Addiction to a Network*

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Abstract

We characterize dynamic rational addiction to a harmful product by informed individuals who are connected to a network of users of the addictive product. The network's accumulated stock of consumption harms each individual and imposes peer pressure on her to consume the addictive product. When harm is concave in aggregate stock, an increase in the network intensifies addiction, and when it is sufficiently convex, a larger network mitigates addiction. "Rehabilitation", achieved by disconnection from the network, can prevent addiction if implemented early enough. The results support regulation of social media platforms' practices encouraging expansion of the individual's network and use.

Keywords: network, addiction, peer pressure, social interactions, social network sites, social media platforms, Facebook, Instagram, TikTok, influencers, rehabilitation, dynamic programming.

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1 Introduction

It is well documented in the psychological literature that people smoke, consume alcohol, and abuse illicit drugs more when around other people who do so and that direct or indirect peer pressure by the others is one of the main causes of initiation of consumption, increased consumption, and relapse after trying to quit (Larsen et al (2012); Bassiony (2013); Etcheverry and Agnew (2008); Bhad et al (2016); Mizanur et al (2016); Dimoff and Sayette (2016); Tikoo et al (2017); Lin et al (2017); Edwards et al (2017) Ramji et al (2019)).[1]

Similarly, psychological studies have found that individuals start using social media platforms, such as Facebook and Instagram, and find it hard to quit, due to indirect peer pressure and the fear of missing out (Subrahmanyama et al (2008); Pelling and White (2009); Kieslinger (2015); Abel et al (2016); Juergensen and Leckfor (2019); Blanca and Bendayan (2018); Tomczyka and Selmanagic-Lizdeb (2018); Pontes et al (2018); Liu and Ma (2018); McCrory et al (2022)). The fear of missing out is defined by these studies as the "feeling that others may be having rewarding experiences from which one is absent, characterized by the desire to stay connected with what others are doing" (Liu and Ma (2018); Przybylski et al. (2013)). This literature has also shown that excessive use of a social media platform is worse when the group-norm about the importance of the social network is stronger (Marino et al (2016)).

Indeed, in recent years, extensive psychological literature shows that many surveyed individuals develop symptoms that have the attributes of addiction to social media platforms, such as Facebook, Instagram and TikTok. The psychological literature shows that this behavior harms users and has attributes similar to ordinary addiction to chemical substances. In particular, such compulsive use of social media platforms has been shown to be associated with salience (permanent thinking about use), tolerance (increased consumption is required to reach previous utility levels) relapse (reverting to a pattern of earlier use after ineffective attempts to reduce consumption), withdrawal (becoming stressed when trying to avoid consumption), social overload due to excessive use, negative mood, depression, lower self-control, anxiety, insomnia, stress, envy, impairment

[1] In the case of smoking, for example, Malhorta et al (2009) find that "[n]icotine users reported peer pressure as a single most important cause for initiation; however after a period of use nicotine withdrawal preempted them from stopping its use."

of offline activities, disordered eating behavior, damage to relationships at work and at home (also known as “conflict”), and, in extreme cases, suicide (Elphinston & Noller, (2011); Kuss & Griffiths, (2011); Andreassen et al, (2012); Maier et al (2012); Wilcox and Stephen (2013); Sagioglou & Greitemeyer, (2014); Andreassen (2015); Kircaburun and Griffiths (2018); Abbasia and Drouinb (2019); Wilksch et al (2020); Marengo et al (2020); Brailovskaia et al (2020); Lemert (2022)). Economists have recently supported the psychological literature with randomized experiments (Allcott et al 2022).

It is well documented that, alongside various benefits, social media platforms cause harm. Allcott et al (2020)'s randomized experiment including 2,743 participants shows that social media users with intensive use would rather decrease their use in order to improve their well-being. Braghieri et al (2022)'s quasi experiment using Facebook's staggered rollout in US colleges finds that Facebook impaired college students' mental health and estimate that Facebook explains 24% of the increased prevalence of severe depression among college students over the last two decades. They show these mental health consequences to be higher the longer the college student was exposed to Facebook. Rosenquist et al (2022) cite internal Instagram and Facebook studies documenting such harm, particularly with regard to teenagers.[2] Harm to the individual by the social media platform has been shown to increase over time (Brailovskaia and Margraf (2017); Brailovskaia et al (2018))). Mark Zuckerberg's published “Blueprint for Content Governance and Enforcement” reveals that user engagement peaks when the content is just barely allowed and when users' ex-post reported well being concerning it is negative.[3] It has been reported that Facebook's algorithm routing content to the user's feed places five times more weight on responses including angry emojies than on ordinary “likes” (Omerus et al (2021)). McCrory et al (2022)'s survey finds that features such as likes and infinite scrolling were associated with negative emotions. Similarly, Fan et al (2014) show that in Weibo, the largest Twitter-like service in China, anger by one user provokes anger by connected users more than joy provokes joy.

Shensa et al (2017) show, in a U.S. nationally representative sample of 1749 young adults aged 19 to 32, that 44% of U.S. young adults have symptoms of mild addiction to social media platforms and 14% have symptoms of more severe addiction. Reer et. al.

[2]Furman et al (2019) and Crémer et al (2019) report harm caused by social media platforms to the privacy of users.

[3]See Lemert (2022), and https://www.facebook.com/notes/751449002072082/.

(2020) show, in a nationally representative sample of 1929 German internet users aged between 14 to 39, that 2.6% of them suffer from disorders associated with addiction to social media platforms. De Cock et al. (2014) had similar findings, of 2.9% of internet users aged 18 and above in a nationally representative Belgian sample. Banyai et al (2017) find, in a nationally representative sample of adolescents in Hungary, that 4.5% of them were at risk of addiction to social media platforms. As Lemert (2022) reports, psychiatric experts on technology addiction estimate that 5% of all Facebook users (i.e., approximately 11.6 million Americans) experience addictive use. Also, studies have shown that adolescents spend 20% to 30% of their waking hours on digital platforms (Twenge et al 2019; Rosenquist et al 2022) and 90% of children aged 13–17 use social media (American Academy of Child and Adolescent Psychiatry (2018)). As of April 2023, it has been reported that Facebook alone has approximately 3 billion users and the 2023 figure for Instagram was over 2.35 billion users.[4] Tiktok was reported having more than 1.677 billion users worldwide.[5] In 2022, social media platforms were used by more than half of the world's population, and the average user spent around two and a half hours per day on social media platforms (McCrory et al (2022); Braghieri et al 2022).

In accordance with these empirical findings, in our framework consumption by the other members of the network harms the individual.[6] We assume the individual has no control over her connection to the network. For example, although an individual could physically disconnect from Facebook or Instagram, she cannot disconnect from her friends. Knowing that these friends will go on using Facebook or Instagram without her, the effects of the network on her (stress, envy, the fear of missing out, etc.) are assumed to persist.[7] Other examples of networks the individual must take as given are adolescent school-mates, or members of the same household, who smoke, consume alcohol, consume

[4]See See https://bit.ly/47TpCoX; https://bit.ly/48cUMr9.

[5]See https://bit.ly/48cq4OM

[6]Our framework could easily be extended to cases where harm from the network begins (or outweighs the benefit) when reaching some threshold of exposure to the network's use. This could capture cases in which moderate consumption (e.g., of alcohol or of using social media platforms) does not involve net harm to the individual.

[7]Our results would not qualitatively change if the individual is connected because she derives a large enough fixed benefit from being connected (or large enough fixed cost of disconnection). Take, for example, an individual who wants to be connected to a network of smoking bosses and colleagues at work, in order to keep her job or be promoted, but she prefers that the quantity of smoking be reduced to zero.

drugs, or develop obesity, together. We assume that the network exerts peer pressure on the individual to consume the addictive product. Peer pressure can involve direct pressure imposed on the individual to consume the product. Alternatively, peer pressure could be indirect: it may be the individual that feels pressured to consume the harmful product due to the fear of missing out. In our model, each individual in the network decides on the quantity she consumes of a non-addictive product (e.g., offline activity) and an addictive product (e.g., use of the social media platform), both of which are assumed to give the individual current benefit. We model peer pressure by assuming that the higher the aggregate stock of consumption by the whole network, the lower the individual's marginal utility from consuming the non-addictive product rather than the addictive product. The effect of each network member i on the aggregate stock affecting another network member j could differ among individuals.

Hence the network in our framework can harm the individual either directly (as in the case of passive smoking or a social media platform exhausting the individual's time or invoking envy or frustration) or indirectly, via the peer pressure. For example, an adolescent who goes to a bar with her friends may individually prefer a soft drink to alcohol. Yet, her friends' peer pressure reduces her marginal utility from the soft drink, so she consumes alcohol instead. Absent the network, she would have consumed the soft drink and derived a larger benefit. In our model, it is the aggregate accumulated stock of consumption by the network that affects the individual and not only the peers' current or lagged consumption. Indeed, most of the psychological literature cited above shows that peer pressure is not caused only by the peers' current consumption of the addictive product, but also by the network's accumulated past consumption. In the case of social media platforms such as Facebook and Instagram too the psychological literature documenting the fear of missing out and peer pressure as a driver of use implies that this fear is increasing in the amount of accumulated use by others in the network, and does not hinge only on contemporary use (Turel and Osatuyi (2017)). For example, the larger the number of posts and stories the individual's friends have posted, the more the individual experiences the fear of missing out if she does not participate too. Our assumption that it is the past accumulated stock of the network's consumption that affects the individual also draws support from Arduini et al (2019)'s empirical study of high school students. Their data includes the amount of use of cigarettes or alcohol by an adolescent's close friends in previous years and they find that the parameters generated by this data affect the adolescent's current use.[8] Also, the harm that the network inflicts on the individual is more reasonably assumed to increase in the accumulated consumption of the network.

Our objective is to characterize equilibrium behavior of network members in a dynamic setting. We wish to show under what circumstances a rational and informed individual can find herself addicted to a harmful product, when she is part of a network of other individuals who consume the product and exert peer pressure on her to consume. This can be a plausible cause for addiction in network settings (e.g., addiction to a social media platform) that may be extremely important. The underlying question is, in a dynamic setting, will a rational individual reduce her own consumption of the addictive product, to counteract the future harm from the network's accumulated stock, or will the individual join in and consume more of the addictive product, due to the network's peer pressure? Which of these two opposing forces dominates?

We study addiction in a network setting under two scenarios. The first assumes that the individual's own consumption does not affect other members of the network. This simple case captures situations in which the individual does not play a pivotal role in the network. Accordingly, the individual assumes that the other members of the network are in a steady state, contributing a constant level of consumption per period. A second scenario we explore is that of a network with strategic players. We prove the existence of an open loop equilibrium (OLE), in which each individual in the network is assumed to know the initial state of stock but she does not observe the subsequent states. Each individual's sequence of consumption levels is the best response to the sequences of the others. We study how changes in the network's parameters (the number of users, their initial stocks of consumption or the influence parameters) affect equilibria and characterize cascade equilibria in which a "rotten apple" with high initial consumption joins the network and causes the network to switch from abstention to consumption of the addictive product. We then demonstrate how results from the OLE framework extend to Markov Perfect equilibria (MPE), in which each individual's strategy relies on the current state of aggregate stock, and how trigger strategies can be used to enforce a

[8]Similarly, Larsen et al (2012) show that alcohol consumption by an individual is increasing in the size of her peers' consumption. See also Cutler and Storm (1975). Another example is obesity, where the literature shows that the chances of becoming obese rise when close peers are obese (e.g., Fowler and Christakis (2008)), and here too it is accumulated consumption that matters.

consumption-less equilibrium.

When discussing addiction by individuals who are not connected to a network, previous literature has dealt with either irrational or rational addiction. In the former strand, the individual does not weigh the product's virtues and harm in a rational way, and hence she becomes addicted (see, e.g., Winston (1980); Gruber and Koszegi (2001); Gul and Pesendorfer (2007) and Bernheim and Rangel (2004). Relatedly, Fershtman and Segal (2018) study social influence affecting an individual with core preferences and behavioral preferences, where the latter determine her behavior. The second strand of the literature assumes that the individual is rational, but nevertheless consumes an addictive product. Stigler and Becker (1977), and Becker and Murphy (1988)'s models of rational addiction imply that the individual is content with her addiction. In order to explain situations in which a rational individual regrets consuming the addictive product, the theory of rational addiction has been further developed by Orphanides and Zervos (1995), who assume that the individual is uninformed as to the harm she may suffer from the addictive product. Wang (2007) studies rational addiction by an individual who is misinformed regarding the level of consumption causing addiction and the level of consumption enabling the individual to quit successfully.

In contrast to this literature, in our paper the individual may consume an addictive product that harms her even though she is both rational and perfectly informed regarding future harm. This occurs when the individual is part of a network of other individuals who consume the addictive product, and is subject to peer pressure from the other members of the network. Hence we offer an alternative explanation for addiction to a harmful product in a dynamic setting that does not hinge on irrationality or misinformation about either future harm or the ability to quit. Our framework also explains why rational and informed individuals initiate consumption of a harmful addictive product even absent a temporary stressful event, assumed to cause initiation in the Becker and Murphy (1988) framework. Allcott et al (2022)'s randomized experiment, while abstracting from network effects, shows that individuals do not reduce their use of social media in a way that is consistent with their awareness of its addictive nature and they interpret this result as inattentiveness to self-control problems. Our theoretical result suggests that peer pressure and the fear of missing out can explain excessive use by individuals even when they are fully rational.

As noted, in a dynamic setting, it is not obvious that the network intensifies the individual's consumption of the addictive product, because she may want to counteract the future harm the network's stock inflicts by reducing her own consumption. Indeed, we show that being part of a network can encourage or discourage the individual to become an addict depending on whether the future harm inflicted on the individual is concave or convex in the network's accumulated consumption. If the harm is concave, the concavity of harm and the peer pressure reinforce each other, so that, due to a strong enough network, an individual who would have abstained from the addictive product absent the network starts consuming it and follows a consumption path that leads to her own addiction. Also, any increase in the network, its consumption, or the degree of influence among individuals causes addiction by the individual to be more severe, with larger consumption of the addictive product. This is consistent with Turel and Osatuyi (2017)'s empirical survey, showing that an observed increase in peers' use of a social media platform augments the individual's compulsive use. Conversely, if the future harm inflicted by the network is sufficiently convex, the network has a chilling effect on the individual's consumption. Here the future marginal harm inflicted by the network outweighs the peer pressure, so our comparative statics flip and the individual counteracts the network's harmful consumption by mitigating her own consumption. Hence, with regard to smoking, or consuming alcohol or drugs within networks, our results depend on the parameters of the case at hand. With social media platforms, however, there are key commercial players clearly encouraging enhancement of the networks and users' mutual influence. Hence, a simple revealed preference argument implies that these key players, operating platforms such as Facebook, Instagram, and TikTok, understand the harm function not to be so convex so as to induce individuals to mitigate their use when the network expands or the influence parameters increase: this would harm the platform's profits. Indeed, the annual 2022 report of Facebook and Instagram's parent company, Meta Platforms, Inc.'s, reveals that Meta "generates substantially all of [its] revenue from advertising," and any loss in user engagement is "likely to have a material and adverse impact" on the revenue Facebook generates. Meta further disclosed that its "financial performance has been and will continue to be significantly determined by our success in adding, retaining, and engaging active users." (Lemert 2022).

There is always a welfare-maximizing consumption-less equilibrium in our framework, as long as members' initial stock of consumption is sufficiently small. Along-side this equilibrium, though, there are equilibria with consumption, including maximum consumption (of spending the individuals' entire incomes on the addictive product). This implies that individuals can benefit from organizations such as Alcoholics Anonymous or weight loss groups, or appropriate guidance from teachers, which help them coordinate on the consumption-less equilibrium.

Our results also shed a new light on the question of rehabilitation from the addictive product. One of the characteristics of harmful addictions that the rational addiction literature dealing with an individual not connected to a network has not yet been able to explain is the incidence of rehabilitation efforts. Under the current rational addiction literature, the individual either prefers not to rehabilitate or quits on her own. By contrast, in our framework, the individual can rationally try to seek intervention that reduces the harm the network inflicts on her. For example, a teenager that was induced to consume drugs or alcohol due to pressure from her friends may rationally prefer that some agency forbid her friends from consuming. Indeed, in the context of smoking, Dimoff and Sayette (2016) discuss disconnection from one's network of smoking friends as a means of helping a smoker quit smoking. Similar methods have been suggested in the context of addiction to alcohol by adolescents (Teunissen et al (2014); Kremer and Levi (2008)). We show that the question whether rehab, in the form of disconnection from the network, is effective depends on whether it is implemented on time, before the individual reaches a point where even when disconnected from the network, she "goes on a binge" rather than "cold turkey" and continues excessive use on her own. This is consistent with Malhorta et al (2009)'s finding that when the individual is disconnected from smoking peers too late, she typically continues smoking due to nicotine withdrawal. Unlike disconnecting an adolescent from a network that uses drugs or alcohol, physical disconnection from a social media platform would not necessarily help, since the fear of missing out would persist. Still, the individual in our framework would benefit from external intervention (e.g., via regulation), that limits the nature and quantity of her friends' content she is exposed to.

