The Development of Career Helping Behaviors

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A paper submitted in fulfillment of the senior thesis of
Major in Mathematical Methods in Social Sciences
in
Northwestern University

Abstract

This study investigates the development of career helping behaviors. First, the repeated game theory model of upstream reciprocity as a by-product of direct-reciprocity was identified in the context of the career helping system. Then, a realistic social network was set up to simulate the evolution of different strategies. Finally, data collected from Northwestern alumni provided ecological validity to the model. It concluded that career resource sharing was beneficial for both donators and recipients, and participants with more gratitude could thrive in the social network.
1. Introduction

It is very common for college students to reach out for career opportunities through networking resources, and to express willingness to help others in the future. The primary purpose of the study is to understand the development of helping behaviors in career networking in two steps.

First, I identified a game-theoretic model of the benign system in career networking, based on the work of Nowak and Roch (2007). Among all the various reasons people help others extend career opportunities, the paper investigated three main motivations: altruism, gratitude, and the potential of co-working. In the mathematical model, players in career networking had a set of strategies representing these motivations. The model derived the conclusion that the level of cooperation and the cost-benefit ratio together could determine which strategies thrive. Following the model, I ran a simulation of the game in a scale-free network generated by the Barabási-Albert (1999) algorithm to test each condition of the mathematical model described in the previous section. The distribution and degree graphs generated interesting patterns and did validate the model.

Second, I analyzed the data collected from 235 Northwestern alumni who graduated within the last 5 years. Intrinsic altruism, gratitude and social network centrality for each participant were measured based on standards. The potential giving back of each student they have helped was also gathered from the survey. The analysis showed the strong correlation between the upstream reciprocity and their popularity in the professional network, which further supported the theoretical model.
The integration of a mathematics model and social phenomena was perfectly presented in this topic of my interest. This study would be impossible without the guidance of Professor Marcia Grabowecky and the lead of Professor Jeff Ely for the MMSS program.

2. Theory

2.1. Literature Review

Reciprocity has long been recognized as an important constituent of human sociality that functions to lubricate social and economic exchange. The theory of reciprocal altruism was originally developed by Trivers (1971), as an attempt to explain cases of (apparent) altruism among unrelated organisms, including members of different species. Trivers' basic idea was straightforward: it may pay an organism to help another, if there is an expectation of the favor being returned in the future. (‘If you scratch my back, I'll scratch yours’.) The cost of helping is offset by the likelihood of the return benefit, permitting the behavior to evolve by natural selection. At the same time, reciprocity also takes many forms depending on the relationship between the beneficiary and the benefactor. When a person does another a favor and receives a benefit in return directly from the same person, it is called direct reciprocity (Axelrod, 1981).

Although the idea of cooperation in game theory usually involves direct reciprocity, Nowak and Sigmund (1997) presented a new theoretical framework based on indirect reciprocity and does not require the same two individuals ever to meet again. When the sender and the recipient of favors involve more than two parties, reciprocity goes beyond a dyad and involves a group or a network. This is referred to as indirect reciprocity (Nowak, 2006). Different theories have attempted to account for why indirect reciprocity can be sustained. Indirect reciprocity operating in this manner can be portrayed as a process whereby one helps another, who in turn

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helps yet a different person, forming a pay-it-forward cascade. In the biological literature, this kind of indirect reciprocity is also termed upstream reciprocity (Nowak, 2007) due to its potential to prompt the new/next beneficiary to reproduce this reciprocity repeatedly.

Boyd and Richerson (1989) is arguably the first study to discuss the upstream reciprocity with social network analysis. Their model considered a ring structure and showed that reciprocity (termed the upstream tit-for-tat in their paper) could emerge only when group size is small, and a special ring structure was under investigation. Nowak and Roch (2007) conceptually distinguished two forms of indirect reciprocity and derive the mathematical condition for upstream reciprocity behaviors to evolve. A major finding of their mathematical model showed that upstream reciprocity provides a beneficial condition for cooperation to evolve if combined with another mechanism such as direct reciprocity or spatial reciprocity (i.e., interaction between players on a one-dimensional lattice). A more recent simulation study (Iwagai & Masuda, 2010) extended the model to different networks beyond a ring, but only focused on strategies with two variables of binary values. And finally, Chiang and Takahashi (2011) manipulated the extent to which actors carry the same behavioral trait linked in networks, and the computer simulation model showed that strong network homophily further helped advance cooperation’s score.

In conclusion, evolutionary theories of reciprocal behaviors have developed, but none of the models fit perfectly with career helping interactions in realistic social networks. The focus of this study is to explore the model that best describes career networking, and to run the repeated game and update in computer simulations.

2.2. Population
To represent the strategies of players in career networking, the model has to include key motivations behind the situation. Each altruistic act involves a donor who offers to give career resources to the recipient. The career resources could be referring to a person who is in charge of hiring potential candidates or give support on a specific work task. If the donor chooses to help, the donor has a cost $c$, representing his or her time and effort during the act, and the recipient has an instant benefit $b$.

If a person has referred you when you were a college student anxiously looking for a job, you will feel grateful and may be inclined to give the same help to other students when you are in the company. These common phenomena are termed "upstream reciprocity" in evolutionary psychology. To represent the inherent differences in individuals, let $q$ be the likelihood that the player will initiate the helping chain without being a recipient before, and $p$ be the likelihood with which, after receiving help, the player will pass on the altruistic behavior the next round of the game.

The other factor people are considering in the real life is potential of the candidate to get through other interviews, and finally work at the same place. In this case, the recipient could directly improve the donor's working environment. In this case, let $r$ be the probability that the recipient will return to the job that could directly help the donor. Therefore, the recipient has $(1 - r)$ chance that passes the helping chain to other directions.

In conclusion, on the basis of a previous study (Nowak & Roch, 2007), I consider the game with a finite population of size $N$. Let $V$ be the set of $N$ players. For any $v \in V$, the strategy used by $v$ is denoted by $S_v(p_v, q_v, r_v)$. The dynamics are defined as follows. Each player initiates an independent random walk. Consider the walk started by the strategy used by $v$. At the
first step, the walk dies with probability \((1 - q_v)\). In particular, if \(q_v = 0\), player \(v\) never initiates a walk. Then a player is chosen uniformly at random in \(V - \{v\}\), say \(w\). The walk moves to \(w\) where one of three things can happen: 1) the walk dies with probability \((1 - p_w)(1 - q_w)\); 2) it is passed along to a uniformly random player in \(V - \{w\}\) with probability \(p_w(1 - q_w)\); or 3) it is passed back to \(v\) with probability \(r_w\). And so on. Every time the walk reaches a player, it brings a profit \(b\) to that player. Every time the walk exits a player (without dying), it costs \(c\) to that player (Figure 1).

