Social Connectedness and Information Markets

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Abstract: This paper investigates information quality in a simple model of socially-connected information markets. Suppliers' payoffs derive from the fraction of consumers who see their stories. Consumers prefer to share and act only on high-quality information. Quality is endogenous and highest when social connectedness is neither too high nor too low. In highly-connected markets, low-quality stories are widely seen, giving suppliers little incentive to invest in quality. Increasing the volume of misinformation and increasing consumers' cost of tuning in to suppliers' broadcasts can each increase equilibrium information quality.

Keywords: social-media networks, news veracity, misinformation, wisdom of the crowd, plight of the crowd

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In September 2020, Facebook announced that users of its Messenger service would be limited to forwarding messages to only five people or groups at a time. Facebook explained, "limiting forwarding is an effective way to slow the spread of viral misinformation and harmful content that has the potential to cause real-world harm" (Facebook (2020)). But limiting sharing also reduces the spread of useful information and could therefore affect consumers and impact the incentives of bona-fide information suppliers.

To study the effect of such policies, we introduce a simple model of a socially-connected "information market." Suppliers produce decision-relevant information, which we call "stories." Each supplier decides whether to incur a cost to produce a high-quality story by, for example, verifying sources for a news article or testing a product for a social-influencer endorsement. Suppliers benefit when consumers view their stories, as when newspapers earn revenue from advertising accompanying their articles or when social influencers gain stature when their posts are viewed more widely. Each consumer can see stories directly from suppliers and from other consumers who they follow in a social network. Each consumer prefers to share and act only on stories that are sufficiently likely to be high quality. Consumers cannot directly observe story quality, but each consumer receives a partially-informative private signal about story quality. Consumers also make inferences about a story's quality based on how many neighbors have shared it.

We use this model to assess the equilibrium impact of consumers' "social connectedness," namely, how many others they follow. We also study how misinformation injected into the market from outside sources affects how much high-quality information is produced in equilibrium by bona-fide suppliers. Finally, we extend the model to explore how consumers' decisions to tune in to information suppliers directly, rather than rely on others to share stories, can impact equilibrium information quality, especially as social connectedness becomes very large.

We find that expected information quality is highest when social connectedness is neither very high nor very low. If consumers have few sharing links, adding connections increases equilibrium information quality because suppliers correctly anticipate that high-quality stories will be shared more frequently. But as consumers become very connected, suppliers' incentives to invest in quality decrease since low-quality stories also spread widely. In the limit as social connectedness goes to infinity, all stories are viewed with probability one and suppliers have no incentive to produce high-quality stories, an outcome we call the "plight of the crowd."

We then consider the impact of third-party misinformation on equilibrium outcomes. Adam Mosseri, the head of product development for Facebook's news feed, wrote in 2017 that "a lot of fake news is [produced by] spammers ... masquerading as legitimate news publishers" (Facebook (2017)). If consumers are unable to easily distinguish between legitimate and fake stories, misinformation producers become part of the information market. We model misinformation producers as low-quality information suppliers who operate alongside bona-fide suppliers. We find that a small amount of misinformation in an otherwise well-functioning market can ultimately induce bona-fide suppliers to produce a greater quantity of high-quality stories. With misinformation in the market, consumers' confidence in stories declines, and they become more judicious when deciding which stories to share. This enhanced information filtering by consumers increases bona-fide suppliers' incentive to invest in producing high-quality stories.

In an extension of our baseline model, we consider how equilibrium outcomes change when consumers choose how much to seek out information directly from suppliers, called "tuning in," rather than relying on others to share stories. Tuning in to a story is costly but a consumer benefits from having the option to share the story and to act on it even if no neighbor shares it. We show that each individual's incentive to tune in declines as others tune in more, i.e., consumers' tuning-in decisions are strategic substitutes. When the cost of tuning in is sufficiently low, each consumer is certain to view all stories in the limit as social connectedness goes to infinity. Suppliers therefore have no incentive to invest and equilibrium information quality is as low as it can possibly be. On the other hand, if tuning-in costs are very high, consumers find it optimal not to tune in and the information market is inactive, in the sense that no one views, shares, or acts on any story. Most interestingly, when tuning-in costs are in an intermediate range, the information market has positive levels of supplier investment and consumer activity even in the limit as each consumer follows infinitely many others. Each consumer's likelihood of tuning in decreases as social connections increase in number in such a way that the expected number of neighbors who tune in remains finite. Thus not all stories are seen, and suppliers have a non-vanishing incentive to invest in quality. Higher tuning-in costs can therefore mitigate the plight of the crowd.

The paper contributes to at least three bodies of literature:

Social learning, information transmission, and social connections. The demand side of our market specifies information transmission and social learning that is both similar to and different from other models. Consumers here receive private signals and rationally update beliefs about the quality of each story based on all their neighbors' sharing decisions. Unlike in the cascades literature (e.g., Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992)), consumers in the present paper observe multiple neighbors' independent sharing decisions in one round of social learning. Unlike much of the network literature on information diffusion (e.g., Acemoglu, Ozdaglar, and ParandehGheibi (2010) and Banerjee et al. (2013), with notable exceptions such as Bloch, Demange, and Kranton (2018) and Chatterjee and Dutta (2016)), consumers in our model *choose* whether or not to pass on information to their neighbors.

On the supply side, to the best of our knowledge, the present paper is the first to endogenize the "product" itself that spreads or diffuses through a social network.[1] Previous research studies the effect of social-network structure on other supplier decisions for a given product, such as relying on traditional versus word-of-mouth advertising (Galeotti and Goyal (2009)) or targeting consumers when launching a new product (Chatterjee and Dutta (2016), Bimpikis, Ozdaglar, and Yildiz (2016)).

Our simple model highlights how suppliers' incentives depend on social connectedness (the number of neighbors people have), abstracting from other aspects of network structure. The model captures the basic features of consumer information-sharing, that consumers both *filter* and *spread* information to their social contacts. These two forces together determine supplier incentives to invest in information quality.

Media markets. Much previous work on news markets studies media bias. In Gentzkow and Shapiro (2006), news suppliers benefit from having a reputation for accuracy and thus have an incentive to slant their news towards consumers' initial beliefs. In Besley and Prat (2006) and Gentzkow, Glaeser, and Goldin (2006), earning revenue from advertising, rather than a sponsor, reduces bias. In Ellman and Germano (2009), however, newspapers bias their news towards their advertisers. The present paper does not consider political slants or opposing views; consumers care only about story quality. A key finding is that when every consumer follows many others, all stories will be widely viewed regardless of quality, resulting in a low incentive to invest for suppliers "paid" for views. Our analysis thus serves as a jumping-off point for future research that examines the impact of media-market institutions and industrial organization when news stories travel broadly

[1] Many papers in diverse fields have examined how network structure impacts the decisions of a third party who cares about outcomes, e.g., a health authority deciding how best to control an epidemic (Peng et al. (2013)) or a supply-chain manager deciding how best to operate its warehouses (Beamon and Fernandes (2004)). The idea of endogenizing what passes through the network is rarely explored in these literatures, but there are exceptions, e.g., Read et al. (2015) on endogenous pathogen virulence and Bimpikis, Fearing, and Tahbaz-Salehi (2018) on upstream sourcing in a supply chain.

via social connections.[2]

Misinformation. In 1923, the Soviet Union launched the first modern black-propaganda office, with the aim of "manipulating a nation's intelligence system through the injection of credible but misleading data" (Safire (1989)), a tactic Joseph Stalin dubbed "dezinformatsiya (disinformation)" (Manning and Romerstein (2004)). State-sponsored disinformation efforts now abound and are often online. Consumers encounter false news from other sources as well, including individuals and social bots who spread conspiracy theories on social media and in memes.[3]. The World Economic Forum has listed digital misinformation in online social media as one of the main threats to society (Howell (2013a,b)). At the same time, scholars have found that misinformation may have limited impact. Allcott and Gentzkow (2017) estimate that on average American adults only saw a few fake news stories in the run up to the 2016 United States presidential election, and Nyhan (2020) provides a critical analysis of how and why misinformation might or might not stick and affect voters' decisions.

Our theory suggests one reason why misinformation campaigns might not be as successful as anticipated a priori: consumers and suppliers change their behavior in the presence of misinformation. We find that a sufficiently large amount of misinformation always leads to equilibria in which bona-fide suppliers invest less, harming consumers who are ultimately less likely to share or act on any story. However, with smaller amounts

[2] Recent papers study other features of contemporary media markets, such as competition for consumers' limited attention (Chen and Suen (2018)), media bias when consumers have heterogeneous preferences and pass on news to like-minded individuals (Redlicki (2017)), consumer echo chambers which emerge from choices to pay attention directly to biased media sources or to like-minded friends (Hu, Li, and Tan (2022)), and competition to break a story that leads to lower-quality news (Andreottola and de Moragas (2018)).

[3] A large and varied literature examines misinformation: how falsehoods and conspiracy theories spread differently than fact-based information on the Internet (del Vicario et al. (2016) and Vosoughi, Roy, and Aral (2018)); how exposure to misinformation can shape memory (Loftus (2005) and Zhu et al. (2010)); and how to identify misinformation and reduce its harmful impact (Qazvinian et al. (2011) and Shao et al. (2016)).

of misinformation, consumers respond by sharing stories more judiciously, which in turn gives bona-fide suppliers an incentive to invest more in quality. In some cases, this increased-investment effect can be large enough that consumers are better off when there is more misinformation.

The paper proceeds as follows. Section 1 presents the model of an information market. Section 2 characterizes all equilibria of the information-market game and studies the impact of social connectedness and misinformation on equilibrium outcomes. Section 3 examines an extension in which consumers choose how much to "tune in" to suppliers' broadcasts. The Conclusion outlines directions for further research.

1 Model: The Market for Information

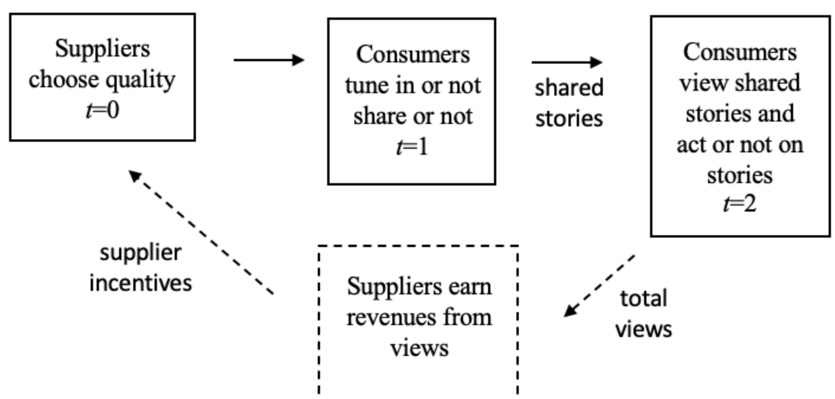

Figure 1: Illustration of the Information-Market Game

The information-market game proceeds in three phases, as shown in Figure 1. At time $t = 0$, suppliers each decide whether to produce and broadcast a high- or low-quality piece of decision-relevant information. For shorthand, we refer to a piece of information as a "story." A high-quality story is more costly to produce but contains factual claims which are sufficiently likely to be true that consumers would want to share the story with their neighbors and take an action based on it. At time $t = 1$, each consumer "tunes in" to an exogenous fraction τ of the suppliers' broadcasts. Consumers cannot directly observe a story's quality, but consumers can evaluate a story (modeled as receiving a private signal, details below) and decide whether to share the story with their followers in a social network, whereupon their followers also see the story. At time $t = 2$, each consumer who has seen a story makes an inference about its quality and decides whether to take a related action, such as voting in an election or purchasing a product. At the end of the game, each supplier receives a benefit, "revenue," equal to the fraction of consumers who have seen their story, while each consumer receives a payoff which depends on how many high- and low-quality stories they have shared and/or acted on.

