Conversational Peers and Idea Generation: Evidence from a Field Experiment *

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Abstract

High quality ideas and the individuals who generate them are critical to the success of organizations. In this article, we take a micro-network perspective on idea generation and incorporate personality theory into a multi-level model of information acquisition and idea generation. We posit that innovator and peer personality are critical factors conditioning who will generate high-quality ideas, and that our proposed mechanisms have implications at both individual and team levels. Using data from a randomized field experiment embedded in a startup bootcamp for early-stage entrepreneurs, our findings show that innovators who are more open to experience do generate better ideas, but only when they converse with extroverted peers. Further, we find that teams populated with such openness-extroversion dyads perform substantially better—having both a higher pool of novel information and better recombinative capability with the team. We discuss implications for future research on the individual and social determinants of innovation.

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Introduction

The eventual success or failure of an entrepreneur can be the difference between having a good idea and an average one. Scholars posit that the capability for developing creative and high-quality ideas depends on the ability to effectively recombine diverse pieces of knowledge (e.g., Fleming, 2001). One important stream of research on creativity has highlighted the role that psychological factors—such as personality—play in setting the micro-foundations for this capability (e.g., Feist, 1998; McCrae, 1987; Barron and Harrington, 1981). Organization theorists, on the other hand, have emphasized structural sources of advantage in creativity over individual ones, namely differential access to external knowledge through patterns of social relationships (Perry-Smith and Mannucci, 2015; Burt, 2004). In the latter models, individual differences in the personalities or cognitive processes of both innovators and their sources of information have been largely abstracted away to focus attention on broader social patterns. This article extends existing research by taking a micro-network perspective on idea generation and incorporates personality theory into a multi-level model of information acquisition and idea generation.

In recent years, scholarship in the micro-network tradition has challenged the predominantly structural theory of social networks—as pipes that primarily channel information—by enriching it with psychological foundations (Kilduff and Krackhardt, 2008, 1994). Scholars have argued that individual differences shape how structural patterns emerge and affect behavior (Fang et al., 2015). Much of this work has focused on how human psychology shapes the formation and activation of networks. Work by Mehra, Kilduff and Brass (2001) and Sasovova et al. (2010), for example, highlight the importance of self-monitoring personality on the ability to bridge structural holes. Casciaro and Lobo (2008) similarly argue that positive and negative affect fundamentally shapes who is sought out for advice in organizations. Smith, Menon and Thompson (2012) show that cognition affects what parts of individuals' networks are activated during times of uncertainty. While the psychological foundations of network emergence have been studied extensively, the causal chain linking the psychological traits of interacting parities to performance outcomes remains limited (for a recent exception, see Burt, 2012). In this article, we extend existing models to examine the interactive effect of ego and alter personalities on the ability to generate high-quality ideas, a crucial organizational outcome.

Our arguments focus on the basic building-blocks of a micro-network theory of innovation: the interactions between an innovator and the sources of her information (who we call *conversational peers*, or *peers*). To develop our theory of innovator capability we extend existing research linking personality differences to creativity. Prior work has highlighted the role of *openness to experience* (hereon, *openness*) in determining creative skill (Feist, 1998; McCrae, 1987). Individuals with higher openness are more creative because they seek out diverse information and experiences, but also recombine these more effectively into novel ideas. Those closed to experience are more conservative in their consumption of new information, and are unlikely to have the ability or desire to develop new combinations of knowledge. However, recent scholarship has begun to show that social and organizational factors substantially condition whether even those with inherent creative skill are able to develop high-quality ideas or merely average ones (e.g., Baer and Oldham, 2006; Burke and Witt, 2002).

A micro-network perspective on creativity enhancing social interactions suggests that *who* one gets external information from should shape creative outcomes (Perry-Smith and Mannucci, 2015). We bring to bear research on personality and social behavior to argue that conversations with peers higher in extraversion (rather than those more introverted) provide innovators with an increased volume of idiosyncratic information relevant at the ideation stage (De Vries, Van den Hooff and de Ridder, 2006; Forret and Dougherty, 2001; McCrae and John, 1992). Such information provides greater grist for new ideas, than its converse. Moreover, we theorize a complementarity between innovator openness and peer extraversion. Greater recombinative capability and a higher volume of diverse information—leads to further enhanced idea quality. Finally, a multi-level implication of our theory is that teams populated with high openness members who have conversed with more extroverted peers, will develop better ideas as a team. This is because such teams will have more creative skill, but also a higher-quality distribution ideas from which to recombine and choose (Girotra, Terwiesch and Ulrich, 2010).

To test our predictions, we embedded a field experiment in an academy for over 100 aspiring entrepreneurs held in June 2014. Prior to entering the academy, participants completed demographic and personality surveys, which provided us with detailed pre-experiment personality data. The experiment that constitutes this study lasted five days. Our key treatment consists of randomly assigning individuals to three conversations, with each conversation lasting 14 minutes. This randomization created exogenous variation in the pairing of different personality traits of both the idea generators and their conversational peers. We captured the ideas generated individually by participants before and after the randomized conversations, and their subsequent double-blinded evaluation. To test our multi-level hypotheses, we randomly assigned participants to teams to develop a single software prototype after their individual-level ideas were generated over a three-day period. These final team-generated prototypes were double-blind evaluated along a range of dimensions.

Contrary to established theory and consistent with recent work on the context dependence of creative ability (e.g., Baer and Oldham, 2006), we find that openness to experience alone does not appear to relate to idea quality. We do, however, find evidence of our micro-network mechanisms: talking to more extroverted peers enhances idea quality, but also that more open individuals are indeed better equipped to use this novel information to generate higher-quality ideas. We also find evidence that the higher-quality ideas generated as a consequence of the experimentally induced conversations continue to impact team outcomes, with the individual-level results replicating at the team-level.

Theory and Hypotheses

Idea Generation and Openness to Experience

Idea generation is the first step in the "idea journey" and is a central function in any entrepreneurial organization (Perry-Smith and Mannucci, 2015). During this stage, an innovator is tasked with generating many ideas, from among which one or a few are chosen for implementation. A growing body of literature suggests that two mechanisms play a critical role at this stage. Perry-Smith and Mannucci (2015) summarized these as "access to non-redundant knowledge" *and* the "cognitive flexibility to recombine disparate knowledge into new associations."

Over the past few decades, scholars have worked to understand what specific characteristics of individuals, social contexts, and processes are most likely to trigger these creativity-enhancing mechanisms. One of the most thorough investigations has focused on the stable personality traits of individuals that correlate to creativity. A rich panoply of research suggest that *openness to experience* a factor in the five factor model of personality (with the other four factors being Extraversion, Agreeableness, Neuroticism, and Conscientiousness) is the trait most strongly related to creativity in both the arts and sciences (Feist, 1999). Openness, according to McCrae (1996) has both an intrapsychic component—indicating skills and dispositions that allow a person to effectively generate ideas—as well as an interpersonal component—which allow individuals to acquire novel information useful for ideation.

Intrapsychic Mechanisms: A vast literature exists on openness to experience and its correlates, especially its relationship to creativity (Feist, 1999). McCrae (1987) in a classic study on openness and creativity argues that these constructs are linked through two broad types of mechanisms—*abilities* and the *dispositions* to use them in creative endeavors. One stream of research on the openness-creativity link has highlighted the skill that more open people have in completing unstructured creative tasks (Williams, 2004). Openness causes people to tolerate complexity, rather than shy away from it (e.g., LePine, Colquitt and Erez, 2000); deploy more representational resources and attention to their tasks and environments; explore a wider range of perspectives when considering ideas or interpreting information; and engage more effectively in divergent thinking (e.g., Hammond et al., 2011; Oldham and Cummings, 1996; McCrae and Costa, 1980). This suite of abilities gives more open individuals facility in developing a wide range of ideas that are more likely to be novel or unconventional (George and Zhou, 2001).

In addition, more open people prefer tasks that let them use these abilities or prefer activities that are complex or incorporate diverse perspectives. Their dispositions include greater curiosity, as well as a desire and willingness to ask questions and seek novel information (McCrae, 1996). Further, more open individuals have a stronger belief in their own creative self-efficacy (e.g., Karwowski et al., 2013). Finally, a key characteristic of those who are more open to experience is a willingness to question convention, leading them to veer from traditional approaches.

Interpersonal Mechanisms: The intrapsychic mechanisms provide insight into the capabilities that open individuals can deploy when tasked with taking available information and recombining it to produce a new idea. Yet, further research by McCrae (1996) suggests that open individuals possess abilities and dispositions that allow them to extract diverse information from their social environments, and are able to adapt to other people's perspectives. Further, the open individual's tolerance for uncertainty allows them to recall information incongruent with their own experiences–thus increasing information diversity (McCrae, 1996). Finally, in conversations, those more open to experience delve into abstract topics (e.g., Funder and Sneed, 1993) and are interested in talking to new people and initiating new conversation threads when old ones have died out (Cuperman and Ickes, 2009).

In contrast, those exhibiting closedness prefer more routine ideas and situations. They are most comfortable when the information is familiar, certain, and does not differ much from their own expectations. Thus, in both the intrapsychic and interpersonal realms more closed individuals will tend to produce ideas that are familiar and less likely to contain unconventional elements or combinations. Thus, we hypothesize:

Hypothesis 1 *Innovators with higher (lower) openness to experience will develop higher quality (lower quality) ideas.*

Social Interactions as Inputs to Ideation: The Value of Extroverts

Yet, Hypothesis 1, is countered by a strong null. The ability of open individuals to acquire diverse knowledge and recombine it into new ideas depends on the requisite informational variety and volume. Therefore, without modeling the informational determinants of creativity jointly with the personality differences of innovators, we may make incorrect inferences about who will generate the best ideas. Good ideas are rarely developed in vacuums (Singh and Fleming, 2010). Innovators often engage in conversations with peers—co-workers, friends, acquaintances or customers—that provide them with the raw material for innovation (Perry-Smith and Mannucci, 2015). Indeed, the modern practice of innovation depends fundamentally on sourcing the opinions, experiences, and knowledge of others (Blank, 2013; Brown et al., 2008). The weight of this external information in idea generation is no different for *open* individuals. While their abilities and dispositions may give them an edge in idea generation, they are nevertheless constrained by the raw information they possess. As a consequence, an open innovator who lacks a sufficient pool of diverse information may generate only average or perhaps weaker ideas.

