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Designing social networks: joint tasks and the formation and endurance of network ties

Sharique Hasan[1*] and Rembrand Koning[2]

* Correspondence: sharique.hasan@duke.edu
[1]Fuqua School of Business, Duke University, 100 Fuqua Drive, Durham, NC 27708, USA
Full list of author information is available at the end of the article

Abstract

Can managers influence the formation of organizational networks? In this article, we evaluate the effect of joint tasks on the creation of network ties with data from a novel field experiment with 112 aspiring entrepreneurs. During the study, we randomized individuals to a set of 15 joint tasks varying in duration (week-long teams to 20-min conversations). We then evaluated the impact of these interactions on the formation and structure of individuals' social networks. We find strong evidence that these designed interactions led to the systematic creation of new friendship and advice relations as well as changes to the participants' network centrality. Overall, network ties formed after a randomized interaction account for about one-third the individuals a participant knows, of their friendships, and their advice relations. Nevertheless, roughly 90% of randomized interactions never become social ties of friendship or advice. A key result from our research is that while joint tasks may serve to structure the social consideration set of possible connections, individual preferences strongly shape the structure of networks. As a consequence, there will likely remain a considerable unpredictability in the presence of specific ties even when they are designed.

Keywords: Entrepreneurship, Social networks, Field experiment, Organization design

Introduction

Scholars have long been interested in understanding how the interplay between formal and informal organization shapes the performance of individuals, teams, and firms (Puranam 2018; McEvily et al. 2014; Soda and Zaheer 2012; Kratzer et al. 2008). One prominent stream of literature touching on this topic highlights how informal networks—of acquaintances, advisors, and friends—lead to differential performance outcomes (Burt 1992; Zaheer and Soda 2009; Burt 2004; Hansen 1999). Given the value of social networks, scholars, as well as managers, have asked whether organizations can proactively influence or design their network microstructures (e.g., Puranam 2018; Catalini 2018; Herbst and Mas 2015; Mas and Moretti 2009). While managers have many levers to induce tie formation—from changing reporting relations to altering workplace microgeography (e.g., Ingram and Morris 2007; Hasan and Koning 2019)—the most common method is by facilitating collaboration on "joint tasks" that require two or more individuals to work toward a common goal. In this article, we test the efficacy of using joint tasks to induce the formation of network ties.

Prior research has suggested that intraorganizational networks may be ineffectively or inefficiently structured. Various frictions in how network ties are formed may lead to such inefficiencies, including homophily (McPherson et al. 2001), as well as geographic isolation (Catalini 2018). One significant friction limiting the formation of new and potentially beneficial connections in organizations are search costs (Hasan and Koning 2019; Catalini 2018). Even in small organizations, individuals are usually aware of or have the bandwidth to interact only with a small subset of physically proximate colleagues (Allen and Cohen 1969). Together, these frictions may hinder organizational performance by priming conflict, creating informational bottlenecks, and limiting the organization's ability to implement strategic changes.

However, theory also suggests that joint tasks can be a critical force in encouraging the formation of new ties, including acquaintanceship, advice, and friendship (Feld 1981). In particular, research argues that three mechanisms link working together on a task to the formation of a new tie. First, working together most often requires co-location. Co-located individuals are more likely to interact regularly, and this interaction intensity is related to increased rates of tie formation, both instrumental and social (Reagans 2011; Allen and Cohen 1969). Second, joint work toward a common goal creates a shared set of experiences and common purpose. Working toward a common goal and the interdependence it leads to can further increase the likelihood that ties are formed and maintained over the longer-term (Elfenbein and Zenger 2014; Dahlander and McFarland 2013). Finally, collaboration on a joint task can promote positive interpersonal affect—leading to liking, respect, and other emotions ascribed to the relationship. Positive affect is a crucial ingredient in tie formation and endurance (Casciaro and Lobo 2008). Together, these mechanisms suggest that working together on a joint task can lead to the formation of new network ties.

There are, nevertheless, countervailing forces that may undermine the tie-inducing mechanisms described above. Research indicates that individuals exercise considerable agency in choosing their acquaintances, friends, and advisors (McPherson et al. 2001; Aral 2011; Manski 1993). Indeed, a voluminous literature highlights a wide range of factors that shape network formation, including demographic factors, (McPherson et al. 2001), cultural tastes (Lizardo 2006), skill or ability (Hasan and Bagde 2013), personality (Burt 2012), as well as a range of other idiosyncratic factors. For example, two individuals who work together may have little in common, and may, after a joint task is complete, decide not to maintain a relationship. Together, the distinctive preferences of individuals could exert an opposing force on the tie-inducing effect of a joint task assignment. Together, the two sets of mechanisms described above make differing predictions. While joint tasks encourage the formation of new ties, idiosyncratic preferences may hinder this process.

In this article, we leverage a novel field experiment that evaluates the effect assigning aspiring entrepreneurs to a set of 15 joint tasks on the formation of their friendship and advice networks. Our interventions include assigning individuals to product development teams, short conversations to gather feedback, and brainstorming sessions at the bootcamp. These represent tasks with a varying range of intensity and time. Overall, we find two broad patterns in our results.

First, network ties formed after a randomized interaction account for one-third of the individuals a participant knows, of their friendships, and their advice relations. Second, however, our models suggest that which ties form after joint tasks are assigned are much less predictable. What is most striking is the fact that a substantial majority of randomized pairs, about 90%, never become friends or advisors.

