Do network dynamics undermine idea-based network advantages? Experimental results from an entrepreneurship bootcamp*

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Abstract

Do networks plentiful in ideas provide early stage startups with performance advantages? On the one hand, network positions that provide access to a multitude of ideas are thought to increase team performance. On the other hand, research on network formation argues that such positional advantages should be fleeting as entrepreneurs strategically compete over the most valuable network positions. To investigate these competing views, I embed a field experiment in a startup bootcamp to test if networks that are plentiful in ideas lead to sustainable network-based performance advantages. Leveraging data on each participant's creative potential, I use peer randomizations and detailed data on network formation to show that ties to more creative individuals improve team performance. Despite the performance benefits of such connections, I find little evidence that entrepreneurs strategically connect to others who have greater creative potential. Instead, entrepreneurs seek feedback from others on dimensions that are more socially salient and verifiable. Beyond providing causal evidence for the durability of network-based performance advantages, these findings provide micro-level support to the importance of knowledge spillovers within bootcamps, accelerators, and startup ecosystems more generally.

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Introduction

Does building a network position plentiful in ideas result in performance advantages? A diverse set of innovation, strategy, and organizational theories (Cohen and Levinthal, 1990; Burt, 1995; Saxenian, 1996; Hargadon and Sutton, 1997; Reagans and McEvily, 2003), supported by a growing body of empirical research (Ahuja, 2000; Burt, 2004; Fleming, Mingo and Chen, 2007; Hsu, Roberts and Eesley, 2007; Azoulay, Graff-Zivin and Wang, 2008; Singh and Fleming, 2010; Hsu and Lim, 2014), suggests that networks rich in ideas, information, and knowledge should improve the performance of innovators and entrepreneurs in a wide variety of contexts. Underlying these theories is the view that having access to a greater pool of ideas increases the chance that individuals, teams, and firms discover novel combinations (Schumpeter, 1934; Fleming, 2001), happen upon one extremely good idea (Girotra, Terwiesch and Ulrich, 2010), or gain otherwise hard-to-learn expertise, skills, and knowledge (Nelson and Winter, 1982; Argote, McEvily and Reagans, 2003). While the exact structure of the optimal position may vary, all else being equal, occupying a network position that provides access to more ideas, information, and knowledge—the raw material necessary for creative production—should improve performance.

The argument that networks and the information that flow through them are consequential for performance is especially strong in the context of entrepreneurship (Stuart and Sorenson, 2005). Researchers have documented how networks shape the decision to become an entrepreneur (Nanda and Sørensen, 2010), the composition of the founding team (Ruef, Aldrich and Carter, 2003), and the resources available to the entrepreneur (Shane and Stuart, 2002; Stuart, Hoang and Hybels, 1999; Roberts and Sterling, 2012). Networks are thought to be particularly important in helping firms learn about new ideas, knowledge, and information that in turn improves their products, growth and performance (Baum, Calabrese and Silverman, 2000; Sorenson and Audia, 2000; Verdes and Stark, 2010; Lerner and Malmendier, 2013). Beyond the performance of an individual firm, scholars see such networks as producing spillovers and agglomeration effects (Almeida and Kogut, 1999; Chatterji, Glaeser and Kerr, 2013), forces that are thought to be necessary to the development of entrepreneurial ecosystems and economic growth (Jaffe, Trajtenberg and Henderson, 1993; Romer, 1994; Saxenian, 1996; Glaeser, Kerr and Kerr, 2015).

Practitioners increasingly recognize these insights. At the organizational level, the exponential growth in startup bootcamps, incubators, and accelerators has resulted in a profusion of organizations in which startup founding teams can learn from one another, share ideas, and develop new business insights (Hochberg, 2015). At the strategic level, contemporary entrepreneurship frameworks emphasize the importance of seeking out and listening to other people when generating new ideas, business models, and products. For example, the design thinking approach emphasizes cultivating empathy with a range of stakeholders to develop richer and more nuanced knowledge (Kelley and Kelley, 2013). Similarly, the lean startup movement pushes entrepreneurs to spend the majority of their time out of the office testing ideas with customers, users, and potential adopters (Ries, 2011; Blank, 2013). In contemporary startup ecosystems, founders are routinely encouraged to build expansive and diverse networks.

Research in entrepreneurship has not been blind to the process of networking and relationship building, though much less attention has been paid to how ties form than to their subsequent effect on performance (Stuart and Sorenson, 2008). Over the last decade research on network formation suggests that an entrepreneur's network emerges as a result of a combination of social and strategic action (Stuart and Sorenson, 2008; Gulati and Srivastava, 2014). Building on the sociological concept of homophily—the tendency of people to interact with others like themselves (McPherson, Smith-Lovin and Cook, 2001)—researchers have demonstrated that entrepreneurs tend to form ties to others who have the same interests, gender, education, and skills (Ruef, Aldrich and Carter, 2003; Vissa, 2011). Beyond homophily, this sociological work has also pointed to the importance of preferential attachment—making connections to popular and high-status others (Rivera, Soderstrom and Uzzi, 2010)—in entrepreneurial network formation (Stuart, Hoang and Hybels, 1999; Hsu, 2004; Stuart and Sorenson, 2008). Complementing this sociological view is the idea that entrepreneurs are strategic in their relationship building (Larson, 1992; Jackson et al., 2008). In this view, entrepreneurs actively seek out others with valuable resources and reputations, complementary skills, and informational advantages (Hsu, 2004; Vissa, 2010, 2011). Put differently; startups do not just benefit from occupying particular network positions, but they also develop relationships to move into such positions (Granovetter, 1985).

While network formation and network performance are often studied independently, models of formation and performance suggest that these network processes are very much interdependent (Stuart and Sorenson, 2008). Theoretical work that jointly models network formation and network-based performance advantages has identified a fundamental tension between agency in network formation and the network's potential performance benefits (Ryall and Sorenson, 2007). If networks are formed strategically, then entrepreneurs should compete away the advantages provided by occupying any particular network position. For example, in the case of structural holes, theoretical work suggests that other entrepreneurs should quickly enter, and so close, valuable brokerage positions (Burt, 2004; Buskens and Van de Rijt, 2008). In the network formation view, performance advantages cannot come from a new venture's network position, but must emerge from other sources, such as capabilities that are internal to the firm. Even if we set aside strategic action, if networks are formed through homophily and preferential attachment, then network positions will not lead to performance advantages, but will primarily reflect underlying differences between the startups (Gould, 2002; Stuart and Sorenson, 2008; Lynn, Podolny and Tao, 2009). This is because entrepreneurs will connect to others like themselves. For example, talented, creative, and knowledgeable founders will form ties to similar others, generating a network rich in ideas and information, but one that primarily reflects assortativity and not the independent performance effect of the network. In short, we are left with a puzzle: *do network positions lead to performance advantages or do pre-existing performance differences drive network formation?*

In this paper, I empirically test this formation-performance trade off using a two-stage experimental design. Building on the peer effects literature, in the first stage I measure each person's creative potential and randomize the feedback and advice network a startup team has access to (Lerner and Malmendier, 2013; Hasan and Bagde, 2013; Sacerdote, 2014; Hasan and Bagde, 2015). By limiting opportunities outside of these exogenous ties, I dampen the influence of network formation and isolate the effect of being assigned to a network higher in creative potential on team performance. I then relax the constraint on network formation. In the second stage, teams are self-selected and network formation is self-directed and endogenous. Using the exogenous ties created berfore the second stage, I can test if the exogenous network generated during the first-stage still provides performance advantages in the face of endogenous network formation.

To implement this design, I embedded a field experiment in a full-time startup bootcamp in New Delhi, India. Bootcamps, accelerators, and incubators are cornerstones of contemporary startup ecosystems and so provide an excellent research site for understanding the effects of social networks on entrepreneurial performance (Hochberg, 2015). The three-week-long, full-time program worked with 112 aspiring entrepreneurs to hone their design-thinking skills and develop their business-model validation abilities; the program also served as a platform where they could meet co-founders and launch a new business venture. The most successful teams won mentorship, the chance to pitch in front of investors, free co-working space, and prizes worth over 35,000 Indian Rupees ($5,500). Crucially, although the program took place in person, it was designed around an online learning management platform that captured the results of brainstorming sessions, coordinated who sought feedback from whom, and managed project evaluations. Using data from this platform, I can measure the creative potential in each team's randomized network, if this network improved performance, and if the performance effects survive in the face of endogenous formation. Furthermore, the platform also measured network activation, allowing me to examine the endogenous network formation dynamics and contribute to a small but growing literature that integrates network formation and the estimation of peer effects (Carrell, Sacerdote and West, 2013; Hasan and Bagde, 2015).

I find that teams that are exogenously connected to partners who have more creative potential perform better as measured by peer evaluations and crowdfunding page views. This effect holds when the network is exogenously fixed and in the face of endogenous team and network formation. Examining the network formation data reveals that the aspiring entrepreneurs do not seek out others who are better at generating ideas. Instead, ties are formed on other dimensions that are more socially salient and verifiable than someone's creative potential. Taken together, I find evidence that performance advantages will persist when the characteristic of interest—creative potential—is hard to observe and difficult to verify through social interaction.

This paper makes three distinct contributions to the study of networks, entrepreneurship, and innovation. First, it provides causal evidence for network-based advantages and contributes to a burgeoning movement to bring field experiments into the study of entrepreneurship and innovation (Boudreau and Lakhani, 2015). Second, the findings advance our understanding of how network formation impacts performance advantages. Similar to work on partially deliberative matching (Azoulay, Liu and Stuart, 2016), the results suggest that while networks diffuse valuable knowledge and ideas, people are either unable to identify or unwilling to form ties, with others who could provide these valuable social spillovers (Carrell, Sacerdote and West, 2013). This implies that the networks that form between people and firms need not be efficient, multiple equilibria with varying benefits are possible. Third and finally, the findings suggest that firm strategies and ecosystem policies that explicitly target social networks through community building and social matching have the potential to improve firm outcomes by increase the flow of information and knowledge. While some firms will benefit more from having a network richer in ideas and information, all firms benefit when they are not isolated but have ties to one another.

Network Formation and Network Advantage

Scholars of innovation and entrepreneurship view the generation of new ideas, breakthroughs, and businesses as a social process. While incentives and competition play an important role in the generation of new ideas and businesses (Lerner and Wulf, 2007; Boudreau, Lacetera and Lakhani, 2011), there is a wealth of evidence that psychological, cognitive, and especially sociological factors matter (Amabile, 1996; Boudreau et al., 2014; Boudreau and Lakhani, 2015). This view of entrepreneurship and innovation as a sociological process builds on the observation that social networks are crucial in the spread of new products and novel information (Coleman, Katz and Menzel, 1957; Granovetter, 1973). Thus, social networks provide a critical pathway for the innovator or entrepreneur to learn about new ideas and gain knowledge, the raw material of creative production (Nelson, 1982). While different types of network positions (i.e., brokerage vs. cohesive positions) may be more or less optimal, scholars largely agree that being in a more central position that provides access to more information increases the chance of entrepreneurial success (Reagans and McEvily, 2003; Stuart and Sorenson, 2008; Aral and Van Alstyne, 2010).