Overcoming this limitation requires that *open* innovators should ideally talk to peers who are *willing* to provide them with a substantial pool of *new and diverse information*. That is, the two mechanisms of *information sharing* and *information variety* determine whether the innovator will receive from her peers the raw information useful for generating novel ideas.

Willingness to Share Information: Not all conversations are created equal. In particular, conversational dynamics depend on the personalities of the parties who are interacting (e.g., Cuperman and Ickes, 2009). One personality trait in particular, *extraversion*, is related to greater sharing behaviors (Matzler et al., 2008). The literature defines extroversion as a stable trait within the five factor model of personality that leads individuals to enjoy interacting with others, talking, and sharing information (Furnham and Bachtiar, 2008; John and Srivastava, 1999) In conversations, extroverts tend to express themselves. Their descriptions of events and experiences are elaborate and interpretive (Beukeboom, Tanis and Vermeulen, 2013). Finally, extroverts are eager and willing to share their knowledge with others (Matzler et al., 2008). These characteristics should provide an innovator who talks to an extrovert with information with three qualities: higher volume, richness of detail and elaboration.

Large Networks and Information Variety: However, a greater willingness to share information should only increase informational volume, but not variety. Another stream of research on extraversion suggests that extroverts have larger and more diverse networks compared with introverts (e.g., Landis, 2016; Watson and Clark, 1997). Totterdell, Holman and Hukin (2008) found that extroverts had a greater behavioral tendency to connect with others, and thus a larger network size. The link between greater extraversion and network size has been found in a wide array of studies. Asendorpf and Wilpers (1998), for example, find that extraversion predicted the size of an individual's network, and Casciaro (1998) and Neubert and Taggar (2004) find further evidence that extraversion is related to centrality in social networks. In recent work, Feiler and Kleinbaum (2015) find that extroverts do indeed have larger networks than do introverts. This ability to build larger networks also comes at the cost of tie strength and relational closeness. Research finds that extroverts, while having larger networks, appear to have *weaker* network connections (Pollet, Roberts and Dunbar, 2011). The structural consequences of these tendencies—large networks with weak ties—suggests that those more extroverted should have networks that expose them more heterogeneous information from their many weaker contacts (Granovetter, 1973).

However, the theorizing that more extroverted peers will lead to a higher volume of idiosyncratic information, useful for ideation, rests upon a set of assumptions regarding the behavior of extroverts and the information they possess. First, it assumes that extroverts are not purely engaging in "small talk" or "idle chatter" which lacks informational content. Second, it may be that more introverted peers are more reflective and as a result may produce greater insight than more extroverted peers, despite the short duration of a conversation (e.g., Cain, 2013; Grant, Gino and Hofmann, 2011). Third, more introverted individual's analytical nature may help them better shape and dissect the idea's of their peers, thus improving them.

On balance, however, the strengths of extroverts—being more talkative, warm, more connected, and willing to share knowledge—should privilege them as sources of information over introverts in the medium of a short conversation, especially with new people. The conversations with extroverts, particularly at the very early stages idea generation, should result in a high volume of diverse information. Thus, we hypothesize the following:

Hypothesis 2 *Individuals who converse with more extroverted peers will develop higher-quality ideas.*

An Openness–Extroversion Complementarity in Ideation: While the mechanisms described above should increase idea quality for the average innovator, more open innovators should capitalize on conversations with extroverted peers more than others. Open individuals are likely to engage better with their extroverted conversational peers who provide a high baseline flow of information (McCrae and Sutin, 2009). Open innovators, compared with closed ones, will ask more probing questions, guide the conversation in more useful directions, and listen more intently (McCrae, 1987). These behaviors should amplify the amount of information that can be received from the extroverted peer. Moreover, in developing their ideas, open innovators will possess more of the abilities and dispositions that would help them develop higher-quality ideas with more fluency and novelty (Karwowski et al., 2013). A higher base of external information from the conversation will give them a richer pool of facts, emotions, ideas, opinions, and perspectives that they can recombine into novel associations. That is, they should have more detailed ideas as well as more novel combinations of ideas than innovators who are less open. Therefore, this complementarity between peer and focal innovator personality—extroverted peers and open innovators—should lead to higher-quality ideas than the baseline effect of just talking to more extroverted peers. Thus, we hypothesize the following:

Hypothesis 3 *More open innovators (versus those more closed to experience) will generate better ideas after talking ton more extroverted peers.*

Openness-Extraversion and Team Performance

The three key predictions from the individual-level theorizing are that: (1) more open individuals will generate higher quality ideas; (2) conversing with individuals who are more extroverted (than less) will lead to better ideas; (3) the open innovator/extroverted peer pairing will further enhance idea quality. What do these individual level predictions mean for the ideal composition of teams tasked to build upon the individually generated ideas and develop them into a singular prototype? At the team level, we argue these predictions replicate through two intervening processes—(a) more team-level skill in recombination and (b) better pool of previously generated ideas and novel information.

Openness within teams: While a vast literature exists on team demography and process and its relationship to team creative outcomes (e.g., Paulus, 2000; Ancona and Caldwell, 1992), the literature on how a team's personality composition affects outcomes is still limited (see Schilpzand, Herold and Shalley (2011) for an exception) . However, several mechanisms lead us to reason that teams with more open members should develop higher quality ideas. First, after generating ideas at the individual level, more open individuals individually, and thus collectively will have a higher-quality pool of ideas from which to select. Thus a shift in the the quality of the idea distribution to the right will increase the average quality of the idea generated. Second, even assuming that the pool of ideas does not improve in quality, more open team members will better recombine the extant ideas into more novel combinations, leading to more creative outcomes. Third, the combination of an improved pool with better team-level recombinative capability should substantially increase the resulting team-level creative product. Thus, we hypothesize:

Hypothesis 4 *Teams whose members are more open to experience on average will develop higher-quality ideas.*

Prior conversations with more extroverts: In addition to the skills and ideas brought to the team by members through their own abilities, team members also bring with them information and ideas sourced through external conversations. Team members who have previously conversed with more extroverted peers will have higher-quality previously generated ideas as well as a store of experiences, insights, and anecdotes (H2). Relative to teams who have not spoken to more extroverted peers, those that have will begin their idea generation process with better raw material for idea generation. A growing body of research suggests that the distribution of ideas within a team affects its ability to innovate (Girotra, Terwiesch and Ulrich, 2010; Kavadias and Sommer, 2009; Taylor and Greve, 2006). First, teams with a higher-quality distribution of ideas should more readily choose better ideas than teams with lower-quality ideas (Terwiesch and Loch, 2004; Dahan and Mendelson, 2001). This is especially true if they are choosing the best idea among the ones they have access to, but it should also hold more generally. Second, teams with raw ideas that are of high quality should also recombine them better into new ideas (Taylor and Greve, 2006). For instance, if individual A brings back novel information from a peer conversation to the team, then another team member B now has access to this information and can use it to generate an idea (Girotra, Terwiesch and Ulrich, 2010). Jointly, the team can engage in an innovation process where the externally accumulated information, or the individual ideas generated from it, are team-level goods.

Hypothesis 5 *Teams whose members have previously conversed with more extroverted peers will generate higher-quality ideas.*

The openness-extraversion complementarity in teams: Finally, the enhanced pool of previously generated ideas, a larger amount of raw information from talking to those more extroverted, as well as a team with more "creative" personality types (e.g., with more members higher in openness to experience) point towards a better team-level idea. Nevertheless, a purely naïve assumption that groups with a higher-quality distribution of pre-existing ideas will also develop better ideas as a group may not hold because of group dynamics. Previous work suggests that group members may discuss redundant ideas, engage in free riding, or be led by the common effect to discuss ideas that are shared, not different (Paulus, 2000; Gigone and Hastie, 1993). Thus, an initial pool of high-quality information may fizzle into mediocre results. Teams with more open members might be shielded from this fate because of their collective inquisitiveness, openness to divergent opinions, and cognitive flexibility; thus, they can more effectively recombine the ideas brought in by other team members (Schilpzand, Herold and Shalley, 2011). Thus, we hypothesize:

Hypothesis 6 *Teams with more open members (versus more closed members) will generate better ideas if these members have previously talked to more extroverted peers.*

Empirical Setting and Methods

Our basic argument is that open innovators who converse with extroverted peers will generate higher-quality ideas individually. Teams with more such individuals will also develop better ideas. Testing these predictions, however, is difficult for four important reasons. First, unlike formal collaborations, conversations, especially with external peers, are difficult for researchers to observe. They are rarely recorded by people participating in them. Moreover, conversations vary dramatically in their structure, purpose, and length, and comparison across conversations to test the impact of peer characteristics is often confounded by these variations. Second, researchers rarely observe the dynamics of the innovation process. What is most often observed is the final product developed by a team and rarely the ideas generated by both individuals and their team. Third, while researchers often have data about peers' level of education, publication records, or patents, more nuanced measures of peer characteristics such as personality are generally difficult to gather, especially for peers with whom an individual only has a conversation. Finally, and perhaps just as importantly, the choice of both team and external conversational partners is endogenous and often self-selected based on peer and individual characteristics that are unobservable to the researcher (Manski, 1993).