A key finding of our research suggests that while joint tasks may serve to structure the social consideration set of possible connections, individual preferences strongly shape the structure of networks. As a consequence, there will likely remain a considerable unpredictability in the presence of specific ties even when they are designed. This finding suggests a persistent disjunction between the formal and informal structures within organizations.

Below we describe the experimental setting, our empirical strategy, and our main results. We conclude with a discussion of our results as they speak to the broader issues of organizational design.

Data and methods

Setting: a startup bootcamp

Our data derive from an experimental organization called Innovate Delhi, a 3-week intensive startup boot camp and pre-accelerator that ran from June 2 (day 1) to June 22 (day 21), 2014, on the campus of IIIT-Delhi. Below we describe the research setting and our experimental design.

Innovate Delhi Entrepreneurship Academy (IDEA) consisted of three modules spread over 3 weeks. The bootcamp was held 6 days a week, Monday through Saturday, from 9 am until 5 pm. The first week focused on design thinking, feedback, and prototyping. Individuals worked in randomly assigned teams of three to develop a software product concept for the Indian wedding industry. Groups were required to get feedback on their ideas and prototypes from a random subset of their peers. At the end of the week, individuals submitted their final prototype for peer evaluation. The second week focused on business models and the building of a product with market potential. Again individuals worked in randomly assigned teams of three to develop a product concept, prototype, and a business plan for a software application in the Indian health sector. Like week one, the curriculum required groups and individuals to get feedback about their idea, prototypes, and business models from a randomly selected set of their peers. At the end of the week, teams submitted their prototypes and business models for peer evaluation.

The third week was less controlled. The Saturday (day 13) before the third week began, individuals self-organized into teams of three. During the third week, the teams chose a problem to solve, developed a prototype of their product, developed a business plan, and composed a “pitch deck” to present to leading members of India’s startup community the following Sunday. At the end of each day, individuals completed a survey asking about tasks, the advice they sought, and their plans for tomorrow. At the end of the week, the teams submitted a complete packet of information about their startup and product. The digital submission included a business model, pitch deck, product prototype walk-through, and additional information about the team and product. Sixty other participants evaluated each submission, then based on aggregated peer feedback, the top 5 teams pitched their idea to a jury of venture capitalists, angel investors, and entrepreneurs. The total prizes awarded to the winning groups and individuals in the final week totaled just over $5500. Furthermore, teams won spots in an accelerator and co-working space for 2 months. Participants nominated one another for the award and chance to pitch in front of the investors.

Participant information

Admission to Innovate Delhi required the completion of an extensive online application, made public September 10, 2013, and with a completion deadline of February 1, 2014. Applicants provided detailed information on their work history, education, and business skills. Furthermore, applicants were encouraged to write an essay explaining why they wanted to enter the program. We recruited applicants through several different means, including Facebook ads, social media posts, entrepreneurship organizations, and word- of-mouth referrals. We received 508 complete applications. In total, we accepted 358 standard applicants and 18 last-minute applicants. From this pool, 112 completed the entire program.

The age of participants ranged from 18 to 36, with a mean age of just over 22. Our program had 25 women. All participants were either enrolled in or had graduated from college. Innovate Delhi was regionally diverse with 62 participants from the state of Delhi and the rest from across India. Participants were primarily engineering and computer science degree holders (78), followed by 18 business degrees, and the rest from the arts and sciences. A total of eight people were enrolled in, or, had graduated from advanced degree programs.

The participants' professional experience and business skills were quite varied. Of the Innovate Delhi graduates, 77 had formal work experience at companies ranging from multi-nationals to large Indian businesses to new startups from across India. Thirty-seven participants started a company, the majority of which had failed. Finally, 36 participants had previously worked for a StartUp that was not their own, and 28 could name a mentor they had in the Indian StartUp ecosystem.

Joint task interventions

Our primary joint task interventions were the random assignment of individuals to product development teams and group feedback conversations. Our approach extends standard peer randomization techniques by randomizing peer interactions multiple times while simultaneously measuring network ties between these interventions. Table 1 lists each joint task assignment, provides a brief description of the task, whether it was randomized, the size of the group or team, and the length of the interaction. In total, we randomize joint tasks 15 distinct times. The most robust assignments are the 2-week-long team interactions in which we randomly assigned individuals to teams of three. We complemented these two intensive task randomizations with 13 shorter randomized tasks. These shorter assignments ranged in length from 20 to 30 min and consisted of working with randomly assigned partners to brainstorm new ideas as well as provide and give feedback on ideas. To simplify our analysis, we group our randomizations into two primary types, the 4-day-long week one and two teams and the smaller 20–120-min short-term group interactions.

Table 1 Timeline of joint task assignments

	Day	Randomized	Group size	Interaction time
Practice design thinking	1	Yes	4	120 min
Wk 1 product development team	2 to 5	Yes	3	4 days
User empathy interview 1	2	Yes	2	20 min
User empathy interview 2	2	Yes	2	20 min
User empathy interview 3	2	Yes	2	20 min
Prototype feedback 1	4	Yes	3	20 min
Prototype feedback 2	4	Yes	3	20 min
Prototype feedback 3	4	Yes	3	20 min
Team interview and fit 1	8	Yes	3	20 min
Team interview and fit 2	8	Yes	3	20 min
Team interview and fit 3*	8	Yes	3	20 min
Week 2 product development team*	9 to 12	Yes	3	4 days
User empathy interview 4	9	Yes	3	30 min
Business model canvas feedback 1	11	Yes	3	20 min
Business model canvas feedback 2	11	Yes	3	20 min
Business model canvas feedback 3	11	Yes	3	20 min
Self-formed week 3 teams	13 to 19	No	3	7 days

Network and background surveys

To measure network structure at Innovate Delhi, we used a custom web application we developed for this study called "Texo." Texo allowed us to pre-program the Innovate Delhi curriculum and the associated experimental procedures. We surveyed participants before the program and at the end of the first, second, and third week of the program. The core of our survey consisted of asking the participant who they knew, who they considered friends, and who they got advice from. The network survey was done as a roster where we provided participants with a list of names and photos of all the other participants in the program. To reduce the cognitive burden, we first asked about knowing ties and then limited the roster to only the people, the respondent indicated that they know or "know of." Participants then selected the set of people for each type of relationship.