Our dynamic framework enables us to study issues that cannot be addressed in static models of peer pressure (e.g., Ballester et al (2006) and Calvó-Armengol et al (2009)), such as rehab, convexity of harm causing comparative statics to flip, and using punishments off the equilibrium path to enforce consumption-less equilibria.

Our formal results can be used to support legal policy papers (e.g., Rosenquist et al (2022); Griffin (2022); Langvardt (2019)) calling for regulation of social media platforms' practices meant to enhance the network and its usage. As we show, when harm is not too convex in aggregate stock, in our constant network model, the larger the network's use and size, the higher the prospects and severity of addiction. In the strategic model, our comparative statics results show that any increase in the number of network members, the influence parameters, or users' initial stock, intensify addiction. As we show, social media platforms' practices allegedly affect these parameters in a way that encourages addiction. Also, features facilitating excessive use, such as infinite scrolling, in which, without changing screens or having to click, the individual can endlessly scroll down content she is exposed to by others with no limit, also facilitate the maximum-consumption equilibria we show to exist.

As reported by Lemert (2022), a former Facebook executive revealed that "the thought process [behind Facebook's business model] was all about, "[h]ow do we consume as much of your time and conscious attention as possible?" and quotes Facebook's experts concluding that "we need to ... give you a little dopamine hit every once in a while, because someone liked or commented on a photo or a post ... and that's going to get you to contribute more content, and that's going to get you more likes and comments. It's a social validation feedback loop." Our results, showing that efforts by the social media platform to expand a user's network and use intensify addiction even when the individual is rational and informed can help supporters of regulation cope with possible allegations from social media platforms that it is supposedly unreasonable to assume users are irrational and uninformed about the risk. Our results further imply that it may not be enough to change default features, as suggested by some of the current legal literature and proposed legislation, such as disabling infinite scrolling or notifications or limiting per-day use, while allowing the individual to opt-in and restore such features.[9] The reason is that due to the network's peer pressure, the individual may well opt-in and restore problematic features. A similar policy implication of our results is that merely making the individual aware of the risk of addiction (as suggested for example by Nikbin et al (2020)) may not be helpful. In the same vein, our results

[9]For such legislative initiatives see Griffin (2022).

could be used to support legal scholars' claims advocating for ex-post tort liability in extreme cases, particularly in the case of adolecents, for the harm caused by the network's efforts to expand their use. These scholars claim that analogies can be drawn between tobacco companies inducing addiction to cigarettes and social media platforms inducing addiction to their networks (e.g., Rosenquist et al 2022; Griffin 2022; Lemert 2022). Similarly, recent law suits have raised claims of liability related to product safety laws. Dozens of product liability suits across the U.S. were brought against Meta (the parent company of Facebook and Instagram), TikTok, Snapchat, and other social media platforms.[10] All of these suits were consolidated and transferred to the Federal district court in Northern California, holding that all of these suits "present common factual questions arising from allegations that defendants' social media platforms are defective because they are designed to maximize user screen time, which can encourage addictive behavior in adolescents. ... including whether Meta's platforms (Facebook and Instagram) encourage addictive behavior ... ."[11] Although the U.S. Congress has enacted, in 1996, section 230 of the Communications Decency Act,[12] which grants immunity from liability to a website platform for content created by third parties, the claim in these suits is that there is no such immunity for the actions of the platform itself that could encourage or intensify harmful addiction to the platform.[13]

Our paper contributes to the sparse literature that combines habit formation by forward-looking individuals with social interactions. Bisin et al (2006) study an equilibrium in which an individual's utility is affected by her neighbor's current actions and has disutility from changing habits. Ozgur et al (2018) extend Bisin et al (2006) and study a linear setting with random preference shocks. They assume that the individual has disutility from deviating from peers' current preference shocks, as well as from the individual's consumption in previous periods. Abel (1990) studies individuals affected by their peers' previous period average consumption as well as their own previous period

[10] See In re Soc. Media Adolescent Addiction/Personal Injury Prods. Liab. Litig., 2022 U.S. Dist. LEXIS 227736.

[11] See id.

[12] 47 U.S.C. §230.

[13] See also Seattle School District No. 1 v. Meta Platforms, Inc., complaint, 1.6.2023, where a school district brought a public nuisance suit against several social media platforms for the harm caused to adolescents and Case 4:23-cv-05448 State of Arizona v. Meta Platforms, Inc. complaint, 24.10.2023, where 41 states, and the district of Columbia, sued Meta claiming Facebook and Instagram encourage addiction, harming children.

consumption. He focuses on the equity premium puzzle. Reif (2018) studies addiction by an individual with quadratic utility who may be affected in a symmetric way by current actions of her peers. His model focuses on positive network effects, causing the individual to consume too little. Binder and Pesaran (2001) study individuals who are affected by their last-period decisions and have a taste for conformity to the previous period's average behavior by others. Their focus is on consumption-savings.

Our paper differs from this literature in various ways. First, in our model accumulated consumption by the network directly affects each individual's state of aggregate stock. We believe this is an important avenue to study since, as noted, the psychological and empirical literature on peer pressure to consume addictive products usually implies that it is the peers' accumulated stock of consumption that matters. This includes the phenomenon of excessive use of social media platforms, where the psychological literature implies that the fear of missing out driving such excessive use is increasing in the accumulated stock of consumption by the rest of the network. Moreover, unlike previous literature, we study the case of a harmful product and of a network's aggregate stock that harms the individual. Also, our model utilizes the possible multiplicity of steady states and equilibria to study the effect of rehabilitation (i.e., disconnection from the network) on binge and cold turkey behavior. Another difference between our paper and previous literature is that we examine how a change in the network, such as the addition of new members, or a change in members' initial stock or the influence matrix, affect the equilibria of the strategic game. This has policy implications for instances in which an entity influencing network size and use, such as a social media platform, utilizes this influence to encourage addiction. To the best of our knowledge, ours is the first theoretical paper to model how actions of social media platforms affect addiction. The rest of the paper is organized as follows. Section 2 describes the model. Section 3 studies the case of a constant network and Section 4 studies the strategic game. Section 5 concludes.

2 Model

Consider n individuals, $i = 1, 2, ..., n$, who form a network. In each period, individual i can consume two products: the non-addictive product, c, and the addictive product, a. The n individuals are connected to the network at time $t = 0$. Time is discrete and there is an infinite number of periods. In each period t individual i consumes a quantity c_t^i of product c and a quantity a_t^i of product a. The aggregate stock of product a, the addictive product, affecting individual i until the beginning of period t, is s_t^i. Accordingly:

$$s_{t+1}^i = \delta s_t^i + \sum_{j=1}^{n} \gamma_{ij} a_t^j \tag{1}$$

Where $\delta \in (0,1)$ is the past consumption's dissipation factor and $\gamma_{ij} \geq 0$ is a parameter depicting how consumption by individual j affects individual i's utility, through its effect on i's aggregate stock. The weights γ_{ij} form the influence matrix $\Gamma \equiv (\gamma_{ij})$. For example, a particularly popular Instagram influencer j is expected to have a large γ_{ij} for all $i \neq j$. Furthermore, $\gamma_{ii} = 1$, so the individual's own consumption enters her aggregate stock as is.[14]

The contribution to the aggregate stock of individual i at time t by all others is therefore $\xi_i(t) \equiv \sum\limits_{j \neq i} \gamma_{ij} a_t^j$. In Facebook, for example, the accumulated stock each individual is exposed to is placed in her "feed", using the infinite scrolling feature mentioned in the introduction, which includes all content and updates from her friends and from pages she follows. The content posted by the individual is placed in her profile, which includes a time-line in which the individual can share, on an ongoing basis, posts, text, photos and videos, with her friends and followers.[15] Instagram has similar features, such as the "feed" (with the infinite scrolling) and the profile, and it also features the "story", in which content expires after 24 hours,[16] though the individual can store this content permanently by including it in the "highlights" feature.[17]

According to (1), the state of the game is an n dimensional vector comprised of the aggregate stocks of all n individuals and is denoted $\underline{s}_t = [s_t^1, s_t^2, ..., s_t^n]^T$. Thus, the evolution of this n dimensional state in matrix notation is:

[14] Note that γ_{ij} can take any non-negative value, including values above 1. We assume for concreteness that the network is well connected in the following sense: for every two individuals i, j, if $\gamma_{ij} = 0$ then there exist k individuals $l_1, ..., l_k$ such that $\gamma_{il_1}, \gamma_{l_1 l_2}, ..., \gamma_{l_k j} > 0$, i.e. j influences l_k, which in turn influences l_{k-1} and so on, until l_1 who influences i. Hence, indirectly, every two individuals influence each other. Our results would carry over, *mutatis mutandis,* to cases in which pairs of individuals not influencing each other exist.

[15] See https://www.facebook.com/help/396528481579093/?helpref=hc_fnav.

[16] This, on one hand, reduces the aggregate stock followers are exposed to, but on the other, it was reported that it causes followers to enter the app more often so as not to miss content from friends and influencers that expires quickly. Also, expiration after 24 hours in the "story" feature is said to encourage posting of additional content that otherwise may not have been shared (Belanche et al (2019)).

[17] See https://bit.ly/3uRePwR (for the "feed"); https://bit.ly/48bIcZ7 (for the profile); and https://bit.ly/4ahZNAt; https://bit.ly/3ThIlWZ (for story and highlights).

$$\underline{s}_{t+1} = \delta \underline{s}_t + \Gamma \underline{a}_t \tag{2}$$

Where $\underline{a}_t \equiv [a_t^1, a_t^2, ..., a_t^n]$.

The utility of individual i in period t is denoted $u(c_t^i, a_t^i, s_t^i)$, assumed to be twice continuously differentiable for $c_t^i, a_t^i, s_t^i \geq 0$, including one-sided differentiation in corners, is increasing and strictly concave in c^i and a^i ($u_1^i > 0$, $u_2^i > 0$, $u_{11}^i < 0$, $u_{22}^i < 0$), and is decreasing with aggregate stock ($u_3 < 0$).[18] This formally captures the characteristics of withdrawal, tolerance and harm that are typical to addiction. Furthermore, the network inflicts peer pressure on the individual, which reduces the individual's marginal utility from product c, the non-addictive product ($u_{13} < 0$).[19] Finally, we mainly focus on the case where $u_{33} > 0$: aggregate stock harms the individual in a decreasing way (that is, harm itself is concave in aggregate stock). This reinforces the peer pressure inflicted on the individual in a way that encourages addiction. As we shall see, if this assumption is relaxed and u_{33} is sufficiently negative (i.e., harm is sufficiently convex in aggregate stock), belonging to a network actually causes the individual to mitigate her consumption of the addictive product and comparative statics in equilibrium are reversed. Each individual has a fixed income per-period, y. We shall normalize the price of product c to 1 per unit and assume, for simplicity, that the "price" per unit of product a, the addictive product, is also 1.[20] All individuals discount future utility by $\beta \in (0, 1)$. Accordingly, the problem faced by individual i when the initial stock vector is $\underline{s}_0$ is:

$$\max \left\{ (1-\beta) \sum_{t=0}^{\infty} \beta^t u(c_t^i, a_t^i, s_t^i) \right\} \tag{3}$$

$s.t.\ c_t^i + a_t^i \leq y,$

$c_t^i, a_t^i \geq 0,$

$s_{t+1}^i = \delta s_t^i + \sum_{j=1}^n \gamma_{ij} a_t^j$[21]

[18] These assumptions are consistent with McCrorry et al (2022)'s qualitative survey of social media users finding that individuals convey a short-lived positive experience together with a long-run negative experience.

[19] To focus on peer pressure, we further assume for concreteness $u_{23} = 0$ and $u_{12} = 0$. None of our results would be affected by allowing $u_{12} \neq 0$, and $u_{23} \neq 0$, as long as $u_{23} - u_{13} > 0$ and $u_{11} + u_{22} < 2u_{12}$.

[20] The price the individual pays for the addictive product need not be monetary. For example, in the case of addiction to social media platforms, although the individual does not pay in monetary terms, she can be assumed to pay by devoting time or privacy. We assume, for concreteness, that this sacrifice is deducted from the individual's per-period income, just like a monetary price.

[21] We multiply the stream of utility by $1 - \beta$ to obtain the average utility per-period that individual

Individual i's problem can be simplified by noting that her utility is strictly increasing in c^i so that her budget constraint is always binding. Thus $c^i = y - a^i$ and the individual's per-period utility and harm can be represented by $w(a^i, s^i) \equiv u(y - a^i, a^i, s^i)$. It follows directly from our assumptions on $u(c^i, a^i, s^i)$ that $w_1 > 0, w_2 < 0, w_{11} < 0, w_{12} > 0, w_{22} > 0$.

The next section discusses the network's effect on an individual whose behavior does not affect other network members, who are assumed to be in a steady state, so that they contribute a constant level of aggregate stock each period. We shall call this the constant network case. Then, in Section 4, we extend the analysis to a strategic network where individuals optimally respond to each other's consumption.

3 Constant network

Consider now a special case of the general model depicted in section 2, in which for a certain individual i, $\gamma_{ji} = 0 \, \forall j \neq i$, i.e., the individual's consumption does not affect the other network members.[22] Nevertheless, consumption by the other network members affects individual i. This corresponds to cases in which individual i is not an important member of the network (e.g., an unpopular adolescent who is part of a network engaged in consumption of cigarettes, drugs or alcohol). Another case this variant of the model depicts is that of a network that is large, so that the individual does not affect it, as is often the case with social media platforms. Assume further that the rest of the network is at a steady state, so that its effect per-period on individual i is constant: $\sum_{j \neq i} a_t^j \gamma_{ij} \equiv \xi \quad \forall t$. Denote the individual's consumption of product a at period t as a_t and the aggregated stock affecting the individual (contributed by the individual and the network) until the beginning of period t as s_t, which is the (one-dimensional) state at time t. The evolution of aggregate stock affecting the individual is given by:

$$s_{t+1} = \delta s_t + a_t + \xi, \tag{4}$$

The individual's utility in period t is $w(a_t, s_t)$. The individual's value function can be represented recursively as:

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i obtains.

[22] Hence, in this section we relax our assumption that the whole network is well-connected.

$$V(s_0) = \max_{\forall t: a_t \in [0,y]} (1-\beta) \sum_{t=0}^{\infty} \beta^t w(a_t, s_t).$$

$$s.t.\ s_{t+1} = \delta s_t + a_t + \xi$$

The corresponding Bellman equation is:

$$V(s) = \max_{a \in [0,y]} (1-\beta) w(a,s) + \beta V(\delta s + a + \xi), \tag{5}$$

Proposition 1 establishes the existence and uniqueness of this value function and the existence of the individual's policy correspondence. All of the proofs are in the appendix.

Proposition 1. *In the constant network case, there is a unique continuous value function, $V(s)$, which satisfies equation (5) and there exists a non-empty, upper hemicontinuous, policy correspondence:*

$$\Phi(s) = \{s' :\ V(s) = (1-\beta) w(s' - \delta s - \xi, s) + \beta V(s')\} \tag{6}$$

Denote by $\mu_{1t} \leq 0$ the Lagrange multiplier on the constraint $a_t \geq 0$ and $\mu_{2t} \geq 0$ the Lagrange multiplier on the constraint $a_t \leq y$. The Lagrangian associated with Equation (5) is

$$L_t = (1-\beta) w(a_t, s_t) + \beta V(\delta s_t + a_t + \xi) + \mu_{2t}(a_t - y) - \mu_{1t} a_t. \tag{7}$$

Denote $\mu_t \equiv \mu_{2t} - \mu_{1t}$. Lemma 1 derives the individual's first order condition:

Lemma 1. *The individual's first order condition is:*

$$w_1(a_t, s_t) + \mu_t + \beta[w_2(a_{t+1}, s_{t+1}) - \delta w_1(a_{t+1}, s_{t+1}) - \delta \mu_{t+1}] = 0. \tag{8}$$

Since we have not imposed a condition of joint concavity, there may be more than one steady state (i.e., a state satisfying $\overline{s} \in \Phi(\overline{s})$) to which optimal paths converge, depending on the initial level of aggregate stock. When studying the case of an individual not connected to a network, Orphanides and Zervos (1994) and Dechert and Nishimura (1983) have shown that in that case, even with multiple steady states, optimal paths of consumption monotonically converge to a steady state. As demonstrated below, this monotonicity property carries over to the case of an individual connected to a constant network. Proposition (2) shows that between any two consecutive steady states there is a unique critical level such that an optimal path starting below the critical level converges to the lower steady state and an optimal path starting above the critical level converges to the upper steady state.

Proposition 2. *Fix $\xi \geq 0$. The optimal path of aggregate consumption of the addictive product has the following properties:*

(i) At least one steady state exists.

(ii) Any optimal path of aggregate stock monotonically converges to a steady state.

(iii) There is one critical level between any two consecutive stable steady states.

