Intermediate Levels of Network Fluidity Amplify Economic Growth and Mitigate Economic Inequality in Experimental Social Networks

Akihiro Nishi, Hirokazu Shirado, Nicholas A. Christakis

Yale University

Abstract: Social connections are mutable. Prior experimental work has shown that circumstances fostering an intermediate rate of forming and breaking social ties ("network fluidity") facilitate the maintenance of optimal levels of cooperation in experimental social networks. Previous observational work has also suggested a relationship between economic outcomes and network structure (measured statically) at a geographic level. However, it is not known how network fluidity might affect economic growth and inequality, particularly in an experimental setting. Using data from a series of online experiments involving a public goods game in 90 independent, dynamic social networks (with N=1,529 subjects), we show that increasing network fluidity simultaneously achieves the highest level of economic growth and the lowest level of economic inequality, up to a point. These effects of network fluidity on economic outcomes are mediated, in these experiments, by the levels of cooperation and tie formation that subjects evince. Finally, we show that wealthier networks are less unequal. Social network fluidity may play an important role in economic outcomes and hence in social welfare.

Keywords: economic inequality; economic growth; fluidity; experimental social networks; public goods game

ECONOMIC inequality is observed very widely in humans (Cingano 2014, OECD 2014, Piketty and Saez 2014, Ravallion 2014), though measured levels of inequality vary. Among industrialized societies, the Gini coefficient (which ranges from 0 for total equality to 1 for the extreme where one person has all the wealth) is presently 0.39 in the USA and 0.26 in Scandinavian countries (Alderson and Nielsen 2002, OECD 2014). Even in pre-industrial societies there can be inequality; for example, the Gini coefficient in five hunter-gatherer societies was approximately 0.25 (Smith et al. 2010), and, among eight pre-industrial agricultural societies, it was 0.48 (Shenk et al. 2010).

One set of theories suggests that inequality is a necessary complement to increasing wealth (Aghion and Bolton 1997, Rawls 1971). However, empirical analysis usually does not support this view. For example, a recent report of the Organisation for Economic Co-operation and Development (OECD) indicates that, while economic inequality has steadily increased since the mid-1980s, economic inequality may actually have retarded economic growth (Cingano 2014). It is reasonable to ask what socioeconomic systems and social circumstances might be optimal for greater economic growth without excess inequality ("equitable growth") and what social institutions might promote or restrain economic inequality (Moller, Alderson and Nielsen 2009).

Here, we focus on the role of one social behavior in explaining the origins of inequality and the relationship between growth and inequality: the making and breaking of social ties, which we term "network fluidity." Real social networks involving volitional ties such as friends (as contrasted with non-volitional kin networks) are not fixed (Cairns et al. 1995, Neckerman 1996, O'Malley and Christakis 2011, O'Malley et al. 2012, Poulin and Chan 2010). Indeed, real social networks avoid both extremes of entirely static, immutable social ties, on the one hand, and entirely impermanent ties (which change all the time), on the other. One study estimates that about 20% of close friendships in US adults turn over in a four-year window (O'Malley and Christakis 2011). Another study found that only 30% of friendship cliques remained the same over a one year period (Neckerman 1996). People rewire their social ties and affect the topology of the networks around them (Fowler, Dawes and Christakis 2009), and this manipulation of this form of social capital in a group of people may affect the economic productivity of the group (Coleman 1988, Eagle, Macy and Claxton 2010).

In previous work, we used a set of experiments to show that "rewiring" behaviors in dynamic social networks affect cooperation (Rand, Arbesman and Christakis 2011, Rand et al. 2014, Shirado et al. 2013) (see also (Fehl, van der Post and Semmann 2011). The results show that intermediate levels of the rewiring rate (a measure of network fluidity) in social networks—i.e., the permissible rate at which social ties can be changed—elicit the highest level of cooperation in group members. However, the effect of rewiring rate on economic growth, inequality, and wealth assortativity (the preferential sorting of the poor and rich into cliques) has not yet been investigated, to our knowledge. Therefore, we examine whether network fluidity is related to wealth, inequality, and wealth homophily in our experimental social systems. We find that social capital investments of this sort have an optimal level (from an economic point of view) at an intermediate network fluidity.

