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Far Above Others

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Far above others*

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Abstract

We study the role of competitive behavior in a social network. Agents gain a competitive premium by obtaining a greater outcome than their neighbors (i.e., their reference group). We consider societies in which the level of competition can be strong, mild or weak (i.e., agents compare themselves with the best, the average or the worst outcome in their reference group). We find that in a more competitive society less aggregate effort is provided. An increase in the density and homogeneity of the network decreases total effort in the strong-competitive case, whereas the opposite occurs in the weak-competitive setting.

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1 Introduction

"*Always be the best and be far above others*," demanded Pelean, father of Achilles the Achaean, to his son when sending him to fight at Troy (Homer, Iliad 11.783).[1] The competitive spirit, illustrated in this passage of the *Iliad*, was highly appreciated by the ancient Greeks and is present in modern Western societies to a greater or lesser extent.[2] Competition levels, however, vary significantly across cultures, as they depend on topics such as religion, law and economy. For example, it is commonly suggested that Protestant societies endorse the idea that competition is necessary and good, more so than non-Protestant societies (see Weber, 1904/1996; Hayward and Kemmelmeier, 2007). Likewise, when comparing the Chinese and American views of competition, Young (1994, p.57) states: "*in the US, to 'stand out from' or 'get ahead from' others is an acceptable part of the competitive spirit. Chinese, on the other hand, are quick to quote old sayings that call attention to the dangers of individual prominence*." There is, therefore, a higher or lower competitive pressure on individuals depending on the culture they are embedded in. Moreover, competitiveness basically represents the desire to outdo others, and thus its formulation yields the need to introduce relative judgements into consideration. However, when individuals compare themselves to others, they rarely do so with respect to the whole population. Instead, they compare their performance to that of their peers (Luttner, 2005). Thus, individual prominence (success) needs to be conceived of in the context of a *social network* under the lens of the culture.

In this paper, we present a stylized model of effort provision to study the role of competitive behavior in a society. We do so by introducing a behavioral component in the agent's utility function, which is inherently dependent on two elements: *the competition level* (intrinsic to the culture) and *the social network*. In particular, agents' sole decision is how much (costly) effort to exert in a certain activity over time (e.g., studying for exams), which then leads to observable individual outcomes (e.g., the grades on such exams) assumed to be concave on efforts. Social comparisons operate via a directed random network in which agents gain a *competitive premium* by obtaining a better outcome than their neighbors (i.e., their reference group). More precisely, the competitive

[1] Remarkably, such a (competitive) demand was not exclusively made to the main character of the classic epic poem. Hippolochus, father of Glaucus the Lycian, also requested the same competitive behavior of his son (Homer, Iliad 6.208).

[2] The idea of competition, reflected by the Greek concept of $\alpha\gamma\omega\nu$ (*agon*), was essential for ancient Greeks who, from their youth, were persistently encouraged to outdo all others (see, for instance, Knox, 1999; Daqing, 2010; and Colaguori, 2012).

setting is defined by a summary statistic of the reference group output that determines the subjective achievements of agents. We consider three exogenous and stylized levels of competition. The strongest level corresponds to cultures that, in line with our opening quotation of the *Iliad*, encourage individuals to "*be the best*". We label such scenario as the "strong-competitive setting", which induces in agents the desire to be above the *maximum* outcome of their peers. The second case corresponds to a less extreme situation in which it is culturally desirable to "*be good enough*" compared to others. We label such scenario as the "mild-competitive setting", which is represented by the desire to be above the *average* outcome of neighbors. Finally, in the third scenario not being identified with the poorest performers suffices. In other words, in this case, labeled "weak-competitive setting", the behavioral rule is "*do not be the worst*", and individuals just aim to be above the *minimum* outcome of their peers.[3]

We study dynamics in which individuals revise their choices regarding effort expenditure by best-responding to the past performance of their neighbors (for instance, in the former example, agents can decide whether to study more or less for the next exam considering their relative performance in the past). In this context, we analyze the long-run prediction (stationary state) of such dynamics and characterize how agents' connectivity in the social network affects their choice of effort depending on the competitive scenario. Consequently, we evaluate how the level of competition in society as well as the connectivity distribution of the network affect aggregate outcomes.