We also used digital technologies to enhance collaboration as well as measurement of the social networks. Each participant was provided with a GoogleApps @innovatedelhi.com account to aid collaboration during the bootcamp. Using their account,[1] participants could email, create calendars, chat, as well as create content using documents, slides, and spreadsheets on Google Drive. Information from GoogleApps gives us observability into digital communication patterns. Second, we used social media to aid coordination. A Facebook group was created to help share information and discuss ideas and topics related to entrepreneurship.

Complementing our network measures, we also measured each participant's entrepreneurial potential, gender, and big five personality traits. Entrepreneurial potential is the standardized average rating each participant's bootcamp application received from

[1]The survey questions were "Select the people you know or know of below," "Who do you seek feedback and advice from about your ideas and entrepreneurship," and "Who do you consider a close friend?"

four independent evaluators before the program began. Gender was self-reported and recorded as part of a pre-bootcamp survey. To measure the big five personality variables—extraversion, neuroticism, openness, conscientiousness, and agreeableness—we administered a standard 44-item questionnaire as part of same the pre-bootcamp survey. All five personality variables were standardized to have mean 0 and standard deviation 1.

Network statistics and balance tests

From the survey data, we have four snapshots of the network—one from before the program started, day 6, day 13, and day 20—of the relationships at Innovate Delhi. Table 2 provides an overview of the knowing, advice, and friendship networks at each time point. Statistics are taken over the largest component in the network when the graph is connected. The table illustrates how sparse the incoming network is compared to the day 20 network, knowing jumps from having a density of 2.5% to nearly 34%. However, the table also indicates that none of the networks become saturated. The directed network diameter of the knowing graph at day 20 is still 3, for advice 9, and friendship 11. In other words, an advice diameter of 9 implies that for at least one pair of participants, the shortest advice path between them is nine hops.

Moreover, other network statistics change, as well. With time, reciprocity in the knowing network increases from 35% of all non-empty dyads to 37%. In contrast, advice reciprocity drops from 30% before the program starts to 19% on day 6 and 15% at the end of the program. As should be expected, friendship had much higher reciprocity rate of 28% at day 20. Transitivity, or the percent of times where C has a relationship with A conditional on A and C having a relationship with B, appears to remain relatively stable once the networks congeal into a single component.

To estimate the causal effect of our interventions, we must ensure two criteria. First, our treatments should be uncorrelated with one another. Second, our interventions should be uncorrelated with observable and unobservable characteristics of the participants.

Table 2 Network evolution summary statistics

	# Isolates	Density	Diameter	Avg. path length	Reciprocity	Transitivity
Incoming knowing	18	0.025	12	4.181	0.351	0.481
Day 6 knowing	0	0.189	4	1.896	0.435	0.344
Day 13 Knowing	0	0.299	3	1.695	0.485	0.442
Day 20 knowing	0	0.337	3	1.657	0.468	0.501
Incoming friendship	61	0.005	4	0.79	0.548	0.418
Day 6 friendship	2	0.027	13	4.815	0.319	0.22
Day 13 friendship	1	0.039	11	3.944	0.248	0.227
Day 20 friendship	0	0.043	9	3.663	0.277	0.234
Incoming advice	48	0.007	5	1.025	0.297	0.25
Day 6 advice	0	0.052	9	3.223	0.194	0.196
Day 13 advice	0	0.065	7	2.897	0.156	0.19
Day 20 advice	0	0.064	9	3.096	0.15	0.239

Table 3 displays the correlations between each of our joint task assignments. As expected, correlations are small, indicating the plausibility of our treatments being sequentially independent. Furthermore, we conduct balance tests examining that our treatments are uncorrelated to the potential, gender, and personality of the participants. For example, we want to ensure that errors in our treatment procedure did not lead women to work with other women at higher rates. If this was the case, then any effect stemming from being assigned to the same joint task could instead be explained by gender homophily. Table 4 presents dyadic linear probability models with QAP imputed standard errors predicting whether persons i and j end up on the same team or group (e.g., being randomly paired into a joint task). QAP accounts for the fact that our observations—dyads—are not independent (e.g., individuals are connected to multiple people in a network). All the predictors with the exception of gender on the right-hand side are dichotomized using a median split. This allows us to interpret the interactions terms as measures of homophily (e.g., extroverts are more likely to be assigned to groups with other extroverts). Our joint task treatments appear strongly balanced as the estimates are near zero and the coefficients small. All but one of the 48 coefficients in Table 4 are insignificant at the 5% level; only two are significant at the 10% level. In a group of nearly 50 coefficients, we would expect that—by chance—roughly three would be significant which is consistent with what we find.[2]

Results

In this section, we describe our findings. We begin by testing the impact of the joint tasks on four aspects of network tie formation. First, we evaluate the direct effect of joint tasks on the creation of new knowing, friendship, advice, and digital communication ties. Next, we assess the impact of joint tasks on indirect tie formation (e.g., a friend of a friend becomes a friend). Third, we evaluate how the assignment to joint tasks affects an individual's membership in a network cluster and centrality in the overall network structure. Finally, we compare the overall effect of joint tasks relative to individual preferences on the formation of new ties (Fig. 1).