Methods

Data

We used data from a series of online experiments executed between January and April, 2012 archived at the Yale Institute for Network Science (Shirado et al. 2013). The experiments were approved by the Yale University Human Subjects Committee. We recruited 1,529 human subjects online through Amazon Mechanical Turk (Buhrmester, Kwang and Gosling 2011). Each subject participated in a single session in our experiments and was not allowed to participate in multiple sessions. A total of 90 sessions were implemented; the average number of subjects per a session was 17.0 (SD = 4.0); and the duration of the experiment was approximately 60 to 90 minutes. Each session had 15 rounds, and each round involved subjects deciding two sorts of actions in sequence: a choice about whether to cooperate with (and hence "invest" in) their network neighbors, and a rewiring step in which subjects could choose to make or break ties.
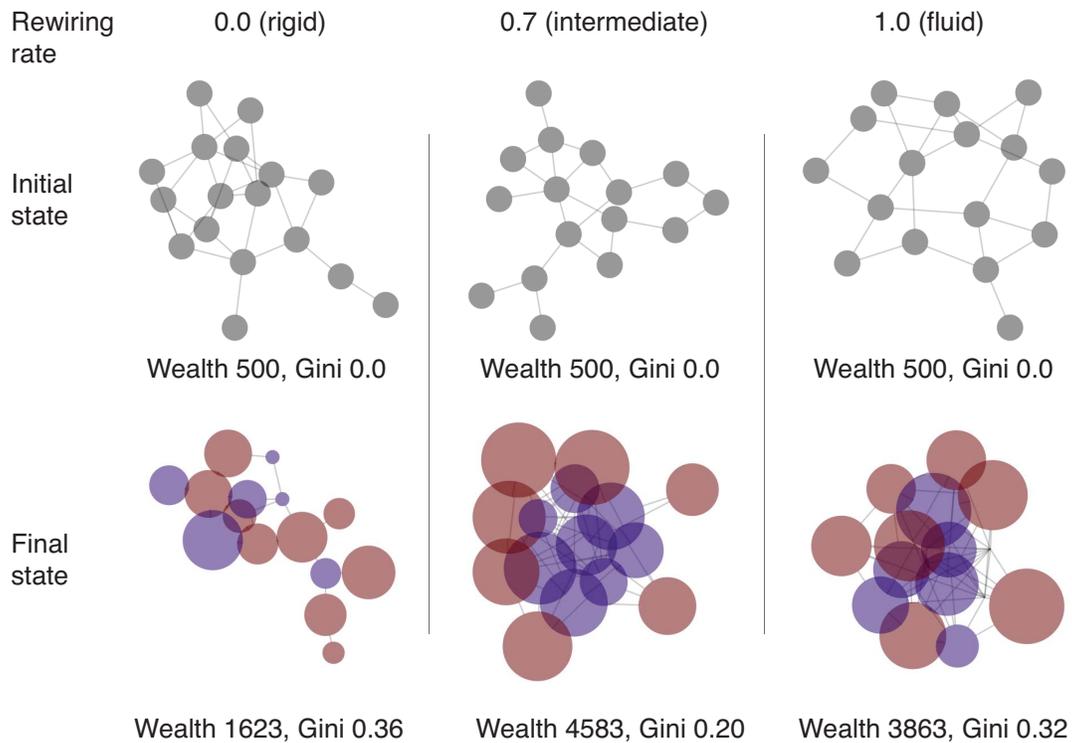
Before the interactions started in the first round, each subject was assigned to one location in an Erdos-Renyi random social network graph (Newman 2010), and

20% of all the possible combinations of two subjects were randomly selected and connected (i.e., the expected value of initial network density [the number of actual ties divided by the number of possible ties] was 0.2). Each subject was given the same initial endowment (500 monetary unit [MU], 1,000 MU = 1 USD). Thus, the initial Gini coefficient (defined below) was 0 for all the sessions.

The cooperation step was a public goods game played by each subject in his or her local social network (i.e., with his or her first degree alters). At the cooperation step in the 1st round, each subject was asked whether s/he wished to cooperate or defect with all the connecting neighbors at once. In keeping with past work, we did not allow subjects to choose individual actions with each of their social connections. For example, in the case where a subject choses to cooperate, when the subject was connected with 6 alters, the subject needed to pay 300 MU (50 MU/subjects × 6 subjects). And, if 4 out of 6 connecting neighbors also chose to cooperate, the focal individual earned 400 MU (100 MU/subjects × 4 subjects). In total, the focal subject obtained 100 MU (–300 MU + 400 MU) in such a round. Conversely, if a subject chose to defect, the subject did not have to pay anything (0 MU); however, the subject might still expect some connecting alters to choose to cooperate and the focal subject could gain wealth ("free-riding"). Decisions were simultaneous at each round, but subjects could refer to the cooperation behaviors of their own and all connecting neighbors at the last round, which allowed them to implement a strategy like "tit-for-tat" (cooperate only when the cooperation rate is high in the local social network in the past round), or any other strategy they wished.

Although subjects were aware of their own wealth at each round (initial endowment plus cumulative payoff), they were not aware of the wealth of connecting neighbors. Wealth status was never visible to others. This feature allowed us to exclude a potential confounding effect of "social comparison" on economic growth and inequality (Fliessbach et al. 2007, Gilbert, Giesler and Morris 1995). If each subject could compare the level of own wealth with that of connecting neighbors, positive or negative emotions or thoughts related to such social comparison might change their behavioral patterns. Therefore, in this experiment, we deliberately investigated the isolated effect of the level of network fluidity per se on economic growth, inequality, and homophily.

At the rewiring step, we implemented nine different rewiring rates which represented the levels of permissible fluidity in social networks, exploring the entire parameter space from 0 (no rewiring possible) to 1 (all ties are up for renewal at each time step), namely, rewiring rates of 0, 0.05, 0.1, 0.3, 0.5, 0.7, 0.8, 0.9, and 1.0. This was the key variable we manipulated in this experiment. Here, the rewiring rate (or rewiring probability) was defined as the probability that each tie was selected at each round; then, one randomly selected subject at either end of the selected tie consisting of the two subjects was asked whether he or she wanted to make the choice to connect (if they were previously unconnected) or disconnect (if they were previously connected) with the other subject. Therefore, decision making at the rewiring step was unilateral. If the selected tie existed at the rewiring step, the option was to keep connecting or to cut it; if the selected tie did not exist, the option was to create a new connection or to stay un-connected. Hence, *while opportunities to re-wire occur at random and are exogenous, tie rewiring was deliberate and volitional*.