Our results are as follows. We first show that agents' best response choices are dichotomous (Lemma 1), i.e., agents optimally choose one of two effort levels, labeled *low effort* and *high effort*, when revising their actions. We then find that in the (unique) stationary state, the probability of choosing high effort crucially depends on the level of competition of the society (Proposition 1). In particular, in the strong-competitive case, the probability of choosing high effort strictly decreases with connectivity or degree (i.e., the number of neighbors); that is, the worst-connected agents in the social network are the ones that exert the highest levels of effort. In contrast, in the weak-competitive scenario it is the opposite; the best-connected agents are those exerting the highest levels of effort. The result for the mild-competitive setting is in-between; it is possible that the probability of choosing high effort is the same for all agents, regardless of their connectivity, or even

[3] The competitive structures defined here are somewhat related with the well-known proverbial question that classifies individuals depending on their reference points: Is the glass half empty or half full? Accordingly, in the strong-competitive setting, agents see the glass half empty, whereas in the weak-competitive case, they see the glass half full.

that such a probability varies nonmonotonically with respect to degree.

We then analyze how the aggregate outcome achieved in the population depends on the competitive level of the society (Proposition 2).[4] We find that the number of agents exerting high effort (and, therefore, the aggregate outcome), decreases with the competitive level of the society. In this sense, our results suggest that societies in which individuals are subject to less competitive pressure do indeed produce greater (aggregate) outcomes. The intuition behind this finding is that in highly competitive cultures, subjects may be discouraged from being prominent due to the difficulty encountered in achieving their induced goals compared to other (less stringent) societies.

Finally, we analyze how changes in the degree distribution of the network affect aggregate outcomes (Proposition 3). To this aim, we focus on the two extreme scenarios (strong- and weak-competitive settings) in order to get sharp predictions, since in the mild-competitive case, the aggregate outcome may indeed be invariant to the degree distribution (Remark 1). In this respect, our comparative statics analysis yields two main results. First, an increase in the density of the network (by a first-order stochastic dominance shift of the degree distribution) decreases the number of agents choosing high effort in the strong-competitive setting, whereas it increases the choice of high effort in the weak-competitive setting. On the other hand, an increase in the variance -in terms of degrees- of the network (by a mean-preserving spread of the degree distribution) increases the number of agents choosing high effort in the strong competitive setting, whereas it reduces the choice of high effort in the weak-competitive setting. These results suggest that in denser social networks, the differences in effort provision (aggregate outcome) between societies with weaker and stronger competitive cultures will be exacerbated, whereas in networks that are more diverse in terms of degrees, such differences will be ameliorated.

The remainder of the paper is organized as follows. In Section 2 we briefly discuss the related literature. In Section 3 we describe the model. In Section 4 we present the results. Finally, in Section 5 we conclude.

[4] Countries and regions are frequently interested in having the highest aggregate outcomes (rather than other measures that might be used to aggregate utilities) in terms of evaluating their performance in international comparisons. For example, the OECD Programme for International Student Assessment (PISA) ranks countries according to the extent to which 15-year-old students have acquired some of the competencies essential for participation in the labor market and society (for instance, by examining proficiency scores in mathematics, science and reading), regardless the effort costs that students may have used to accomplish such competencies. Likewise, universities care about the aggregate level of published works produced, no matter the time and effort invested by their researchers (employees) in such activity.

2 Related literature

There is an abundant body of literature that highlights the importance of reference points for understanding preferences. For instance, Koszegi and Rabin (2006) assume a person's reference point is her rational expectations held in the recent past about current outcomes. They provide some implications of this framework for consumer and labor-supply decisions. More recent studies have considered that instead of expectations, the reference point could be derived from social comparisons, a premise that has been supported empirically. For instance, it has been documented that individuals feel worse off when others around them earn more (Luttmer, 2005). In addition, disclosing information on relative payment to workers has a significant impact on their economic output (Blanes i Vidal and Nossol 2011, Netessine and Yakubovich 2012), providing information on relative performance influences the academic achievements of high school students (Azmat and Iriberri 2010), and reporting households' relative energy usage has a significant effect on energy consumption rates (Schultz et al. 2007). From a theoretical viewpoint, Roels and Su (2014) analyze a model in which all agents have as a reference point the overall behavior of the population. They focus on the role of a social planner that can potentially adjust the amount of information provided to agents (e.g., the full distribution of outcomes versus the average outcome) to pursue some preestablished objectives. Similarly, Frank (1985) and, more recently, Hopkings and Kornienko (2004) show that if individuals care about both their own consumption and status, where the latter is defined by an individual's position in the distribution of consumption in the population, they spend an inefficiently large amount of resources on the status good in equilibrium.[5]