Time $t = 0$: information production. There are S suppliers, each of whom has the opportunity to produce a story on a distinct topic and decides whether to invest in story quality. Each supplier's investment decision is unobservable to consumers, and suppliers cannot commit to invest in high quality or develop individual reputations for high-quality production.[4] The cost of producing a low-quality story is zero. The cost of a high-quality story is c, a privately-observed atomless random variable that is i.i.d. across suppliers with c.d.f. $F(\cdot)$, continuous p.d.f. $f(\cdot)$, and full support on $\mathbb{R}$; we refer to c as "investigation cost." For example, for a news reporter, c would include the cost of investigating and verifying information by interviewing multiple sources for an article; for a product endorsement by an influencer, c would include the cost of testing the product and verifying its features; and for a biomedical researcher, c would include the cost of

[4] Our analysis can be extended to allow for reputational costs. In particular, a supplier with reputational cost R of producing a low-quality story will act as if their cost of producing a high-quality story is $c - R$, shifting down the distribution of supplier costs and increasing their ex ante likelihood of being "intrinsically motivated" to invest in quality, as described below.

properly validating antibodies and other binding reagents to ensure that their research is reproducible (Uhlen et al. (2016)). We assume that $0 < F(0) < 1/2$ so that, as discussed below, some suppliers always have an incentive to invest in quality.[5]

Each supplier is assumed to receive revenue equal to the fraction of all consumers who see their story.[6] For example, news-media outlets display advertisements next to articles and advertisers pay according to the number of consumers who view the article;[7] social-media content creators with more views enjoy better search- and recommendation-engine placement for their future content; and academic researchers benefit when their papers are more widely seen.

Each supplier's expected revenue is equal to the ex ante likelihood that any given consumer will see their story, what we call the story's "visibility." Let V_H and V_L be the visibility of a high- and low-quality story, respectively, and let $\Delta V = V_H - V_L$ be the extra visibility of high-quality stories.

Time $t = 1$: tuning in and sharing. There are I consumers, each of whom "tunes in" to each supplier's time-0 broadcast with i.i.d. probability $\tau \in (0, 1)$. In the benchmark model in Section 2, τ is a fixed exogenous parameter. In the extension of Section 3, τ emerges endogenously as the equilibrium likelihood that each consumer chooses to tune in to stories.

Each consumer who sees a story directly from the supplier decides whether to "share" the story after receiving a private signal about its quality.[8] Consumers are socially linked

[5] Our analysis and main qualitative findings easily carry over to the alternative cases when $F(0) = 0$ or $F(0) > 1/2$.

[6] The assumption that supplier revenue is linear in the number of consumers who see the story simplifies formulas but is not essential.

[7] Clicking on an article might be required for a news publication to receive advertising revenue, but news reporters and news outlets, just like influencers and academic researchers, receive other sorts of benefits from their output being simply seen. For a reporter, for example, having one's news articles seen and shared on social media can boost career prospects. See e.g. Granger (2022).

[8] We assume that there is only one round of sharing by consumers. This simplified model captures how consumers' sharing decisions filter and spread stories and allows us to focus on the interplay between

to others, with a link from consumer i to consumer j indicating that i sees the stories j shares, described as i "follows" j. Let d_i denote the number of others who consumer i follows. We assume for simplicity that $d_i = d$ for all i and refer to the parameter $d \geq 0$ as "social connectedness." We use the term "neighbors" to describe consumers who are linked, with the context indicating the link's direction.

Consumers are assumed to prefer to share high-quality stories but not low-quality stories.[9] For each story consumer i shares, i earns utility $u_H^S > 0$ at the end of the game if the story is high quality or $-u_L^S < 0$ if the story is low quality. A consumer i then maximizes expected utility by sharing the story only when i believes that the story's likelihood of being high quality exceeds "sharing threshold" $p^S \equiv \frac{u_L^S}{u_H^S + u_L^S} \in (0, 1)$. For notational simplicity, we normalize $u_H^S = u_L^S = u^S$; so, $p^S = \frac{1}{2}$.

Consumers cannot directly observe story quality but have individual, story-specific expertise, experience, or access to other information with which to evaluate a story, modeled as an imperfectly informative private signal about the story's quality.[10] Each consumer i receives private signal $s_i \in \{H, L\}$ that matches the true state (High or Low quality) with probability $\rho_i \in (1/2, 1)$. "Signal precision" ρ_i is itself a privately-observed random variable with commonly known c.d.f. $G(\cdot)$ and continuous density $g(\cdot)$.[11] We

consumer sharing and supplier investment.

[9]Future work could consider other aspects of stories in addition to quality which affect consumers' incentives to share stories. For example, consumers may enjoy sharing funny, novel, or shocking content. A consumer's payoffs from sharing stories would then depend on stories' expected mix of observable and unobservable characteristics. Our focus in this paper is on equilibrium quality, an unobservable characteristic, holding all observable characteristics fixed.

[10]Another interpretation of this private signal is that consumers imperfectly observe supplier investment. For example, a consumer who reads a news article does not know for sure whether the reporter has carefully or cursorily investigated sources. But an article in which the sources have been carefully checked is more likely to generate a favorable signal.

[11]The analysis is easily adapted to an alternative setting in which each consumer's expertise is observable to others. If all private signals have the same precision $\rho \in (1/2, 1)$, then the resulting equilibrium set possesses various knife-edge properties that obscure some of the key insights that emerge from our analysis. For example, in such a model, no equilibrium can ever have very high expected story quality (greater than ρ) or very low but positive expected story quality (between 0 and $1 - \rho$). For details, see the earlier working-paper version Kranton and McAdams (2020).

refer to signal H as "favorable" and signal L as "unfavorable." We assume that (s_i, ρ_i) is conditionally i.i.d. across consumers and across stories, and $g(\rho) > 0$ for all $\rho \in (1/2, 1)$. Since signals and sharing behavior about one story are uninformative about other stories, we can consider each story in isolation.

Time $t = 2$: learning and taking action based on a story. Consumers who have viewed a story directly from a supplier and/or socially from a neighbor decide at time $t = 2$ whether to take a related action, based on their own private signal and what they infer from others' sharing behavior. For each story, any consumer i who acts on that story receives utility $u_H^A > 0$ if the story is high quality or $-u_L^A < 0$ if it is low quality. A consumer i then maximizes expected utility by acting on a story whose likelihood of being high quality exceeds "action threshold" $p^A \equiv \frac{u_L^A}{u_H^A + u_L^A} \in (0, 1)$. For simplicity, we assume that $u_H^A = u_L^A = u^A$ so that $p^A = \frac{1}{2}$.

We analyze the Bayesian Nash equilibria (or simply "equilibria") of this game.

2 Equilibria in the Market for Information

This section characterizes all equilibria in the market for information in our baseline model in which each consumer tunes in to each supplier's broadcast with exogenous ex ante probability $\tau \in (0, 1)$. We have three main findings. First, an equilibrium in which most stories are high quality can only exist if social connectedness is neither too high nor too low (Proposition 2). Second, in the limit as social connectedness goes to infinity, only intrinsically-motivated suppliers invest and equilibrium expected story quality falls to the lowest possible level (Proposition 3). Finally, if most stories would be high quality in equilibrium absent any misinformation, adding a small amount of misinformation into the market lowers average story quality in equilibrium but leads to a greater expected volume of high-quality stories being produced (Proposition 4).

Equilibrium characterization. Here we characterize the set of equilibria for any given social connectedness $d \geq 0$. Let p_0 be the probability that any given story is high quality. For shorthand, we refer to p_0 as the "veracity" of stories in the information market. In the baseline model analyzed here, an equilibrium exists with story veracity p_0 if, when consumers believe that fraction p_0 of all stories are high quality and share optimally, suppliers find it optimal to invest in high quality with probability p_0.

Optimal consumer sharing. Consider a consumer i with belief p_0 who has seen a story directly from a supplier and who has received private signal s_i with precision ρ_i. Let $p_1(s_i, \rho_i; p_0)$ be consumer i's interim belief that the story is high quality derived using Bayes' Rule. Consumer i finds it strictly optimal to share the story when $p_1(s_i, \rho_i; p_0) > 1/2$ and strictly optimal not to share when $p_1(s_i, \rho_i; p_0) < 1/2$. (If $p_1(s_i, \rho_i; p_0) = 1/2$, then consumer i is indifferent whether to share. However, because ρ_i is an atomless random variable, this event occurs with zero probability.)

For any prior $p \in [0, 1]$, let $\beta_H(p)$ and $\beta_L(p)$ be the probabilities that a consumer i's private signal (s_i, ρ_i) is sufficiently favorable that i's interim belief exceeds 1/2, conditional on the story being high or low quality, respectively. If most stories are high quality ($p_0 \geq 1/2$), then a consumer i who sees a story's broadcast will share the story unless i receives an unfavorable private signal ($s_i = L$) that is sufficiently precise ($\rho_i > p_0$) to lower i's updated belief below 1/2. The likelihood of receiving such a signal is $\int_{p_0}^{1} (1 - \rho_i) g(\rho_i) \mathrm{d}\rho_i$ if the story is high quality or $\int_{p_0}^{1} \rho_i g(\rho_i) \mathrm{d}\rho_i$ if it is low quality. Thus,

$$\beta_H(p_0) = 1 - \int_{p_0}^{1} (1 - \rho_i) g(\rho_i) \mathrm{d}\rho_i \text{ for all } p_0 \geq 1/2 \tag{1}$$

$$\beta_L(p_0) = 1 - \int_{p_0}^{1} \rho_i g(\rho_i) \mathrm{d}\rho_i \text{ for all } p_0 \geq 1/2. \tag{2}$$

Similarly, if most stories are low-quality ($p_0 \leq 1/2$), then a consumer i will share a story only if i receives a favorable private signal ($s_i = H$) that is sufficiently precise ($\rho_i > 1-p_0$) to raise i's updated belief above 1/2. Thus,

$$\beta_H(p_0) = \int_{1-p_0}^{1} \rho_i g(\rho_i) \mathrm{d}\rho_i \text{ for all } p_0 \leq 1/2 \tag{3}$$

$$\beta_L(p_0) = \int_{1-p_0}^{1} (1-\rho_i) g(\rho_i) \mathrm{d}\rho_i \text{ for all } p_0 \leq 1/2. \tag{4}$$

If $p_0 = 0$, then $\beta_H(0) = \beta_L(0) = 0$ and no one ever shares. If $p_0 = 1$, then $\beta_H(1) = \beta_L(1) = 1$ and everyone who sees a story's broadcast shares it. In between these extremes when $0 < p_0 < 1$, high-quality stories are more likely to be shared: $0 < \beta_L(p_0) < \beta_H(p_0) < 1$. Furthermore, from equations (1-4), $\beta'_H(p_0) > \beta'_L(p_0) > 0$ for all $p_0 < 1/2$ and $\beta'_L(p_0) > \beta'_H(p_0) > 0$ for all $p_0 > 1/2$. Thus, $\beta_H(p_0) - \beta_L(p_0)$ is increasing when $p_0 < 1/2$ and decreasing when $p_0 > 1/2$.

Intuitively, if most stories are low quality ($p_0 < 1/2$), then each consumer i applies a stringent filter, only sharing after sufficiently precise favorable signals. As p_0 increases from 0 to 1/2, the range of favorable signals that are precise enough for sharing expands. Since high-quality stories are more likely to generate favorable signals, $\beta_H(p_0)$ rises more rapidly than $\beta_L(p_0)$. By contrast, if most stories are high quality ($p_0 > 1/2$), each consumer also shares after sufficiently imprecise unfavorable signals. As p_0 increases from 1/2 to 1, the range of unfavorable signals that are imprecise enough for sharing expands, which now causes $\beta_L(p_0)$ to rise more rapidly than $\beta_H(p_0)$.