These network models rest on the underlying idea that having access to a larger and more diverse pool of information increases performance in creative tasks. The mechanisms underlying this linkage are myriad. One stream of research, building on Schumpeter's (1934) conception of innovation as a process of novel recombination, argues that the probability of valuable recombination increases as the pool of ideas drawn upon becomes both wider and more diverse (Fleming, 2001). While this line of work has concentrated on the efficiency of brokerage positions in providing diverse knowledge relative to more "redundant" positions (Burt, 2004; Fleming, Mingo and Chen, 2007), the underlying argument is that having access to more ideas increases the chance of discovering a novel recombination. Another stream of research focuses not on recombination, but instead on discovery (Diehl and Stroebe, 1991; Amabile, 1996; Dahan and Mendelson, 2001). In this view, innovation is modeled as a two-stage process. In the first stage, people generate ideas. In the second stage, they evaluate and select one of these ideas for further development. Since the goal of the innovator is to find one extremely good idea, having access to a larger pool increases the probability that she will find an idea in the extreme right tail of the quality distribution (Dahan and Mendelson, 2001). Evidence from the lab by Girotra, Terwiesch and

Ulrich (2010) supports this assertion.

Returning to the social nature of innovation, scholars increasingly believe that entrepreneurs and innovators often turn to their social networks to increase the quantity of information, knowledge, and ideas they have access to. Often we learn from others because the knowledge we seek is tacit and so difficult to gain outside of social relations (Kogut and Zander, 1992). Learning must take place in person, be it through working together, conversations over coffee, or gossip around the office water cooler (Sorenson and Audia, 2000). Recent work examining the death of superstar scientists affirms this view. Even though scientific research is codified in journal articles and lab procedures, the sudden death of a creative and knowledgeable scientist adversely impacts the scholarly production of the deceased scientists' co-authors (Azoulay, Graff-Zivin and Wang, 2008). In short, networks connect us to others who can increase the pool of ideas we have to work with.

In the specific case of early stage startup teams, the effect of network position should be especially important. New ventures have limited resources and thus are especially reliant on inter-firm networks for everything from capital to information (Powell, 1990; Larson, 1992). While there is clearly a variety of complementary resources that are needed, recent work had identified the importance of the product idea and the business plan as an important predictor of future success (Delmar and Shane, 2003; Åstebro and Elhedhli, 2006; Kornish and Ulrich, 2014). Complementing this research is observational analysis which points to the central role networks play in spreading knowledge and shaping firm strategy and performance (Baum, Calabrese and Silverman, 2000; Hsu and Lim, 2014). Building on these findings concerning the performance of new ventures, and the more general arguments outlined above, I expect the following relationship to hold:

Hypothesis 1 *An early stage startup with a network that connects the team more ideas will outperform a startup whose network connects the team to fewer ideas.*

While past work using observational data has found evidence for this hypothesis, the specter of endogeneity is an increasing concern in the innovation, strategy, and entrepreneurship literatures (Stuart and Sorenson, 2008; Baum, Cowan and Jonard, 2013; Boudreau and Lakhani, 2015). This concern is not pedantic. Work on network diffusion has demonstrated that network effects estimated on observational data can vastly overstate the effects of networks on outcomes (Aral, Muchnik and Sundararajan, 2009). Regarding firm performance, there is a concern that firms with greater capabilities form ties to one another, and to better investors and advisors, and thus network positions are better thought of as signals of quality rather than as a causal force that improves performance (Podolny, 2005; Baum, Cowan and Jonard, 2013). As with many types of social or business networks, the process of homophily provides a compelling alternative explanation (Stuart and Sorenson, 2008). If networks are merely an epiphenomenon of underlying differences, there are very different implications for firm strategy, ecosystem policy, and our theories of entrepreneurship and innovation.

Even if one can exogenously shift a startup's network position, the problem of endogenous network formation remains. This is because entrepreneurs are thought to have large amounts of agency in how they build their networks (Stuart and Sorenson, 2008; Vissa, 2011). Therefore, if network ties to people who have more ideas, knowledge, and information are thought to improve performance (Burt, 1995, 2004; Fleming, Mingo and Chen, 2007; Aral and Van Alstyne, 2010), then we should expect entrepreneurs to build ties to these creative and knowledgeable people. An example is illustrative. Imagine two entrepreneurs, Dianne and Larry. Larry is randomly introduced to advisors who bring with them a wealth of ideas and information, Dianne to less knowledgeable partners. Formal models of strategic action imply that Dianne will not maintain her relationships with her exogenously assigned partners. Given that ties are costly to maintain (Burt, 1995; Jackson et al., 2008; Rivera, Soderstrom and Uzzi, 2010) both in terms of time and effort, entrepreneurs should seek out partners who maximize the "return" on each relationship. In this example, Dianne should seek out more knowledgeable advisors in order to maximize the benefits from her network (Ryall and Sorenson, 2007; Buskens and Van de Rijt, 2008). Thus, while the exogenous network of advisors differs, the actual network of advice may not. In these stylized models, Dianne's strategic networking may undermine Larry's performance advantages provided by the exogenous difference in initial network position.

However, one does not need to assume wholly instrumental actors to arrive at similar conclusions. Sociological models based on homophily, reciprocity, and preferential attachment also predict that exogenous differences in the network may be largely washed away by endogenous responses. Formal models of reciprocity and preferential attachment imply that actors both try to form ties to those who are better than they, but sever relations with those who do not reciprocate even if they sit higher in the pecking order. When reciprocity and preferential attachment are modeled together, the result is that actors form relationships with others of similar ability (Gould, 2002). In the context of entrepreneurship and ideas, this implies that networks will come to reflect underlying differences in knowledge and creativity despite any initial differences in network position. Even more directly, there is the possibility that homophily will overwhelm any exogenous differences in network position. Recent work has demonstrated the presence of strong homophily effects despite organizational mixing (Kleinbaum, Stuart and Tushman, 2013) and even in the face of deliberately optimized exogenous variation (Carrell, Sacerdote and West, 2013).

In both the instrumental and more sociological views, founders of new ventures actively build out their social networks. In all these models, teams will seek out others who can provide many ideas. The opposite is also true; we expect that they should dissolve ties to others who have little to share since maintaining social ties is costly, and the benefits of being connected to those who provide little in the way of knowledge or information will be minimal. Be it through reciprocity, homophily or strategic action, the result of the network formation process is social clustering and assortativity. Given Hypothesis 1, it should be the case that founders will end up connected to others who are similar in creative potential. This leads to my second hypothesis:

Hypothesis 2 *Founders of early stage startups will (a) attempt to build networks to others who can provide more ideas, (b) drop ties to those who have fewer ideas, and so (c) will tend to be connected to others who are similarly creative.*

Critically, if hypothesis 2 strongly holds, then the potential performance advantages of exogenously determined network positions are greatly limited. As teams rewire their networks, network position will come to reflect each team's underlying differences. The exogenous network will quickly become irrelevant as the entrepreneurs largely ignore their initial exogenous ties and form networks on their own. Without the exogenous network serving a meaningful conduit for ideas, the performance advantages of any exogenous position will dissipate. Taking Hypothesis 1 and 2 together leads to the following implication:

Corollary 1 *As the networking behavior of founders becomes increasingly strategic ($H2$), the quantity of ideas in a startup's exogenous network will provide diminishing performance advantages ($\neg H1$).*

No matter a startup's initial position, if founders are strategic then the network rewiring processes described above will iron out the performance advantages provided by exogenously created network ties. Conversely, if Hypothesis 1 strongly holds, then the network formation process should significantly differ from the network formation models predicted in Hypothesis 2. While there is some evidence for both hypotheses in the literature (Stuart and Sorenson, 2008; Vissa, 2011), there is almost no work directly examining the trade-off between these two sets of predictions. The next section described the field setting and experimental design that are used to test these hypotheses.

Data and methods

Overview of the field setting

The setting used to test the predictions outlined above is an entrepreneurship bootcamp. The full-time program took place over three weeks in June of 2014 in in Delhi, India and was designed by the authors and volunteers from the Indian Software Product Roundtable. Figure 1 provide an overview of the structure of the bootcamp and experimental design. The bootcamp trained 112 aspiring entrepreneurs from across India in idea generation, design thinking, prototype development, and business model validation. During the third week of the program, the participants self-formed into teams of three. From this pool of nascent startup teams, the best teams won mentorship, the chance to pitch in front of angel investors, free co-working space, and prizes worth 35,000 Indian Rupees ($5,500).

[Figure 1 about here.]

Similar to other incubators, accelerators, and bootcamps (Hochberg, 2015), admission into the bootcamp required the completion of an extensive online application, made public September 10, 2013 and with a completion deadline of February 1st, 2014. Applicants had to provide a detailed overview of their work history, education, technology and business skills. The bootcamp received 508 fully completed applications. After a selective admission process, 116 aspiring entrepreneurs enrolled and attended at least the first day of the program. Four participants dropped out before the end of the bootcamp, leaving 112 individuals who participated over the entire three weeks.

The age range of the 112 graduates ran from 18 to 36, the program had 25 women, and everyone had graduated from or was enrolled in college. The participants were primarily engineering and computer science degree holders (78), followed by 18 business degrees, and the rest from the arts and sciences. The majority of participants came from elite Indian universities such as Delhi University, IIIT-Delhi, Delhi Technological University, and the IITs. It is important to note that universities in India are composed of relatively independent colleges. Thus most of the participants in our program did not know one another even if they came from the same university. Everyone in the program spoke English. While younger than the average entrepreneur (Ruef, Aldrich and Carter, 2003), the characteristics of the bootcamp participants roughly mirrors what is seen in software-startup bootcamps and incubators in the US (Hochberg, 2015).

The participants professional experience and business skills were quite varied. Nearly 80 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, had a very rough idea for a startup coming into the program. Regarding their skills 63 had a background in web programming, 50 experience in marketing, 38 in data analysis, 30 in sales, and many in accounting, PR, operations, and market analysis.

The bootcamp was designed around three week-long modules. It was held six days a week, Monday through Saturday, from 9am to 5pm, but participants could work longer hours if desired. The first week focused on design thinking, feedback, and prototyping. Individuals worked in assigned teams of three to develop a software product concept for the Indian wedding industry. During this week, teams and individuals received feedback about their ideas and prototypes from an assigned subset of their peers. At the end of the week, individuals submitted their final prototype for peer evaluation. To simplify the deployment of our surveys, and to leverage our measurement strategy as a meaningful part of the program's curriculum, the majority of the project evaluation, 360 feedback, and network surveys were bundled into a single "Full Circle" module that was deployed using our web-based learning management platform. Using this learning management platform, participants reflected on what they learned, evaluated how their team operated and graded one another's projects. The top three teams at the end the first week, determined by the peer evaluations and an expert panel of judges, won prizes totaling just over 750 USD.

The second week focused on developing a software product in the Indian health sector. During this week the program focused on training the participants in evaluating market potential, developing a business model, and how to validate business ideas with data. Again individuals worked in randomly assigned teams of three to develop a product concept but with a strong focus on developing the most convincing business plan they could. Like week one, groups and individuals were required to get feedback from an assigned set of their peers about their ideas, prototypes and business models. In total, each participant was assigned to work with seven distinct groups during the second week. These highly collaborative interactions promoted the sharing of knowledge and information among participants. At the end of the week, teams submitted their product concepts and business models for peer evaluation. Again, the top teams from this week won prizes totaling just over 750 USD.

The third week was much less regimented than the first two weeks. The Saturday before the third week began, individuals self-organized into teams of three. During the third week, the teams selected a problem to solve, built a prototype of their product, developed a business plan, and composed a pitch deck to be presented to leading members of India's startup community the following Sunday. Each evening, individuals were required to complete a daily progress report asking them what tasks they completed during the day, who they got or gave different types of advice to and their plans for the next day. At the end of the week, the teams submitted a complete packet of information about their startup and product. The packet, submitted digitally, included everything from a pitch deck to a description of the team. See *Appendix: Submission Packet* for the full set of items that were required. Each submission was then evaluated by peers. The top five submissions got to pitch in front of luminaries from the Indian startup community on the final Sunday of the three-week program. All teams got to present their business ideas, and build their professional networks, during an all-inclusive "poster-session" before the final pitches.