When do joint tasks lead to new ties?

Visualizing the impact of joint tasks and new ties

We begin our analysis by visualizing the advice network before the bootcamp started, as well as the end of week 1 (day 6) and the end of week 3 (day 20). In these graphs presented in Fig. 2, the white dots represent participants and are held constant across each plot. The lines between the dots represent advice ties. Gray ties are endogenous advice relationships formed between participants who were not assigned to a joint task. Blue lines are potentially exogenous advice relationships formed between participants who were assigned to a joint task. The figure shows that a substantial number of network connections appear to be the result of our treatments. Descriptively, we find that our interventions account for a meaningful proportion of the overall ties formed. At the end of weeks 1 and 3, roughly one-third of the observed advice ties are between individuals who worked on a joint task together. While it appears that joint tasks significantly affect the aggregate structure of the network, many more potential ties remain

[2] Multiway clustered standard errors give nearly identical results.

Table 3 Correlations between the 15 randomized joint task interventions. None significant at conventional levels

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Wk 1 team (1)														
D.school (2)	0.01													
Empathy 1 (3)	− 0.01	− 0.003												
Emapthy 2 (4)	− 0.01	− 0.003	− 0.01											
Empathy 3 (5)	–0.01	− 0.01	− 0.01	− 0.01										
Feedback 1 (6)	− 0.01	− 0.01	− 0.01	− 0.01	0.01									
Feedback 2 (7)	− 0.01	− 0.02	0.04	− 0.01	0.01	− 0.01								
Feedback 3 (8)	− 0.01	0.003	0.02	− 0.01	0.01	0.004	0.003							
Team fit 1 (9)	0.03	− 0.005	0.01	− 0.01	0.001	0.02	− 0.01	0.02						
Team fit 2 (10)	0.002	0.004	− 0.01	0.01	0.03	− 0.01	− 0.002	0.02	− 0.02					
Wk 2 team (11)	− 0.01	0.004	0.001	0.001	− 0.01	− 0.01	− 0.002	0.01	− 0.02	− 0.02				
BMC 1 (12)	− 0.01	− 0.01	− 0.01	− 0.01	0.01	0.004	0.003	0.003	− 0.003	0.01	− 0.01			
BMC 2 (13)	0.02	0.003	− 0.01	− 0.01	− 0.01	− 0.01	− 0.01	0.003	− 0.003	− 0.003	− 0.01	–0.01		
BMC 3 (14)	− 0.01	0.02	0.01	0.01	− 0.01	− 0.01	− 0.01	0.003	0.02	0.01	− 0.01	− 0.01	− 0.01	
Empathy4 (15)	0.01	0.02	0.0004	0.01	− 0.01	0.05	0.01	0.03	0.02	0.01	− 0.02	− 0.01	− 0.003	–0.004

Table 4 Balance test showing team and group assignment is unrelated to individual and dyad characteristics

	Dependent variable	
	Same team	Same group
	[1]	[2]
Entrepreneurial potential [Ego]	− 0.002	− 0.017
	[0.006]	[0.013]
Entrepreneurial potential [Alter]	− 0.002	− 0.017
	[0.006]	[0.013]
Pre-Camp indegree [Ego]	0.002	0.008
	[0.005]	[0.009]
Pre-Camp indegree [Alter]	0.002	0.008
	[0.005]	[0.009]
Female [Ego]	0.002	0.003
	[0.005]	[0.009]
Female [Alter]	0.002	0.003
	[0.005]	[0.009]
Agreeableness [Ego]	− 0.005	− 0.002
	[0.005]	[0.010]
Agreeableness [Alter]	− 0.005	− 0.002
	[0.005]	[0.010]
Conscientiousness [Ego]	0.004	− 0.01
	[0.005]	[0.010]
Conscientiousness [Alter]	0.004	− 0.01
	[0.005]	[0.010]
Extraversion [Ego]	0.002	0.00003
	[0.004]	[0.009]
Extraversion [Alter]	0.002	0.00003
	[0.004]	[0.009]
Neuroticism [Ego]	− 0.006	− 0.013
	[0.005]	[0.010]
Neuroticism [Alter]	− 0.006	− 0.013
	[0.005]	[0.010]
Openness [Ego]	0.001	0.01
	[0.005]	[0.010]
Openness [Alter]	0.001	0.01
	[0.005]	[0.010]
Entrepreneurial potential [Ego × Alter]	0.004	0.022
	[0.008]	[0.015]
Pre-Camp indegree [Ego × Alter]	− 0.009	− 0.017
	[0.007]	[0.013]
Female [Ego × Alter]	0.0002	− 0.016
	[0.010]	[0.019]
Agreeableness [Ego × Alter]	0.01	0.007
	[0.007]	[0.013]
Conscientiousness [Ego × Alter]	− 0.006	0.026*

Table 4 Balance test showing team and group assignment is unrelated to individual and dyad characteristics *(Continued)*

	Dependent variable	
	Same team	Same group
	[1]	[2]
	[0.007]	[0.013]
Extraversion [Ego × Alter]	– 0.004	– 0.001
	[0.007]	[0.013]
Neuroticism [Ego × Alter]	0.011*	0.027**
	[0.007]	[0.013]
Openness [Ego × Alter]	– 0.007	– 0.015
	[0.007]	[0.013]
Constant	0.038***	0.169***
	[0.009]	[0.019]
Observations	12,432	12,432
$R^{\{2\}}$	0.001	0.001
F statistic [df = 24; 12,407]	0.448	0.622

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

unformed than formed. Nearly 90% of potential advice ties between joint task partners are never formed.