An important additional perspective in the analysis of social comparisons is the existence of individual-specific reference points derived from the location of agents in a social network. In this regard, network considerations have been included into a model of conspicuous consumption by Ghiglino and Goyal (2010) and status seeking by Immolica et al. (2017). In both papers it is assumed that agents, embedded in a structured network, play a static game with their neighbors. Ghiglino and Goyal (2010) show that an agent's consumption level depends on how central she is relative to others in the network and that, as segregated communities become integrated, inequality rises. On the other hand, Immolica et al. (2017) define a measure of cohesion that captures the intensity of incentives for status seeking and allocates agents into social classes.

[5] From a different perspective, Villar (1988) also studies a context where individual welfare depends on relative consumption.

We add a novel view to this network perspective, in which societies are compared in terms of their competitive structure; rather than focusing on a static setting, we consider a dynamic model in a random network context, a framework that has been largely used to study diffusion (see, e.g., López-Pintado and Jackson, 2013).[6] Somewhat related to this viewpoint, several studies have considered adoption rules in networks (characterized by local summary statistics) in static games of incomplete information (see, e.g., Galeotti et al., 2010; Feri and Pin, 2016), a context that has been explored in the lab by Charness et al. (2014) in order to identify behavioral effects of network characteristics, such as connectivity and clustering.

3 The model

Consider a finite (but large) set of agents $N = \{1, ..., n\}$. Each agent $i \in N$ is connected with a subset of the population, which determines a (directed) social network. Formally, let $N_i \subset N$ be the set of neighbors of individual $i \in N$, and let d_i be the cardinality of such set (i.e., individual i's degree). Thus, N_i represents the subset of the population individual i compares herself to.[7] We assume that the network is randomly generated and that it is characterized by a degree distribution $P(d)$, i.e., for each $d \geq 1$, $P(d)$ is the fraction of agents in the population with degree d.

Agents decide over time a level of effort $e_i \in [0, +\infty)$, which is transformed into a certain observable output (e.g., the grade obtained in an exam). For simplicity, assume that all agents have the same technology function $f(e)$, which provides an output to every level of effort. We assume $f : [0, +\infty) \to \Re$ is a continuous (strictly) increasing and (strictly) concave function of effort. Moreover, agents have a constant marginal cost $c > 0$ of exerting effort. The payoff obtained by an individual corresponds to her output net of costs plus a *competitive premium* (parametrized by $\theta > 0$) that materializes only when her output exceeds a *reference point*. In particular, for each $i \in N$, the reference point R_i is derived from a statistic R that resumes the outcomes of i's neighbors, denoted

[6] The study of random networks in dynamic models of diffusion has been comprehensively addressed by several authors (Jackson and Rogers, 2007; Jackson and Yariv, 2007; López-Pintado, 2008, 2012, among others). We apply this methodology to a different setting, namely, a model of effort provision and social comparisons.

[7] Note that, since the network is directed, we do not impose that links are reciprocated, meaning that the fact that one individual pays attention to another does not mean that the reverse holds.

as

$$R_i = R(\{f(e_j)\}_{j\in N_i}). \tag{1}$$

The payoff function is, therefore, described as follows:

$$\pi_i(e_i, e_{-i}) = \begin{cases} f(e_i) - c\cdot e_i + \theta\cdot(f(e_i) - R_i) \text{ if } f(e_i) > R_i \\ f(e_i) - c\cdot e_i \text{ otherwise.} \end{cases}. \tag{2}$$