Story visibility. Let $V_H(p_0; d)$ and $V_L(p_0; d)$ be the visibility of high- and low-quality stories, respectively, viewed as functions of story veracity p_0 and social connectedness d. A consumer i with d neighbors sees a given story unless i misses the broadcast, which occurs with probability $(1-\tau)$, and none of i's neighbors sees the broadcast and shares, which occurs with probability $(1-\tau\beta_H(p_0))^d$ for a high-quality story and $(1-\tau\beta_L(p_0))^d$ for a low-quality story. Thus,

$$V_H(p_0;d) = 1-(1-\tau)(1-\tau\beta_H(p_0))^d \tag{5}$$

$$V_L(p_0;d) = 1-(1-\tau)(1-\tau\beta_L(p_0))^d. \tag{6}$$

A supplier's incentive to invest in story quality derives from the extra visibility of high-quality stories, denoted by $\Delta V(p_0;d)$. By equations (5-6),

$$\Delta V(p_0;d) = (1-\tau)\left((1-\tau\beta_L(p_0))^d - (1-\tau\beta_H(p_0))^d\right). \tag{7}$$

We note important features of $\Delta V(p_0;d)$ with respect to p_0 and d. For a given p_0: In an unconnected network ($d=0$), consumers only see stories directly from suppliers; so, $V_H(p_0;0) = V_L(p_0;0) = \tau$ and hence $\Delta V(p_0;0) = 0$ for all p_0. On the other hand, in a highly-connected network (d large), each consumer is essentially certain to have at least one sharing neighbor for any story. In particular, for any $p_0 > 0$, we have $\lim_{d\to\infty} V_H(p_0;d) = \lim_{d\to\infty} V_H(p_0;d) = 1$ and hence $\lim_{d\to\infty} \Delta V(p_0;d) = 0$.

For a given d, $\Delta V(p_0;d)$ is increasing then decreasing in p_0. Differentiating (7) with respect to p_0 yields

$$\begin{aligned}\frac{\partial \Delta V(p_0;d)}{\partial p_0} &= (1-\tau)\tau d\left(\beta_H'(p_0)(1-\tau\beta_H(p_0))^{d-1} - \beta_L'(p_0)(1-\tau\beta_L(p_0))^{d-1}\right)\\ &\gtrless 0 \text{ if and only if } \frac{\beta_H'(p_0)}{\beta_L'(p_0)} > \left(\frac{1-\tau\beta_L(p_0)}{1-\tau\beta_H(p_0)}\right)^{d-1}.\end{aligned} \tag{8}$$

Differentiating equations (1-4), we have $\frac{\beta_H'(p_0)}{\beta_L'(p_0)} = \frac{1-p_0}{p_0}$, which is strictly decreasing in p_0 and equal to infinity at $p_0 = 0$, one at $p_0 = \frac{1}{2}$, and zero at $p_0 = 1$. On the other hand, $\frac{1-\tau\beta_L(p_0)}{1-\tau\beta_H(p_0)}$ is increasing in p_0 over the range $p_0 \in [0, 1/2]$ and never falls below one (details in the Appendix).

Consequently, there is a unique $\hat{p}(d) \in (0, 1/2)$ such that $\Delta V(p_0; d)$ is increasing in p_0 from zero to $\hat{p}(d)$ and decreasing in p_0 from $\hat{p}(d)$ to one.[12]

Lemma 1. *For any fixed d, $\Delta V(p_0; d)$ is single-peaked in p_0 and strictly decreasing in p_0 when $p_0 > 1/2$, with $\Delta V(0; d) = \Delta V(1; d) = 0$.*

Proof: All formal proofs are provided in the Appendix.

Optimal supplier investment. Each supplier maximizes ex ante expected profits by investing in high quality when it has cost $c \leq \Delta V(p_0; d)$. The ex ante probability that a supplier invests, what we refer to as "high-quality supply," is therefore $F(\Delta V(p_0; d))$. Overall, $SF(\Delta V(p_0; d))$ high-quality stories are produced in expectation.

Because each supplier has a dominant strategy to invest in story quality for investigation cost $c < 0$, equilibrium story veracity can never be less than $\underline{p}_0 \equiv F(0)$. We refer suppliers with these cost draws as "intrinsically motivated" to produce high quality.

Equilibrium condition. Since each supplier optimally invests with probability $F(\Delta V(p_0; d))$, an equilibrium exists with story veracity p_0 if and only if

$$F(\Delta V(p_0; d)) = p_0. \tag{9}$$

This equilibrium condition is illustrated in Figure 2, for a fixed social-connectedness level d. Consumers' beliefs about story veracity p_0 are on the x axis, while high-quality supply $F(\Delta V(p_0; d))$ is on the y axis. An equilibrium is a crossing-point of $F(\Delta V(p_0; d))$ with the 45°-line. In the scenario depicted in Figure 2, there is a unique equilibrium, with story veracity denoted as $p_0^*(d)$.

[12] A similar single-peakedness property appears in Coate and Loury (1993)'s model of affirmative action, where workers invest in skills at different rates depending on employers' beliefs.

Equilibrium existence follows in a straightforward way from the continuity of the curve $F(\Delta V(p_0; d))$ and the fact that this curve (i) starts above the 45°-line, since $F(\Delta V(0; d)) = F(0) = \underline{p}_0 > 0$, and (ii) ends below the 45°-line, since $F(\Delta V(1; d)) = F(0) = \underline{p}_0 < 1$. When $d = 0$, in the unique equilibrium story veracity is $\underline{p}_0$. For any $d \geq 1$, equilibrium story veracity must be strictly greater than $\underline{p}_0$ because $V_H(p_0; d) > V_L(p_0; d)$ for all $p_0 \in (0, 1)$.

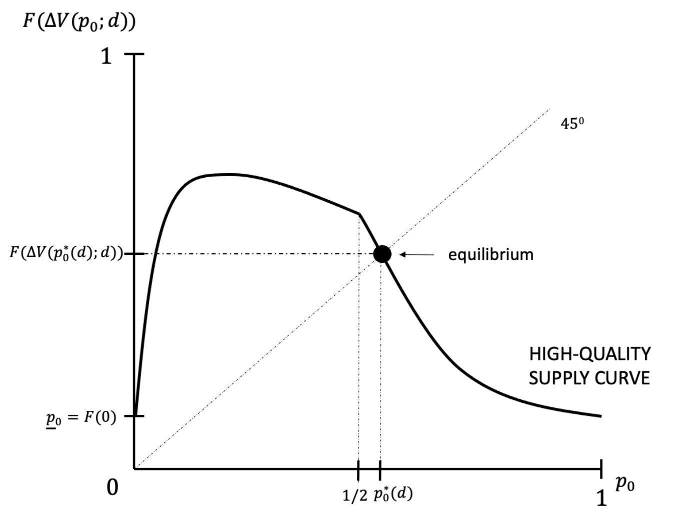

Figure 2: High-Quality Supply and Equilibrium for a given d

Proposition 1. *(i) An equilibrium exists in the information-market game. (ii) For* $d = 0$*, there is a unique equilibrium with story veracity* $p_0 = \underline{p}_0$*. (iii) For any* $d \geq 1$*,* $p_0 \in (\underline{p}_0, 1)$ *in any equilibrium.*

Impact of social connectedness on story veracity. How does social connectedness affect equilibrium outcomes? For each social-connectedness level d, we focus on the maximal equilibrium story veracity, denoted $p_0^{max}(d)$, and consider how $p_0^{max}(d)$ changes with d. Our key observation is that the extra visibility of high-quality stories, which determines suppliers' incentives to invest, is non-monotonic in d.

Lemma 2. *For any* $p_0 \in (0,1)$*,* $\Delta V(p_0; d)$ *is single-peaked in* d *with* $\Delta V(p_0; 0) = \lim_{d\to\infty} \Delta V(p_0; d) = 0$*.*

To gain intuition, recall that high-quality stories are more likely to be shared than low-quality stories. When each consumer follows one person rather than zero, the visibility of high-quality stories increases more than the visibility of low-quality stories. On the other hand, a story which a consumer i sees from a $(d+1)$-st neighbor which has not been shared by d other neighbors is increasing likely to be low quality as d increases. Eventually when d is sufficiently large, adding a $d+1$st neighbor therefore boosts the visibility of low-quality stories more than high-quality stories.

Proposition 2 leverages Lemma 2 to show that an equilibrium in which more than half of all stories are high quality can only exist if d is neither too high nor too low.

Proposition 2. *Either* $p_0^{max}(d) \leq 1/2$ *for all* d *or thresholds* $0 < \underline{d} < \overline{d} < \infty$ *exist such that* $p_0^{max}(d) > 1/2$ *if and only if* $\underline{d} < d < \overline{d}$*. Moreover, if* $p_0^{max}(d) > 1/2$*, then there is a unique equilibrium with* $p_0 > 1/2$*.*

Plight of the crowd. As social connectedness increases to infinity, what we call the "crowd limit," the extra visibility of high-quality stories falls to zero as all stories become essentially certain to be seen by all consumers. Consequently, only intrinsically-motivated suppliers invest in story quality and maximal equilibrium story veracity falls to $\underline{p}_0$, the lowest possible level. We refer to this outcome as the "plight of the crowd."

Proposition 3. $\lim_{d\to\infty} p_0^{max}(d) = \underline{p}_0$.

In the crowd limit, supplier profits converge to their highest possible level, since stories are widely seen even if low quality. (See the Appendix for a full specification of suppliers' equilibrium profits and consumers' equilibrium payoffs in equilibrium). For consumers, however, there are both pros and cons associated with the crowd limit. On one hand, consumers are able to discern perfectly which stories are high quality, based on the fraction of their infinitely-many neighbors who share. Due to this "wisdom of the crowd" effect, consumers are able to act on all high-quality stories and avoid acting on low-quality stories. On the other hand, consumers suffer from the fact that supplier investment in story quality is at its lowest possible level.

Impact of misinformation. We now consider the impact of misinformation on the information market. Consider $M \geq 0$ misinformation agents who each produce one low-quality story, where $m \equiv \frac{M}{S} \in [0, \infty)$ is the number of misinformation agents relative to the S "bona-fide suppliers." There are $M + S$ total stories, and the expected volume of high-quality stories is $SF(\Delta V(p_0; d))$. The fraction of stories that are high quality is $\frac{S}{M+S} F(\Delta V(p_0; d)) = \frac{F(\Delta V(p_0;d))}{1+m}$. The equilibrium condition therefore becomes

$$F(\Delta V(p_0; d)) = (1 + m)p_0. \tag{10}$$

Graphically, an equilibrium is a crossing-point of the high-quality supply curve $F(\Delta V(p_0; d))$ with a line out of the origin that is now steeper than the 45°-line by a factor of $(1 + m)$, as shown in Figure 3.

Dropping "d notation" to simplify equations, let $p_0^{max}(m)$ denote the maximal equilibrium veracity, now as a function m. We find that as misinformation increases, $p_0^{max}(m)$ decreases (Proposition 4(i)) but the expected volume of high-quality stories in the maximal-veracity equilibrium, $S(1+m)p_0^{max}(m)$, increases if most stories would otherwise be high quality (Proposition 4(ii)).

Proposition 4. *(i)* $\frac{\mathrm{d}p_0^{max}(m)}{\mathrm{d}m} < 0$. *(ii) If* $p_0^{max}(m) > 1/2$, *then* $\frac{\mathrm{d}\left((1+m)p_0^{max}(m)\right)}{\mathrm{d}m} > 0$.

To gain intuition for this result, suppose that an equilibrium exists in which most stories are high quality when $m = 0$, as shown in Figure 3. Holding the level of high-quality

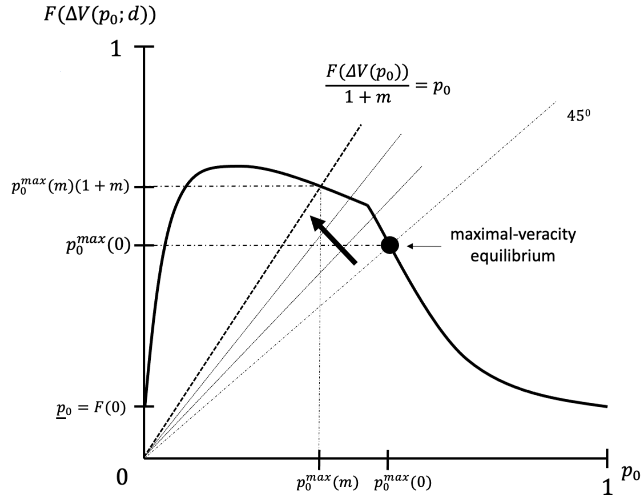

Figure 3: Impact of Misinformation on Veracity and High-Quality Supply.

investment fixed, introducing a small amount of misinformation reduces the average quality of information. This reduction induces consumers to apply a more stringent filter for sharing stories. In particular, those who receive unfavorable private signals become less likely to share. This reaction to misinformation reduces the visibility of low-quality stories more than high-quality stories, thereby increasing bona-fide suppliers incentive to produce high-quality information. The overall effect of a small amount of information is therefore to reduce story veracity but increase the expected number of high-quality stories produced.