The impact of joint tasks on tie formation

Next, to formally test whether joint task interventions can change network ties and structure, we estimate linear probability models. We regress the knowing, advice, and friendship networks on the joint task assignment. Since these are network models, we correct our significance tests using the Quadratic Assignment Procedure (QAP) for social network data (Dekker et al. 2007). Table 5 presents our main effects and Fig. 2 plots these estimates.

Complementing the descriptive analysis above, we find that common joint task assignment—be it working on the same product team or as part of a short feedback group—impact the end of bootcamp network. Specifically, the week 1 product team assignment dramatically increase the probability of seeking advice (β = .213, $p \leq .01$) and

Fig. 1 Advice network between participants. Gray lines are advice ties between participants who had not been assigned to the same joint. Blue lines are between participants who had been assigned to the same joint task

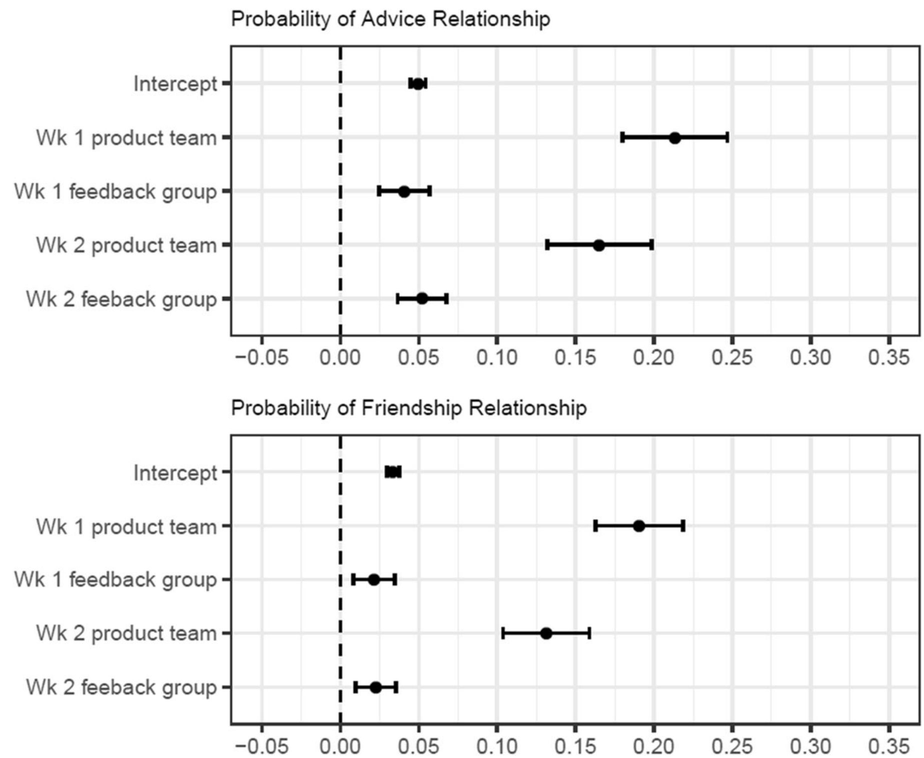

Fig. 2 Coefficient plot for Table 5

Table 5 Linear probability models showing that the joint task treatments increase the chance that *i* nominates *j* as someone they know, get advice from, or consider a friend

	Dependent variable		
	Know on day 20	Advice on day 20	Friend on day 20
	[1]	[2]	[3]
Wk 1 product team	0.562***	0.213***	0.191***
	[0.032]	[0.017]	[0.014]
Wk 1 feedback group	0.198***	0.041***	0.022***
	[0.015]	[0.008]	[0.007]
Wk 2 product team	0.578***	0.165***	0.131***
	[0.031]	[0.017]	[0.014]
Wk 2 feedback group	0.195***	0.052***	0.023***
	[0.015]	[0.008]	[0.006]
Constant	0.285***	0.050***	0.034***
	[0.004]	[0.002]	[0.002]
Observations	12,432	12,432	12,432
R^2	0.073	0.025	0.023
F statistic [df = 4; 12,427]	244.995***	81.074***	74.171***

friendship (β = .191, $p \leq .01$) at the end of week 3, even though week 1 teams were disbanded 2 weeks earlier. We also find that the short-duration interactions from week 1 affect both the advice (β = .041, $p \leq .01$) and friendship (β = .022, $p \leq .01$) on day 20. We find a similar pattern of results for our interaction treatments from week 2. Week 2 teammates have an increased probability of forming advice (β = .165, $p \leq .01$) and friendship ties (β = .131, $p \leq .01$); week 2 short-duration interactions also increase the probability of advice (β = .052, $p \leq .01$) and friendship (β = .023, $p \leq .01$). Figure 2 shows that when task assignments are more intensive, the effects are significantly stronger than when tasks are fleeting in nature.