The possibility that optimal paths and steady states are not unique and the feature that an optimal consumption path beginning above a critical level monotonically converges to an upper steady state while an optimal path beginning below the critical level monotonically converges to a lower steady state is meaningful for modeling addiction. It can capture behavior such as going on a binge (converging to an upper steady state of consuming the addictive product) or going cold turkey (converging to a lower steady state). Also, note that we do not require that optimal paths be interior solutions.[23] This allows for optimal abstinence from the addictive product or acute addiction of using the individual's entire income to consume the addictive product. The next lemma emphasizes that in our model, the network and aggregate stock harm the individual:

Lemma 2. *(the individual suffers from the network) Fix s_0 to be some initial state and define by $V(s_0;\xi)$ the value of the decision problem in (5) for a specific ξ. Then $V(s_0;\xi)$ is decreasing in both arguments.*

This follows directly from our assumption that $w_2(a_t, s_t) < 0$. For example, if the individual is present in a network of smokers, the larger this network, the worse off is the individual (regardless of her own smoking). That is, the increase in the individual's own smoking brought about by an increase in the network's smoking, despite its immediate benefit to the individual, never outweighs the harm inflicted on the individual by the aggregate stock of consumption. The same could apply to social media platforms, such

[23]In particular, $w_1(0, s) \neq \infty$.

as Facebook and Instagram: Obviously, these networks bring utility to the individual, and this utility may well be higher for a larger network. We focus, however, on the harm: Suppose that a multitude of friends on Facebook causes the individual harm that outweighs the above-mentioned benefit. This harm could stem, for example, from distress, envy, less productivity, problems with relations, and so forth, as documented by the vast psychological and economic literature and internal Facebook and Instagram studies cited in the introduction.

Suppose that absent the network, the individual would have abstained from the harmful product. Can a large enough network induce a rational and informed individual to become an addict? We show that the answer is yes. To prove this result, we first show that if a path of aggregate stock is increasing for a particular network size, it must be increasing for a larger network. This further implies that a critical level (above which if the individual begins consumption then her future consumption converges to a higher steady state) is non-increasing with the network. These findings are established in the following lemma:

Lemma 3. *(i) Let* $\widehat{\xi} < \xi$ *be two network levels and let* s_0 *be an initial state. If the path of aggregate stock starting from* s_0 *increases over time when the network is* $\widehat{\xi}$*, it also increases over time when the network is* ξ*.*

(ii) Critical levels are non-increasing in the size of the network ξ*.*

According to the first part of Lemma 3, the individual does not react to an increase in the network by reducing her own consumption in a way that makes aggregate stock decrease over time (so as to reduce future harm from aggregate stock). The driving force behind this result is the peer pressure inflicted by the network ($w_{12} > 0$) and the fact that harm is concave in aggregate stock ($w_{22} > 0$). Intuitively, what could have caused the individual to try to counteract the harm caused to her by the network by decreasing her own consumption is the detrimental long-term effects of aggregate stock on her utility. Yet, the individual knows that the network's peer pressure, reducing her marginal utility from the non-addictive product, will grow into the future, while the marginal harm diminishes. The second part of Lemma 3 follows directly from the first: If an optimal path starting from any s_0 slightly above the critical level of a small network is rising, we know from the first part of the proposition that the optimal path must also

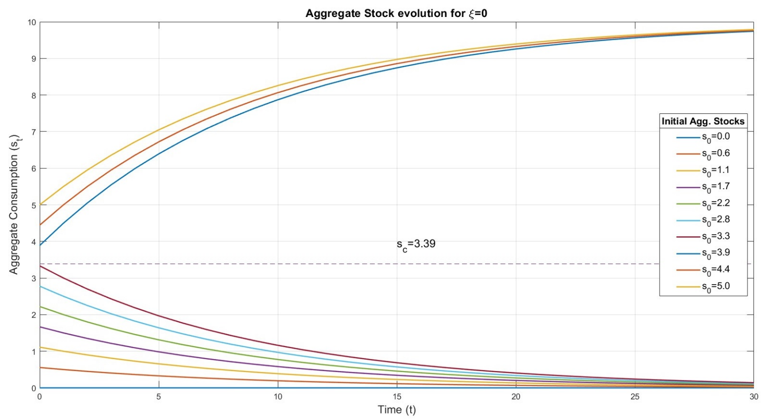

Figure 1: No network

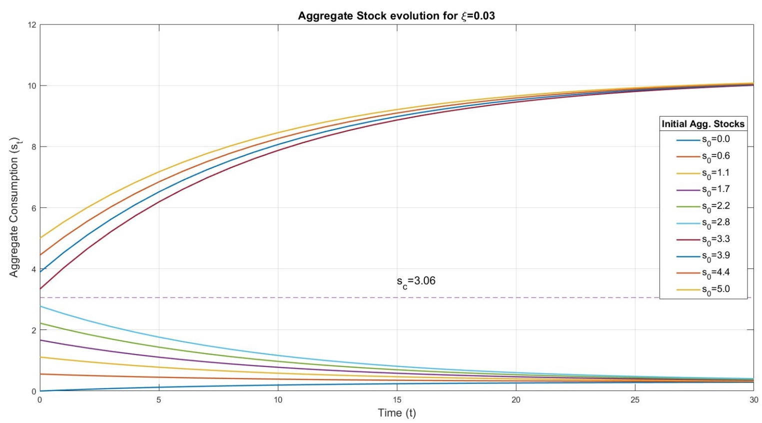

Figure 2: Small network

rise from s_0 for a larger network. Hence it cannot be that the critical level is higher in the larger network. The following figures illustrate a numerical example in which a larger network strictly lowers the critical level.[24] Figure 1 depicts the $\xi = 0$ case while in figure 2 $\xi = 0.03$, causing the critical level to decrease from 3.39 in the no-network case to 3.06 with a network.

The first part of Lemma 3 can be used to show that a large enough network induces an individual who would have abstained from the addictive product to become an addict. This is shown in the following proposition:

Proposition 3. *(a large enough network induces an abstainer to become an addict) Suppose that for $\xi = 0$ the lowest steady state is 0 (accompanied by a constant consumption of 0) and the second lowest steady state is $\overline{s}$, and let s_c be the critical level between these two steady states. Then for any $\xi > (1-\delta)s_c$, the individual never consumes 0 in a*

[24]In this example $w(a, s) = as + a(2y - a) + xs(s - 2M)$ where $x = 0.05$ and $M = \frac{2y}{1-\delta} + \frac{y}{2}$.

steady state.

The individual fully understands that her current consumption will cause her future harm. Nevertheless, she consumes the addictive product due to the network's peer pressure. The network will harm the individual more and more into the future, and the individual cannot do anything about it. Thus, the individual joins in on consumption, in order to minimize the harm via current benefit from consumption.

The fact that critical levels can strictly decrease with the network (part (ii) of Lemma 3 and the example in figures 1 and 2), introduces a second mechanism, besides that of Proposition 3, by which an abstainer can start consuming the addictive product when connected to a network. Without a network, the critical level may be above the individual's initial stock. Hence her aggregate stock converged to a lower steady state, corresponding to zero consumption. When connected to the network, the critical level may be reduced below the individual's initial stock. In such a case, the individual starts consuming and aggregate stock converges to a positive level.[25]

The conclusion that for a network larger than $\xi = (1-\delta)s_c$, stock crosses the critical level that prevailed even absent the network, has another important implication: "rehab", in the form of disconnecting the individual from the network, is no longer effective if and only if aggregate stock passed this critical level. This is summarized in the next corollary:

Corollary 1. *(condition for timeliness of rehab) For any network of size* $\xi > (1-\delta)s_c$*, if rehabilitation of the individual, via an intervention that disconnects her from the network, is implemented: i) After period* $t_h \equiv \lceil \frac{\ln\left(1-\frac{s_c}{\xi}(1-\delta)\right)}{\ln\delta} - 1 \rceil$*, it is no longer effective;*
ii) Before period $t_l = \lfloor (\frac{\ln\left(1-\frac{s_c}{\xi+y}(1-\delta)\right)}{\ln\delta} - 1) \rfloor$*, it is effective.*

Part (i) follows from a calculation of the number of periods that it takes the network (even absent consumption by the individual) to reach the critical level s_c. If intervention that disconnects the individual from the network (immediately reducing ξ to zero) occurs after period t_h, and therefore after aggregate stock had already crossed s_c, it will not help and the individual will continue consuming on her own up to her upper steady state. Part (ii) calculates the number of periods it takes the network to reach s_c assuming

[25]This mechanism is not relevant to an abstainer with zero initial stock, since the critical level cannot be reduced below zero. Then, only the first mechanism, of Proposition 3, can cause her to consume. Hence guidance encouraging total abstinence is beneficial not merely because then the individual inflicts less harm on herself, but also because it eliminates the second mechanism by which the network invokes addiction.

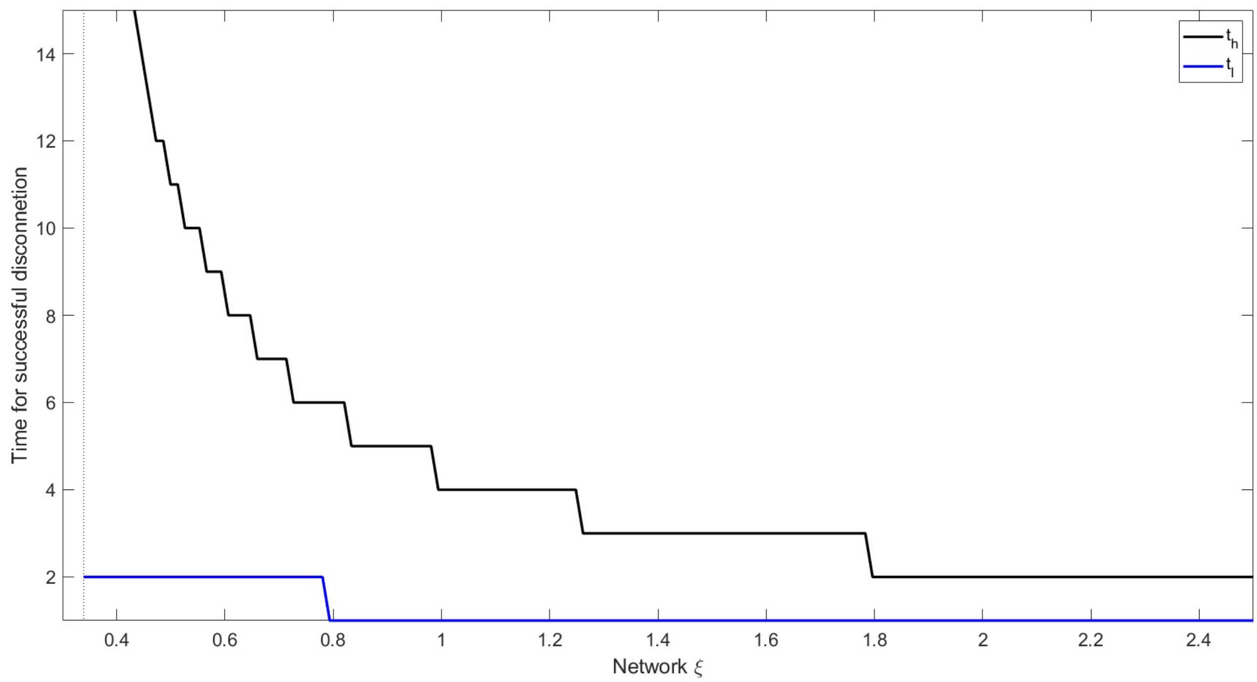

Figure 3: Effect of ξ on rehab

maximum per-period consumption by the individual. If disconnection occurred before period t_l, it is surely effective, since at this time aggregate stock did not reach s_c. Note that t_h and t_l are decreasing with ξ: the larger the network, the higher the chances of untimely rehab. Figure 3 plots t_h and t_l as a function of ξ, using the same parameters as those of figure 1. In this example, for $\xi \geq 2$, $t_h - t_l = 1$, so disconnection at $t = 1$ is both necessary and sufficient for effective rehab.[26]

Suppose now that the individual is already addicted, in the sense that she consumes a positive quantity of the addictive product in a steady state. Our next question is whether an increase in the network intensifies addiction. To this end, in the next lemma we derive a feature of the individual's second order condition that will prove useful:

Lemma 4. *According to the individual's second order condition, the requirement that constant deviations from the optimal strategy are not profitable demands that:*

$$(1-\beta\delta)w_{11}(\overline{a},\overline{s}) + 2\beta w_{12}(\overline{a},\overline{s}) + \tfrac{\beta(1+\beta\delta)}{1-\beta\delta^2} w_{22}(\overline{a},\overline{s}) < 0. \tag{9}$$

[26] As noted, physical disconnection from a social media platform does not necessarily help, due to the individual's fear of missing out even when disconnected. In such cases, the type of external intervention that would be helpful is some regulation limiting the size of the network, or the scope and type of content the individual's peers expose her too.

where $\overline{s}$ is the steady state and $\overline{a} = (1-\delta)\overline{s} - \xi$ is consumption in the steady state.

The intuition for Lemma 4 is that in a steady state, the individual balances between the marginal benefit she derives from consuming more of the addictive product and the marginal loss caused by the future increase in aggregate stock this consumption causes. The larger is w_{12}, the more present consumption, inflating future stock, induces more consumption in the future, which, in turn, further inflates future stock. Indeed, a large w_{12} increases the left hand side of (9), making it more easily violated. Furthermore, the individual knows that she will not be able to restrain herself from consuming in the future if w_{22} (the concavity of the harm from increased stock) is too large and w_{11} (the concavity of marginal utility due to consumption) is too small in absolute value. Indeed, (9) is violated when w_{12} and w_{22} are too large relative to w_{11}'s absolute value.

We can use the result in Lemma 4 to prove that any increase in the network increases both the aggregate stock and the individual's own consumption in any internal steady state:

Proposition 4. *(steady state consumption and stock increase with the size of the network) Fix $\xi \geq 0$. Let $\overline{s}$ be an internal steady state (i.e. a steady state that is supported by a non-corner consumption, $\overline{s} \neq \frac{\xi}{1-\delta}, \frac{y+\xi}{1-\delta}$) and let $\overline{a} = (1-\delta)\overline{s} - \xi$ be the supporting consumption. Both the steady state and the individual's consumption increase with ξ.*

Proposition 4 shows that the network has a positive effect not only on the occurrence of addiction, as shown in proposition 3, but also on the severity of addiction: When harm is concave in aggregate stock, an addict connected to a network always consumes larger quantities of the addictive product when the network is larger. When the network grows, the individual faces a trade off: on the one hand, the network's peer pressure presses her to consume more. On the other hand, the individual knows that current consumption has negative effects on her well being in the future. Nevertheless, proposition 4 shows that when the network grows, the first effect always dominates when harm is concave in aggregate stock. In particular, had the individual attempted to mitigate the effect of a larger network on her by consuming less, she would have violated the second order condition in Lemma 4. This second order condition already takes account of the above-mentioned trade-off between the current benefit from consuming the addictive product and the negative future repercussions. The results of this section imply that practices by social media platforms, cited in the introduction, expanding the size of the stock (ξ) the individual is exposed to, can induce the individual to initiate consumption and become addicted, and also intensify her addiction in any internal steady state. For example, Facebook, Instagram and TikTok do not limit the volume of content the individual's friends expose her to. Much to the contrary, they have been consistently using practices such as infinite scrolling and algorithms that have been alleged to encourage excessive use. Griffin (2022) surveys testimonies of industry experts according to which social media platforms use practices such as noisy and alerting notifications, "rewards" and invitations to react such as the "like" buttons, comment boxes, and "pull to refresh" buttons, allegedly designed to resemble slot machines, and claimed by psychologists to encourage individuals to use the platform excessively.[27] The frequent alerts and notifications encourage engagement and reciprocal responses, e.g., by notifying the sender when the recipient saw her message ((Barker (2023); (Langvardt (2019); Harris (2016)).

4 Strategic network members

In this section we extend our analysis to a strategic game in which individuals in the network react optimally to each other's consumption. This is unlike the previous section, in which other network members were assumed to be in a steady state and the individual was assumed not to affect their behavior. Our main focus is on an Open Loop Equilibrium ("OLE") solution concept. Based on the initial state vector of stock, $\underline{s}_0$, each individual in the network chooses a time-dependent consumption plan and commits to it. These strategies form an equilibrium in time-dependent strategies: given the consumption paths of all players $j \neq i$, the best response of player i is her equilibrium strategy. That is, a strategy profile $(\underline{a}_t^i)$ is an OLE if for every consumption plan b_t^i for consumer i, $U_i(b_t^i, \underline{a}_t^{-i}) \leq U_i(\underline{a}_t)$ (where, $U_i(\underline{a}_t)$ is the β-discounted payoff of individual i when all individuals use the strategy profile $\underline{a}_t$). The strategies are not state-dependent, so the consumption of the players remains the same even if others deviate or make errors. This solution concept can be interpreted, inter alia, as a lack of the individual's ability to observe whether her peers had deviated from their equilibrium consumption paths. As

[27] See, e.g., Hilary Andersson, Social Media Apps Are 'Deliberately' Addictive to Users, BBC NEWS (July 4, 2018), https://www.bbc.com/news/technology-44640959 [https://perma.cc/3WKV-9NCF]; Langvardt (2019).

noted by Fudenberg and Tirole (1995, p. 131-132), the OLE solution concept, in addition to its tractability, can be a good approximation for a Markov Perfect Equilibrium if there are many individuals. In such a case, an unexpected deviation by one individual can have little influence on player i's optimal strategy, so we assume she does not observe this deviation. We start from the existence of a zero-consumption OLE (Section (4.1)) and of a maximum-consumption OLE (one where all individuals in the network spend their entire income y on the addictive product each period) (Section (4.2)). Then, in Section (4.3), we prove the existence of an OLE for any vector of initial states and any influence matrix and study comparative statics and the possibility that an addition of an individual to the network will cause a cascade of equilibrium consumption of the addictive product by other network members. Section 4.4 demonstrates how results from the OLE framework carry over to a Markov-Perfect Equilibrium (MPE) framework, in which individuals' strategies are state-dependent and shows when trigger strategies can enforce a zero-consumption MPE.