![Diagram](image)

**Figure 1.** In a single chain of the game, a player initiates an independent random walk. Consider the walk started by the strategy used by \(v\). At the first step, the walk dies with probability \((1 - q_v)\). Then a player is chosen uniformly at random in \(V - \{v\}\), say \(w\). The walk moves to \(w\) where one of three directions can happen.

2.3. Random Walk

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Nowak and Roch put the game in the standard framework of evolutionary game dynamics and derived the payoff matrix by the Markov Chain Theory (Nowak & Roch, 2007).

Assume type 1 players, denoted \( V_1 \subseteq V \), use strategy \( S_1 = S(p_1, q_1, r_1) \) and comprises \( N_1 = xN \) players. Likewise, type 2 players, denoted \( V_2 \subseteq V \), use strategy \( S_2 = S(p_2, q_2, r_2) \) and comprises \( N_2 = (1 - x)N \) players. The payoff matrix is as follows:

\[
\begin{array}{ccc}
S_1 & S_2 \\
S_1 & \alpha_1 \beta_1 & \alpha_1 \beta_2 \\
S_2 & \alpha_2 \beta_1 & \alpha_2 \beta_2 \\
\end{array}
\]

, where \( \alpha_i = q_i / [(1 - r_i)(1 - p_i)] \) is the cooperativeness of strategy \( S_i \), and \( \beta_i = (br_i - c)(1 - r_i) \) is the responsiveness of strategy \( S_i \).

The results can be calculated from the evolutionary game dynamics between two strategies \( S_1 = S(p_1, q_1, r_1) \) and \( S_2 = S(p_2, q_2, r_2) \):

1. If both \( r_1 \) and \( r_2 \) exceed \( c/b \), then selection favors the strategy with higher cooperativity.
2. If \( r_1 > c/b > r_2 \) and \( \alpha_1 < \alpha_2 \), then there is stable equilibrium between the two strategies.
3. If \( r_1 > c/b > r_2 \) and \( \alpha_1 > \alpha_2 \), then both strategies are best replies to themselves.
4. If both \( r_1 \) and \( r_2 \) are less than \( c/b \), then selection favors the strategy with lower cooperativity.

From the simplified payoff function, we can see immediately that a strategy \( S(p, q, r) \), is evolutionarily stable against invasion by another strategy with lower cooperativity if \( r > c/b \). The probability to reflect the random walk to the donor, \( r \), has to exceed the cost-to-benefit ratio \( c/b \), of the altruistic act. In this case, direct reciprocity allows the evolution of cooperation,
and upstream reciprocity can hitch-hike on direct reciprocity. The interpretation of this finding is: if there is direct reciprocity in a population, then upstream reciprocity will evolve too.

2.4. Network

Although college students are new to the industry, we could also have valuable acquaintances that the donor may make use to expand professional reach. It is much easier for students to get help from alumni. The sense of community and community pride are essential in human evolution. In the computer simulation of the model, I took advantage of established the scale-free network instead of random walk from the previous study, because a fundamental characteristic of many social networks is that the number of contacts of a node, which we call the degree, has a right-skewed distribution. In particular, scale-free networks, i.e., networks with power-law degree distributions are widely found (Newman, 2003). In social networks relevant to evolutionary games, scale-free networks have been found in, for example, email social networks (Newman, Forrest, & Balthrop, 2002).

Consider a contact network with a population of $N = 8000$ players. As a model of heterogeneous network, we use the scale-free network generated by the Barabási–Albert (1999) algorithm (Figure 2). To generate the scale-free network, the graph was started with $2m + 1$ nodes (i.e., each pair of nodes is connected by an edge). Then, nodes with degree $m$ were added one-by-one according to the so-called linear preferential attachment; the probability that an already existing node $v_i$ forms an edge with a newly introduced node is proportional to the degree $k_i$. Multiple edges (i.e., more than one edge connecting a pair of nodes) are disallowed. In the generated network, the degree follows the power-law distribution $p(k) \propto k^{-3}$ with a lower
cutoff at $k = m$ and the mean degree of $<k> = 2m$ (Barabási & Albert, 1999). I used $<k> = 8$, i.e. $m = 4$.

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Figure 2. Barabási–Albert model is one of several proposed models that generate scale-free networks. It incorporates two important general concepts: growth and preferential attachment. Both growth and preferential attachment exist widely in real networks. In the generated network, the degree follows the power-law distribution $p(k) \propto k^3$ with a lower cutoff at $k = m$ and the mean degree of $<k> = 2m$ (Barabási & Albert, 1999).

2.5. Payoff

Every time the walk reaches a player, it brings a profit $b$ to that player. Every time the walk exits a player (without dying), it costs $c$ to that player. Notably, $b > c > 0$ is assumed so that the game represents a social dilemma: a single act of help increases the average payoff of the entire population by $(b - c)/N$, while each player is better off by not helping other players. Without loss of generality, I set $c = 1$ and $b = 2$. Therefore $b/c = 0.5$.

A single chain is initiated by each player, which could extinct immediately or last for long time. Note that a chain is considered to be empty if the initial player does not help a neighbor. The one-round payoff of player $v_i$ is defined as the sum of the payoffs gained by $v_i$ in $N$ chains of cooperation. The payoff that $v_i$ gains in around is equal to $b \times$
The frequency at which the chains are brought to \( v_i \) 

The frequency at which the chains are passed from \( v_i \) without being terminated. A chain of cooperation may traverse the same players more than once.

### 2.6. Update Rule

The simulation principally uses the deterministic update rule, which is described in the following. The numerical results do not qualitatively change on using relatively realistic stochastic rules. I refer to time in the evolutionary dynamics as around and denote it by \( t (= 0, 1, 2, \ldots) \). One round consists of \( N \) chains of helping behavior. At the end of each round, the strategies of \( N_u \) out of \( N = 8000 \) players are updated synchronously. I set \( N_u = \frac{N}{50} = 160 \). \( N_u \) players were randomly and independently selected from the population with equal probability. In the deterministic update rule, each selected player \( v_i \) examines the strategy of the neighbor with the largest payoff, denoted by \( v_j \). If the payoff of \( v_j \) is larger than that of \( v_i \), \( v_i \) will copy the strategy of \( v_j \). If there are more than one neighbors with the same largest payoff, I select one of them uniformly by the reservoir sampling algorithm. After tentatively determining \( N_u \) copying events, the code replaces the strategies of the selected nodes simultaneously. Mutation was not assumed. This marks the end of one round. Specifically, I set the number of rounds to 400, at which point the divergence of different groups are pretty obvious in each situation. See the complete algorithm in Python 2.7 in Appendix A.