Experimental Design: An Innovation Competition

To overcome these empirical challenges we embedded a field experiment in the first week of an entrepreneurship academy held in New Delhi, India, in July 2014[1]. During the boot camp, 112 aspiring entrepreneurs from across India participated in a three-week program that help them develop skills in idea generation, design thinking, prototype design, and business model development. The ages of the 112 graduates ranged from 18 to 36, with a mean age of just over 22. Our program had 25 women. Everyone had at least a college degree or was enrolled in college, with 60 of the participants enrolled in a college, master's, or PhD program. Our program was regionally diverse, with 62 of the participants from the state of Delhi and the rest from across India. The class was composed primarily of engineering and computer science degree holders (78), followed by 18 business degree holders; the rest were from the arts and sciences. Eight people were enrolled in or had graduated from advanced degree programs.

The boot camp provided instruction from leading members of India's startup ecosystem, including successful entrepreneurs, designers, and venture capitalists. The program was structured into three week-long modules. The first week, which was the most structured (and on which we base this study), focused on the

[1]The experimental nature of the boot camp was reviewed by our university's Institutional Review Board. All participants signed two consent forms: an online form at the time of application and a paper-based form on the first day of the boot camp.

idea-generation process. To incentivize participation and effort, the three most highly rated proposals and prototypes from this week won prizes totaling 45,000 Indian rupees (INR; 789.47 USD). The major prizes were team based. The first prize was 20,000 INR, the second was 10,000 INR, and the third was 7,500 INR. The prize allocation was based on the average rating received by a team's proposal during the peer review process, with the three highest teams winning the top three prizes. The second week focused on business models. The final week was the least structured; participants could select their own teams of three people from the boot camp to develop a business concept and prototype to receive up to 8,000 USD in funding and support to implement their idea.

We used the activities from the first week and data collected before the boot camp to test our six hypotheses. Before the boot camp began, we asked all participants to complete surveys, chief among which was the 44-item Big Five Inventory (John and Srivastava, 1999). All participants allowed us to collect pre-bootcamp (thus, pre-treatment) measures of extraversion, openness to experience, neuroticism, agreeableness, and conscientiousness. We discuss the construction of our key variables using this inventory in the variables section below.

The first day (Monday) was dedicated to logistics, an introduction to the program, and a short icebreaker in a randomized group at the end of the day. We did not collect any data during this day, as it was not part of the experimental setup for the week. The second day (Tuesday) began with individuals reporting to one of 40 tables, where they sat with their icebreaker group and were asked to individually generate as many or as few ideas as they wished for innovative software products for the Indian wedding industry. The text of the prompt read as follows:

> *On November 27, 2011, over 60,000 weddings took place on this 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 one to two lakhs to book even the smallest halls. Even on less auspicious days, Indian weddings are big, fun, complex, loud, colorful, 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 products and services such as marriage gardens, matchmaking, clothing, decorations, makeup, gifts, and jewelry. 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 application that will reinvent part of the wedding experience—either before, during, or after the wedding—in India.*

On to reinventing!

We chose the Indian wedding industry as our prompt for three reasons. First, based on conversations with Indian entrepreneurs and venture capitalists, the Indian wedding industry is large and has significant market potential. Several venture capital firms are actively investing in software products for this large market. The choice of the wedding industry was therefore based in part on concerns of external validity. Second, unlike finance or biotechnology, the "Indian wedding" was something that the vast majority of boot camp participants had experienced, but it was an industry where a subset of individuals would not have a systematic skill or knowledge advantage. Third, we chose this industry because it was a relatively diverse domain, composed of problems ranging from finding mates to buying wedding dresses to honeymoon selection and even post-marital counseling. Thus, the Indian wedding context had the potential to produce differentiation in the types and quality of ideas generated by the participants. For one hour, the participants entered each discrete idea into a software application as short texts. Individuals generated 6.6 ideas, with each idea having a length of approximately 505 characters. We call these ideas "pre-treatment" ideas.

Conversational peer randomization. To test our hypotheses, we randomized a set of three empathy interviews that participants had with other members of the boot camp. These interviews are a staple of the design-thinking approach (Kelley and Kelley, 2013). Each empathy interview lasted 14 minutes and consisted of a random pairing between two individuals at the boot camp. We put each pair in random and pre-assigned seats across from each other, with participants assigned (randomly) to an "A" and a "B" position. The protocol of the interview was semi-structured, and participants were asked to learn about their conversational peers' experience with an Indian wedding. We began with person A interviewing and listening to person B's perspective for four minutes, followed by person B interviewing and listening to person A's perspective for the same amount of time. Next, person A was asked to "dig deeper" by asking person B more questions for three more minutes. Person B then repeated this process with person A. During and after the conversation, the participants could take notes about their conversation and record it in the sheet depicted in Figure 1. After the first pairwise peer interaction, individuals were re-randomized to two more pairwise interactions following the same structure. After all three randomizations, individuals were instructed to return to their original assigned table and generate new ideas for one hour. Participants generated an average of 4.5 ideas, with the average idea having 476 characters. We call these "post-treatment" ideas.

[Figure 1 about here.]

Anonymous Peer Evaluations of Individual Ideas. The next morning, from 9:30 am to 11:00 am (Wednesday, day 3), all participants anonymously evaluated a random subset of both the pre- and post-treatment ideas of other boot camp participants. Our choice of double-blind anonymous peer evaluations arises from three considerations. First, peer evaluation is perhaps the most common evaluation in many contexts. In academia, research articles are evaluated by anonymous peers, as are grants (Marsh, Jayasinghe and Bond, 2008). In organizations, many decisions about products and design choices are evaluated by peers. In education, peer evaluations are becoming increasingly common for evaluating classroom projects (Cooper and Sahami, 2013; Reily, Finnerty and Terveen, 2009). Second, many prior studies of creativity have used peer ratings as measures of the creative output of teams and individuals (Amabile et al., 2005, 2004). Third, peer evaluation, particularly in this context, is superior to evaluations by external or online parties who may not have either the incentive or the ability to effectively assess an idea's worth. Finally, research has indicated that peer evaluations are more accurate when evaluators are blinded to the identity of the subject. They are also harsher and more accurate when evaluating more than three items (Marsh, Jayasinghe and Bond, 2008; Boudreau et al., 2016). Thus, we asked individuals to rate approximately 50 ideas in three dimensions on a 5-point Likert scale from *strongly disagree* to *strongly agree*: whether the idea was novel, whether the product was something that the rater would buy, and whether the idea had business potential. Each idea received approximately 6.24 ratings. The average ratings were 2.45 for business value, 2.59 for buy likelihood, and 2.43 for novelty.

Idea development in teams. At the end of the evaluation session on day 3, individuals were randomly assigned to teams of approximately three individuals. Within these teams, individuals worked on days 3, 4, and 5 to develop a mock-up prototype and business plan. The teams were given the freedom to work on any idea that they jointly chose. The idea could be one from the pre-treatment ideation session, the post-treatment session, a combination of both, or neither. By midnight of day 5 (Friday), participants submitted a complete project of the prototype, which included a "splash page" consisting of a graphic describing their product, a presentation walk through of their software prototype, a text description of their product and the problem it was intended to solve, a one-sentence description of their product, and a product name.

Final project submission evaluations On day 6 (Saturday), we assigned the 112 participants five random and anonymous project submissions to evaluate (excluding their own). Participants evaluated their assigned submissions using an online system where students both rated (on a 5-point Likert scale, equivalent to the individual ideas) and ranked five randomly assigned submissions. Each team's project therefore received approximately 14 evaluations on 12 dimensions, including product novelty, unique insight, display of empathy for customer needs, feasibility, business potential, as well as the quality of the prototype walk through and splash page (Girotra, Terwiesch and Ulrich, 2010). Our results are strongly consistent across both the ratings and rankings.[2]

Figure 2 summarizes the process of the experiment, the randomizations, and the data collection.

[Figure 2 about here.]

Testing the Individual-Level Hypotheses

Dependent variables. Our first set of hypotheses concerns the relationship between conversational peer extraversion and the quality of *post-treatment* ideas generated by more open individual innovators. The key dependent variables for this analysis derive from the anonymous peer evaluations (day 3) of the raw ideas generated by individuals on day 2. The first of these dependent variables is *Idea Quality*; it is the sum of the evaluations an idea receives from an anonymous evaluator on the dimensions of business value, buy likelihood, and novelty.[3] To understand how our treatment changes the content of the ideas generated, we also construct two dependent variables using the raw text of the ideas themselves. The first variable, *idea development*, counts the number of *unique* words used by an innovator in describing their idea. Development, as measured by unique terms, has been used in a wide variety of prior studies and has been shown to correlate with success in a fields ranging from poetry to the hard sciences (Simonton, 1990; Feist, 1997). Our second content-based variable, *recombination*, measures the extent to which the words used by an innovator in the write-up of an idea connect disparate semantic domains. To generate our measure of recombination, we construct a semantic similarity network between the ideas generated using the word overlaps as a measure of connectedness. Using this semantic network, we then calculate the betweenness centrality for each idea to measure how recombinative each idea likely is. Research on what makes products, articles and patents successful finds that ideas that sit between different and distinct idea "domains" often represent novel recombinations with greater potential (Hargadon and Sutton, 1997; Uzzi et al., 2013). Full details on how we construct these text-based measures can be found in the Appendix.

Independent variables. To examine the relationship between an innovator's openness and peer extraversion on quality of the idea generated, we create three variables. First, we create a variable *Openness (self)* which measures the average of an individual's responses to the 10-item openness scale deployed before the bootcamp. This variable is normalized to have mean 0 and standard deviation 1. Second, we create a variable *extraversion (Peer)* which measures the average extraversion score of an individual's three randomly

[2] The ranking analysis is available upon request.

[3] While most ideas received evaluations on all dimensions, some received evaluations on only one. For the construction of *Idea Quality*, we coded the score as missing if it did not receive evaluations on all three dimensions. We find no systematic relationship between the variable of interest and the likelihood that a project evaluation was missing.

assigned conversational peers. Extraversion is calculated using the average of the the 8-item extraversion scale, and is standardized at the individual level before being aggregated into our average peer measure. Third, we create an interaction variable *Extraversion (Peer)* × *Openness (Self)* to test Hypothesis 3, that open individuals especially benefit from talking with extraverted partners.