As m increases, equilibrium story veracity and equilibrium supplier investment are determined by the crossing-point of the high-quality supply curve with increasingly steep lines from the origin, as shown in Figure 3. Misinformation ultimately leads bona-fide suppliers to invest more as long as this crossing-point is to the right of the peak of the high-quality supply curve. Beyond that point, however, additional misinformation induces bona-fide suppliers to invest less, until in the limit as $m = \frac{M}{S}$ goes to infinity, story veracity converges to $\underline{p}_0$.

Misinformation affects supplier profits and consumer welfare as follows. More misinformation unambiguously decreases suppliers' expected profits since consumers respond to misinformation by sharing less, which reduces all stories' visibility. For consumers, the overall welfare impact of increased misinformation is ambiguous and depends on the magnitude of suppliers' increased-investment response as story veracity falls. Whether more misinformation is good or bad for consumers depends on the elasticity of high-quality supply with respect to changes in the return to quality ΔV. On one extreme, with zero elasticity, the volume of high-quality stories stays the same, story veracity falls, and consumers are unambiguously worse off. On the other extreme with infinite elasticity, the volume of high-quality stories rises sufficiently so that story veracity stays the same. In that case, consumers are unambiguously better off, as shown in the following example.

Suppose that investigation costs are always equal to $\hat{c}$, where $\hat{c}$ is sufficiently small that suppliers strictly prefer to invest if consumers believe that at least half of all stories are high quality, i.e., $\hat{c} < \Delta V(1/2)$. Absent misinformation, p_0^{max} is at the level, between $1/2$ and 1, where cost-$\hat{c}$ suppliers are indifferent between investing or not in quality.[13] Now, suppose that a relatively small number of misinformation agents enter the market. Story veracity must remain constant in order for cost-$\hat{c}$ suppliers to remain indifferent to investing. Therefore, the overall number of stories in the market increases from S to $S + M$ without any loss in average quality. Since consumers have access to more stories of the same average quality, consumer welfare increases by a factor of $\frac{S+M}{S} = 1 + m$, making consumers strictly better off than in a market without any misinformation.

[13] Given any lower veracity $p_0 < p_0^{max}$, all suppliers strictly prefer to invest, leading to a contradiction in which all stories are high quality. On the other hand, if $p_0 > p_0^{max}$, then all suppliers strictly prefer not to invest, leading to zero investment and another contradiction.

3 Endogenous Tuning In

Thus far in our analysis, each consumer tunes in to each supplier's broadcast with fixed and exogenous probability $\tau > 0$. Under this assumption, all stories are almost certain to be seen as d grows very large, giving suppliers little incentive to invest in quality and causing equilibrium story veracity to fall to $\underline{p}_0$, the lowest possible level. But as social connectedness d increases and story veracity changes, consumers' incentives to tune in to suppliers' broadcasts could also change. In this section, we examine how strategic feedback between consumers' tuning-in choices and suppliers' investments in quality shapes outcomes in the information market, especially in the crowd limit (as $d \to \infty$). To do so, we extend our previous analysis by making tuning in costly and endogenous, with consumers choosing how much to tune in to suppliers' broadcasts. We find that equilibrium story veracity strictly above $\underline{p}_0$ can be maintained in the $d \to \infty$ limit, escaping the plight of the crowd, but only if consumers' tuning-in costs are neither too high nor too low.

Model: endogenous tuning in. At time $t = 1$, each consumer i chooses how many of the S stories to observe directly from suppliers' broadcasts ("tuning in"). Tuning in to a story allows consumer i to share the story and to act on the story if none of i's neighbors shares it. The cost of tuning in to n stories is $\sum_{l=1}^{n} \kappa_l$, where $0 \equiv \kappa_0 \leq \kappa_1 < \kappa_2 < ... < \kappa_S$ and $\kappa_{S+1} = \infty$. Formally, each consumer i chooses tuning-in volume $S_i \in [0, S]$, with the interpretation that i tunes in to $\lfloor S_i \rfloor$ randomly-selected stories and also a randomly-selected $\lceil S_i \rceil$-th story with probability $S_i - \lfloor S_i \rfloor$.[14] Consumer i's ex ante probability of seeing any given supplier's broadcast, called i's "tuning-in intensity," is $\tau_i \equiv \frac{S_i}{S} \in [0, 1]$.

[14]By definition, $\lfloor S_i \rfloor$ is the greatest integer less than or equal to S_i, while $\lceil S_i \rceil$ is the lowest integer greater than or equal to S_i. For example, if $S = 10$ and $S_i = 2.3$, then consumer i tunes in to $\lfloor 2.3 \rfloor = 2$ randomly-selected stories and a third story selected at random with probability 0.3. Overall, consumer i sees each of the ten stories with probability 2.3/10=0.23.

Viewed as a function of τ_i, consumer i's expected tuning-in cost, denoted $\kappa(\tau_i)$, is given by

$$\kappa(\tau_i) = \sum_{n=1}^{\lfloor S\tau_i \rfloor} \kappa_n + (S\tau_i - \lfloor S\tau_i \rfloor)\kappa_{\lceil S\tau_i \rceil}. \tag{11}$$

In an equilibrium of this extended game, each consumer i chooses τ_i optimally given other consumers' tuning-in intensities. We consider "symmetric equilibria" in which all consumers choose the same tuning-in intensity.[15]

We have two main findings. First, consumers' tuning in strategies are strategic substitutes, and we can characterize all symmetric equilibria in terms of a simple equilibrium condition that extends condition (9) for any social connectedness d. Second, whether there is a plight of the crowd depends on κ_1, the cost of tuning in to a single story. In particular, let $p_0^{max}(d)$ and $p_0^{min}(d)$ be the maximal and minimal equilibrium story veracities, respectively, for any given social connectedness d. We show that there are thresholds $0 < \underline{\kappa} < \overline{\kappa}$ such that (i) $\lim_{d\to\infty} p_0^{max}(d) = \underline{p}_0$ when $\kappa_1 < \underline{\kappa}$ but (ii) $\lim_{d\to\infty} p_0^{min}(d) > \underline{p}_0$ when $\kappa_1 \in (\underline{\kappa}, \overline{\kappa})$. Thus, the plight of the crowd must arise whenever κ_1 is sufficiently low but cannot arise when κ_1 lies in an intermediate range.

Consumer benefits of tuning in. Consumer i has two sorts of benefits from tuning in to a supplier's broadcast. First, i has the opportunity to share that story with neighbors at time $t = 1$ and earn a sharing payoff. Second, i does not need to rely on neighbors to share the story in order to be able to act on it at time $t = 2$.

Sharing benefits: Let $\Delta U^S(p_0)$ denote the expected sharing-related benefit of tuning in to any given story. Any consumer who has not tuned in to a supplier's broadcast cannot share that story and so receives zero sharing payoff for that story. A consumer who tunes in and shares earns $+u^S$ if the story is high quality or $-u^S$ if the story is low

[15]Future research could consider asymmetric equilibria, possibly with heterogeneous consumers as discussed in the Conclusion.

quality. Since each story is high quality with probability p_0 and consumers optimally share high- and low-quality stories with respective probabilities $\beta_H(p_0)$ and $\beta_L(p_0)$, we have

$$\Delta U^S(p_0) = u^S \left[p_0 \beta_H(p_0) - (1-p_0)\beta_L(p_0)\right]. \tag{12}$$

Increasing a story's likelihood of being high quality unambiguously increases the expected benefit of being able to share that story; thus, $\Delta U^S(p_0)$ is increasing in p_0.

Acting benefits: Let $\Delta U^A(p_0, \tau_{-i})$ denote the expected acting-related benefit of tuning in to any given story. A consumer i who does not tune in still has the option to act on the story if at least one of i's neighbors shared. Thus, tuning in to a story gives i the option to act on that story should no neighbor share the story. The probability that no neighbor shares any given high- and low-quality story is, respectively, $(1 - \tau_{-i}\beta_H(p_0))^d$ and $(1 - \tau_{-i}\beta_L(p_0))^d$. Let $p_0^{\emptyset}$ be shorthand for consumer i's belief about a story's veracity given that none of her d neighbors has shared, updated by Bayes' rule.[16] Seeing no neighbor share, consumer i will act on the story only when her private signal is sufficiently favorable that the story is more likely to be high quality, which occurs with probability $\beta_H(p_0^{\emptyset})$ when the story is high quality and with probability $\beta_L(p_0^{\emptyset})$ when the story is low quality. Overall,

$$\Delta U^A(p_0, \tau_{-i}) = u^A \left[p_0(1 - \tau_{-i}\beta_H(p_0))^d \beta_H(p_0^{\emptyset}) - (1-p_0)(1 - \tau_{-i}\beta_L(p_0))^d \beta_L(p_0^{\emptyset})\right]. \tag{13}$$

Consumer i's acting benefit from tuning in $\Delta U^A(p_0, \tau_{-i})$ is strictly decreasing in the tuning-in intensities of i's neighbors τ_{-i} (shown in the proof of Lemma 3). For intuition, note that consumer i is more likely to see any given story from neighbors when neighbors

[16] $p_0^{\emptyset}$ is derived in the Appendix; it is increasing in p_0, decreasing in τ_{-i}, and decreasing in d.

tune in more. Thus, the expected volume of stories that i sees *only* by tuning in directly decreases as i's neighbors tune in more. Moreover, the stories that no neighbor shares become increasingly adversely selected as neighbors tune in more, since neighbors are more likely to share high-quality than low-quality stories.[17]

Optimal tuning-in. Let $\Delta U(p_0, \tau_{-i}) \equiv \Delta U^S(p_0) + \Delta U^A(p_0, \tau_{-i})$ be consumer i's ex ante expected benefit of tuning in to any given supplier's broadcast. Since consumer i tunes in to $S\tau_i$ suppliers on average and pays $\kappa(\tau_i)$ to do so, i's net expected tuning-in payoff is $S\tau_i \Delta U(p_0, \tau_{-i}) - \kappa(\tau_i)$.

For any given story veracity p_0, consumers are playing a "tuning-in game" with best-response functions $\tau_i(p_0, \tau_{-i}) \equiv \arg\max_\tau \left(S\tau_i \Delta U(p_0, \tau_{-i}) - \kappa(\tau_i)\right)$. We find that this game exhibits strategic substitutes (Lemma3(i)) and has a unique symmetric equilibrium (Lemma3(ii)). As discussed above, the more that a consumer i's neighbors tune in, the lower consumer i's individual benefits from tuning in.

Lemma 3. *For each $p_0 \in [0,1]$: (i) $\tau_i(p_0, \tau_{-i})$ is non-increasing in τ_{-i}; (ii) there is a unique $\tau^*(p_0)$ such that $\tau^*(p_0) \in \tau_i(p_0, \tau^*(p_0))$; and (iii) $\tau^*(p_0)$ is continuous in p_0.*

Equilibria with endogenous tuning in. In the information market game, a symmetric equilibrium exists with story veracity p_0 and tuning-in intensity τ if and only if two conditions are satisfied. First, $\tau = \tau^*(p_0)$ so that each consumer finds it optimal to tune in to each story with i.i.d. probability τ. Second, $p_0 = F(\Delta V(p_0, \tau))$ so that each supplier finds it optimal to invest in story quality with i.i.d. probability p_0. Combining

[17] However, $\Delta U^A(p_0, \tau_{-i})$ is not necessarily increasing in p_0. As story veracity increases, consumers benefit more from being able to act on any given story, but others are also more likely to share stories, reducing the need to tune in oneself to have the opportunity to act.

these two conditions, a symmetric equilibrium exists with story veracity p_0 if and only if

$$p_0 = F(\Delta V(p_0, \tau^*(p_0))). \tag{14}$$

Proposition 5 establishes existence of a symmetric equilibrium and provides conditions on tuning-in costs under which equilibria exist in which no consumer tunes in to any story ($\tau = 0$) or all consumers tune in to all stories ($\tau = 1$) regardless of social connectedness d. This result also establishes critical bounds on consumers' costs of tuning in to stories.

