Online Appendix
Prior ties and the limits of peer effects on startup team performance

February 1, 2019

A1 Retreat setting, recruiting and selection criteria, and experimental procedures

A1.1 Setting description, participant recruitment and participant characteristics

The Innovate Delhi startup bootcamp was a 3-week program that ran from June 2 (Day 1) to June 22 (Day 21), 2014 on the campus of IIIT-Delhi. The program consisted of three week-long modules. The bootcamp was held six days a week, Monday through Saturday, from 9am until 5pm. The first week focused on design thinking, feedback, and prototyping. Individuals worked in randomly assigned teams to develop a software product concept for the Indian wedding industry.

Admission into the Innovate Delhi program required the completion of an extensive online application, made public September 10, 2013, and with a submission deadline of February 1, 2014. Applicants provided a detailed overview of their work history, education, and business skills. We recruited applicants through Facebook ads, social media posts, entrepreneurship organizations, and word-of-moth referrals. Over 1,247 people started the full application, 58 started a short version of the standard application we launched after the February 1st deadline, and 71 people completed a wait-list Google Form application that was designed to attract last-minute applicants; a total of 1,376 applications were started. We received 508 fully completed applications, of which 437 were standard applications and 71 were from the last-minute Google Form applications (these applications did not allow the user to save their work and submit at a later date, hence providing the perfect pass through rate).

From these applications we accepted 358 standard applicants and 18 last-minute applicants. From this pool of accepted students, 178 enrolled by May 1st and signed our initial online IRB consent form. This form clearly stated that the program was being conducted for research purposes and that digital, video, and audio data would be collected. In the end 135 formally paid the registration fee, signed up for a Google Apps @innovatedelhi.com account, and completed a battery of pre-program surveys. Of these 135 students who formally enrolled, 118 attended the first day of the program and signed our second physical consent form. Of those who attended on the first day, 95 percent (112) of these students continued on to the second day and completed the three-week program. Team and workbench assignment took place on the second day. Participants were unaware of their assignments on the first day.

The age range of the 112 graduates was from 18 to 36, with a mean age of just over 22. Our program had 25 women and everyone had, or was enrolled in, college, with 60 of the participants enrolled in a college, master's, or Ph.D. program. Our program was regionally diverse, with 62 of the participants from the state of Delhi and the rest from across India. The class was primarily comprised of engineering and computer science degree holders (78), followed by 18 business degrees, and the rest came from the arts and sciences. A total of eight people were enrolled in or had graduated from advanced degree programs. The participants came from a broad spectrum of universities including Delhi University, IIIT-Delhi, Jaypee University, Delhi Technological University, and the IITs. It is important to note that universities in India are composed of relatively independent colleges, and thus most of the participants in our program did not know one another, even when they came from the same university. For example, of the 26 participants from Delhi University, half are the only representative from their college, and the most popular college from Delhi University supplied only three participants. Everyone in the program spoke English since proficiency in English was an application requirement, and nearly all the participants were multi-lingual, with Hindi, Urdu, Bengali, Punjabi, and Tamil being the most common other languages.

The participants' professional experience and business skills were varied. Of the Innovate Delhi graduates, 77 had formal work experience at companies ranging form multi-nationals to large Indian businesses to new startups from across India. As expected, the group was quite entrepreneurial, with 37 of the participants having started a company, the majority of which were suspended or had folded before the start of the program. In terms of having a prior connection to the Indian startup ecosystem, 36 had worked for a startup that was not their own and 28 could name a mentor they had in the Indian StartUp ecosystem. Just over half, 65, have a very rough idea for a startup coming into the program. In terms of skills, 63 had a background in web programming, 50 had experience in marketing, 38 had experience in data analysis, 30 had experience in sales, and many were experienced in accounting, PR, operations, and market analysis. Unsurprisingly for a program focused on software startups, the most common industry the participants were interested in entering (58 people) was Internet and Technology. Beyond this, the participants' core interests were diverse, with 39 people interested in education, 35 in financial services, 27 in advertising, 17 in media, 13 in health care, 12 in food and beverage, and others interested in everything from manufacturing to agriculture to corporate social responsibility.