The competitive premium term, $\theta \cdot (f(e_i) - R_i)$, is measured as the excess of agent i's output with respect to her reference point, weighted by θ. Hence, the functional form for R defines the competitive premium, and different specifications of the statistic R reflect different *competition levels* (which may be inherent to different cultures/societies).[8] We consider three stylized competition levels:

(i) The first level, which we label the "*strong-competitive case*" (or case S), reflects the highest competition level. In such a case an agent only enjoys the competitive premium if she is the best (in terms of outcomes) among her neighbors. Thus,

$$R^S(\{f(e_j)\}_{j\in N_i}) = \max_{j\in N_i}\{f(e_j)\}.$$

(ii) The second level, which we label the "*mild-competitive case*" (or case M), reflects an intermediate competition level. In such a case an agent only enjoys the competitive premium if she is good enough, in particular, if she is above (in terms of outcomes) the average of her neighbors. Thus,

$$R^M(\{f(e_j)\}_{j\in N_i}) = \frac{1}{d_i}\sum_{j\in Ni} f(e_j).$$

(iii) The third level, which we label the "*weak-competitive case*" (or case W), reflects the lowest competition level. In such a case an agent only enjoys the competitive premium if she is not the worst (in terms of outcomes) among her neighbors. Thus,

$$R^W(\{f(e_j)\}_{j\in N_i}) = \min_{j\in N_i}\{f(e_j)\}.$$

We shall now define the dynamics that describe the evolution of agents' choices. Time is considered continuous. At any time t, each agent revises her strategy at a rate $\lambda \geq 0$ and chooses an effort level that is a myopic-best response to her neighbors' current choices, given the payoff function defined by (1)-(2). In what follows, we study the long-run outcome of the dynamics.

[8] We assume for concreteness that a society is composed by a homogeneous population; agents are assumed to be equal in ability (e.g., all agents have the same cost of putting in effort) and in competition level (e.g., all agents use the same summary statistic to evaluate their performance with respect to others).

4 Results

4.1 The best response function

Before presenting the main results of the paper, let us derive the best response function. To do so, we define two different effort levels, which turn out to be key for our analysis: the low effort level, $e_L = \arg\max_{e \geq 0} f(e) - c \cdot e$, and the high effort level, $e_H = \arg\max_{e \geq 0} f(e) - c \cdot e + \theta \cdot f(e)$. Moreover, let us define a threshold r satisfying $f(e_L) - c \cdot e_L = f(e_H) - c \cdot e_H + \theta \cdot (f(e_H) - r)$. It directly follows that:

$$f'(e_L) = c \tag{3}$$

$$f'(e_H) = \frac{c}{1+\theta} \tag{4}$$

$$r = \frac{(1+\theta)f(e_H) - f(e_L) - c(e_H - e_L)}{\theta} \tag{5}$$

Notice that, due to the concavity of f, $e_L < e_H$. The best response function is derived in the following lemma.

Lemma 1 *For an agent i with reference point R_i the best response function is*

$$BR_i = \begin{cases} e_H & \text{if } R_i < r \\ \{e_H, e_L\} & \text{if } R_i = r \\ e_L & \text{if } R_i > r \end{cases} \tag{6}$$

where $f(e_L) < r < f(e_H)$.

Proof. Consider first a reference point for agent i, R_i, such that $f(e_L) \leq R_i \leq f(e_H)$. The agent's choice reduces to selecting the high effort e_H if aiming to receive the competitive premium, or the low effort e_L otherwise. Thus, given the payoffs defined by (1) and (2) the best response would be e_H if and only if

$$f(e_L) - ce_L < f(e_H) - ce_H + \theta(f(e_H) - R_i)$$

or, analogously

$$\frac{(1+\theta)f(e_H) - f(e_L) - c(e_H - e_L)}{\theta} \equiv r < R_i.$$

Notice that $f(e_L) < r$ since

$$r - f(e_L) = \frac{(1+\theta)f(e_H) - (1+\theta)f(e_L) - c(e_H - e_L)}{\theta}$$

is positive due to the concavity of f and the definition of e_H given by (4). That is,

$$\frac{f(e_H) - f(e_L)}{e_H - e_L} > \frac{c}{1+\theta} = f'(e_H).$$

Notice that $r < f(e_H)$ since

$$r - f(e_H) = \frac{f(e_H) - f(e_L) - c(e_H - e_L)}{\theta}$$

is negative as $(f(e_H) - ce_H) - (f(e_L) - ce_L) < 0$ by the definition of e_L.