Proposition 5. *In the information market game with endogenous tuning-in: (i) A symmetric equilibrium exists. (ii) A symmetric equilibrium with $\tau(d) = 0$ exists for all d if and only if $\kappa_1 \geq \overline{\kappa} \equiv \frac{u^S+u^A}{u^S}\Delta U^S(\underline{p}_0)$. (iii) A symmetric equilibrium with $\tau(d) = 1$ exists for all d if and only if $\kappa_S \leq \underline{\kappa} \equiv \Delta U^S(\underline{p}_0)$.*

Symmetric equilibrium existence follows in a straightforward way from the continuity of best replies (Lemma 3(iii)), which ensures that the right-hand side of (14) is continuous in p_0. To verify Proposition 5(ii), suppose that no consumer tunes in to any broadcast. Because stories are not viewed by consumers, only intrinsically-motivated suppliers invest and story veracity must equal $\underline{p}_0$. If a consumer i were to tune in, i would share and act whenever i's private signal is sufficiently favorable to boost i's updated belief above 1/2. This occurs with probability $\beta_H(\underline{p}_0)$ for high-quality stories and with probability $\beta_L(\underline{p}_0)$ for low-quality stories. The overall expected benefit to i of tuning in is then $\Delta U(\underline{p}_0, 0) = (u^S + u^A)\left(\underline{p}_0\beta_H(\underline{p}_0) + (1-\underline{p}_0)\beta_L(\underline{p}_0)\right)$, which by equation (12) simplifies to

$$\Delta U(\underline{p}_0, 0) = \frac{u^S + u^A}{u^S}\Delta U^S(\underline{p}_0) \equiv \overline{\kappa}. \tag{15}$$

Thus, a consumer i with belief $\underline{p}_0$ whose neighbors tune in with zero probability also finds it optimal to not tune in to any broadcasts if and only if $\kappa_1 \geq \overline{\kappa}$, as desired.

To gain intuition for Proposition 5(iii), suppose all consumers tune in to all suppliers' broadcasts. Because all stories are viewed by all consumers, only intrinsically-motivated suppliers invest and again story veracity must be $\underline{p}_0$. Each consumer i's likelihood of having at least one sharing neighbor for each story increases to one as $d \to \infty$. Consequently, i's acting-related benefit from tuning in falls to zero as $d \to \infty$. If $\kappa_S \leq \underline{\kappa} \equiv \Delta U^S(\underline{p}_0)$, then i's sharing-related benefit is still enough to motivate i to tune in to all S stories, and an equilibrium exists with $\tau = 1$ for all d. On the other hand, if $\kappa_S > \underline{\kappa}$, then such an equilibrium cannot exist once d is sufficiently large.

3.1 Highly-connected information markets

Next, we extend the crowd-limit analysis of Section 2 to allow for endogenous tuning-in intensity. We find that the qualitative features of equilibrium depend on the cost of tuning in to a single story. In particular, there is a plight of the crowd when κ_1 is less than $\underline{\kappa}$ but not when κ_1 lies in an intermediate range between $\underline{\kappa}$ and $\overline{\kappa}$, where $\underline{\kappa}$ and $\overline{\kappa}$ are the thresholds defined earlier in Proposition 5. Moreover, when $\kappa_1 \in (\underline{\kappa}, \overline{\kappa})$, the equilibrium story veracity is strictly greater than p_0 in the crowd limit.

Let $p_0^{max}(d)$ and $p_0^{min}(d)$ denote the maximal and minimal equilibrium story veracity, respectively, for any given social-connectedness level d.

Proposition 6. *In the information-market game with endogenous tuning-in: (i) if* $\kappa_1 \leq \underline{\kappa}$*, then* $\lim_{d\to\infty} p_0^{max}(d) = \underline{p}_0$*; but (ii) if* $\underline{\kappa} < \kappa_1 < \overline{\kappa}$*, then* $\lim_{d\to\infty} p_0^{min}(d) > \underline{p}_0$.

Figure 4 summarizes the implications of Proposition 6. First, when κ_1 is below $\underline{\kappa}$, every consumer tunes in to at least one story as social connectedness goes to infinity; so, each consumer has infinitely-many neighbors who tune in to any given story. Each consumer can then perfectly discern, based on their neighbors' sharing behavior, which stories are high quality. There is a wisdom of the crowd, and consumers act only on high-quality stories. However, because even low-quality stories are sure to be viewed by all consumers, only intrinsically-motivated suppliers invest in quality. Story veracity is $\underline{p}_0$. On the other extreme when $\kappa_1 > \overline{\kappa}$, tuning-in costs are so high that an equilibrium exists for all d in which all consumers choose to not tune in to any broadcasts, and no stories are ever viewed by consumers. Equilibrium story veracity is again $\underline{p}_0$.

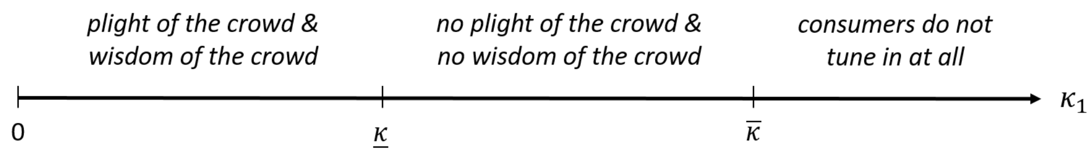

Figure 4: Summary of Equilibrium Outcomes in the limit as $d \to \infty$.

The most interesting case is when κ_1 lies in the intermediate range between $\underline{\kappa}$ and $\overline{\kappa}$. Decreases in consumers' equilibrium likelihood of tuning in to each story counterbalance the increases in social connectedness as $d \to \infty$ in such a way that each consumer's expected number of neighbors who tune in, $d\tau(d)$, converges to a finite positive number. Consequently, high-quality stories are strictly more likely to be viewed than low-quality stories in the crowd limit, giving suppliers a non-vanishing incentive to invest in story quality. The plight of the crowd is averted. At the same time, because each consumer only has finitely-many expected neighbors who tune in, consumers cannot perfectly infer story quality from neighbors' sharing behavior. There is no wisdom of the crowd.

For further intuition and an outline of the proof, consider the feedback between consumers' benefits of tuning in and suppliers' incentives to invest in high quality as social connectedness $d \to \infty$. Define $\lambda(d) \equiv d\tau(d)$. By (5), the probability that a high-quality story is viewed by a consumer for any given d can be written as

$$V_H(p_0(d), \tau(d); d) = 1 - \left[1 - \frac{\lambda(d)\beta_H(p_0(d))}{d}\right]^d. \tag{16}$$

Using the math fact that $\lim_{d\to\infty}(1+a/d)^d = e^a$, (16) implies that high-quality stories' crowd-limit visibility, denoted by V_H^∞, is $V_H^\infty = 1 - e^{-\lambda^\infty \beta_H(p_0^\infty)}$, where $p_0^\infty = \lim_{d\to\infty} p_0(d)$ and $\lambda^\infty = \lim_{d\to\infty} \lambda(d)$. Similarly, low-quality stories have crowd-limit visibility $V_L^\infty = 1 - e^{-\lambda^\infty \beta_L(p_0^\infty)}$. The extra visibility of high-quality stories in the crowd limit is therefore

$$\Delta V^\infty = e^{-\lambda^\infty \beta_L(p_0^\infty)} - e^{-\lambda^\infty \beta_H(p_0^\infty)}. \tag{17}$$

There are three possibilities for the crowd limit.

Possibility #1: $\lambda^\infty = 0, V_H^\infty = V_L^\infty = 0$, *and* $p_0^\infty = \underline{p}_0$ *(inactive market).* In this case, each consumer i's individual likelihood of tuning in, $\tau(d)$, converges to zero so quickly that i's expected number of sharing neighbors converges to zero, even as the number of i's neighbors goes to infinity. All stories' visibility converges to zero as $d \to \infty$. Suppliers' incentive to invest therefore also converges to zero, so story veracity converges to $\underline{p}_0$. Moreover, since the only way a consumer can see a story is to tune in, a consumer who tunes in receives expected benefit $\overline{\kappa} = \frac{u^S+u^A}{u^S}\Delta U^S(\underline{p}_0)$, capturing both the sharing and acting benefit from tuning in; see the discussion surrounding equation (15). If $\kappa_1 < \overline{\kappa}$, then consumers strictly prefer to tune in to at least one story whenever d is sufficiently large, $\tau(d) \geq \frac{1}{S}$, a contradiction. We conclude that this first possibility can only arise when $\kappa_1 \geq \overline{\kappa}$, in which case an equilibrium exists for all d in which no consumer ever tunes in to any story (Proposition 5 (ii)).

Possibility #2: $\lambda^\infty = \infty$, $V_H^\infty = V_L^\infty = 1$, *and* $p_0^\infty = \underline{p}_0$ *(plight of the crowd).* In this case, each consumer is sure to have at least one neighbor who tunes in and shares any given story in the limit as $d \to \infty$. Consequently, there is no acting benefit from tuning in. The benefit of tuning in comes entirely from having the opportunity to share. Since all stories are viewed in the limit, suppliers have no incentive to invest and $p_0^\infty = \underline{p}_0$. The overall benefit from tuning in to any given story is therefore $\underline{\kappa} = \Delta U^S(\underline{p}_0)$. If $\kappa_1 > \underline{\kappa}$, then consumers strictly prefer to not tune in to any stories whenever d is sufficiently large, $\tau(d) = 0$ for all d large, a contradiction. We conclude that Possibility #2 can only arise when $\kappa_1 \leq \underline{\kappa}$. Moreover, because $\underline{\kappa}$ is the lowest possible benefit of tuning in to a story, $\kappa_1 \leq \underline{\kappa}$ implies that all consumers must tune in to at least one story in any equilibrium given any d. Thus, each consumer must have infinitely-many sharing neighbors in the crowd limit as $d \to \infty$, making Possibility #2 the only possibility in this case.

Possibility #3: $0 < \lambda^\infty < \infty$, $1 > V_H^\infty > V_L^\infty > 0$, and $p_0^\infty > \underline{p}_0$ (non-vanishing supplier investment). In this case, each consumer i's expected number of neighbors who tune in, $d\tau(d)$, converges to a finite positive number as $d \to \infty$. Consequently: (i) high-quality stories are strictly more likely to be seen than low-quality stories in the crowd limit, giving suppliers a non-vanishing incentive to invest and hence giving consumers a non-vanishing sharing-related benefit from tuning in as $d \to \infty$; and (ii) consumer i fails with some positive probability to see each story socially in the crowd limit, ensuring that i also receives a non-vanishing acting-related benefit in the crowd limit. If these effects are sufficiently large that consumers strictly prefer to tune in to at least one story as $d \to \infty$, then all stories would be sure to be seen in the crowd limit (as in Possibility #2), a contradiction. However, if these effects are just the right size so that consumers are indifferent whether to tune in to one or zero stories, both V_H and V_L are between 0% and 100% even as $d \to \infty$. Since $V_H > V_L$, suppliers' incentives to invest remain strictly positive, supporting p_0^∞ strictly greater than $\underline{p}_0$. (See the Appendix for further analysis characterizing the equilibrium story-veracity levels that can arise in the crowd limit in this case.)

