I \mid c_i) = U_i(\varnothing \mid c_i) = (1-\beta)u_0.$$

  Thus, both influencers and uneducated followers obtain $(1-\beta)u_0$, and their combined surplus,

$$\left[(1-\mu_e^*) + (1-\eta)\mu_e^*\right](1-\beta)u_0,$$

  is independent of c_I.

- Endogenous amusement surplus. Now let $u_0 = H(k)\psi(\mu_{in}) = \psi(\mu_{in})$, where $\psi(0) = 0$, $\psi' > 0$, and $\lim_{\mu_{in}\to\infty} \psi(\mu_{in}) < \infty$. Assume $\eta b + \eta(1-p(1))R > 1$, so that $\underline{u}_0 > 0$.

There are two cases.

(a) Suppose $c_I = 0$ and $\mu_e^* \in (\eta b, 1)$. As $c_I \to \infty$, we have $u_0 < \underline{u}_0$ and hence $\mu_e^* = 1$. Let $\bar{c}_I$ denote the cutoff such that $\mu_e^* = 1$ for all $c_I > \bar{c}_I$. By Eq. (A.3), further increases in c_I reduce u_0 and therefore lower welfare; thus W is decreasing in c_I for $c_I > \bar{c}_I$.

For $c_I < \bar{c}_I$, increasing c_I reduces μ_{in} and hence u_0. By Lemma 1, $\partial\mu_e/\partial u_0 < 0$, so μ_e^* rises as c_I increases. Since welfare is increasing in μ_e^* for $\mu_e^* \in (\eta b, 1)$, welfare increases in c_I for $c_I < \bar{c}_I$.

(b) Suppose instead that $\mu_e^* = \eta b$ when $c_I = 0$. Either $\lim_{c_I\to 0^+} \mu_e^*(c_I) > \eta b$ or $\lim_{c_I\to 0^+} \mu_e^*(c_I) = \eta b$. In the former case, a small increase in c_I prevents market breakdown in investment and generates a discrete upward jump in welfare; subsequent increases in c_I first raise and then

reduce welfare, as in case (a). In the latter case, there exists $\underline{c}_I > 0$ such that $\mu_e^* = \eta b$ for all $c_I < \underline{c}_I$ and $\mu_e^* > \eta b$ for $c_I \geq \underline{c}_I$. For $c_I < \underline{c}_I$, welfare decreases as u_0 falls; for $c_I \geq \underline{c}_I$, the analysis in case (a) applies. This establishes the non-monotonicity of welfare in c_I.

(iii) Search friction α. When α is small, educated followers earn little surplus and switch to influencing; when α is large, intense competition drives experts to exit. In both extremes, total welfare is minimized.

(iv) Labor benefits b. We show that both thresholds $\underline{u}_0$ and $\bar{u}_0$ increase weakly in b.

First,

$$\inf_{\mu_e \in [0,1]} D(\mu_e) = \eta b - \eta(1-\beta)u_0 + \inf_{\mu_e \in [0,1]} \big(\eta(1-p(\mu_e))R(\alpha, M) - \mu_e\big),$$

which increases strictly in b. Moreover,

$$D(1) = \eta b - \eta(1-\beta)u_0 + \eta(1-p(1))R(\alpha, M) - 1$$

also increases strictly in b, implying that $\underline{u}_0$ is weakly increasing in b.

For $\bar{u}_0$, note that $\inf\{u_0 : \sup_{\mu_e \in (\eta b, 1]} D(\mu_e) < 0\}$ increases strictly in b, while $\inf\{u_0 : \alpha R(\alpha, M)/(\alpha + 1) < (1-\beta)u_0\}$ is independent of b. Since $D(\mu_e)$ increases in b, raising b is equivalent to lowering u_0. By local stability (i.e., $\partial \mu_e^* / \partial u_0 < 0$), μ_e^* increases with b, implying that $\bar{u}_0$ increases weakly.

Next, let $0 \leq b_1 < b_2$ and define $\tilde{D}(\mu_e, u_0) = D(\mu_e, u_0 \mid b = b_1)$. Then $D(\mu_e, u_0 \mid b = b_2) = \tilde{D}(\mu_e, \tilde{u}_0)$, where $\tilde{u}_0 = u_0 - \frac{b_2 - b_1}{1-\beta}$. By local stability, $\mu_e^*(b_2) \geq \mu_e^*(b_1)$.

Finally, consider three regions. (i) If $u_0 \leq \underline{u}_0(b_1)$, then $u_0 \leq \underline{u}_0(b_2)$ and $W(b_2) > W(b_1)$ by Eq. (21). (ii) If $u_0 \in (\underline{u}_0(b_1), \bar{u}_0(b_1)]$, then $u_0 \leq \bar{u}_0(b_2)$; since W increases in μ_e^* and μ_e^* is weakly increasing in b, welfare rises in b. (iii) If $u_0 > \bar{u}_0(b_1)$, then $W(b_1) = (1-\beta)u_0 + \frac{1}{2}(\eta b_1)^2 \leq W(b_2)$.

This completes the proof. □

A.9 Proof of Corollary 1

Proof. First, set $T_{if} = (1-\beta)(u - u_0) > 0$. Under condition (ii), the induced change in total welfare equals $W(u) - W(u_0) + T_{if}\mu_{if}(u)$.

Second, since $(1 - \lambda\beta_M)u_0 + c_I > 0$, imposing an influencer tax $T_{in} > 0$ generates positive welfare gains by saving the entry cost c_I and generating amusement surplus u_0 (net of monetization income transferred to influencers) for each influencer who switches to follower status. Hence, the maximal welfare gain from taxing digital consumption alone is bounded above by $\mu_{in}(u)\big((1 - \lambda\beta_M)u_0 + c_I\big)$.

When taxes on digital consumption and influencers are combined, total welfare becomes

$$W(u) + \mu_{in}^*(u)\big((1 - \lambda\beta_M)u_0 + c_I\big) + (1-\beta)(u_0 - u)\mu_{if}(u), \tag{A.4}$$

which strictly exceeds $W(u_0)$, the welfare level prior to taxation.

Finally, under taxation of influencers alone, the maximal total welfare (including influencer tax revenue) is

$$W(u_0) + \mu_{in}^*(u_0)\big((1 - \lambda\beta_M)u_0 + c_I\big). \tag{A.5}$$

Comparing (A.4) and (A.5) yields condition (iv). This completes the proof. □

Online Appendix: Extended Discussions

OA.1 A Micro-Foundation of Entertainment Utility

Consistent with the baseline model, we assume random matching between influencers and followers on livestreaming platforms. Each follower may be matched with multiple influencers of distinct types. This can be interpreted as improved recommendation diversity without changing total time spent on platforms such as TikTok. We treat influencer follow-up as a variety good.

Let $t \in [0,1]$ denote total time spent on livestreaming. Entertainment utility is concave, $h(0) \geq 0$, $h'(t) > 0$, $h''(t) < 0$. If a follower is matched with k influencers, time is evenly allocated, yielding

$$u_0 = H(k) \equiv k\, h(t/k).$$

By concavity, $H(k)$ is strictly increasing in k.