A1.2 Assignment procedure

The 112 participants who attended the camp on Tuesday morning were randomly assigned to one of forty teams that morning. The randomization was done in the bootcamp's learning management platform. The learning management platform used the javascript **Math.random()** function to assign each participant a random number. The platform then ordered these random numbers and assigned the first 99 participants in the randomly ordered list into 33 teams of three, the next 12 participants to teams of two, and then added the remaining participant to the first team of three. These 40 teams (32 of size 3, 6 of size 2, and one of size 4) were then assigned a new random number, rank ordered on this random number, and then assigned to one of the forty numbered workbench locations.

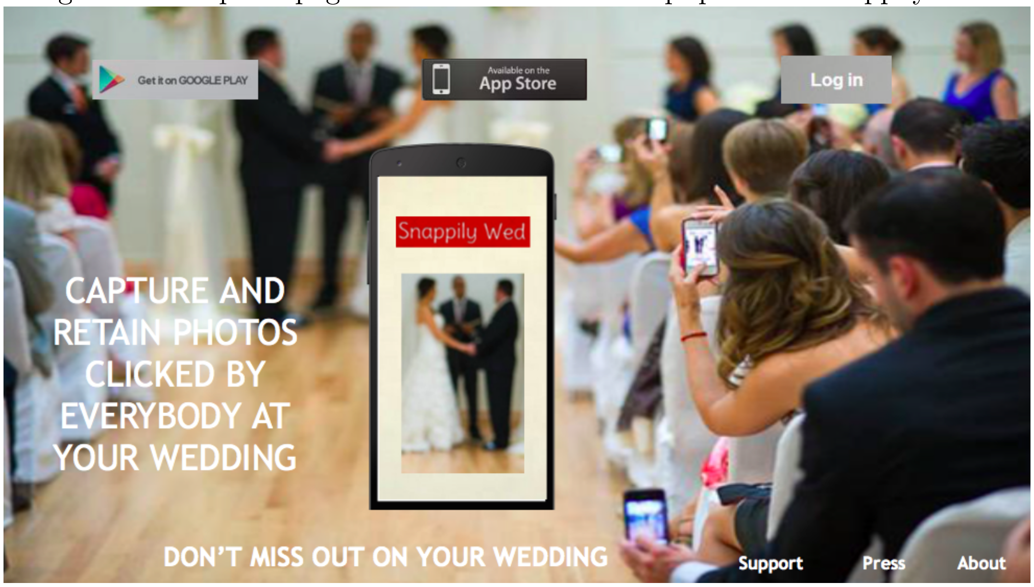
A1.3 Team projects and Evaluations

Below we provide examples of the projects. The projects are from the top, middle, and bottom quartiles of submissions in terms of total score. The visuals and descriptions show clear differences in project quality.

An example of a submission in the top quartile was a prototype for mobile app called "Snappily Wed." The team's description of the product is as follows:

> *Your guests use smart phones to take photos at the wedding but don't share them with you. For you it's a loss of precious memories. Our App solves the problem by allowing your Guests to take pictures and directly saving them on the cloud. Don't miss out on your wedding. Capture and retain every photo taken by Everybody at your wedding (be it your uncle playing with your nieces or your brother taking photos of the food served). The marrying couple (you or the person maintaining your account) will have access to these pictures and will retain and share the ones which are great, while discarding the rest, for your loved ones to view.*

Figure A1.1: Splash page for submission in the top quartile—Snappily Wed.