Rewiring
rate   0.0 (rigid)   0.7 (intermediate)   1.0 (fluid)

Initial
state

Wealth 500, Gini 0.0   Wealth 500, Gini 0.0   Wealth 500, Gini 0.0

Final
state

Wealth 1623, Gini 0.36   Wealth 4583, Gini 0.20   Wealth 3863, Gini 0.32

Figure 1: Examples of the results in experimental human social networks. The initial state (before the first round) and the final state (after the final round) in three out of 90 sessions are shown. For simplicity, we display typical results from three conditions of experimentally specified rewiring rates, which represent the level of network fluidity drawn from the full range of rewiring rates (0.0–1.0). Node size indicates wealth in monetary units (nodes with larger area are richer). Therefore, larger differences in node sizes in one network graph imply the existence of a larger wealth inequality. Node color indicates the cooperation behavior at the last round (blue: cooperate, red: defect, and grey: no history). "Wealth" represents the average wealth of all the subjects. "Gini" represents the Gini coefficient (the indicator for the level of wealth inequality among all the subjects) The (small) difference in the number of nodes between the initial and the final states comes from subject drop-outs across the rounds.

The assigned rewiring rate was constant across all the rounds of each session. Each setting was run ten times (i.e., ten sessions of ten different social networks with unique subjects). At this rewiring step, subjects are also given the information regarding the cooperation behaviors of neighbors.

The cooperation step and rewiring step, which comprise a single round, were repeated for 15 rounds. Subjects were not informed of how many rounds were planned to avoid end-game effects ...(Rand et al. 2009). At the end of the 15 rounds, subjects on average obtained $3.60 USD = 3,600 MU (interquartile range [IQR]: 1.80 USD – 5.06 USD), in addition to a $3.00 show-up fee. As a result, some of subjects became richer than others depending on their behaviors and their neighbors' behaviors, yielding the session-level dynamics of economic growth and inequality Figure 1.

Measure of economic inequality

We used the Gini coefficient to measure economic inequality:

$$\text{Gini coefficient } = (\Sigma\Sigma|x_i - x_j|)/2n^2\mu,$$

where x_i is wealth of i-th subject, x_j is wealth of j-th subject, n is the population size, and μ is the mean wealth of the population (Allison 1978). The Gini coefficient is 0 when the wealth distribution is perfectly equal, and 1 when it is perfectly unequal.

In our experiment, subjects' decision-making regarding cooperation or defection in the public goods game shaped the dynamics of the Gini coefficient. Economic games, including public goods games, have been used in laboratory settings and simulations to understand the dynamics of wealth and inequality (Chiang 2015, Du, Cao and Hu 2009, Hamada 2003, Nishi et al. 2015). In a hypothetical public goods game involving just two subjects, there are four possible combinations that can result. First, if both a richer subject and a poorer neighbor choose to cooperate, the Gini coefficient decreases because the initial wealth difference between the two becomes relatively less important after the wealth gain of both. Second, if a richer subject chooses to cooperate and a poorer neighbor chooses to defect, the Gini coefficient decreases by a larger amount because the wealth of the richer subject is transferred to the poorer neighbor. Third, if a richer subject chooses to defect and a poorer neighbor chooses to cooperate, the Gini coefficient increases because the wealth of the poorer neighbor is transferred to the richer subject. Fourth and finally, if both a richer subject and a poorer neighbor choose to defect, the Gini coefficient does not change because no economic transaction happens. Since there are more than two subjects in the experiments, these dyad-level Gini dynamics occur multiple times, and they can be aggregated to the session-level (Du, Cao and Hu 2009, Hamada 2003).

Analytic procedure

First, we calculated the average wealth and Gini coefficient at each round of each session. Since we aimed to examine the cumulative effect of the rewiring rate, we statistically examined the results at the 15th round (N = 90 sessions). Then, we calculated the mean and the standard error of mean (s.e.m.) of the average wealth and Gini coefficient at the 15th round, stratified by the nine different rewiring rate conditions Figure 2, Panels A and B. In order to understand the impact of network fluidity on average wealth and Gini inequality, we regressed these two outcome measures separately on a continuous variable of rewiring rate (ranging from 0 to 1) and another continuous variable of the rewiring rate squared in linear regression models (Ordinary Least Squares [OLS]) Table 1, Columns A and C since the associations are visually curvilinear Figure 2, Panels A and B and since the association of the rewiring rate and cooperation was reported to be curvilinear in a previous study (Shirado et al. 2013). The quadratic lines estimated by the regression models were added to Figure 2, Panels A and B. Next, in order to examine how much network density and the cooperation rate mediated the effect of the rewiring

rate on these two outcome measures, we included them in the regression models (with a conventional method (Baron and Kenny 1986)) Table 1, Columns B and D.