Control Variables To further assess the robustness of our results, we also control for a number of additional variables in our models. To test that open innovators benefit from talking with extraverts, and that it is not the case that extraverts benefit from talking with open innovators, we parallel the operations described above and construct *extraversion (Self)*, *Openness (Peer)*, and *Extraversion (Self)* × *Openness (Peer)* variables. For completeness, we also generate *Openness (Self)* × *Openness (Peer)* and *Extraversion (Self)* × *Extraversion (Peer)* variables.

We also include three non-personality controls in our primary models that capture the ability and talent of the participants. The first of these control is a person's pre-treatment idea quality, the average of the evaluations of each person's pre-conversation ideas. This allows us to test if what matters is not openness or extraversion, but being paired with some one who simply generates higher quality ideas. The second control is a measure of each person's general ability and talent as measured by their bootcamp independently evaluated admission score.[4] The admission score allows us to rule out the possibility that extraversion is simply capturing differences in human capital and talent. The third control is each person's educational background; we construct a binary measure that indicates if the participant has an engineering degree. Given the technological focus of the bootcamp, this allows us to control for familiarity and experience developing web applications.

[Table 1 about here.]

Table 1 presents summary statistics for our dependent, independent and control variables at the individual level. We also include the other three personality measures for completeness. As expected, the standard deviations are smaller for the averaged personality scores of each participant's three randomly assigned peers. Table 6 in the Appendix provides a table of bivariate correlations. We find little evidence that a person's personality traits are correlated with those of their randomized peers, providing evidence that our randomization was successful. Table 7 in the Appendix tests for balance more formally by regressing an individual's personality measures on the *Extraversion (Peer)* variable. We find no evidence for imbalance.

Modeling strategy To test our three individual-level hypotheses, we used ordered logistic regression models

[4] Each participants bootcamp application was rated by four independent admissions evaluators. The evaluations were on a 1 to 5 scale and based on grades in college; the prestige of their college; the quality of their application essay; their skills in business topics such as finance, marketing, and sales; and their technical skills such as interaction design and programming.

to regress all evaluations e of idea d by individual i on the openness of the innovator, the randomized conversational peers' average level of extraversion, and the interaction. Since peers were randomly assigned and assignment does not appear imbalanced, our estimate of *Extraversion (Peer)* can be interpreted as a causal peer effect. We use ordered logistic regression since our dependent variable takes on integer values between 3 and 15. Since we have multiple evaluations and multiple ideas for individuals i, we included fixed effects at the evaluator level and corrected our standard errors by clustering them at the individual level. The evaluator fixed effects increases our power by removing idiosyncratic between-evaluator differences. The clustering reduces our power by accounting for the fact that the ideas generated by the 108 brainstorming participants are not independent.[5] We next turn to our team-level measures before discussing our results.

Testing the Team-Level Hypotheses

Dependent variables. To test our team-level predictions, hypotheses 4 through 6, we again use blinded peer evaluations to construct a measure of each team's project quality. As mentioned earlier, at the week's end (Saturday, day 6), individuals conducted double-blind evaluations of five projects randomly selected from the 39 other submissions (excluding one's own submission) on 12 different dimensions ranging from novelty to prototype quality to estimated demand. We average these 5-point rankings across the 12 dimensions to construct our *Project Quality* measure.

Independent variables and controls. To generate team-level measures we average the openness of members within the team and the extraversion of the peers each person worked with on the second day of the camp. Specifically, we calculate *Openness (Team)* which measure the average level of extraversion of the team's members. We create *Extroversion (Peers)*, which measures the average of all team members' peers extraversion scores. To test Hypothesis 6, we create create a variable *Openness (Team)* $\times$ *Extroverted Peers (Peers)* which is the interaction between these measures. We construct our team-level controls similarly, calculating the within team and randomized peer averages of extraversion, openness, admission score, engineering background, and pre-treatment idea quality.

[Table 2 about here.]

Table 2 presents summary statistics for our team-level measures. Compared to the individual level measures, the standard deviations are smaller, which is to be expected since the measures are averages over 3 people for the within team measures and over 9 people in the case of the peer measures. Table 8

[5]While the larger study had 112 participants, four participants were absent or unable to connect to the wireless Internet during the brainstorming exercise. These four participants do not to appear to differ from the larger population of participants in terms of personality or ability.

in the Appendix presents a table of correlations between these measures. Again, we find little evidence that a team's average personality scores are correlated with the average of the team's randomized peers. Table 9 in the Appendix explicitly tests for balance by regressing a team's average personality scores on the *Extraversion (Peer)* variable for the team. We find no evidence for imbalance.

Modeling strategy To test theses hypotheses, we use linear regression models to regress all evaluations e of project p by team i on the team's average openness, the average level of extraversion of the team member's randomized peers, and the interaction. As our team project quality measure is quite continuous, unlike the evaluations at the individual level, we use standard linear regression instead of ordered logistic models. Since we have multiple evaluations and multiple ideas for individuals i, we included fixed effects at the evaluator level and corrected our standard errors by clustering them at the team-level.

Results

Individual-level results

We begin our analysis by examining whether individuals develop better-rated ideas if they are higher in openness, Hypothesis 1. In Table 3 we regress each evaluation of idea quality on the focal innovator's openness score. Column 1 presents estimates of the innovator's openness on the aggregate post-treatment *Idea Quality* measure. The coefficient is negative, -0.077, but the standard error and p-value imply that the estimate is not statistically significant (SE=-0.065, $p > 0.1$). This suggests that individuals who are high in openness do not necessarily generate better ideas and may, in fact, generate worse ideas on average.

[Table 3 about here.]

Column 2 in Table 3 tests the main effect of being randomly assigned to extroverted peers, Hypothesis 2. The coefficient on Extraversion (Peers) is 0.305, nearly four-times the magnitude of the Openness (Self) estimate, and the p-value ($p < 0.05$) and standard error (SE=0.123) indicate that the effect is greater is statistically different than zero. This coefficient indicates that when individuals have conversations with extroverted peers, they generate better-rated ideas. By exponentiating the coefficient, we find that the log odds for the peer extraversion variable is 1.36. This suggests that for individuals who have extroverted peers, one standard deviation higher than the population average are about 36% more likely to receive a one-point higher rating than individuals who converse with a peer at the mean level of extraversion. A one-point increase is non-trivial, moving an idea up a decile in the idea quality distribution (e.g from being at the 60th percentile to 70th percentile).

Column 3 tests our third hypothesis, that open innovators who converse with extroverts will produce higher quality ideas. Specifically, in Column 3 we include a variable for individuals' level of openness, the average peer extraversion and an interaction of this variable with their peers' average extraversion. The coefficients on the main effects of Openness (Self) and Extraversion (Peers) remain relatively unchanged. The coefficient on the interaction term is similar in size and significance to the Extraversion (Peers) variable. The estimate is 0.300 and the standard error of (0.142) and p-value ($p < 0.05$) indicate the effect can be distinguished from zero. The coefficient indicates that individuals who are one-standard deviation higher in openness get twice the benefit when they talk with extroverts. Furthermore, since the main effect of Openness (Self) is a fourth the size of the interaction effect, we find that open individuals do generate better ideas *but only after they have had conversations with extroverts.*

Column 4 builds on the model in Column 3 by including the full set of self-peer interactions between extraversion and openness. This model allows us to check the robustness of our results in the face of alternative self-peer personality interactions. Including the additional interactions increases the magnitude of the coefficients on Extraversion (Peers) and its interaction with Openness (Self) and does not meaningfully change the width of the estimated standard errors. Consistent with our expectations that those who share large volumes of information may not be listening, the estimate on Extraversion (Self) is negative at $-.103$ ($SE = .066, p > 0.1$) though not significant at conventional levels. Furthermore, having peers high in openness does not appear to help an innovator generate better ideas. The estimate on the Openness (self) measure is $-.219$ ($SE = 0.106, p < 0.05$). Thus the matching appears to be asymmetric, open innovators matching with extraverts perform better while their extraverted partners perform worse, especially when matched with a peer who is open.

Column 5 includes our three non-personality ability measures to further assess robustness. The first control is pre-treatment idea quality, the average of the evaluations of each person's pre-conversation ideas.[6] The second control is our measure of each person's estimated generalized ability as measured by their admission score. The third control is our dummy for if the individual has or is pursuing an engineering degree. Including these controls at the self and peer level does not substantively change our primary results. Thus it does not appear that our results are driven by the peer's pre-treatment idea quality, their talent or educational backgrounds. It is not necessarily the quality of the peer, but it appears to be the fact that the peer is sharing a large volume of varied information.

To further test our argument that talking with extroverts, especially for innovators high in openness,

[6] We have complete observations for all 108 brainstorming participants, except for one individual who only participated in the post-treatment brainstorming session. In Column 9 we drop this person's 9 idea evaluation from the analysis.

results in the transfer of larger amounts of varied information and so the generation of more developed and recombinative ideas we next turn to analyzing the text of the idea itself. Specifically, we test if our treatment effects shape how how developed and recombinative an idea is and if these changes mediate the effects on idea quality. Tables 4 presents results from this analysis, allowing us to see if our hypothesized causal pathway is present.

[Table 4 about here.]

In Column 1 of Table 4 we test if our treatment affected an idea's development. We regress an idea's development score (the log of the number of unique terms) on Openness (Self), Extraversion (Peers), the interaction, and the average development score of the innovator's pre-treatment ideas.[7] Similar to the models in Table 3, we find that the coefficients on Extraversion (Peers) and its interaction with Openness (Self) are positive and similar in magnitude. A one-standard deviation increase in Extraversion (Peers) increases the number of unique terms in the idea by 0.38 standard deviations ($SE = 0.160, p < 0.05$) and the effect appears larger for those higher in Openness, increasing the number of unique terms used by an additional 0.34 standard deviations ($SE = 0.205, p < 0.1$). Column 2 tests the effects on recombination and finds similar results with an one-standard deviation increase in Extraversion (Peers) leading to an increase in an idea's recombination score of 0.245 standard deviations ($SE = 0.118, p < 0.05$) and with the effect increasing by another 0.24 for innovators high in openness ($SE = 0.138, p < 0.1$). We find evidence that talking with extroverts, especially for those high in openness, results in more developed and more recombinative ideas.