4.1 Zero-consumption equilibrium

Suppose that individuals' utility function w supports zero consumption in the no-network case so that a single individual with this utility function, with an initial state $s_0 = 0$ and without a network optimally will abstain from the addictive product. The following proposition shows that, even when such an individual is connected to a network of similar individuals, with a low enough initial state, the entire network will avoid consumption in equilibrium.

Proposition 5. *(Consumption-less OLE) Suppose that the optimal strategy of an individual without a network with a utility function w and initial state $s_0 = 0$ is to avoid consumption for all t. Then there exists $\bar{\xi} \geq 0$ such that for all initial states in the set $[0, \bar{\xi}]^n$, avoiding consumption for all t is an OLE.*

Proposition 5 shows that a network need not induce the consumption of the addictive product if all individuals manage to coordinate on zero consumption, even if individuals reach the network after consuming minor amounts of the addictive product. Similarly, depending on the parameters of the case, small enough consumption by network members will not break the consumption-less equilibrium. As we show below, there are also other equilibria, with consumption. It is straightforward that in our framework, where, by Lemma 2, the network harms the individual, the consumption-less equilibrium characterized in Proposition 5 is the best one in terms of welfare.[28] Accordingly, members of the network face a coordination game. They collectively prefer the consumption-less equilibrium, but may find themselves in an inferior equilibrium with positive consumption. For example, a group of adolescents with small enough initial stock of smoking, or the use of drugs or alcohol, would benefit from guidance, of teachers or instructors, that helps them coordinate on collectively remaining with no consumption. Joint guided discussions, such as those of Alcoholics Anonymous and weight loss groups, can help solve this coordination problem as well.

The consumption-less equilibrium, however, is fragile, in the sense that if an individual with a high enough initial state of consumption of the addictive product joins the network, this may induce consumption of the addictive product by others in the network-a cascade. Indeed, as we shall see in Proposition 8 below, when the consumption-less equilibrium is broken, an OLE with consumption always exists. Hence the addition to the network of a problematic individual, with high enough consumption, causes the network to switch to a new equilibrium with consumption by other individuals, to the detriment of the whole network. We explore this possibility in Lemma 7 and the discussion following it.

Individuals' coordination problem may lead them to the worse kind of equilibrium, where all network members spend their entire income on the addictive product. This is studied in the next section.

4.2 Maximum consumption equilibrium

This section shows that if network members are prone to severe addiction, in the sense that for a large enough stock of consumption, they consume their entire income y per period on the addictive product, then for a large enough network or large enough influence parameters, it is an OLE for all of them to consume y each period:

Proposition 6. *Suppose that without a network, one of the individuals' steady states involves maximum consumption of the addictive product. Then there exist* N' *and* γ'

[28] We demonstrate this formally in the online appendix, available at https://en-law.tau.ac.il/profile/gilod, under "recent working papers".

such that in either of the following cases there exists an OLE in which all the individuals consume y in each period, regardless of the initial state:

(i) Given the influence matrix Γ, $n > N'$

(ii) Given n, $\min_{\gamma_{ij} \neq 0, i \neq j} \gamma_{ij} > \gamma'$,[29]

Recall though that by Proposition 5, if network members are prone to severe addiction on one hand but also have a steady state of total abstention, on the other, a consumption-less OLE always exists as well, regardless of the number of individuals. Our next result is that when the network supports a maximum-consumption equilibrium, these two extremes are the only OLE's, and no OLE with intermediate consumption, between zero and y, exists:

Proposition 7. *Suppose that the optimal strategy of an individual without a network and a low initial state $s_0 = 0$ is to avoid consumption for all t, while with some initial state s_0 and constant network ξ_0, her optimal action is to consume y. Then for a network comprising such individuals and the low initial states, which is strong enough pursuant to parts (i) or (ii) of Proposition 6, there could be either a 0-consumption OLE or a y-consumption OLE.*

Accordingly, interventions to reduce consumption of the addictive product should be aimed, *inter-alia*, at a reduction of the number of network members or of the influence parameters, in a way that reduces the prospects of a maximum-consumption equilibrium, and second, improving the prospects of a consumption-less equilibrium, by preventing individuals with high initial stock, high influence over others, or those who are highly influenced by others, from joining the network. We elaborate further on the latter implication in Section (4.3). The damage from a maximum-consumption equilibrium can be mitigated by interventions that make maximum consumption less likely. Take, for example, Facebook, Instagram and TikTok's infinite scrolling feature discussed in the introduction. This feature facilitates maximum consumption. Regulatory intervention that limits the use of this feature, or even places a cap on per-period consumption, at least when it comes to adolescents, can allegedly help reduce the damage.

In the next section, we consider the general existence of an OLE, not only in the

[29]Section 4.4 shows the existence of a maximum-consumption Markov-Perfect equilibrium and the online appendix shows how a large enough constant network induces maximum consumption.

special cases of no consumption or maximum consumption, and we study the effect of changes in the model's parameters on such equilibria.

4.3 Internal equilibria and comparative statics

In what follows we establish, using Tarski's fixed point theorem, that for any vector of initial stock and any influence matrix, a pure strategy OLE always exists. Hence, when the extreme OLE's of zero and maximum consumption do not exist, an OLE with intermediate consumption always exists.[30] We start by proving the existence of best responses, in the following lemma:

Lemma 5. *Let $\underline{s}_0$ be some initial state and fix $\underline{a}^{-i} = (a_t^{-i})_{t \in N}$ to be the consumption strategy of all individuals except individual i. Then there exists a best-response for individual i and the correspondence that assigns the set of best-replies to each $\underline{a}^{-i}$ is non-empty, compact valued, and upper hemicontinuous.*

Proposition 8. *For any vector of initial stock $\underline{s}_0 = [s_0^1, s_0^2, ..., s_0^n]^T$ and for any influence matrix Γ a pure strategy OLE always exists.*

Let us now study the effect of changes in the number of network members, of the influence matrix, or in network members' initial states, on the OLE. To do this, consider a particular intermediate-consumption OLE. Individual i's utility and state evolution is:

$$U_i(\underline{a}) = \sum_{t=0}^{\infty} \beta^t w(a_t^i, s_t^i) \tag{10}$$

$$s_t^i = \delta s_{t-1}^i + \sum_{k=1}^{n} \gamma_{ik} a_{t-1}^k \tag{11}$$

Her marginal utility of additional consumption at time τ is:

$$\frac{\partial U_i(\underline{a})}{\partial a_\tau^i} = \beta^\tau w_1(a_\tau^i, s_\tau^i) + \sum_{t=\tau+1}^{\infty} \beta^t \delta^{t-\tau} w_2(a_t^i, s_t^i) \tag{12}$$

The next lemma shows that in any OLE, any small parameter change that induces some individuals in the network to consume more causes the network to switch to a new OLE in which all individuals consume more, and vice versa:

[30] Note though that zero and maximum consumption equilibria could co-exist with internal ones.

Lemma 6. *Let μ be a parameter of the model, and σ_μ some OLE in the game with this parameter. Consider a new identical situation with μ' instead of μ, such that $\mu' > \mu$, and let $\emptyset \neq I \subset N$ be the set of individuals who have a profitable deviation from σ_μ when the parameter is in-fact μ'. If all individuals in I now want to consume [weakly] more (less) than in σ_μ then there exists an OLE $\sigma_{\mu'}$ where all individuals in the network want to consume [weakly] more (less) than in σ_μ.*

Lemma 6 applies generally to all of the model's parameters.[31] We now use the result in Lemma 6 to study comparative statics regarding key parameters of interest – particularly those that social media platforms focus on increasing:

Corollary 2. *Consider an intermediate-consumption OLE. All of the following changes yield a new OLE in which per-period consumption of all network members (weakly) increases (decreases):*

(i) Any increase (decrease) in an influence parameter γ_{ij} $(i = 1, ..., n,\ i \neq j)$.

(ii) Any addition (omission) of a network member i.

(iii) Any increase (decrease) in an individual's initial stock of consumption.

The first part of Corollary 2 shows that for any intermediate consumption OLE, if the influence of one network-member on another network member is increased, this has detrimental repercussions for the whole network and it is not only this other network member, who became more influenced, that consumes more in the new OLE. This implies that it is all the more important from a welfare perspective to try to intervene so as to reduce such influence. For example, a teacher or psychologist could try to separate two adolescents that grew to be particularly close to each other and it is suspected that they, together with others, use drugs or alcohol. Such efforts would reduce overall drug or alcohol consumption in the whole group.

Part (i) of Corollary 2 also presents straightforward policy implications regarding social media platforms' practices. Facebook, for example, provides popular users, including influencers, with a "Top Fan Badge" that enables the user " ... to more easily identify your most engaged followers and to encourage them to engage more on your Page."[32]

[31] Note that for an individual with positive consumption in the original OLE, the change from μ to μ' causes consumption to strictly (and not only weakly) increase. The only case where the change could have no effect is where $a_t^i = 0$ or $a_t^i = y$ in some OLE.

[32] See https://www.facebook.com/gpa/blog/top-fan-badge.

Also, social media platforms provide influencers with monetary incentives to increase their influence. Translated to our framework, this intensifies the already large influence parameters these popular users have on their most influenced followers. Analogous practices are social media platforms' algorithms exposing individuals to the content posted by those who influence them the most, such as Instagram's "explore" feature".[33] Since the individual has limited time to spend, such practices are analogous to increasing the influence parameters themselves. TikTok uses the "for you" feature, which automatically includes in the user's "feed" she is exposed to the content she is expected to engage with the most, including the content released by network members with the strongest influence over the individual.[34] Tiktok's challenges, encouraging a competition among connected users to perform a task, is analogous to intensifying mutual influence. Facebook's algorithm pushing a notification to a friend whose photo appears in a photo posted by another friend, encouraging her to respond (Langvardt (2019)), is similarly analogous to artificially boosting the second friend's influence over the first friend.

The second part of Corollary 2 implies that when an individual who influences others, or is influenced by others, is added to the group, the whole group consumes more of the addictive product. This result is consistent, for example, with Facebook executive Lars Backstrom's statement that use of Facebook increases with the number of the user's friends.[35] Moreover, this individual herself will consume more of the addictive product after joining the network than what she would have consumed on her own. This implies that in our framework, any addition of individuals to the network is harmful, regardless of how well they behaved before they had joined the network. For example, an individual may abstain from the addictive product when alone. Yet, in our framework, it is never sound policy to add her to the network with the hope that she would have a good influence on others. Since what matters is the accumulated stock of consumption, the network's original consumption will have a bad influence on the new network-member: she may start consuming the addictive product herself, and this, in turn, will have a bad influence on the original members of the group. They too will consume more of the addictive product in the new OLE. Social media platforms are alleged to consistently encourage users to significantly expand their networks. Facebook, for example, has a

[33] See https://help.instagram.com/140491076362332/?helpref=hc_fnav.
[34] See https://later.com/blog/tiktok-algorithm/.
[35] See http://www.graphanalysis.org/SIAM-AN10/01_Backstrom.pdf.

generous ceiling, of 5000, on the number of friends an individual can have.[36] Instagram allows a user to follow up to 7500 other individuals,[37] and it was reported that TikTok's threshold is 10,000.[38] All three networks have no limit on the number of followers a user, or a user's page, have. Popular users, including influencers, are encouraged to increase the number of their followers and increase their followers' exposure to the network, via monetary incentives.[39] The platforms' constant alerts and notifications with unanswered friend requests were alleged to exploit human vulnerabilities of needing to reciprocate social gestures (Neyman (2017); Turel and Osatuyi (2017)). It is similarly claimed that Facebook paying phone manufacturers to pre-install it on most android phones is also a potential driver of the network's expansion.[40] Facebook's "people you may know" feature, encouraging expansion using the user's contacts from other apps, was reported to be impossible to opt out of (Kashmir Hill (2018)). Additionally, TikTok encourages the individual to import her phone contacts and friends on Facebook and Instagram to connect with her via TikTok, suggests the user's account to her phone contacts and suggests her account to people who sent her links or who opened links sent by her via other apps.[41] TikTok encourages enlargement of one's network by allowing only people with more than 1000 followers to upload live videos,[42] and by enabling users to monetize their use by reaching usage and follower thresholds.[43] These practices are likely to make users' networks significantly larger than they would be absent the practices.

Part (iii) of the corollary implies that the higher is the initial stock of consumption by an individual, the larger is consumption of the addictive product by the whole network. Interestingly, Facebook and Instagram have designed their platforms in a way that even a user who has deactivated her account, but later decided to reconnect, automatically retains all of the friends and content that she was exposed to when disconnected.[44] This

[36]See https://www.facebook.com/help/211926158839933/?helpref=uf_share

[37]See https://help.instagram.com/408167069251249/?helpref=uf_share

[38]See https://bit.ly/3RFlDqg.

[39]See https://bit.ly/3GACPqV; https://creators.instagram.com/earn-money/badges.

[40]See, e.g., https://www.digitalinformationworld.com/2020/10/heres-why-android-phones-in-some.html; https://www.searchenginejournal.com/facebook-cannot-be-deleted-from-certain-android-phones/285713/#close.

[41]See https://www.wired.com/story/tiktok-friends-contacts-people-you-may-know/.

[42]See https://www.adobe.com/creativecloud/video/hub/guides/how-to-go-live-on-tiktok#:~:text=First%2C%20you%20must%20be%20at,the%20capability%20to%20go%20Live.

[43]See https://www.tiktok.com/creators/creator-portal/en-us/getting-paid-to-create/creator-next/.

[44]See https://www.facebook.com/help/250563911970368; https://help.instagram.com/370452623149242; https://www.guidingtech.com/instagram-delete-vs-deactivate-difference/.

inflates her initial stock upon her return to the platform and, by Part (iii) of Corollary 2, enhances equilibrium consumption of the whole network. Practices of Facebook, Instagram and TikTok that encourage new users to offer links to their profile in other networks in which they have already shared content are also a form of inflation of the initial stock. For example, a new TikTok user who has been using Facebook and Instagram is encouraged to provide those following her on TikTok with links to all of her content in the other two networks.[45]

By the three parts of Corollary 2, if a new member must be added to the network, it is better to add one with the smallest initial stock of consumption, the smallest influence on others and smallest influence of others on her, and the converse is true regarding the question who is it best to remove from the network.

The above-mentioned comparative statics hinge on our assumption that harm is concave in aggregate stock. When harm is sufficiently convex, these comparative statics are reversed, because then individuals' reaction functions are downward sloping rather than upward sloping. Hence, while our OLE existence result remains intact, any increase in an influence parameter, any addition of a new member to the network, and any increase of an individual's initial stock, cause per-period equilibrium consumption of the addictive product by all network members to decrease. This is summarized in the next corollary:

Corollary 3. *(reversal of comparative statics for sufficiently convex harm) If:*

$$\max_{a\in[0,y];s\in[0,\infty)} w_{22}(a,s) < -\tfrac{1-\beta\delta^2}{\beta\delta} \max_{a\in[0,y];s\in[0,\infty)} w_{12}(a,s) \tag{13}$$

then the direction of the comparative statics in Corollary 2 is reversed.

Intuitively, peer pressure (w_{12}) affects the individual's marginal utility in the current period, while the convexity of harm (a negative w_{22}) affects marginal harm into the future. Hence the larger are β and δ, the more weight the individual places on future harm and the more easily is condition (13) met, flipping the direction of the comparative statics. Conversely, for $\beta\delta \to 0$, only infinitely convex harm can flip the direction of the comparative statics.[46]

[45]https://support.tiktok.com/en/getting-started/setting-up-your-profile/linking-another-social-media-account.

[46]In the online appendix, we show how with sufficiently convex harm, a large enough network ensures aggregate consumption is bounded either in the OLE, MPE or constant network frameworks.