Second, we examined the association of the Gini coefficient and average wealth across different rewiring rates. Unlike the foregoing analyses, there is no strictly causal interpretation for this association here. We drew a scatter plot of average wealth and Gini coefficient at the 15th round stratified by rewiring rate Figure 2, Panel C. In order to understand the trends of Gini coefficient and average wealth, we regressed average wealth on a continuous variable of Gini coefficient (ranging from 0 to 1) and another continuous variable of Gini coefficient squared in a linear regression model Table 1, Column E. The quadratic lines estimated by the regression model were added to Figure 2, Panel C. Next, in order to examine the role of network density, cooperation rate, and rewiring rate, we included them in the regression model Table 1, Column F.

In addition, we calculated the assortativity coefficient for wealth at each round of each session (negative values are well mixed or disassortative [heterophily], 0 represents random mixing, positive values are more segregated or assortative [homophily]) (Newman 2002), and examined its relationship with the rewiring rate at the 15th round ($N = 90$ sessions). To control for the influence of the wealth variation in each round of each session, we calculated the assortativity coefficient in artificially generated social networks in which wealth was permuted across the subjects within each round of each session, iterated this process 10,000 times, obtained the average assortativity coefficient in the permutated social networks, and calculated the difference between that of the observed social networks and the average of the permuted social networks (a positive value represents excess wealth assortativity in the observed social networks) Figure 2, Panel D. Similar to the other outcome variables, we regressed this outcome measure separately on a continuous variable of the rewiring rate and a continuous variable of the rewiring rate squared in linear regression models with and without covariates Table 1, Columns G and H.

Results

First, we report the effect of network fluidity on the average wealth of populations after all the interactions end Figure 2, Panel A. Since average wealth is a session-level variable, we analyze the data only at the session level (i.e. N = 90). The results show that intermediate levels of the exogenous rewiring rate produce the highest average wealth (maximum average wealth = 4,712 MU at rewiring rate = 0.7). In a regression model, the quadratic function of the rewiring rate fits fairly with the outcome variable of average wealth Table 1, Column A, which suggests an inverse-U-shaped relationship between rewiring rate and average wealth. When we include cooperation rate and network density (interconnectedness; the number of actual ties divided by the number of possible ties) as covariates in the regression model, the inverse-U-shaped relationship disappears Table 1, Column B, suggesting that the effect of network fluidity on wealth is mediated by cooperation behavior and tie formation.

Second, we report the effect of the exogenous rewiring rate on the Gini coefficient after all the interactions end (i.e., the level of inequality of the final MU's of the
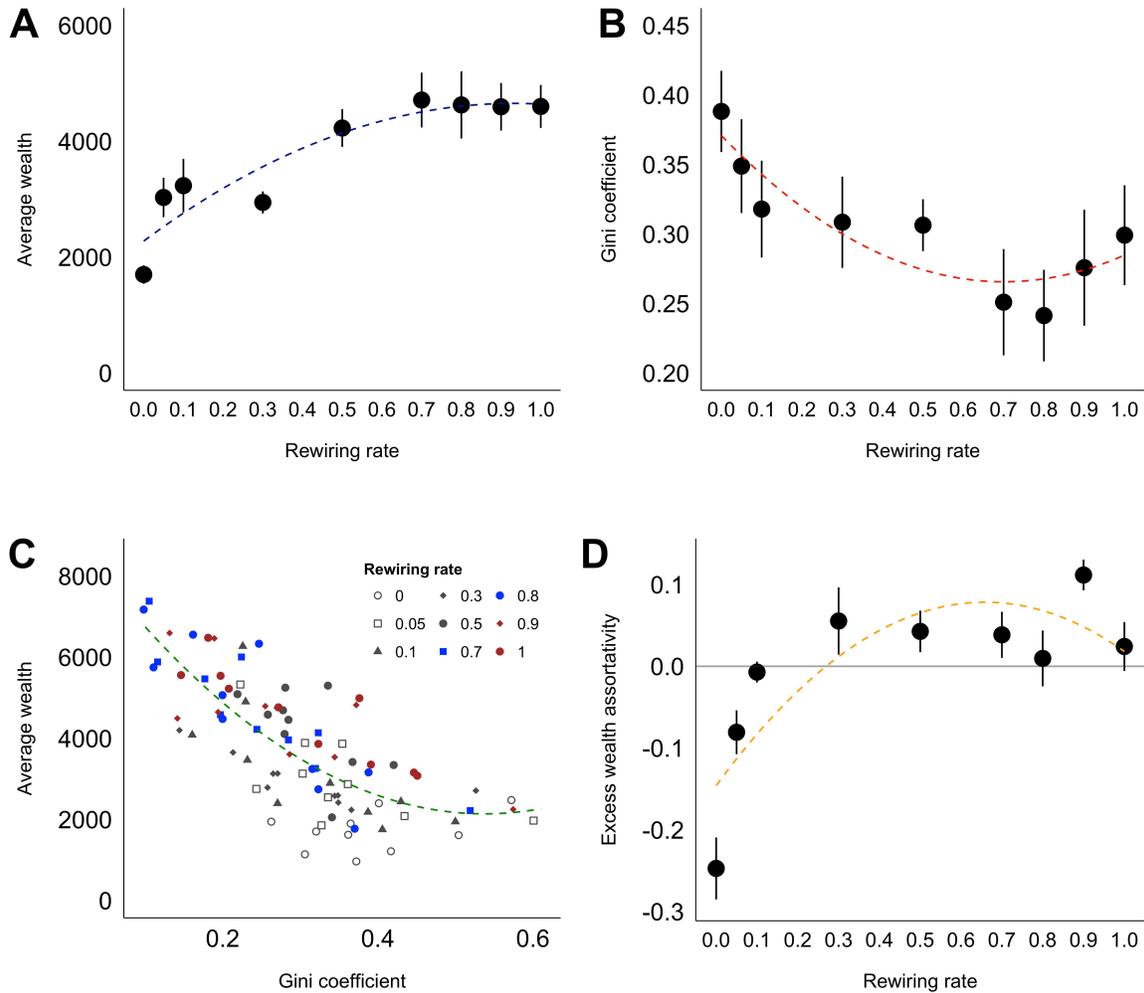
Figure 2: Intermediate levels of the rewiring rate (network fluidity) achieve the highest economic growth and the lowest economic inequality, where average wealth is correlated with Gini coefficient. Results at the final round are shown in all the panels **(A)** The impact of rewiring rate on Gini coefficient at the final round fits with a quadratic function (blue dashed line). **(B)** The impact of rewiring rate on average wealth at the final round fits with a quadratic function (red dashed line). **(C)** The association of Gini coefficient with average wealth at the final round fits with a quadratic function (green dashed line). **(D)** The association of rewiring rate with excess wealth assortativity fits with a quadratic function (orange dashed line); a horizontal line at 0 represents no assortativity or disassortativity (>0 for assortative, and <0 for disassortative) Error bars, mean $\pm$ s.e.m.