In Column 3 we examine if higher recombination and development scores are associated with better evaluations. Indeed, we find that idea's with higher development scores are better ideas. A one standard-deviation increase in an idea's development score leads to an increase in idea quality of 0.314 points ($SE = 0.076, p < 0.01$). We find a somewhat weaker but significant effect for recombination, with a one-standard deviation increase improving idea quality by 0.195 points ($SE = 0.096, p < 0.05$).

At the bottom of Column 3 we report the results of our formal mediation analysis (Baron and Kenny, 1986). Specifically, our mediation analysis tests if the effect of Extraversion (Peers) and Openness (Self) X Extraversion (Peers) is mediated by recombination and development. Using a multiple-mediation model we show that it is, though primarily through our measure of development. The total effect of Extraversion (Peers) and Openness (Self) X Extraversion (Peers) on Idea Quality is 0.806 ($SE = 0.243, p < 0.01$). Of this effect, we estimate that 0.31 (about 38%) is mediated by development and recombination ($SE = 0.112, p <$

[7] Three ideas, which each received 5 evaluations, used only very common words and so after parsing the text ended up having zero terms. For these terms, the recombination score could not be calculated since betweenness cannot be calculated for isolates in the semantic network. We drop these 15 observations from our analysis.

0.05). Examining each measure separately, we find that roughly 85% of the mediated effect appears to flow through development and about 15% of the quality effect may come from recombination, though the indirect effect through recombination is not statistically significant. However, our measures of development and recombination are quite correlated. This correlation makes simultaneously identifying the two effects empirically challenging. That said, the models in Table 4 provide evidence for our causal pathway: talking with extroverts, especially for innovator's high in openness, leads to developed and recombinative ideas which in turns leads to higher quality ideas.

We report a number of additional robustness tests in the Appendix. Appendix Table 10 replicates Table 3 using Ordinary Least Squares instead of ordered logistic regression to check that the interaction effect between Openness (Self) and Extraversion (Peers) is not an artifact of the non-linear specification (e.g., Ai and Norton, 2003). We find evidence for the interaction effect in the linear specification, and in further robustness checks we find that plots of our interaction terms are consistent over the range of the data. In Appendix Table 11 we test if what matters is not the extraversion of an innovator's peers, but the neuroticism, conscientiousness, agreeableness, or self-monitoring of the peers. These measures are largely insignificant, even when interacted with the innovator's openness. Furthermore, they do not meaningfully change the coefficients on our openness and extraversion measures. Appendix Table 12 tests if idea generation is improved not by talking with extroverts only, but by talking with a mix of extroverts and introverts or by talking first to extraverts and then to intraverts. We test for the value of talking to a mix of peers by including the standard deviation of extraversion; we test for potential order or sequence effects by separately including in our regression model the peer extraversion of an innovator's first, second and third conversation partner. We find little evidence for either. Appendix Table 13 tests if the effects on idea quality impact each of the underlying dimensions of novelty, business, and buy ratings. We find our effects hold across these dimensions. Finally, Appendix Table 9 includes controls for if the idea evaluator knows, is friends with, or provides advice with the participant who generated the idea. While the evaluations did not include any information about who generated the idea, perhaps people were able to determine who generated the idea and favored their friends. Controlling for the evaluator-innovator relationship status does not impact our findings. We find little evidence that evaluators provided their friends with better scores.

Team-level results

Our second set of hypotheses concerns the relationships between team openness, inter-team peer extraversion, and if their is a complementarity between these two measures. Similar to our individual level analysis, we regress measures of each team's final project quality on the team-level measures of peer extraversion, team member openness, and their interaction. Table 5 presents our results. All models include evaluator fixed effects and cluster standard errors at the team level.

[Table 5 about here.]

Column 1 in Table 5 regresses the project quality score on team-level measures of our key independent variables. Our results provide modest support for Hypothesis 4 that team's with members higher in Openness generate higher quality projects, with a point estimate of 0.124 ($SE = 0.063, p < 0.10$). It appears a team with a one-standard deviation higher openness average will generate projects that are about 0.58 standard deviations higher in project quality. Column 2 in Table 5 regresses project quality on the average extraversion of the 9 people each team member talked to during the second day brainstorming exercise. We find little evidence for any effect, though the coefficient is positive. Column 3 includes the Openness (Team) $\times$ Extraversion (Peers) term. We find strong evidence for Hypothesis 6.= The coefficient is 0.311 ($SE = 0.162, p < 0.05$) positive, significant, and meaningful in magnitude; about 2.5 times larger in magnitude than the Openness (Team) measure.

Columns 4 and 5 in Table 5 test if these results are robust to the inclusion of additional personality measures and ability measures. In Column 4, which includes the full set of extraversion and openness interactions, we find that the results remain relatively unchanged, though the magnitude of the interaction term increases in size. The model reported in Column 5 includes the team's and peers' average admission score, pre-treatment idea quality, and if they have an engineering degree. While none of the ability measures are significant, inclusion appears to increase our power: the coefficient on Extraversion (Peers) increases in magnitude to 0.183 and becomes statistically significant ($SE = 0.083, p < 0.05$). In this final model, we find evidence for all our team-level hypotheses.

We report further robustness tests in the Appendix. Specifically, in Appendix Table 15 we test if what matters for project quality is having a mix of open and closed members in a team or talking to a mix of extraverts and intraverts. Our effects remain largely unchanged when including the standard deviation of team openness or the standard deviation of peer extraversion. It does not appear that extraversion or openness diversity drives differences in a team's project quality.

Discussion

In this article, we propose and empirically test a micro-network theory of information acquisition and idea generation by enriching the fundamental building-block of a network theory of creativity–dyadic conversations. Our model incorporates personality theory to specify both the personality of the innovator—*openness to experience*—as well as the personality of her conversational peer—*extraversion*—most conducive to generating high-quality ideas. Further, we theorize how these individual-level mechanisms aggregate to the level of teams.

Contrary to prior research, we find that being *open to experience* alone does not lead individuals to generate better ideas (e.g. McCrae, 1987; Feist, 1998). Our findings suggest that this individual capability depends on the types of peers with whom a focal innovator converses. When open innovators are exposed to *extroverted peers*, they are more likely to develop higher quality ideas–ones that are evaluated higher, are more detailed, and have more distinct word usage compared to other ideas. Conversely, more open innovators whose peers are not extroverted appear to produce mostly *average* ideas. In terms of magnitude, while this effect alone will not make the lowest-quality ideas the best ones, it can shift ideas at the margins of "good" to "very good" or "very good" to "great." This is equivalent of moving an idea from being at the 80th percentile of quality to being in the top decile. Overall, our findings highlight the importance for considering the specific nature of social inputs in to the production of good ideas. Moreover, this insight—about the value of a dyadic interaction for information acquisition and ideation—can fruitfully be used to design teams that have a preponderance of those individuals who can help develop high-quality ideas within teams.

This study holds several implications for organizational research, particularly the role that social interaction plays in the generation of novel ideas at the level of both the team and the individual. The primary contribution of this article is the embedding of social-psychological processes in a structural model of innovation. First, we build on the work of micro-network scholars (e.g., Kilduff and Krackhardt, 2008, 1994) who have highlighted the importance of incorporating individual differences into structural theories of action (e.g., Fleming, Mingo and Chen, 2007; Burt, 2004). Our model pushes the micro-network approach forward along two directions—(a) by extending micro-network mechanisms beyond network formation to their effects on performance and (b) by showing the the personality of alters—in addition to the focal actor or ego—shapes network processes. Second, our work provides a multi-level perspective on team performance—(a) by elucidating how individual and network level processes of idea generation can be used to shape the demography of teams and (b) further highlighting the critical role of personality in team performance, both within the team and of external ties (Schilpzand, Herold and Shalley, 2011).

In terms of managerial implications, there are at least three. First, managers should seek out team members who are more open. Our findings and the findings of other scholars suggest that more open team members help the team develop better ideas (Schilpzand, Herold and Shalley, 2011; Neuman, Wagner and Christiansen, 1999). Second, innovators who are interested in developing new ideas should seek out conversational partners who have traits that are correlated with extroversion: large networks, higher verbal fluency, and a willingness to share. Finally, if potential alters possess valuable insight and knowledge but are not extroverted, then innovators should devise other strategies for communication besides short interactions. Such alternative approaches to interaction—longer conversations, perhaps over multiple occasions—may yield high value (Cain, 2013; Grant, Gino and Hofmann, 2011).

Our study also contributes to the literature from a methodological perspective. In this article, we used data from a field setting (an entrepreneurship boot camp) in which we embedded a randomized field experiment. By randomizing social interaction, namely external peer conversations and team assignments, as well as measuring detailed data ideation and individual characteristics, we could trace a nuanced and dynamic process from its earliest inception (a conversation with an external peer) to the performance of teams several days after. While the specific context of our study is not generalizable to all contexts, longer field experiments with a subset of the methodological innovations introduced in our study could be used to study, for instance, how external peer conversation affects the success of startups in more naturalistic contexts. This can be accomplished, for example, by working with incubators to facilitate external conversations between startups or an external pool of entrepreneurs, venture capitalists, and customers.