Further, in Tables 6 and 7, we show that our findings generalized to the networks of cash award nominations and the digital communication network. In Table 6, we find that a person's week 1 teammates are more likely to nominate them for a substantial cash award (β = .203, $p \leq .01$) as are their week 2 teammates (β = .191, $p \leq .01$). We also find that their feedback group partners are also more likely to nominate them for an award. In Table 7, we test the impact on the email and facebook network. Since emails and facebook likes were relatively sparse during the final week of the program, we aggregate our team and feedback group treatments into week 1 and 2 variables to increase statistical power. We find that even after teams have been disbanded, the joint task treatments continue to increase the probability of emails being sent (β = .065, $p \leq .01$) and Facebook posts being liked (β = .034, $p \leq .01$). That said, we find no evidence that the shorter feedback group interactions have a lasting impact on the digital communication network, though the sign on the coefficients is positive.

Do joint tasks lead to the formation of indirect ties?

The prior theory also indicates that network formation can also have cascading effects (Hasan and Bagde 2015)—individuals paired together are more likely to introduce each

Table 6 Linear probability models showing that joint task assignment increases the chance that *i* nominates *j* for an award during the final week of the program

	Dependent variable
	Nominates for cash award
Wk 1 team	0.203***
	[0.018]
Wk 1 group feedback	0.032***
	[0.009]
Wk 2 team	0.191***
	[0.018]
Wk 2 group feedback	0.041***
	[0.008]
Constant	0.062***
	[0.003]
Observations	12,432
R^2	0.021
Adjusted R^2	0.021
Residual Std. Error	0.259 [df = 12,427]
F statistic	67.959*** [df = 4; 12,427]

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 7 Linear probability models showing that the joint task assignments increase the chance that *i* emails *j* using their @innovatedelhi.com account or likes *j*'s posts to the Innovate Delhi Facebook group. To ensure our outcomes are measured after treatment assignment, we restrict our data to communication that occurred after day 13

	Dependent variable	
	Email	Facebook like
	[1]	[2]
Wk 1 and 2 product teams	0.065***	0.034***
	[0.008]	[0.012]
Wk 1 and 2 feedback groups	0.005	0.005
	[0.004]	[0.006]
Constant	0.026***	0.064***
	[0.002]	[0.002]
Observations	12,432	12,432
R^2	0.005	0.001
F statistic [df = 2; 12,429]	32.149***	4.308**

other to their wider network of contacts. That is, joint task assignment also shapes the processes of triadic closure in the bootcamp's network. For example, individual *i* assigned to a teammate *j* in week 2 is more likely to connect with j's week one tie k. Table 8 shows that an individuals' day 20 advice network grows through this closure process (β = .039, $p \le .01$). On the other hand, we do not find evidence that friendship networks change in the same way (β = − .001, $p = .894$). Although the magnitude of the second-order effect on the advice network is smaller than the direct effect, because of

Table 8 Linear probability models showing that the joint task assignments increase the chance that *i* goes to teammate *j*'s advice partner *k* for advice. We find no evidence for indirect effects when it comes to friendship

	Dependent variable	
	Advice on day 20	Friend on day 20
	[1]	[2]
Wk 1 product team	0.213***	0.191***
	[0.017]	[0.014]
Wk 1 feedback group	0.041***	0.022***
	[0.008]	[0.007]
Wk 2 product team	0.168***	0.131***
	[0.017]	[0.014]
Wk 2 feedback group	0.052***	0.023***
	[0.008]	[0.006]
Wk 1 adviser of Wk 2 teammate	0.039***	
	[0.007]	
Wk 1 friend of Wk 2 teammate		− 0.001
		[0.008]
Constant	0.046***	0.034***
	[0.002]	[0.002]
Observations	12,432	12,432
R^2	0.028	0.023
F statistic [df = 5; 12,426]	71.209***	59.337***

the many indirect connections brokered through direct interaction, the overall change in the network is comparable. The median number of indirect advice-givers an individual has through her team in the second week is 9; thus, the average growth is approximately .351 individuals ($9 * .039 = .351$). Furthermore, the indirect effect is of similar magnitude to the short-duration interactions ($\beta = .039$ vs. $\beta = .040$). These results indicate that exogenous variation in network structure is induced through second-order ties, in addition to direct connections.

Do joint tasks affect membership in network clusters?

Next, we test if the joint task assignment explains the clusters that emerge in the social network. Using the week three advice network, we generate clusters using the leading eigenvector of the community matrix. We find that the network is best represented as five clusters, with each roughly equal in size. We then test if week 1 and 2 product development teammates are more likely to belong to the same cluster. Using a simulation where we randomly assign clusters to teammates as our null, we find that teammates are about 80% more likely to all belong to the same cluster than would be expected by chance. Additional file 1: Figure S4 plots the team membership network along with the estimated clustering assignments generated from the week-three network.

Do joint tasks affect individual centrality in the network?

Social network theory posits that a person's centrality—i.e., structural position in a network graph—affects their behavior and outcomes (Kadushin 2012; Burt 2004; Wasserman 1994). For example, research has found that a person's indegree is correlated to their visibility and power in a network (Burkhardt and Brass 1990); their betweenness is related to their ability to acquire novel information (Burt 2004; Freeman 1977); and their eigenvector centrality correlates to status and reputation (Podolny 1993). However, because a person's centrality is endogenous to their traits and networking strategy, it remains an open question if organizations can ever deliberately "engineer" centrality for individuals who lack it.