An implication of this analysis is that reducing consumers' tuning-in costs can ultimately reduce consumer welfare in highly-connected information markets. This possibility is easiest to see when suppliers are rarely intrinsically motivated, i.e., $\underline{p}_0 \approx 0$. In this case, equilibrium consumer welfare in the crowd limit is approximately zero whenever κ_1 is either less than $\underline{\kappa}$ or more than $\overline{\kappa}$, but positive whenever κ_1 lies between $\underline{\kappa}$ and $\overline{\kappa}$.

4 Conclusion

This paper considers consumer behavior and suppliers' incentives in socially-connected markets for decision-relevant information, which we call "stories." Consumers value high-quality stories and share stories they believe are likely to be high quality. Suppliers face costs to produce high quality and receive revenue when consumers view their stories. A central finding is that the equilibrium quality of stories is non-monotone in social connectedness. When consumers are not highly connected, adding more links increases suppliers' incentives to produce high quality. However, very high connectedness ultimately leads to poor information quality since any story is widely viewed, giving suppliers little incentive to invest. Forces that slow the spread of or encourage more stringent social filtering of information can mitigate this latter effect. Misinformation can ironically promote more high-quality production by bona-fide suppliers since consumers rationally respond to the presence of misinformation by sharing stories more cautiously. Increasing consumer costs of tuning in to suppliers' broadcasts can also support high-quality information production, even as social connectedness goes to infinity.

Several directions for future work could build on our analysis. On the consumer side, a natural next step would be for consumers to choose how many and which people to follow. With endogenous link formation, policies that make it easier for consumers to follow others could also impact suppliers' incentives to invest in high quality, which in turn could feed back on how much consumers benefit from forming links. If consumers are heterogeneous, with some consumers having lower tuning-in costs or higher utility returns from sharing stories, endogenous link formation could also potentially lead to core-periphery consumer networks in which most consumers rarely tune in themselves but instead follow a core of endogenously-determined "social influencers."

On the supply side, a natural next step would be to study the industrial organization of information suppliers and the equilibrium impact of different business models. In the present paper, suppliers benefit when consumers view stories, as in news media that earns revenues from accompanying advertising. However, some news-media organizations have (re)instituted subscription-based revenue models (*New York Times* (2015)).[18] A supplier that earns revenues only from subscribers might have an incentive to block readers from sharing content outside of its walled garden. Information suppliers could also earn revenue from sponsors who want to influence consumers to take particular actions.[19] Suppliers who earn content-sponsor revenue might prefer to enable stories to be more widely shared by subscribers. Future research could also explore the role of platforms which curate stories and serve as intermediaries between consumers and suppliers, such as news aggregators for news articles and academic journals for scientific studies. In a curated information market, suppliers could have an incentive to invest in quality even when consumers do not share stories.

For misinformation, a natural next step would be to consider strategic misinformation providers. The quantity of misinformation would then be endogenous and depend on the incentives of bona-fide suppliers, the social connectedness of consumers, and the motives of the misinformation providers. Misinformation suppliers could benefit from views (like the fake-news site denverguardian.com that earns money from ads shown alongside its

[18] Hybrid business models are also possible, where subscriber engagement drives advertising revenue. As the *New York Times* explained: "By focusing on subscribers, *The Times* will also maintain a stronger advertising business than many other publications. Advertisers crave engagement: readers who linger on content and who return repeatedly" (New York Times (2017)).

[19] News outlets such as Fox News, MSNBC, Breitbart, and Sinclair Media earn payoffs from advertising but can also be supported by owners who care about advancing their own political views. For an exposé of Sinclair Media and CEO David Smith, see Kroll (2017).

false content[20]), benefit when consumers act on their stories (like the Russian-sponsored Heart of Texas website[21]), or in the case of disinformation warfare, benefit when consumers are unable to act confidently on any story.

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[20]Most famously, denverguardian.com published a false story linking Hillary Clinton to the death of an FBI agent (Borchers (2016)).

[21]The Russia-based Internet Research Agency created *Heart of Texas*, a fictitious advocacy group that promoted Texas secession from the United States and other provocative positions. When its Facebook page called for a protest against "the Islamification of Texas" in 2017, real people showed up to protest and counter-protest (Allbright (2017)).

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Appendix: Proofs

Proof of Lemma 1. $\Delta V(p_0; d)$ is continuous in p_0 (obvious) and, as shown in the text, strictly decreasing in p_0 when $p_0 > 1/2$. To establish that $\Delta V(p_0; d)$ is single-peaked in p_0 over the full range $p_0 \in [0, 1]$, it therefore suffices to show that $\Delta V(p_0; d)$ is single-peaked in p_0 over $[0, 1/2]$. By equation (8), $\frac{\partial \Delta V(p_0;d)}{\partial p_0} \gtreqless 0$ exactly when $\frac{\beta'_H(p_0)}{\beta'_L(p_0)} \gtreqless \left(\frac{1-\tau\beta_L(p_0)}{1-\tau\beta_H(p_0)}\right)^{d-1}$. By equations (3,4), $\frac{\beta'_H(p_0)}{\beta'_L(p_0)} = \frac{1-p_0}{p_0}$ which decreases from ∞ to 1 as p_0 goes from 0 to 1/2. Moreover, because $\beta_H(p_0) > \beta_L(p_0)$ and $\beta'_H(p_0) > \beta'_L(p_0)$, it is easy to check that $\frac{1-\tau\beta_L(p_0)}{1-\tau\beta_H(p_0)}$ is increasing in p_0 and equal to 1 when $p_0 = 0$.[22] Thus, there is a unique $\widehat{p}_0 \in (0, 1/2)$ such that $\frac{\partial \Delta V(\widehat{p}_0;d)}{\partial p_0} = 0$, with $\frac{\partial \Delta V(\widehat{p}_0;d)}{\partial p_0} > 0$ for all $p_0 \in [0, \widehat{p}_0)$ and $\frac{\partial \Delta V(\widehat{p}_0;d)}{\partial p_0} < 0$ for all $p_0 \in (\widehat{p}_0, 1/2)$, as desired. Finally, $V_H(0; d) = V_L(0; d) = 0$ and $V_H(1; d) = V_L(1; d) = 1 - (1-\tau)^{d+1}$ imply $\Delta V(0; d) = 0$ and $\Delta V(1; d) = 0$ for all d. $\square$

Proof of Proposition 1. (i) $F(x)$ is continuous because supplier investigation cost is drawn from an atomless distribution, and $\Delta V(p_0; d)$ is continuous in p_0 by equation (7); thus, $F(\Delta V(p_0; d))$ is continuous in p_0 for all d. Next, because $\Delta V(1; d) = \Delta V(0; d) = 0$ for all d, we have $F(\Delta V(0; d)) = \underline{p}_0 > 0$ and $F(\Delta V(1; d)) = \underline{p}_0 < 1$. By the Intermediate Value Theorem, there exists $p_0 \in (0, 1)$ such that $F(\Delta V(p_0; d)) = p_0$. Thus, an equilibrium exists. (ii) When $d = 0$, all stories are equally visible, $\Delta V(p_0; 0) = 0$ for all p_0, and the equilibrium condition $F(\Delta V(p_0; 0)) = p_0$ is only satisfied at $p_0 = \underline{p}_0$. (iii) For all $d \geq 1$, $\Delta V(p_0; d) \in (0, 1)$ for all $p_0 \in (0, 1)$ and $\Delta V(0; d) = \Delta V(1; d) = 0$. Since $\underline{p_0} \in (0, 1/2)$ by assumption, $F(\Delta V(\underline{p}_0; d)) > \underline{p}_0$ and $F(\Delta V(1; d)) = \underline{p}_0 < 1$. Thus, any equilibrium must have story veracity greater than $\underline{p}_0$ and less than 1, as desired. $\square$

[22] To see this: $\frac{\partial\left(\frac{1-\tau\beta_L(p_0)}{1-\tau\beta_H(p_0)}\right)}{\partial p_0} = \frac{-\tau\beta'_L(p_0)}{1-\tau\beta_H(p_0)} + \frac{\tau\beta'_H(p_0)(1-\tau\beta_L(p_0))}{(1-\tau\beta_H(p_0))^2} > 0$ iff $\beta'_H(p_0)(1-\tau\beta_L(p_0)) > \beta'_L(p_0)(1-\tau\beta_H(p_0))$. But this inequality follows directly from $\beta_H(p_0) > \beta_L(p_0)$ and $\beta'_H(p_0) > \beta'_L(p_0)$.

Proof of Lemma 2. Differentiating equation (7) with respect to d yields

$$\frac{\partial \Delta V(p_0;d)}{\partial d} = (1-\tau)\left(\ln(1-\tau\beta_L(p_0))(1-\tau\beta_L(p_0))^d - \ln(1-\tau\beta_H(p_0))(1-\tau\beta_H(p_0))^d\right)$$

and hence $\frac{\partial \Delta V(p_0;d)}{\partial d} > 0$ if and only if $\frac{\ln(1-\tau\beta_L(p_0))}{\ln(1-\tau\beta_H(p_0))} > \left(\frac{1-\tau\beta_H(p_0)}{1-\tau\beta_L(p_0)}\right)^d$. Since $1 > \tau\beta_H(p_0) > \tau\beta_L(p_0) > 0$ for all $0 < p_0 < 1$, both sides of this inequality are between zero and one, but the left-hand side is constant while the right-hand side decreases exponentially with d. Thus, the inequality holds if and only if d is less than some threshold. Moreover, by inspection of equation (7), $\Delta V(p_0;0) = 0$ and $\lim_{d\to\infty} \Delta V(p_0;d) = 0$. $\square$

Proof of Proposition 2. First, we show $p_0^{max}(d) > 1/2$ if and only if $F(\Delta V(1/2;d)) > 1/2$ or, equivalently, $\Delta V(1/2;d) > H^{-1}(1/2)$. Suppose that $F(\Delta V(1/2;d)) > 1/2$. By equation (8), $\frac{\partial \Delta V(p_0;d)}{0} < 0$ when $p_0 > 1/2$. Since $F'(\Delta V) = f(\Delta V) > 0$, we conclude $\frac{\partial F(\Delta V(p_0;d))}{0} < 0$ when $p_0 > 1/2$. Moreover, $F(\Delta V(1;d)) = F(0) = \underline{p}_0 < 1/2$ for all d. Thus, there is a unique $p_0 \in (1/2, 1)$ with $F(\Delta V(p_0;d)) = p_0$; in particular, $p_0^{max}(d) > 1/2$. On the other hand, if $F(\Delta V(1/2;d)) \leq 1/2$, then $F(\Delta V(p_0;d)) < p_0$ for all $p_0 > 1/2$; so, no equilibrium exists with $p_0 > 1/2$ and hence $p_0^{max}(d) \leq 1/2$. By Lemma 2, $\Delta V(1/2;d)$ is single-peaked in d. Thus, $\Delta V(1/2;d) > H^{-1}(1/2)$ and hence $p_0^{max}(d) > 1/2$ if and only d lies in a (potentially empty) finite interval not including zero, as desired. $\square$

Payoffs in Equilibrium *Supplier payoffs.* A supplier maximizes profits by investing in high quality when $c \leq \Delta V(p_0;d)$. Overall, each supplier's ex ante profit is given by

$$\begin{aligned}\Pi(p_0;d) &= (1-F(c))V_L(p_0;d) + \int_0^{\Delta V(p_0;d)} (V_H(p_0;d) - c) f(c)\mathrm{d}c \\ &= V_L(p_0;d) + \int_0^{\Delta V(p_0;d)} (\Delta V(p_0;d) - c) f(c)\mathrm{d}c.\end{aligned}$$

