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A Model of Social Media Participation and Depression

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Abstract

We provide a theory which explains the link between depression and participation in social media. Opportunities to be captured and posted to one's social media randomly arrive and the participant chooses which of them are posted. Utility is a ``keeping-up-with-the-Joneses'' type. The network's socioeconomic reference point continues to rise as a result of participation in the network. Participants find it increasingly difficult to isolate opportunities which are above the reference point, decreasing aggregate utility.

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1 Introduction

The linkage between depression and participation in social media has been established by a vast literature (Kross et al. (2013); Christakis and Shakya (2017); Aalbers et al. (2019); Lin et al. (2016); Rosenquist et al. (2011); Twenge (2019)). While the lion's share of this research focuses on the statistical relationship, a model explaining this link is absent. The contribution of this paper is a model which explains why participants in a social network can become endogenously depressed as a result of participation in the network.

The importance of studying depression cannot be overstated; Recent studies place economic costs upwards of $210 billion (Greenberg et al. (2015)). While the linkage between episodes of depression and economic conditions is well established (McInerney et al. (2013)), Weinberger et al. (2018) show that between 2005 and 2015, rates of depression have been continually rising, even though the latter half of this period can be characterized as one of consistent economic expansion; this implies that trends in the aggregate rate of depression cannot be explained by the business cycle alone.[1]

Our theory utilizes the Easterlin Paradox (Easterlin (1974)) which states that at one point in time income varies directly with happiness across and within nations but remains unchanged with the rising GDP of all. For example, Easterlin shows that real per capita GDP in the United States nearly doubled between 1947 and 1973 while the happiness of its citizens remained virtually unchanged. Easterlin suggests that judgments about individual well-being are made by comparing one's personal status relative to the status of others around them (Chugh (2008); Dupor and Liu (2003); Frank et al. (2014); al Nowaihi and Stracca (2005)). If everyone's real income increased by the same amount, the positive effect of the increased income on individual happiness will be offset by the fact that the general standard of living of everybody else rose by the same amount leaving the individual's position relative to others unchanged. On the other hand, if the real income of individuals increases relative to their peers, then their happiness will also increase with their improved relative position.

Our model demonstrates that social media networks serve as the perfect medium for the Easterlin Paradox. Since people tend to post on social media their more positive experiences, those who see the posts may compare them to their own life experiences and be saddened to find that their lives relative to others fall short. As a result, while social networks are positively associated with individual well-being, online relationships may prove to be less satisfying than person-to-person offline activities.

[1] One explanation for the rise in the rate of depression is that the underlying rate has stayed the same, but more individuals are seeking treatment, largely due to the de-stigmatization of the disease; for more details, see BCBS (2018).

2 The Model

A social network is comprised of a set of individuals indexed by i, each with iso-elastic utility

$$U_{i,t} = \frac{\left(m_{i,t} - \overline{\mu}_t\right)^{1-\theta}}{1-\theta}, \quad \theta > 0 \tag{1}$$

where m_i is the social value of individual i's post to the social media network, θ is the degree of risk aversion, and $\overline{\mu}$ represents a "keeping-up-with-the-Joneses" reference point. Thus, the utility an individual derives from posting m_i depends on their relative socio-economic position described by $\overline{\mu}$ (Chugh (2008); Dupor and Liu (2003); Frank et al. (2014); al Nowaihi and Stracca (2005)).

For the sake of clarity rather than reality, we define social media as a photograph individual i takes as evidence of having dinner at restaurant j which is then posted to their social network. Exclusivity is the only factor which differentiates restaurants, and we define the opportunity for individual i to eat dinner at restaurant j as ω_j. There is a continuum of such restaurants ordered from α (least exclusive) to β (most exclusive) and where individual i eats dinner can be considered a random draw from a distribution with support $[\alpha,\ \beta]$.

While the exclusiveness of dinner opportunity ω is exogenous/random, the decision individual i makes in whether or not to post the photograph of the dinner experience to their social media is a choice variable. If individual i decides ω is to be posted to their social media, it then becomes m_i and generates utility in accordance with (1).[2]

For simplicity, we assume ω is distributed uniform so that

$$\omega_j \in \text{Unif}\left[\alpha,\ \beta\right]. \tag{2}$$

Figure 1 provides an illustration.

Lastly, $\overline{\mu}$, the reference point for the social network is

$$\overline{\mu}_t = \frac{1}{N}\sum_{i=1}^{N} m_{i,t-1}, \tag{3}$$

where N represents the number of participants in i's social network. (3) is the unweighted average of period $t-1$'s content. The $t-1$ lag in (3) is motivated by assuming it takes one period for all participants to evaluate the social value of the media posted to the network and formulate where the "social average" $\overline{\mu}$ lies.[3] (3) shows that the average level of exclusivity of the dinner photographs posted to the social network serves as the benchmark by which

[2] An extension to the model involving some type of network reinforcement/peer feedback such as "likes-in-the-utility-function" instead of actual social media might be warranted; since we assume that all individuals i share the same utility function and perfect information, a mechanism such as "likes" would be redundant.