Their splash page depicted in figure A1.1, is clear and visually appealing:

An example of a submission in near the 50th percentile is "Tender my Wedding." The team describes their idea as:

> *TenderMyWedding is a platform which turns the process of finding vendors for a wedding upside down. Rather than the customer looking for vendors for their wedding needs, we let Vendors look for them. All they do is simply post their requirements with budget and within no time, top service providers from everywhere would be competing to get them as their customer. It's a win-win as you get multiple cost-effective quotes for the requirements without stepping out of your home and Vendors get new business.*

Their splash page submission, depicted in figure A1.2:

An example of a submission in the bottom quartile of the ratings is "Invite My Pals," which is described as:

> *Invite My Pals makes inviting people a much easier task with superb efficiency! Be it wedding or any other occasion, using this app you can send invitations to people that will not just directly reach them but also would let you keep track of how many people are going to join you on your day. With the video invites and e-cards best suiting to your taste you send invitations in more personalised way than ever before!!*

Their splash page submission, depicted in figure A1.3:

Figure A1.2: Splash page for submission in the middle quartile—Tender my Wedding.

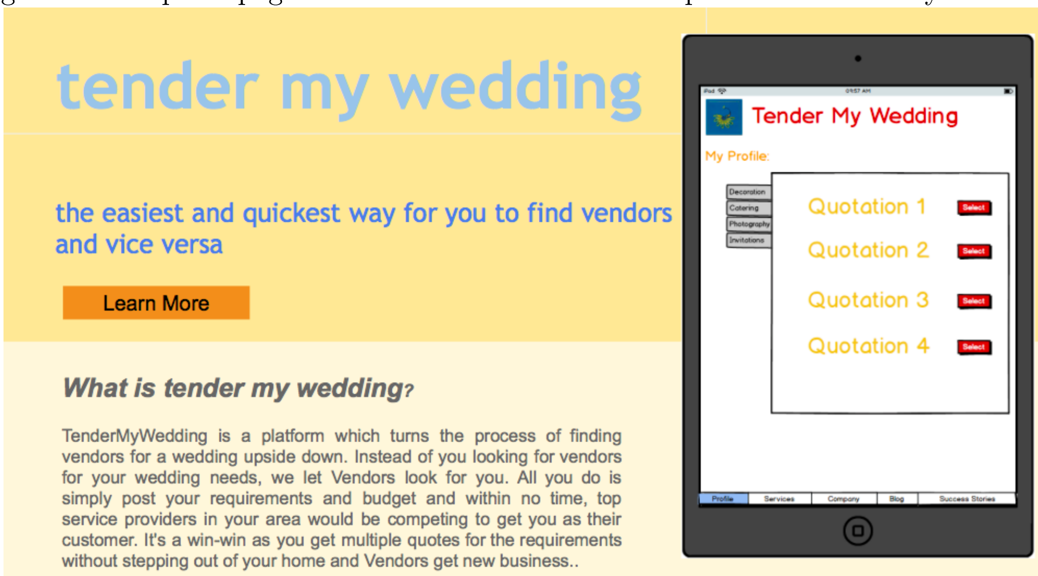
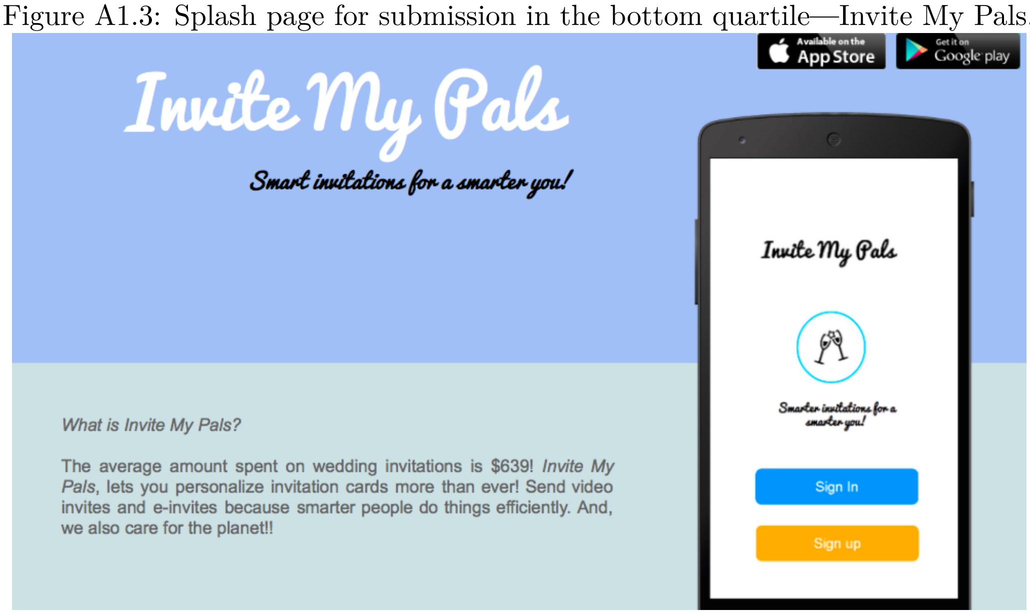