In conclusion, we note several limitations, both theoretical and empirical, of the present study. First, we have narrowed in on a concrete social interaction and specific personality traits (Perry-Smith and Mannucci, 2015). However, it is likely that a more general theoretical account would require us to think more about how our proposed mechanisms should or should not vary depending on task content, incentives, and organizational cultures (Sauermann and Cohen, 2010; Sørensen, 2002). Second, we have also constrained conversations to those that are one-off and short; such a constraint may play to the strengths of extroverts (Cain, 2013). Introverts may be as valuable, or perhaps more valuable, if the interaction is ongoing or longer (Grant, Gino and Hofmann, 2011). Thus, future theory must extend the types of social interactions studied. Third, our theory and empirics are limited in examining only singular facets of both peer and focal innovator personalities—e.g., extraversion and openness. However, different facets of a individuals personality may jointly shape how they behave in certain situations or when different incentives are at play. Extroverts who are neurotic may behave differently in highly competitive situations, as compared to extroverts that are not. In terms of empirical limitations, our findings, though benefiting from randomized peer interaction and detailed measurement, rely on a very specific context: an entrepreneurship boot camp held in New Delhi, India. Thus, our findings may not have broad generalizability outside of the entrepreneurial context. Although our findings are internally consistent and we have ruled out many possible mechanisms and confounders through our research design and measurement, more research needs to be conducted to pinpoint the set of actual mechanisms at play. Finally, we think that future theory and empirical analysis should account for the types of personalities present a person's networks in more naturalistic settings (Feiler and Kleinbaum, 2015). For instance, it would be interesting to understand whether some individuals' networks have more of the types of personalities that would give them access to useful information for ideation than others.

Several opportunities exist for extending our results and adding even further nuance. One key limitation of this study is that the conversations between the focal individual and the peer are not captured (McFarland, Jurafsky and Rawlings, 2013). Thus, we are limited to inferring the nature and volume of the information transmitted based on our understanding of the structure of the interaction and psychological theory. Similarly, other types of measurement of interpersonal interaction are likely to give greater depth to our theories. Another possibility for extending the work in this paper is to take the idea of matching and formally incorporate it into our empirical tests. In this article, we used randomization to create variation in peer and focal individual characteristics within a set of pairings. Matches are therefore a by-product of the randomization process and not explicitly designed. Future studies, particularly for match effects estimated in purely randomized contexts, should be designed to see whether these effects hold with experiments designed to specifically test them against a stronger null. Recent work by Carrell, Sacerdote and West (2013) suggested that implementing policy based on findings from randomized studies may not necessarily yield expected results due to interpersonal dynamics. Further, we have have modeled the impact of our constructs on the mean of the evaluations received by an individual's or team's ideas. However, social interaction may also shift the distribution of the types of ideas generated, perhaps reducing or increasing variance in quality, reactions or content. An exciting direction for future research would be to model higher order moments of the idea distribution. Finally, an important future direction for this research is studying the implications of our findings on a macro scale: more connections between individuals and organizations increase the overall innovative capabilities of ecosystems and regions (Saxenian, 1996). The ideal situation would be that network ties such as the ones created here increase performance for all members and not just reshuffle the outcome distribution.

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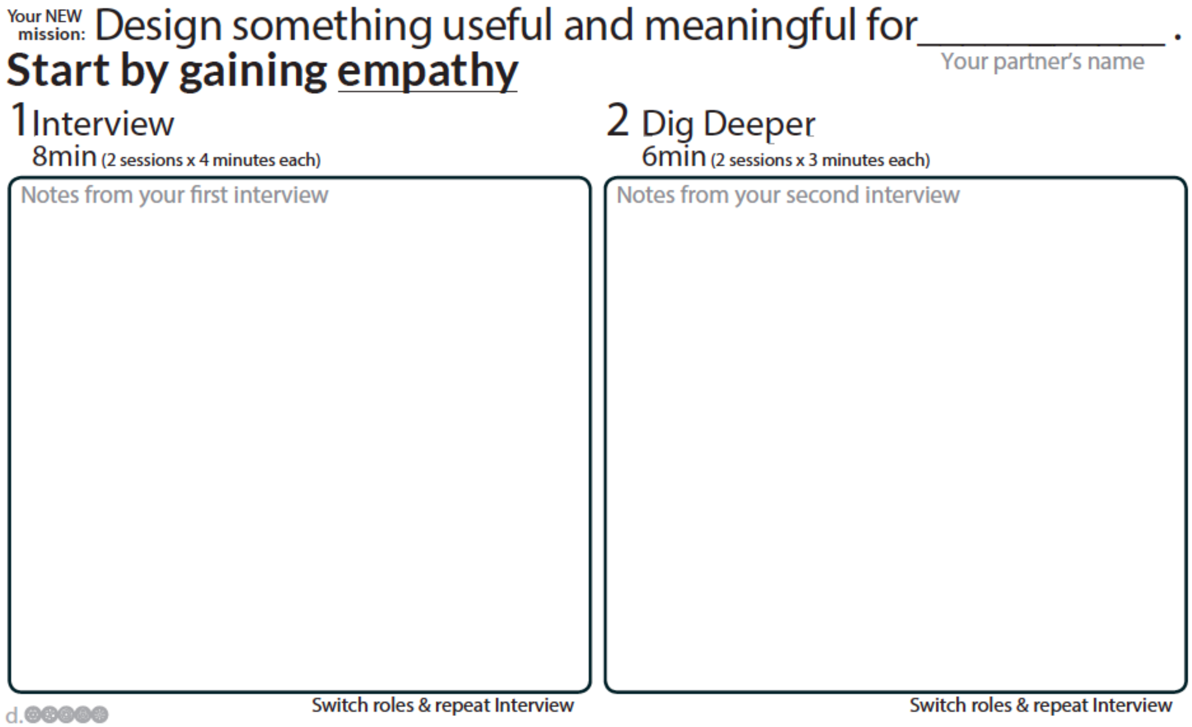
Figure 1: Note-taking sheet for each empathy interview.



Your NEW mission: Design something useful and meaningful for ____________ .

Your partner's name

Start by gaining empathy

1 Interview

8min (2 sessions x 4 minutes each)

Notes from your first interview

Switch roles & repeat Interview

2 Dig Deeper

6min (2 sessions x 3 minutes each)

Notes from your second interview

Switch roles & repeat Interview

d.

Figure 2: Visual summary of experimental procedure and data collection.

Data + Treatments	Measures of: ***Extraversion*** and ***Openness*** for each individual; ***Ability*** score from application rating. Team measures calculated from these individual measures.		Treatment: **Three 20 minute Peer Random-izations.** Measures of: ***Pre-treatment and post-treatment idea text.***	Measures of: ***Pre- and Post-Treatment Idea Ratings by Peers for: Business, Buy, Novelty, Idea Quality.***		Team Final Projet Submission.	Ratings of team projects by anonymous peers. Ratings on Novelty, Business, Prototype, and others. Within team evaluation of member effectiveness.
Schedule	Pre-bootcamp measures of ability and BFI survey completed by participants before arriving.	Logistics, Introduction, Icebreaker.	Individual brainstorming (Pretreatment), 3, 14 minute, empathy interviews, Post-treatment individual brainstorming.	Morning: Evaluate 50 ideas on three dimensions: Business, Buy, Novelty. Afternoon: Work on Product Prototype.	Work on Product design and Submission Packet.	Work on Product design and Submission Packet. Submit product prototype submission packet.	Final submissions are evaluated by peers, Team members evaluate each other on Manager Effectiveness Scale.
	Pre Bootcamp (Before Day 0)	*Monday (Day 1)*	*Tuesday (Day 2)*	*Wednesday (Day 3)*	*Thursday (Day 4)*	*Friday (Day 5)*	*Saturday (Day 6)*

Table 1: Summary statistics at the individual participant level

	count	mean	sd	min	max
Average Idea Quality (Self)	108	7.696	1.245	5.000	12.000
Extraversion (Self)	108	-0.025	1.005	-2.988	2.291
Openness (Self)	108	0.018	1.010	-2.953	1.986
Conscientious (Self)	108	0.011	0.988	-2.211	2.359
Agreeableness (Self)	108	-0.008	0.998	-2.646	2.066
Neuroticism (Self)	108	0.018	1.005	-2.212	2.237
Admission Score (Self)	108	-0.009	1.016	-2.284	1.777
Engineer (Self)	108	0.713	0.454	0.000	1.000
Pre-treatment Idea Quality (Self)	107	2.544	0.327	1.759	4.022
Extraversion (Peers)	108	0.002	0.569	-1.841	1.603
Openness(Peers)	108	0.031	0.596	-1.142	1.492
Conscientious (Peers)	108	0.004	0.613	-1.380	1.866
Agreeableness (Peers)	108	0.020	0.603	-1.524	1.589
Neuroticism (Peers)	108	-0.037	0.574	-1.808	1.159
Admission Score (Peers)	108	0.005	0.574	-1.269	1.342
Engineer (Peers)	108	0.686	0.270	0.000	1.000
Pre-treatment Idea Quality (Peers)	108	2.539	0.180	2.114	3.096
Observations	108				

Table 2: Summary statistics at the team level.

	count	mean	sd	min	max
Average Project Quality (Team)	40	2.791	0.205	2.439	3.294
Extraversion (Team)	40	0.008	0.624	-1.267	1.144
Openness (Team)	40	0.015	0.567	-1.142	1.368
Conscientious (Team)	40	0.004	0.550	-1.103	1.321
Agreeableness (Team)	40	-0.004	0.626	-1.300	1.168
Neuroticism (Team)	40	0.005	0.631	-1.201	1.361
Admission Score (Team)	40	-0.009	0.534	-1.124	1.051
Engineer (Team)	40	0.702	0.275	0.000	1.000
Pre-treatment idea quality (Team)	40	2.544	0.156	2.191	2.919
Extraversion (Peers)	40	-0.002	0.355	-0.846	0.838
Openness (Peers)	40	0.021	0.361	-0.731	0.806
Conscientious (Peers)	40	-0.009	0.399	-1.048	0.717
Agreeableness (Peers)	40	-0.002	0.389	-0.839	0.894
Neuroticism (Peers)	40	-0.046	0.328	-1.178	0.507
Admission Score (Peers)	40	0.005	0.413	-0.931	0.939
Engineer (Peers)	40	0.700	0.158	0.389	1.000
Pre-treatment idea quality (Peers)	40	2.532	0.099	2.282	2.766
Observations	40				

Table 3: Do conversations with extroverted peers increase an open individual's idea quality?