Overview of the experimental design

Beyond training entrepreneurs and supporting the emergence of new Indian ventures, each of the week-long modules also enables the estimation of peer effects models and so causal tests of the central arguments presented in this paper. Peer effects models have been used to look at the influence of peers on academic achievement (Sacerdote, 2001; Hasan and Bagde, 2013), the decision to become an entrepreneur (Lerner and Malmendier, 2013), CEO compensation (Shue, 2013), and more (Sacerdote, 2014). To overcome the dual identification problems of reflection and selection (Manski, 2000), peer effects studies first measure each person's abilities and then randomize, most often naturally but increasingly deliberately, peer interactions. More details on the estimation of peer effects models can be found in Sacerdote (2014).

In the case of the bootcamp, in week one each participant's creative potential—their ability to generate and share ideas in a given unit of time—is measured (See Figure 1 for a visual time line of the experiment). Described in more detail below, this week one measure of creative potential provides a pre-treatment measure of how many ideas a person is likely to share during a brainstorming session or conversation (Amabile, 1996; Shalley, Zhou and Oldham, 2004; Girotra, Terwiesch and Ulrich, 2010). In week two, teams and the inter-team feedback network are randomly assigned, and performance is measured at the end of the week during the Saturday full circle session. This structure allows for the estimation of the following simple linear model:

$$Y_i = \alpha + \beta X_i + \epsilon_i \tag{1}$$

where Y_i is the performance of the team at the end of week 2 and X_i is the total creative potential of the team's randomized feedback partners. Since peers are randomized selection bias can be ruled out. Since each person's creative potential is measured both before treatment and before the dependent variable is measured, the problem of reflection and reverse causality is accounted for. Therefore β provides a causal estimate for the effect of increasing the creative potential in a team's network on team performance.

While week one and two of the bootcamp test the effect of the network on performance, the random assignment of teams and feedback partners largely rules out the possibility of testing the effect when endogenous network formation operates. Week three remedies this constraint. In the third week, teams were self-formed and were free to seek advice and feedback at their own discretion. However, an element of exogeneity remains in the third week. Using the week two feedback and team randomizations, I can construct a measure of the exogenous creative potential each week-three team was exposed to during the second week. Unlike the week two network measure, this measure captures the effects of both past exposure, along with any feedback a week two partner may also provide during the third week (Boudreau et al., 2014; Hasan and Bagde, 2015). If entrepreneurs form networks according to hypothesis 2, then the estimate for β should be greatly diminished when estimating the peer-effects model using the week three data.

Beyond estimating the effects on performance, during the third week, the network formation dynamics between the teams were also measured. Using data from daily progress reports I can directly test if, as argued in Hypothesis 2, entrepreneurs are more likely to seek out others who have more creative potential, if they avoid those who provide fewer ideas, and if they end up with network ties to similar others. Before turning to model estimation, the next section provides further detail on how I measure and construct variables for the creative potential in each team's network, the characteristics of the teams, and how the teams form their networks during the third week.

Independent variables

Measuring creative potential

Clearly, measuring how many ideas a person has, and can convey, is a difficult task (Amabile, 1996). While past work has primarily relied on structural position to proxy for information diversity and volume (Burt, 1995; Reagans and McEvily, 2003), doing so relies on the assumption that different parts of the network reflect distinct pools of ideas and knowledge. In a three-week-long program where networks are deliberately randomized, this assumption does not hold. Instead, I rely on a half-day-long brainstorming exercise from the first week of the program to construct a measure of how many ideas each participant can convey in a fixed unit of time, which I refer to as a person's creative potential. Similar to macro-work that uses counts of patents to measure knowledge spillovers between firms and regions (Acs, Anselin and Varga, 2002; Owen-Smith and Powell, 2004), creative potential provides a micro-level quantitative measure of how much information and knowledge a person can share.

Specifically, to measure each person's creative potential, I count the number of ideas they generated during the week one brainstorming session. Counts on the quantity of ideas generated are used in a range of literatures—from small groups research to design studies to operations research—as a measure of creativity and ideation ability (Torrance, 1972; Amabile, 1996; Paulus and Yang, 2000; Shah, Smith and Vargas-Hernandez, 2003; Girotra, Terwiesch and Ulrich, 2010). That said, this measure has traditionally been used as a dependent variable. However, recent work has begun to model the quantity of ideas not as an end in and of itself, but emphasize the quantity of ideas as an important input in the innovation process (Girotra, Terwiesch and Ulrich, 2010). Furthermore, research from psychology and organizational behavior has found that creativity, while dependent on contextual factors, is a relatively stable characteristic of the individual and thus can be treated as a stable individual difference (Shalley, Zhou and Oldham, 2004).

Returning to the brainstorming session, each participant was tasked with generating ideas about how to "Reinvent the Indian wedding experience." Then, using the program's learning management platform, they typed in their ideas over the course of two thirty minute brainstorming sessions. The full prompt and protocol for the brainstorming exercise can be found in *Appendix: Brainstorming*. The individuals varied in their creativity: the average numbers of ideas generated was 7.87 with a standard deviation of 4.48 ideas. I refer to this measure, which is similar to the concept of fluency in creativity research (Torrance, 1972; Kim, 2006), as creative potential to distinguish that it measures a person's capacity to generate ideas and not the content of the ideas. During the second week of the program teams were tasked with working on health related business ideas and during the third week no team developed a business idea related to the Indian wedding industry. Thus, the results of the brainstorming exercise should be seen as a measure of generalized creativity and ideation ability, similar to a SAT score or Intelligence test.

Creative potential in a team's network

With a measure of each person's creative potential in hand, the next task is to randomize each team's inter-team network ties to induce variation in the creative potential of each team's set of network partners. To do so, I rely on the feedback and brainstorming sessions that occurred during the second week of the program. As mentioned above, each participant was randomized into a team of three people, though five teams ended up with only two members because of both logistical constraints and the fact that two participants dropped out after the first week. This leaves thirty-four teams of three and five teams of two. As mentioned above, team members were required to get feedback from a randomly selected set of their peers about their ideas, prototypes and business models. Feedback outside of these randomized interactions was relatively limited. In total, each participant was randomized into approximately seven distinct groups during the second week. Not all team members were randomized into the same feedback groups; often one team member would meet with another randomly selected person from another team. In total, each team was exposed to approximately 20 external feedback partners. These highly collaborative interactions promoted the sharing of knowledge and information among participants. Furthermore, the norms of the bootcamp were designed to promote information sharing and collaboration to mitigate strategic information withholding from rival teams. A full description of the week two randomizations can be found in *Appendix: Week Two Feedback Groups.*

Creative potential in the week two team's network, my measure of the quantity of ideas provided by a team's exogenously assigned network ties, is calculated as follows. First I generate a participant-level 112×112 adjacency matrix F^{wk2}. F_{ij} is set to 1 if person i and person j ever collaborated in the same feedback group during the second week. I also construct a matrix P^{wk2} that maps from each week-two team to each participant. It has 39 rows and 112 columns, with an entry set to 1 if person j was on team i. Writing each participant's creative potential as a vector Z^{wk1}, I then calculate the total creative potential of each team's network as:

$$X_i^{wk2} = [P_{t\times p}^{wk2} F_{p\times p}^{wk2} > 0] Z_{p\times 1}^{wk1} \tag{2}$$

The dichotomization removes double counting if a team is exposed to the same person twice to account for potential redundancy in the ideas and knowledge that they would provide to the team. However, using the non-dichotomized counts generates results that are qualitatively similar to those presented below.

Creative potential in the week three team's network is constructed in a similar fashion to the week 2 variable. I again rely on the week two randomizations. As discussed above, while the teams and inter-team interactions during the third week are endogenous, the team and feedback groups each person was exposed to during the second week were randomized. Thus, I can test if these exogenous ties from the second week still provide performance advantages in the face of endogenous formation during the third week. To do so, I construct a matrix P^{wk3} that maps from each of the 37 self-formed week-three team to each of the 112 participants.[1] I also include each person's randomized week-two teammates, in the form of an adjacency matrix T^{wk2}, as a network tie each person was exposed to during the second week. If someone's feedback partners still have an influence during the third week is seems incredibly likely that their teammates will also have an influence. For week three, I then calculate the total creative potential of each

[1]The only constraint during the third week was that teams had to be of size three. Since we had 112 participants, one individual selected to work alone instead of joining as a fourth team member. This single one-person team is excluded from all analysis, leaving 37 week-three teams.

team's network as follows:

$$X_i^{wk3} = [P_{t\times p}^{wk3}((F_{p\times p}^{wk2} + T_{p\times p}^{wk2}) > 0)(1 - T_{p\times p}^{wk3})]Z_{p\times 1}^{wk1} \tag{3}$$

The second to last term in this expression excludes week three team members from the team's external network. Since this measure depends on the endogenous week three team formation process, the effect captured by this measure can be from two sources. On the one hand, as argued above, it could be because the team gets more information from its network ties, either during the second or third week. On the other hand, it could be that participants randomized into interactions with alters who have greater creative potential use this information to sort into higher quality teams. In this alternative, what matters is not the flow of information in the network, but how the network shaped the team formation process. However, if this alternative holds, it must be the case that team formation occurs on the basis of creative potential. As the results on network formation show below, teams and networks do not appear to form on the basis of creative potential, and so the team-formation-to-performance alternative is unlikely to be the mechanism underlying the observed effect of this measure.

Dependent Variables

Peer Evaluated Performance

Measuring very-early-stage startup performance is demanding. Traditional measures, such as the number of users or revenues, are uninformative since nearly all teams will have none. However, scholars of entrepreneurship have developed other measures that tend to correlate with performance. This literature has shown that external ratings of how complete a startup's business plan is, and how developed the product and technology are, are informative of the startup's future success (Delmar and Shane, 2003; Åstebro and Elhedhli, 2006). Work on innovation has found that the quality of the raw business idea, as rated by crowds of experts and consumers, is predictive of the idea's future performance as a product or business (Kornish and Ulrich, 2014). Similarly, work analyzing peer evaluation of creative tasks in massive online open courses finds that peers can do as well as experts when evaluating complex and creative outputs (Kulkarni et al., 2015).

Building on these literatures, I developed an online evaluation tool which the participants used to rate one another's projects on the each Saturday of the bootcamp. Each team submitted a packet of materials online. This packet included a paragraph describing the business idea, a lean model canvas, a pitch deck, and assorted other materials. The full list of materials required is presented in *Appendix: Team Submission Packet*. Each of these team submission packets was then randomly evaluated by eight of the bootcamp participants in week two and 56 of the bootcamp participants in week three. Participants did not rate their own teams, and the order in which the packets were presented was randomized. After browsing through all the packets for thirty minutes, evaluators then had 10 minutes per packet to read through each team's material. After reading through the lean model canvas, pitch deck, prototype page, and splashpage, evaluators were asked to rate the startup using a 5-point Likert on ten dimensions: Novelty, Business Potential, Product Need, Prototype Quality, Splashpage Quality, Purchase Intent, Pitch Deck Quality, Team Quality, Lean Model Canvas Quality, Problem Quality. The prompts and scales for each of these dimensions are listed in *Appendix: Team Evaluation Rubric*.

To better distinguish between the best and worst submissions, the evaluators also rank order each team on each dimension. This was done by presenting the evaluator with a rank-order pop-up whenever the evaluator rated two startups as having the same Likert score on a given question. For example, if I rated the first team as having a score of 4 on novelty and I then rated the second team as also having a novelty score of 4 then a dialog would pop up asking me to rank the two teams against one another. By prompting the user whenever projects were tied, I can back out a full rank ordering for each of the projects rated by each participant. The analysis below uses these rank scores.