Our results show that an individual's direct and indirect network connections can be changed through joint task assignment. In Table 9, we test if our randomized joint task assignments change three types of centrality (Wasserman 1994): indegree, betweenness, and eigenvector. Indegree is the total number of inbound connections an actor i in the network receives from all other actors j; betweenness is the extent to which a person i lies on the shortest paths between all other actors j and k in the network; and eigenvector centrality is a recursively weighted measure of how many connections a person i's connections j have, the number of connection's j's connections have, and so on.

We begin by examining whether a person's indegree in the friendship and advice networks are functions of the number of individuals who they have worked with on a joint task assignment. To test this, we regress a person's indegree in both the advice and friendship networks on the number of people a person i has been assigned to worked with. Since some individuals, by chance, work with the same partners multiple times, we have variation in the number of joint task partners each individual has. We find strong support that a person's advice indegree can be exogenously varied ($\beta = .213$, $p \leq .05$), but no evidence of such change in the friendship network ($\beta = .019$, $p = .838$).

Table 9 Linear regression of randomized network centrality on centrality in the advice and friendship networks on day 20

Logged and standardized dependent variables	Advice Indegree [1]	Advice Betweenness [2]	Advice EV Centrality [3]	Friend Indegree [4]	Friend Betweenness [5]	Friend EV Centrality [6]
Number of randomized team and group partners	0.213** [0.093]			0.02 [0.095]		
Sum of Wk 2 teammates' Wk 1 Advice betweenness+		0.239** [0.093]				
Sum of Wk 2 teammates' Wk 1 Advice EV centrality+			0.320*** [0.090]			
Sum of Wk 2 teammates' Wk 1 friend betweenness+					− 0.061 [0.095]	
Sum of Wk 2 teammates' Wk 1 friend EV centrality+						0.131 [0.095]
Constant	0 [0.093]	0 [0.092]	0 [0.090]	0 [0.095]	0 [0.095]	0 [0.094]
Observations	112	112	112	112	112	112
R^2	0.045	0.057	0.103	0.0004	0.004	0.017
F statistic	5.216**	6.657**	12.563***	0.042	0.412	1.927

Figure 3 plots the association. While there is an upward slope in the advice network, the relationship is noisy and the R-squared is only 4.5%. Overall, we find that joint tasks assignment can indeed be used to influence the indegree centrality of individuals in an organization's social network.

We then examine whether having week two teammates with high betweenness affects person i's betweenness. We find a stronger and statistically significant effect for the advice network (β = .239, $p \leq .05$), but not the friendship network (β = .061, $p = .522$). It appears that by connecting with teammates who are connected to diverse clusters, the focal individual i also gets broader exposure to different clusters, thereby increasing her betweenness.

Finally, we test whether interaction with people with high eigenvector centrality also increases i's eigenvector centrality. Again, we find exogenous change in one's eigenvector centrality due to this treatment in the advice (β = .320, $p \leq .01$), but not the

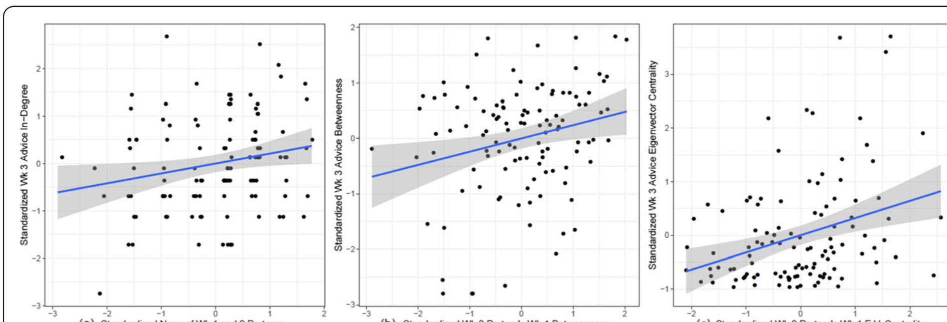

Fig. 3 Joint task assignment and advice network centrality

friendship network (β = .131, $p = .168$). These results show that exogenous variation can be introduced into a person's centrality by varying the composition of their joint task partners. We believe a key reason why centrality in the friendship network does not seem to vary in response to our treatments is because of the limited closure effects we find in this network that may be driven by the greater importance of individual preferences. The results suggest that joint task assignment can impact about 10% of a person's eigenvector centrality.

What is the relative importance of joint tasks versus individual preference on tie formation?

In this section, we examine the power of our treatments in shaping the overall network relative to individual preferences; we estimated a saturated model presented in Table 10. These models include several additional variables measuring the traits of both i and j captured before the start of the bootcamp and their interactions with our inter- action treatments. These variables include measures of pre-bootcamp entrepreneurial potential, network size, gender, and scores on the big five personality test.

Additional factors affecting network formation include the lower likelihood of female participants to both name advice-givers (β = – 0.028, $p \leq .01$) and friends (β = – 0.015, $p \leq .01$), be named as advice-givers (β = −.027, $p \leq .01$) and friends (β = −.016, $p \leq .01$). In a similar vein, we find that female-to-female pairs are more likely to form in both the advice (β = .039, $p \leq .01$) and friendship networks (β = .044, $p \leq .01$). We also find that individuals who are agreeable are more likely to receive friendship nominations from both outside (β = .005, $p \leq 0.05$) and within their teams (β = −.025, $p \leq 0.05$). Perhaps the most striking result is that the full models explain approximately 4.9% of the variation in the advice network and 4.4% of the variation in the friendship network.[3] These findings dovetail with our descriptive results that suggest that nearly 90% of such potential ties from joint task assignment do not form. Thus, even with a large number of predictive variables—including a near complete set of all formal interactions inside this organization—a large portion of variation in the network remains unexplained. In relative terms, our purely exogenous joint task assignments explain approximately 2.4% of the variation in the advice network and 2.2% of the variation in the friendship network (Additional file 1: Table S11).

