**The Origin of Happiness under Economic Inequality in Experimental Social Networks**

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**Project Summary**

**Overview:** The objective of the present proposal is to experimentally study the dynamic relationship between individual socioeconomic status and emotional well-being (which is related to psychological well-being, happiness, or mental health, as measured by subjective measures) in social settings. The broader goal is to understand human nature – when people become happy and why. Using thousands of subjects recruited online and placed into artificial social systems, with real financial stakes, the socioeconomic gradient in emotional well-being whereby people with a lower socioeconomic position have lower levels of well-being will be modeled experimentally, and various interventions that might modify this relationship will be evaluated.

Experimental social network approaches have allowed scientists to investigate the origins and consequences of phenomena such as economic inequality, network interactions, and cooperative behavior since 2009 (including Nishi, Shirado, Rand, and Christakis, 2015, *Nature*). However, they (as well as other similar frameworks) have not previously been used to explore and manipulate the social gradient in emotional well-being or to experimentally evaluate its disparity.

We constructed pilot study with an experimental framework to dynamically observe the wealth-well-being linkage using a network experiment platform based on Nishi, Shirado, Rand, and Christakis, 2015, *Nature*. In artificial social networks, real people (N = 575) were randomly assigned to different socioeconomic positions. The study has successfully confirmed that people with a lower socioeconomic position in the experimental framework feel less happy.

However, it is not known what social rules (social “treatments”) can mitigate the wealth-well-being linkage at the social network level. Here, the present proposal aims to explore several untested social rules (and therefore, trials and errors are needed to identify the best social rule mitigating the wealth-well-being linkage). For example, it is hypothesized that (a) a social rule that makes comparison of wealth impossible (making wealth invisible) should make poorer individuals feel better by preventing the spread of negative feelings over social ties, or that (b) the introduction into these social networks of autonomous agents (“bots”) programmed to behave in a particular way should attenuate the wealth-well-being linkage.

**Intellectual Merit:** In such as experimental setting, scientists can closely explore some of the behavioral and cognitive mechanisms underlying the wealth-well-being linkage in relation to experimentally introduced social treatments using validated measures of decisional conflict (e.g., response latency) and attentional focus (e.g., gaze duration). For instance, the treated conditions (e.g., a social rule of “no social comparison in wealth is possible”) would reduce the level of eye movements indicative of engagement in social comparison. Overall, using this model system (involving real people interacting for short periods online), a set of questions that are not easily tractable using non-experimental methods will be explored experimentally. Such an approach allows scientists to understand the origin of happiness and the evolution of happiness more deeply.

**Broader Impact:** Scientists may realize, of course, that this proposal, while (in our view) appealing because of its (1) experimental control, (2) large sample size, and (3) use of innovative software and approaches, is, in the end, an ‘in vitro’ model of the complex psychological and social processes that are explored. And model interventions (making wealth invisible, happy bots, etc.) may point the way forward to practical policies. For example, “making wealth invisible” may have several real-world examples such as a school uniform policy in an educational setting and a pay secrecy policy in a labor setting. This approach also offers great promise for substantial insights and robust causal inference regarding important questions in social psychology, sociology, social epidemiology, and disparity research.

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**INTRODUCTION**

The social environment in the USA today seems to present enhanced opportunities for people to compare themselves with others and to perceive economic inequality in their daily life (Gachter 2015, Sands 2017) – for example, by reading lists of billionaires or public information about employee pay, or by observing conspicuous consumption (Veblen 1899). Such *transient perceptions of economic inequality* can cause negative emotions and evoke a complex set of social-psychological processes, such as awareness of “relative deprivation” (Kawachi and Kennedy 1999), violation of “belief in a just world” (Lerner 1980), status anxiety (Buttrick and Oishi 2017), mistrust (Buttrick and Oishi 2017, Kawachi and Kennedy 1999), status competition (Buttrick and Oishi 2017), and risk aversion (Haushofer and Fehr 2014) – especially among those with a lower economic position. Life-course epidemiology has investigated how social comparison in unequal worlds can create stress (Kawachi and Kennedy 1999, Muramatsu 2003) and how such stress in turn can produce maladaptive wear-and-tear (“allostatic load” (Dowd, Simanek and Aiello 2009, McEwen and Gianaros 2010)) and affect physical and psychological health over the life span (Kawachi and Kennedy 1999, Kondo et al. 2009, Marmot 2005). Social psychology has long understood that relative deprivation can have psychological consequences (Haushofer and Fehr 2014). Given the complex relationship between economic position and emotional states in social interactions, we propose to evaluate an online model to explore some of these phenomena occurring over short time periods.

**BACKGROUND**

***Wealth-emotion linkage.*** Absolute poverty and, distinctly, relatively lower socioeconomic status, are major social determinants of mental health and emotional well-being (Andrews and Withey 2012, Lorant et al. 2003, Lund et al. 2011, Turner 1981, World Health Organization and Calouste Gulbenkian Foundation 2014)*.* The social gradient (disparity) in emotional well-being is observed in diverse populations; across gender and ethnoracial groups; and across developed and developing countries (Lund et al. 2010). Although there is diminishing marginal utility of greater levels of wealth, in general, richer people are happier than poorer people (Easterlin et al. 2010, Kahneman and Deaton 2010).

To enhance *causal inference* regarding the social gradient in emotional well-being, quasi-experimental study designs have frequently been used (e.g., the natural experiment of the Dutch Hunger Winter Families Study, or lottery winners) (Gardner and Oswald 2007, Stein et al. 1972, Susser, Hoek and Brown 1998). There have also been prior experiments. A randomized controlled trial (RCT) is rare, but exists – the housing mobility experiment (“Moving to Opportunity”) showed that having the chance to move from a high-poverty to lower-poverty neighborhood resulted in a long-term (10-15-year) *improvement* in emotional well-being particularly among poorer people (Ludwig et al. 2012). One meta-analysis of 51 psychological intervention studies showed that some achieved lasting improvement in well-being (Sin and Lyubomirsky 2009). However, these studies did not typically examine the gradient in emotional well-being by socioeconomic position (instead, some focused on social relationships (Hilpert et al. 2016) or on social isolation (Weiss, Westerhof and Bohlmeijer 2013)). Although important, many of these studies require more than a decade to see if a single treatment is effective in the improvement of emotional well-being.

***Theories and findings regarding the wealth-emotion linkage.*** Theories and findings in social psychology, sociology, and social epidemiology shed light on the life-course pathway linking low economic wealth status with lower emotional well-being, and on how this relationship depends on inequality over longer time frames. For example, Wilkinson’s “social stress mechanism” posits that inequality is a contextual social stressor (Kawachi and Kennedy 1999, Muramatsu 2003, van Deurzen, van Ingen and van Oorschot 2015, Wilkinson 1999). There is much evidence to show an association of stressful events with emotional well-being such as depression over time (Turner, Wheaton and Lloyd 1995, van Deurzen, van Ingen and van Oorschot 2015). Social psychological theories further demonstrate how social class predicts levels of positive emotions and well-being (Boyce, Brown and Moore 2010, Diener et al. 2010, Howell and Howell 2008). Life-course epidemiology has repeatedly investigated how such daily-life stress produces maladaptive wear-and-tear (“allostatic load” (Dowd, Simanek and Aiello 2009, McEwen and Gianaros 2010)) and cumulatively affects physical and mental health (Kawachi and Kennedy 1999, Kondo et al. 2009, Marmot 2005).