Leisure costs are given by $L(t)$, with $L'(0) = 0$, $L'(1) = \infty$, and $L''(t) > 0$. The follower chooses

$$t^*(k) \in \arg\max_{t \in [0,1]} \{kh(t/k) - L(t)\},$$

which satisfies

$$h'(t^*/k) = L'(t^*).$$

Since $h'' < 0$, $t^*(k)$ is increasing in k, implying

$$\frac{\mathrm{d}H(k, t^*(k))}{\mathrm{d}k} = \frac{\partial H}{\partial k} + h'(t/k)\frac{\mathrm{d}t^*(k)}{\mathrm{d}k} > 0.$$

In Section OA.4, we further allow influencer variety to affect utility via

$$u_0(k, \mu_{in}) = H(k)\psi(\mu_{in}),$$

where $H(k)$ exhibits diminishing returns. This specification permits non-monotonic welfare effects through endogenous influencer entry.

OA.2 Expert Advising and Investment

This section microfounds the match-dependent payoff $R(\alpha, M)$. When an educated worker matches with an expert of signal precision ρ_i, the expected investment surplus is

$$M(2\rho_i - 1),$$

which is strictly increasing in ρ_i.[34] The scale parameter $M > 0$ captures the importance of educational expertise.

Formally, an educated worker chooses an investment $d_j \in \{-1, 1\}$ with payoff

$$u_j^{ew}(d_j \mid \rho_i, \omega) = M\big(\mathbb{1}_{\{d_j = \omega\}} - \mathbb{1}_{\{d_j \neq \omega\}}\big),$$

[34] Only monotonicity in ρ_i is required.

where the expert observes a signal $s_i \in \{G, B\}$ satisfying $\Pr(s_i = G \mid \omega = 1) = \Pr(s_i = B \mid \omega = -1) = \rho_i \geq \frac{1}{2}$. Correct decisions yield payoff M, incorrect ones yield zero, implying expected surplus $M(2\rho_i - 1)$.

If expert i charges fee f_i, an educated worker obtains

$$u(f_i, \rho_i) = M(2\rho_i - 1) - f_i,$$

net of an independent labor benefit b. Uneducated followers cannot interpret expert signals and therefore generate zero surplus.

Matching follows the reduced-form technology of Fainmesser and Galeotti (2021a).[35] The density with which an educated worker matches expert i is

$$n_i(\mathbf{f}) = \frac{u(f_i, \rho_i)^\alpha}{\int_m u(f_m, \rho_m)^\alpha \, dm}. \tag{OA.1}$$

Expert i chooses f_i to maximize

$$u_i^{ex}(\rho_i, f_i) = \frac{\mu_{ew}}{\mu_{ex}} \, n_i(\mathbf{f}) \, f_i,$$

which yields the optimal fee

$$f_i^* = \frac{1}{\alpha + 1} M(2\rho_i - 1).$$

Substituting f_i^*, an educated worker receives $u(f_i^*, \rho_i) = \frac{\alpha}{\alpha+1} M(2\rho_i - 1)$. Hence the interim expected payoff of an educated worker is

$$\begin{aligned}
\mathbb{E}[u_j^{ew} \mid a_j = E, c_j] &= \int_{\underline{\rho}}^{\overline{\rho}} \frac{1}{\overline{\rho} - \underline{\rho}} u(f_i^*, \rho_i) n_i(f) d\rho_i + b + A(\theta, \mu_{ex}, \mu_{ew}) \\
&= \frac{\alpha}{\alpha + 1} R(\alpha, M) + b + A(\theta, \mu_{ex}, \mu_{ew}),
\end{aligned}$$

while after matching, the expert's payoff is given by

$$u_i^{ex}(\rho_i, f_i | a_i = E, c_i) = \frac{\mu_{ew}}{\mu_{ex}} * n_i(f) * f_i + b + A(\theta, \mu_{ex}, \mu_{ew}).$$

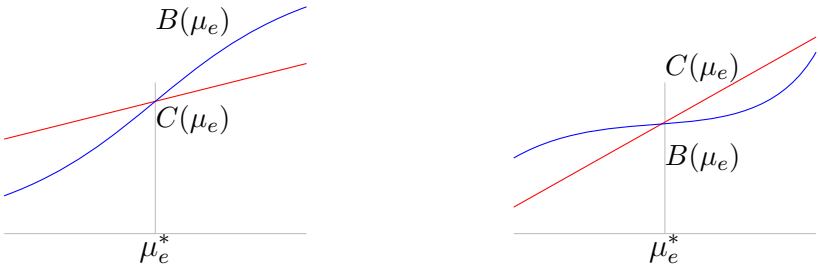
[35] Matching probabilities depend only on service quality (skill, expertise, and signal precision) and can be extended to two-sided heterogeneity. Suppose experts and workers draw types a_i and b_j, with only top agents becoming experts with probability $\eta p(\mu_e)$. A follower j derives utility $q_{i,j}(f_i, a_i, b_j) = a_i b_j - f_i$ from expert i, and matches according to density $n_{i,j}(\mathbf{f})$. One formulation,

$$n_{i,j}(\mathbf{f}) = \frac{q_{i,j}^\alpha(f_i, a_i, b_j)}{q_j(\mathbf{f})}, \qquad q_j(\mathbf{f}) = \int_i q_{i,j}^\alpha(f_i, a_i, b_j) \, di,$$

is generally intractable. An alternative,

$$n_{i,j}(\mathbf{f}) = \frac{q_{i,j}^\alpha(f_i, a_i, b_j)}{q(\mathbf{f})}, \qquad q(\mathbf{f}) = \int_i \int_j q_{i,j}^\alpha(f_i, a_i, b_j) \, dj \, di,$$

retains tractability while capturing search frictions, yielding aggregate demand $n_i(\mathbf{f}) = \int_j n_{i,j}(\mathbf{f}) \, dj$.



(a) Unstable Equilibrium (b) Stable Equilibrium

Figure OA.1: Equilibrium Refinement

which further implies that the interim expected payoff of an expert is

$$\mathbb{E}[u_i^{ex} \mid a_i = E, c_i] = \frac{\mu_{ew}}{\mu_{ex}} \frac{R(\alpha, M)}{\alpha + 1} + b + A(\theta, \mu_{ex}, \mu_{ew}),$$

where

$$R(\alpha, M) = M \frac{\alpha + 1}{\alpha + 2} \frac{(2\bar{\rho} - 1)^{\alpha+2} - (2\underline{\rho} - 1)^{\alpha+2}}{(2\bar{\rho} - 1)^{\alpha+1} - (2\underline{\rho} - 1)^{\alpha+1}}$$

denotes the expected investment surplus.

OA.3 Equilibrium Stability

We study local equilibrium stability under small perturbations in beliefs, as defined in Definition 2. An equilibrium is stable if small belief deviations induce agent responses that restore the original belief, implying mean reversion. When $p(\cdot)$ is continuously differentiable, this condition reduces to $D'(\mu_e^*) < 0$.