To continue with the proof, assume now that $R_i < f(e_L)$. The agent's choice reduces to selecting the high effort e_H if wanting to receive the competitive premium or the effort $\widehat{e}_i$ such that $f(\widehat{e}_i) = R_i$, otherwise. Thus, the best response would be e_H since

$$\begin{aligned} f(\widehat{e}_i) - c\widehat{e}_i &< f(e_L) - ce_L = f(e_H) - ce_H + \theta(f(e_H) - r) \\ &< f(e_H) - ce_H + \theta(f(e_H) - R_i) \end{aligned}$$

To conclude assume that $f(e_H) < R_i$. Obtaining a competitive premium here is not optimal and thus the agent would have to settle with the effort level e_L, which maximizes profits conditional on not receiving such a premium. ■

Notice that agents face a trade-off when deciding which effort level is optimal. On the one hand, agents may target an effort level that is high enough to guarantee them the competitive premium; on the other hand, by selecting such a high effort, the standard part of the utility (absent of social comparisons) decreases. Consequently, if the reference point is above a certain threshold (i.e., $R_i > r$), agents do not find it worthy to aim for the competitive premium and thus choose low effort (i.e., e_L is selected). In contrast, for lower reference points (i.e., $R_i < r$), benefiting from such a premium is worthwhile and thus choosing high effort is optimal (i.e., e_H is selected). Finally, if $R_i = r$ agents are indifferent about both effort levels (e_L or e_H), and hereafter, we assume that, in such a case, they choose among them randomly with uniform probability.

We observe that the threshold r may yield a simple expression. For instance, if $f(e) = \sqrt{e}$, then it is straightforward to show that $r = \frac{f(e_L)+f(e_H)}{2}$, that is, precisely the middle point between the low and high output levels.

4.2 The stationary states

Recall that at any time t, each agent revises her strategy at a rate $\lambda \geq 0$ and chooses an effort level that is a myopic best response to her neighbors' current choices, given the payoff function defined by (1)-(2). Hence, given (6) it follows that, for some finite t, the dynamics will eventually lead to a situation where, for all $i \in N$, $e_i(t) \in \{e_L, e_H\}$. Therefore, in order to calculate the stationary state, without a loss of generality, we can focus on the discrete case where all agents choose between two levels of effort when revising their choices: e_L and e_H.

In particular, for each $d \geq 1$ let us denote by $\rho_d(t)$ the fraction of agents with degree d that are choosing e_H at time t, and by $\rho(t) = \sum_{d\geq 1} P(d)\rho_d(t)$ the overall fraction in the population. In a stationary state $\{\rho_d^*\}_{d\geq 1}$, it must hold that $\frac{\partial \rho_d(t)}{\partial t} = 0$ for all $d \geq 1$. The following proposition describes the choices of efforts of individuals with different degrees in the stationary state for each one of our scenarios.

Proposition 1 *For any given $P(d)$ and $R \in \{R^S, R^M, R^W\}$, the (unique) stationary state is such that:*

(i) in the strong-competitive case (S), the probability of choosing a high effort strictly decreases with degree.

(ii) in the weak-competitive case (W), the probability of choosing a high effort strictly increases with degree.

(iii) in the mild-competitive case (M), the probability of choosing a high effort may be independent of degree or even nonmonotonic.

Proof. The probability that any given link points to an agent choosing a high effort (e_H) at time t is given by $\rho(t)$. Thus, the deterministic approximation of the evolution of $\rho_d(t)$ is:

$$\frac{d\rho_d(t)}{dt} = -\lambda \rho_d prob_L(\rho, d) + \lambda(1-\rho_d) prob_H(\rho, d)$$

where λ is the rate at which agents revise their effort level, $prob_L(\rho, d)$ is the probability of choosing a low effort for an agent with degree d, and $prob_H(\rho, d)$ is the probability of choosing a high effort for an agent with degree d. Hence,