### 2.7. Results

To verify each condition of conclusion derived from the model, the simulation considered four levels of probability were tested: 0, .3, .6, and .9 to satisfy the relation between the
likelihood of giving help and the cost-benefit ratio. Two groups have an even split between the population in the beginning, i.e. each has a size of 4 000.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_1, r_2 &gt; c/b$ and $\alpha_1 &gt; \alpha_2$</td>
<td>$S_1$ dominates</td>
</tr>
<tr>
<td>$r_1, r_2 &gt; c/b$ and $\alpha_1 &lt; \alpha_2$</td>
<td>$S_2$ dominates</td>
</tr>
<tr>
<td>$r_1 &gt; c/b &gt; r_2$ and $\alpha_1 &gt; \alpha_2$</td>
<td>Shares are fairly stable</td>
</tr>
<tr>
<td>$r_1 &gt; c/b &gt; r_2$ and $\alpha_1 &lt; \alpha_2$</td>
<td>Slow and inconsistent.</td>
</tr>
<tr>
<td>$r_1, r_2 &lt; c/b$ and $\alpha_1 &gt; \alpha_2$</td>
<td>$S_2$ dominates</td>
</tr>
<tr>
<td>$r_1, r_2 &lt; c/b$ and $\alpha_1 &lt; \alpha_2$</td>
<td>$S_1$ dominates</td>
</tr>
</tbody>
</table>

Table 1. Game of players in pair. Strategy values, conditions, and results are shown.

Domination of one group of players over the other is determined by both the distribution of two groups as well as the average degree (number of neighbors) in the network. Higher degree in the network means the player has more resources and opportunities. The graphs of average degree and group size on the change of round are shown in Figure 3 and 4. The average degree of a player always starts around 8, and the group size always starts at 4 000.
Figure 3. The simulation of condition A, B, and C. The letters p, q, r in the legend of the distribution graph mean the higher value of the strategy, while the letter o means lower value. Interestingly, the condition C shows a fairly comparable share of degrees and their distribution does not monotonically increase or decrease since the beginning.
Figure 3. The simulation of condition D, E, and F. The distribution change of condition D shows a linear pattern instead of a curvy change. At the same time, the simulation for D takes way longer than other setup, and different runs generate inconsistent result.
2.8. Discussions

The simulation with the deterministic update rule supported the theory in random walks discussed in Section 2.1 to 2.3. Without the loss of generality, I set cost-benefit ratio to .5, and adjust the values of $p, q, r$ lower, higher than the ratio. The results were measured through the patterns of distributions and average degrees of each strategy profiles. For theoretical conditions that have clear dominance of one group over the other, the simulation results were pretty consistent, even if the values change a little bit. However, the conditions of stable competition and best replies to themselves had a couple of inconsistency after several trials.

Overall the theoretical model shows that, the upstream reciprocity behaviors in career networking could be evolutionary adaptive, when direct reciprocity exists above a certain threshold. It suggested that, in the real world, the ubiquity and popularity of the career helping behaviors are heavily based on both altruistic motivations and players’ potential to give back.

3. Survey

Based on the mathematical model that the evolution of career helping behaviors is largely a combined effect of spontaneous helping, upstream helping and direct helping, I investigated these factors in real life based on a survey of 235 Northwestern alumni who graduated within the last five years. The data showed that there was a mild association between altruism score and gratitude score of the same person, and that the willingness to help was not significantly explained by altruism, gratitude and student talent in regression. However, the long-term social network in-degree centrality was significantly predicted by out-degree centrality and the score of gratitude. It indicates that the more actively a person give help and the more grateful he or she

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feels, the more opportunities the individual could reach in the social network, which supports the 
theory of upstream reciprocity. This study could apply to maintenance of mentorship programs in 
professional or academic institutions.

3.1. Literature Review

The motivations behind people's generosity have long been studied by psychologists. 
Researchers have defined gratitude as a type of positive emotion that is typically experienced 
when an individual perceives another person's generosity toward that individual (McCullough, 
Kilpatrick, Emmons, & Larson, 2001). However, the gratitude is usually not expressed by direct 
reciprocity. Empirical evidence has suggested the emotion of gratitude also increases the 
likelihood that the recipient will assist an unrelated third party in the future (Bartlett & DeSteno, 
2006). Thus, chains of altruistic behaviors facilitate the social connections of people.

The benefit of the chain of generosity is most obvious for college students when it is 
linked to tangible career resources. Students have been advised and educated to actively engage 
in career networking, including activities such as joining professional associations, attending 
alumni networking events, and maintaining relationships with potential career assistance. 
Although the association between networking behaviors and both objective and perceived career 
outcomes has been well established (Forret & Dougherty, 2004), the motivations of those 
“opportunity givers” have not been comprehensively studied in social psychology.

The purpose of the current study was to explore the motivations behind college alumni 
who intentionally provide career resources to college students, at a cost of their own, and have no 
immediate benefits. Participants were recruited among the Northwestern alumni who graduated 
within the last five years. I hypothesized that the behavior to expand career opportunities was
associated with the altruism, gratitude, and the talent of the candidates, and high cooperativity puts the individual in an advantageous position in the social network.

3.2. Method

3.2.1. Participants

The survey was limited to Northwestern alumni whose contact information was recorded in the Our Northwestern community directory. The invitations were sent to people who graduated in recently years and belonged to one of the six schools available for undergraduates in Northwestern University: Weinberg College of Arts and Sciences, School of Communications, School of Education & Social Policy, McCormick School of Engineering & Applied Sciences, Medill School of Journalism, and Bienen School of Music. Participants could be currently in academic institutions, any industry, and any location in the world. Since the condition of year graduation was controlled, most participants who recently graduated kept their previous email address available. More importantly, they were not very likely to be in an executive position in the company and to hire a new person solely for his or her own profits.