Figures OA.1a and OA.1b contrast unstable and stable equilibria. In the unstable case, the expected benefit of education for the cutoff type $c_i = \mu_e$ exceeds the opportunity cost when $\mu_e > \mu_e^*$ and falls short when $\mu_e < \mu_e^*$,[36] so any local deviation is amplified. By contrast, in the stable case, deviations reverse incentives on the margin, inducing belief adjustments that return μ_e to μ_e^*.

Imposing local stability yields two implications. First, equilibrium multiplicity may persist, but equilibria with $D'(\mu_e^*) \geq 0$ are eliminated—for example, ruling out μ_e^1 in Example 1 when $u_0 \in (2, \frac{14}{5})$. Second, monotonicity on the intensive margin holds more generally, since only mean-reverting equilibria remain.

OA.4 Influencer Variety and Platform Design

Introducing influencer variety into entertainment utility clarifies additional welfare distortions under endogenous platform design. For tractability, we set $c_I = 0$ and assume

$$u_0 = H(k)\psi(\mu_{in}), \qquad \psi(0) = 0, \quad \psi'(\mu_{in}) > 0.$$

[36] The cutoff $c_i = \mu_e$ follows from the consistency requirement.

We first establish that both algorithmic intensity and influencer monetization incentives reduce aggregate education in equilibrium.

Proposition A.1 (Algorithmic intensity, influencer share, and aggregate education)**.** *Consider any stable equilibrium with interior mixing (i.e., $D(\mu_e) = 0$). Then:*

(i) $\partial\mu_e/\partial k < 0$ *for any fixed* β_M*; and*

(ii) $\partial\mu_e/\partial\beta_M \leq 0$ *for any fixed* k*.*[37]

Welfare distortions. We compare platform design to a social planner. Let (k^{pl}, β_M^{pl}) denote a platform optimum and (k^{sp}, β_M^{sp}) a planner's choice under a stable interior-mixing equilibrium.

Algorithmic intensity. In general, $k^{pl} \geq k^{sp}$. The platform's marginal payoff from increasing k is

$$\frac{\partial\Pi}{\partial k} = \lambda(1-\beta_M)\left(\frac{\partial u_0}{\partial k}\mu_{if} + u_0\frac{\partial\mu_{if}}{\partial k}\right) > 0,$$

where $\partial u_0/\partial k > 0$ and $\partial\mu_{if}/\partial k > 0$ follow from Proposition A.1. Hence, absent convex costs, the platform selects the maximal feasible intensity.

By contrast, the planner's marginal welfare effect is

$$\frac{\partial W}{\partial k} = (1-\beta)\frac{\partial u_0}{\partial k} + \mu_e^*\frac{\partial\mu_e^*}{\partial k} - \lambda\beta_M\left(\frac{\partial u_0}{\partial k}\mu_{if} + u_0\frac{\partial\mu_{if}}{\partial k}\right).$$

While the first term captures higher follower amusement, the latter two terms are negative: higher k crowds out education and amplifies monetization distortions. Since $\partial\mu_e^*/\partial k < 0$, the planner internalizes an educational loss ignored by the platform. For sufficiently strong monetization incentives (λ large), low follower surplus share ($(1-\beta)$ small), or strong educational resonance, the planner optimally chooses a strictly lower k, potentially $k^{sp} = 0$.

Influencer monetization incentives. A similar divergence arises for β_M. The platform's marginal profit effect is

$$\frac{\partial\Pi}{\partial\beta_M} = -\lambda u_0\mu_{if} + (1-\beta_M)\lambda\mu_{if}\frac{\partial u_0}{\partial\beta_M} + (1-\beta_M)\lambda u_0\frac{\partial\mu_{if}}{\partial\beta_M}.$$

Raising β_M reduces the platform's revenue share but may increase influencer variety and expand the influence market. When variety effects dominate, the platform favors a higher β_M, though $\beta_M < 1$ is always interior since marginal gains vanish as $\beta_M \to 1$.

The planner's marginal welfare effect is

$$\begin{aligned}\frac{\partial W}{\partial\beta_M} = &-\lambda u_0\mu_{if} - \beta_M\lambda\mu_{if}\frac{\partial u_0}{\partial\beta_M} - \beta_M\lambda u_0\frac{\partial\mu_{if}}{\partial\beta_M} \\ &+ (1-\beta)\frac{\partial u_0}{\partial\beta_M} + \mu_e^*\frac{\partial\mu_e^*}{\partial\beta_M}.\end{aligned}$$

[37] The result can be shown by mimicking the proof of Proposition 4.

Unlike the platform, the planner does not value monetization income, which is a pure transfer, but places weight on education. Since $\partial\mu_e^*/\partial\beta_M \leq 0$, higher influencer shares crowd out aggregate education, offsetting any gains from amusement or variety.

This difference is transparent from the decomposition

$$W = \Pi + (1-\beta)u_0 + \tfrac{1}{2}(\mu_e^*)^2 - \lambda E(u_0, \mu_{if}),$$

which shows that the planner trades off follower surplus against educational losses and monetization distortions absent from the platform's objective. When education resonance and monetization incentives are strong, the platform optimally selects a more aggressive influencer share, implying $\beta_M^{pl} > \beta_M^{sp}$.

Implications. Combining Proposition A.1 with the above comparisons yields $\mu_e^{pl} < \mu_e^{sp}$ when follower surplus is small, monetization incentives are strong, and educational resonance is pronounced. Relative to the baseline case in Proposition 4, influencer variety sharpens the institutional misalignment: the platform simultaneously chooses excessive algorithmic intensity and overly generous influencer incentives. Both distortions reinforce educational crowding out, leading to inefficient outcomes in the education and influencer labor markets.

OA.5 Simultaneous Education & Influence Choices

This section considers a robustness exercise in which agents simultaneously choose among "acquiring education" (E), "acquiring influence" (I) and "doing nothing" ($\varnothing$), i.e., $a_i \in \{E, I, \varnothing\}$. Compared to the baseline setup, we do not allow ex-post switching, i.e., agents cannot acquire influence after educational outcomes are revealed.

Observe first that $\mu_e^* < 1$. Assume that $\mu_e^* = 1$ if this were not the case. Then, as long as $\beta u_0 \neq 0$, there exists a measure of $(1-\eta)\mu_e^* > 0$ of uneducated followers, resulting in an unbounded return for becoming an influencer. Given this observation, there are three possible cases, including: (i) $\mu_e^* > \eta b$ and $U_i(I|c_i) = U_i(\varnothing|c_i) = U_i(E|c_i)$; (ii) $\mu_e^* > \eta b$ and $U_i(I|c_i) = U_i(E|c_i) > U_i(\varnothing|c_i)$; and (iii) $\mu_e^* = \eta b$ and $U_i(I|c_i) = U_i(\varnothing|c_i) > U_i(E|c_i)$. Note that cases (i) and (iii) coincide with those of the baseline model.

Next, we characterize the equilibrium. For simplicity, we assume that $b = 0$ and $A = 0$.