	Dependent variable: Idea Quality				
	(1)	(2)	(3)	(4)	(5)
Openness (Self)	-0.077		-0.092	-0.074	-0.111**
	(0.065)		(0.060)	(0.060)	(0.056)
Extraversion (Peers)		0.305**	0.323***	0.428***	0.371***
		(0.123)	(0.109)	(0.117)	(0.104)
Openness (Self) × Extraversion (Peers)			0.300**	0.342**	0.328**
			(0.142)	(0.153)	(0.141)
Extraversion (Self)				-0.103	
				(0.066)	
Openness(Peers)				-0.220**	
				(0.106)	
Openness (Self) × Openness (Peers)				0.023	
				(0.137)	
Extraversion (Self) × Openness (Peers)				-0.138	
				(0.149)	
Extraversion (Self) × Extraversion (Peers)				-0.177	
				(0.158)	
Pre-Treatment Idea Quality (Self)					0.456*
					(0.247)
Pre-treatment Idea Quality (Peers)					0.314
					(0.378)
Admission Score (Self)					0.013
					(0.059)
Admission Score (Peers)					0.199*
					(0.107)
Engineer (Self)					-0.158
					(0.152)
Engineer (Peers)					-0.045
					(0.283)
Observations	1150	1150	1150	1150	1141

Standard errors in parentheses
Ordered Logistic Regression with evaluator fixed effects.
All tests are two tailed. Standard errors clustered at the individual innovator level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Do conversations with extroverted peers change the content of an individual's ideas?

	Dependent variable:		
	Idea Development	Idea Recombination	Standardized Idea Quality
	(1)	(2)	(3)
Openness (Self)	-0.114	-0.104^{*}	-0.050
	(0.084)	(0.059)	(0.069)
Extraversion (Peers)	0.379^{**}	0.245^{**}	0.271^{**}
	(0.160)	(0.118)	(0.114)
Openness (Self) X Extraversion (Peers)	0.340^{*}	0.240^{*}	0.230
	(0.205)	(0.138)	(0.148)
Pre-Treatment Development (Self)	0.304^{**}		
	(0.129)		
Pre-Treatment Recombination (Self)		0.066	
		(0.087)	
Idea Development			0.360^{***}
			(0.072)
Idea Recombination			0.098
			(0.073)
Constant	-0.231^{**}	-0.00001	0.083
	(0.108)	(0.072)	(0.072)
Indirect Treatment Effect (Development)			0.259^{**}
			(0.103)
Indirect Treatment Effect (Recombination)			0.047
			(0.037)
Indirect Treatment Effect (Dev. and Rec.)			0.306^{**}
			(0.112)
Total Effect			0.806^{***}
			(0.217)
Observations	1,135	1,135	1,135

Note: *p<0.1; **p<0.05; ***p<0.01
Ordinary Least Squares with evalutor fixed effects.
Standard errors clustered at the individual innovator level.

Table 5: Do teams with open members that conversed with extroverted peers generate higher quality projects?

	Dependent variable: Project Quality				
	(1)	(2)	(3)	(4)	(5)
Openness (Team)	0.124^{*}		0.133^{*}	0.130^{**}	0.138^{**}
	(0.063)		(0.067)	(0.064)	(0.062)
Extraversion (Peers)		0.107	0.124	0.095	0.183^{**}
		(0.093)	(0.085)	(0.087)	(0.083)
Openness (Team) × Extraversion (Peers)			0.331^{**}	0.825^{***}	0.335^{**}
			(0.162)	(0.197)	(0.149)
Extraversion (Team)				-0.120^{**}	
				(0.052)	
Openness (Peers)				-0.022	
				(0.095)	
Openness (Team) × Openness (Peers)				-0.463^{***}	
				(0.170)	
Extraversion (Team) × Openness (Peers)				0.043	
				(0.123)	
Extraversion (Team) × Extraversion (Peers)				0.113	
				(0.140)	
Pre-treatment idea quality (Team)					0.325
					(0.254)
Pre-treatment idea quality (Peers)					0.146
					(0.326)
Admission Score (Team)					0.103
					(0.074)
Admission Score (Peers)					0.024
					(0.095)
Engineer (Team)					-0.111
					(0.099)
Engineer (Peers)					-0.188
					(0.221)
Constant	2.803^{***}	2.806^{***}	2.797^{***}	2.771^{***}	1.810^{*}
	(0.031)	(0.033)	(0.030)	(0.027)	(1.057)
Observations	556	556	556	556	556

Standard errors in parentheses
Linear Regression with evaluator fixed effects.
All tests are two tailed. Standard errors clustered at theteam level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1 Overview of the Appendix

In this appendix, we provide a series of additional summary statistics, details on how we constructed our text-based measures, a variety robustness checks, a detailed description of the bootcamp, and further information about the ideas and projects generated.

Sections 2 and 3 report summary statistics. In Section 2 we report individual level bivariate correlations along with balance tests. In Section 3 we report a the team level bivariate correlations along with balance tests.

Section 4 details how we construct our idea development and recombination measures.

In Sections 5 through 9 we report robustness checks at the individual level. In Table 5 we replicate the results in Table 3 but using linear regression to ensure that our estimated interaction effect is not an artifact of the non-linear model we use. In Section 6 we test if alternative peer-personality interactions explain our findings, but we find little evidence for these alternatives. In Section 7 we test if what matters is not talking to extroverts, but talking to a mix of extroverts and introverts, perhaps in a particular order. We find little evidence for this alternative. In Section 8 we test if our effects hold across the three different dimensions (purchase intention, novelty, and business potential) each idea was evaluated on. We find our effects holds relatively evenly on each dimension. In section 9 we show that the participants are no more or less likely to give positive evaluations to the ideas generated by their friends and advice partners, confirming that our quality measure is not biased by the relationships between participants.

In Section 10 we report robustness checks at the team level. Specifically, we show that personality diversity, in the form of teams with a mix of open and closed individuals or talking to peers who are a mix of extraverts or intraverts, does not appear to increase, nor decrease, team performance. Similar to the individual level results, what matters is the level of openness and extraversion and not personality diversity.

In the final three sections we provide more details about the bootcamp and ideas generated. In Section 11 we describe the recruitment process and bootcamp in more detail. Section 12 provides further details on the ideas generated and Section 13 provides examples of the projects generated at the end of the first week.

2 Individual level correlations and balance tests

Table 6 presents the correlations between the variables used in our primary analysis. Table 7 regresses our measure of peer extraversion on an individual's personality measures. We find not significant relationship, indicating that are randomization was successful at the individual level.

[Table 6 about here.]

[Table 7 about here.]

3 Team level correlations and balance tests

Table 8 presents the correlations between the variables used in our primary analysis. Table 9 regresses our measure of peer extraversion on a teams's average personality score. We find not significant relationship, indicating that are randomization was successful at the team level.

[Table 8 about here.]

[Table 9 about here.]

4 Idea Development and recombination variable construction

As briefly discussed in the main body of the paper, we calculated two content-based measures of the ideas generated. The first measure, commonly used in the creativity literature, captures how "developed" an idea is by counting the number of unique words used to describe the idea. Idea development has been shown to correlate with poetic success and scientific success (Simonton, 1990; Feist, 1997). To generate a content-based measure of idea development, we took all the ideas generated during the brainstorming sessions and first cleaned the raw text. To do so, we took the text from each idea, stripped out all the punctuation, removed common English "stop words" (of, the, a), and then stemmed the remaining words so that words capturing the same concept (e.g., "run" and "running") mapped to the same underlying meaning ("run"). Using this cleaned corpus, we counted the number of unique terms to generate a measure of development. Since the distribution of term counts is fat-tailed, we generated a final "development score" measure by taking the log of the count of distinct terms in each idea and then standardize the variable to have mean 0 and standard deviation 1.

While the number of unique terms reflects how developed the idea is, it is only one of many dimensions that explain why an idea is more creative and innovative. While the traditional Torrance model (Torrance, 1972; Kim, 2006) treats creativity as a composite of four dimensions (elaboration and development, fluency, flexibility, and originality and novelty), more recent work has argued that creativity encapsulates a larger set of concepts, including the evolutionary fitness of an idea, its surprisingness in a Bayesian sense, and how recombinative it is (Simonton, 1999; de Vaan, Vedres and Stark, 2015). The idea of recombination is especially rooted in the sociology of knowledge and innovation. Within this research stream, scholars treat ideas, new products, or patents as embedded within a larger semantic network. Some ideas are central in this network, others are peripheral, and some sit on the boundaries between different "communities" of ideas. It is this last position of spanning boundaries that has received the most attention, with research finding that ideas sitting at the interaction of many other ideas represent novel recombinations with greater potential (Hargadon and Sutton, 1997; Uzzi et al., 2013; de Vaan, Vedres and Stark, 2015).

To measure how recombinative the idea is, we drew on the literature that treats ideas as embedded in a larger semantic network. We began by building a network between all the ideas generated during the brainstorming session. In this network, ideas are connected if they are similar, and they remain unconnected if they are distant. We generated a measure of distance by first calculating a term-frequency-inverse-document-frequency weighted idea-by-term matrix Manning and Schütze (1999). As with the idea development score discussed above, terms represent cleaned and stemmed words. Using this idea-by-term matrix, we then calculated the cosine distance between each idea within this matrix. Conceptually, ideas that are farther apart in terms of cosine distance share few terms, whereas ideas that are closer together share many overlapping terms. We treated two ideas as connected in the final semantic network if they had a cosine distance in the top decile of similarity (less than 0.92).[8] We then calculated each idea's betweenness centrality in this network of ideas. Ideas high in betweenness centrality are those that sit on the shortest paths between all the other ideas generated and are thus ideas that are most central in connecting disparate idea domains. As with many measures of centrality, betweenness centrality is fat-tailed. Therefore, to generate a final "recombination score," we took the log of each idea's betweenness centrality in the semantic network and then standardize the variable to have mean 0 and standard deviation 1.