$$\frac{d\rho_d(t)}{dt} = \lambda(-\rho_d + prob_H(\rho, d))$$

since $prob_L(\rho, d) + prob_H(\rho, d) = 1$. In the stationary state $\frac{d\rho_d(t)}{dt} = 0$ and, thus, $\rho_d^* = prob_H(\rho, d)$. Consequently, given $P(d)$ and R, a stationary state $(\rho_d^*)_{d\geq 1}$ and consequently $\rho^* = \sum_{d\geq 1} P(d)\rho_d^*$ must satisfy

$$\rho^* = H_{P,R}(\rho^*) \equiv \sum\nolimits_{d\geq 1} P(d) prob_H(\rho^*, d). \tag{7}$$

Given $R \in \{R^S, R^M, R^W\}$ and any possible $P(d)$, there exists a unique equilibrium value $\rho^* \in (0, 1)$ solution of condition (7) since $H_{P,R}(\rho)$ is a continuous and decreasing function of ρ such that $H_{P,R}(0) = 1$ and $H_{P,R}(1) = 0$. In fact, it is straightforward to show that in the strong-competitive case $\rho_d^{S*} = prob_H(\rho^*, d) = (1 - \rho^*)^d$ and thus the probability of choosing a high effort decreases with degree. Analogously, in the weak-competitive case $\rho_d^{W*} = prob_H(\rho^*, d) = 1 - \rho^{*d}$ and thus the probability of choosing a high effort increases with degree. Finally, in order to analyze the mild-competitive case we first need to show that the best response dynamics induces a threshold on the fraction of agents choosing high effort, above which agents would choose low effort. In particular, let x correspond with the fraction of neighbors that must be choosing e_H in order for an agent to be indifferent between e_L or e_H. That is,

$$xf(e_H) + (1-x)f(e_L) = r = \frac{(1+\theta)f(e_H) - f(e_L) - c(e_H - e_L)}{\theta}$$

and thus

$$x = \frac{(1+\theta)f(e_H) - (1+\theta)f(e_L) - c(e_H - e_L)}{\theta(f(e_H) - f(e_L))} \tag{8}$$

which is above 0 due to the concavity of f since this implies that

$$\frac{f(e_H) - f(e_L)}{e_H - e_L} > \frac{c}{1+\theta} = f'(e_H).$$

Also x is below 1 since

$$f(e_H) - ce_H < f(e_L) - ce_L$$

by definition of e_L. Let $\lfloor xd \rfloor$ be the integer part of xd. In the mild-competitive case, the probability of choosing high effort for an agent with degree d is equal to

$$\rho_d^{M*} = \begin{cases} \sum_{a\geq 0}^{\lfloor xd \rfloor} \binom{d}{a} (\rho^*)^a (1-\rho^*)^{d-a} \text{ if } xd \text{ is not an integer} \\ \sum_{a\geq 0}^{xd-1} \binom{d}{a} (\rho^*)^a (1-\rho^*)^{d-a} + \frac{1}{2}\binom{d}{xd} (\rho^*)^{xd} (1-\rho^*)^{d-xd} \text{ otherwise.} \end{cases} \tag{9}$$

In the particular case where $f(e) = \sqrt{e}$ equation (8) implies that $x = \frac{1}{2}$. Thus, applying the development of the Binomial of Newton and simple combinatorial properties, we find that $\rho_d^{M*} = \frac{1}{2}$ for all $d \geq 1$. This shows that, in this case, the probability of choosing a high effort is independent on degree.[9] To conclude with the proof, let us provide an example where the the probability of choosing high effort is non-monotonic with respect to

[9]Notice that, given the development of the binomial of Newton, $(1+1)^d = \sum_{a\geq 0}^{d} \binom{d}{a}$, and since $\binom{d}{a} = \binom{d}{d-a}$ for all $0 \leq a \leq d$ then $2^{d-1} = \frac{(1+1)^d}{2} = \sum_{a\geq 0}^{\lfloor \frac{d}{2} \rfloor} \binom{d}{a}$ if d is odd (and thus the number of sums in the binomial is even) and $2^{d-1} = \sum_{a\geq 0}^{\frac{d}{2}-1} \binom{d}{a} + \frac{1}{2}\binom{d}{\frac{d}{2}}$ if d is even (and thus the number of sums in the binomial is odd).