Table 1: Session-level linear regression analyses show that the associations of rewiring rate with average wealth and Gini coefficient are explained by cooperation rate and network density (interconnectedness).

Outcome	Average wealth		Gini coefficient		Average wealth		Excess wealth assortativity	
Model	A	B	C	D	E	F	G	H
Gini coefficient					−25870† (4326)	−13706† (4076)		
Gini coefficient squared					24066† (6446)	12129* (5573)		
Rewiring rate	5102† (1492)	1802.4 (1323)	−0.3* (0.125)	−0.142 (0.116)		1381 (1180)	0.68† (0.128)	0.581† (0.156)
Rewiring rate squared	−2736 (1503)	−372.8 (1242.1)	0.214 (0.126)	0.109 (0.109)		−137 (1107)	−0.43† (0.147)	−0.515† (0.129)
Network density		1977.3* (792)		−0.041 (0.069)		1451* (712)		0.11 (0.093)
Cooperation rate		3669† (508.6)		−0.33† (0.045)		1622† (594)		−0.034 (0.06)
Constant	227† (265)	200.9 (348.8)	0.371† (0.022)	0.507† (0.031)	9092† (683)	4453† (982)	−0.146† (0.023)	−0.174† (0.041)
Observations	90	90	90	90	90	90	90	90
R^2	0.3643	0.6711	0.1256	0.506	0.59	0.752	0.3705	0.381

(A) The quadratic association of rewiring rate with average wealth is shown. (B) The inclusion of network density and cooperation rate in the model attenuates the association of rewiring rate with average wealth. (C) The quadratic association of rewiring rate with the Gini coefficient is shown. (D) The inclusion of cooperation rate in the model attenuates the association of rewiring rate with the Gini coefficient. (E) The quadratic association of Gini coefficient with average wealth is shown. (F) The inclusion of network density, cooperation rate, and rewiring rate in the model does not fully attenuate the association of Gini coefficient with average wealth. (G) The quadratic association of rewiring rate with excess wealth assortativity is shown. (H) The inclusion of network density and cooperation rate in the model does not change these results. No sign for $p \geq 0.05$.

* $p < 0.05$; † $p < 0.01$.

subjects) Figure 2, Panel B. The results show that intermediate levels of the rewiring rate exhibit the lowest Gini coefficient (minimum average Gini = 0.24 at rewiring rate = 0.8). In a regression model, the quadratic function of rewiring rate also fits fairly with the outcome variable of the Gini coefficient Table 1, Column C, which suggests a U-shape relationship between the rewiring rate and inequality. Once again, when we include the cooperation rate as a covariate in the regression model, the U-shape relationship disappears Table 1, Column D.

Third, we report the association of the Gini coefficient and average wealth (given different rewiring rates) to explore the idea of "equitable growth." Figure 2, Panel C shows that higher average wealth is associated with a lower Gini coefficient, which suggests that "successful" interactions of a group of subjects within a single session do achieve higher wealth without sacrificing economic equality. When the rewiring rate is intermediate (around 0.7 or 0.8), the population has a greater chance to obtain both high growth and low inequality (upper left in Figure 2, Panel C) rather than low growth and high inequality (lower right in Figure 2, Panel C) – as compared with higher or lower rewiring rates. A regression model confirms that the negative association of Gini coefficient with average wealth is attenuated when the Gini coefficient increases Table 1, Column E. Even after we include the cooperation rate, network density, and the rewiring rate as covariates in the regression model, the quadratic relationship between Gini coefficient and average wealth is robustly present Table 1, Column F.