Lemma A.3. *(i) If* $\sup_{\mu_e\in[0,1]} D(\mu_e) < 0$, $\mu_e^* = 0$ *is the unique equilibrium, and* μ_{in}^* *and* μ_{if}^* *satisfy Eq. (12) and (13);*

(ii) If $\inf_{\mu_e\in[0,1]} D(\mu_e) > 0$, *all potential equilibrium* μ_e^* *satisfy that*

$$D(\mu_e^*) + (1-\beta)u_0 = \frac{(1-\eta) * \mu_e^*}{(1-\mu_e^*)} * \beta u_0 - c_I \tag{OA.2}$$

and $\mu_{in}^* = (1-\mu_e^*)$ *and* $\mu_{if}^* = (1-\eta) * \mu_e^*$.

(iii) If $\sup_{\mu_e\in[0,1]} D(\mu_e) \geq 0 \geq \inf_{\mu_e\in[0,1]} D(\mu_e)$, *all* $\mu_e^* < 1$ *satisfying* $D(\mu_e^*) = 0$ *and* $\frac{(1-\eta)\mu_e^*}{(1-\mu_e^*)} * \beta u_0 - c_I \leq (1-\beta)u_0$, *together with* μ_{in}^* *and* μ_{if}^* *satisfying Eq.s (12) and (13), forms a potential equilibrium.*

Furthermore, for all $\mu_e^* < 1$ such that $D(\mu_e^*) > 0$, any μ_e^* that satisfies Eq. (OA.2) also forms a potential equilibrium. If $D(0) < 0$, $\mu_e^* = 0$, together with Eq. (12), also constitutes an equilibrium. Lastly, a potential equilibrium $\mu_e^* > 0$ forms an equilibrium when $(\alpha \wedge (1/p(\mu_e^*) - 1) * \frac{R(\alpha,M)}{\alpha+1} \geq (1-\beta)u_0$ holds; otherwise, if this is violated for all potential equilibrium $\mu_e^* > 0$, $\mu_e^* = 0$.

An interesting observation is that a high entry cost c_I may increase total welfare. To see this, by Eq. (OA.2), we can compute total welfare $\tilde{W}$ as: $\widetilde{W} = D(\mu_e^*) + (1-\beta)u_0 + \frac{1}{2}(\mu_e^*)^2$.[38] With Eq. (14), we can further compute the effect of c_I on the total welfare as:

$$\frac{d\widetilde{W}}{dc_I} = \frac{d\widetilde{W}}{d\mu_e^*}\frac{d\mu_e^*}{dc_I} = (\mu_e^* + D'(\mu_e^*)) * \frac{d\mu_e^*}{dc_I} = \big((\mu_e^* - 1) - \eta R(\alpha, M)p'(\mu_e^*)\big)\frac{d\mu_e^*}{dc_I} \tag{OA.3}$$

Furthermore, by differentiating over Eq. (OA.2), we get

$$\frac{d\mu_e^*}{dc_I} = \frac{1}{-D'(\mu_e^*) + \frac{(1-\eta)}{(1-\mu_e^*)^2}} \tag{OA.4}$$

To understand the implication of Lemma A.3 , we first consider a large c_I such that $\mu_e^* \to 1$. Then, by Eq. (OA.4), we have $\frac{d\mu_e^*}{dc_I} > 0$, and thus $\frac{d\widetilde{W}}{dc_I} \to -\eta R(\alpha, M)p'(1)\frac{d\mu_e^*}{dc_I} > 0$, i.e., total welfare strictly increases in influencer training cost c_I.[39] The intuition is as follows. If ex-post switching is allowed, it is best for all agents to obtain education when $D(\mu_e) > 0$ for all $\mu_e \in [0, 1]$. Rather, when ex post switching is prohibited, a positive proportion of agents always opt to gain influence in the simultaneous game in anticipation of a missing market. However,when the return on investment is high, it is costly to acquire influence ex ante. Therefore, the higher the influencer entry cost, the higher the total welfare. In summary, this extension gives two insights. First, equilibrium multiplicity and thus anti-intellectualism influence still ensue.[40] Second, a sufficiently large influencer training cost may improve total welfare.

OA.6 A Second Chance at Education

Here, we allow for two rounds of education, in which agents can choose to acquire education, acquire influence, or do nothing. It turns out that every equilibrium in our baseline model is also an equilibrium in this extended setup with two rounds of education.

Lemma A.4. *Every equilibrium in the baseline model is also a SPNE in the extended setup with two rounds of education.*

This suggests that our baseline model holds in more general setups, and the key reasons behind this include the complementarity in education acquisition among agents and the ex post free entry

[38]Note that $U_i(E|c_i = \mu_e^*) = D(\mu_e^*) + (1-\beta)u_0$, which also equals $U_i(I|c_i = \mu_e^*) = \frac{(1-\eta)*\mu_e^*}{(1-\mu_e^*)} * \beta u_0 - c_I$. All agents who acquire influence get a payoff of $U_i(I|c_i = \mu_e^*)$, and an agent of type $c_i \leq \mu_e^*$ gets a payoff of $U_i(E|c_i) = U_i(E|c_i = \mu_e^*) + (\mu_e^* - c_i)$ from acquiring education. By integrating over c_i and utilizing the equilibrium property that all agents with $c_i \leq \mu_e^*$ acquires education and those with $c_i > \mu_e^*$ acquire influence, we get the total welfare formula $\widetilde{W}$.

[39]Note that when c_I is relatively small, the relation between the influencer training cost and the total welfare can still be non-monotonic.

[40]This holds whenever $D(\mu_e^*) = 0$ admits multiple solutions, or there exists $\mu_e^* > 0$ such that $D(\mu_e^*) = 0$ and $D(0) < 0$, with a proper upper bound condition imposed on β.

in the influencer market. However, there might also be other equilibrium(s) in this game with two rounds of education. For example, there might exist an equilibrium in which $\mu_{e,1} = \mu_{e,2}$ because agents are infinitesimal and their price-taking behavior means that they are indifferent between acquiring education in either rounds.

OA.7 Mixed Strategy Equilibrium

Unlike the baseline model, we now consider mixed strategy equilibria in which a fraction of experts switch to following influencers when the pool of educated workers is insufficient for investment. Formally, given $\mu_e \in [0,1]$ and assume that $A = 0$, we posit the following strategy: (i) if the participation constraint for experts (i.e., Eq. (6)) holds, all experts remain in investment; (ii) otherwise, a fraction $(1-\delta)$ of experts follow influencers until

$$\frac{1-p(\mu_e)}{\delta p(\mu_e)} \cdot \frac{R(\alpha, M)}{\alpha+1} = (1-\beta)u_0. \tag{OA.5}$$