The psychological consequences of income inequality have also been explored. An experience of economic inequality leads people to perceive relative deprivation (defined as “the aggregated shortfall in income between that individual and everyone else with higher incomes in that person’s reference group” in Runciman’s theory of relative deprivation (Kondo et al. 2008, Runciman 1966, Yitzhaki 1979)) and to perceive a violation of “belief in a just world” (defined as “the belief that all of the people’s actions are rewarded when they are noble” in Lerner’s “just-world hypothesis”) (Lerner 1980). These negative social perceptions can lead to greater stress (Haushofer and Fehr 2014), anxiety and negative emotions (“status anxiety hypothesis”) (Buttrick and Oishi 2017), increased mistrust in others (Buttrick and Oishi 2017, Kawachi and Kennedy 1999), competitive behavior with others (Buttrick and Oishi 2017), and risk-averse behavior (Haushofer and Fehr 2014).

***Evolutionary perspective:*** see BOX (in relation to Hypotheses 1 and 2.1).

***Wealth visibility:*** see section 5.1 (in relation to Hypothesis 2.1).

***Human-AI interaction and last-place aversion:*** see section 5.3 (in relation to Hypothesis 2.2).

**Motivation for the Proposed Study**

***Our experience in online experiments.*** We plan to recruit subjects using an online worker website, Amazon Mechanical Turk (Mturk) (Buhrmester, Kwang and Gosling 2011, Rand 2012) and let them interact with each other anonymously in a virtual laboratory setting using *breadboard*. Mturk workers participate in our experiments via their own laptop, tablet, or smart phone. A virtual laboratory setting with Mturk online workers has several advantages as compared with a conventional setting of behavioral experiments using college students. First, its larger diversity in age-range and geographic setting than college students can assure the better generalizability. It is known that the socio-demographic characteristics and behaviors of Mturk workers are roughly comparable to general populations in survey data (Huff and Tingley 2015, Rand 2012), and 20 – 30% of them are older people, giving us the ability to examine moderating or interactive effects of gender and race/ethnicity on hypothesized outcomes (Huff and Tingley 2015). Second, the cost of the experiments, including participant fees, is substantially lower than in-person behavioral experiments, and much larger samples are possible (involving thousands of subjects).

Our research team has been one of the earliest to use Mturk workers for behavioral experiments, particularly in relation to social networks. *Breadboard* (ver. 1.0) was developed as an open-sourced software of experimental social network in 2009 (Rand, Arbesman and Christakis 2011), and the current version (ver. 2.3) has a wider flexibility in experimental settings with user-friendly interfaces, which is embedded in the Mturk website. We have made *breadboard* publicly available. Our research team has published numerous papers using Mturk and *breadboard* on evolutionary dynamics, evolution of cooperation, network fluidity, and inequality at a variety of multidisciplinary journals including *Nature*, *PNAS*, *Nature Communications*, and *Sociological Science* (Nishi, Shirado and Christakis 2015, Nishi et al. 2015, Rand, Arbesman and Christakis 2011, Rand et al. 2014b, Shirado and Christakis 2017, Shirado, Iosifidis and Christakis 2019, Shirado et al. 2019, Shirado et al. 2013). However, use of this online experimental framework specifically in social epidemiology and mental health science is still limited (Nishi 2015).

***Application to emotional well-being studies.*** A key aspect of the significance of our work is the novel deployment of contemporary techniques in computational social science to enhance causal inference and mechanism elucidation in a topic of longstanding interest, along with our evaluation of possible interventions in this area. Our experimental setting provides opportunities to observe inequality-driven negative emotional states and behaviors and to test selected interventions based on these theories so as to alter the complex relationship between wealth or economic position and transient emotional states in dynamic social networks.

Our research team, primarily located at UCLA Epidemiology and Yale Sociology, has spent a decade developing a novel experimental framework used for exploring diverse social phenomena. Among the various frameworks in experimental economics, experimental psychology, and evolutionary dynamics, we have focused on dynamic social networks of online study participants, where multiple individuals who are recruited from online worker websites (e.g., Mturk (Buhrmester, Kwang and Gosling 2011, Rand 2012) **[Fig. 1a]**) connect with each other and create social ties with other people, and interact with them in various ways **(Fig. 1b)**.

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| **Fig. 1. Amazon Mechanical Turk (Mturk) for the recruitment of online workers (a), and the *breadboard* software platformfor web-based economic interactions in artificial social networks (b).** These sample pictures are retrieved from a previous experiment (Nishi et al. 2015). **(a)** The website of Mturk, where we put an advertisement in order to recruit Mturk workers, is shown. **(b)** Mturk workers participate in our experiment through their own devices. |

*Breadboard* is a web-based software infrastructure that we have developed with in-house computer engineers (Rand, Arbesman and Christakis 2011). Using a *Groovy*-based programming language, users can easily construct their own experiments with online workers (or with online and offline subjects). For example, we have used *breadboard* to conduct studies showing that intermediate levels of network fluidity (the rate of forming new social ties and breaking existing social ties) can promote cooperation in social networks and improve social welfare (e.g. economic growth, level of interconnectedness) of study participants (Nishi, Shirado and Christakis 2015, Rand, Arbesman and Christakis 2011, Shirado et al. 2013); that visibility of wealth (making the wealth of neighbors in social networks available to a focal individual) can facilitate economic inequality and undermine social welfare (published in 2015, in *Nature*) (Nishi et al. 2015); and that a static social network structure can stabilize cooperation among people in some settings (published in 2014 in *PNAS*) (Rand et al. 2014b); and that AI bots can facilitate human coordination (published in 2017, in *Nature*) (Shirado and Christakis 2017). Our work connects experimental social science (“in-vitro” human experiments) with certain kinds of computational social science (“in-silico” computer simulations) (Lazer et al. 2009) and experimentally tests diverse theoretical predictions in social psychology, economics and social epidemiology.

**OBJECTIVES AND HYPOTEHSES**

Our overall goal here is to *understand and experimentally model the dynamic association of individual economic status with emotional well-being in social settings.* In concrete terms, we aim to identify social settings that shape, and strategies that might alter, the dynamic interplay between wealth and well-being, in relation to the social gradient in well-being, using a framework of network experiments. Our experimental framework can provide us with an adequate *in-vitro* model, and can avoid unintentional negative mental health consequences due to possibly not-carefully-organized community/policy interventions.

**Objective 1: Establish an experimental framework to dynamically observe the wealth-emotion linkage.**  We will use our publicly available *breadboard* software platform (Rand, Arbesman and Christakis 2011) to investigate the wealth-well-being linkage over time in short-lived (1-2 hour) experiments. Our experimental approach has not previously been used to explore emotional states. Using this tested framework for experiments involving networks and economic games (Nishi et al. 2015), and with real-time assessments of positive and negative emotional states over multiple economic interactions, we now propose to gain a better understanding of the relationship between economic events (gains and losses), overall “wealth” (here modeled using small but real sums of money), and emotional states (here modeled using subjective, validated short-term reports). Extending our preliminary study (N = 59), Objective 1 will recruit a larger number of online workers from Mturk (N = 2,000 [20 individuals/network]), and intends to confirm that individuals with lower wealth are more likely to experience negative emotion **(Hypothesis 1)**.