The survey was administrated through Qualtrics, an online survey platform, and participants accessed the survey through an anonymized link. Responses in analysis were collected from February 12th, 2018 to February 22th, 2018. Three waves of the survey were administrated to different candidates, and after each iteration, minor clarifications were made, and a few typos were fixed. None of the participants were compensated. A total of 344 people participated in the survey, and after eliminating incomplete entries, the valid sample of the survey had a size of 235 with 147 females, 85 males, and 3 other gender identities.

3.2.2. Materials
The survey with the claimed purpose of "potential factors in student and alumni interactions" was composed of four main sections. In the first section, participants were asked to provide their interactions of getting and giving help, and their level of activeness in expanding network relationships. Due to the limited time they had been out of college, they still had a fresh memory of college life and connections acquired in college. The survey asked them to estimate the number of people giving them help while they were in college, as well as the number of students they have helped. For each student that they had helped (up until 20 loops), I collected the best option that described their relationship (such as being friends, from the same fraternity etc.), and the potential of giving back from the student. The second item was meant to evaluate the talent of the student, in terms of four tiers (see full descriptions in Appendix B). At the end of the quantitative items, participants could choose to answer an open question of the motivations behind helping students.

The second page was The Self Report Altruism Scale or SRAS (Rushton, Chrisjohn, & Fekken, 1981). SRAS is a 20-item scale designed to measure altruistic tendency by gauging the frequency one engages in altruistic acts primarily toward strangers. Participants answer on a 5-point scale ranging from Never (1) to Always (5). It was designed to measure the intrinsic altruism of the subject toward unfamiliar people. When I asked a friend to review the questions, he pointed out that the frequency of meeting these situations would vary a lot among people. Hence, I added a "when presented with the opportunity" as a condition for the situations, i.e. "how often do you do these things" became "When presented with the opportunity, how often do you do these things".

Following the 20-question matrix, the Gratitude Questionnaire-Six-Item Form (GQ-6) was presented in the third page. GQ-6 was a six-item self-report questionnaire designed to assess
individual differences in the proneness to experience gratitude in daily life. Respondents endorse each item on a seven-point Likert-type scale (where 1 = strongly disagree and 7 = strongly agree).

Finally, the last page was the demographics questions such as the gender, graduation year, and the school attended. The full survey is included in Appendix B.

3.3. Results

3.3.1. Motivation Free Responses

Other than the assessment of participant traits, I perused the answers to the free questions for their motivation behind helping students. Although these responses were not included in any of the following statistical analysis, they reflected the perceived motivations of people in real life and inspired me to interpret the overall results better. Eighty-three participants filled in the answer, and unsurprisingly, there was much overlap between the answers. They could be divided into four categories. The most common category (43.4% of answers) was "altruism" or "I want to help", followed by the other factor as I hypothesized, gratitude (21.3%), whose answers were typically like "paying it forward" or "when I was a student, I really appreciated people speaking with me". The third frequent category was the quality or the talent of the student (18.1%), which was described as "he was good fit for my company" or "she was passionate and could handle our work". The fourth answer category, however, was unexpected. These participants expressed their empathy to student in the rest (13.3%). They complained that they struggled a lot before and did not want to make younger generations to suffer from the same stress. Some examples were "I was riding same boat and realized any help would be really great". They focused more on the suffering of difficulty instead of appreciating getting through the difficulty, so it could not be
attributed to gratitude. However, empathy-concern is a form of altruism based on feelings for others. Results of the over 30 experiments have led to the tentative conclusion that feeling empathic concern for a person in need does indeed evoke altruistic motivation to see that need relieved (Batson, Ahmad, & Lishner, 2009), so it is considered an essential ingredient of putting altruistic feelings into actions.

3.3.2. Altruism Assessment

Despite the length of 20 questions in the Altruism Assessment, 228 participants completed every item and the total score was the simple sum (α = .87). Each item was encoded from 1 Never to 5 Always, so the possible score range is 5-100. The shape of Altruism score displayed a normal (bell-shaped) curve, ranging from the lowest 26 to highest 91 (M = 58.35, SD = 13.33) as shown in Figure 5.
3.3.3. Gratitude Assessment

Among the six questions, the third and sixth questions were encoded reversely, to prevent participants from inattentive or acquiescent answering, but no response was detected to have clear bystander effect, so none was excluded for analysis. I added these six statements to create a summed score with possible range of 6-42 ($\alpha = .78$), and there were 234 valid participants completing the Gratitude Assessment. The results showed a negatively skewed shape ranging from 20 to 42 ($M = 36.42, SD = 4.46$).

**Figure 5.** The sum scores of Altruism Assessment displayed a normal distribution.
The sum scores of Gratitude Questionnaire displayed a positively-skewed distribution.

The correlations between the scores of gratitude and altruism were calculated by the two-tailed Pearson Correlation. The data showed a moderate positive association, $r(228) = .31$, $p < .01$. It was interesting to see the mild correlation between altruism and gratitude even if it is not part of the hypothesis. A closer examination of two standard scales shows that the Altruism Assessment focuses more on the behavior, while the Gratitude Questionnaire is based on people's belief and attitudes. It makes sense because altruism is more like an attribute or trait of personality, while gratitude is a cognition that humans develop throughout time. This difference in the question setup might also influence the relevance of results to later interaction questions.
Figure 7. From the scatterplot of scores between gratitude and altruism, the data did not contain much noise, and there was a mild correlation between the gratitude score and the altruism score.

3.3.4. Interaction of Altruism and Gratitude on Help-Givings

To analyze the factors affecting the number of mentoring relationships, I only selected people who graduated within the last five years, aka alumni of class year 2013 to 2017, resulting in 228 answers. The number of help-givings was collected based on participants’ self-report recall. Given that they have not graduated for long, this information should be reliable.

Subjects were divided to low (lower than or equal to the median 58) and high (higher than 58) altruism level. On the other hand, scores rendered by GQ-6 already has standard
encoding for low and high gratitude groups. A total point between 6 and 35 corresponds to a low gratitude level, and a total point higher than or equal to 36 indicates a high gratitude level.