A key distinction from the baseline is that investment never collapses solely because experts are under-compensated. Define $\hat{\mu}_e$ such that Eq. (6) holds with equality,

$$\frac{1-p(\hat{\mu}_e)}{p(\hat{\mu}_e)} \cdot \frac{R(\alpha, M)}{\alpha+1} = (1-\beta)u_0,$$

and focus on $\hat{\mu}_e > \eta b$ so that experts' incentive compatibility is nontrivial. Set $\hat{\mu}_e = 1$ if

$$\frac{1-p(1)}{p(1)} \cdot \frac{R(\alpha, M)}{\alpha+1} < (1-\beta)u_0.$$

For $\mu_e \geq \hat{\mu}_e$, $U_i(E|c_i)$ is unchanged, and $D(\mu_e)$ follows Eq. (14). For $\mu_e < \hat{\mu}_e$,

$$U_i(E|c_i) = -c_i + \eta b + \eta(1-p)R(\alpha, M) + (1-\eta+\eta p)(1-\beta)u_0,$$

and we define $\widetilde{D}(\mu_e) := U_i(E|c_i = \mu_e) - U_i(\varnothing|c_i = \mu_e)$ and thus:

$$\widetilde{D}(\mu_e) = \eta b + \eta(1-p(\mu_e))\left(\frac{\alpha R(\alpha, M)}{\alpha+1} - (1-\beta)u_0\right) - \mu_e, \quad \text{for} \quad \mu_e < \hat{\mu}_e. \tag{OA.6}$$

Correspondingly, the following identity holds, analogous to Eq. (13):

$$\mu_{if} + \mu_{in} = (1-\delta)\eta p(\mu_e)\mu_e + (1-\eta)\mu_e + (1-\mu_e). \tag{OA.7}$$

Lemma A.5 (Mixed Strategy Equilibrium)**.** *Assume $\eta b \ll 1$ and $p(\cdot)$ is continuous.*

(i) If $\alpha R(\alpha, M)/(\alpha+1) < (1-\beta)u_0$, then $\mu_e^* = \eta b$.

(ii) If $\alpha R(\alpha, M)/(\alpha+1) \geq (1-\beta)u_0$ and $\hat{\mu}_e = 1$: (1) any $\mu_e^* < 1$ such that $\widetilde{D}(\mu_e^*) = 0$ is an equilibrium; (2) if $\widetilde{D}(1) \geq 0$, then $\mu_e^* = 1$ is also an equilibrium.

(iii) If $\alpha R(\alpha, M)/(\alpha+1) \geq (1-\beta)u_0$ and $\hat{\mu}_e < 1$: (1) any $\mu_e^* < \hat{\mu}_e$ such that $\widetilde{D}(\mu_e^*) = 0$ is an equilibrium; (2) any $\mu_e^\dagger \geq \hat{\mu}_e$ such that $D(\mu_e^\dagger) = 0$ is an equilibrium; (3) if $D(1) \geq 0$, then $\mu_e^\dagger = 1$ is also an equilibrium.

Moreover, δ, μ_{if}^*, and μ_{in}^* are jointly determined by Eqs. (OA.5), (12), and (OA.7).
Finally, all asymmetric equilibria are outcome-equivalent to the mixed-strategy equilibria.

Analogous to Proposition 1, Lemma A.5 characterizes both mixed-strategy and asymmetric equilibria, and establishes the possibility of multiple equilibria.

Corollary A.1. *Suppose: (1) $p(\cdot)$ is continuous; (2) $\alpha R(\alpha, M)/(\alpha+1) \geq (1-\beta)u_0$; (3) $\hat{\mu}_e \in (\eta b, 1)$; (4) $\inf_{\mu_e \in (\eta b, \hat{\mu}_e)} \widetilde{D}(\mu_e) < 0$; and (5) $\sup_{\mu_e > \hat{\mu}_e} D(\mu_e) > 0$. Then there exist at least two equilibria: $\mu_e^* \in (\eta b, \hat{\mu}_e)$ and $\mu_e^\dagger > \hat{\mu}_e$.*

Conditions (1)–(3) ensure that the participation constraint for educated workers is satisfied and exclude trivial cases. Condition (4) guarantees that agents with $c_i > \eta b$ abstain from education under pessimistic beliefs $\mu_e \in (\eta b, \hat{\mu}_e)$, anticipating some experts' exit from the investment market. Condition (5) ensures the existence of an equilibrium in which all experts remain in the investment market.

OA.8 Endogenous Labor Wages

This section introduces endogenous labor payoffs for experts. Educated workers and experts earn wages w_1 and w_2, determined in an external labor market. We assume $w_1 = b_1 > 0$ and

$$w_2(\rho_i, \mu_{ex}) = \frac{b_2}{\mu_{ex}} \frac{\rho_i}{\mathbb{E}[\rho_i]}. \tag{OA.8}$$

Educated workers earn a uniform wage, while experts' wages increase in ability ρ_i and decrease in the mass of experts μ_{ex}. As in the baseline model, experts decide whether to enter investment before observing their ability. The baseline case corresponds to $w_1 = w_2 = b$.

An expert receives a wage of $\mathbb{E}[w_2 \mid \mu_{ex}] = b_2/\mu_{ex}$. Then, the term ηb in (10) is replaced by

$$\eta p(\mu_e) \frac{b_2}{\mu_e} + \eta(1 - p(\mu_e))b_1.$$

Abstracting from network effects ($\theta = 0$), define

$$\widehat{D}(\mu_e) := \frac{b_2}{\mu_e} + \eta(1 - p(\mu_e))b_1 + \eta(1 - p(\mu_e))R(\alpha, M) - \big(\eta(1-\beta)u_0 + \mu_e\big). \tag{OA.9}$$

Let

$$\underline{\mu} := \sup\left\{\mu_e \in [0,1] : \frac{b_2}{\mu_e} + \eta(1 - p(\mu_e))b_1 \geq \mu_e\right\},$$

the highest education level consistent with collapse of the investment market, and assume $\underline{\mu} < 1$.

Lemma A.6 (Equilibrium Education)**.** *In equilibrium, μ_e^* satisfies:*

(i) If $\big(\alpha \wedge (1/p(1) - 1)\big)\frac{R(\alpha,M)}{\alpha+1} < (1-\beta)u_0$, then $\mu_e^* = \underline{\mu}$ uniquely.

(ii) If $\big(\alpha \wedge (1/p(1) - 1)\big)\frac{R(\alpha,M)}{\alpha+1} \geq (1-\beta)u_0$, then any $\mu_e^* \in [\underline{\mu}, 1]$ satisfying

$$\widehat{D}(\mu_e^*) = 0 \quad \textit{and} \quad \big(1/p(\mu_e^*) - 1\big)\frac{R(\alpha, M)}{\alpha + 1} \geq (1-\beta)u_0$$

is an equilibrium. If $\widehat{D}(1) \geq 0$*, then* $\mu_e^* = 1$ *is also an equilibrium. If* $\big(\alpha \wedge (1/p(\underline{\mu}) - 1)\big)\frac{R(\alpha,M)}{\alpha+1} < (1-\beta)u_0$*, then* $\mu_e^* = \underline{\mu}$ *remains an equilibrium.*

Equilibrium multiplicity may arise. Define

$$\widehat{\mu}_e := \inf\left\{\mu_e \in [0,1] : \big(\alpha \wedge (1/p(\mu_e) - 1)\big)\frac{R(\alpha,M)}{\alpha+1} \geq (1-\beta)u_0\right\}.$$