Despite the fact the startups were rated on ten dimensions exploratory analysis reveals that the teams primarily varied on one underlying quality dimension. Using Principle Component Analysis I generate orthogonal linear combinations for the average ranking each team received on the ten evaluation dimensions. The first principle component explains over 60% of the variance. Furthermore, all the scores move in the same direction. For example, for the first dimension, teams higher in novelty also score better in business potential. Given the magnitude of the first component and the lack of interpretable dimensions in the other dimensions, I treat the rankings as capturing a single underlying dimension of each team's performance.

Performance Rating is the average of the rank each team receives across all ten dimensions and across all of the randomized evaluators. To ease interpretation, I standardize the average score to have mean 0 and standard deviation 1.

Crowdfunding Page Views

For the third week, I also have an external measure of performance, crowdfunding page views. Working with one of India's largest equity crowdfunding platforms I was able to match each startup's crowdfunding profile (if they generated one) to the number of angel investors who viewed a team's crowdfunding profile page. Given the increasing importance of crowdfunding and angel investing in early stage startup performance (Bernstein, Korteweg and Laws, 2015), this measure provides a complementary and more general measure of performance.

Network Activation

The third and final dependent variable I analyze is who each person seeks advice and feedback from during the third week of the program. This measure allows me to directly test Hypothesis 2. I use daily progress reports from the third week of the bootcamp to measure the team's self-initiated interactions. At the end of each day during the third week each person was required to write down the progress they made that day, who they talked to outside of the program, the ideas they considered, their plans for the next day, and who they had interacted within the program. To indicate who they had interacted with each participant was presented with a roster of all the other participants and asked to select anyone who met the following criteria:

> *Select anyone from outside of your team who you gave or got feedback from, brainstormed with, sought advice from or worked with on you startup idea. Also, it doesn't have to be formal feedback, it could be someone you had lunch with who provided valuable insight or a friend you had coffee with who you gave a good business model idea.*

After selecting the people who fit this criterion the participants were then presented with a list asking them to select if the gave or got feedback from that person on their business model, prototype, point of view, pitch, or simply received general advice. The full list of questions is listed in *Appendix: Daily Progress Report* along with an example of what the roster interface looked like.

Does ego i receive advice and feedback from alter j? is calculated by first aggregating the network survey data across the entire week. I then construct a dichotomous measure of advice seeking. This measure equals 1 if someone on the team indicated that they received feedback or if someone outside of the team stated that they provided feedback to the team.

Control Variables

Beyond the primary dependent and independent variables described above, I also include some control variables in the analysis to assess robustness and evaluate the mechanisms driving the estimated treatment effects.

Creative potential in the team is the sum of the creative potential over each of the team's members. This variable allows me to control for team level differences in creative potential and to test if having a team higher in creative potential, as against having a network, improves startup performance.

Number of female members counts the number of team members who are female. A little over 20 percent of the program participants were female. Given the importance of gender in network formation (Ibarra, 1992), and the barriers women face in the world of technology and entrepreneurship (Brooks et al., 2014), this control is also of substantive interest.

Average startup experience in the team measures the average amount of startup experience the team has. This variable allows me to test if the mechanism is driven not by creative potential but by underlying differences in experience, a related but distinct concept. Before the start of the bootcamp, each participant typed responses to the following questions: "If you have started a startup(s), please describe it and its current status.", "Please list any mentors you have in the Indian startup ecosystem." and "Please list any startups that you have worked at, the size of the team, and your role." To convert this free-text data into quantitative measures, I first dichotomize each question as having a value of 1 if the participant entered a response other than "none." I then sum the answer across these three questions for each person, creating an index of startup experience that ranges from zero to three. I then standardize this variable to ease interpretation.

Average admission score in the team measures the average score each teammate received on their application to the bootcamp. Each applicant was rated on a five-point Likert scale by two to four independent evaluators during the admissions process. Better candidates received a one, worse candidates a 5. Raters assessed the applicants based on their college grades, the prestige of the educational institutions they had attended, the quality of their application essay, as well as their skills in business and technical topics. To ease interpretation, this variable has been reverse coded and standardized to have mean 0 and standard deviation 1. Higher values indicate better admission scores. Average admission score allows me to control for each participant's incoming "quality," allowing me to better identify if the estimated peer effect emerges because of differences in creative potential in the network as against the mechanism being mere differences general "talent."

Average 360 feedback score in the team measures how well the team members work with others. At the end of the first week, as part of the full circle exercise described above, each participant evaluated their two teammates using a standard 360 feedback survey. The 24 question survey asked about the person's leadership ability, ability to seek input, and receptivity to feedback. The questions are listed in *Appendix: 360 Feedback Survey Items* and come from the Society of Human Resources Management recommended battery of 360 feedback questions. To generate the 360 feedback score, I averaged the 5-point Likert scores for each participant on each of the 24 questions. In all cases, higher scores indicate a more collaborative and in many ways "better" teammate. The team-level measure averages these scores across teammates and is then standardized. The average 360 feedback score allows me to rule out the possibility that individuals with more creative potential are not transferring more ideas, but are simply being more helpful and collaborative.

Beyond these controls, additional robustness variables are described in the results section below. Summary statistics and correlations for all the variables described above can be found in tables 1, 2, 3, and 4

[Table 1 about here.]

[Table 2 about here.]

[Table 3 about here.]

[Table 4 about here.]

Results

Do networks higher to creative potential improve team performance?

To begin, I analyze the performance of the teams during the second week of the program. Even though the teams and feedback groups were randomly assigned, there remains the possibility that, by chance, the randomization was not balanced, and so variation in network position is correlated with within team differences (Gerber and Green, 2012). To test for balance across observables, I regress *Creative potential in the team's network* on each a series of team-level control variables— the number of female members, average startup experience, average admission score, average 360 feedback score, and average creative potential in the team—using ordinary least squares. The results, presented in Table 5, show that the characteristics of each team are not significantly correlated with the team's network position at conventional levels of significance. This provides strong evidence that the network randomizations succeeded and that the creative potential in the team's network can be treated as exogenous.

[Table 5 about here.]

Table 6 examines the relationship between the performance of teams in the second week and their randomly assigned feedback network. Given the fact that having three, as against two, team members increases the size of the team by 50% all models either control for team size or only include the three-person teams. Model 1 in Table 6 regresses the team's performance rating on two variables: if the team is composed of only two people and the team's average creative potential. Neither variable is significant, but smaller teams do appear to perform worse, and team's with members who have higher average creative potential do appear to perform better. Model 2 tests Hypothesis 1 by including the team-size indicator and the variable for creative potential in the team's randomly assigned week two network. This model lends some support for Hypothesis 1. A one standard deviation increase in creative potential leads to a 0.25 standard deviation increase in performance, though this relationship is only significant at the 10% level. As described in the discussion of equation 1, since the teams and feedback partners are randomly assigned the estimate should not suffer from selection bias.

[Table 6 about here.]

Models 3 through 5 in Table 6 include team-level controls. Doing so both increases the probability that the randomized network is uncorrelated with team-level characteristics and increases statistical power by controlling for alternative sources of variation (Gerber and Green, 2012). Model 3 includes both the team's creative potential and the creative potential in the team's network. Controlling for the team's creative potential does not weaken the effect of the network on performance. Instead, the effect size becomes both slightly larger and the estimate becomes significant at the 5% level. However while the within team creative potential is positive the coefficient is still insignificant, lending some support to the theory that internally sourced ideas may be less useful because team members will argue, scrutinize and compete over their ideas as against externally sourced ideas at higher rates (Menon and Pfeffer, 2003). Model 4 controls for the team's gender composition and average startup experience, admission score, and 360 feedback score. Including the full-set of controls only strengthens the effect, with a one standard deviation increase in the creative potential of the network leading to a 0.31 standard deviation increase in the team's performance ($p < 0.05$). Finally, Model 5 restricts the sample to teams with three members to ensure that differences in team-size are not driving the results. The effect of the network on performance remains.

[Table 7 about here.]

The week two results provide support for Hypothesis 1, teams that are randomly assigned to network partners with greater creative potential perform better. However, the models in Table 6 provide evidence for this relationship *but only in conditions where networks are fixed*. Week three allow me to test what happens when networks are allowed to form endogenously. As with the week two teams, I first test if the *Creative potential in the team's network* is correlated with team-level characteristics. Since the week three teams are self-formed and not randomized, there is the definite possibility that the variables will not be balanced across team characteristics if the randomized network shaped the team formation process. Table 7 presents balance tests for the week three teams. As with week two, none of the coefficients in the six models are significant at conventional levels. This provides support for the idea that the creative potential in the team's network does not shape team formation dynamics, and so any effect on performance is the result of the network ties and not the team formation process.

[Table 8 about here.]

Table 8 tests if the exogenous week-two network still generates performance differences in the face of endogenous network formation. Unlike week two, all teams were of size three except for one team which included a single individual and is dropped from the analysis. Using data from the third week of the bootcamp, Model 1 regresses performance on creative potential within the team and finds an insignificant but positive relationship between the two. Model 2 regresses performance on creative potential in the team's network and finds a positive, significant relationship ($p < 0.05$), lending support to the idea that exogenous changes in network position can provide performance advantages in the face of endogenous formation. Model 3 includes both the team and network-level measures. Both coefficients are positive and significant, though the within-team measure is only significant at the 10% level. Thus, while having a team high in creative potential may be beneficial, it appears that having creative potential in the inter-team network may have a larger impact on performance. Model 4 includes the full set of controls, and while the within-team creative potential loses significance, the coefficient on the creative potential within the network remains significant. A one standard deviation increase in the network measure leads to a 0.35 standard deviation increase in the team's performance ($p < 0.05$).

[Table 9 about here.]

Table 9 complements the analysis in Table 8 by testing if the performance effects go beyond peer evaluations and shape an increasingly important early-stage outcome: crowdfunding page views. Unlike the analyses presented thus far, the models in Table 9 are not fit using OLS. Since the outcome is a count variable and the majority of the team's received no page views, I model the relationship using zero-inflated Poisson regression. Models 1 through 3 display results from the second stage. Because so few teams received any investor interest, I am unable to include controls beyond the team's creative potential. In Model 1, I regress the number of page views on the team's creative potential, and while the coefficient is positive, the relationship is not significant. Model 2 tests if being randomly assigned to a network high in creative potential increases performance. The coefficient on *Creative potential in the team's network* is positive and significant at the 5% level. The effect is substantial. A one standard deviation increase the measure increases the number of page views by roughly 40%. In Model 3, there is evidence for both within-team and network-based creative potential leading to more page views by angel investors.

The models presented in Tables 6, 8 and 9 each lend support to Hypothesis 1. Exogenous networks that provide more ideas and information improve a team's performance startup; *even in the face of endogenous formation.* Before analyzing the endogenous network effects to see if Hypothesis 2 holds, I first explore the mechanisms underlying this effect in more detail below.

Testing alternative network-to-performance mechanisms

While the estimates discussed do not suffer from problems of selection and reflection, they do not rule out the possibility that the causal mechanism is not the quantity of ideas flowing through the team's network, but some other correlated, but theoretically distinct, mechanism (Sacerdote, 2014). For example, perhaps someone's creative potential is correlated with work experience and what matters is not ideas but experience. The treatment effect, exposing a team to others with more creative potential, would still be true, but the reason for the effect would be different. In this example, what would matter is getting feedback from someone with work experience and not necessarily their creativity or the quantity of ideas they share.