The number of help-givings were subjected to a two-way analysis of variance having two levels of altruism and two levels of gratitude. All effects were not statistically significant at the .05 significance level. The main effect of altruism yielded an F ratio of $F(1, 217) = .43, p = .51$, indicating that the mean number of helping did not have a significant difference between low levels of altruism ($M = 2.10, SD = 3.52$) and high ones ($M = 2.51, SD = 3.57$). The main effect of the gratitude level yielded an F ratio of $F(1, 217) = 1.43, p = .23$, indicating that the mean number of helping did not have a significant difference between the low-gratitude participants ($M = 1.80, SD = 2.49$) and the high-gratitude ones ($M = 2.53, SD = 3.93$). The interaction effect was also non-significant, $F(1, 217) = .07, p = .80$.

Due to the large volume of participation, the variation of data was too large to show a focused association. However, the graphs of interactions showed interesting dynamics of their effects on the means of helping frequencies. In both graphs, higher gratitude levels and higher altruism levels had positive effects on the number of help-givings. To take a closer look, the slopes of the second graph, which represented the effect of gratitude when the altruism level was fixed, were steeper than the slopes of the first graph, which represented the effect of altruism when the gratitude was fixed. This difference implied that, while not considering the talents of help recipients, the learned attitude (gratitude) has a larger effect than the intrinsic trait (altruism) for sharing career opportunities.
Figure 8. The graph of estimated marginal means of giving help showed that, the learned attitude (gratitude) has a larger effect on the intrinsic trait (altruism) for sharing career opportunities.

3.3.5. Student Talent on Alumnus-Student Interactions
The tricky part of analyzing the effects of talents is that the unit of comparison should be a single interaction of help ($N = 515$), instead of the profile of a single subject. In the survey, I asked each participant to give details for each help they have given to the student. Specifically, they had to choose the options that best described their relationship with the students, and the direct career resources they expected students to give back in the future. There was not a clear way to quantify the closeness of two persons, or the expected gains from the student, but four options served as a graded measurement. Specifically, from the closest to the farthest, relations were categorized into Kinship, Friendship, Program Relation, and No Relation. Notably, because I restricted the scope of the entire study to people currently in or graduated from Northwestern University, each interaction was at least based on the connection of the same college. There were also four categories describing the potential of giving back career resources: Same Company, Same Industry, Other Industry, and No Potential at all.

Based on my hypothesis, if the help donor and the help recipient were very close, for example, they were related, then the alumnus would very likely help the student without considering much about the future giving-back of the student. On the other hand, if the alumnus interacted with a non-familiar student, he could be prompted to share career resources if the student had good potential for entering his own company, and thus increase the likelihood of getting direct benefits. In observed reality, alumni who are willing to help usually do not think too much about getting the help back, supported by participants’ free responses (a few people mentioned “karma” as their main motivations, but this was beyond the scope of my study).

The cross tabulation of relation and talent of each alumni-students interaction (Table 1) showed that no matter what the relationship is, most students were not expected to give any help back at all, 42.9% for Kinship, 33.0% for Friendship, 41.7% for Program Relation, and 66.3%
for No Relation. Cognitive bias could partially explain the phenomenon, because people in general show more criticism to strangers than do so to oneself or close friends. The second most frequent choice of talent was Same Industry for Friendship (30.9%), Program Relation (32.3%) and No Relation (14.3%), but Other Industry for Kinship (28.6%). This data supported the hypothesis that closer relationship would require less recipient potential, while the Pearson Chi-Square Tests showed statistical significance, \( \chi^2(9, N = 515) = 50.93, p < .01, \varphi = .31 \).

### Table 2.

The cross tabulation between relation and talent in each alumnus-student interaction showed that most people considered their help recipients to no connection and did not expect any benefit return in the future. Most responses were squeezed in the situation of “useless strangers”.

#### 3.3.6. Multivariable Linear Regression for Willingness to Help

As described above, there was no control group to show the factors of chances that alumni refused to help students, so the relationship between the donor and the recipient was used
to the measurement of willingness to help. Previous evidence has shown that, across a variety of scenarios, people tend to be more helpful to members of their own group rather than to those of other groups (Tajfel & Billig, 1974). The closer two persons are, the donor is more likely to help the recipient out of in-group favoritism. On the other hand, the reasons that the donor helps an unfamiliar recipient should be attributed to the factors that this study was interested in. Therefore, the dependent variable – relation – indicated the overall motivations for the sake of helping.

I hypothesized that a higher talent, a higher altruism score and a higher gratitude score would all be positively associated with higher willingness to help. However, these three variables only explained 3% of the relation score, $F(3, 503) = 5.62, p = .001, R^2 = .03$. Although all these three factors together had a positive association with the dependent variable, neither the altruism score ($\beta = -.01, p = .21$) nor the gratitude score ($\beta = .01, p = .45$) had a significant coefficient explaining the dependent variable. Contrary to the hypothesis, talent of the student actually had a slight but significant negative association with willingness to help, $\beta = -.105, p = .002$ (see Table 2 for detailed regression statistics).
Table 3. Regression of willingness to help explained by altruism score, gratitude score, and student talent. Talent was a significant negative predictor on the willingness to help, while altruism and gratitude did not play significant roles at all.

These results could be due to a few reasons. First, the measurement of dependent variable did not accurately capture the willingness to help. Ideally, the dependent variable should be the presence of help as 1 and the absence of help as 0 across all alumni-students interactions. However, it was not collected in survey because most people hardly remember the rejected (or simply dismissed) help requests. Participants who reported more than 10 help-givings could even hardly remember the details of these past interactions. Additionally, the measurement of the student talent was more a categorical classification rather than an incremental quantification. The options could be interpreted as double barreled, because a student could both be a “stranger” and
“from the same academic program”. These two options were indeed the most frequent among all responses. There was a similar situation for the measurement of relation, as a talented student could be both “potentially enter into my industry” and “have no career resource for me in the future”, which were also the top two choices.

Second, as another effect of weak measurement, most responses were squeezed together at a specific combination: “useless strangers”. I used the term to describe the situation that participants helped students with no prior encounter and no indication of direct giving-backs. This part of the survey did not generate enough between-groups differences, and thus the ceiling effect led to the negative association between talent and willingness to help (1 for being useless, and 4 for being strangers). To improve the design, the student talent could possibly be measured better a seven-point Likert-scale asking how useful the student would be in the future, and the another seven-point Likert-scale describing the closeness between the two parties, although this scaling could be affected by the variations of subjective perceptions. Manipulation checks and pilot distribution could also help increasing the discernibility of the measurement.