Consumer payoffs. Consumers earn payoffs from sharing stories and acting on stories. In equilibrium, a consumer who has tuned in to a high-quality story shares that story with probability $\beta_H(p_0)$ and earns sharing payoff $+u^S$. Similarly, a consumer who has tuned in to a low-quality story shares the story with probability $\beta_L(p_0)$ and earns $-u^S$. Since consumers see each story with probability τ and stories are high quality with probability p_0, each consumer's per-story expected payoff from sharing is

$$U^S(p_0) = u^S \tau \left(p_0 \beta_H(p_0) - (1 - p_0)\beta_L(p_0)\right).$$

Consumers can act on a story if they have seen the supplier's broadcast directly or have had at least one neighbor share the story. Consumers decide whether to act on a story after making inferences about the story's quality based on neighbors' sharing behavior and their own private signal. The likelihood that a consumer acts on a story therefore depends on social connectedness d and others' sharing strategies, as well as story veracity p_0. Let $\alpha_H(p_0; d)$ be the ex ante likelihood that each consumer will act on any high-quality story, earning acting payoff $+u^A$. Similarly, let $\alpha_L(p_0; d)$ be the likelihood of acting on a low-quality story, earning $-u^A$. Each consumer's per-story expected payoff from acting is

$$U^A(p_0; d) = u^A \left(p_0 \alpha_H(p_0; d) - (1 - p_0)\alpha_L(p_0; d)\right).$$

In our baseline model without misinformation, there are S stories and each consumer's overall expected payoff in an equilibrium with story veracity p_0 is $S\left(U^S(p_0) + U^A(p_0; d)\right)$. In our misinformation extension, there are $S + M$ stories and each consumer's overall expected payoff in an equilibrium with story veracity p_0 is

$$(S + M)\left(U^S(p_0) + U^A(p_0; d)\right). \tag{18}$$

Proof of Proposition 3. $\lim_{d\to\infty} p_0^{max}(d) \geq \underline{p}_0$ since $p_0^{max}(d) > \underline{p}_0$ for all $d \geq 1$ (Proposition 1). Now consider any $p_0 > \underline{p}_0$, so that $F^{-1}(p_0) > 0$. By equation (7), the equilibrium condition $F(\Delta V(p_0; d)) = p_0$ is equivalent to

$$(1 - \tau\beta_L(p_0))^d - (1 - \tau\beta_H(p_0))^d = \frac{H^{-1}(p_0)}{1-\tau} \tag{19}$$

As shorthand, let $X(p_0) \equiv \frac{H^{-1}(p_0)}{1-\tau} > 0$ and define $\hat{d}(p_0)$ implicitly by $(1-\tau\beta_L(p_0))^{\hat{d}(p_0)} = X(p_0)$. For all $d > \hat{d}(p_0)$, the left-hand side of (19) is strictly less than $X(p_0)$; thus, no equilibrium exists with story veracity equal to p_0. Moreover, because consumers are more likely to share stories when veracity is higher, $(1 - \tau\beta_L(p_0'))^d < (1 - \tau\beta_L(p_0))^d$ for all $p_0' > p_0$. Since $X(p_0)$ is increasing in p_0, we conclude that $(1-\tau\beta_L(p_0'))^d - (1-\tau\beta_H(p_0'))^d < X(p_0')$ for all $d > \hat{d}(p_0)$ and all $p_0' > p_0$. Thus, $p_0^{max}(d) < p_0$ for all $d > \hat{d}(p_0)$. Since this argument applies to all $p_0 > \underline{p}_0$, we conclude that $\lim_{d\to\infty} p_0^{max}(d) = \underline{p}_0$, as desired. $\square$

Proof of Proposition 4. (i) We first show that $p_0^{max}(m)$ is strictly decreasing in m. Because $p_0^{max}(m)$ is the maximal equilibrium story veracity, $F(\Delta V(p_0^{max}(m))) = p_0^{max}(m)(1+m)$ and $F(\Delta V(p_0)) < p_0(1+m)$ for all $p_0 > p_0^{max}(m)$. But then, for any $m' > m$, we have $F(\Delta V(p_0)) < p_0(1+m')$ for all $p_0 \geq p_0^{max}(m)$; so, $p_0^{max}(m') < p_0^{max}(m)$. Finally, since $\Delta V(p_0; d)$ is continuously differentiable in p_0 for all $p_0 > 1/2$ (see equation (7)) and $F(\Delta V)$ is continuously differentiable in ΔV (by assumption), the derivative $\frac{\mathrm{d}p_0^{max}(m)}{\mathrm{d}m}$ exists so long as $p_0^{max}(m) > 1/2$ by the Implicit Function Theorem. (ii) For all m, $F(\Delta V(p_0^{max}(m))) = p_0^{max}(m)(1+m)$ by the equilibrium condition. The desired conclusion that $\frac{\mathrm{d}\left(p_0^{max}(m)(1+m)\right)}{\mathrm{d}m} > 0$ follows from the combined observations that: $F'(\Delta V) > 0$ by the assumption that suppliers' investigation cost has full support; $\frac{\mathrm{d}\Delta V(p_0;d)}{\mathrm{d}p_0} < 0$ for all $p_0 > 1/2$ (Lemma 1); and $\frac{\mathrm{d}p_0^{max}(m)}{\mathrm{d}m} < 0$ (shown in part (i)). $\square$

Proof of Lemma 3. (i) Recall that each consumer pays $\kappa_1 > 0$ to tune in to their first story, $\kappa_2 > \kappa_1$ for the second story, and so on. Therefore, *either* $\kappa_n < \Delta U(p_0, \tau_{-i}) < \kappa_{n+1}$ for some $n \geq 0$ and consumer i strictly prefers to tune in to exactly n stories, in which case $\tau_i(p_0, \tau_{-i}) = \frac{n}{S}$, *or* $\Delta U(p_0, \tau_{-i}) = \kappa_{n+1}$ for some $n \geq 0$ and consumer i is indifferent whether to tune in to a $(n+1)$-st story, meaning that $\tau_i(p_0, \tau_{-i}) = \left[\frac{n}{S}, \frac{n+1}{S}\right]$. In order to prove that $\tau_i(p_0, \tau_{-i})$ is a non-increasing correspondence in τ_{-i}, it suffices to show that $\Delta U(p_0, \tau_{-i})$ is a strictly decreasing function in τ_i. Since the sharing-related benefit $\Delta U^S(p_0)$ does not depend on τ_{-i}, we only need to show that the acting-related benefit $\Delta U^A(p_0, \tau_{-i})$ is strictly decreasing in τ_i.

Equation (13) provides a formula for $\Delta U^A(p_0, \tau_{-i})$ in terms of $p_0^\emptyset(\tau_{-i}, d)$, consumer i's updated belief about story quality in the event that her d neighbors have all chosen tuning-in intensity τ_{-i} but not shared. By Bayes' Rule,

$$\frac{p_0^\emptyset(\tau_{-i}, d)}{1 - p_0^\emptyset(\tau_{-i}, d)} = \frac{p_0}{1 - p_0} \left(\frac{1 - \tau_{-i}\beta_H(p_0)}{1 - \tau_{-i}\beta_L(p_0)} \right)^d . \tag{20}$$

Shortening $p_0^\emptyset(\tau_{-i}, d)$ to $p_0^\emptyset$ for readability, (20) allows us to simplify (13) to

$$\begin{aligned} \Delta U^A(p_0; \tau_{-i}) &= u^A \Pr(d_i = 0) \left(p_0^\emptyset \beta_H(p_0^\emptyset) - (1 - p_0^\emptyset)\beta_L(p_0^\emptyset) \right) \\ &= \frac{u^A}{u^S} \Pr(d_i = 0) \Delta U^S(p_0^\emptyset) \end{aligned} \tag{21}$$

where $\Pr(d_i = 0) = p_0(1 - \tau_{-i}\beta_H(p_0))^d + (1 - p_0)(1 - \tau_{-i}\beta_L(p_0))^d$ is the ex ante probability that consumer i has no sharing neighbors.[23] Finally, note that $\Delta U^A(p_0, \tau_{-i})$ depends on

[23] This formulation of $\Delta U^A(p_0, \tau_{-i})$ has a natural intuition: Tuning in is only relevant for actions when no neighbor has shared. Conditional on this event, which occurs with probability $\Pr(d_i = 0)$, story veracity is $p_0^\emptyset$ and consumer i will choose to act if and only if her private signal is favorable enough to boost her updated belief above 50%, and get realized payoff $\pm u^A$ depending on whether the story is truly high quality. The acting-related benefit of tuning in when story veracity equals p_0 is therefore $\Pr(d = 0)$ times the sharing-related benefit if story veracity were actually $p_0^\emptyset$, scaled by $\frac{u^A}{u^S}$ to capture the relative importance of acting versus sharing.

(p_0, τ_{-i}) only through their effect on $\Pr(d_i = 0)$ and on $\Delta U^S(p_0^{\emptyset})$. Moreover, $\Pr(d_i = 0)$ is strictly decreasing (and continuous) in τ_{-i} while $\Delta U^S(p_0^{\emptyset})$ does not depend on τ_{-i}. Thus, $\Delta U^A(p_0, \tau_{-i})$ is strictly decreasing (and continuous) in τ_{-i}, as desired.

(ii-iii) By definition, $\tau_i(p_0, \tau_{-i}) = \arg\max_{\tau_i} (S\tau_i \Delta U(p_0, \tau_{-i}) - \kappa(\tau_i))$. The marginal benefit of tuning in, $MB(\tau_{-i}) \equiv S\Delta U(p_0, \tau_{-i})$, is constant in consumer i's tuning-in intensity τ_i but is strictly decreasing and continuous in τ_{-i} (shown in part (i)). Now define the marginal cost correspondence $MC(\tau_i) \equiv [\kappa'(\tau_i-), \kappa'(\tau_i+)]$, i.e., $MC(\tau_i) = S\kappa_n$ for all $\tau_i \in \left(\frac{n-1}{S}, \frac{n}{S}\right)$ and $MC(\tau_i) = [S\kappa_n, S\kappa_{n+1}]$ for all $\tau_i = \frac{n}{S}$ and $n = 1, ..., S-1$. By construction: $\tau_i(p_0, 0) = 0$ iff $MB(0) \leq MC(0) = S\kappa_1$; $\tau_i(p_0, \tau) = \tau$ for some $\tau \in (0, 1)$ if and only if $MB(\tau) \in MC(\tau)$; and $\tau_i(p_0, 1) = 1$ iff $MB(1) \geq MC(1) = S\kappa_S$. Since $MB(\tau)$ is a continuous and strictly decreasing function and $MC(\tau)$ is a continuous and weakly increasing correspondence, we conclude that there is a unique τ satisfying $\tau_i(p_0, \tau) = \tau$, which we refer to as $\tau^*(p_0)$. Moreover, because $\Delta U(p_0, \tau_{-i})$ is continuous in p_0, by equations (12,13), $\tau^*(p_0)$ is also continuous in p_0. □

Proof of Proposition 5. (i) Because $\tau^*(p_0)$ is continuous in p_0 (Lemma 3(iii)), Brouwer's Fixed Point Theorem ensures that there is at least one story veracity level p_0 satisfying condition (14). Thus, a symmetric equilibrium exists. (ii) Proven in the main text. (iii) In any equilibrium with $\tau = 1$, every story is seen with probability one by all consumers and only intrinsically-motivated suppliers invest; so, an equilibrium exists with $\tau = 1$ for all d if and only if an equilibrium exists with $\tau = 1$ and $p_0 = \underline{p}_0$ for all d. Given $(p_0, \tau) = (\underline{p}_0, 1)$, consumers optimally tune in to all stories if and only if $\kappa_S \leq \Delta U^S(\underline{p}_0) + \Delta U^A(\underline{p}_0, 1; d)$. Because $\underline{p}_0 > 0$, we have $\beta_H(\underline{p}_0) > \beta_L(\underline{p}_0) > 0$ and $\lim_{d \to \infty} \Delta U^A(\underline{p}_0, 1; d) = 0$ by equation (13); so, $\lim_{d \to \infty} \Delta U(\underline{p}_0, 1; d) = \Delta U^S(\underline{p}_0) = \underline{\kappa}$. We conclude that an equilibrium with $\tau = 1$ exists for all d if and only if $\kappa_S \leq \underline{\kappa}$, as desired. □

Proof of Proposition 6. Consider any sequence of equilibria having story veracity $p_0(d)$ and tuning-in intensity $\tau(d)$ for $d = 0, 1, 2, ...$ Without loss of generality, we may focus on convergent sequences, where the crowd limits $p_0^\infty = \lim_{d\to\infty} p_0(d)$ and $\tau^\infty = \lim_{d\to\infty} \tau(d)$ are well-defined. Other shorthand notation used in the proof for equilibrium objects in the crowd limit: $V_\omega^\infty \equiv \lim_{d\to\infty} V_\omega(p_0(d), \tau(d); d)$ for $\omega \in \{H, L\}$; $\Delta V^\infty \equiv V_H^\infty - V_L^\infty$; $\lambda^\infty = \lim_{d\to\infty} \lambda(d)$, where $\lambda(d) \equiv d\tau(d)$; $\Delta U^{S\infty} \equiv \lim_{d\to\infty} \Delta U^S(p_0(d))$; and $\Delta U^{A\infty} \equiv \lim_{d\to\infty} \Delta U^A(p_0(d), \tau(d); d)$.