Figure A1.3: Splash page for submission in the bottom quartile—Invite My Pals.



A2 Ability, experience and personality do not predict prior ties

Does our measure of prior ties instead reflect a related, but distinct concept? For example, perhaps extroverts enter the camp with more connections and are more likely to interact with others irrespective of how near or far they are from them. In this scenario our estimates reflect not the impact of prior connections on peer interactions and effects, but instead reflect the impact of personality differences on peer interactions and effects.[1] Alternatively, perhaps those with more experience or greater ability are more self-assured and so seek out connections to others who are useful no matter their location. Again, our estimates may not reflect the presence of prior ties.

We test for these alternatives by regressing our measure of prior ties on measures of each participants ability, experience and personality. Our measure of ability comes from the admissions process. We use the average *Admissions score* each participant received from three raters who evaluated each participant's resume, GPA, a list of skills, and a statement of purpose. Participants were rated on a Likert scale ranging from 1 to 5. There is substantial variation in these scores, with average scores ranging from 5 to 1.67. To measure experience we draw on a question that asked if the participant had launched a startup in the past. We use this variable to construct a dummy variable, *Founded a startup?*, to capture differences in experience with the Indian startup ecosystem. There are 37 founders—mostly of failed ventures—among the 112 participants. Finally, as part of the pre-bootcamp survey, participants had to fill out a 44-item big-five personality scale along with a 25-item self-monitoring scale. We then scale our measures of agreeableness, conscientiousness, extraversion, neuroticism, openness and self-monitoring to have mean 0 and standard deviation 1. The distribution of prior ties is both "fat tailed" and has a modal value of zero (Figure 2 in the main text). To account for this skew, we log transform the number of prior ties plus one.

We find little evidence that our measure of prior ties reflects differences in ability, experience or personality. In Table A2.1 none of the coefficients on our ability, experience, or personality measures are significant at the 10% level. Further, the coefficient sizes are relatively modest. The largest observed effect size is for experience. We find that participants that founded a startup have roughly 16% fewer prior ties, though the estimate must be taken with a grain of salt as the estimated standard error is larger than the point estimate. Across models 1 through 8 the best R-squared is 0.013. The lack of results continues in Model 9 which includes the full set of 8 predictors. In Model 10 we use a quasi-Poisson regression to check that the log-transform of the dependent variable is not driving the observed null results. The results from this non-linear model are consistent with Models 1-9. prior ties do not appear to reflect differences in ability, experience or personality.

[1]Though the extrovert explanation is appealing it is worth noting that participants with more prior ties interact with new peers at lower rates. We would expect extroverts to interact at higher rates.

Table A2.1: What predicts if a participant has preexisting connections?

	Dependent variable:									
	log(# of prior ties + 1)									# prior ties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Admission score	−0.128 p=0.440								−0.188 p=0.302	−0.248 p=0.438
Founder		−0.161 p=0.389							−0.274 p=0.159	−0.170 p=0.639
Self-Monitoring			−0.051 p=0.581						−0.093 p=0.352	−0.064 p=0.713
Agreeableness				−0.056 p=0.512					−0.085 p=0.306	−0.040 p=0.776
Conscientiousness					0.105 p=0.251				0.145 p=0.121	0.204 p=0.290
Extraversion						0.061 p=0.459			0.121 p=0.203	0.262* p=0.056
Neuroticism							0.039 p=0.647		0.053 p=0.597	0.074 p=0.647
Openness								−0.096 p=0.299	−0.120 p=0.252	−0.225 p=0.185
Constant	1.109 p=0.002	0.903 p=0.000	0.849 p=0.000	0.849 p=0.000	0.849 p=0.000	0.849 p=0.000	0.849 p=0.000	0.849 p=0.000	1.321 p=0.002	1.501 p=0.028
Observations	112	112	112	112	112	112	112	112	112	112
R^2	0.007	0.007	0.003	0.004	0.013	0.005	0.002	0.011	0.077	