Coming back to concave harm functions (or ones that are not too convex), another type of change we wish to study is the addition of a new member to the network where, prior to this addition, the network enjoyed a consumption-less equilibrium. In other words, we wish to examine whether a "rotten apple", with high enough initial stock, can "spoil the barrel" in the sense that this rotten apple causes other network members to start consuming. We can gain more insight on individuals' equilibrium behavior in such scenarios by establishing next that any individual's optimal reaction to a changing network is between her reaction to a constant network that is smaller than the changing network and her reaction to a constant network that is larger. This will enable us to apply our results from the constant network case, in which we have shown that a large enough constant network can cause an abstainer to start consuming the addictive product, to the strategic case:

Lemma 7. *Let $\xi_i(t)$ be individual i's aggregate stock per period for a network that changes with time such that $\underline{\xi} \leq \xi_i(t) \leq \overline{\xi}$ for all t and let $\underline{\xi}$ and $\overline{\xi}$ be two constant networks. Let a_t^i be individual i's optimal reaction given the changing network, $\underline{a}_t^i$ her optimal reaction given $\underline{\xi}$ and $\overline{a}_t^i$ her optimal reaction given $\overline{\xi}$. Then $\underline{a}_t^i \leq a_t^i \leq \overline{a}_t^i$.*

According to Lemma 7, if the individual consumes in response to the lower constant network, she surely consumes in response to the higher changing network. This follows from the game being supermodular, as we show in the proof of Proposition 8. To illustrate, suppose that individual j was in a consumption-less OLE corresponding to Proposition 5. Suppose now that some new individual, $i \neq j$ is added to the network, and her initial stock is such that she consumes the addictive product. The minimum stock individual j is exposed to each period due to individual i's consumption is $L_j \equiv \gamma_{ji} \inf a_t^i$. By Lemma 7, individual j's best-response to the changing network caused by individual i is larger than individual j's best-response to a constant network of L_j.

Our results on constant networks (Section 3) imply two mechanisms from which we can deduce individual j's consequent consumption of the addictive product. First, if, given a constant network of L_j, the critical level is reduced such that $s_j^0 > s_c(L_j)$, where s_j^0 is individual j's initial stock, and $s_c(L_j)$ is the critical level caused by a constant network of L_j,[47] then j's best response to such a constant network is to consume. Alternatively,

[47] Recall that by Lemma 3 and figure 1, critical levels are non-increasing in network size and, at least in certain cases, they are strictly decreasing.

if L_j is large enough (in particular, $L_j > (1-\delta)s_c$, as in Proposition 3, where s_c is the smallest critical level without a network), individual j will surely consume due to the rotten apple's consumption (even ignoring j's initial state). Consequently, by Lemma 7, positive consumption is j's best response to the changing network caused by the rotten apple as well. Now consider the aggregate stock contributed by these two consuming individuals, i and j. By a similar reasoning, their consumption forms a changing network that the remaining individuals in the network are exposed to. This changing network too is bounded from below by some constant network that, by the results in Section 3, induce consumption by other network members, and so forth. By the existence result of Proposition 8, we know that the positive consumption induced by this cascade forms an OLE.[48]

4.4 Markov Perfect Equilibria

In this section we extend our analysis to Markov Perfect Equilibria ("MPE"). That is, we consider state dependent strategies, so a strategy for consumer i is a function from the state space $[0,\infty)^n$ to $[0,y]$, and it does not depend on the time or the history. A strategy profile $\underline{a}(\underline{s})$ is an MPE if for every $b(\underline{s})^i$ for consumer i, $U_i(b^i(\underline{s}), \underline{a}^{-i}(\underline{s})) \leq U_i(\underline{a}(\underline{s}))$ (where, $U_i(\underline{a}(\underline{s}))$ is the β-discounted payoff of individual i when all individuals use the strategy profile $\underline{a}(\underline{s})$). Hence, a deviation from $a^i(\underline{s})$ at time t changes the state at time $t+1$, possibly causing all individuals to change their consumption plan. In the next two propositions, we show that our results regarding the existence of a consumption-less equilibrium path and a maximum-consumption equilibrium carry over to this case. We use these results to find MPE's including trigger strategies with punishments that enforce zero consumption. We then illustrate, with a few simulations, how our comparative statics results carry over as well. Consider first consumption-less behavior:

Proposition 9. *Suppose that the optimal strategy of each individual when disconnected from the network and with initial state $s_0 = 0$ is to avoid consumption for all t. Then there exists $\overline{\xi}$ such that in the strategic model with n individuals, for all initial states in the set $[0,\overline{\xi}]^n$, all individuals avoid consumption along the equilibrium path.*

[48]The online appendix includes an algorithm characterizing the set of individuals who end up consuming the addictive product in such a cascade.

Note that although the consumption-less strategy profile is a series of best-responses, it is not a fully characterized MPE, since it does not specify situations outside the equilibrium path with sufficiently positive consumption. For example, if one individual makes a mistake and does not play according to her best reply, thereby consuming in a way causing the initial stock to be outside $[0, \overline{\xi}]^n$, the path starting from this sub-game may well induce consumption by other individuals.

Turning to a maximum-consumption equilibrium, the following proposition shows that, as in the OLE case, when either the network or influence parameters are large enough, there exists an MPE in which all network members consume their entire income on the addictive product each period:

Proposition 10. *Suppose that without a network, one of the individuals' steady states involves maximum consumption of the addictive product. Then there exist N' and γ' such that in either of the following cases there exists an MPE in which all the individuals consume y in each period regardless of the initial state:*

(i) Given the influence matrix Γ, $n > N'$

(ii) Given n, $\min_{\gamma_{ij} \neq 0, i \neq j} \gamma_{ij} > \gamma'$.

Note that it is possible that the conditions of Propositions 9 and 10 are satisfied at the same time. Thus, for a strong enough network and small enough initial states, if network members fail to coordinate on the consumption-less strategy profile, they all might find themselves in a maximum-consumption MPE.

Propositions 9 and 10 imply that when the network or influence parameters are large enough, trigger strategies can enforce a consumption-less equilibrium via punishments for deviation, as established in the next corollary.

Corollary 4. *If the conditions of Propositions 9 and 10 hold, the following strategies are MPEs: $a(\underline{s}) = 0$ if the initial state is in $A = [0, x_1] \times ... \times [0, x_n] \subseteq [0, \overline{\xi}]^n$ for every $x_1, ...x_n \in [0, \overline{\xi}]$ and $a(\underline{s}) = y$ otherwise.*

This follows directly from Propositions 9 and 10. If the state is in A, and everyone else consumes 0, the best response is to consume 0 too (by Proposition 9). If the state is outside of A and everyone else consumes y, for large enough n or influence parameters, the best response is to consume y too (by Proposition 10). Since our state space is n-dimensional, these equilibria are all MPEs (i.e., the strategies depend only on the current state) enforced via the threat of punishments: starting from a consumption-less profile, each individual can experiment (sub-optimally and off the equilibrium path) with the addictive product, as long as her consumption is low enough. But if such consumption causes some individual i's aggregate stock to cross some threshold level x_i, this moves the n-dimensional state $\underline{s}$ outside A, triggering a punishment by the peers in which they all switch to a maximum-consumption equilibrium (and a lower payoff, by Lemma 2). Participants can set $x_i = \overline{\xi}$ for $i = 1, ..., n$, to give more flexibility to experiment without triggering the punishment, or lower levels of x_i, to allow for less experimentation.

We next turn to briefly demonstrating how comparative statics results from our OLE framework can carry over to the MPE framework. We reconsider the utility function depicted in figure 1: $w(a, s) = as + a(2y - a) + 0.05s(s - 2M)$ where $M = \frac{2y}{1-\delta} + \frac{y}{2}$. In the following simulations, we set $\delta = \beta = 0.9$, $y = 1$, $n = 2$. Figures 4 and 5 report the changes in MPE behavior when individual 2's influence over individual 1 increases. Individual 1 influences individual 2 with $\gamma_{21} = 0.1$, individual 1's initial stock is 2.2, and individual 2's initial stock is 3.1, such that individual 2 would consume even absent a network (i.e., 2 is a "rotten apple") and individual 1 would abstain. Figure 4 depicts individual 1's MPE consumption. It shows that when individual 2's influence over individual 1 is $\gamma_{12} = 0$, individual 1's equilibrium stock decreases to zero, while when γ_{12} increases to 0.5 or 1, individual 1's equilibrium consumption becomes positive and equal to maximum consumption, and her aggregate stock increases accordingly. Figure 5 depicts individual 2's equilibrium behavior under such an increase in individual 2's influence over individual 1. It demonstrates that when individual 2's influence over individual 1 increases, individual 2 expects individual 1 to consume more and this, in turn, induces individual 2 to consume more: When γ_{12} grows from zero to 0.5 or 1, individual 2's MPE behavior switches to maximum consumption (the red and yellow lines overlap).

Figures 6 and 7 depict MPE behavior when $\gamma_{12} = \gamma_{21} = 0.1$ and individual 1's initial stock increases while individual 2's initial stock is 2. Figure 6 shows that both individuals are in a consumption-less MPE when individual 1's initial stock, s_0^1, is 0, 1 or 2, while when individual 1's initial stock increases to 3, 4, and 5, individual 1's MPE consumption becomes positive, and higher the higher is individual 1's initial stock. Individual 1's initiation of consumption stems not only from her higher initial stock, but

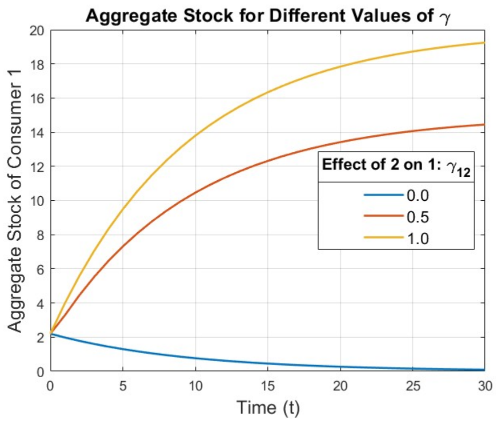

Figure 4: γ_{12}'s effect on 1

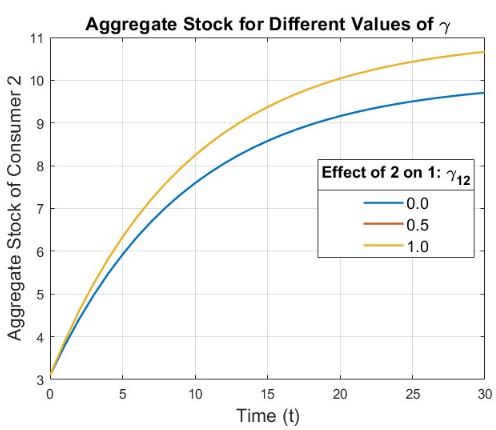

Figure 5: γ_{12}'s effect on 2

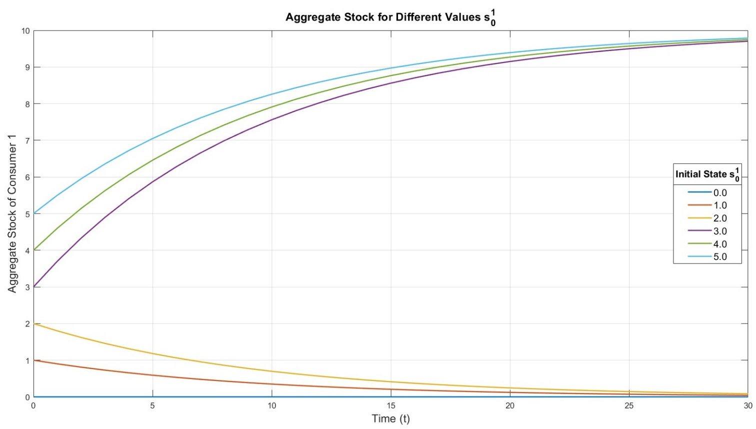

Figure 6: s_0^1's effect on 1

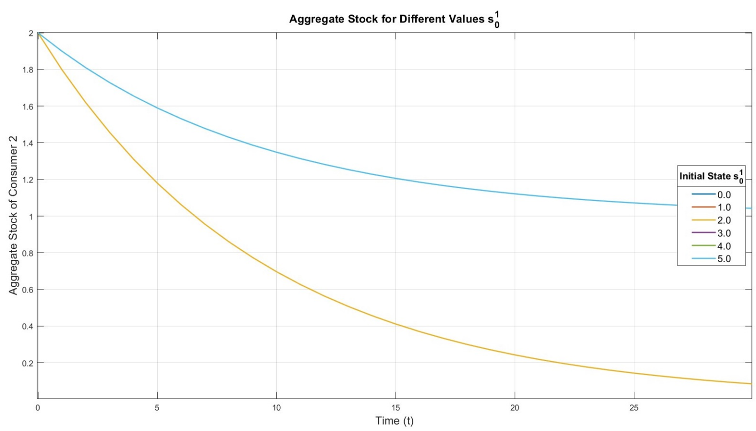

Figure 7: s_0^1's effect on 2

from the combination of this higher initial stock and being in a network with individual 2. Recall from figure 1, illustrating the no-network case and using the same utility function, that with initial stock of 3, individual 1 would not have consumed when detached from a network. This is while, by the current simulation, when individual 1 is connected to individual 2, initial stock of 3 suffices for individual 1 to start consuming. Figure 7 shows individual 2's MPE behavior when individual 1's initial stock increases. Individual 2's optimal reaction when individual 1's initial stock is 0, 1 or 2 is not to consume, so all of these lines overlap, while individual 2's optimal reaction when individual 1's initial stock is 3, 4 or 5 is to engage in maximum consumption, so the latter three lines overlap as well.

4.5 Timeliness of rehab

Consider now the possibility of rehabilitation, in the form of some external intervention that disconnects the individual from the network, when absent rehabilitation an OLE or MPE with consumption is predicted. We summarize the result in the next corollary:

Corollary 5. *(condition for timeliness of rehab) Suppose that without a network the individual's lowest steady state is* 0 *and the second lowest steady state is* $\overline{s}$*, and let* s_c *be the critical level between these two steady states. If rehabilitation of the individual, via an intervention that disconnects the individual from the network, is implemented at a period before* $t_c = \frac{\ln\left(1 - \frac{s_c(1-\delta)}{y\sum_{j=1}^{n}\gamma_{ji}}\right)}{\ln \delta} - 1$*, it is effective.*

Corollary 5 follows from a calculation of the number of periods that it takes a network in which all members consume y each period to reach the critical level that prevails absent the network s_c. If the aggregate stock contributed by such a network is larger than $(1-\delta)s_c$, it eliminates zero consumption as a steady state, but if disconnection from the network is implemented before the time indicated in Corollary 5 it is surely effective, as in any consumption profile, network members cannot consume above y per period. Note that t_c is decreasing with n and with the influence parameters, i.e., the larger the network and the larger are γ_{ij} $(i, j = 1, ..., n, i \neq j)$, the higher the chances of untimely rehab.[49]

5 Conclusion

We have studied rational addiction by an informed individual to a harmful product in a dynamic setting, when the individual is attached to a network of other individuals. The network harms the individual and exerts peer pressure on her to consume the addictive product. Consumption by the individual's peers accumulates and contributes to the aggregate stock affecting the individual's utility. Even though the individual is aware of the future negative results of her current consumption, a large enough network nevertheless induces her to become addicted, as long as harm is concave, or not too convex, in aggregate stock. Even when the individual would have abstained from the addictive product

[49] Note also that Corollary 5 does not hinge on the type of equilibrium the network is in, or on whether the network is in equilibrium at all.

without the network, she becomes addicted to it with a large enough network. The individual follows the idiom "if you can't beat them, join them": current consumption mitigates the harm inflicted on the individual by the network, so she initiates consumption, despite the future harm this consumption causes her. We have shown that for any initial stock and influence matrix, an OLE among strategic individuals always exists. In such an equilibrium, any addition of a new member to the network, any increase in the influence matrix and any increase in a network member's initial stock increase equilibrium consumption of the addictive product. When the harm function is sufficiently convex, these comparative statics are reversed. We have demonstrated that results from our OLE framework carry over to the MPE case as well, where trigger strategies can enforce equilibrium abstention for large enough networks or influence parameters.

Our results imply that merely making the individual aware of the risks of an addictive product, or changing defaults so that the individual would need to opt-in for features encouraging addiction, may not be enough. They imply that more attention should be dedicated to addressing the individual's network of other users when trying to rehabilitate her from addiction or mitigate its harm. In cases such as groups of adolescents using drugs or alcohol together, intervention helping the individual to disconnect from the network could fully rehabilitate her if exercised on time, before aggregate stock has passed the individual's critical level. Even short of complete disconnection from the network, we show that any decrease in the size of the network, or the influence parameters, or limitation of the time the individual is exposed to the network or of others' consumption, can help the individual reduce consumption of the addictive product. Our results can be used to support calls for regulation limiting or deterring social media platforms from inducing young individuals to be exposed to larger networks with higher influence parameters and excessive peer content.

Appendix

The proofs of Propositions 1-2 and Lemma 1 replicate Orphanides and Zervos (1994, 1995) to incorporate a constant network affecting the individual. Hence we relegate them to the online appendix.