Corollary A.2. *Suppose* $\underline{\mu} < 1$*,* $\widehat{\mu}_e < 1$*, and* $\big(\alpha \wedge (1/p(1) - 1)\big)\frac{R(\alpha,M)}{\alpha+1} \geq (1-\beta)u_0$*. Then there exist at least two equilibria,* $\mu_e^* = \underline{\mu}$ *and some* $\mu_e^* > \underline{\mu}$*, if either:*

(i) $\widehat{D}(\mu_e) \geq 0$ *for all* $\mu_e \geq \underline{\mu}$ *and* $\widehat{\mu}_e > \underline{\mu}$*; or*

(ii) $\widehat{D}(\underline{\mu}) < 0$ *and* $\widehat{D}(\mu_e) \geq 0$ *for some* $\mu_e \in [\widehat{\mu}_e, 1]$*.*

Corollary A.2 is immediate. Case (i) captures belief-driven exit: with low search frictions, experts leave under pessimistic beliefs but remain under optimistic ones, despite high education returns absent breakdown. Case (ii) highlights complementarity-driven multiplicity when $p(\mu_e)$ rises sharply around $\widehat{\mu}_e$. Two remarks follow. First, higher outside wages ($b_1 \uparrow$, $b_2 \uparrow$) shrink the multiplicity region by strengthening education incentives even without expert-led investment, mirroring the role of b in the baseline model. Second, since labor-market welfare is taken as exogenous, welfare comparisons remain partial equilibrium.

OA.9 Vertical Labor Sorting

This section studies vertical labor sorting. Agents with more successful educational outcomes possess strictly stronger labor skills and can therefore switch to jobs requiring weaker credentials. In particular, experts may switch to investing as educated followers or to following influencers, whereas the reverse is infeasible. This contrasts with the baseline model of horizontal sorting, where experts cannot invest as educated followers. Two implications follow. First, higher educational attainment endogenously yields higher payoffs through vertical skill classification. Second, market breakdown does not arise from experts' participation constraints, as experts can always switch to investing.

Set $b = 0$ and $A(\theta, \mu_{ex}, \mu_{ew}) = 0$. Educated followers do not switch to following influencers if

$$\frac{\alpha}{\alpha+1}R(\alpha,M) \geq (1-\beta)u_0.$$

Similarly, experts do not mimic educated followers if

$$\frac{\mu_{ew}}{\mu_{ex}}\frac{R(\alpha,M)}{\alpha+1} \geq \frac{\alpha}{\alpha+1}R(\alpha,M). \tag{OA.10}$$

When no expert switches, $\mu_{ew}/\mu_{ex} = (1-p(\mu_e))/p(\mu_e)$, implying $p(\mu_e) \leq 1/(\alpha+1)$.

If instead $p(\mu_e) > 1/(\alpha+1)$, a positive measure of experts switches to investing. Let $(1-\delta)$ denote the fraction of experts who switch. The remaining mass of experts is $\delta\,\eta p(\mu_e)\mu_e$, implying

$$\frac{\mu_{ew}}{\mu_{ex}} = \frac{1}{\delta}\left(\frac{1}{p(\mu_e)} - 1\right) + \frac{1-\delta}{\delta}.$$

Switching continues until (OA.10) binds, or equivalently,

$$\frac{1}{\delta}\left(\frac{1}{p(\mu_e)}-1\right)+\frac{1-\delta}{\delta}=\alpha. \tag{OA.11}$$

For any μ_e satisfying $p(\mu_e) > 1/(\alpha+1)$, a sufficiently small δ solves (OA.11).

When experts switch to investing, the expected payoff from acquiring education is

$$U_i(E \mid c_i) = \eta\frac{\alpha}{\alpha+1}R(\alpha, M) + (1-\eta)(1-\beta)u_0 - c_i.$$

Imposing consistency, $c_i = \mu_e$, yields the payoff gap

$$\tilde{D}(\mu_e) = \eta R(\alpha, M)\left((1-p(\mu_e)) \vee \frac{\alpha}{\alpha+1}\right) - \big(\eta(1-\beta)u_0 + \mu_e\big), \tag{OA.12}$$

where $x \vee y \equiv \max\{x, y\}$.

If $p(0) \leq 1/(\alpha+1)$, then $p(\mu_e) < 1/(\alpha+1)$ for all μ_e, implying $\tilde{D}(\mu_e) = D(\mu_e)$. Define

$$\hat{\mu}_e = \eta\left(\frac{\alpha}{\alpha+1}R(\alpha, M) - (1-\beta)u_0\right) \wedge 1.$$

When $p(\hat{\mu}_e) > 1/(\alpha+1)$, $\hat{\mu}_e$ constitutes an equilibrium with a positive measure of experts switching to investing.

Lemma A.7 (Vertical Labor Sorting)**.** *Assume $p(\cdot)$ is continuous on $[0,1]$. Then:*

(i) If $\frac{\alpha}{\alpha+1}R(\alpha, M) < (1-\beta)u_0$, the unique equilibrium is $\mu_e^* = 0$.

(ii) If $\frac{\alpha}{\alpha+1}R(\alpha, M) \geq (1-\beta)u_0$ and $\inf_{\mu_e}\tilde{D}(\mu_e) > 0$, then $\mu_e^* = 1$.

(iii) If $\frac{\alpha}{\alpha+1}R(\alpha, M) \geq (1-\beta)u_0$ and $p(\hat{\mu}_e) > 1/(\alpha+1)$, then $\hat{\mu}_e$ is an equilibrium with expert switching.

(iv) If $\frac{\alpha}{\alpha+1}R(\alpha, M) \geq (1-\beta)u_0$, any μ_e^* solving $\tilde{D}(\mu_e^*) = 0$ with $p(\mu_e^*) \leq 1/(\alpha+1)$ is an equilibrium.

Given μ_e^*, μ_{in}^* and μ_{if}^* satisfy (12) *and* (13)*.*

Lemma A.7 fully characterizes equilibria under vertical sorting. Education markets do not break down under perfect search, as experts can always switch to investing and secure a lower bound on payoffs.

If $\tilde{D}'(\mu_e) < 0$, monotonicity on the intensive margin holds: $\mathrm{d}\mu_e^*/\mathrm{d}u_0 \leq 0$. Define

$$\underline{u}_0 = \inf\{u_0 : \inf_{\mu_e}\tilde{D}(\mu_e) \leq 0\}, \qquad \bar{u}_0 = \frac{\alpha R(\alpha, M)}{(\alpha+1)(1-\beta)}.$$

Assuming $\inf_{\mu_e}\tilde{D}(\mu_e) > 0$ at $u_0 = 0$, total welfare is

$$W = \begin{cases} \eta\Big((1-p(1)) \vee \frac{\alpha}{\alpha+1}\Big) R(\alpha, M) + (1-\eta)(1-\beta)u_0 - \frac{1}{2}, & u_0 \leq \underline{u}_0, \\ \frac{1}{2}(\mu_e^*)^2 + (1-\beta)u_0, & \underline{u}_0 < u_0 \leq \bar{u}_0, \\ (1-\beta)u_0, & u_0 > \bar{u}_0. \end{cases}$$

Proposition A.2. *If* $\mathrm{d}\mu_e^*/\mathrm{d}\alpha \geq 0$*, total welfare increases in the search-friction parameter* α*.*

Proposition A.2 contrasts with the baseline model: reducing search frictions always improves welfare. The nonmonotonic welfare–search-friction relationship in Proposition 6 arises from expert-side market breakdown. Allowing experts to invest eliminates this participation constraint and removes the source of inefficiency.