**Objective 2: Identify social settings that experimentally mitigate the wealth-emotion linkage using online worker sample.** We plan a series of cluster randomized controlled trials (cluster RCTs (Nishi et al. 2015, Rutterford, Copas and Eldridge 2015)) at the social network level using Mturk online workers. For example, we hypothesize that a social rule of “no social comparison in wealth is possible” could make poorer individuals feel better by preventing the spread of negative emotions across social ties (N = 2,000) **(Hypothesis 2.1)**. We also hypothesizethat a social setting with a programmed artificial intelligence (AI) player (a “bot”) (Shirado and Christakis 2017) connecting with the poorest individual could make poorer individuals feel better by preventing them from excessive social comparisons of their wealth with richer individuals (N = 2,000) **(Hypothesis 2.2)**. This is related to other observational and experimental studies suggesting that people with the similar economic positions live closer together (income segregation) (Reardon and Bischoff 2011), and that depression and diverse measures of well-being evince emotional contagion (Fowler and Christakis 2008, Hill et al. 2010, Rosenquist, Fowler and Christakis 2011, Stein et al. 1972).

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| **Table 1. Project timeline** | | | | |
| **Event (Year ending)** | **1** | **2** | **3** | **4** |
| Setting up the experiments |  |  |  |  |
| Objective 1\*: implementation |  |  |  |  |
| Objective 1: data analysis |  |  |  |  |
| Objective 2-1\*: implementation |  |  |  |  |
| Objective 2-1: data analysis |  |  |  |  |
| Objective 2-2\*: implementation |  |  |  |  |
| Objective 2-2: data analysis |  |  |  |  |
| Dissemination of research |  |  |  |  |

**Objective 3: Determine behavioral mechanisms explaining the wealth-well-being linkage.** We aim to determine *some* of the behavioral and cognitive mechanisms underlying the wealth-well-being linkage in relation to experimentally introduced social settings. Using validated measures of decisional conflict (e.g., response latency (Kosinski 2013, Rand et al. 2014a, Zaki and Mitchell 2013)) and attentional focus (e.g., gaze time and duration (Noh, Lohani and Isaacowitz 2011, Wadlinger and Isaacowitz 2008)) using an eye-tracking system, we will examine the processes involved in these social settings, and how they may mediate the relationship between wealth and emotional well-being. For instance, we hypothesize that our treated conditions (e.g., a social rule of “no social comparison in wealth is possible”) in **Objective 2** will reduce the level of eye movements for social comparison **(Hypothesis 3)**.

**RESEARCH PLAN**

**1. Research team**

We have assembled a multidisciplinary team of expert investigators, with a track record of long-term collaboration. **PI Akihiro Nishi** at UCLA is a social epidemiologist with expertise in computational social science and mental health. **Co-PI Nicholas A. Christakis** at Yale University, is an internationally recognized medical sociologist, and network scientist. He co-directs the Yale Institute for Network Science and maintains several in-house computer engineers and designers in his laboratory (Human Nature Lab). He has collaborated with PI Nishi since 2009 (including Nishi et al, 2015, *Nature* regarding wealth visibility (Nishi et al. 2015)). Both these investigators have much experience with social network experiments. **Co-I June Gruber** at the University of Colorado Boulder is an experimental and clinical psychologist with expertise in positive emotion and its clinical and psychological health effects and has previously collaborated with PI Nishi and Co-PI Christakis. She has rich experience in eye-tracking (Gruber et al. 2018, Purcell et al. 2018, Raila, Scholl and Gruber 2015). This multidisciplinary team has also established a strong liaison with network scientists and statisticians (including **Dr. Edo Airoldi** [consultant] at Harvard University).

**2. Work schedule**

The timeline of the present grant application is described in **Table 1**. We plan to perform 100 sessions of online experiments for **Objective 1** (N = 20/session; a total of 2,000 individuals), 150 sessions of online experiments for **Objective 2.1** (N = 20/session; a total of 3,000 individuals), and 150 sessions of online experiments for **Objective 2.2** (N = 20/session; a total of 3,000 individuals) (**Table 2**). The experiments for **Objective 3** will be implemented with **Objectives 1, 2-1, and 2-2**.

**3. Basic settings of the network experiments**

***3.1. Study participants.*** In their daily life, people (who are “nodes” in a social networks) interact socially and economically with multiple other people (to whom they have “links” or “ties”): they buy and sell goods or services and increase their utility or emotional well-being.In our experimental social networks, we aim to replicate such social interactions with some simplifications. In a single session of our experiment, for example, we will recruit a total of 19 individuals through Mturk at a given time, put them into our virtual laboratory setting, and conduct well-known economic games such as the Public Goods Game (PGG). We randomly assign subjects to a location in an Erdos-Renyi random graph configuration in which 30% of ties are present, as in past work (Nishi et al. 2015). (*All this can be experimentally modified, of course, including the number of people, the network topology, the interaction game, and so on – see below*.) We initially give an average of 500 points ($0.50 equivalent) to each study participant. In a random social network of 20 (19+1: see below) individuals, each study participant is randomly assigned to one location in the network, and randomly assigned to be initially rich (1,150 points, in 30% of the subjects) or to be initially poor (200 points, in 70% of the subjects), with the initial Gini coefficient of, say, 0.4. We plan to repeatedly execute experiments (e.g., 50 sessions for each treatment arm) (**Table 2**). Our sample size is based on the equations for the three-level cluster RCTs (allocation ratio between the treatment and the control group is 1) (Teerenstra et al. 2008) with the effect sizes in the pilot studies (details are available upon request).

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| **Table 2. Study participant recruitment** | | | | |
|  | **#participants/session** | **#sessions/treatment arm** | **#arms** | **#participants** |
| **Objective 1 (wealth-well-being linkage)** | 20 (19+1) | 50 | 1 | 1,000 |
| **Objective 2-1 (visibility)** | 20 (19+1) | 50 | 3 | 3,000 |
| **Objective 2-2 (human-AI interaction)** | 20 (19+1) | 50 | 3 | 3,000 |

In addition,we plan to recruit one college student per session in UCLA, who participates in our online experiment session with 19 Mturk workers. We plan to recruit UCLA students through advertisements in flyers and e-mails. Although online experiments using Mturk workers have several critical advantages as described, there are several specific purposes for us also conducting in-person experiments. Such purposes include the use of smile intensity estimation (see **Measures** section below) and eye-tracking (see **Objective 3**). Local undergraduate students in the hybrid (online + in-person) experiments will use computers and computer screens that we provide them with and will get paid in cash right after a session finishes. At UCLA, we plan to prepare a computer in which *breadboard*, the smile intensity estimation tool, and the eye-tracking tool are installed.

***3.2. Basic experiment settings.*** Before the actual interactions in the artificial social networks begin, we will implement a tutorial session and practice rounds to make sure that the study participants are familiar with the rules of our experiments, as we have done in all our prior experiments (Nishi, Shirado and Christakis 2015, Nishi et al. 2015, Shirado et al. 2013). In PGG, participants interact economically with a group of neighbors at the same time, and gain or lose real money. In the cooperation decision-making step of PGG, there are two options. If a focal individual chooses to cooperate with a group of neighbors, the focal individual needs to pay 50 points per neighbor (cost). As a result, each neighbor is better off by 100 points (benefit). If the focal individual chooses to defect against the neighbors, the focal individual does not have to pay anything, but, as a result, the neighbors are not better off. Since they are informed about the neighbors’ decision on cooperation, they can cooperate back with their neighbors at the next round (constructing a win-win relationship) or may cut a social tie with some of the neighbors who are not cooperative **(Fig. 1b)**. In this sense, an adjustment of social ties according to their quality (“rewiring”) is allowed, and therefore, the shape of the social network is dynamic. Over 15 rounds of interactions (repeated PGG), which will take around two hours, some study participants are going to become richer, and some others are going to become poorer. It is empirically known that the evolution of cooperation reaches a stable state after 7-10 rounds (Horton, Rand and Zeckhauser 2011, Nishi et al. 2015, Rand, Arbesman and Christakis 2011, Shirado et al. 2013).