Significance stars (*) are omitted.
Models 1-9 are linear regressions and model 10 is a quasi-poisson regression.
Robust standard errors.

A3 Balance tests

To test the balance of our spatial randomization we run three regressions. First, we regress the distance between i and j on whether participant i knew j before the bootcamp. The results are presented in Table A3.1 Model 1. We find no evidence that distance correlates with prior ties. In Model 2 we test if participants with more prior ties are more likely to be closer or farther away from other participants. We again find little evidence that those with more incoming connections systematically differ in their distance to other participants. In Model 3 we include the eight control variables analyzed in the Section A2.1. We find no evidence that participants with higher ability, more experience, or of certain personalities are farther or closer away from others.

Table A3.1: Was the spatial randomization successful?

	Dependent variable:		
	Distance between i and j (meters)		
	(1)	(2)	(3)
i has p prior tie to j	0.298 p = 0.506	0.099 p = 0.791	0.071 p = 0.848
log(i's number of prior ties + 1)		0.148 p = 0.273	0.185 p = 0.238
Admission score			0.067 p = 0.761
Founder			0.698 p = 0.089
Self-Monitoring			0.084 p = 0.567
Agreeableness			−0.049 p = 0.739
Conscientiousness			−0.143 p = 0.084
Extraversion			−0.048 p = 0.732
Neuroticism			−0.163 p = 0.432
Openness			−0.251 p = 0.306
Constant	13.217 p = 0.000	13.096 p = 0.000	12.701 p = 0.000
Observations	12,222	12,222	12,222

Significance stars (*) are omitted.
Linear regression models with standard errors in parenthesis.
Robust SEs clustered at ego team, alter team, and team-dyad levels.
Individual-level between-team dyads

A4 The results hold when we use linear models

We replicate Table 3, but using linear regression instead of non-liner models. Our findings hold.

Table A4.1: Linear models of peer interaction

	Dependent variable:					
	Know		Advice		Messages	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance between i and j (meters)	−0.003	−0.002	−0.001	−0.001	−0.001	−0.001
	p=0.017	p=0.037	p=0.014	p=0.007	p=0.014	p=0.007
i has prior ties	−0.045		−0.034		−0.034	
	p=0.073		p=0.002		p=0.002	
Has prior ties X Distance	0.002		0.001		0.001	
	p=0.052		p=0.033		p=0.033	
Log(Number of prior ties + 1)		−0.009		−0.019		−0.019
		p=0.534		p=0.001		p=0.001
Log(Number...) X Distance		0.001		0.001		0.001
		p=0.152		p=0.007		p=0.007
Constant	0.211	0.192	0.064	0.059	0.064	0.059
	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Observations	11,918	11,918	11,918	11,918	11,918	11,918

Models 1-9 linear regression.
Robust SEs clustered at ego team, alter team, and team-dyad levels.
Individual-level between-team dyads.
Dyads where i knew j pre-camp are excluded.

A5 The results hold when including fixed effects and participant controls

To further test that our results are not the result of individual differences, we replicate Table 3 but include fixed effects for each participant and the controls described in Section A2.1. Since the models include fixed effects individuals differences are not identified. However, the interaction between distance—which varies within individuals—and individual differences can be identified (Allison, 2009). Our results hold even when including fixed effects and controlling for the interaction between distance and individual differences; the only exception is that the standard errors on the distance coefficient in Model 3, which predicts knowing, trebles in size leading the point estimate to become statistically insignificant.