OA.10 Skipped Proofs in the Appendix

OA.10.1 Proof of Lemma A.1

Proof. First, we come to show that for all $\alpha \geq 0$ and $x > 1$,

$$(x^{\alpha+1}-1)(x^{\alpha+2}-1) > (\alpha+1)(\alpha+2)x^{\alpha+1}(x-1)\log(x) \tag{OA.13}$$

To show this inequality, we first prove the following inequality

$$x^{\alpha+2}-1 > (\alpha+2) * x^{\frac{\alpha+1}{2}}(x-1) \tag{OA.14}$$

To see this, we define $J_1(x) = (x^{\alpha+2}-1) - (\alpha+2)x^{\frac{\alpha+1}{2}}(x-1)$. Obviously, $J_1(1) = 0$ and $J_1'(x) = (\alpha+2)x^{\frac{\alpha+1}{2}}J_2(x)$, where $J_2(x) = x^{\frac{\alpha+1}{2}} - 1 - \frac{(x-1)}{x} * \frac{\alpha+1}{2}$. Then, note that $J_2(1) = 0$ and for all $x > 1$, $J_2'(x) = \frac{\alpha+1}{2}x^{-2} * (x^{\frac{\alpha+1}{2}+1} - 1) > 0$, which implies that $J_2(x) > 0$ and $J_1'(x) > 0$ for all $x > 1$. Combined with $J_1(1) = 0$, we have $J_1(x) > 0$ for all $x > 1$. Similarly, we can show that $(x^{\alpha+1}-1) > (\alpha+1) * x^{\frac{\alpha}{2}}(x-1)$.

Define $J_3(x) = (x-1) - \log(x)\sqrt{x}$. Then, using Eq. (OA.14), we get

$$(x^{\alpha+1}-1)(x^{\alpha+2}-1) - (\alpha+1)(\alpha+2)x^{\alpha+1}(x-1)\log(x) \;=\; (\alpha+1)(\alpha+2)(x-1)x^{\alpha}J_3(x)$$

We can show that $J_3(x) > 0$ for all $x > 1$. To see it, note that $J_3(1) = 0$, and that

$$J_3'(x) = \frac{\sqrt{x} - 1 - \log(x)/2}{\sqrt{x}} \overset{\mathrm{x=t^2}}{=} \frac{t - 1 - \log(t)}{t} > 0$$

because it is easy to verify that $(t-1) - \log(t) > 0$ for all $t > 1$.

Second, by definition, $R(\alpha, M) = M * \frac{(\alpha+1)}{(\alpha+2)} * \frac{p^{\alpha+2}-q^{\alpha+2}}{p^{\alpha+1}-q^{\alpha+1}}$, where $p = 2\bar{\rho} - 1 > 2\underline{\rho} - 1 = q \geq \frac{1}{2}$. Furthermore, $\frac{dR(\alpha,M)}{d\alpha} \propto (x^{\alpha+1}-1)(x^{\alpha+2}-1) - (\alpha+1)(\alpha+2)x^{\alpha+1}(x-1)\log(x)$, where $x = p/q$. By Eq. (OA.13), we have $\frac{dR(\alpha,M)}{d\alpha} > 0$ for all α.

Third, $\frac{\alpha}{(\alpha+1)}R(\alpha, M)$ increases strictly in α because $\frac{\alpha}{(\alpha+1)}$ is positive and increases in α.

Fourth, we can directly differentiate $R(\alpha, M)/(\alpha+1)$ to get:

$$\frac{d}{d\alpha}\left(\frac{R(\alpha,M)}{\alpha+1}\right) \propto -\Big\{(p^{\alpha+1}-q^{\alpha+1})(p^{\alpha+2}-q^{\alpha+2}) + (2+\alpha)p^{\alpha+1}q^{\alpha+1}(p-q)(\log(p)-\log(q))\Big\}$$

and thus $\frac{d}{d\alpha}\left(\frac{R(\alpha,M)}{\alpha+1}\right) < 0$ because $p > q > 0$. □

OA.10.2 Proof of Lemma A.5

Proof. **Case (i).** All educated followers quit the investment market. Thus, $\mu_e^* = \eta b$.

Case (ii). First, note that $U_i(E|c_i) - U_i(\varnothing|c_i) = \widetilde{D}(\mu_e) + (\mu_e - c_i)$. Then, $\widetilde{D}(\mu_e^*) = 0$ implies that for all agents with $c_i \leq \mu_e^*$, $U_i(E|c_i) \geq U_i(\varnothing|c_i)$ and vice versa. The condition that $\hat{\mu}_e = 1$ guarantees that $U_i(E|c_i)$ is correctly specified. Furthermore, $\widetilde{D}(1) \geq 0$ implies that $U_i(E|c_i) - U_i(\varnothing|c_i) = \widetilde{D}(1) + (1 - c_i) > 0$ for all $c_i \leq 1$, so $\mu_e^* = 1$.

Case (iii). First, statement (1) follows from case (ii). Second, when $\mu_e \geq \hat{\mu}_e$, we have $U_i(E|c_i) - U_i(\varnothing|c_i) = D(\mu_e) + (\mu_e - c_i)$, and thus any $\mu_e^\dagger$ such that $D(\mu_e^\dagger) = 0$ forms an equilibrium because $U_i(E|c_i) - U_i(\varnothing|c_i) \geq 0$ only for $c_i \leq \mu_e^\dagger$. The condition that $\mu_e^\dagger \geq \hat{\mu}_e$ guarantees that $U_i(E|c_i)$ is correctly specified as in the baseline model. Third, when $D(1) > 0$ and $\hat{\mu}_e < 1$, this case is already proved in the baseline model. □

OA.10.3 Proof of Corollary A.1

Proof. Since $p(\cdot)$ is continuous, both $\widetilde{D}(\cdot)$ and $D(\cdot)$ are continuous in their own domains.

First, note that by Eq. (OA.6) and $\alpha R(\alpha, M)/(\alpha + 1) \geq (1 - \beta)u_0$, $\widetilde{D}(\eta b) \geq 0$. Furthermore, $\inf_{\mu_e \in (\eta b, \hat{\mu}_e)} \widetilde{D}(\mu_e) \geq 0$ means that $\widetilde{D}(\mu_e) < 0$ for some $\mu_e \in (\eta b, \hat{\mu}_e)$, and thus there exists some $\mu_e^* \in (\eta b, \hat{\mu}_e)$ such that $\widetilde{D}(\mu_e^*) = 0$. By Lemma A.5, this forms an equilibrium.