(i) Suppose that $\kappa_1 < \underline{\kappa}$. The acting-related benefit of tuning-in is non-negative and the sharing-related benefit $\Delta U^S(p_0)$ is increasing in p_0 with $\Delta U^S(\underline{p}_0) = \underline{\kappa}$; so, a consumer i's overall benefit of tuning in is bounded below by $\underline{\kappa}$ for all d no matter what other consumers do. Each consumer therefore strictly prefers to tune in to at least one story, meaning that $\tau(d) \geq \frac{1}{S}$ for all d and hence $\tau^\infty \geq \frac{1}{S}$. Next, any consumer who sees a story directly from a supplier shares the story with probability bounded below by $\beta_L(\underline{p}_0) > 0$. By equation (6), the overall visibility of any given story is therefore bounded below by $1 - (1 - \frac{1}{S})\left(1 - \frac{\beta_L(\underline{p}_0)}{S}\right)^d \to 1$ as $d \to \infty$. Since all stories are sure to be seen in the crowd limit, the extra visibility of high-quality stories converges to zero and story veracity must converge to $\underline{p}_0$, as desired.

(ii) Suppose next that $\underline{\kappa} < \kappa_1 < \overline{\kappa}$. By equations (5-7) and the math fact that $\lim_{d\to\infty}(1 + a/d)^d = e^a$, we have

$$V_H^\infty = 1 - (1 - \tau^\infty)e^{-\lambda^\infty \beta_H(p_0^\infty)} \tag{22}$$

$$V_L^\infty = 1 - (1 - \tau^\infty)e^{-\lambda^\infty \beta_L(p_0^\infty)} \tag{23}$$

$$\Delta V^\infty = (1 - \tau^\infty)\left(e^{-\lambda^\infty \beta_L(p_0^\infty)} - e^{-\lambda^\infty \beta_H(p_0^\infty)}\right). \tag{24}$$

The key step of the proof is to show that $0 < \lambda^\infty < \infty$.

Suppose for the sake of contradiction that $\lambda^\infty = \infty$. By (22-24), $V_H^\infty = V_L^\infty = 1$

and $\Delta V^\infty = 0$, implying that $p_0^\infty = F(\Delta V^\infty) = \underline{p}_0$. Moreover, because each consumer is sure to see each story socially in the crowd limit, there is no action-related benefit of tuning in, i.e., $\Delta U^{A\infty} = 0$. Thus, the per-story benefit of tuning in is $\Delta U^S(\underline{p}_0) = \underline{\kappa}$. Since $\kappa_1 > \underline{\kappa}$, each consumer strictly prefers to set $S_i = 0$ whenever d is sufficiently large; so, $\tau(d) = 0$ and hence $\lambda(d) = 0$ for all sufficiently large d, implying that $\lambda^\infty = 0$, a contradiction. Note that, because $\lambda^\infty < \infty$, it must be that $\tau^\infty = 0$.

Next, suppose for the sake of contradiction that $\lambda^\infty = 0$. By (22-24), $V_H^\infty = V_L^\infty = 0$ and $\Delta V^\infty = 0$, implying that $p_0^\infty = \underline{p}_0$. Moreover, because each consumer never sees stories socially in the crowd limit, the action-related benefit of tuning in is the same as in an equilibrium with zero tuning in, namely, $\Delta U^{A\infty} = (u^S+u^A)\left(\underline{p}_0\beta_H(\underline{p}_0) - (1-\underline{p}_0)\beta_L(\underline{p}_0)\right) = \frac{u^S+u^A}{u^S}\Delta U^S(\underline{p}_0) = \overline{\kappa}$ (see the proof of Proposition 5). Since $\kappa_1 < \overline{\kappa}$, each consumer strictly prefers to tune in to at least one story whenever d is sufficiently large; so, $\tau(d) \geq \frac{1}{S}$ for all sufficiently large d, implying that $\lambda^\infty = \infty$, a contradiction.

So far, we have shown that $0 < \lambda^\infty < \infty$ and $\tau^\infty = 0$. Because $0 < \beta_L(p_0^\infty) < \beta_H(p_0^\infty)$, equation (24) implies that $\Delta V^\infty > 0$. Thus, $p_0^\infty = F(\Delta V^\infty) > F(0) = \underline{p}_0$, as desired. □

Characterizing endogenous tuning-in equilibria in the crowd limit. Here we continue the analysis in the proof of Proposition 6 to characterize the veracity levels that can be supported in equilibrium as $d \to \infty$, focusing on the case when $\underline{\kappa} < \kappa_1 < \overline{\kappa}$.

The proof of Proposition 6 (ii) establishes that, for any sequence of equilibria as $d \to \infty$, it must be that $\liminf_{d\to\infty} d\tau(d) > 0$ and $\limsup_{d\to\infty} d\tau(d) < \infty$. Thus, $\limsup_{d\to\infty} \tau(d) = 0$ but also $\tau(d) > 0$ for all large d. Without loss, we focus on equilibrium sequences where the limits $\lambda^\infty = \lim_{d\to\infty} d\tau(d)$ and $p_0^\infty = \lim_{d\to\infty} p_0(d)$ exist.

Proposition 6(ii) tells us that $p_0^\infty > \underline{p}_0$. We show next how to derive the entire set of story-veracity levels that can be supported in equilibrium in the crowd limit.

Supply condition. Given tuning-in limit λ^∞ and story-veracity limit p_0^∞, consumers' tuning-in and sharing behavior results in high- and low-quality stories having crowd-limit visibility $V_H^\infty = 1 - e^{-\lambda^\infty \beta_H(p_0^\infty)}$ and $V_L^\infty = 1 - e^{-\lambda^\infty \beta_L(p_0^\infty)}$, respectively; see equations (22-23). Optimal supplier investment leads to fraction $H(V_H^\infty - V_L^\infty)$ of all stories being high quality. We conclude that, for a sequence of equilibria to have limits $(p_0^\infty, \lambda^\infty)$, it must be that

$$p_0^\infty = H\left(e^{-\lambda^\infty \beta_L(p_0^\infty)} - e^{-\lambda^\infty \beta_H(p_0^\infty)}\right). \tag{25}$$

As can be easily checked, the function $e^{-\lambda\beta_L(p_0)} - e^{-\lambda\beta_H(p_0)}$ is quasiconcave and continuous in λ and maximized at $\lambda(p_0) = \frac{\ln \beta_H(p_0) - \ln \beta_L(p_0)}{\beta_H(p_0) - \beta_L(p_0)}$ for any given p_0. Consequently, if p_0^∞ is less than $H\left(e^{-\lambda(p_0^\infty)\beta_L(p_0^\infty)} - e^{-\lambda(p_0^\infty)\beta_H(p_0^\infty)}\right)$, then there are two levels of λ^∞ (one above and one below $\lambda(p_0^\infty)$) given which the supply condition is satisfied. On the other hand, if p_0^∞ exceeds $H\left(e^{-\lambda(p_0^\infty)\beta_L(p_0^\infty)} - e^{-\lambda(p_0^\infty)\beta_H(p_0^\infty)}\right)$, the supply condition fails for all λ^∞.

Tuning-in indifference condition. Because $\tau(d)$ converges to zero as $d \to \infty$, we have $\tau(d) \in (0, \frac{1}{S})$ for all sufficiently large d, meaning that each consumer tunes in to one story with probability $S\tau(d)$ and otherwise tunes in to zero stories. In particular, consumers must be indifferent whether to tune in to a first story. Because this "tuning-in indifference condition" holds for all sufficiently large d, it also must hold in the crowd limit, i.e.,

$$\Delta U^{S\infty}(p_0^\infty) + \Delta U^{A\infty}(p_0^\infty, \lambda^\infty) = \kappa_1 \tag{26}$$

where $\Delta U^{S\infty}(p_0^\infty) \equiv \lim_{d\to\infty} \Delta U^S(p_0(d))$ is the crowd-limit sharing benefit from tuning in to a story and $\Delta U^{A\infty}(p_0^\infty, \lambda^\infty) \equiv \lim_{d\to\infty} \Delta U^A(p_0(d), \tau(d); d)$ is the crowd-limit acting benefit.

By continuity of $\Delta U^S(p_0^\infty)$ and equation (12), we have

$$\Delta U^{S\infty}(p_0^\infty) = \Delta U^S(p_0^\infty) = u^S[p_0^\infty \beta_H(p_0^\infty) - (1 - p_0^\infty)\beta_L(p_0^\infty)]. \tag{27}$$

The crowd-limit acting benefit of tuning in can also be simply derived. Tuning in gives a consumer the option to act on a story *conditional* on that story not otherwise being seen socially. Because $\lim_{d\to\infty} \tau(d) \to 0$, each consumer's likelihood of seeing stories directly from suppliers goes to zero in the crowd limit, and the likelihood of seeing a high- or low-quality story socially converges to V_H^∞ and V_L^∞, respectively. Let $\hat{p}_0^\infty$ be the likelihood that a story is high quality conditional on not being seen socially in the crowd limit. Applying Bayes' Rule, $\hat{p}_0^\infty$ is given by

$$\frac{\hat{p}_0^\infty}{1-\hat{p}_0^\infty} = \frac{p_0^\infty}{1-p_0^\infty} \times \frac{1-V_H^\infty}{1-V_L^\infty} \tag{28}$$

where V_H^∞ and V_L^∞ are functions of p_0^∞ and λ^∞ derived earlier. Conditional on having tuned in and not having any sharing neighbors, the expected acting-related benefit of tuning in is therefore

$$\Delta U^{A\infty}(p_0^\infty, \lambda^\infty) = (p_0^\infty(1-V_H^\infty) + (1-p_0^\infty)(1-V_L^\infty)) \times \frac{u^A}{u^S} \Delta U^S(\hat{p}_0^\infty) \tag{29}$$

The first of the two main terms in (29) is the ex ante probability that a story will not be shared socially, so that tuning in enables a consumer to act on the story. The second main term is the expected benefit that a consumer receives by being able to act on a story, conditional on no one else sharing it. (By assumption, the payoffs that a consumer receives from acting are the same as what they receive from sharing, just scaled by the factor $\frac{u^A}{u^S}$. The expected benefit of being able to act on the adversely-selected set of stories that have not been shared socially is therefore $\frac{u^A}{u^S}$ times the expected value of being able to share in a hypothetical context in which story veracity equals $\hat{p}_0^\infty$ rather than p_0^∞.)

As discussed in the main text, the acting-related benefit of tuning in is not necessarily increasing in story veracity, since higher story veracity induces more sharing which in turn reduces the value of tuning in. However, it is easy to check that $\Delta U^{A\infty}(p_0^\infty, \lambda^\infty)$ is decreasing and continuous in λ^∞.[24] Thus, for any given p_0^∞, there is at most one level of λ^∞ satisfying the tuning-in indifference condition.

Combining the supply condition and tuning-in indifference condition gives the full set of crowd-limit equilibrium outcomes. Multiple equilibria are possible and comparative statics are complicated by the complex interplay between story veracity and consumers' tuning-in behavior.

[24] As λ^∞ increases, (i) the ex ante probability that no one shares falls, reducing the first main term in (29), and (ii) the set of stories that are not shared become even more adversely selected, reducing $\hat{p}_0^\infty$ and hence reducing the second main term in (29).