Tables 10 and 11 test a variety of alternative mechanisms. First, there is the possibility that it is not the quantity of ideas and information that people provide the team, but simply the quantity of people the team is exposed to. Model 1, in tables 10 and 11, tests this possibility in the week two and week three data, respectively. In neither model is the *Number of people in the team's network* significant and in both models *Creative potential in the team's network* remains significant. Thus variation in people's creative potential has implications for who a team should get advice from. Simply talking to more people is an effective networking strategy.

[Table 10 about here.]

[Table 11 about here.]

Model 2 in Tables 10 and 11 tests an alternative operationalization of creative potential. Instead of counting the number of ideas a person generates, I calculate the average quality of the ideas. The day after the week-one brainstorming exercise each idea was anonymously rated by approximately five other bootcamp participants in terms of its novelty, business potential, and purchase intention. Averaging across these scores, and across ideas, I create a measure of the average idea quality generated by each person. Then, similar to the procedure described for the quantity of ideas in the network, I generate a measure of the average ideation quality in each team's randomized network. As can be seen in Model in Tables 10 and 11 , I find no evidence for a quality-based mechanism. Instead, it appears—consistent with models of innovation and creativity—that the input that matters for creative performance is the quantity of ideas available and not necessarily their average quality (Girotra, Terwiesch and Ulrich, 2010).

Finally, Model 3 in Tables 10 and 11 includes network-level versions of the four control team-level variables: number of women, admission score, 360 feedback score, and startup experience. In each case, I calculate the average over the team's randomized networks. For week two, I find no significant effect for any of these variables and in all models creative potential remains significant at the 5% level. Thus we can rule out mechanisms that rely on differences in gender norms or a person's generalized ability. More importantly, it allows me to rule out that the mechanism is helpfulness of the peer or their experience as alternative explanations for the effect, two mechanisms that have been identified as sources of peer effects in the study of entrepreneurship and innovation (Oettl, 2012; Lerner and Malmendier, 2013). This pattern of results holds in the third week with the exception of average 360 feedback score in the network, which is negative and significant at the 5% level. Though unexpected, a potential explanation for this effect is that participants who are helpful and collaborative teammates (high 360 scores) self-sort into teams together and so reduce the number of inter-team ties that they have to others with high 360 feedback scores. If teams who work well together perform better, which we find evidence for in Model 8 in Table 4, then a negative effect of having higher average scores in the network would emerge. That said, the effect of interest—creative potential in the network—remains positive and significant at the 10% level.

Before turning to the network formation dynamics, I test two more complementary mechanisms using the week three data. The first tests if ties external to the bootcamp substitute for a team's intra-program network. Work studying the decision to become an entrepreneur has demonstrated such substitution effects, showing that ties to co-workers become less influential in the decision to become an entrepreneur when one already has ties to family members who are entrepreneurs (Nanda and Sørensen, 2010). In the context of the bootcamp, I measure external feedback using the daily progress reports from week three. As part of these reports, each person described who they talked to outside of the program. To generate a quantitative measure of the quantity of external feedback, I sum the number of times the team members entered text in this field during the third week. Model 1 in Table 12 interacts this measure of external feedback with the creative potential in the team's network. While the main effect of the getting more external feedback is positive and significant at the 1% level, the interaction is small and insignificant. Thus it does not appear that the two types of networks are substitutes in this setting.

[Table 12 about here.]

The second complementary mechanism I test is related to ties within the team. Prior research argues that network ties are only useful for a team if it can absorb, understand, and use the ideas and information the network provides (Cohen and Levinthal, 1990). Thus, teams that are internally cohesive should benefit more from being randomly assigned networks more plentiful in ideas (Reagans and McEvily, 2003). To calculate cohesion, I sum the number of advice ties within the team using network survey data collected at end of the first week of the bootcamp. Because the distribution of the number of advice ties within teams is highly skewed, making interpretation difficult, I generate a dichotomous measure of cohesion by setting this variable to one if the team had more internal advice ties than the median of two ties.

Model 2 in Table 12 tests the moderating effect of team cohesion. I find some support for the idea that only cohesive teams benefit from networks rich in ideas and information. Interacting *Creative potential in teams network* with the dummy *Is the team internally cohesive?* reduces the baseline effect of the network to nearly 0. However, the interaction term is positive and substantive. For cohesive teams, being exposed to a network one standard deviation more plentiful in ideas increases performance by 0.58 standard deviations ($p < 0.10$).

Taken as a whole, tables 5 through 12, provide evidence for Hypothesis 1: teams that are randomly assigned to networks with more creative potential perform better than those in less idea-rich networks. The effect holds when networks are "fixed" and when endogenous networking dominates. The next section explores why endogenous network formation does not appear to undermine the exogenous advantage of network positions high in creative potential.

Do people form ties to others with more creative potential?

Hypothesis 2 predicts that the nascent entrepreneurs who took part in the program will seek advice and feedback from others with greater creative potential. To test this prediction, I model advice and feedback during the third week of the program using dyadic regression models (Kleinbaum, Stuart and Tushman, 2013; Boudreau et al., 2014; Hasan and Bagde, 2015). While network formation data can be modeled using Exponential Random Graphs or Stochastic Actor Network Models (Wimmer and Lewis, 2010; Snijders, Van de Bunt and Steglich, 2010), dyadic regression allows for a simple and robust test of ego effects, alter effects, and homophily effects. In dyadic models, each potential relationship is treated as an observation. Thus, instead of having 112 person-level observations a dyadic data-set would have 12,432 directed ego-alter pairs. Since I am interested in inter-team networks, I exclude within-team pairs. To maintain comparability with the analysis above, I exclude pairs where the ego was the only person on their week-three team. This leaves 11,988 ego-alter pairs.

I then model the dichotomous dependent variable, *Does ego i receive advice and feedback from alter j?*, as a function of ego, alter and ego-alter covariates using a linear probability model. [2] The 11,988 ego-alter observations are clearly not independent. To account for this lack of independence, I follow the network formation literature and adjust standard errors using multi-way clustering (Cameron, Gelbach and Miller, 2011; Kleinbaum, Stuart and Tushman, 2013). I cluster on the ego, on the alter, and on the ego-alter pair.

Table 13 models who each participant got advice and feedback from. Model 1 tests if the week two treatments carry through to week three. Indeed, they do. Having been randomly assigned to collaborate with someone during week two increases the chance of interaction by 7.9 percentage points ($p < 0.01$), a 50% increase over the baseline probability of interaction during any given day. Participants are also more likely to get advice and feedback from the week two partners of their week three teammates. Thus the exogenous networks appear to influence feedback behavior even when people are free to seek out advice without constraint.

[Table 13 about here.]

Model 2 in Table 13 includes characteristics of the ego, alter, and the pair. Including gender, startup experience, admission score, 360 feedback score, and creative potential hardly alters the coefficients on the week two randomization variables. The only robust alter-level effect is that all participants appear to get advice from others with a more startup experience at greater rates. Creative potential appears to have little effect on how the network forms. Not only is the coefficient on *Creative potential (alter)* insignificant but the size is tiny and negative at -0.001. It does not appear that people sought out alters with greater creative potential, despite the performance advantages they could provide. Nor does it appear that those with more (fewer) ideas get feedback from others with more (fewer) ideas. The coefficient on *Creative potential (ego X alter)* is insignificant and near zero. However, homophily does exist in this setting; women are more likely to get feedback from women. Finally, Models 3 and 4 include fixed effects at the team-level and ego-level, respectively, to rule out the possibility that team and person-level variation is masking, or magnifying, any underlying network formation effects. The effects of the week two feedback randomizations remain significant in explaining the network formation

[2] Results are similar when using logistic regression.

in the third week; creative potential effects remain insignificant and near zero.

The results presented in Table 13 strongly reject Hypothesis 2, and with it Corollary 1. Network formation is structured by past interaction, an alter's startup experience and is homophilous. Networks do not form on the basis of creative potential. Unlike creative potential, these variables are both socially salient and verifiable. While one can claim to be "creative," past startup experience is much harder to socially falsify. As the results in Table 10 and 11 show, connecting to women or alters with startup experience does not provide a team with performance benefits. Networks appear to provide durable performance advantages because network formation occurs on dimensions that are orthogonal to the dimensions that improve performance.

While these results reject Hypothesis 2, it is unclear if the network formation results emerge because people don't want to connect with or if they prefer to connect to people with greater creative potential, but are constrained when forming ties. While the daily progress reports provide insight about who got advice from whom, they cannot reveal the preferences or reasons underlying this observed behavior.

To disentangle the preference as against constraint mechanisms, I use network survey data collected at the end of the second week of the bootcamp. As part of the full-circle exercise at the end of each week, the aspiring entrepreneurs were asked to indicate anyone in the program whom they thought would be useful to get to know more. Unlike realized networking behavior, this survey provides a measure of instrumental networking intention. Model 1 in Table 14 regresses this measure of strategic intention on if the alter is in the ego's week two network along with a number of the alter's characteristics, including their creative potential. If the participants thought creative potential was a valuable characteristic of an alter, then the coefficient on the variable should be positive. Participants think it would be useful to get to know alters with more experience, higher admission scores, and higher 360 feedback scores; evidence that the nascent entrepreneurs are at not entirely averse to forming their networks instrumentally (Kuwabara, Hildebrand and Zou, 2016). However, they are agnostic to creative potential. The coefficient is insignificant and near zero. Thus there does not appear to be a preference to form relationships to others with greater creative potential.

[Table 14 about here.]

As a final mechanism check, I test if people can learn who has creative potential over time. It could be that it takes time for information about who is creative to diffuse through the network. Thus, teams during week three may begin by connecting with anyone but over time prune their network towards those with greater creative potential. To do so, I use the progress reports from week three. Instead of aggregating over the week, I generate feedback measures for each day of the week. Table 15 displays dyadic linear probability models with these measures as the dependent variable. These models also include three one-day lagged variables: if the ego gave advice to an alter, if ego got advice from the alter, and the popularity (indegree) of the alter. These three variables measure consistency, reciprocity and preferential attachment effects, three processes that are present in almost all human social networks (Rivera, Soderstrom and Uzzi, 2010). Indeed, as the first three variables demonstrate, there is evidence that network ties are sticky, that reciprocity occurs, and that people are more likely to seek out popular participants for advice. Turning to an alter's creative potential, I find weak evidence for learning and search behavior. While the coefficients for the first three days are negative and insignificant, for the final two days they are positive, though small, and significant at the 1% and 10% levels, respectively. It may be the case that entrepreneurs can learn who provides valuable ideas and performance enhancing information spillovers. Future studies, with longer time scales, should more rigorously study such effects. That said, the learning is slow and the time line of the bootcamp is not unusual for many types of innovation and entrepreneurship programs. Taken as a whole, Tables 13 through 15, find little evidence for Hypothesis 2.

[Table 15 about here.]

Discussion and Conclusion

This paper uses a field experiment to test if networks rich in ideas improve a team's performance. While theorists have developed compelling models for why network advantages, especially idea-based advantages, should vanish in the face of network formation, direct and causal evidence has been greatly lacking (Ryall and Sorenson, 2007; Buskens and Van de Rijt, 2008; Stuart and Sorenson, 2008). This paper provides some of the first evidence from the field that exogenous variation in network positions has important performance implications, and so supports a large body of observational work that suggested the existence of such an effect (Stuart and Sorenson, 2008). In particular, I find evidence that having connections to peers who have more creative potential improves a team's performance. In the context of very early stage entrepreneurship, ties to others with better ideas or more experience seems to matter less than being connected to a fire hose of ideas and information.