Third, an alternative reasoning could explain phenomenon of less talented people getting more help. When an alumnus has only limited time or a limited time of reference, but a lot of students asking for help, he could give the opportunity for the candidate who could get a lot benefit from a single lift from the alumnus. Additionally, if a candidate is apparently over-qualified, then not much attention could even be paid to this requested help. Therefore, less talented students getting help would actually produce more gratitude and establish stronger long-term bond.

Finally, the multivariable linear regression did not take care of many factors influencing the prosocial behavior, such as social economic status (Guinote, Cotzia, Sandhu, & Siwa, 2015),
moral norms (Linden, 2011) and religions (Galen, 2012). It led to much noise that interfered with the attribution of factors that this study was interested in.

3.3.7. Evolutionary View of Social Network

Social network analysis was also in the hypothesis of the study. In particular, centrality of a person’s positive is usually and most simply defined as two separate measures of degree centrality, namely in-degree and out-degree. Accordingly, in-degree is a count of the number of ties directed to the node and out-degree is the number of ties that the node directs to others. When ties are associated to some positive aspects such as friendship or collaboration, in-degree is often interpreted as a form of popularity, and out-degree as gregariousness (Wasserman & Faust, 1994). In this case, in-degree was measured by a five-point scale (where 1 = far below average, and 5 = far above average) for the level of activity in expanding one’s own career network, while the out-degree was measured by another five-point scale (where 1 = far below average, and 5 = far above average) for the level of activity in attending mentorship programs or alumni panels.

Three stable factors of the donators, a high altruism level, a high gratitude level and a high engagement in information sharing would enhance the opportunities of getting more career resources in my hypothesis. A multiple linear regression was calculated to predict in-degree centrality based on altruism, gratitude, and out-degree centrality. A significant regression equation was found for their overall effect \( F(3, 224) = 28.47, p < .001 \), with an \( R^2 \) of .21. Participant’s predicted in-degree centrality in social network is equal to 

\[
-0.253 + 0.468 (\text{OUTDEGREE}) + 0.003 (\text{ASUM}) + 0.050 (\text{GSUM})
\]

where ASum and GSum were encoded as the total scores of altruisms assessment and gratitude questionnaire respectively. In-degree centrality increased .468 for each unit of out-degree centrality \( (p < .001) \), and .050 for
each score of gratitude ($p < .001$) significantly, while the effect of altruism score ($p = .51$) was not significant (Table 4).

### Table 4

#### ANOVA

<table>
<thead>
<tr>
<th>Model</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Regression</td>
<td>64.012</td>
<td>3</td>
<td>21.337</td>
<td>28.473</td>
<td>.000b</td>
</tr>
<tr>
<td>Residual</td>
<td>167.865</td>
<td>224</td>
<td>.749</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>231.877</td>
<td>227</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. Dependent Variable: Indegree
b. Predictors: (Constant), GSum, Outdegree, ASum

#### Coefficients

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Constant)</td>
<td>-.253</td>
<td>-.523</td>
<td>.602</td>
<td></td>
</tr>
<tr>
<td>Outdegree</td>
<td>.468</td>
<td>.430</td>
<td>7.447</td>
<td>.000</td>
</tr>
<tr>
<td>ASum</td>
<td>.003</td>
<td>.039</td>
<td>.653</td>
<td>.514</td>
</tr>
<tr>
<td>GSum</td>
<td>.050</td>
<td>.223</td>
<td>3.702</td>
<td>.000</td>
</tr>
</tbody>
</table>

a. Dependent Variable: Indegree

Table 4. Regression analysis for variables predicting in-degree centrality. Both the out-degree centrality and the gratitude scores were significant positive predictors for the in-degree centrality in this model. It suggested that more actively a person engages in giving help and feels grateful, the more likely he or she will expand network resources.

Again, this regression did not adjust for all potential factors involved for social network in-degree centrality, but given the similarity of age, background and experience among participants, the results have fair validity. As a caveat of no-reward participation in general, subjected who completed responses are usually more altruistic than people who did not click the link or finish all items. The over-representation of altruistic population could explain the insignificance of the altruism score as a predictor variable.

### 3.4. Discussion
The results of the current study provide realistic evidence of the mathematical model of career helping behaviors. Based on the responses collected from 235 Northwestern alumni, the phenomenon of upstream reciprocity is strongly grounded in reality, because the gratitude and the activeness of mentoring were significant predictors for the in-degree centrality in the social network. While spontaneous altruism was not directly affecting sharing career resources, it was mildly associated with the sense of gratitude of the same person, and many participants did explicitly perceive their motivation as altruism or empathy-concern. On the contrary, the student talent, reflecting the potential of giving back, turned out to be a slight negative predictor for willingness to help. This analysis did not align perfectly with the mathematical model because all data were compared within all the fulfilled help requests, but it backed up the theory that direct reciprocity plays a fairly complicated role in the evolution of cooperation in social dynamics.

To further examine the factors accounting for the career helping chain in real life, a better measurement of willingness to help could substantially improve its construct reliability. Also, the current study did not investigate helping experiences out of a single private elite college. A more generalized research could be done to take care of other relevant factors to see the effects in a broader context.

Career networking does make lots of opportunities accessible for students, but it could also be frustrating due to intangible benefits. This study showed that, while individual alumnus has a variety of motivations perceived by him or herself, this benign system as a whole is formed closely with participants’ altruism, feeling of gratitude, as well as the potential of giving back. When a mentee is seeking professional help from someone without previous connections, he or she could still contribute to the helping practice by expression gratitude in the future.
4 Conclusion

This study investigates the development of career helping behaviors. To do so, I first explored the mathematical models of altruistic reciprocity, and identified important ingredients of alumni-students interactions within the model. Then I utilized the social network graph setup to observe the evolutionary change via computer simulation. And finally, I utilized the Northwestern alumni database to collect data on their motivations behind career resources sharing and their current network expansion. The repeated game theory model suggested that potential of giving back from students actually enhances the cooperativity of alumni in long-term. At the same time, altruistic and grateful individuals get more professional opportunities, and thus the positive feedback loop continues to grow a career helping chain. The real-life data largely supported the effects of upstream reciprocity, but the donators’ expectation for their recipients were usually pretty low, so it did not play a significant role in donators’ motivations.