degree. For instance, if $f(e) = \ln e$ then, after simple algebraic computations, we deduce from equation (8) that $\frac{1}{2} < x$. In particular, x is a continuous function of θ satisfying that $lim_{\theta \to 0} x = \frac{1}{2}$. Hence, for sufficiently low θ we can assure that $\frac{1}{2} < x < \frac{2}{3}$. Note that, in such a case, $\rho_1^{M*} = 1 - \rho^* < \rho_2^{M*} = 1 - (\rho^*)^2 > \rho_3^{M*} = (1-\rho^*)^2(1+2\rho^*)$, which proves the nonmonotonicity of $\{\rho_d^{M*}\}_{d \geq 1}$. ■

In Proposition 1, we characterize the stationary state of the best response dynamics. The fraction of agents choosing a high effort conditional on the degree, i.e., ρ_d^*, varies with the competitive settings (S, M or W). In particular, we observe that the higher the degree of an agent is, the higher the probability of exerting high effort in the weak-competitive case, whereas the opposite holds for the strong-competitive case.

The next result compares the aggregate effort in the stationary state (i.e., ρ^*) for the three different competitive structures given the social network.

Proposition 2 *For any given $P(d)$, the fraction of agents choosing high effort in the stationary state decreases with the competitive level of the population.*

Proof. It is straightforward to show that

$$H_{P,S}(\rho) \leq H_{P,M}(\rho) \leq H_{P,W}(\rho) \tag{10}$$

since

$$\rho_d^S = (1-\rho)^d \leq \rho_d^M \leq (1-\rho^d) = \rho_d^W \tag{11}$$

for all $\rho \in (0,1)$ and $d \geq 1$ given the value of ρ_d^M described in (9). This implies that, since in equilibrium condition (7) must be satisfied, ρ^* is higher for the weak-competitive case than for the mild-competitive case, and higher for the mild-competitive case than for the strong-competitive case.[10] ■

This proposition shows that, provided other characteristics (e.g., the social network) remain equal, the more competitive a society is, the lower its aggregate outcome (or total effort). The reason for this counterintuitive finding is that enjoying the competitive premium is more challenging in more competitive societies; as a consequence, in such cases agents become discouraged to exert effort.

[10]It can also be shown that the inequalities in condition (11) and consequently in condition (10) may be strict. In particular, $\rho^* \geq \frac{1}{2}$ in the weak-competitive case (as $\frac{1}{2} \leq H_{P,W}(\frac{1}{2})$ for any given $P(d)$) and $\rho^* \leq \frac{1}{2}$ in the strong-competitive case (as $\frac{1}{2} \geq H_{P,S}(\frac{1}{2})$ for any given $P(d)$), where inequalities are strict if $P(1) < 1$. Moreover, if the technology function is such that $x = \frac{1}{2}$ (as e.g., if $f(e) = \sqrt{e}$) , then $\rho^* = \frac{1}{2}$ which lies strictly in between the predictions found for the two extreme scenarios (strong and week-competitive cases).

To continue, we take as given the competitive structure of the society and explore how changes in the social network affect our predictions. In particular, we compare the stationary state for different degree distributions. We start by commenting on the mild-competitive setting in the following remark.

Remark 1 *If the technology function is $f(e) = \sqrt{e}$ then, in the mild-competitive case (M) half of the population exerts high effort in equilibrium, regardless of the degree distribution. That is, $\rho^* = \frac{1}{2}$ for any possible $P(d)$.*

This result follows directly from the fact that, if $f(e) = \sqrt{e}$, then $\rho_d^{M*} = \frac{1}{2}$ for any $d \geq 1$, as shown in the proof for part (iii) of Proposition 1. Hence, since in the mild-competitive case the aggregate outcome may indeed be invariant to the degree distribution, in order to get sharp predictions, the following result focusses on the two extreme scenarios.

Proposition 3 *For any given $P(d)$, the following holds:*

(i) A first-order stochastic dominance (FOSD) shift of $P(d)$ decreases (increases) the fraction of agents choosing high effort in the stationary state for the strong-competitive (weak-competitive) case.