While I can rule out a variety of alternative mechanisms, future work should further explore the mechanisms underlying the identified effect. Is the information provided by peers recombined or does having access to many ideas primarily allow a team to select one extremely good option? (Dahan and Mendelson, 2001; Fleming, Mingo and Chen, 2007) Alternatively, perhaps being exposed to others who generate many ideas mainly increases the amount of feedback a team receives on the ideas it has already developed. From the entrepreneurship as experimentation perspective, having more information in the form of feedback is akin to having a larger number of "experiments" that (in)validate business and product ideas (Kerr, Nanda and Rhodes-Kropf, 2014). Hearing lots of negative peer feedback could give an entrepreneur more confidence that she may be on the wrong track than if she gets only minimal feedback, allowing her to jettison a bad idea more quickly. More generally, while this paper looks at the role of social ties and ideas in the innovation process, more work, especially experimental work, needs to be done to understand how innovations and new business ideas are shared, developed, and tested.

Turning to the effects of network formation, I show that network-based advantages can hold when networks are fixed and in the face of endogenous network formation. The durability of these advantages emerges because entrepreneurs do not strategically seek out others with more creative potential. Specifically, the analysis of the formation process implies that they either don't know or don't want to build relationships with others who have more creative potential. A possible explanation for this finding is that a person's creative potential is hard to evaluate through social interaction. Perhaps creativity is not socially salient, being dominated by other characteristics like someone's gender or personality. This explanation is similar to work on partially-deliberative matching that shows that scientists seek out positions at labs based on their research domain, but then are influenced by the patenting behavior within the lab (Azoulay, Liu and Stuart, 2016). Alternatively, it could be that people are trying to evaluate one another's creativity during social interaction. However, if it is easy for everyone to claim that they have great ideas, lots of knowledge, and lots to say. In this case, the interaction will provide little more than cheap talk (Crawford and Sobel, 1982). Thus, unlike gender or someone's prior work experience, creativity may simply be hard to verify socially and so hard to build a network on. Consistent with the idea that network formation will occur on socially salient and verifiable dimensions, I find that network formation occurs on hard-to-fake and noticeable characteristics like gender and startup work experience. That said, future work should explore this explanation by deliberately manipulating the saliency and veracity of particular social dimensions.

As is the always the case, this paper has limitations. First, the sample size, though similar to research that has exogenously manipulated networks in the lab (Cook and Emerson, 1978), is relatively small. The sample consists of only 112 people partitioned into 39 teams during the second week and 37 teams during the third week. While powerful enough to detect main effects, the sample size limits my ability to test for heterogeneous treatment effects and so explore a wider variety of causal mechanisms. Second, the program and teams represent the "fruit flies" of the new venture world. While the fact that very-early-stage teams move fast, try many ideas and fail quickly is advantageous for the time-constrained researcher, it limits generalizability. Perhaps the spillovers and networking behavior that occur in the context of established and longer lived ventures are markedly different from early stage startups. Third, the context is very specific, an entrepreneurship bootcamp in New Delhi, India. That said, the results build on a larger literature that has studied entrepreneurial performance and networks at different stages and in varying geographies. Therefore one can interpret the findings as validating and extending a larger set of research on the importance of networks in the entrepreneurial process (Stuart and Sorenson, 2005).

These limitations also serve as signals for where more research is needed. First and foremost, while the bounded and specific nature of the entrepreneurship bootcamp allowed for detailed analysis, even the team with the least abundant network was exposed to people who had ideas to share and information to provide. Therefore, while network position no doubt matters, it is likely that mere participation in entrepreneurship bootcamps, accelerators, and incubators has a significant effect since being exposed to anyone is likely beneficial when compared to operating along (Singh and Fleming, 2010). Similar to work on inequality and networks (Small, 2009), future research should examine how decisions to participate at an organizational level shape the networks of entrepreneurs and innovators. Such effects are likely large and may have important consequences for the development of startup ecosystems. Given that entrepreneurs do not appear to know who would be valuable to connect with, such programs and organizations may be especially valuable in fostering the spillover of knowledge and ideas. While analyzing very-early-stage startups provided a complete and comparable set of teams; future research should explore how networks between established and geographically separated firms help them grow and succeed over longer time horizons.

Methodologically, this paper provides a template for future work studying team and firm-level network processes. By randomizing networks at the individual level, I can generate variation in the team-level network. This approach could be extended to experimentally study more macro networks such as inter-firm alliances, investor networks, regional spillovers and the linkages between scientists and firms (Zaheer, Gulati and Nohria, 2000; Sorenson and Stuart, 2008; Owen-Smith and Powell, 2004; Singh and Marx, 2013; Agrawal et al., 2014), bringing additional causal clarity to research on entrepreneurship and innovation at the macro-level (Chatterji et al., 2016; Boudreau and Lakhani, 2015). Furthermore, by embedding a learning management platform into the entrepreneurship bootcamp, I am able to collect detailed data on mechanisms that lead to differences in performance. Future work should explore how such digital tools can be adapted to study other aspects of the innovation and entrepreneurship process, providing more insight into the ideas, knowledge, and creative acts that are part and parcel of generating scientific breakthroughs and high-growth business.

Managerially, this paper demonstrates that designing social networks is not a fools errand. Valuable network positions can be built and maintained, though identifying the dimensions of value may be quite difficult. However, gaining expertise in determining these dimensions may be a source of competitive advantage. This view provides one possible explanation for the emergence of full-service venture capital firms and incubators like Andreessen Horowitz and YCombinator. Beyond providing capital, these firms explicitly build and collect data on the networks of their portfolio companies and promising individuals in the startup ecosystem.[3] These venture capital firms may have developed an important source of network-based competitive advantage by building out their capability to identify and create valuable social connections for their portfolio companies. Unlike other firms that have devoted less effort to measuring the ecosystem, these VC firms have built systems to discover, evaluate and measure who would be valuable to connect to their portfolio.

Finally, from a theoretical perspective, this article highlights the importance of network formation in the study of peer effects, network spillovers, and network-based performance advantages. Specifically, it provides a simple and testable reason why network-based advantages may persist: network formation occurs on dimensions independent of the performance enhancing spillover. While there has been increasing attention paid to network dynamics in the social

[3]See Peter Sim's Medium post How Andreessen Horowitz Is Disrupting Silicon Valley goo.gl/YfG6IV for a brief overview of how VC firms are leveraging the network within the Silicon Valley ecosystem.

networks literature, much is still unknown (Burt, Kilduff and Tasselli, 2013). Future work should investigate under what conditions network formation aligns with the spillover of interest, especially in regards to how socially salient and verifiable the dimensions of interest is.

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Appendices

Appendix: Brainstorming

The brainstorming session took place on the second day of the bootcamp bootcamp. The students were presented with the following prompt:

> *On November 27, 2011, over 60,000 weddings took place on this one single day in New Delhi, just because the day was auspicious. Every wedding hall in Delhi was booked for every shift and families paid large premiums of at least 1 to 2 lakhs, or more to book even the smallest halls. Even on less auspicious days, Indian weddings are big, fun, complex, loud, colourful, and most of all expensive. Today, the size of the Indian wedding industry is estimated to be around 2.25 trillion Indian rupees or 38 billion US dollars. The industry is also diverse—it includes such products and services as marriage gardens, match-making, clothing, decorations, makeup, gifts, jewelry, and a lot more. Startups in India have only scratched the surface of this industry—the most prominent example is Shaadi.com which has revolutionized matchmaking and made many aunties across India obsolete. Your task for this week is to develop a product concept for a mobile and web app that will reinvent part of the wedding experience– either before the wedding, during the wedding and after the wedding—in India. On to reinventing!*

After reading the prompt, they had approximately thirty minutes to individually generate ideas in response to the prompt.The photo below is of one of the participants entering an idea in the online learning platform.

After entering ideas, the participant was randomly paired with someone else in the program to conduct an "empathy interview," a standard design thinking activity (Kelley and Kelley, 2013). After doing three of these interviews, the second brainstorming session commenced. Since assignment to empathy interview partners is orthogonal to each individual's characteristics, I can use the ideas generated during both sessions to construct a more informative, and less noisy measure, of each person's creative potential.

Appendix: Week Two Feedback Groups

The randomized week two interactions were roughly thirty minutes in length and involved intense collaboration, continuous converstations and idea sharing. Each person participated in three hiring simulations that involved brainstorming with two randomly selected alters. They also did an empathy interview with two other people, which involved both describing health problems they had and listening to the problems of their partners. Finally, they participated in three Lean Model Canvas Feedback sessions in which they gave advice, and received advice, about the business model canvas they were developing. The average person collaborated with 9.3 people outside of their team during the second week.

Appendix: 360 Feedback Survey Items

At the end of each week, participants would rate each of their two teammates on the following dimensions. The items come from the Society of Human Resources Management recommended battery of 360 feedback questions.

1. Seeks input from all team members.
2. Shows genuine concern for team members.
3. Keeps the focus on fixing problems rather than finding someone to blame.

4. Treats people fairly.
5. Encourages others to express different ideas and perspectives.
6. Is open to other perspectives and is willing to change his/her position when presented with compelling information.
7. Open to negative and/or constructive feedback.
8. Gives open and constructive feedback.
9. Effectively deals with conflict.
10. Moves fast and doesn't get stuck on tangential problems.
11. Involves others in decision-making when appropriate.
12. Sets a clear direction for our team.
13. Seeks input/feedback from diverse individuals and groups, including internal/external people.
14. Treats everyone with respect and fairness.
15. Encourages and embraces change by challenging status quo.
16. Action and behaviors are consistent with words.
17. Is trustworthy.
18. Is a role model for continuous improvement.
19. Uses a coaching approach to leadership, rather an authoritarian boss style
20. Spends time making sure others work well together.
21. Deals with issues that need to be addressed.
22. Provides a clear sense of purpose and direction for our group.
23. Provides a larger vision that guides our everyday decisions.
24. Provides leadership within our team.

Appendix: Team Submission Packet

At the end of each week, the team's would submit an online "packet" with the items listed below. This packet would then be evaluated by the mentors and other participants.

1. **Required Text**
   - ⋆ The startup's name
   - ⋆ Is the startup is B2B or B2C?
   - ⋆ Industry
   - ⋆ One sentence overview of the startup
   - ⋆ One sentence describing how the startup meets potential user needs
   - ⋆ A paragraph describing the business potential
   - ⋆ A paragraph describing the team
   - ⋆ A paragraph describing the resourced (funding, talent, ...) they item would need to move forward with the idea
2. **Required Links**
   - ⋆ A link to their Lean Model Canvas
   - ⋆ A link to their Pitch Deck
   - ⋆ A link to a prototype page or deck

  - ⋆ A link to their splashpage
  - ⋆ Optional Links

3. **Optional Links**
   - ◦ A link to their LetsVenture Crowdfunding profile if avaliable (optional)
   - ◦ A link to a pitch video (optional)

Appendix: Team Evaluation Rubric

Participants evaluated a randomly selected subset of the projects generated during the week. Below is the rubric used during the third week of the program. Evaluations were done individually, and each persons' rankings of the other projects remained private.