Table A5.1: Entering the camp knowing at least one other peer wipes out the effect of proximity on new peer interactions

	Know			Advice			Messages		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance between i and j (meters)	-0.020 p=0.000	-0.019 p=0.000	-0.016 p=0.340	-0.024 p=0.016	-0.026 p=0.005	-0.061 p=0.054	-0.018 p=0.000	-0.015 p=0.000	-0.036 p=0.000
Distance × Has prior tie?	0.012 p=0.112			0.025 p=0.080			0.022 p=0.000		
Distance × log(# of prior ties + 1)		0.007 p=0.089	0.007 p=0.100		0.020 p=0.020	0.023 p=0.012		0.012 p=0.000	0.013 p=0.000
Distance X Admission Score			-0.001 p=0.919			0.014 p=0.299			0.007 p=0.071
Distance X Founded a Startup?			-0.004 p=0.611			0.014 p=0.418			0.019 p=0.001
Distance X Self-Monitoring			0.000 p=0.948			0.010 p=0.234			-0.002 p=0.435
Distance X Agreeableness			-0.002 p=0.716			-0.007 p=0.478			-0.003 p=0.229
Distance X Extraversion			0.003 p=0.496			-0.003 p=0.752			-0.002 p=0.485
Distance X Conscientiousness			0.001 p=0.819			0.009 p=0.288			0.002 p=0.438
Distance X Neuroticism			-0.006 p=0.187			0.005 p=0.567			-0.007 p=0.008
Distance X Openness			0.002 p=0.723			0.008 p=0.332			-0.003 p=0.253
Participant Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,811	11,811	11,811	9,935	9,935	9,935	11,918	11,918	11,918

Number of observations shifts as participants with no variation in the D.V. are dropped.
Robust SEs clustered at the ego, alter, and dyad levels.

A6 The wall and particular locations do not impact formation over and above distance

To test the robustness of our distance measure we run a series of models controlling for the architectural details of the bootcamp space. We test three potential concerns. The first is that teams near the entrance (right edge of tables in Figure 1) and bathrooms (bottom row of tables in Figure 1) may have more peers walks by. These teams might be less likely to interact with one another as a result. Given these "edge" teams are farther away from "middle" teams these architectural differences could drive our findings and not distance. To control for this concern we generate a variable *i near entrance/bathroom* that indicates if a participant is seated in these locations. We also generate a variable *j near entrance/bathroom* to test if what matters is not the participants location, but the location of the peer.

The second concern is that the distance effect merely reflects the fact that 26 of the teams sit on "higher ground" and 14 sit on "lower ground" a few steps down (the area above, to the left, and to the right of the wall in Figure 1). This could lead to two communities of interaction, perhaps with no distance effects in these communities. To test for this community possibility we generate three variable: *i in lower area*, *j in lower area*, and *i and j in lower area.*

The third concern is that the low-wall in the middle of the space did not prevent interaction and thus accounting for the wall in our distance calculations may bias our measure. To test if the wall reduces interaction we generate a variable *i and j across wall* if participants *i* and *j* sit across the low wall from one another. The coefficient on this variables should be positive and significant if the wall did not prevent interaction.

Table A6.1 replicates the knowing and advice models from Table 3, but includes these "architectural" variables to test if these alternatives explain our results.[2] In none of the models are any of the these "architectural" coefficients significant at the 10% level. The standard errors are often larger than the coefficient estimates. Our pattern of results hold even when including the full set of "architectural" control in Models 5 and 10. In Model 4 we find a insignificant though positive effect of being across the wall on knowing, though in Model 8 we find an insignificant and negative effect on advice. Being across-the-wall neighbors does not appear to increase the likelihood of interaction despite the absolute proximity.

[2]The results for digital messaging, available upon request, are similar to the advice and knowing models.

Table A6.1: Differences in architectural details do not explain our findings.