(ii) A mean-preserving spread (MPS) of $P(d)$ increases (decreases) the fraction of agents exerting high effort in the stationary state for the strong-competitive (weak- competitive) case.

Proof. Part (i) of the proof follows from the fact that $(1 - \rho^d)$ is an increasing function of degree whereas $(1 - \rho)^d$ is decreasing. Part (ii) is obtained as a consequence of $(1 - \rho^d)$ being a concave function of degree and $(1 - \rho)^d$ being convex. Notice that if $\widetilde{P}(d)$ FOSD $P(d)$ then for any increasing function $u(d)$ we have that

$$\sum\nolimits_{d\geq 1} u(d)P(d) \leq \sum\nolimits_{d\geq 1} u(d)\widetilde{P}(d),$$

where the opposite inequality holds if the function $u(d)$ is decreasing. Moreover, if $\widetilde{P}$ is a MPS of P then for any concave function $u(d)$

$$\sum\nolimits_{d\geq 1} u(d)\widetilde{P}(d) \leq \sum\nolimits_{d\geq 1} u(d)P(d),$$

where the opposite inequality holds if the function $u(d)$ is convex. ■

A first-order stochastic dominance shift of the degree distribution, in particular, implies an increase in the density of the network, whereas a mean-preserving spread leads to more dispersion in the network in terms of degrees. Hence, the first part of Proposition 3 suggests that in denser social networks, the difference in effort provision between societies with weaker and stronger competitive cultures is exacerbated. On the other hand, the second part of the proposition indicates that in more dispersed networks, these discrepancies are reduced.

5 Conclusion

We have presented a model that combines behavioral economics with network analysis to better understand how the competitive culture of societies determines aggregate production.[11] Notably, we find that in order to maximize outcomes, a weak-competitive setting is optimal since strong competition may lead to agents' discouragement and, therefore, lower effort provisions. These insights highlight the counterproductive effects of extremely ambitious attitudes and are in line with the introduction of apparently nonproductive measures in highly competitive institutions. For instance, in recent years, leading top companies in Silicon Valley, such as Google, have facilitated the practice of meditation and yoga during working hours to encourage well-being in the labor environment.[12] Similarly, the implementation of inclusion policies in schools, an issue highly present in current political debates, is aligned with the view that some severe forms of competition may reduce aggregate performance.[13]

Moreover, we study network effects with a focus on the degree distribution, a large-scale property of the network that can be easily estimated with the growing availability of data. We find that in a weak-competitive setting, aggregate production increases with the density of the network, whereas the opposite occurs in the strong-competitive case. This result implies that in an era of globalization, in which social networks are progressively becoming denser, the differences between our predictions for the strong and weak competitive paradigms become larger (in favor of the weak-competitive setting). However, our results also suggest that these differences would be alleviated if the social

[11] In a recent essay dealing with the progress of economic design, Jackson (2018) elaborates on the role of economic theory in an age of big data and prognosticates that behavioral and network economics may yield the major theoretical advances in the near future.

[12] See, e.g., Nellie Bowles' article "Where Silicon Valley is going to get in touch with its soul" in The New York Times, Dec. 4, 2017.

[13] Related to this idea, Azmat et al. (2018) have recently provided evidence suggesting that increasing transparency in grades in higher education decreases performance.

networks became more heterogeneous in terms of connectivity.[14]

In summary, we have considered a stylized model aimed at understanding the driving forces at play regarding the effects of competitive culture on outcomes in situations of social comparisons with local reference points. We believe, however, that this work is just a stepping stone to a much broader area of study. There are several directions in which our analysis could be extended. The random network assumption constitutes an initial approximation to the more complex and structured networks observed in reality. In addition, heterogeneity within a society could be considered, both regarding the ability of individuals and their competition levels. In this sense, the analysis of networks with some level of homophily or clustering with heterogenous agents may add interesting insights to the problem at hand. Our current work could also lead to future research in which theoretical and applied studies combining behavioral and network economics can provide a better understanding of the interplay between social networks, peer comparisons and production. Improved behavioral network theory may well be the result of the knowledge gleaned from this and future studies.

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