[3] Assuming μ represents the time t (rather than $t-1$) average does not alter the results of the model. (3) can allow for "social influencers" by relaxing the assumption of homogeneous weighing of m_i posted.

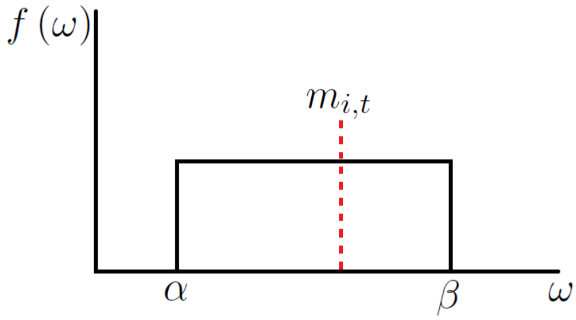

Fig. 1. Uniform distribution with support from α to β from which opportunities to post social media ω are randomly drawn from. The cutoff m_i chosen by i is shown by the red, dashed line; only photographs from dinners at restaurants with exclusivity $m_i < \omega_j \leq \beta$ will be posted by i.

the participants compare the social standing of the exclusivity of their dinner relative to their peers.

The utility max problem can be formulated as individual i maximizing (1) subject to (2) and (3). Although $\overline{\mu}$ is not chosen by i, it is influenced by i's actions, making it a classic case of an externality. The first-order condition for m consistent with utility maximization is[4]

$$m_t^* = \frac{\beta(1-\theta) + \overline{\mu}_t}{2-\theta}. \tag{4}$$

(4) illustrates that the quality of media posted is a function of parameters from the distribution (β), the utility function (θ); more importantly, it shows that m is increasing in the network's socio-economic reference point $\overline{\mu}$.

2.1 The model's predictions regarding participant behavior over time

1. ***As time passes, the reference point rises; this makes it more difficult to "keep up with the Joneses".***

   Substitution of (4) into (3) results in

$$\overline{\mu}_t = \frac{\beta(1-\theta) + \overline{\mu}_{t-1}}{2-\theta}.$$

   In steady-state,

$$\overline{\mu}^{ss} = \frac{\beta(1-\theta) + \overline{\mu}^{ss}}{2-\theta} \implies \overline{\mu}^{ss} = \beta, \tag{5}$$

   which is the upper end of the distribution support from (2).

[4]Please refer to the online technical appendix for details.

2. ***As time passes, while participants continue to participate in the network, they post media with decreasing frequency.***

   The CDF for (2) is

$$CDF(m) = \frac{m-\alpha}{\beta-\alpha}$$

   which implies that the expected time to successfully draw an opportunity ω above m is

$$m < \omega \leq \beta = \frac{\beta-\alpha}{\beta-m}. \tag{6}$$

   (6) illustrates that as the reference point μ migrates towards the upper end of the distribution in accordance with (5), it takes longer to draw a dinner opportunity ω which is exclusive enough that it exceeds the cutoff m given by (4).

3. ***As time passes, utility from participating in the network will decrease; participants will become increasingly depressed.***

   Substitution of (5) into a steady-state version of (4) results in

$$m^* = \frac{\beta(1-\theta)+\beta}{2-\theta} \implies m^* = \beta. \tag{7}$$

   (7) illustrates the collapse of (2) and that $m^* = \overline{\mu}^{ss} = \beta$. From (1), we can see this results in a decrease in the aggregate level of utility of all participants in the social network because of the change in μ in individual i's utility function: all participants i become disheartened that they simply cannot "keep up".

3 Conclusion

We have provided a model which explains the linkage between participation in social media and depression. An important question which comes to mind: does the model provide any solutions or ways to minimize the ensuing depression?

A perfect solution would seek to minimize or altogether eliminate μ from the utility function in (1). However, there is research which demonstrates that reliance on internal/external reference points may be hard-wired into our DNA (Rayo and Becker (2007)). For example, for early hunters, having fewer kills than previous years or than their peers was an indication that they needed to improve their hunting skills and those who did, survived and reproduced. Thus the survival gene measuring one's position relative to others may have been handed down through the survival of the fittest and is genetically hard wired into the way we think and feel about our own personal well-being.

Another solution may be to relax the stationarity assumption of (2) by allowing individuals to "invest" in their happiness by experiencing a greater array of increasingly exclusive dinner opportunities. However, this may not be a sustainable solution for two reasons: on the one hand, this may be economically infeasible for many participants in the network. On the other hand, since individuals' own past income also serves as an internal reference or benchmark to measure well-being, a rise in the general level of opportunities ω may only exert a temporary effect on well-being because as the benchmark rises, people quickly adapt to their new standard of living (Brickman et al. (1978) and Van praag and Frijters (1999)).

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