	Dependent variable:									
	Know					Advice				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distance between i and j (meters)	−0.023 p=0.017	−0.025 p=0.010	−0.025 p=0.041	−0.023 p=0.020	−0.026 p=0.035	−0.029 p=0.017	−0.030 p=0.014	−0.031 p=0.037	−0.029 p=0.017	−0.031 p=0.040
i has prior tie	−0.305 p=0.057	−0.281 p=0.102	−0.308 p=0.058	−0.310 p=0.057	−0.271 p=0.108	−0.834 p=0.001	−0.818 p=0.002	−0.839 p=0.002	−0.841 p=0.002	−0.810 p=0.002
i near entrance/bathroom	0.132 p=0.483				0.245 p=0.240	0.076 p=0.725				0.210 p=0.431
j near entrance/bathroom	−0.123 p=0.341				−0.066 p=0.648	−0.148 p=0.485				−0.156 p=0.506
i in lower area		0.082 p=0.605			0.214 p=0.214		0.142 p=0.472			0.252 p=0.311
j in lower area		0.141 p=0.311			0.106 p=0.512		0.047 p=0.779			−0.026 p=0.893
i and j in lower area			−0.045 p=0.652		0.011 p=0.887			−0.048 p=0.759		0.001 p=0.995
i and j across wall from each other				0.195 p=0.555	0.283 p=0.377				−0.108 p=0.866	0.035 p=0.954
Has prior tie X Distance	0.016 p=0.069	0.015 p=0.111	0.016 p=0.069	0.016 p=0.069	0.015 p=0.106	0.029 p=0.082	0.028 p=0.083	0.029 p=0.083	0.029 p=0.082	0.029 p=0.079
Constant	−1.307 p=0.000	−1.360 p=0.000	−1.251 p=0.000	−1.298 p=0.000	−1.459 p=0.000	−2.630 p=0.000	−2.699 p=0.000	−2.596 p=0.000	−2.648 p=0.000	−2.735 p=0.000
Observations	11,918	11,918	11,918	11,918	11,918	11,918	11,918	11,918	11,918	11,918

Models logistic regressions.
Robust SEs clustered at ego team, alter team, and team-dyad levels.
Individual-level between-team dyads.
Dyads where i knew j pre-camp are excluded.

A7 The peer effect results hold when using alternative measures of prior ties and when controlling for team size.

As a final robustness check, we test if our results hold when using alternative measures of a team's prior ties. We think there are four reasonable alternative constructions. The first is to use the log of the number of connections to account for the fat-tailed preexisting connection distribution. While this alternative is appealing given Figure 2 in the main text, we see in Figure A7.1 that at the team level the total number of prior ties is approximately uniformly distributed. The second is to use the average instead of the total number of connections in a team. This implicitly accounts for variation in team size. The third alternative is to count the total number of unique prior ties to other participants. Thus, if both members know the same person j only one of those connections is counted. This alternative places less weight on the impact of redundant connections. The fourth alternative is to count the number of prior ties to unique teams. Thus, if a team has connections to j and k, but both sit on team t, then only one of the connections would be counted. This alternative places less weight on connections to individuals who are on the same team. To further account for team size we also include a control for if a team has fewer members.[3]

Table A7.1 tests if our findings are robust to these alternative measures. To begin, in Model 1, we include the measure we use in the primary paper along with a control for team size. While smaller teams appear to have lower performance, the standard errors are large. In Model 2 we test if a logged version leads to similar results. The results hold, though significance drops to the 10% level for the interaction effect. In Model 2 we use the average number of ties, in Model 3 the total number of unique connections, and in Model 5 the total number of unique team-level connections. No matter how we construct our measure of a team's prior ties we find that having more prior ties reduces the impact of neighboring teams.