Second, by the assumed condition that $\sup_{\mu_e > \hat{\mu}_e} D(\mu_e) > 0$, there are two cases: (1) $\exists \mu_e^1, \mu_e^2 \in (\hat{\mu}_e, 1)$ such that $D(\mu_e^1)D(\mu_e^2) \leq 0$, implying the existence of $\mu_e^\dagger$ such that $D(\mu_e^\dagger) = 0$; or (2) $D(\mu_e) \geq 0$ for $\mu_e > \hat{\mu}_e$, implying that $D(1) \geq 0$. Thus, we can take $\mu_e^\dagger = 1$. Again, by lemma A.5, this forms an equilibrium. □

OA.10.4 Proof of Lemma A.3

Proof. **Case (i).** When $\sup_{\mu_e \in [0,1]} D(\mu_e) < 0$, then $U_i(E|c_i) < U_i(\varnothing|c_i) = (1-\beta)u_0$ for all $c_i \in [0, 1]$. Thus, $\mu_e^* = 0$. Furthermore, $\mu_{in}^* = \frac{\beta u_0}{c_I + u_0}$ and $\mu_{if}^* = 1 - \mu_{if}^*$.

Case (ii). When $\inf_{\mu_e \in [0,1]} D(\mu_e) > 0$, then $U_i(E|c_i) > U_i(\varnothing|c_i)$ for all $c_i \in [0, 1]$, and thus no agent chooses $a_i = \varnothing$. Furthermore, since $\mu_e^* < 1$, agents acquire only influence or education, and the indifference condition is given by Eq. (OA.2). Thus, $\mu_{in}^* = 1 - \mu_e^*$ and $\mu_{if}^* = (1 - \eta)\mu_e^*$.

Case (iii). By Proposition 1, a potential equilibrium must first satisfy $D(\mu_e^*) = 0$. The condition $\frac{\mu_e^*(1-\eta)}{(1-\mu_e^*)} * \beta u_0 - c_I \leq (1 - \beta)u_0$ ensures that we can find $\mu_{in}^* \leq (1 - \mu_e^*)$ such that

$$\frac{\mu_e^*(1 - \eta) + (1 - \mu_{in}^*)}{\mu_{in}} * \beta u_0 - c_I = (1 - \beta)u_0$$

Otherwise, $U_i(I|c_i = \mu_e^*) = \frac{\mu_{if}^*}{\mu_{in}^*} * \beta u_0 - c_I > (1 - \beta)u_0$. However, this contradicts $D(\mu_e^*) = 0$, i.e., $U_i(\varnothing|c_i = \mu_e^*) = U_i(E|c_i = \mu_e^*)$.

Furthermore, by case (ii), any solution μ_e^* to Eq. (OA.2) forms an equilibrium, as long as $D(\mu_e^*) > 0$. If $D(0) < 0$, then $U_i(\varnothing|c_i = \mu_e^*) > U_i(E|c_i = \mu_e^*)$ at $\mu_e^* = 0$ and no agent acquires education. Thus, $\mu_{in}^* = 1 - \mu_{if}^*$ satisfies Eq. (12).

Finally, to support $\mu_e^* > 0$, the condition $(\alpha \wedge (1/p(\mu_e^*) - 1) * \frac{R(\alpha,M)}{\alpha+1} \geq (1 - \beta)u_0$ guarantees that both experts and educated investors remain in the investment market. □

OA.10.5 Proof of Lemma A.4

Proof. We show that if $\mu_e^* > 0$ in the sequential game, it is also an equilibrium in the game with two rounds of education. To see this, construct an equilibrium in which $\tilde{\mu}_{e,1}^* = \mu_e^*$, $\tilde{\mu}_{e,2}^* = 0$, $\tilde{\mu}_{in,2} = \mu_{in}^*$ and $\tilde{\mu}_{in,1} = 0$. We specify that experts in round 1 are matched with educated investors in that round and leave the matching before the round 2 education starts. Under this specification, we can verify that for all $c_i \leq \mu_e^*$, it is optimal to acquire education in round 1 and delaying education acquisition to round 2 does not help and decreases the payoff by $D(\mu_{e,1}^*) - D(\mu_{e,2}^*) = \eta(p(0) - p(\mu_{e,1}^*))R(\alpha, M) > 0$. Furthermore, acquiring influence always leads to a payoff of $(1-\beta)u_0$ in both round 1 and round 2. All the remaining parts for equilibrium construction follow from the baseline model. □

OA.10.6 Proof of Lemma A.7

Proof. **Case (i).** All educated followers leave the investment market. Thus, $\mu_e^* = \eta b$.

Case (ii). If $\frac{\alpha}{\alpha+1}R(\alpha, M) \geq (1-\beta)u_0$ and $\inf_{\mu_e \in [0,1]} \tilde{D}(\mu_e) > 0$, then for any $\mu_e \leq 1$, it is always optimal for all agents to acquire education and thus $\mu_e^* = 1$.

Case (iii). If $\frac{\alpha}{\alpha+1}R(\alpha, M) \geq (1-\beta)u_0$ and $p(\hat{\mu}_e) > \frac{1}{\alpha+1}$, then $\frac{1}{p(\mu_e)} - 1 < \alpha$ at $\mu_e = \hat{\mu}_e$. Therefore, some experts will switch to follow influencers. By choosing an appropriate δ that satisfies Eq. (OA.5), all agents with $c_i \leq \hat{\mu}_e$ acquire education with a fraction of $(1-\delta)$ of experts switching to investing.

Case (iv). By Eq. (OA.12), any solution such that $\tilde{D}(\mu_e^*) = 0$ and $p(\mu_e^*) \leq \frac{1}{\alpha+1}$ forms an equilibrium without experts switching to investing. □

OA.10.7 Proof of Proposition A.2

Proof. First, note that both $\underline{u}_0$ and $\bar{u}_0$ increase strictly in α because $R(\alpha, M)$ and $\frac{\alpha}{\alpha+1}$ increase strictly in α. Meanwhile, W is continuous at $u_0 = \underline{u}_0$, strictly increasing in μ_e^* for $\mu_e^* < 1$ and also strictly increasing in α when $\mu_e^* = 1$.

Then, consider any $\alpha_1 < \alpha_2$ and fix u_0. For $u_0 \leq \bar{u}_0(\alpha_1)$, then $u_0 \leq \bar{u}_0(\alpha_1) < \bar{u}_0(\alpha_2)$. By the observation stated above, we have $W(\alpha_2) \geq W(\alpha_1)$ since $\frac{d\mu_e^*}{d\alpha} \geq 0$.

For $\bar{u}_0(\alpha_1) < u_0 \leq \bar{u}_0(\alpha_2)$, $W(\alpha_2) = \frac{1}{2}(\mu_e^*(\alpha_2))^2 + (1-\beta)u_0 \geq (1-\beta)u_0 = W(\alpha_1)$.

Last, for $u_0 > \bar{u}_0(\alpha_2)$, $W(\alpha_2) = W(\alpha_1) = (1-\beta)u_0$. The proof concludes. □