In the baseline setting, study participants can know they are relatively richer or poorer than their neighbors. We will NOT assign the initial wealth (rich: 1,150 points or poor: 200 points) based on the study participants’ socioeconomic position in the real world (either education, income, or subjective social class). It is at random. This means that we primarily aim to purely isolate the effect of a higher or a lower experimental socioeconomic position on transient emotional well-being in our settings. Meanwhile and interestingly, we will be able to see that some rich individuals in the real world are randomly assigned to be initially poor, while some poor individuals in the real world others are randomly assigned to be initially poor in our experimental game settings. Therefore, we can investigate the difference in the behavior of rich individuals and poor individuals in the real world when they face poorness (or richness) in our experimental game settings. *This investigation allows us to bridge the observed behaviors in our experimental game settings and those in the real world.*

***3.3. Measures.*** We plan to measure the level of emotional well-being over the rounds. In concrete terms, we will use a single-item 5-scale measure: “how do you feel right now?: very good, good, neutral, bad, and very bad” after the cooperation decision is made and at the point that information regarding self and neighbors is updated at every round. The wording of the question is based on past literature on the day reconstruction method (Kahneman et al. 2004), General Social Survey (Ludwig et al. 2012), and the Hardy-Rejeski Feeling Scale (Hardy and Rejeski 1989). Although it is known that emotional well-being has multiple subcomponents (e.g., positive well-being and negative well-being) in multiple domains (e.g., evaluation, experience, and purpose) (Dolan and Metcalfe 2012, Huppert and Whittington 2003, Kahneman and Krueger 2006, Krueger and Stone 2014, Organisation for Economic Co-operation and Development (OECD) 2013), getting the information of the subcomponents in multiple domains every round is less feasible. Instead, we plan to use a multi-scale measure of emotional well-being (Kahneman et al. 2004) before the experiment begins (Round 0) and after the experiment ends (Round 15), so that we can confirm the relationship between the single-item measure and the multi-scale measure. This procedure allows us to confirm the reliability of the single-time measure of emotional well-being over the rounds (Kahneman et al. 2004, Oswald and Wu 2010). Moreover, the validity of a single-item measure of emotional well-being can be confirmed by objective measures such as state-by-state quality-of-life ranking in the US (Oswald and Wu 2010).

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| **Fig. 2. Smile intensity estimation technique.** A computer algorithm with a digital camera can measure the level of smile in each face in a real-time manner (Konishi et al. 2008). |

Moreover, we can validate the self-reported measure of emotional well-being, by using the “smile intensity estimation” technique, which is not feasible for online only experiments. The *smile intensity* estimation technique can measure the level of smile in a real-time manner by analyzing the facial expression of each study participant. There are several different algorithms and tools available (e.g. *Smile-Scan* from Omron, another one provided by a research team of National Institute of Advanced Industrial Science and Technology [AIST] in Japan) (Konishi et al. 2008, Shimada, Noguchi and Kuria 2013), and the other one is provided by *Microsoft Azure* as a part of emotion application programming interface (API) (Microsoft). For example, *Smile-Scan* provides us with a scale of the smile intensity from 0% to 100% on a real-time basis **(Fig. 2)**.

We also plan to collect social-demographic information (sex, age, race/ethnicity, education, income, and marital status), subjective social status (a sense of one’s place in the social ladder) (Kopp et al. 2004), level of daily hassles (Holm and Holroyd 1992), health variables (body-mass index [BMI], self-rated health (Jylha 2009), and psychological distress [K6] (Furukawa et al. 2003, Kessler et al. 2003, Sakurai et al. 2011)) and health-related behavior patterns (coffee, smoking and drinking).

**4. Objective 1: Establish an experimental framework to observe the wealth-happiness linkage**

We first aim to confirm that our experiments can re-create the wealth-well-being linkage. We have conducted pilot studies on this topic, confirming that this is feasible, but will greatly expand on this here.

***4.1. Analytic Approach to Objective 1.*** We hypothesize that wealth at a present round is always positively associated with the level of emotional well-being, controlling for the variation in social settings and the trend in the round (**Hypothesis 1**). The simplest equation for the data analysis at the individual level is as follows:

(well-being)ijt = b0 + b1(wealth)ijt + ∑tbt+1I((round) = t) + e1ij + e2i (1)

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| **Fig. 3. A pilot study exhibits a positive wealth-well-being linkage in our experimental framework.** The x axis represents wealth, and the y axis represents the level of well-being. Each line represents the linear trend of the wealth-well-being linkage at each round. P value is calculated based on equation 1. As the number of the round increases, the color of the trend line is darker (0: lightest, 10: darkest). |

In equation (1), i represents the ith network (or group of 20 people), j represents jth individual, and t represents tth round (0 – 15), and I(.) is an indicator function that takes value 1 when its argument is true and zero otherwise. Multiple decisions are nested in individuals, and multiple individuals are nested in a single social network session. Therefore, we plan to use a multi-level analysis framework to account for the data structure. The variation in rounds is controlled by multiple indicator variables (i.e., I((round) = t)), where round 0 (before the interactions start) is the reference category (i.e. b3I((round) = 1) + b4I((round) = 2) + …). (well-being)ijt represents the level of emotional well-being of the jth individual at the ith social network at tth round; (wealth)ijt is the level of wealth of the jth individual at the ith social network at the tth round; e1ij is the error term explaining the variation at the individual level; and e2i is the error term explaining the variation at the network level. b1 represents the level of association of wealth with well-being, which is the main interest of **Objective 1** (**Hypothesis 1**).

We will also consider specifications with added lags in well-being (the dependent variable) to (t-1)th round and similarly in the key independent variable (e.g., wealth), on the right hand side. We also run ordered logit models, in which the outcome variable of well-being is treated as an ordinal variable as a robustness check.

***4.2. Pilot studies for Objective 1.*** We performed a series of experiments with 59 individuals (recruited from Mturk), divided among three sessions lasting up to 10 rounds. Other than the number of the rounds, we used the same settings as described above: we conducted PGG with networks comprised of average of 20 individuals **(Fig. 3)**. We used the regression models described above (equation 1). The regression results show that a 1,000-point increase in current wealth is associated with a 0.40-point increase in emotional well-being (P = 8.65 × 10-13), and this tendency holds across the 10 rounds **(Fig. 3)**.

The results also show that the level of average wealth increases, as the rounds go on, which is inherent since we (experimenters) permit additional points (money) to enter the system as some of the of the subjects choose to cooperate due to the PGG rule. More interestingly, the impact on the level of emotional-well-being does *not* improve, as the rounds progress **(Fig. 3)**. In later rounds, typical study participants are much better off (e.g. average wealth at Round 0 is 506 points [equivalent to $0.50], and that at Round 10 is 3,905 points [equivalent to $3.90]); however, this does not produce incremental emotional well-being. Although we have not yet determined why this happens, it seems that the “happiness-income paradox” is reproduced

in our experimental social networks, which is similar to the observations of the real world (income is associated with well-being at a point in time among and within nations, while well-being does not increase when national wealth rises over decades [e.g., in the World Values Survey data]) (Clark, Frijters and Shields 2008, Easterlin 2003, Easterlin et al. 2010, Graham 2009). All the results stated above were confirmed in a different set of experiments using 555 study participants (see section **5.2**).