Finally, we report the effect of the rewiring rate on wealth assortativity (the tendency of relatively wealthy individuals to be connected to wealthy individuals and poor individuals with poor individuals) Figure 2, Panel D. The results show that high levels of the rewiring rate exhibit the highest assortativity (maximum excess assortativity = 0.11 at rewiring rate = 0.9), although the level of assortativity itself is not significantly different from 0 when the rewiring rate = 0.10, 0.30, 0.50, 0.70, 0.80, and 1.00. In a regression model, the quadratic function of rewiring rate fits fairly with the outcome variable of the excess assortativity Table 1, Columns G and H; however, this inverse-U-shape relationship is largely (but not completely) affected by a single outlier at the rewiring rate = 0. Excluding this static (non-fluid) network condition still reveals a U-shaped relationship (data not shown).

Discussion

Here, in a series of circumscribed online experiments, we find that intermediate levels of permissible dynamism or fluidity in social ties amplifies economic growth and mitigates economic inequality. Such "favorable" consequences on growth and inequality appear to arise in part because humans come to cooperate more frequently and thus to connect with a larger number of neighbors in certain circumstances. That is, the intermediate levels of network fluidity appear to be a favorable environment to successfully evoke cooperative and more interconnected human social networks, which leads to higher economic growth and, simultaneously, lower economic inequality.

There are several explanations for the dynamics of economic growth and inequality in these experiments. With respect to economic growth itself, the explanation

is simple: when subjects choose to cooperate when they are connected to a larger number of neighbors, the amount of wealth gained in a group of subjects in each session is larger. For economic inequality, however, we find that cooperation plays a more important role than network density. The potentially dominant mechanism is as follows: when the cooperation rate is higher, dyadic economic interactions that might reduce the Gini coefficient (specifically, where a richer subject and a poorer subject cooperate with each other) are probabilistically more likely to occur. In this case, both the richer individual and the poorer individual are better off, and thus the wealth difference at the prior round becomes relatively less important after a focal round. For example, a wealth distribution of 500 MU and 250 MU at a previous round (Gini coefficient = 0.17) yields higher inequality than that between of 600 MU and 350 MU at a subsequent round (Gini coefficient = 0.13). Moreover, these two associations (the positive association of cooperation rate with average wealth and the negative association of cooperation rate with Gini coefficient) jointly yield the negative association between Gini coefficient and average wealth. This explains how the wealthier social networks as a whole achieve a lower degree of economic inequality and allow the poorer to become better off) (Aghion and Bolton 1997, Sowell 2012), at least in our experimental setting.

Prior work has used large-scale observational data to explore a number of social explanations for geographic variation in economic inequality—including relative rates of economic development, labor force changes, educational changes, and urbanization (Moller, Alderson and Nielsen 2009). The role of social networks has also been explored, using phone data for the entire UK, along with economic measures, to make ecological inferences that one measure of network diversity is positively associated with greater economic development (Eagle, Macy and Claxton 2010). To these explanations, we add the idea that network fluidity, in terms of the permissible turnover in social ties, may play a role, using small-scale, experimental data. Network fluidity might vary from place to place, just as other attributes of social structure or institutions do, and it may, in turn, be associated with economic outcomes.

Regarding wealth assortativity, we found a strong disassortativity when the social networks are static (i.e. rewiring rate = 0), and generally no assortativity or disassortativity when social networks are not static (i.e. rewiring rate >0). Therefore, although prior work suggests a relationship between economic inequality and economic segregation in the real world (Reardon and Bischoff 2011), the implication from our findings, at least in our setting, is more circumscribed. In part, this may relate to the nature of our public goods game setting; when the social networks are static, dyadic wealth transfer from repetitive cooperators to repetitive defectors innately can result in wealth disassortativity. The impact of assortativity and disassortativity in social networks upon economic growth and inequality (DiMaggio and Garip 2012) is an important direction for future research.

While experimental social science offers substantial control and robust causal inference, laboratory experiments must often sacrifice verisimilitude and breadth. Such experiments can elucidate sufficient conditions for social phenomena more than necessary conditions. Put another way, there is a large design space for social experiments, including with respect to inequality, and, by necessity, we explore only

a part of this space. There are many other interesting features of social interactions that may affect wealth and inequality that our experiments do not explore. These include, for example: whether the resources at the beginning of the games were earnings or windfalls; the extent to which inequality might arise from positively zero-sum interactions, such that individuals producing public goods earn more than those who do not; the relevance of the payoff structure, group size, or network topology; the effect of requiring bilateral rather than unilateral decision-making regarding social ties; the effect of making wealth visible locally or globally within the groups; or the inclusion of peer sanctions or features that emulate large-scale social institutions (like taxation, courts, or policing).

Still, we report a novel effect of network fluidity on group-level wealth and inequality. Although the results of laboratory experiments do not translate directly into the real world, the evidence presented here suggests that mechanisms or social institutions that provide for intermediate levels of network fluidity may be optimal for the promotion of social welfare, at least as measured in this highly artificial environment. Previous studies suggested the roles of network fluidity in sustaining engagement (Shirado et al. 2013), group-level ability to promote smoking cessation (Cobb, Graham and Abrams 2010), group-level ability to bring innovation to workplaces (Jones, Wuchty and Uzzi 2008), and the sustained existence of groups (Palla, Barabási and Vicsek 2007). The present study adds a potential role of network fluidity to economic outcomes. And it suggests that social institutions that foster network fluidity, but that also constrain it from getting too extreme, may provide a suitable substrate for equitable growth.