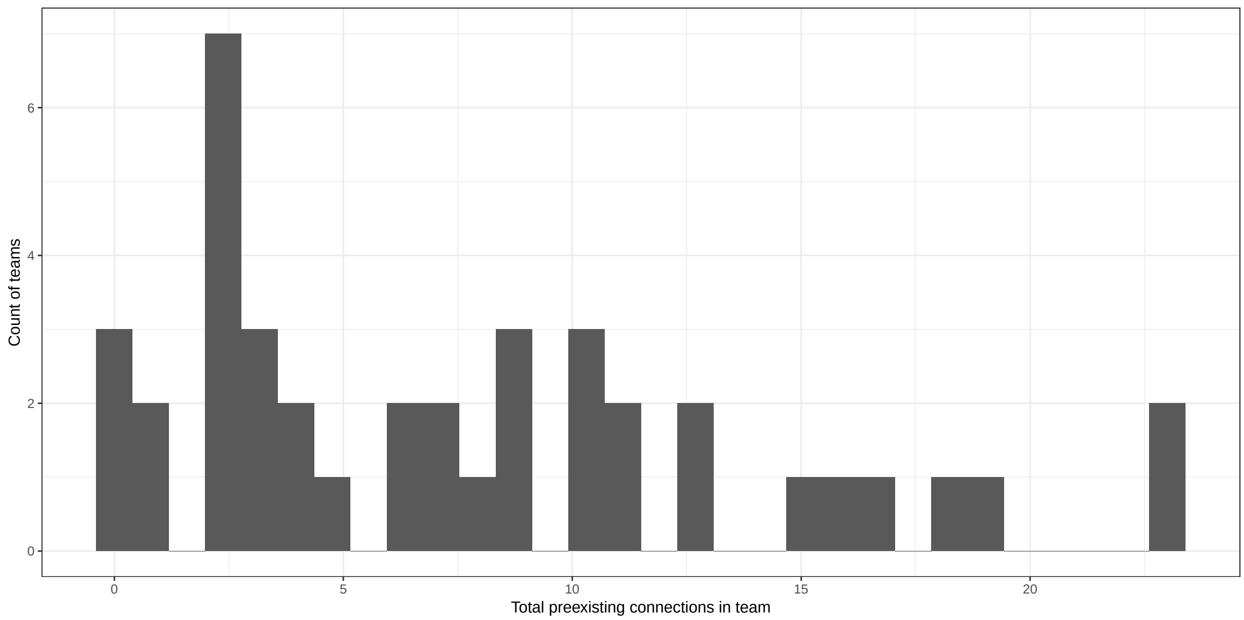
[3] The 112 participants were randomized into 40 teams. Thirty-three teams were of size three, six of size two, and one team had four members. In the regressions we include a dummy of if the team is size two given we have only one observation for four member teams. Our results remain unchanged when we drop the one team of size four from our analysis.

Table A7.1: Testing alternative operationalizations of a team's prior ties

	Dependent variable:				
	Team Performance				
	(1)	(2)	(3)	(4)	(5)
Neighbors' team performance (mean)	1.731	2.281	1.706	1.734	1.823
	p = 0.002	p = 0.016	p = 0.002	p = 0.002	p = 0.002
Two member team?	−0.376	−0.420	−0.341	−0.377	−0.382
	p = 0.545	p = 0.551	p = 0.555	p = 0.545	p = 0.537
Total prior ties	0.016				
	p = 0.488				
Neighbors' team performance × Total preexisting connections	−0.129				
	p = 0.066				
Log(Total prior ties +1)		0.179			
		p = 0.488			
Neighbors' team performance × Log(Total preexisting connections +1)		−0.875			
		p = 0.100			
Mean prior ties			0.043		
			p = 0.480		
Neighbors' team performance × Mean prior ties			−0.376		
			p = 0.080		
Total unique ties				0.017	
				p = 0.488	
Neighbors' team performance × Total unique ties				−0.133	
				p = 0.062	
Total team-level unique ties					0.020
					p = 0.492
Neighbors' team performance × Total team-level unique ties					−0.156
					p = 0.050
Constant	0.824	0.774	0.747	0.821	0.823
	p = 0.941	p = 0.833	p = 0.931	p = 0.943	p = 0.937
Number of Neighbors	8	8	8	8	8
Observations	40	40	40	40	40
R^2	0.246	0.235	0.235	0.250	0.255

Models linear regressions.
We report pseudo-p-values generated from a permutation bootstrap test with 1,000 runs.

Figure A7.1: The total number of prior ties in each team is relatively uniformly distributed.



References

Allison, Paul D. 2009. "Fixed effects regression models." 160.