Overall, our results suggest that joint tasks such as ours can reliably create exogenous variation in network structure even at the aggregate level as evidenced by the substantial increased likelihood of direct and indirect tie formation, membership in a network cluster, and network centrality. However, individual traits and preferences, both observed and unobserved, continue to affect tie formation.

Discussion

Do managerial interventions designed to change network structure lead to meaningful effects? Using a novel research design, we find that both extended- and short-duration interventions introduce significant variation into friendship and advice networks. Indeed, we find evidence that interventions lead to new first-order connections, second-order connections, as well as changes to an individual's indegree, betweenness, and

[3]The full set of coefficients are reported in the appendix.

Table 10 Saturated linear probability models including all pairs of interactions between the network treatments and pre-program measures of entrepreneurial potential, popularity, gender, and personality

	Dependent variable	
	Advice on day 20	Friend on day 20
	[1]	[2]
Wk1 and Wk2 product teams	0.219***	0.203***
	[0.016]	[0.014]
Wk1 and Wk feedback groups	0.047***	0.022***
	[0.008]	[0.007]
Entrepreneurial potential [Ego]	− 0.004	− 0.002
	[0.003]	[0.002]
Entrepreneurial potential [Alter]	0.010***	− 0.001
	[0.003]	[0.002]
Pre-camp Indegree [Ego]	0.001	− 0.0005
	[0.003]	[0.002]
Pre-camp Indegree [Alter]	0.013***	0.001
	[0.003]	[0.002]
Female [Ego]	− 0.028***	− 0.015***
	[0.007]	[0.006]
Female [Alter]	− 0.027***	− 0.016***
	[0.007]	[0.006]
Agreeableness [Ego]	0.008***	0.005**
	[0.003]	[0.002]
Agreeableness [Alter]	0.006**	0.005**
	[0.003]	[0.002]
Conscientiousness [Ego]	0.0003	0.001
	[0.003]	[0.002]
Conscientiousness [Alter]	− 0.004	0.001
	[0.003]	[0.002]
Extraversion [Ego]	0.001	− 0.003
	[0.003]	[0.002]
Extraversion [Alter]	0.002	− 0.00004
	[0.003]	[0.002]
Neuroticism [Ego]	0.004	0.002
	[0.003]	[0.002]
Neuroticism [Alter]	0.004	0.003
	[0.003]	[0.002]
Openness [Ego]	0.008***	0.006***
	[0.003]	[0.002]
Openness [Alter]	0.004	0.0003
	[0.003]	[0.002]
Constant	0.061***	0.039***
	[0.003]	[0.003]
All Pairwise interactions	\textit{Yes	\textit{Yes
Observations	12,432	12,432
R^2	0.049	0.044
F statistic	8.520***	7.772***

eigenvector centralities. Moreover, we can link our interventions to the distribution of award nominations and the extent of information seeking—two mechanisms central to network theories of human behavior.

Overall, network ties formed after a randomized interaction account for about one-third of the individuals a participant knows, their friendships, and of their advice relations. Yet, roughly 90% of randomized interactions never become social ties of friendship or advice. A key result from our research is that while joint tasks may serve to structure the social consideration set of possible connections, individual preferences strongly shape the structure of networks. As a consequence, there will likely remain a considerable unpredictability in the presence of specific ties even when they are designed.

We believe our estimates are useful for managers looking to influence the structure of their organization's networks. Specifically, our estimates provide insight into the potential implications of organizational design interventions: simple interventions can lead to substantial changes to networks at the aggregate level. Joint tasks can be used to organize informal clusters and shape individual centrality. These changes may suggest policy interventions that can be designed to help individuals develop better and more productive networks. For example, joint tasks may be fruitfully used to reduce some sources of persistent inequality in organizations (Carrell et al. 2013). However, one caveat from our findings is that joints tasks may be a blunt instrument of change. Our results suggest that any one pairing of individuals to joint work may not yield in a formed connection. Thus, there is the possibility of needing many such interventions to create a durable change in the network structure of any one individual.

Finally, our study has several limitations that should be noted. First, although we randomize many interactions and collect measures of many individual characteristics and outcomes, our measurements are still coarse. Although we do find strong effects of our treatments on network change, the underlying mechanisms driving such effects are always tricky to observe, even in our data. Future work should focus on understanding why some treatments result in realized friendships, while others do not or why some triads close and others do not. Second, our study was conducted in a particular context—a startup bootcamp in India—which limits the generalizability of our specific results.

Supplementary information

Supplementary information accompanies this paper at https://doi.org/10.1186/s41469-020-0067-4.

Additional file 1. Online Appendix.

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Authors' contributions

SH and RK contributed equally to the manuscript including the design of the study, the execution of the experiment, analysis of the data, and writeup of the manuscript. Both authors read and approved the final manuscript.

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Availability of data and materials
Because of human subjects' requirements per our IRB approval for this study, the data from this study cannot be disclosed as it pertains to identifiable data on individuals in our study.

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Fuqua School of Business, Duke University, 100 Fuqua Drive, Durham, NC 27708, USA. [2]Harvard Business School, Harvard University, Soldiers Field, Boston, MA 02163, USA.

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