Albeit imperfect, the findings of this study have implications for everyone seeking professional opportunities. It may be crucial for students or mentees to maximize their values to the target that they were requesting. And for the alumni or mentors having trouble expanding their current network, it may be advisable for them to offer help for students who did not seem to provide immediate benefits. They could approach the pro-social manners by gratitude, empathy or considering the talent of candidates. This study is illuminating in that career helping behaviors activity are relatively inexpensive to execute but broadly beneficial, so they should be encouraged, for not only inner wellbeing, but also tangible welfares.
5 References


*May 31st, 2018*
The Gratitude Resentment and Appreciation Test (GRAT) (Revised GRAT and Short Form GRAT). (n.d.). doi:10.13072/midss.100

import networkx as nx
import matplotlib.pyplot as plt
import numpy as np
from random import *

class Network:
    """The object of the social network""
    def __init__(self, n, m):
        self.b = 2
        self.c = 1
        self.n = n
        self.m = m
        self.g = nx.barabasi_albert_graph(n, m)
        self.distribution_graph_title = 'Distribution Graph'
        self.degree_graph_title = 'Degree Graph'

def populate_eight_strategies(self):
    """even distribution of strategies""
    for i in range(0, self.n, 8):
        self.g.add_node(i, p=self.l, q=self.l, r=self.l)
        self.g.add_node(i+1, p=self.l, q=self.l, r=self.l)
        self.g.add_node(i+2, p=self.l, q=self.l, r=self.l)
        self.g.add_node(i+3, p=self.l, q=self.l, r=self.l)
        self.g.add_node(i+4, p=self.l, q=self.l, r=self.l)
        self.g.add_node(i+5, p=self.l, q=self.l, r=self.l)
        self.g.add_node(i+6, p=self.l, q=self.l, r=self.l)
        self.g.add_node(i+7, p=self.l, q=self.l, r=self.l)

def populate_two_strategies(self, pl, ql, rl, p2, q2, r2):
    self.compete_str = str(pl) + '+str(ql) + '+str(rl) + '+str(p2) + '+str(q2) + '+str(r2)
    print self.compete_str
    for i in range(0, self.n, 2):
        self.g.add_node(i, p=pl, q=ql, r=rl)
        self.g.add_node(i+1, p=p2, q=q2, r=r2)

def get_next_node_index(self, curr_node_index, prev_node_index = None):
    """A single helping behavior""
    donor = self.g.nodes[curr_node_index]
    recipient_index = None
    if chance(donor['r']):
        recipient_index = prev_node_index
    elif chance(donor['p']):
        sample_nbr = sample(self.g[curr_node_index], 2)
        if (sample_nbr[0] == prev_node_index):
            recipient_index = sample_nbr[1]
        else:
            recipient_index = sample_nbr[0]
    return None

    if recipient_index == None:
        old_donors_payoff = donor['payoff']
        self.g.add_node(curr_node_index, payoff=old_donors_payoff-self.c)
        recipient = self.g.nodes[recipient_index]
        old_recipient_payoff = recipient['payoff']
        self.g.add_node(recipient_index, payoff=old_recipient_payoff+self.b)
        return recipient_index

def get_chain(self, initiator_index):
    sequence = [initiator_index]
    prev_node_index = None
    curr_node_index = initiator_index
    while (curr_node_index != None):
        next_node_index = self.get_next_node_index(curr_node_index, prev_node_index)
        prev_node_index = curr_node_index
        curr_node_index = next_node_index
def get_round(self):
    """One round consisted of n chains of helping, and one chain is initiated by each player""
    self.clear_payoff()
    for i in range(self.n):
        self.get_chain(i)
    self.get_round_update()

def get_round_update(self):
    """After each round, deterministic update runs ""
    update_num = self.n/50
    update_node_indices = sample(range(self.n), update_num)
    update_profiles = dict()
    # for each updating node v, v copies the strategy profile with the neighbor of max payoff
    for update_node_index in update_node_indices:
        update_node = self.g.nodes[update_node_index]
        max_payoff = update_node['payoff']
        max_payoff_node_index = update_node_index
        reservoir_sample_index = 1
        for nbr in self.g[update_node_index]:
            nbr_payoff = self.g.nodes[nbr]['payoff']
            if (nbr_payoff > max_payoff):
                max_payoff = nbr_payoff
                max_payoff_node_index = nbr
                reservoir_sample_index += 1
                max_payoff_node_index = reservoir_sampling(max_payoff_node_index, nbr, reservoir_sample_index)
        best_nbr = self.g.nodes[max_payoff_node_index]
        best_profile = (best_nbr['p'], best_nbr['q'], best_nbr['r'])
        update_profiles[update_node_index] = best_profile
    for update_node_index in update_node_indices:
        update_profile = update_profiles[update_node_index]
        self.g.add_node(update_node_index, p=update_profile[0], q=update_profile[1], r=update_profile[2])

def clear_payoff(self):
    for i in range(self.n):
        self.g.add_node(i, payoff=0)

def get_strategy_distribution(self):
    stra_counts = [0, 0, 0, 0, 0, 0, 0]
    for i in range(self.n):
        node = self.g.nodes[i]
        stra_index = strat_to_index(node['p'], node['q'], node['r'], self.lv)
        stra_counts[stra_index] += 1
    return stra_counts

def draw_degree_graph(self, rounds, stra_index1, stra_index2):

    round_list = list()
    avg_degrees1 = list()
    avg_degrees2 = list()

    for i in range(rounds):
        """calculate degree and count before update ""
        count1 = 0
        degree1 = 0
        payoff1 = 0
        count2 = 0
        degree2 = 0
        payoff2 = 0

        for j in range(self.n):
            node = self.g.nodes[j]
            stra_index = strat_to_index(node['p'], node['q'], node['r'], self.lv)
            if stra_index == stra_index1:
                count1 = count1 + 1
                degree1 = degree1 + len(self.g[j])
            else:
                count2 = count2 + 1
                degree2 = degree2 + len(self.g[j])
degree2 = degree2 + len(self.g[1])

round_list.append(i)
avg_degrees1.append((1.0*degree1)/count1)
avg_degrees2.append((1.0*degree2)/count2)

self.get_round()

line1, = plt.plot(round_list, avg_degrees1, label=str(a_index1))
line1.set_label(index_to_strat(str(a_index1)))

line2, = plt.plot(round_list, avg_degrees2, label=str(a_index2))
line2.set_label(index_to_strat(str(a_index2)))

plt.xlabel('Rounds')
plt.ylabel('Degree')
plt.legend()
plt.title("Degree Graph "+self.compete_str)
plt.savefig('Temp'+str(self hv)+" +str(self lv)+str(a_index1)+ vs '+str(a_index2)+'.png')
plt.show()

def draw_distribution_graph(self, rounds):
    rounds_of_dis = list()
    for i in range(rounds):
        self.get_round()
        rounds_of_dis.append(self.get_strategy_distribution())