1. **Novelty**
   - **Prompt:** *Rate the novelty and creativity of the entire proposal from 1 (Meh) to 5 (Awesomely Creative!). Dont worry about technical feasibility, market demand, or value but really focus on how original the idea is.*
   - **Scale:** 1 Meh, 2 A little creative, 3 Creative, 4 Really creative, 5 Awesomely Creative!
2. **Business Potential**
   - **Prompt:** *How much business potential does the startup have from 1 (Meh) to 5 (Amazing business potential). Take into account the whole idea: from technical feasibility to novelty; from market demand to the team.*
   - **Scale:** 1 Meh, 2 Limited potential, 3 Good business, 4 Great potential, 5Amazing business potential
3. **Compelling**
   - **Prompt:** *How compelling and clever is the product or service from 1 (Meh) to 5 (Extremely compelling and clever). A compelling product or service represents a novel and insightful solution to a well defined problem.*
   - **Scale:** 1 Meh, 2 Alright product/service, 3 Solid product/service, 4 Great product/service, 5 Extremely compelling product/service
4. **Prototype Quality**
   - **Prompt:** *How well designed is the prototype walk-through from 1 (Hard to imagine how to use it) to 5 (Excellent Design). Real looking interfaces dont necessarily translate into a better score, sketches can be equally good if you feel like you have been walked through what it would be like to use the product. Better designs are easier to imagine and more clearly convey how someone would actually use the product or service.*
   - **Scale:** 1 Hard to imagine how to use it, 2 Somewhat confusing design, 3 Solid Design, 4 Great Design, 5 Excellent Design
5. **Splashpage Quality**
   - **Prompt:** *How compelling and informative is the splash page from 1 (Meh) to 5 (A visitor would know what it is and download it immediately).*
   - **Scale:** 1 Meh, 2 Somewhat, 3 Compelling and Informative, 4 A visitor would want to learn more, 5 A visitor would know what it is and download it immediately
6. **Ideal User Purchase**
   - **Prompt:** *How willing do you think their ideal user be to purchase the proposed solution from 1 (Meh) to 5 (They would buy it today!)*

- **Scale:** 1 Meh, 2 Probably not, 3 Maybe, 4 They would consider buying it, 5 They would buy it today!

7. **Pitch Deck Quality**
   - **Prompt:** *How compelling, well argued and convincing is their pitch deck from 1 (Meh) to 5 (Extremely Compelling)?*
   - **Scale:** 1 Meh, 2 A little, 3 Somewhate Compelling, 4 Very Compelling, 5 Extremely Compelling
8. **Team Quality**
   - **Prompt:** *Rate the ability of the team to actually build their startup from 1 (Would be difficult) to 5 (Very strong team for this idea)?*
   - **Scale:** 1 Would be difficult, 2 Alright team for the idea, 3 Good Team, 4 Strong Team, 5 Very strong team for this idea
9. **Lean Model Canvas Quality**
   - **Prompt:** *How strong and well argued is their Lean Model Canvas from 1 (Not really) to 5 (Extremely Compelling)? Lean Model Canvases with more tested assumptions, reasonable revenue/cost assumptions, and precise customers, users, and channels are more compelling. LMCs with higher scores should increase your belief that the startup can one day turn a profit.*
   - **Scale:** 1 Meh, 2 A little, 3 Somewhat Compelling, 4 Very Compelling, 5 Extremely Compelling
10. **Problem Quality**
    - **Prompt:** *How well defined, real and large is the problem the team is solving from 1 (Not a problem) to (Substantial and well defined problem)? Good problems do NOT have to be social problems nor does the proposed product or service have to solve the problem well in order for the problem to be substantial.*
    - **Scale:** 1 Not a problem, 2 Small and limited problem, 3 Somewhat of a problem, 4 Notable problem, 5 Substantial and well defined problem

Appendix: Daily Progress Report Diary

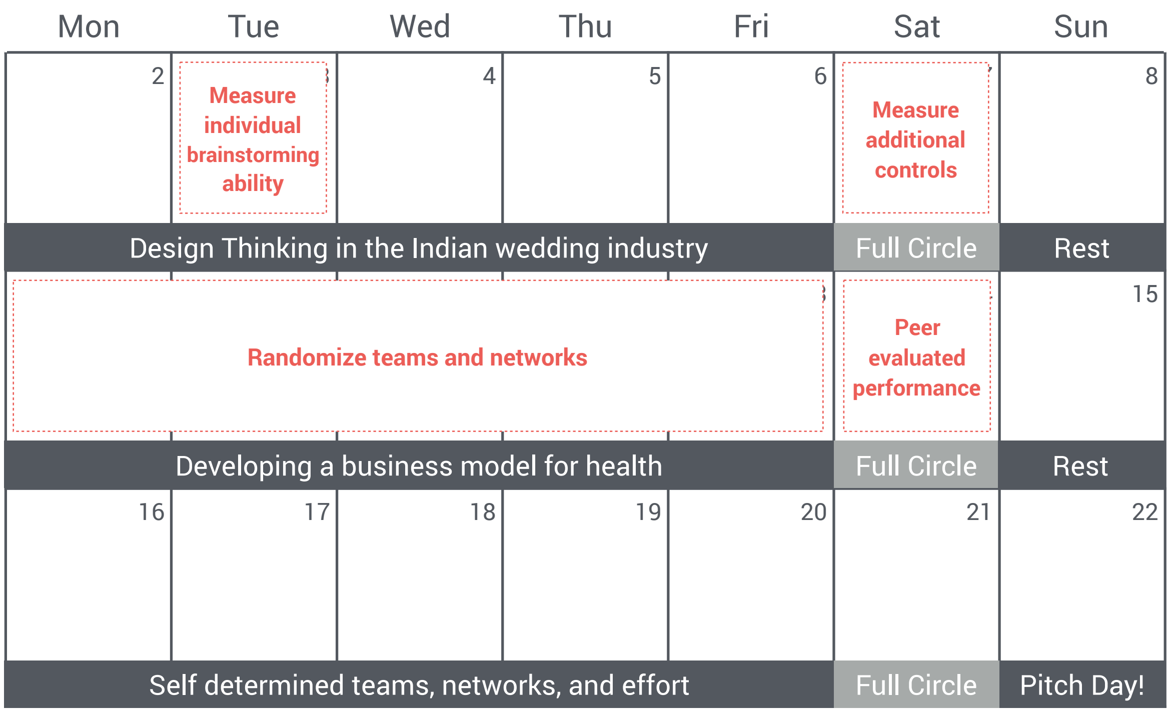
At the end of each day during the third week of the bootcamp each participant was required to complete the following online survey.

- A short paragraph describing what you did and what your learned today:
- A short paragraph describing what you will do tomorrow:
- A short paragraph describing what your teammates did today:
- A short paragraph describing what your teammates will do tomorrow:
- If you have talked with Sharique, Randy or Rem TODAY please describe the feedback you received and which of them you talked with
- Select the people in the program you interacted with over the last 24 hours and then select what type of feedback and advice they provided:
  - I got feedback on my team's business model
  - I gave feedback on their team's business model
  - I got feedback on my team's product, prototype, and/or solution
  - I gave feedback on their team's product, prototype, and/or solution
  - I got feedback on my team's problem statement and point of view

- I gave feedback on their team's problem statement and point of view
  - I got feedback on my team's pitch
  - I gave feedback on their team's pitch
  - I got general feedback and advice about my team's startup ideas
  - I gave general feedback and advice about their team's startup ideas
- Please list any other people you interacted with over the last 24 hours. Maybe you asked your brother or interviewed some folks at the metro station. Whatever the interactions, please describe who you interacted with and what you interacted about. Examples include customer validation, feedback, testing, finding partners and technical advice.

List of Figures

Figure 1: Structure of the bootcamp and experimental design.



List of Tables

Table 1: Summary statistics for unstandardized week two variables.

Statistic	N	Mean	St. Dev.	Min	Max
Two person team	39	0.1	0.3	0	1
Num of female members	39	0.7	0.8	0.0	3.0
Avg startup experience in the team	39	0.9	0.5	0.0	2.0
Avg admission score in the team	39	0.02	0.6	−1.1	1.2
Avg 360 feedback score in the team	39	−0.000	0.6	−1.1	1.6
Creative potential in the team	39	7.9	2.4	2.3	12.0
Creative potential in the team's network	39	179.6	32.6	95	245
Performance rating	39	3.5	0.6	2.2	4.8

Table 2: Correlations for unstandardized week two variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Two person team								
(2) Num of female members	-0.03							
(3) Avg startup experience in the team	0.1	-0.2						
(4) Avg admission score in the team	0.4	0.2	0.2					
(5) Avg 360 feedback score in the team	-0.004	-0.2	0.3	0.1				
(6) Creative potential in the team	0.3	-0.1	0.03	0.3	-0.04			
(7) Creative potential in the team's network	-0.6	0.005	0.05	-0.2	0.1	-0.2		
(8) Performance rating	0.1	0.3	-0.2	0.3	-0.2	0.2	0.1	

Table 3: Summary statistics for unstandardized week three variables.

Statistic	N	Mean	St. Dev.	Min	Max
Num of female members	37	0.7	0.8	0	3
Avg startup experience in the team	37	0.9	0.6	0.0	2.0
Avg admission score in the team	37	−0.003	0.6	−1.3	1.6
Avg 360 feedback score in the team	37	0.01	0.7	−1.8	1.2
Creative potential in the team	37	7.9	3.0	3.0	16.0
Creative potential in the team's network	37	239.0	29.2	177	296
Performance rating	37	10.0	1.3	7.1	12.7
Crowdfunding pageviews	37	0.8	2.5	0	14

Table 4: Correlations for unstandardized week three variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Num of female members								
(2) Avg startup experience in the team	-0.1							
(3) Avg admission score in the team	0.2	0.5						
(4) Avg 360 feedback score in the team	-0.01	0.4	0.4					
(5) Creative potential in the team	0.2	0.1	0.5	0.2				
(6) Creative potential in the team's network	-0.04	0.1	-0.04	-0.2	0.01			
(7) Performance rating	-0.1	0.3	0.1	0.3	0.2	0.3		
(8) Crowdfunding pageviews	-0.1	0.3	0.2	0.3	0.3	0.3	0.4	

Table 5: Balance test regressions examaning if pre-treatment variables are uncorrelated with the creative potential of a team's randomized network in week two.

	Dependent variable:					
	Creative potential in the team's network					
	(1)	(2)	(3)	(4)	(5)	(6)
Num of female members	0.005					0.094
	(0.150)					(0.157)
Avg startup experience in the team		0.048				0.062
		(0.196)				(0.207)
Avg admission score in the team			−0.230			−0.249
			(0.157)			(0.170)
Avg 360 feedback score in the team				0.130		0.152
				(0.135)		(0.179)
Creative potential in the team					−0.166	−0.090
					(0.129)	(0.134)
Constant	0.000	0.000	0.000	0.000	0.000	0.000
	(0.162)	(0.162)	(0.158)	(0.161)	(0.160)	(0.163)
Observations	39	39	39	39	39	39
R^2	0.00002	0.002	0.053	0.017	0.028	0.096
Note:						*p<0.1; **p<0.05; ***p<0.01
						Orindary Least Squares with team level data.
						Robust standard errors in parenthesis.
						Variables standardized to have mean 0 and S.D. 1.

Table 6: Does incraesing a network's creative potential increase a team's performance in week two?

	Dependent variable:				
	Performance rating				
	(1)	(2)	(3)	(4)	(5)
Two person team	−0.032	−0.595	−0.444	−0.170	
	(0.393)	(0.403)	(0.482)	(0.391)	
Creative potential in the team	0.213		0.220	0.181	0.181
	(0.185)		(0.179)	(0.173)	(0.203)
Creative potential in the team's network		0.247^{*}	0.255^{**}	0.310^{**}	0.306^{**}
		(0.130)	(0.123)	(0.125)	(0.132)
Num of female members				0.188	0.174
				(0.176)	(0.185)
Avg startup experience in the team				−0.121	−0.118
				(0.166)	(0.242)
Avg admission score in the team				0.339^{**}	0.357^{*}
				(0.171)	(0.204)
Avg 360 feedback score in the team				−0.228	−0.214
				(0.196)	(0.267)
Constant	0.028	0.519	0.387	0.149	−0.018
	(0.312)	(0.332)	(0.395)	(0.290)	(0.181)
Observations	39	39	39	39	34
R^2	0.047	0.047	0.092	0.334	0.313
Note:	*p<0.1; **p<0.05; ***p<0.01				
	Orindary Least Squares with team level data.				
	Robust standard errors in parenthesis.				
	Variables standardized to have mean 0 and S.D. 1.				