**5. Objective 2: Identify social settings that mitigate the wealth-well-being linkage**

Having developed an “in vitro” model of emotional well-being disparity in our experimental social networks, we will next explore several potential social settings to *improve population well-being* and to *mitigate the well-being disparity* in our experiments. We plan to perform a cluster RCT, where *different rules of social interactions are randomly assigned*, and each social network is a cluster. We are primarily interested in the improvement of emotional well-being among poorer individuals. We will consider several potential social settings for the cluster RCTs, two of which we explain in detail below (**Hypotheses 2.1 and 2.2**). Since we plan to recruit up to 2,000 individuals for each of the several social settings we examine, we plan to recruit thousands of individuals for the online experiments (and perhaps a fifth as many for the in-person experiments). We will not allow online workers to participate in any given experiment multiple times. We have successfully recruited over 15,000 subjects in our prior experiments to date (Rand, Arbesman and Christakis 2011, Rand et al. 2014b, Shirado and Christakis 2017, Shirado et al. 2013).

***5.1. Example of social settings: Wealth invisibility to suppress social comparison (Hypothesis 2.1).***

***Theoretical background.*** Evidence from observational studies suggests that a large portion of the wealth-well-being linkage comes from relative wealth (higher/lower than others in social networks) and not just from absolute wealth (purchasing power, including health care access) (Kawachi, Adler and Dow 2010, Kondo et al. 2008, Lund et al. 2010). The impacts of relative wealth come from social comparison, which is a process of comparing one’s social characteristics and outcomes to other people (Festinger 1954, Taylor and Lobel 1989). Social comparison is observed among other animals (e.g. baboons) as well as humans (Dumas et al. 2017). Social comparison has a history of theorization for more than a half century (e.g. Festinger’s theory of social comparison processes in 1954 (Festinger 1954)), and it alters one’s emotion because it induces a feeling of being left behind and relatively deprivation (Ball and Chernova 2008, Bertram-Hümmer and Baliki 2015, Karen E. Dynan 2007). For example, evidence shows that relative income is at least twice as important for individual emotional well-being as absolute income (Fliessbach et al. 2007b, Knight, Song and Gunatilaka 2009). It is known that the feelings of relative deprivation and diminished emotional well-being from social comparison under an economically unequal condition have plenty of negative consequences including poor health (Brunner 1997, Deaton 2001, Dickerson and Kemeny 2004, Eibner and Evans 2005, Graham 2008, Layard 2005, McEwen 2012, Ura et al. 2012), poor economic status and decision-making such as violation (Macours 2011, Moghaddam 2005). A series of neuroimaging studies also shows that the brain regions related to a rewarding process (ventral striatum) are activated when there is a relatively lower monetary reward rather than an equal reward (Fliessbach et al. 2007a). However, none of the above real-world data allow scientists to purely isolate the effect of relative wealth on emotional well-being.

Therefore, if there were a method to literally switch off social comparison between individuals in a group, we might successfully reduce the negative effect of “relative” income on emotional well-being, which has a larger impact on poorer individuals. In this sense, wealth invisibility, which is defined as the state where a focal individual can know his or her own wealth but cannot know connecting neighbors’ wealth (Nishi et al. 2015), could be an important factor in well-being promotion policy. Real-world examples of this phenomenon could include pay secrecy policies (Clark and Oswald 1996, Colella et al. 2007) or school uniform policies (Ball, Bowe and Gewirtz 1996). There are, of course, many examples of making wealth of neighbors visible, such as the Forbes magazine “World’s Billionaire List” or the possessions ordinary people display every day. Especially in the present digital world, we have had the greatest access to a peer’s salary and wealth – for example, the University of California makes the salary information of all employees publicly available online.

Prior evidence from experimental social networks shows that making wealth *invisible* promotes the construction of cooperative social networks (Alesina and La Ferrara 2002, Anderson, Mellor and Milyo 2006, Tavoni et al. 2011), and reduces the overall level of wealth inequality (Côté, House and Willer 2015, Nishi et al. 2015). The results of our past work was nicely reproduced by a third party (Camerer et al. 2018). Making wealth invisible can suppress all of the forms of social comparison in wealth (e.g., feelings of being exploited by richer individuals, last-place aversion, effort-reward imbalance); however, these studies (Alesina and La Ferrara 2002, Anderson, Mellor and Milyo 2006, Côté, House and Willer 2015, Nishi et al. 2015, Tavoni et al. 2011) have not investigated whether or not making wealth invisible has a *positive impact on emotional well-being or the disparities therein*. Moreover, since conventional observational studies have had difficulty in distinguishing the effect of relative wealth from that of absolute wealth (by their very nature).

***Methods.*** Here, we plan to quantify the causal effect of wealth invisibility on emotional well-being and the disparity therein, where the treatment variable is wealth visibility **(Fig. 4)**. We hypothesize that the invisible condition can achieve lower mental health disparity than the visible condition (**Hypothesis 2.1**). Analytic details, including model specification (expanding equation 1), for all our (similarly designed and analyzed) experiments are given below, in Section **5.4**.

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| **Fig. 4. No visibility vs. local visibility vs. global visibility in experimental social networks: images of study participants’ game screens.** A focal individual (previous cooperator with 5,000 points and with an intermediate level of emotional well-being) is located in the center, and connects with three neighbors with different cooperation, economic, and well-being statuses. The information regarding connecting neighbors is shown, when the focal individual points the cursor to each circle of the connecting neighbors. **(a)** No visibility of wealth condition. The information of neighbors’ wealth is not shown, while the information of neighbor’s cooperation and well-being status is shown. **(b)** Local visibility of wealth condition. The information of neighbors’ wealth is shown, in addition to that of cooperation and well-being status. **(c)** Global visibility of wealth condition.We summarize the information, and provide each focal individual with the maximum/minimum/average wealth of the entire population, along with characterizing the rank of the focal individual (e.g. 11th rank within the 17 individuals playing the game). |

Furthermore, a potential additional feature of the proposed research would be to examine the effects of (local) visibility **(Fig. 4b)** vs. global visibility **(Fig. 4c)**, which has not previously been examined (Nishi et al. 2015). When wealth is *locally* visible, a focal individual can refer to the wealth only of immediate neighbors. On the other hand, when wealth is *globally* visible, a focal individual can refer to summary measures of the wealth of *all* the individuals in the whole group at the same time (Hauser and Norton 2017). As our “information society” progresses, a larger amount of information has become available through the Internet in the name of information transparency – which increases the chance of people knowing the existence of richer others; however, such excessive information availability could have a negative impact on emotional well-being. Here, we anticipate that the local visible condition can achieve a lower mental health disparity than the globally visible condition (**Hypothesis 2.1.a**).

***5.2. Pilot studies for Hypothesis 2.1.*** We performed a second series of pilot experiments with 555 individuals from Mturk, divided into 50 sessions lasting up to 10 rounds (25 sessions for making wealth visible locally and 25 sessions for making wealth invisible). The results show the association of wealth (standardized) for emotional well-being in the visible condition is much stronger (b1+b3 =0.143) than in the invisible condition (b1 = 0.053, interaction P for b3 < 0.001) **(Fig. 5a)**. These preliminary results suggest that the social rule of modifying the visibility wealth could i­­­mprove the level of emotional well-being, especially among poorer individuals. This result supports **Hypothesis 2.1**. However, 555 is a small sample size, which is not sufficient to draw a conclusion.