    # Draw the plot between Round Count and Distribution of Strategies
    for stra_index in range(8):
        X = [0]
        Y = [self.n/8]
        for i in range(rounds):
            X.append(i+1)
            Y.append(rounds_of_dis[i][stra_index])

        #print X
        line, = plt.plot(X, Y, label=stra_index)
        line.set_label(index_to_strat(str(a_index)))
        plt.xlabel('Distribution')
        plt.ylabel('Round Count')
        plt.legend()
        plt.title("Distribution Graph "+self.compete_str)
        #plt.savefig(str(self b)+" +str(self hv)+" +str(self lv)+'.png')
        plt.show()

    def change(prob):
        return random() < prob

    def reservoir_sampling(curr_selected, new_arrival, resevoir_sample_index):
        if (random() < 1/resevoir_sample_index):
            return new_arrival
        return curr_selected

    def index_to_strat(ind):
        return strategy_dict[ind]

    def strat_to_index(p, q, r, lv):
        result = ''
        if p > lv:
            result += '1'
        else:
            result += '0'
        if q > lv:
            result += '1'
        else:
            result += '0'

    def
APPENDIX B. Student-Alumni Interaction Survey

Student-Alumni Interactions Research

Start of Block: Default Question Block

Q1 Hello, thanks for your time to check the survey!
This research is to understand the potential factors in career networking between students and alumni. This project is conducted for Mathematical Methods in Social Sciences program in Northwestern University. You are invited to participate because you are in Northwestern Alumni Directory.

Q2 Your participation in this research study is voluntary, and you may withdraw at any time. This survey will take 5 to 10 minutes. Your responses will be confidential and we do not collect identifying information. The results will be used for scholarly purposes only.

ELECTRONIC CONSENT: Please select your choice below.
Clicking on the "agree" button below indicates that:
• you have ready the above information
• you voluntarily agree to participate
• you are one of Northwestern University alumni

- Agree (1)
- Disagree (2)

End of Block: Default Question Block

Start of Block: Section 1

Q3 Please estimate the number of people who HELPED you with useful career resources when you were a student.
Q4 Please give the EXACT number of Northwestern students you HAVE HELPED, with whom you have exchanged contact info and provided with career opportunities.

________________________________________________________________

End of Block: Section 1

Start of Block: Block 2

Q6 For the student you have helped, how close is the relationship between you and student?

○ We are related. (1)

○ We were close friends. (2)

○ We were from the same academic program/fraternity/club. (3)

○ We were not familiar. (4)

End of Block: Block 2

Start of Block: Block 3

Q7 For the student you have helped, before you offered the help, how likely did you think the student would positively affect your career in the future?

○ The student was very likely to get into my company. (1)

○ The student was likely to get a competitive job in my industry. (2)

○ The student was likely to have career resources that I would be interested in. (3)

○ The student was not likely to help my career at all. (4)
Q8 How actively do you expand or maintain your career network resources?

- Far above average (1)
- Somewhat above average (2)
- Average (3)
- Somewhat below average (4)
- Far below average (5)

Q9 How actively do you attend alumni panels, mentorship program?

- Far above average (1)
- Somewhat above average (2)
- Average (3)
- Somewhat below average (4)
- Far below average (5)

Q10 If you did help any student find career opportunities, what was your most important reason (optional)?

__________________________________________________________________
Q11 Please select the category that conforms to the frequency with which you have carried out the following acts, when presented with the opportunity.

<table>
<thead>
<tr>
<th>I have helped push a stranger's car that was broken down or out of gas. (1)</th>
<th>Always (1)</th>
<th>Most of the time (2)</th>
<th>Half the time (3)</th>
<th>Sometimes (4)</th>
<th>Never (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I have given directions to a stranger. (2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I have made change for a stranger (3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I have given money to a charity. (4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I have given money to a stranger who needed it. (5)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I have donated goods or clothes to a charity. (6)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I have done volunteer work for a charity. (7)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I have donated blood. (8)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I have helped carry a stranger's belongings (books, parcels, etc). (9)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
</tbody>
</table>
I have delayed an elevator and held the door open for a stranger. (10)

I have allowed someone to go ahead of me in a lineup (in the supermarket, at a copy machine, at a fast-food restaurant). (11)

I have given a stranger a lift in my car. (12)

I have pointed out a clerk's error (in a bank, at the supermarket) in undercharging me for an item. (13)

I have let a neighbor whom I didn't know too well borrow an item of some value to me (eg, a dish, tools, etc). (14)

I have bought 'charity' holiday cards deliberately because I knew it was a good cause. (15)
I have helped a classmate who I did not know that well with an assignment when my knowledge was greater than his or hers. (16)

I have, before being asked, voluntarily looked after a neighbor’s pets or children without being paid for it. (17)

I have offered to help a handicapped or elderly stranger across a street. (18)

I have offered my seat on a bus or train to a stranger who was standing. (19)

I have helped an acquaintance to move households. (20)
Q12 Please indicate how much you agree with each statement below.

<table>
<thead>
<tr>
<th></th>
<th>Strongly agree (1)</th>
<th>Agree (2)</th>
<th>Somewhat agree (3)</th>
<th>Neither agree nor disagree (4)</th>
<th>Somewhat disagree (5)</th>
<th>Disagree (6)</th>
<th>Strongly disagree (7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I have so much in life to be thankful for.</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>If I had to list everything that I felt</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>grateful for, it would be a very long</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>list.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When I look at the world, I don't see</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>much to be grateful for.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am grateful for a wide variety of people.</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>(4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>As I get older, I find myself more able</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>to appreciate the people, events, and</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>situations</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
that have been part of my life history. (5)

Long amounts of time can go by before I feel grateful to something or someone. (6)
Q13 Thanks for completing the survey! Please leave your demographic info for the last section.

Q15 Which gender do you identify yourself?

▼ Male (1) ... Others (3)

Q16 Which year did you graduate from Northwestern?

▼ 2006 (1) ... 2017 (12)

Q18 Which school in Northwestern did you go as an undergrad (if you have multiple, please choose the one most related to your career)?

▼ Weinberg College of Arts and Sciences (1) ... Bienen School of Music (6)