Proof of Lemma 2:

Let $\xi_1 < \xi_2$ be two possible networks, and define by a_t the optimal strategy when starting from s_0 with the network ξ_2. Define by s_t^a the state at time t when taking into account only the actions and the initial state and by $\kappa_t = \frac{1-\delta^t}{1-\delta}$ for $t \neq 0$ and $\kappa_0 = 0$ the network accumulation coefficient. The state is therefore $s_t = s_t^a + \kappa_t \xi_2$. By definition:

$$\begin{aligned} V(s_0;\xi_2) &= (1-\beta)\sum_{t=0}^{\infty}\beta^t w(a_t,s_t) = (1-\beta)\sum_{t=0}^{\infty}\beta^t w(a_t,s_t^a+\kappa_t\xi_2) \\ &< (1-\beta)\sum_{t=0}^{\infty}\beta^t w(a_t,s_t^a+\kappa_t\xi_1) \leq V(s_0;\xi_1) \end{aligned} \tag{14}$$

Where the first inequality is true since $w_2 < 0$ and the second inequality is due to the fact that a_t is not necessarily the optimal strategy when the network is ξ_1. Similarly, let $s^1 < s^2$ be two initial states and fix ξ. If a_t is the optimal strategy when starting at s^2, then

$$\begin{aligned} V(s^2;\xi) &= (1-\beta)\sum_{t=0}^{\infty}\beta^t w(a_t,s_t) = (1-\beta)\sum_{t=0}^{\infty}\beta^t w(a_t,s_t^a+\delta^{t-1}s^2) \\ &< (1-\beta)\sum_{t=0}^{\infty}\beta^t w(a_t,s_t^a+\delta^{t-1}s^1) \leq V(s^1;\xi) \end{aligned} \tag{15}$$

where here s_t^a also represents the effect of the network but not the discounted initial state which is written explicitly.■

Proof of Lemma 3:

We prove part (i) by contradiction. Assume that the optimal path with $\hat{\xi}$ is increasing (the actions are $\hat{a}_t$ and the states are $\hat{s}_t$) and the optimal path with ξ is decreasing (the actions are a_t and the states are s_t). The path with $\hat{\xi}$ increases, hence $\hat{s}_{t+1} = \delta\hat{s}_t + \hat{a}_t + \hat{\xi} > \hat{s}_t$ which implies $\hat{a}_t > (1-\delta)\hat{s}_t - \hat{\xi}$. Similarly, the path with ξ decreases, hence $s_{t+1} = \delta s_t + a_t + \xi < s_t$ which implies $a_t < (1-\delta)s_t - \xi$. Since $\hat{s}_t > s_0 > s_t$ and $\hat{\xi} < \xi$ we get $(1-\delta)\hat{s}_t - \hat{\xi} > (1-\delta)s_t - \xi$ which ultimately implies $\hat{a}_t > a_t$. In addition, using the wrong actions is sub-optimal, so the following two inequalities hold (s_t^a and $s_t^{\hat{a}}$

represent the state evolution due to the actions only, without the network):

$$\sum_{t=0}^{\infty} \beta^t w(\hat{a}_t, \hat{s}_t^{\hat{a}} + \kappa_t \hat{\xi}) \;>\; \sum_{t=0}^{\infty} \beta^t w(a_t, s_t^a + \kappa_t \hat{\xi}) \tag{16}$$

$$\sum_{t=0}^{\infty} \beta^t w(a_t, s_t^a + \kappa_t \xi) \;>\; \sum_{t=0}^{\infty} \beta^t w(\hat{a}_t, \hat{s}_t^{\hat{a}} + \kappa_t \xi) \tag{17}$$

Summing and rearranging yields:

$$\sum_{t=0}^{\infty} \beta^t [w(\hat{a}_t, \hat{s}_t^{\hat{a}} + \kappa_t \hat{\xi}) - w(\hat{a}_t, \hat{s}_t^{\hat{a}} + \kappa_t \xi)] > \sum_{t=0}^{\infty} \beta^t [w(a_t, s_t^a + \kappa_t \hat{\xi}) - w(a_t, s_t^a + \kappa_t \xi)] \tag{18}$$

Since $\hat{a}_t > a_t$ for all t, $\hat{s}_t^{\hat{a}} > s_t^a$ as well. In addition, $w_{12} > 0$ and $w_{22} > 0$ so $w_2(a_t, s_t^a + x) < w_2(\hat{a}_t, \hat{s}_t^{\hat{a}} + x)$ for every $x \in [\kappa_t \hat{\xi}, \kappa_t \xi]$. Integrating both sides

$$\int_{\kappa_t \hat{\xi}}^{\kappa_t \xi} w_2(a_t, s_t^a + x)dx < \int_{\kappa_t \hat{\xi}}^{\kappa_t \xi} w_2(\hat{a}_t, \hat{s}_t^{\hat{a}} + x)dx \tag{19}$$

results in

$$w(a_t, s_t^a + \kappa_t \xi) - w(a_t, s_t^a + \kappa_t \hat{\xi}) < w(\hat{a}_t, \hat{s}_t^{\hat{a}} + \kappa_t \xi) - w(\hat{a}_t, \hat{s}_t^{\hat{a}} + \kappa_t \hat{\xi}) \tag{20}$$

or equivalently

$$w(\hat{a}_t, \hat{s}_t^{\hat{a}} + \kappa_t \hat{\xi}) - w(\hat{a}_t, \hat{s}_t^{\hat{a}} + \kappa_t \xi) < w(a_t, s_t^a + \kappa_t \hat{\xi}) - w(a_t, s_t^a + \kappa_t \xi) \tag{21}$$

Multiplying by β^t and summing over all t we get a contradiction to (18). Part (ii) easily follows. If the critical level would rise with ξ, all the initial states between the old and the new critical level would have to converge downward with the higher ξ, while they converged upward with the lower ξ, a contradiction.■

Proof of Proposition 3:

Let s_c be the critical level between the steady state 0 and the steady state $\overline{s}$ for $\xi = 0$. Set $\xi = (1 - \delta)(s_c + \epsilon)$ for $\epsilon > 0$ small enough. Regardless of consumption, after enough time the state passes s_c. By the principle of optimality, we can start our discussion here. The optimal path starting from all initial states in the range $(s_c, \overline{s})$ rises to $\overline{s}$ (for $\xi = 0$)

so the optimal path must also rise for this ξ. Thus, $\frac{\xi}{1-\delta} = s_c + \epsilon$ (which is in this range for ϵ small enough) cannot be a steady state, since it will force some of the other values in this range to downward converge to it, instead of upward. Alternatively, the proof of Lemma 3 can be repeated to show that since the path starting from $s_c + \epsilon$ converged upward for $\xi = 0$, it cannot be a steady state (converge downward with a $\geq$ sign instead of $>$). Either way, $\frac{\xi}{1-\delta}$ is not a steady state and thus in any steady state the individual consumes more than 0. Moreover, any steady state that existed at $\xi = 0$ is above s_c for all ξ, which means that even after rehab (resetting ξ to be 0) the aggregate stock is too large for abstention.■

Proof of Corollary 1:

To prove part (i), by Proposition 3, for any network of size $\xi > (1-\delta)s_c$, ignoring the individual's own consumption, aggregate stock exceeds the critical level absent the network and if the individual is disconnected from the network after time:

$$t_c = \frac{\ln\left(1 - \frac{s_c}{\xi}(1-\delta)\right)}{\ln \delta} - 1. \tag{22}$$

the individual's critical level absent the network has been passed, so the disconnected individual's optimal consumption path will converge to the higher steady state. Part (ii) is proven similarly, with a per period stock of $\xi + y$.■

Proof of Lemma 4:

We use a standard analysis of variation approach. Suppose that the initial state is $\bar{s}$ and consider a consumption policy $a_t = \bar{a} + \epsilon b_t$ where ϵ is small enough and b_t is some bounded series. The term ϵb_t represents possible small deviations from the individual's optimal consumption strategy in an internal steady state. The overall payoff (divided by $(1-\beta)$) when using this policy is $f(\epsilon) = \sum_{t=0}^{\infty} \beta^t w(\bar{a} + \epsilon b_t, \bar{s} + \epsilon \sum_{k=0}^{t-1} \delta^{t-k-1} b_k)$. The first argument is the individual's consumption at time t and the second argument is aggregate stock, after calculating the cumulative effect of the deviation terms. Because consumption of $\bar{a}$ supports the steady state, the function $f(\epsilon)$ attains its maximum at 0, which means that $f'(0) = 0$ and $f''(0) < 0$. The small deviations from the optimal consumption path, ϵb_t, could take various forms. Fix $\xi \geq 0$ and let $\bar{s}$ be an internal steady state (i.e. a steady state that is supported by a non-corner consumption, $\bar{s} \neq \frac{\xi}{1-\delta}, \frac{y+\xi}{1-\delta}$).

Clearly, $s_1 = \delta s_0 + \bar{a} + \xi + \epsilon b_0 = \bar{s} + \epsilon b_0$, $s_2 = \delta s_1 + \bar{a} + \xi + \epsilon b_1 = \bar{s} + \epsilon\delta b_0 + \epsilon b_1$

and in general $s_t = \bar{s} + \epsilon \sum_{k=0}^{t-1} \delta^{t-k-1} b_k$. The overall payoff (upto $(1-\beta)$) when using this policy is $f(\epsilon) = \sum_{t=0}^{\infty} \beta^t w(\bar{a} + \epsilon b_t, \bar{s} + \epsilon \sum_{k=0}^{t-1} \delta^{t-k-1} b_k)$. According to intermediate Lemma 2 in the proof of Proposition 2 (see the online appendix), the only optimal strategy that starts at state $\bar{s}$ is $\bar{a}$, hence the function $f(\epsilon)$ attains its maximum at 0, which means that $f'(0) = 0$ and $f''(0) < 0$.

We start with the first-order condition.

$$f'(\epsilon) = \sum_{t=0}^{\infty} \beta^t [b_t w_1(\bar{a}+\epsilon b_t, \bar{s}+\epsilon \sum_{k=0}^{t-1} \delta^{t-k-1} b_k) + (\sum_{k=0}^{t-1} \delta^{t-k-1} b_k) w_2(\bar{a}+\epsilon b_t, \bar{s}+\epsilon \sum_{k=0}^{t-1} \delta^{t-k-1} b_k)] \tag{23}$$

For every t, b_t appears in this summation once when multiplied by w_1 and an additional time for every $T > t$ multiplied by w_2 with a proper discount. Changing the order of summation to account for that, we get:

$$f'(\epsilon) = \sum_{t=0}^{\infty} \beta^t b_t \cdot \tag{24}$$
$$\left[w_1 \left(\bar{a} + \epsilon b_t, \bar{s} + \epsilon \sum_{k=0}^{t-1} \delta^{t-k-1} b_k \right) + \sum_{T=t+1}^{\infty} \beta^{T-t} \delta^{T-t-1} w_2 \left(\bar{a} + \epsilon b_T, \bar{s} + \epsilon \sum_{k=0}^{T-1} \delta^{T-k-1} b_k \right) \right]$$

Set $\epsilon = 0$:

$$f'(0) = \sum_{t=0}^{\infty} \beta^t b_t [w_1(\bar{a}, \bar{s}) + \sum_{T=t+1}^{\infty} \beta^{T-t} \delta^{T-t-1} w_2(\bar{a}, \bar{s})] = \sum_{t=0}^{\infty} \beta^t b_t [w_1(\bar{a}, \bar{s}) + \tfrac{\beta}{1-\beta\delta} w_2(\bar{a}, \bar{s})] \tag{25}$$

Note that the summation is only on $\beta^t b_t$ as the $[\ldots]$ term is fixed. It should hold that $f'(0) = 0$ regardless of the series b_t, so the term $[\ldots]$ should be zero, which is exactly the expression we get by setting $a_{t+1} = a_t = \bar{a}$ and $s_{t+1} = s_t = \bar{s}$ in the individual's first order condition for a constant network (equation (8)). To derive the second-order condition, we differentiate (24) once again:

$$\begin{aligned} f''(\epsilon) &= \sum_{t=0}^{\infty} \beta^t b_t \Big[b_t w_{11}(\bar{a} + \epsilon b_t, \bar{s} + \epsilon \sum_{k=0}^{t-1} \delta^{t-k-1} b_k) \\ &+ (\sum_{k=0}^{t-1} \delta^{t-k-1} b_k) w_{12}(\bar{a} + \epsilon b_t, \bar{s} + \epsilon \sum_{k=0}^{t-1} \delta^{t-k-1} b_k) \\ &+ \sum_{T=t+1}^{\infty} \beta^{T-t} \delta^{T-t-1} [b_T w_{12}(\bar{a} + \epsilon b_T, \bar{s} + \epsilon \sum_{k=0}^{T-1} \delta^{T-k-1} b_k) \\ &+ (\sum_{k=0}^{T-1} \delta^{T-k-1} b_k) w_{22}(\bar{a} + \epsilon b_T, \bar{s} + \epsilon \sum_{k=0}^{T-1} \delta^{T-k-1} b_k)] \Big] \end{aligned}$$

Set $\epsilon = 0$ and, to avoid cumbersome notation, we drop the brackets after the partial derivatives. They are all evaluated at $(\bar{a}, \bar{s})$ and $f''(0)$ is

$$\sum_{t=0}^{\infty} \beta^t b_t \left[b_t w_{11} + \left(\sum_{k=0}^{t-1} \delta^{t-k-1} b_k \right) w_{12} + \sum_{T=t+1}^{\infty} \beta^{T-t} \delta^{T-t-1} \left[b_T w_{12} + \left(\sum_{k=0}^{T-1} \delta^{T-k-1} b_k \right) w_{22} \right] \right]$$

For every t, the term b_t^2 appears twice in the summation: once multiplied by w_{11} and once for every T when $k = t$. Hence, in total, we have $\sum_{t=0}^{\infty} \beta^t b_t^2 [w_{11} + w_{22} \sum_{T=t+1}^{\infty} \beta^{T-t} \delta^{T-t-1} \delta^{T-t-1}] = \sum_{t=0}^{\infty} \beta^t b_t^2 [w_{11} + w_{22} \frac{\beta}{1-\beta\delta^2}]$

For every $i > j$, the term $b_i b_j$ appears in the following cases:

- $t = i$: as part of the sum $(\sum_{k=0}^{t-1} \delta^{t-k-1} b_k) w_{12}$ when $k = j$.
- $t = i$: as part of the sum $(\sum_{k=0}^{T-1} \delta^{T-k-1} b_k) w_{22}$ for every $T \geq i + 1$ whenever $k = j$.
- $t = j$: for $T = i$ in the term $\beta^{T-t} \delta^{T-t-1} b_T w_{12}$.
- $t = j$: for $T \geq i + 1$ and $k = i$, as part of the sum $(\sum_{k=0}^{T-1} \delta^{T-k-1} b_k) w_{22}$

Hence, in the expression of $f''(0)$, for every $i > j$ there should also appear $b_i b_j$ multiplied by

$$\begin{gathered} \beta^i \delta^{i-j-1} w_{12} + \beta^i \sum_{T=i+1}^{\infty} \beta^{T-i} \delta^{T-i-1} \delta^{T-j-1} w_{22} \\ + \beta^j \beta^{i-j} \delta^{i-j-1} w_{12} + \beta^j \sum_{T=i+1}^{\infty} \beta^{T-j} \delta^{T-j-1} \delta^{T-i-1} w_{22} = 2 w_{12} \beta^i \delta^{i-j-1} + 2 w_{22} \beta^i \frac{\beta \delta^{i-j}}{1-\beta\delta^2} \end{gathered} \quad (26)$$

To conclude,

$$f''(0) = \sum_{t=0}^{\infty} \beta^t b_t^2 [w_{11} + w_{22} \tfrac{\beta}{1-\beta\delta^2}] + 2 \sum_{i=0}^{\infty} \sum_{j<i} \beta^i \delta^{i-j-1} b_i b_j [w_{12} + w_{22} \tfrac{\beta\delta}{1-\beta\delta^2}] \tag{27}$$

Denote $A = w_{11} + w_{22} \frac{\beta}{1-\beta\delta^2}$ and $B = w_{12} + w_{22} \frac{\beta\delta}{1-\beta\delta^2}$. The last expression can be written as $f''(0) = \underline{b}^T M \underline{b}$ where $\underline{b} = (b_0, b_1, \ldots)$ and M is the operator

$$\begin{pmatrix} A & \beta B & \delta\beta^2 B & \ldots \\ \beta B & \beta A & \beta^2 B & \ldots \\ \delta\beta^2 B & \beta^2 B & \beta^2 A & \ldots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}. \tag{28}$$

The calculations are done at a steady state, so $f''(0) < 0$ for every $\underline{b} \neq \underline{0}$, which means that M is a definite negative operator. By the Sylvester criteria, this is equivalent to $(-1)^n M_n > 0$ for all n, where M_n is the n^{th} primary minor of M. For special cases, we can obtain relatively simple conditions that need to hold. In particular, if we consider constant deviations from the optimal strategy ($\underline{b} = (b, b, \ldots)$) then, after some computation, we have:

$$(1 - \beta\delta) w_{11}(\bar{a}, \bar{s}) + 2\beta w_{12}(\bar{a}, \bar{s}) + \tfrac{\beta(1+\beta\delta)}{1-\beta\delta^2} w_{22}(\bar{a}, \bar{s}) < 0. \tag{29}$$

■

Proof of Proposition 4:

Let ξ be some network and $\overline{s}$ some steady state. For every $\epsilon > 0$ small enough, the optimal path starting from $\overline{s} - \epsilon$ converges upward to $\overline{s}$. Hence, by Lemma 3 it converges upward for every larger ξ, which implies that the steady state cannot decrease with ξ because it would force some of the states between the old and the new steady state to converge downward to the new steady state. Hence $\frac{d\overline{s}}{d\xi} > 0$. We now calculate this expression explicitly. Let $\overline{s}$ be an internal steady state. Define the LHS of the first order condition in a steady state (this can be derived by setting $a_{t+1} = a_t = \overline{a}$ and $s_{t+1} = s_t = \overline{s}$ in the individual's first order condition along an optimal consumption path (8)) by:

$$R(\overline{s},\xi) \equiv (1-\beta\delta)w_1((1-\delta)\overline{s}-\xi,\overline{s}) + \beta w_2(((1-\delta)\overline{s}-\xi,\overline{s})) \tag{30}$$

The solutions of the equation $R(\overline{s},\xi) = 0$ define the steady states for ξ. The response of the steady state to an increase in the network's consumption can be evaluated using implicit differentiation:

$$\frac{d\overline{s}}{d\xi} = -\frac{\frac{\partial R}{\partial \xi}}{\frac{\partial R}{\partial \overline{s}}} = \frac{(1-\beta\delta)w_{11} + \beta w_{12}}{(1-\beta\delta)(1-\delta)w_{11} + (1-2\beta\delta+\beta)w_{12} + \beta w_{22}} \tag{31}$$

where all second derivatives are evaluated at $((1-\delta)\overline{s}-\xi,\overline{s})$ and assuming that $\frac{\partial R}{\partial \overline{s}} \neq 0$. Let s_0 be some initial state from which the path of aggregate stock converges to $\overline{s}$ when using the optimal time-dependent strategy $a_0, a_1, \ldots$. If the individual keeps this behavior even when ξ increases by ϵ, the path of aggregate stock will converge to $\overline{s} + \frac{\epsilon}{1-\delta}$. Hence, if the new steady state is larger than $\overline{s} + \frac{\epsilon}{1-\delta}$, this cannot be optimal and the individual must consume more along the optimal path (not necessarily for every t, but on average and for $t \to \infty$). Similarly, if the new steady state is smaller than $\overline{s} + \frac{\epsilon}{1-\delta}$, the individual must reduce consumption to reach the steady state. These conditions can be phrased as $\frac{d\overline{s}}{d\xi} \gtrless \frac{1}{1-\delta}$ where $>$ corresponds to an increase in consumption and $<$ to a decrease. To conclude, an increase in consumption in response to an increase in the network occurs when

$$\frac{(1-\beta\delta)w_{11} + \beta w_{12}}{(1-\beta\delta)(1-\delta)w_{11} + (1-2\beta\delta+\beta)w_{12} + \beta w_{22}} > \frac{1}{1-\delta} \tag{32}$$

which is equivalent to

$$\frac{(1-\beta\delta)w_{12} + \beta w_{22}}{(1-\beta\delta)(1-\delta)w_{11} + (1-2\beta\delta+\beta)w_{12} + \beta w_{22}} < 0 \tag{33}$$

Note that the nominator is positive, so this expression holds if and only if the denominator is negative. Recall that the second order condition for a constant deviation (9) is

$$(1-\beta\delta)w_{11} + 2\beta w_{12} + \tfrac{\beta(1+\beta\delta)}{1-\beta\delta^2} w_{22} < 0 \tag{34}$$

and the LHS can be re-written as

$$[(1-\beta\delta)w_{11}+\beta w_{12}]+[\beta w_{12}+\tfrac{\beta(1+\beta\delta)}{1-\beta\delta^2}w_{22}] \tag{35}$$

Since the right [] are positive, the left [] must be negative, which means that $(1-\beta\delta)w_{11}+\beta w_{12}<0$ and an increased network encourages increased consumption in a steady state.■

Proof of Proposition 5:

To prove the proposition, let us first prove the two following intermediate lemma's, utilizing our results from Section 3:

Lemma: Suppose that for a constant network $\xi=0$ the lowest steady state corresponds to zero-consumption. Denote the set of all constant network levels for which $\frac{\xi}{1-\delta}$ is a steady state by I. Then I is a closed interval.

Proof: Let ξ_n be some converging series in I, and let ξ be its limit. To show that I is closed, we need to show that $\xi\in I$. For every n, $\xi_n\in I$, thus $\frac{\xi_n}{1-\delta}$ is a steady state when the network is ξ_n. Let $(a_t)_{t\in N}$ be some strategy which is different from constant zero-consumption. Since $\frac{\xi_n}{1-\delta}$ is a steady state, the unique optimal strategy starting from it is zero-consumption:

$$\sum_{t=0}^{\infty}\beta^t w(0,\tfrac{\xi_n}{1-\delta})>\sum_{t=0}^{\infty}\beta^t w(a_t,s_t^a+\tfrac{\xi_n}{1-\delta}). \tag{36}$$

Taking the limit $n\to\infty$ on both sides and taking account of the fact that we can change the order of summation and limit since w is continuous on $[0,y]\times[0,\frac{y+\sup_n \xi_n}{1-\delta}]$ and hence bounded, yields:

$$\sum_{t=0}^{\infty}\beta^t w(0,\tfrac{\xi}{1-\delta})\geq\sum_{t=0}^{\infty}\beta^t w(a_t,s_t^a+\tfrac{\xi}{1-\delta}). \tag{37}$$

Inequality (37) is in fact strong because, as demonstrated in intermediate Lemma 2 in the proof of Proposition 2 (see the online appendix), if zero consumption is one optimal continuation consumption following zero consumption, it is the only optimal continuation consumption. Hence, the strategy of not consuming when the network is ξ and the initial state is $\frac{\xi}{1-\delta}$ outperforms the strategy $(a_t)_{t\in N}$. This is true for every $(a_t)_{t\in N}$, so not consuming is the optimal strategy, which implies that $\frac{\xi}{1-\delta}$ is a steady state and $\xi\in I$. Therefore, I is closed. To prove that I is an interval, let $\xi_1,\xi_2\in I$ and consider the function f that maps each ξ to the lowest steady state with the constant network ξ. Suppose first that f is continuous. f satisfies $f(\xi_1) = \frac{\xi_1}{1-\delta}$ and $f(\xi_2) = \frac{\xi_2}{1-\delta}$. In addition, $f(\xi) = \frac{\xi}{1-\delta}$ for all networks in $[\xi_1, \xi_2]$. This is because f increases at least as fast as the function $\frac{\xi}{1-\delta}$: For 0-consumption steady states, $f(\xi) = \frac{\xi}{1-\delta}$, and if we assume positive consumption, it follows from Proposition 4 that f increases faster than $\frac{\xi}{1-\delta}$. But had there been positive consumption in $[\xi_1, \xi_2]$, f would have departed upwards from the function $\frac{\xi}{1-\delta}$, and then meet $\frac{\xi}{1-\delta}$ again at $\xi = \xi_2$, which contradicts the fact that f increases faster than $\frac{\xi}{1-\delta}$ for all ξ. Consider now discontinuities of f. Denote as $\hat{\xi}$ a point of discontinuity. Upward discontinuity $(\lim\limits_{\xi \to \hat{\xi}^-} f(\xi) < \lim\limits_{\xi \to \hat{\xi}^+} f(\xi))$ is overruled by the fact that, in order to meet $\frac{\xi}{1-\delta}$ again at $\xi = \xi_2$, f needs to increase more slowly than $\frac{\xi}{1-\delta}$. Downward discontinuity is overruled because it would imply the existence of initial states in $[\lim\limits_{\xi \to \hat{\xi}^+} f(\xi), \lim\limits_{\xi \to \hat{\xi}^-} f(\xi)]$ which are upward converging for smaller networks than $\hat{\xi}$ and downward converging for larger networks (in contradiction to Lemma 3). Thus, $f(\xi) = \frac{\xi}{1-\delta}$ for all networks in $[\xi_1, \xi_2]$, so $[\xi_1, \xi_2] \subseteq I$. To conclude, I is a convex closed subset of R and hence it is a closed interval.

Now let I be the interval of all networks for which 0-consumption is a steady state. Denote by I_0 the set of all corresponding steady states, i.e., $I_0 = [0, \frac{\max I}{1-\delta}]$. In the following intermediate lemma, we show that if the initial state and network are small enough, the individual abstains from consumption even if the initial state is above the network's consumption-less steady state, and the steady state converges downward to the network's own consumption-less steady state:

Lemma: Suppose that for $\xi = 0$ the lowest steady state corresponds to zero-consumption and let I be the set of all constant network levels for which $\frac{\xi}{1-\delta}$ is a steady state. Then for every $\hat{\xi}, \xi \in I$ s.t. $\hat{\xi} < \xi$, the optimal path that starts at $s_0 = \frac{\xi}{1-\delta}$ when the network is $\hat{\xi}$ is a path without consumption by the individual.

Proof: This is proven in a similar manner to Lemma 3. Assume by contradiction that when the network is $\hat{\xi}$, the optimal consumption path starting at s_0 is $a_t \geq 0$ with a strict inequality for at least one t. In addition, the optimal consumption path when the network is ξ starting from s_0 is 0:

$$\sum_{t=0}^{\infty} \beta^t w(a_t, s_t^a + \kappa_t \hat{\xi}) > \sum_{t=0}^{\infty} \beta^t w(0, s^0 + \kappa_t \hat{\xi}) \tag{38}$$

$$\sum_{t=0}^{\infty} \beta^t w(0, s^0 + \kappa_t \xi) > \sum_{t=0}^{\infty} \beta^t w(a_t, s_t^a + \kappa_t \xi) \tag{39}$$

Combining these two inequalities yields:

$$\sum_{t=0}^{\infty} \beta^t w(a_t, s_t^a + \kappa_t \hat{\xi}) - \sum_{t=0}^{\infty} \beta^t w(a_t, s_t^a + \kappa_t \xi) > \sum_{t=0}^{\infty} \beta^t w(0, s^0 + \kappa_t \hat{\xi}) - \sum_{t=0}^{\infty} \beta^t w(0, s^0 + \kappa_t \xi) \tag{40}$$

On the other hand, $a_t \geq 0$ and $s_t^a \geq s_t^0$ so $w_2(a_t, s_t^a + x) > w_2(0, s^0 + x)$. Integrating $(\int_{\kappa_t \hat{\xi}}^{\kappa_t \xi} \cdot dx)$ both sides results in:

$$w(a_t, s_t^a + \kappa_t \xi) - w(a_t, s_t^a + \kappa_t \hat{\xi}) > w(0, s_t^0 + \kappa_t \xi) - w(0, s_t^0 + \kappa_t \hat{\xi}) \tag{41}$$

i.e:

$$w(0, s_t^0 + \kappa_t \hat{\xi}) - w(0, s_t^0 + \kappa_t \xi) > w(a_t, s_t^a + \kappa_t \hat{\xi}) - w(a_t, s_t^a + \kappa_t \xi) \tag{42}$$

which, after multiplying by β^t and summing over t, contradicts (40).

These two intermediate lemmas show that there exists an interval $I_0 = [0, \overline{\xi}]$ such that for an individual without a network ($\xi = 0$) and with initial state $s_0 \in I_0$, the optimal strategy is to consume 0 while converging to the steady state $s = 0$. Let $\underline{s} \in I_0^n$ be the n-dimensional initial state in which for all individuals $1, ..., n$ initial stock $s_0^i \in I_0$, and suppose that all individuals except individual i to consume 0 for all t. For individual i, the initial state is within I_0 and the constant network she observes is $\xi^i = 0$, so according to the above-mentioned intermediate lemmas, her best response is to consume 0 for all t. It follows that the best response to 0 consumption of all others is also 0 consumption, so this strategy profile is an OLE. On the equilibrium path, all users avoid consumption and the state monotonically converges to a steady state, $\underline{s} = \delta^t \underline{s} \to 0$.■

Proof of Proposition 6:

We show, in the following intermediate lemma, that when exposed to a large enough constant network, the individual consumes y each period for any initial stock. Hence, when all individuals use this strategy, the network a single individual sees is a constant network of $\sum_{j \neq i} \gamma_{ij} y$. Thus, for n or $\min_{\gamma_{ij} \neq 0, i \neq j} \gamma_{ij}$ large enough, the best response is to consume y too.

Lemma: Fix ξ and s_0. If consuming y for all $t \in N$ is not optimal in this initial state, it is not optimal for all smaller initial states. Thus, the set of initial states for which consuming y for all t is optimal is of the form $[\underline{s}, \infty)$ (or $\emptyset$, if $\frac{y+\xi}{1-\delta}$ is not a steady state).

Proof: Let $\hat{s}_0$ be an initial state smaller than s_0. Assume by contradiction that the optimal strategy starting with $\hat{s}_0$ is to consume y whereas the optimal strategy starting with s_0 is some $(a_t)_{t \in N}$. Then

$$\sum_{t=0}^{\infty} \beta^t w(a_t, \delta^t s_0 + s_t^a + \kappa_t \xi) > \sum_{t=0}^{\infty} \beta^t w(y, \delta^t s_0 + s_t^y + \kappa_t \xi)$$

and

$$\sum_{t=0}^{\infty} \beta^t w(y, \delta^t \hat{s}_0 + s_t^y + \kappa_t \xi) > \sum_{t=0}^{\infty} \beta^t w(a_t, \delta^t \hat{s}_0 + s_t^a + \kappa_t \xi).$$

Summing these two equations leads to

$$\sum_{t=0}^{\infty} \beta^t \left[w(a_t, \delta^t s_0 + s_t^a + \kappa_t \xi) - w(a_t, \delta^t \hat{s}_0 + s_t^a + \kappa_t \xi) \right] >$$
$$\sum_{t=0}^{\infty} \beta^t \left[w(y, \delta^t s_0 + s_t^y + \kappa_t \xi) - w(y, \delta^t \hat{s}_0 + s_t^y + \kappa_t \xi) \right]$$

Note that $a_t \leq y$ and $s_t^a \leq s_t^y$, so for every x, $w_2(a_t, x + s_t^a + \kappa_t \xi) < w_2(y, x + s_t^y + \kappa_t \xi)$. Hence, performing $\int_{\delta^t \hat{s}_0}^{\delta^t s_0} \cdot dx$ on both sides leads to:

$$w(a_t, \delta^t s_0 + s_t^a + \kappa_t \xi) - w(a_t, \delta^t \hat{s}_0 + s_t^a + \kappa_t \xi) < w(y, \delta^t s_0 + s_t^y + \kappa_t \xi) - w(y, \delta^t \hat{s}_0 + s_t^y + \kappa_t \xi).$$

Multiplying by β^t and summing leads to a contradiction. Accordingly, if y is not optimal for s_0 it cannot be optimal for $\hat{s}_0 < s_0$ and vice versa – if it is optimal for s_0 it is optimal for all initial states $\hat{s}_0 > s_0$. Proving that this interval is closed is proven in the same way as in the proof of the intermediate lemma in the proof of Proposition 5, by continuity. Note that $\underline{s}$ is a decreasing function of ξ. To see this, consider

$$f(\xi) = \sum_{t=0}^{\infty} \beta^t w(y, \delta^t \hat{s}_0 + s_t^y + \kappa_t \xi) - \sum_{t=0}^{\infty} \beta^t w(a_t, \delta^t \hat{s}_0 + s_t^a + \kappa_t \xi), \tag{43}$$

and

$$f'(\xi) = \sum_{t=0}^{\infty} \beta^t \kappa_t w_2(y, \delta^t \hat{s}_0 + s_t^y + \kappa_t \xi) - \sum_{t=0}^{\infty} \beta^t \kappa_t w_2(a_t, \delta^t \hat{s}_0 + s_t^a + \kappa_t \xi). \qquad (44)$$

Since $y \geq a_t$ and $s_t^y \geq s_t^a$, combined with $w_{12}, w_{22} > 0$, we see that term-by-term the first series is greater than the second, so $f'(\xi) > 0$. Thus, if $f(\hat{\xi}) > 0$ for some initial state $\hat{s}_0$ (meaning that always consuming y is better than the consumption path a_t) it is also true for all $\xi > \hat{\xi}$ (and, in-fact, the gain from consuming y compared to the other strategy is even larger). The only question remaining is how low $\underline{s}$ can go with ξ. We now show that for large enough ξ, $\underline{s} = 0$. That is, $\lim\limits_{\xi \to \infty} \underline{s} = 0$, so that for a large enough ξ, the optimal consumption plan is to consume y for every initial state. Since consuming y each period is one of the individual's steady states even absent a network, there exists some initial state s' and some network ξ' such that starting from s' with a network ξ', the optimal path is to consume y in every stage. From now on we consider only networks $\xi > \max\{s', \xi'\}$ and the initial state $s_0 = 0$. For such networks, the state after $t = 1$ surpasses s' (regardless of the actions of the individual) and the network is stronger than ξ', so by the principal of optimality, the optimal path starting from $t = 1$ is to consume y. It is left to determine if this is also optimal for $t = 0$ or not for large enough ξ. If the individual consumes a in the first stage, the payoff can be written as

$$f(a) = w(a, 0) + \sum_{t=1}^{\infty} \beta^t w(y, \delta^{t-1} a + \kappa_t \xi + \kappa_{t-1} y). \qquad (45)$$