References

Aghion, Philippe and Patrcik Bolton. 1997. "A Theory of Trickle-Down Growth and Development." *Review of Economic studies* 64(2):151-72. http://dx.doi.org/10.2307/2971707.

Alderson, Arthur S. and François Nielsen. 2002. "Globalization and the Great U-Turn: Income Inequality Trends in 16 Oecd Countries." *American Journal of Sociology* 107(5):1244-99. http://dx.doi.org/10.1086/341329.

Allison, Paul D. 1978. "Measures of Inequality." *American Sociological Review* 43(6):865-80. http://dx.doi.org/10.2307/2094626.

Baron, Reuben M. and David A. Kenny. 1986. "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic and Statistical Considerations." *Journal of Personality and Social Psychology* 51:1173-82. http://dx.doi.org/10.1037/0022-3514.51.6.1173.

Buhrmester, Michael, Tracy Kwang and Samuel D. Gosling. 2011. "Amazon's Mechanical Turk: A New Source of Inexpensive, yet High-Quality, Data?". *Perspectives on Psychological Science* 6(1):3-5. http://dx.doi.org/10.1177/1745691610393980.

Cairns, Robert B., Man-Chi Leung, Lisa Buchanan and Beverley D. Cairns. 1995. "Friendships and Social Networks in Childhood and Adolescence - Fluidity, Reliability, and Interrelations." *Child Development* 66(5):1330-45. http://dx.doi.org/10.1111/j.1467-8624.1995.tb00938.x.

Chiang, Yen-Sheng. 2015. "Good Samaritans in Networks: An Experiment on How Networks Influence Egalitarian Sharing and the Evolution of Inequality." *PLoS One* 10(6):e0128777. http://dx.doi.org/10.1371/journal.pone.0128777.

Cingano, Federico. 2014. "Trends in Income Inequality and Its Impact on Economic Growth." *OECD Social, Employment and Migration Working Papers, No. 163*. http://dx.doi.org/10.1787/5jxrjncwxv6j-en.

Cobb, Nathan K., Amanda L. Graham and David B. Abrams. 2010. "Social Network Structure of a Large Online Community for Smoking Cessation." *American Journal of Public Health* 100(7):1282-89. http://dx.doi.org/10.2105/AJPH.2009.165449.

Coleman, James S. 1988. "Social Capital in the Creation of Human-Capital." *American Journal of Sociology* 94:S95-S120. http://dx.doi.org/10.1086/228943.

DiMaggio, Paul and Filiz Garip. 2012. "Network Effects and Social Inequality." *Annual Review of Sociology* 38:93-118. http://dx.doi.org/10.1146/annurev.soc.012809.102545.

Du, Wen-Bo, Xian-Bin Cao and Mao-Bin Hu. 2009. "The Effect of Asymmetric Payoff Mechanism on Evolutionary Networked Prisoner's Dilemma Game." *Physica a-Statistical Mechanics and Its Applications* 388(24):5005-12. http://dx.doi.org/10.1016/j.physa.2009.08.026.

Eagle, Nathan, Michael Macy and Rob Claxton. 2010. "Network Diversity and Economic Development." *Science* 328(5981):1029-31. http://dx.doi.org/10.1126/science.1186605.

Fehl, Katrin, Daniel J. van der Post and Dirk Semmann. 2011. "Co-Evolution of Behaviour and Social Network Structure Promotes Human Cooperation." *Ecol Lett* 14(6):546-51. http://dx.doi.org/10.1111/j.1461-0248.2011.01615.x.

Fliessbach, Klaus, Bernd Weber, Peter. Trautner, Thomas Dohmen, Uwe Sunde, Christian E. Elger and Armin Falk. 2007. "Social Comparison Affects Reward-Related Brain Activity in the Human Ventral Striatum." *Science* 318(5854):1305-08. http://dx.doi.org/10.1126/science.1145876.

Fowler, James H., Christopher T. Dawes and Nicholas A. Christakis. 2009. "Model of Genetic Variation in Human Social Networks." *Proc Natl Acad Sci U S A* 106(6):1720-4. http://dx.doi.org/10.1073/pnas.0806746106.

Gilbert, Daniel. T., R. Brian Giesler and Kathryn A. Morris. 1995. "When Comparisons Arise." *Journal of Personality and Social Psychology* 69(2):227-36. http://dx.doi.org/10.1037/0022-3514.69.2.227.

Hamada, Hiroshi. 2003. "A Generative Model of Income Distribution: Formalization with Iterated Investment Game." *Journal of Mathematical Sociology* 27(4):279-99. http://dx.doi.org/10.1080/00222500390240939.

Jones, Benjamin F., Stefan Wuchty and Brian Uzzi. 2008. "Multi-University Research Teams: Shifting Impact, Geography, and Stratification in Science." *Science* 322(5905):1259-62. http://dx.doi.org/10.1126/science.1158357.

Moller, Stephanie, Arthur S. Alderson and François Nielsen. 2009. "Changing Patterns of Income Inequality in Us Counties, 1970-2000." *American Journal of Sociology* 114(4):1037-101. http://dx.doi.org/10.1086/595943.