Furthermore, we have discovered a role of gender (females vs males) in the effect of “visibility of wealth” (the difference in the steepness of the “visible” and “invisible” curves). Results show that the “making wealth invisible” has a stronger effect among poor females than among poor males **(Fig. 5b)** (slope difference between two pink lines for females = 0.203 [two lines are crossing; interaction P < 0.001] and that between two cyan lines for males = 0.027 [two lines look almost parallel interaction P = 0.343]). The

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| **Fig. 5. Preliminary studies with 555 individuals exhibit the positive wealth-well-being linkage only when the wealth of connecting neighbors is visible (Hypothesis 2.1).** The x axis represents the wealth at the present round, and the y axis represents the level of emotional well-being. Each line represents the predicted linear trend of the wealth-well-being linkage for each condition of Hypothesis 2.1, controlling for the round effect. **(a)** for males and females jointly, and **(b)** for males and females separately. | |

results may suggest that “making wealth invisible” has a more crucial and substantial role in females’ cognitive processes especially when they are poorer. Social comparison may matter more in females. This finding is similar to a large-scale observational study (Jebb et al. 2018), which showed that a wealth-well-being linkage exhibits a gender difference: using the data from the Gallup World Poll II (N = 1.7 million people from 164 countries), the income-happiness linkage is stronger in women than in men (and a higher satiation point in women [$100,000 for women and $90,000 for men]). This latest empirical result differs from a past hypothesis based on the conventional masculine gender norms and emphasis on achievement and social status among men (Adelmann 1987, Levant and Richmond 2007, Parent and Moradi 2009). The role of gender in the wealth-well-being linkage and its mechanism remains in controversy. Explaining the gender difference in behavioral mechanisms will be one of the scopes of **Objective 3.** For example, females may spend longer time comparing their own wealth with others than males.

***5.3. Example of social settings: Poor-but-happy bots (Hypothesis 2.2).***

***Theoretical background.*** Evidence shows that emotions can spread over social ties (Fowler and Christakis 2008, Rosenquist, Fowler and Christakis 2011) via means of “emotional contagion” (Centola 2011, Gesell, Barkin and Valente 2013, Hatfield, Cacioppo and Rapson 1994, Valente 2012). Human-robot interactions and the significance of robots in human life (e.g. *Siri*, *Alexa*, *iRobot Roomba*, or care-robots) have received great attention recently (Dautenhahn 2007, Pfeifer, Lungarella and Iida 2007). The role of AI players (“bots”) in social interactions has also been investigated in fields such as game theory (e.g., in coordination games (Centola 2011, Centola and Baronchelli 2015)). And co-PI Christakis has shown that AI-bots can affect group interactions, in a paper published in *Nature* in 2017 (Shirado and Christakis 2017). However, the role of online bots in emotional well-being is not known or theorized.

If we could strategically put bots with a specific behavioral pattern as a "fake" participant in online groups, we might be able to improve the overall situation of population well-being and reduce its disparity (at the potential cost of deceiving subjects (Aoyagi and Frechette 2009, Rand, Fudenberg and Dreber 2015, Slater et al. 2006)). The advantages of AI players in our experimental networks include (1) AI players are never emotionally influenced by humans; (2) study participants cannot know which are AI players and which are real humans or even do not know the existence of AI players (though this can be manipulated in our social settings); and (3) experimenters can manipulate AI players’ behavioral patterns.

***Methods.*** Here, we plan to explore the impact of AI players on emotional well-being **(Fig. 6)**. We plan on conducting a cluster RCT where the treatment variable is the behavioral pattern of attachment by the AI players (two treatment arms). The first treatment arm involves an AI player connecting with human participants at random (Random AI condition), which is the control condition. The second treatment arm has an AI player connecting with human participants having relatively similar wealth as the AI player (Homophilic AI condition). In both the treated arms, the AI players are set to always be *the poorest* in their social networks,

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| **Fig. 6. Poor-but-happy AI players (“bots”) in experimental social networks.** In the control condition (no AI condition), there are (hypothetically) four individuals who are interconnected with each other in an experimental social network, and there is a mental health disparity by wealth. In the treated condition, the AI player (bot) with the lowest wealth but a high level of emotional well-being is connected with the four individuals, and is expected to make these real humans feel better. |

are always cooperative, and always show the best emotional well-being to their connecting neighbors in the social network, which we expect to cause a cascade of emotional well-being. The other settings are going to be the same as the **Hypothesis 2.1**. Again, we will have 50 replicates of social network for each condition (150 replicates in total).

In the experiments, we hypothesize that the “homophily AI condition” can achieve higher population well-being and less mental health disparity than the “random AI condition” (**Hypothesis 2.2**). This hypothesis is based on two theoretical backgrounds: AI players can prevent human players from feeling relative deprivation (Kondo et al. 2008) and from negative feeling related to “last-place aversion” (aversion to feeling that one is in last place) (Kuziemko et al. 2014) thanks to the poorest AI player. Since such negative feelings relate to being surrounded by a majority of richer study participants or to last-place aversion (Kuziemko et al. 2014), the placement of a poor AI player next to poor subjects might be able to stop it. In addition, since the AI player shares “poverty” with a focal study participant, but feels happy, such well-being of somebody else with a similar or worse wealth status could encourage the focal study participant to feel better even when at a poorer wealth status (promotion of social contagion of well-being), even though, we acknowledge, this is a sort of delusion.

***5.4. Other examples of social settings.*** We will also evaluate a broad array of possible extensions or further experiments, which we note here in order to illustrate the range of possibilities beyond the specific aims noted above. For example, we could experimentally give some of the study participants to get a huge extra bonus (a “lottery” (Gardner and Oswald 2007), e.g. 20,000 points [equivalent to $20]) totally at random and evaluate the hypothesis that *introducing a lottery* deteriorates population well-being. We could also introduce a *social insurance program* to guarantee a minimum wage (e.g., the amount of money that we pay after the final-round interaction as a bonus is $3, if subjects’ final-round wealth is less than $3 [3,000 points]) regardless of the performance of the subjects and evaluate the hypothesis that a social insurance program can enhance sense of security (Nishi et al. 2012), and improve emotional well-being among poorer study participants. Or, in yet another possible extension, it is known that intermediate levels of network fluidity (the rate of forming and breaking social ties) improve the level of cooperation and social welfare and mitigate economic inequality (Nishi, Shirado and Christakis 2015, Rand, Arbesman and Christakis 2011, Shirado et al. 2013). However, it is not known that this can also mitigate the strength of wealth-well-being linkage, which we could explore. These plans are not budgeted at the proposed work, but held as back-up and/or future plans.

***5.5. Analytic Approach to Objective 2.*** In all the cluster RCTs for these different interventions, we hypothesize that the interventions improve the level of emotional well-being of study participants (overall effect), and the effect size of the well-being improvement is larger among poorer individuals than among richer individuals (interaction effect) (and thus and if so, we can say the social rule or strategy addresses the well-being disparity). The equation here is as follows:

(well-being)ijt = b0 + b1(wealth)ijt + b2I((treatment)i = 1) + b3I((treatment)i = 2) + b4(wealth)ijt ×I((treatment)i = 1) + b5(wealth)ijt ×I((treatment)i = 2) + ∑tbt+2I((round) = t) + e1ij + e2i (2)

In equation (2), we simply add the treatment variables, the interaction terms of the treatment variables, and the present wealth. Otherwise, the model specification in equation (2) is the same as that of the equation (1). b1 represents the level of association of wealth with well-being regardless of the type of the treatment variable (overall effect), while b4 and b5 represent the causal effect of the treatment variable on the level of emotional well-being specific to the wealth size (interaction effect).