We first compare the payoff when consuming 0 to the payoff when consuming y:

$$f(y) - f(0) = w(y, 0) - w(0, 0) + \sum_{t=1}^{\infty} \beta^t [w(y, \delta^{t-1} y + \kappa_t \xi + \kappa_{t-1} y) - w(y, \kappa_t \xi + \kappa_{t-1} y)] \quad (46)$$

Using the Lagrange theorem, we can turn the [...] into $\delta^{t-1} y w_2(y, c_t)$ (where $c_t \in [\kappa_t \xi + \kappa_{t-1} y, \kappa_t \xi + \kappa_{t-1} y + \delta^{t-1} y]$). Since $c_t \to \infty$ when $\xi \to \infty$, in this limit $w_2(y, c_t) \to 0$ (since $w_{22} > 0$) and $f(y) - f(0) = w(y, 0) - w(0, 0) > 0$. It follows that for large enough ξ, consuming y is better than consuming 0. This ensures that y is the optimal consumption whenever $f'' > 0$ (so that the maximum is not an internal solution). Suppose now that $f'' < 0$, and the maximum is an internal solution rather than y. The optimal a^* should be chosen such that $f'(a^*) = 0$, i.e.:

$$w_1(a^*, 0) + \sum_{t=1}^{\infty} \beta^t \delta^{t-1} w_2(y, \delta^{t-1} a^* + \kappa_t \xi + \kappa_{t-1} y) = 0 \tag{47}$$

Since $w_{22} > 0$, the w_2 part is increasing with ξ, so for higher ξ the equality holds only if w_1 is smaller, which happens for larger a^* (recall that $w_{11} < 0$). Note also that by increasing ξ, the derivative of f w.r.t. to a at the optimal action corresponding to the smaller network becomes positive, so optimally consumption is increased. Either way, $a^*(\xi)$ is an increasing bounded function of ξ and let $\overline{a} = \lim_{\xi \to \infty} a^*(\xi)$. Moreover, following a similar argument, if $a^*(\xi) = y$ then $\forall \xi' > \xi, a^*(\xi') = y$. Assume that $a^*(\xi) \in (0, y)$ for all ξ large enough. Then the equation $f'(a^*) = 0$ holds for all ξ and it should also hold in the limit $\xi \to \infty$. But since $w_2 \to 0$, in the limit we are left with $w_1(\overline{a}, 0) = 0$, a contradiction to $w_1 > 0$. Hence, $f'(a^*) = 0$ cannot hold for infinitely many ξ, and starting from some ξ, the optimal solution is a corner one. As we already established, y is the only candidate and the proof is complete.■

Proof of Proposition 7:

By Proposition 5, the consumption-less OLE exists (provided that all individuals' initial states are small enough). We prove for the case of $n > N'$ and the proof for $\min_{\gamma_{ij} \neq 0, i \neq j} \gamma_{ij} > \gamma'$ is analogous. Suppose there exists another equilibrium for some n with positive consumption. By Corollary 2, when adding individuals to the network, all network members consume more in equilibrium. Let a_t^i be the consumption of some individual and $\overline{a}_t^i = \liminf_{n \to \infty} a_t^i > 0$. Assume by contradiction that $\overline{a}_t^i < y$. There exists n large enough so that the limit is (almost) obtained and the total network seen by each individual is larger than the one causing y-consumption with a constant network. In such a network, the optimal best-response of each individual is to consume y. Hence, in equilibrium, $\overline{a}_t^i < y$ cannot hold and the limit is y. More generally, if ξ is a constant network where the best response is to consume y in each period, it is also a best response to consume y in each period for any non-constant network $\xi_t > \xi$. This follows because $w_{12} > 0$, so $w_2(a_t, x) < w_2(y, x)$ for all x.■

Proof of Lemma 5:

Let $\underline{a}^1 = (a_t^1)_{t \in N}$ be some consumption strategy of individual 1 (w.l.o.g.) and $\underline{a}^{-1} = (a_t^{-1})_{t \in N}$ the consumption strategy of all the others. Denote the utility of individual 1 by $U_1(\underline{a}^1, \underline{a}^{-1}) = (1-\beta)\sum_{t=0}^{\infty}\beta^t w(a_t^1, \underline{s}_t)$, where $\underline{s}_t$ is the evolution of the states according to (2) with the above mentioned strategy profiles. Each partial sum of the form $U_{1,k}(\underline{a}^1, \underline{a}^{-1}) = (1-\beta)\sum_{t=0}^{k}\beta^t w(a_t^1, \underline{s}_t)$ is continuous in $\underline{a}^1$ and $\underline{a}^{-1}$ (as a finite sum of continuous functions w) and $U_{1,k} \to U_1$ uniformly (bounded by a geometric series), so by the uniform limit theorem, U_1 is a continuous function as well. A similar argument shows that U_1 is c^2 with respect to any a_t^1. Fix $\underline{a}^{-1}$. The function $U_1(\cdot, \underline{a}^{-1}) : [0, y]^\infty \to R$ is continuous over the compact domain, so the maximum is attained. Thus, the best response correspondence $\Phi(\underline{a}^{-1}) = \arg\max_{\underline{a}\in[0,y]^\infty} U_1(\underline{a}, \underline{a}^{-1})$ is well defined and $\Phi(\underline{a}^{-1}) \neq \emptyset$ for all $\underline{a}^{-1}$. Moreover, Φ is a closed-valued correspondence. Indeed, let $\underline{a}^1(k)$ be a converging series[50] whose all elements are in $\Phi(\underline{a}^{-1})$, and denote the limit by $\underline{a}^1$. Let $\underline{c}^1$ be some possible policy of individual 1. Since all $\underline{a}^1(k)$ are in $\Phi(\underline{a}^{-1})$ they are best-replies to $\underline{a}^{-1}$, so $U_1(\underline{a}^1(k), \underline{a}^{-1}) \geq U_1(\underline{c}^1, \underline{a}^{-1})$. By taking the limit $k \to \infty$ and using the continuity of U, we get $U_1(\underline{a}^1, \underline{a}^{-1}) \geq U_1(\underline{c}^1, \underline{a}^{-1})$ which implies $\underline{a} \in \Phi(\underline{a}^{-1})$. Finally, Φ is u.h.c.. Indeed, let $\underline{a}^{-1}(k)$ be a series of strategies that converges to $\underline{a}^{-1}$, and $\underline{a}^1(k)$ a series of best replies ($\underline{a}^1(k) \in \Phi(\underline{a}^{-1}(k))$) that converges to $\underline{a}^1$. It follows that for every strategy $\underline{c}$ of individual 1, $U_1(\underline{a}^1(k), \underline{a}^{-1}(k)) \geq U_1(\underline{c}, \underline{a}^{-1}(k))$. Again, this inequality is true in the limit $k \to \infty$, so for every $\underline{c}^1 \in [0, y]^\infty$, $U_1(\underline{a}^1, \underline{a}^{-1}(k)) \geq U_1(\underline{c}^1, \underline{a}^{-1}(k))$, which implies that $\underline{a}^1$ is a best reply to $\underline{a}^{-1}$, $\underline{a}^1 \in \Phi(\underline{a}^{-1})$, and Φ is u.h.c. Note that Φ is also a function of $\underline{s}_0$, but since it is fixed for the entire proof, the dependence on it was omitted.■

Proof of Proposition 8:

W.l.o.g consider individual 1 and assume each other individual j uses the open-loop strategy $(a_t^j)_{t\in N}$. When individual 1 uses the strategy $(a_t^1)_{t\in N}$, her payoff is

$$U_1(\underline{a}^1, \underline{a}^{-1}) = \sum_{t=0}^{\infty}\beta^t w(a_t^1, s_t) \tag{48}$$

where $s_{t+1}^1 = \delta s_t^1 + \sum_{j=1}^{n}\gamma_{1j}a_t^j$. Let $t', t'' \in N$ and assume $t' \geq t''$. Fix individual $j \neq 1$. Then

$$\frac{\partial U_1}{\partial a_{t''}^j} = \sum_{t=t''+1}^{\infty}\beta^t\delta^{t-t''-1}\gamma_{1j}w_2(a_t^1, s_t) \tag{49}$$

[50]We can use the sup-norm to measure distance between strategies.

and

$$\frac{\partial^2 U_1}{\partial a^j_{t''}\partial a^1_{t'}} = \sum_{t=t'+1}^{\infty} \beta^t \delta^{t-t''-1}\delta^{t-t'-1}\gamma_{1j}\gamma_{11}w_{22}(a^1_t, s_t) + \beta^{t'}\gamma_{1j}w_{12}(a^1_{t'}, s_{t'})\delta^{t'-t''-1} \tag{50}$$

Since $w_{12}, w_{22}, \gamma_{11}, \gamma_{1j} > 0$, we get that $\frac{\partial^2 U_1}{\partial a^j_{t''}\partial a^1_{t'}} > 0$. This is also true when $t' < t''$ (then the w_{12} term drops). To conclude, the game is supermodular, i.e. an increase in the action of j at some time causes player 1 to increase her action in all times. This is true for all players. Now, let $F : ([0,y]^\infty)^n \to ([0,y]^\infty)^n$ be the best response function, i.e. $F(\underline{a}^1, \ldots, \underline{a}^n) = (BR_1(\underline{a}^2, \ldots, \underline{a}^n), \ldots, BR_n(\underline{a}^1, \ldots, \underline{a}^{n-1}))$. From the above argument, this function is order-preserving on a complete lattice, so according to Tarski's fixed point theorem, it has a fixed point. This fixed point is an OLE equilibrium (in pure strategies). Note that if harm is sufficiently convex in aggregate stock so that (50) is negative, reaction functions are downward sloping. Here too, by similar reasoning, an OLE exists.■

Proof of Lemma 6:

Consider the best response function $F(\sigma_\mu)$ for the case in which the parameter is μ'. We have established that this is an increasing function and in addition it is u.h.c., by Lemma 5. Hence, the series $x^{k+1} = F(x^k)$ converges to a fixed point, which is an OLE equilibrium. σ_μ is some equilibrium for some parameter μ, and it is no longer an equilibrium when the parameter changes to μ', since all individuals in I want to consume more (less). In response, all the other individuals will consume more (less) according to $F(\sigma_\mu)$. In response, all network members will want to consume even more (less) according to $F(F(\sigma_\mu))$, and so forth. This iterated process converges to a new equilibrium $\sigma_{\mu'}$ where all network members consume more (less) than in σ_μ.■

Proof of Corollary 2:

Proof of part (i):

We differentiate (12) according to γ_{ij}. It appears implicitly in the equation via the state variable in (11):

$$\frac{\partial s^i_t}{\partial \gamma_{ij}} = \delta\frac{\partial s^i_{t-1}}{\partial \gamma_{ij}} + a^j_{t-1} = \ldots = \sum_{k=0}^{t-1} \delta^{t-1-k} a^j_k \tag{51}$$

Thus,

$$\frac{\partial^2 U_i(\underline{a})}{\partial a^i_\tau \partial \gamma_{ij}} = \beta^\tau w_{12}(a^i_\tau, s^i_\tau) \sum_{k=0}^{\tau-1} \delta^{\tau-1-k} a^j_k + \sum_{t=\tau+1}^{\infty} \beta^t \delta^{t-\tau} w_{22}(a^i_t, s^i_t) \sum_{k=0}^{t-1} \delta^{t-1-k} a^j_k > 0 \quad (52)$$

where the inequality follows from $w_{12}, w_{22} > 0$. Thus individual i's marginal utility from additional consumption increases with γ_{ij} (unless individual j abstains for all t in equilibrium), so the current strategy profile is not an equilibrium. Individual i now wishes to consume more. By Lemma 6, all network members want to consume more.

Proof of part (ii):

Consider an individual j who is disconnected from the network. This is equivalent to adding j to the network and setting $\gamma_{ij} = \gamma_{ji} = 0\,\forall i, j = 1, ...n$. If we now increase γ_{ij} and γ_{ji} one by one, by part (i) above, we switch to a new OLE with higher consumption by all network members in each step.

Proof of part (iii):

We differentiate (12) according to s^i_0. It appears implicitly in the equation via the state variable in (11), and $\frac{\partial s^i_t}{\partial s^i_0} = \delta^t$. Thus,

$$\frac{\partial^2 U_i(\underline{a})}{\partial a^i_\tau \partial s^i_0} = \beta^\tau \delta^\tau w_{12}(a^i_\tau, s^i_\tau) + \sum_{t=\tau+1}^{\infty} \beta^t \delta^{t-\tau} \delta^t w_{22}(a^i_t, s^i_t) > 0 \quad (53)$$

where the inequality follows from $w_{12}, w_{22} > 0$. Hence marginal utility from additional consumption increases with the initial state, so the current strategy is not an equilibrium and individual i wishes to consume more. By Lemma 6, all network members want to consume more.■

Proof of Corollary 3:

We require that the reaction functions are downward sloping (i.e., (50) is negative), that an increase in the initial stock causes consumption to decrease (i.e., (53) is negative), and that an increase in an influence parameter causes consumption to decrease (i.e., (52) is negative). For each such case, we bound the second derivatives by their maximal value and compute directly the sum over t. For example, the requirement that (53) is negative leads to

$$0 > \beta^\tau \delta^\tau w_{12} + \sum_{t=\tau+1}^{\infty} \beta^t \delta^{2t-\tau} w_{22} = \max w_{12} + \max w_{22} \frac{\beta\delta^2}{1-\beta\delta^2}$$

Or equivalently,

$$\max_{a\in[0,y];s\in[0,\infty)} w_{22}(a,s) < -B_2 \max_{a\in[0,y];s\in[0,\infty)} w_{12}(a,s) \tag{54}$$

where $B_2 \equiv \frac{1-\beta\delta^2}{\beta\delta^2}$. A similar computation for the other cases results in a different coefficient instead of B_2: $B_1 \equiv \frac{1-\beta\delta^2}{\beta\delta}$ corresponds to the condition that reaction functions are downward sloping (i.e., (50) is negative) and $B_3 \equiv \frac{1-\beta\delta}{\beta\delta}$ corresponds to the condition that an increase in an influence parameter causes consumption to decrease (i.e., (52) is negative). Note that the sum in the first term of (52) is included in the summation in the second term, while the second summation in this second term ($\sum_{k=0}^{t-1} \delta^{t-1-k} a_k^j$) is strictly positive, and hence can be ignored to derive the desired sufficient condition. It is clear that $B_3 < B_1 < B_2$, so that the condition for B_2 is the most strict and if (54) holds, it also holds when replacing B_2 by B_1 or B_3.

Proof of Lemma 7:

This follows directly from the game being supermodular, as shown in the proof of Proposition 8.■

Proof of Proposition 9:

For each i, by the two intermediate lemma's in the proof of Proposition 5, there exists an interval $I_0^i = [0, \bar{\xi}^i]$ such that for a single decision maker i without a network ($\xi = 0$) and with initial state $s_0 \in I_0^i$, the optimal strategy is to consume 0 while converging to the steady state $s = 0$. Let $\bar{\xi}{=}\min_i \bar{\xi}^i$ and $I_0 = [0, \frac{\bar{\xi}}{1-\delta}]$. Now let $s_0 \in I_0$ be an initial state, and suppose that all consumers except individual i to consume 0 for all $s \in I_0$. Individual i has three types of possible responses: (a) consume nothing for $s \in I_0$, (b) consume something small enough to keep the state within I_0 for all t, or (c) consume something large enough to eventually move the state outside I_0. When following option (b), all the others refrain from consuming for all t. So, it is equivalent to a constant network scenario with $\xi^i = 0$ and an initial state within I_0. According to the above-mentioned intermediate lemmas, her best response is to consume 0 instead, so option (b) cannot be a best reply. Option (c) is not a best reply either. Any consumption plan $(a_t)_{t\in\mathbb{N}}$ was also possible in the constant network model with $\xi = 0$, but due to the intermediate lemmas and the initial state being in I_0, was sub-optimal relative to not consuming. By consuming enough to raise the state above $\bar{\xi}$, individual i might invoke consumption from others, which will only increase the state in every time step. Since $w_2 < 0$, this can only decrease her utility so this is even more sub-optimal. To conclude, only option (a), in which $a(s) = 0$ for all $s \in I_0$, is a best response. It follows that on the equilibrium path, all individuals avoid consumption and the state monotonically converges to a steady state, $s_t = \delta^t s_0 \to 0$.

Proof of Proposition 10:

This is proven similarly to Proposition 6. When all individuals consume y each period, the network a single individual sees is a constant network of $\sum\limits_{j \neq i} \gamma_{ij} y$. Thus, for n or $\min\limits_{\gamma_{ij} \neq 0, i \neq j} \gamma_{ij}$ large enough, the best response is to consume y too, regardless of the initial state, forming an MPE.

Proof of Corollary 5:

The proof is analogous to the proof of Corollary 1, noting that if all network members consume y, it is as if the individual is exposed to a constant network of $\xi = y \sum_{j=1}^{n} \gamma_{ji}$.$\blacksquare$

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