Neckerman, Holly J. 1996. "The Stability of Social Groups in Childhood and Adolescence: The Role of Classroom Social Environment." *Social Development* 5:131-45. http://dx.doi.org/10.1111/j.1467-9507.1996.tb00076.x.

Newman, Mark E. J. 2002. "Assortative Mixing in Networks." *Physical Review Letters* 89(20). doi: 10.1103/PhysRevLett.89.208701. http://dx.doi.org/10.1103/PhysRevLett.89.208701.

Newman, Mark E. J. 2010. *Networks: An Introduction*. New York: Oxford Univesity Press. http://dx.doi.org/10.1093/acprof:oso/9780199206650.001.0001.

Nishi, Akihiro, Hirokazu Shirado, David G. Rand and Nicholas A. Christakis. 2015. "Inequality and Visibility of Wealth in Experimental Social Networks." *Nature*. http://dx.doi.org/10.1038/nature15392.

O'Malley, A. James and Nicholas A. Christakis. 2011. "Longitudinal Analysis of Large Social Networks: Estimating the Effect of Health Traits on Changes in Friendship Ties." *Statistics in Medicine* 30(9):950-64. http://dx.doi.org/10.1002/sim.4190.

O'Malley, A. James, Samuel Arbesman, Darby M. Steiger, James H. Fowler and Nicholas A. Christakis. 2012. "Egocentric Social Network Structure, Health, and Pro-Social Behaviors in a National Panel Study of Americans." *PLoS One* 7(5). http://dx.doi.org/10.1371/journal.pone.0036250.

OECD. 2014. "Income Distribution and Poverty - Country Table." http://stats.oecd.org/Index.aspx?DataSetCode=IDD..

Palla, Gergely, Albert-László Barabási and Tamás Vicsek. 2007. "Quantifying Social Group Evolution." *Nature* 446(7136):664-67. http://dx.doi.org/10.1038/nature05670.

Piketty, Thomas and Emmanuel Saez. 2014. "Inequality in the Long Run." *Science* 344(6186):838-43. http://dx.doi.org/10.1126/science.1251936.

Poulin, François and Alessandra Chan. 2010. "Friendship Stability and Change in Childhood and Adolescence." *Developmental Review* 30(3):257-72. http://dx.doi.org/10.1016/j.dr.2009.01.001.

Rand, David G., Anna Dreber, Tore Ellingsen, Drew Fudenberg and Martin A. Nowak. 2009. "Positive Interactions Promote Public Cooperation." *Science* 325(5945):1272-75. http://dx.doi.org/10.1126/science.1177418.

Rand, David G., Samuel Arbesman and Nicholas A. Christakis. 2011. "Dynamic Social Networks Promote Cooperation in Experiments with Humans." *Proc Natl Acad Sci U S A* 108(48):19193-8. http://dx.doi.org/10.1073/pnas.1108243108.

Rand, David G., Martin A. Nowak, James H. Fowler and Nicholas A. Christakis. 2014. "Static Network Structure Can Stabilize Human Cooperation." *Proc Natl Acad Sci U S A* 111(48):17093-98. http://dx.doi.org/10.1073/pnas.1400406111.

Ravallion, Martin. 2014. "Income Inequality in the Developing World." *Science* 344(6186):851-55. http://dx.doi.org/10.1126/science.1251875.

Rawls, John. 1971. *A Theory of Justice*. Cambridge, Mass.: Belknap Press of Harvard University Press.

Reardon, Sean F. and Kendra Bischoff. 2011. "Income Inequality and Income Segregation." *American Journal of Sociology* 116(4):1092-153. http://dx.doi.org/10.1086/657114.

Shenk, Mary K., Monique B. Mulder, Jan Beise, Gregory Clark, William Irons, Donna Leonetti, Bobbi S. Low, Samuel Bowles, Tom Hertz, Adrian Bell and Patrizio Piraino. 2010. "Intergenerational Wealth Transmission among Agriculturalists Foundations of Agrarian Inequality." *Current Anthropology* 51(1):65-83. http://dx.doi.org/10.1086/648658.

Shirado, Hirokazu, Feng Fu, James H. Fowler and Nicholas A. Christakis. 2013. "Quality Versus Quantity of Social Ties in Experimental Cooperative Networks." *Nat Commun* 4:2814. http://dx.doi.org/10.1038/ncomms3814. \smallskip

Smith, Eric. A., Kim Hill, Frank W. Marlowe, David Nolin, Polly Wiessner, Michael Gurven, Samuel Bowles, Monique B. Mulder, Tom Hertz and Adrian Bell. 2010. "Wealth Transmission and Inequality among Hunter-Gatherers." *Current Anthropology* 51(1):19-34. http://dx.doi.org/10.1086/648530.

Sowell, Thomas. 2012. *"Trickle Down" Theory and "Tax Cuts for the Rich"*. Stanford, CA: Hoover Institution Press.

Akihiro Nishi: Yale Institute for Network Science and Department of Sociology, Yale University.
E-mail: akihiro.nishi@yale.edu.
Hirokazu Shirado: Yale Institute for Network Science and Department of Sociology, Yale University.
E-mail: hirokazu.shirado@yale.edu.
Nicholas A. Christakis: Yale Institute for Network Science, Department of Sociology, Department of Ecology and Evolutionary Biology, and Department of Medicine, Yale University.
E-mail: nicholas.christakis@yale.edu.