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| **Box. Evolutionary perspective and agent-based simulations**  The present proposal is also motivated by theories in evolutionary biology (Nishi 2015) and evolutionary dynamics (Nowak 2006). If a certain behavior is advantageous in the environment that people face, the behavior will be transferred to others and become increasingly common(social evolution or cultural evolution) (Centola and Baronchelli 2015, Richerson, Boyd and Henrich 2010). Here, we can observe that people choose their behavioral option based on whether or not they think it may lead them to be happier later (i.e. a behavior leading to a higher expected utility). Such an observed linkage between human behavioral decision-making and the expected emotion afterward implies that human emotion might have played a certain role in cultural evolution. However, it has not been well understood - *to be better off (i.e. to be favored by natural selection), do humans necessitate emotion (or emotional feedback regarding their behavioral decision-making) in addition to the actual feedback?* *More broadly, does natural selection play a role in the evolution of happiness?* (Buss 2012)  If the actual feedback (e.g. results in wealth gain or loss in the economic games such as PGG in the present proposal) is sufficient for optimizing an environment-behavior function (with which individuals can be better off), emotional feedback is unnecessary and redundant, which typically happens when AIs make a decision. On the other hand, if emotional feedback contains signals that actual feedback does not contain, it can help to optimize the environment-behavior function. If this is the case, referring to emotional feedback can be advantageous and can co-evolve with the behavior. Indeed, emotions in humans affect their behavioral decision making (Gruber, Mauss and Tamir 2011, Rand, Kraft-Todd and Gruber 2015). For example, it is known that individuals who just finish a mindfulness meditation course are more cooperative (Nishi et al, under review).  Repeated cooperation games such as Prisoner’s Dilemma (PD) and Public Goods Game (PGG) are some of the best settings to explore the role of emotion in evolutionary dynamics (in typical PD and PGG, when people cooperate, they pay to help others; when they defect, they do not pay and others do not receive help). Theory of cooperation, in which cooperation is defined as “one individual pays a cost for another to receive a benefit”, is a well-studied areas in evolutionary dynamics and experimental economics (Fehr and Schmidt 1999, Rand and Nowak 2013). These short-lived games can provide unique settings in which the dynamics of behavioral choices and their consequences can be observed and recorded. Scientists have identified various rules in the evolution of cooperation (Ohtsuki et al. 2006, Rand, Ohtsuki and Nowak 2009, Rand et al. 2014b). Since the long-term reciprocal cooperation can make reciprocal cooperators outperform others in the end or repeated games, cooperation behavior can evolve.  If an unhappy emotion comes after a focal individual loses resource and if a happy emotion comes after the focal individual gain resource, the wealth-wellbeing linkage will emerge as a consequence or a by-product of the evolution of cooperation. However, it is not really known whether the level of happiness can affect the evolution of cooperation. Therefore, from the evolutionary perspective, we would have several additional questions to explore. **Objective 1** includes the two following questions.  **Question 1. Are happier people more generous and better off than unhappier people?** It is known that if subjects cooperate with cooperators and defect against defectors (Tit-For-Tat [TFT] strategy (Rand, Ohtsuki and Nowak 2009)), cooperation can evolve. Since a mistake (cooperators unintentionally or intentionally choose to defect one time) may evoke a cascade of defection across social networks, they would rather be somewhat generous (e.g. keep cooperating with first-time or second-time defectors) on the top of tit-for-tat strategy (Generous Tit-For-Tat [GTFT] strategy (Rand, Ohtsuki and Nowak 2009, Rand and Nowak 2013)). However, if they are too generous (e.g. keep cooperating with a group of regular defectors), those who are too generous will be exploited and cannot outperform defectors (a feeling of the fear to lose (Kahneman and Tversky 1984) may let people not too generous). Therefore, we hypothesize that human emotion has a role in regulating the level of generosity. As a result, such a generous strategy at the appropriate/intermediate level may make happy individuals easy to construct a long-term cooperation relationship, which leads to an upward spiral (happier are richer, which enhances the wealth-well-being linkage).  **Question 2. Do agents with emotion can outperform agents without emotion in simulations? (Do winners refer to their emotion upon decision-making?)** We will develop an environment-behavior function (drawn from all the experiment data except happiness) and an environment-behavior function (drawn from all the experiment data including happiness) based on machine learning techniques (i.e. we develop the models with the highest predictive ability). The former agent has no emotion, while the latter agent has emotions. In agent-based simulations, we mix two groups of the agents and observe which group natural selection favors.  Although “wealth” in **Objective 1** is an absolute one because information of others’ wealth is not available or visible, in the real world, “wealth” has a relative existence (Solnick and Hemenway 1998). It is known that (statistically) being richer than others provoke a positive feeling (Clark and Oswald 1996, Gardner and Oswald 2007) while being poorer provokes a negative feeling. However, the degree may depend on individuals – some will be more affected by others’ wealth than some others. Therefore, regarding **Objective 2a**, we would explore the following question.  **Question 3. Does natural selection favor relative-wealth-well-being linkage?** Although people compare their own wealth to others (social comparison (Gerber, Wheeler and Suls 2018, Gilbert, Price and Allan 1995)) and usually feel better when their own wealth is better, it is not well known where such a feeling originates from.Therefore, we aim to define two groups in our data – one for the individuals who connect relative income with their happiness level (sensitive people), and the other one for those who do not connect relative income with their happiness level (insensitive people) before the first round begins. We will compare the final score (wealth) of the sensitive and insensitive people. (Also, we compare the strategies of sensitive people with those of insensitive people in simulations as in **Question 2**.) We hypothesize that sensitive people will achieve higher scores because they are more motivated to climb up and optimize their behavioral strategy. Instead, insensitive people may achieve higher scores because relative wealth is merely noise in terms of the evolution of cooperation, which does not have to be referred to. |

**6. Objective 3: Evaluate possible behavioral mechanisms explaining intervention effects in the wealth-well-being linkage.**

Assuming our interventions (e.g. “making wealth invisible” [**Hypothesis 2.1**], “homophily with a poor-but-happy AI player” [**Hypothesis 2.2**]) can make poorer study participants happier, we will next investigate what behavioral patterns of study participants are behind this improvement. *Why can some of the social settings successfully make poorer study participants happier?* To answer these questions, we need to think how each of the social settings can alter human behaviors. We plan to use the eye-tracking method (for local study participants recruited at UCLA in the hybrid experiments) and the response time (both in the online experiments and in the hybrid experiments) to help shed light on these possibilities.