Table 7: Balance test regressions examaning if pre-treatment variables are uncorrelated with the creative potential in a team's randomized network in week three.

	Dependent variable:					
	Creative potential in the team's randomized network					
	(1)	(2)	(3)	(4)	(5)	(6)
Num of female members	−0.038					0.094
	(0.147)					(0.157)
Avg startup experience in the team		0.119				0.062
		(0.175)				(0.207)
Avg admission score in the team			−0.037			−0.249
			(0.181)			(0.170)
Avg 360 feedback score in the team				−0.159		0.152
				(0.174)		(0.179)
Creative potential in the team					0.013	−0.090
					(0.184)	(0.134)
Creative potential in the team's network	−0.000	−0.000	−0.000	−0.000	−0.000	0.000
	(0.167)	(0.166)	(0.167)	(0.165)	(0.167)	(0.163)
Observations	37	37	37	37	37	39
R^2	0.001	0.014	0.001	0.025	0.0002	0.096

Note: *p<0.1; **p<0.05; ***p<0.01
Orindary Least Squares with team level data.
Robust standard errors in parenthesis.
Variables standardized to have mean 0 and S.D. 1.

Table 8: Does incraesing a network's creative potential increase a team's performance in week three?

	Dependent variable:			
	Performance rating			
	(1)	(2)	(3)	(4)
Creative potential in the team	0.219		0.214^{*}	0.278
	(0.137)		(0.118)	(0.171)
Creative potential in the team's network		0.343^{**}	0.340^{**}	0.349^{**}
		(0.166)	(0.165)	(0.153)
Num of female members				−0.035
				(0.157)
Avg startup experience in the team				0.215
				(0.201)
Avg admission score in the team				−0.257
				(0.234)
Avg 360 feedback score in the team				0.292^{*}
				(0.156)
Constant	−0.000	−0.000	0.000	0.000
	(0.163)	(0.157)	(0.155)	(0.150)
Observations	37	37	37	37
R^2	0.048	0.117	0.163	0.304

Note: *p<0.1; **p<0.05; ***p<0.01
Orindary Least Squares with team level data.
Robust standard errors in parenthesis.
Variables standardized to have mean 0 and S.D. 1.

Table 9: Does increasing a network's creative potential increase a team's investor page views at the end of week three?

	Dependent variable:		
	Crowdfunding page views		
	(1)	(2)	(3)
Creative potential in the team	0.230		0.578^{**}
	(0.169)		(0.257)
Creative potential in the team's network		0.347^{**}	0.528^{***}
		(0.176)	(0.201)
Constant	1.214^{***}	1.142^{***}	0.490
	(0.256)	(0.266)	(0.465)
Observations	37	37	37
Log Likelihood	−37.043	−36.663	−31.740
Note:			*p<0.1; **p<0.05; ***p<0.01
			Zero-inflated poissson regression.
			Variables standardized to have mean 0 and S.D. 1.

Table 10: Do alternative network measures explain the effect in week two?

	Dependent variable:		
	Performance rating		
	(1)	(2)	(3)
Creative potential in the team's network	0.411*	0.283*	0.330**
	(0.215)	(0.149)	(0.135)
Number of people in the network	−0.229		
	(0.377)		
Avg idea quality in the network		−0.215	
		(0.183)	
Num of women in the network			0.183
			(0.147)
Avg admission score in the network			−0.240
			(0.172)
Avg teammate quality in the network			0.283
			(0.190)
Avg startup experience in the network			−0.312
			(0.213)
Constant	−0.040	−0.066	−0.054
	(0.196)	(0.188)	(0.186)
Observations	34	34	34
R^2	0.073	0.095	0.282

Note: *p<0.1; **p<0.05; ***p<0.01
Orindary Least Squares with team level data.
Robust standard errors in parenthesis.
Variables standardized to have mean 0 and S.D. 1.

Table 11: Do alternative network measures explain the effect in week three?

	Dependent variable:		
	Performance rating		
	(1)	(2)	(3)
Creative potential in the team's network	0.377^{*}	0.336^{**}	0.376^{*}
	(0.225)	(0.170)	(0.205)
Number of people in the network	-0.051		
	(0.179)		
Avg idea quality in the network		0.066	
		(0.145)	
Num of women in the network			-0.196
			(0.197)
Avg admission score in the network			0.081
			(0.166)
Avg teammate quality in the network			-0.367^{**}
			(0.159)
Avg startup experience in the network			0.230
			(0.249)
Constant	0.000	-0.000	-0.000
	(0.159)	(0.159)	(0.157)
Observations	37	37	37
R^2	0.119	0.122	0.215

Note: *p<0.1; **p<0.05; ***p<0.01
Orindary Least Squares with team level data.
Robust standard errors in parenthesis.
Variables standardized to have mean 0 and S.D. 1.

Table 12: Do external idea sources or a team's internal cohesion moderate the effect of creative potential in a team's network during the third week?

	Dependent variable:	
	External feedback	
	(1)	(2)
Creative potential in team's network	0.346^{**}	-0.023
	(0.156)	(0.241)
Quantity of external feedback	0.413^{***}	
	(0.136)	
Creative potential X External feedback	-0.035	
	(0.127)	
Is the team internally cohesive?		0.319
		(0.322)
Creative potential X Internally cohesive		0.588^{*}
		(0.327)
Constant	0.0002	-0.187
	(0.144)	(0.202)
Observations	37	37
R^2	0.293	0.224
Note:	*p<0.1; **p<0.05; ***p<0.01	

Orindary Least Squares with team level data.
Robust standard errors in parenthesis.
Variables standardized to have mean 0 and S.D. 1.

Table 13: How do the aspiring entrepreneurs form their advice and feedback networks in week three?

	Dependent variable:			
	Does ego i receive advice and feedback from alter j?			
	(1)	(2)	(3)	(4)
Alter in ego's week 2 network	0.079^{***}	0.080^{***}	0.079^{***}	0.079^{***}
	(0.011)	(0.011)	(0.011)	(0.011)
Alter in team's week 2 network	0.028^{***}	0.028^{***}	0.027^{***}	0.027^{***}
	(0.008)	(0.008)	(0.008)	(0.007)
Female (ego)		-0.024^{***}	-0.002	
		(0.009)	(0.011)	
Female (alter)		-0.015^{*}	-0.015^{*}	-0.015^{*}
		(0.009)	(0.009)	(0.009)
Startup experience (ego)		0.011^{***}	0.006	
		(0.004)	(0.004)	
Startup experience (alter)		0.026^{***}	0.026^{***}	0.026^{***}
		(0.004)	(0.004)	(0.004)
Admission score (ego)		0.005	-0.002	
		(0.004)	(0.005)	
Admission score (alter)		-0.001	-0.001	-0.001
		(0.004)	(0.004)	(0.004)
360 feedback score (ego)		-0.003	0.011^{**}	
		(0.003)	(0.004)	
360 feedback score (alter)		0.001	0.0005	0.0005
		(0.003)	(0.003)	(0.003)
Creative potential (ego)		0.008^{**}	0.004	
		(0.003)	(0.004)	
Creative potential (alter)		-0.001	-0.001	-0.001
		(0.003)	(0.003)	(0.003)
Female (ego X alter)		0.051^{***}	0.051^{***}	0.050^{***}
		(0.019)	(0.019)	(0.018)
Startup experience (ego X alter)		0.006^{*}	0.006^{*}	0.006^{*}
		(0.003)	(0.003)	(0.003)
Admission score (ego X alter)		0.004	0.004	0.004
		(0.003)	(0.003)	(0.003)
360 feedback score (ego X alter)		0.009^{***}	0.009^{***}	0.009^{***}
		(0.003)	(0.003)	(0.003)
Creative potential (ego X alter)		-0.001	-0.001	-0.002
		(0.003)	(0.003)	(0.003)
Constant	0.134^{***}	0.140^{***}		
	(0.004)	(0.005)		
Team-level fixed effects	N	N	Y	N
Ego-level fixed effects	N	N	N	Y
Observations	11,988	11,988	11,988	11,988
R^2	0.006	0.015	0.013	0.013

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Dyadic linear probability models
Multiway-clustered standard errors.
Variables standardized to have mean 0 and S.D. 1.

Table 14: Do aspiring entrepreneurs think it would be useful to talk to others with greater creative potential in week three?

	Dependent variable:
	Who do you think would be useful to get to know more?
Alter in ego's week 2 network	0.058^{***}
	(0.006)
Female (alter)	0.010^{**}
	(0.005)
Startup experience (alter)	0.018^{***}
	(0.002)
Admission score (alter)	0.012^{***}
	(0.002)
360 feedback score (alter)	0.005^{***}
	(0.002)
Creative potential (alter)	0.001
	(0.002)
Ego-level fixed effects	Y
Observations	11,988
R^2	0.026
Note:	*p<0.1; **p<0.05; ***p<0.01
	Dyadic linear probability models
	Multiway-clustered standard errors.
	Variables standardized to have mean 0 and S.D. 1.

Table 15: How do aspiring entrepreneurs search for feedback and advice partners over the third week?

	Does ego i receive advice and feedback from alter j?				
	Day 1	Day 2	Day 3	Day 4	Day 5
	(1)	(2)	(3)	(4)	(5)
Yesterday ego gave advice to alter		0.101^{***}	0.096^{***}	0.077^{***}	0.095^{***}
		(0.010)	(0.009)	(0.010)	(0.012)
Yesterday alter gave advice to ego		0.210^{***}	0.170^{***}	0.194^{***}	0.197^{***}
		(0.010)	(0.009)	(0.010)	(0.012)
Yesterday's advice degree (alter)		0.003^{***}	0.003^{***}	0.002^{***}	0.002^{***}
		(0.0005)	(0.0004)	(0.0004)	(0.001)
Alter in ego's week 2 network	0.028^{***}	0.027^{***}	0.022^{***}	0.012^{**}	0.021^{***}
	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)
Alter in team's week 2 network	0.011^{**}	0.013^{***}	0.005	0.001	0.005
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Female (alter)	-0.007	-0.016^{***}	0.005	0.003	-0.004
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)
Startup experience (alter)	0.013^{***}	0.001	0.004^{*}	0.005^{***}	0.003^{*}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Admission score (alter)	0.001	-0.004^{*}	-0.002	-0.003^{*}	0.0003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
360 feedback score (alter)	-0.002	0.003	0.001	-0.0002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Creative potential (alter)	-0.003	-0.002	-0.002	0.005^{***}	0.003^{*}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female (ego X alter)	0.030^{***}	0.010	-0.0003	0.021^{**}	0.027^{***}
	(0.012)	(0.011)	(0.010)	(0.009)	(0.010)
Startup experience (ego X alter)	0.005^{**}	0.004^{**}	0.003	0.002	-0.0002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Admission score (ego X alter)	0.003	-0.002	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
360 feedback score (ego X alter)	0.002	0.004^{**}	0.003	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Creative potential (ego X alter)	-0.002	0.002	-0.0002	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ego-level fixed effects	Y	Y	Y	Y	Y
Observations	11,988	11,988	11,988	11,988	11,988
R^2	0.007	0.088	0.085	0.087	0.060

Note: *p<0.1; **p<0.05; ***p<0.01
Dyadic linear probability models
Multiway-clustered standard errors.
Variables standardized to have mean 0 and S.D. 1.