***Eye-tracking.*** Continuous eye-tracking (Jacob and Karn 2003, Meso 2012, Skulmowski et al. 2014) allows naturalistic and unobtrusive measurement of participant’s visual gaze and fixation patterns which reflect potential attention biases, and has been used successfully by Co-I Gruber in studies on positive affectivity and attentional bias (Gruber et al. 2018, Purcell et al. 2018, Raila, Scholl and Gruber 2015)). We plan to use a screen-based eye tracker, *Tobii Pro* (see the letter of support), the most cutting-edge eye-tracking system available now, which has advantages including unobtrusive measurement of eye gaze and seamless synchronization with concurrent subjective and behavioral measures of affectivity. Visual fixation patterns will be recorded throughout the experiment. We pre-define Areas Of Interest (AOI) on the study participant’s computer screen **(Fig. 7)**, which distinguishes the region of the information of a focal individual from that of connecting neighbors and is consistent with approaches used in prior eye tracking and affect research (Noh, Lohani and Isaacowitz 2011, Wadlinger and Isaacowitz 2008). To obtain validation ratings on the pre-defined AOIs, we adopted a coding procedure similar to that used in previous

eye-tracking studies (Noh, Lohani and Isaacowitz 2011, Wadlinger and Isaacowitz 2008). Specifically, 100 independent judges will be recruited to obtain validation ratings on the AOIs for both valence and arousal dimensions (Buhrmester, Kwang and Gosling 2011, Gosling et al. 2004). AOIs in the cooperation decision-

making task will include the regions displaying the nodes of self and connecting others and those displaying the instructions of cooperation decision-making with the icons for Cooperation and Defection (**Fig. 7**). A focal individual is supposed to move his or her eyes to obtain information of self and connecting neighbors, and to reach the AOI of the icons for Cooperation and Defection (AOI 12 in **Fig. 7**).

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| **Fig. 7. Eye-tracking method can help us to directly capture a “social comparison” behavior in relation to Hypothesis 2.1.** The eye-tracking device (e.g. Tobii Pro) is placed at a bottom (or top) of a computer screen.Blue rectangles represent Areas Of Interest (AOI) 1 – 21. Eye movement (red arrows) starts from the self big circle in the center (AOI 9), and walks through AOIs 17, 16, 8, 2, 3, 9, 10, and 9, and finally reaches the defection decision (AOI 12). In this case, the number of the eye movement paths is 9.The number in each circle represents present wealth points of each study participants. The color of each circle represents cooperation behavior at a prior round of each study participant (orange = cooperated [option A], blue = defected [option B]). For this illustration, wealth of neighbors is visible. |

First, we aim to count the number of eye movement paths between self and neighbors before the cooperation decision, as an indicator of social comparison. This variable will be used as the main outcome variable. Second, we aim to measure the time of fixation on the AOI of the icons for Cooperation (option A) and Defection (option B), after study participants finish gathering information (AOI 12 in **Fig. 7**). Since it takes longer to choose to cooperate or defect at AOI 12 when the information that subjects get about self and connecting neighbors is more complicated (e.g. a focal individual is a cooperator surrounded by defecting neighbors, and much poorer than them) (Nishi et al. 2016), the two measures (the number of eye movement paths and the time of fixation at AOI 12) may be correlated with each another.

***Response time.*** Response time is defined as the time between a step in which each subject was asked to choose using a clickable icon appearing on the screen and when each subject clicked either the option A or option B icon **(Fig. 7b)** (Nishi et al. 2016), and this definition can be extended to the other choices (e.g., rewiring, and rating well-being). Response time has been commonly used in both social science and neuroscience (Deary, Liewald and Nissan 2011, Kosinski 2013, Rand, Greene and Nowak 2012, Rand et al. 2014a, Rubinstein 2007, Wansink, Just and Payne 2009, Zaki and Mitchell 2013). Since *breadboard* has time stamping, we can measure how long it takes for each participant to make a cooperation decision (as we have successfully done before (Nishi et al. 2016)). Therefore, we can corroborate our explanation using the data from hybrid experiments and eye-tracking with data from the online experiments. We assume that, as the number of eye movement paths is larger before the cooperation decision is made, the response time is longer. Therefore, we predict that the two variables are strongly and positively correlated.

***6.1. Data analysis.*** We hypothesize that our treated conditions (e.g., a social rule of “no social comparison in wealth is possible”) in **Objective 2** will reduce the level of eye movements for social comparison **(Hypothesis 3)**.We construct a generalized linear model with a log link (because the dependent variables we consider below are non-negative) to predict the number of eye movement paths or response time before the cooperation decision (for example) is made, by using multiple independent variables including the treatment variable (e.g. making wealth of neighbors visible or invisible) and the current wealth of each individual. The equation for the data analysis at the individual level, on the log scale, is as follows:

log(number of eye movement paths or response time)ijt = b0 + b1(wealth)ijt + b2I((treatment)i = 1) + b3I((treatment)i = 2) + b4(wealth)ijt ×I((treatment)i = 1) + b5(wealth)ijt ×I((treatment)i = 2) + ∑tbt+2I((round) = t) + e1ij + e2i (3)

In equation (3), we simply replace the outcome variable of equation (2) with the number of the eye-movement path (or response time) of the jth individual at the ith social network at the tth round. Other than this replacement, the model specification in equation (5) is the same as that of the equation (2). We plan to apply the same regression model to the other outcome variable of gaze time at AOI 12, and that of response time (the other continuous variable, which can fit with the exactly same generalized linear model). If the distribution of the outcome variables is skewed, we will plan to specify an adequate link-function, instead of the log link, in the generalized linear model analysis (we note that a direct log-transformation of the data is typically adequate in the response time literature (Rand, Greene and Nowak 2012, Rand et al. 2014a) and thus we expect the log-link to also be adequate). Responding to **5.2** (preliminary studies for **Objective 2**), we stratify the data into female study participants and male study participants (with calculating an interaction P value) to see the gender difference in eye movement. Especially, we hypothesize that the number of eye movement paths among female study participants is higher than that of male study participants when wealth is visible. We also plan to investigate other differences such as ones based on age and race/ethnicities as well as the gender difference.

**SIGNIFICANCE**

**Contributions to education and human resources:** Although the results of the pure online experiment in the present proposal is not directly applicable to the real world, we may provide hints of being happy and becoming more happier even in an equal world. Such hints may be provided in education.

**Intellectual Merit:** In such as experimental setting, we can closely explore some of the behavioral and cognitive mechanisms underlying the wealth-well-being linkage in relation to experimentally introduced social treatments using validated measures of decisional conflict (e.g., response latency) and attentional focus (e.g., gaze duration). For instance, the treated conditions (e.g., a social rule of “no social comparison in wealth is possible”) would reduce the level of eye movements indicative of engagement in social comparison. Overall, using this model system (involving real people interacting for short periods online), a set of questions that are not easily tractable using non-experimental methods will be explored experimentally. We believe that our approach allows scientists to understand the origin of happiness and the evolution of happiness more deeply.

**Broader Impact:** We realize, of course, that this research, while (in our view) appealing because of its (1) experimental control, (2) large sample size, and (3) use of innovative software and approaches, is an ‘in vitro’ model of the complex psychological and social processes we are exploring. We are using people interacting online, with small financial stakes, for short durations, and with measures of “wealth” and “emotional state” that are proxies for the real, lived experience of these phenomena. But our interest is also affirmatively in transient emotional states, and our experiments clearly can address this. And we are investigating model interventions (invisibility, happy bots, etc.) that, we believe, may point the way forward to practical policies. We believe this approach offers great promise for substantial insights and robust causal inference regarding important questions in social and clinical psychology, sociology, social epidemiology, public health, and disparity research.

**Results from prior NSF Support: PI Nishi** is a recent awardee of NSF EAGER:AI-DCL for developing a hybrid AI system with humans in the loop to ensure that decisions are robust, unbiased and fair (1927554: Nishi as a co-PI), which is not related with the present proposal on happiness. There are no overlaps. There are no results published (the funding start date is 10/1/2019).

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