5 Individual-level results hold when using OLS

We replicate Table 3 using standard linear regression instead of ordered logistic regression. This model returns the marginal effects at the group means and so helps us test if our results, and especially our interaction term, are robust to model specification. Indeed, the interaction terms remains positive and significant. For example, in Column 3 the coefficient is 0.418 with a standard error of 0.193.

[Table 10 about here.]

6 Alternative personality matches do not explain our results

Table 11 tests is other personality interactions are driving our results. We find little evidence that our findings are being driven by other personality constructs.

[Table 11 about here.]

7 Testing for variance and order effects

One possible alternative is that idea generation is improved not by talking with extroverts only, but by talking with a mix of extroverts and introverts. Building on this idea that it is the variance that matters, perhaps what really matters is the sequence of conversations. Perhaps introverts improve idea quality when encountered after

[8]Results are similar at other percentile cutoffs, although the results weaken as the networks become more connected and as variation in measures of centrality decline.

talking with extroverts? Table 12 tests these alternative models. Model 1 shows that the standard deviation of peer extraversion does not appear to improve idea quality nor does its interaction with the focal innovator's openness. Model 2 disaggregates the effects, including separate extraversion measures for the first, second, and third peer with which the focal actor conversed. For both the interactions and the main effects, we find little evidence that the order of who an innovator talks to matters. None of the estimates are substantially different from one another, though the estimates have wider standard errors since we lose power by estimating the extraversion of each conversation partner separately.

[Table 12 about here.]

8 Do our results hold on dissaggregated quality measures?

In Table 13, we examine whether our results hold in the more disaggregated versions of the post-treatment idea ratings. We find that peer Extraversion (Peers) and the interaction with the Openness of the innovator increases the quality of ideas in the dimensions of business value, buy likelihood, and novelty. Consistent with our theorizing, we find that our effects increase idea quality across the board and not simply in terms of one idiosyncratic dimension.

[Table 13 about here.]

9 Does bias in the evaluation process lead to bias in the peer effects estimation?

Though the evaluations of ideas was double-blinded, we still wanted to ensure that our estimates were not biased by whether evaluators had knowledge of or interacted with the individual generating the idea that they were evaluating. To do this, we conducted an analysis where we controlled for the presence of a relationship prior to the treatment between an evaluator and the focal innovator. Our results, presented in Table 14, indicate that such a bias does not appear to exist or does not affect our key results. Knowing, being friends with, or going to another participant for advice does not appear to change the rating of the idea in any appreciable way. In Column 4 we drop all evaluations conducted by evaluators who knew the individual whose blinded idea they were evaluating. Again, our results remain robust.

[Table 14 about here.]

10 Testing for variance effects at the team level

To test if teams benefit from having a mixture of open and closed individuals, or from talking to a mix of intraverts and extraverts, we include the standard deviation of these two measures in Table 15. Consistent with the individual-level results, we find little evidence that talking to a mix of intraverts and extraverts improves a team's performance. Furthermore, we find no evidence that teams with a mix of open and closed individuals perform better. If anything, such teams appear to generate lower quality projects.

[Table 15 about here.]

11 Setting Description, Participant Recruitment and Participant Characteristics

The organization, Innovate Delhi, was a 3-week intensive startup boot camp and pre-accelerator that ran from June 2 (Day 1) to June 22 (Day 21), 2014 on the campus of IIIT-Delhi. The program consisted of three modules spread over three weeks. The bootcamp was held six days a week, Monday through Saturday, from 9am until 5pm. The first week (on which this experiment is based) focused on design thinking, feedback, and prototyping. Individuals worked in randomly assigned teams of three to develop a software product concept for the Indian wedding industry. During this week, teams and individuals were required to converse with three other participants about their experience with weddings. At the end of the week, individuals submitted their final prototype for peer evaluation.

Admission into the Innovate Delhi program 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, and business skills. Furthermore they were strongly encouraged to write an essay explaining why they wanted to enter the program and, as part of the application, we asked them to email people they thought may also be interested. We recruited applicants through a number of different means including facebook ads, social media posts, entrepreneurship organizations and word-of-moth referrals. Over 1,247 people started the full application, 58 started a short version of the standard application we launched after the February 1st deadline, and 71 people completed a wait-list Google Form application that was designed to attract last-minute applicants; a total of 1,376 applications were started. We received 508 fully completed applications of which 437 were standard applications and 71 were from the last-minute Google Form applications (these applications did not allow the user to save their work and submit at a later date hence the perfect pass through rate).

From these applications we accepted 358 standard applicants and 18 last-minute applicants. From this pool of accepted students 178 enrolled by May 1st and signed our initial online IRB consent form. This form clearly stated that the program was being conducted for research purposes and that digital, video, and audio data would be collected. From this group we still had a sizable attrition rate: 135 formally paid the registration fee, signed up for a Google Apps @innovatedelhi.com account, and completed a battery of pre-program surveys. Of these 135 students who formally enrolled 118 attended the first day of the program and signed our second physical consent form. Of those who attended on the first day 95 percent (112) of these students continued on to the second day and completed the three-week program. Of the 112 program graduates 104 people completed the full standard application, 5 the the shorter standard application, and 3 the last-minute application. From these 112 graduates of the program 38 found out about Innovate Delhi through a friend, 24 heard about it from a Facebook ad campaign, 13 through the university where we ran the program, 8 through Internet searches for entrepreneurship boot-camps and accelerators, and the remainder through an assortment of social media and word-of-mouth means.

The age range of the 112 graduates ran from 18 to 36, with a mean age of just over 22. Our program had 25 women and everyone had, or was enrolled in, college with 60 of the participants enrolled in a college, masters, or phd program. Our program was regionally diverse with 62 of the participants from the state of Delhi and the rest from across India. The class was primarily engineering and computer science degree holders (78), followed by 18 business degrees, and the rest from the arts and sciences. A total of 8 people were enrolled in, or, had graduated from advanced degree programs. The participants came from a broad spectrum of universities including Delhi University, IIIT-Delhi, Jaypee University, Delhi Technological University, and the IITs. It is important to note that universities in India are composed of relatively independent colleges, thus most of the participants in our program did not know one another even if they came from the same university. For example, of the 26 participants from Delhi University half are the only representative from their college and the most popular college from Delhi University supplied only 3 participants. Everyone in the program spoke English since proficiency in English was an application requirement and nearly all the participants were multi-lingual with Hindi, Urdu, Bengali, Punjabi, and Tamil being the most common.

The participants professional experience and business skills were quite varied. Of the Innovate Delhi graduates, 77 had formal work experience at companies ranging form multi-nationals to large Indian businesses to new startups from across India. As expected, the group was quite entrepreneurial with 37 of the participants having started a company, the majority of which were suspended or had folded before the start of the program. In terms of having a prior connection to the Indian startup ecosystem, 36 had worked for a StartUp that was not their own and 28 could name a mentor they had in the Indian StartUp ecosystem. Just over half, 65, have a very rough idea for a startup coming into the program. In terms of skills 63 had a background in web programming, 50 experience in marketing, 38 in data analysis, 30 in sales, and many in accounting, PR, operations, and market analysis. Unsurprisingly for a program focused on software startups, the most common industry the participants were interested in entering (58 people) was Internet and Technology. Beyond this core interests were diverse with 39 people interested in education, 35 in financial services, 27 in advertising, 17 in media, 13 in health care, 12 in food and beverage, and others interested in everything from manufacturing to agriculture to corporate social responsibility. The incoming within-program networks of the participants are very sparse, with the average participant not knowing 98% of the other participants and were not friends with 99.5% of the other participants.

12 Individual Ideas and evaluation

To provide context for the nature of the ideas generated during the individual idea generation process, we, present examples of raw ideas generated immediately after the three randomized interviews that were rated highly as well as poorly on the three dimensions of business potential, buy likelihood and novelty.

Examples of highly rated ideas include:

> *Feast on demand lets the wedding planners minimise food wastage during the feasts in the events. Through this app, the wedding planners can generate a link and forward it to all the guests. On opening that link, the guests are confronted with a set of choices of food items/dishes they wish to consume during the event. After the guests give their preferences, the wedding planner gets the data and can arrange the food according to these estimates. Also, the dishes with low preference can be eliminated to the reduce wastage.*

> *Behavioral analysis of bride and grooms online profiles on key social networks. This could be done exclusively by a company which would give a detailed analysis by psychologists. This would definitely aid the match-making process, making it more thorough.*

> *Renting of Wedding Dresses. Most women don't sell off jewelry bought, but dresses cannot be re-worn. Since branding is all that matters when it comes to second hand, the dresses could be dry washed and repacked in bags and delivered.*

Examples of ideas that received low ratings include:

> *PERSONALISED CARDS. [my interviewee] said that it gets to be highly painful to write names on cards and thus I propose that an agency that sends personalised cards and tracks whether they have reached.*

> *connectivity of app event and fb event is a nice way to spread info easily*

> *Build an app that would give users a complete guide on personal grooming tips for weddings (from deciding on what to wear to how to wear the make-up to how to carry yourself,etc) customized according to the user's built, complexion, and personality.*

13 Project examples and evaluation

To provide reference points for how evaluators rated the final team submissions, we provide examples of submissions in the top, middle, and bottom quartiles of submissions in terms of total score.

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

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

Their splash page depicted in figure 3, is clear and visually appealing:

[Figure 3 about here.]

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

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

Their splash page submission, depicted in figure 4:

[Figure 4 about here.]

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

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

Their splash page submission, depicted in figure 5:

[Figure 5 about here.]

Figure 3: Splash page for submission in the top quartile—Snappily Wed.

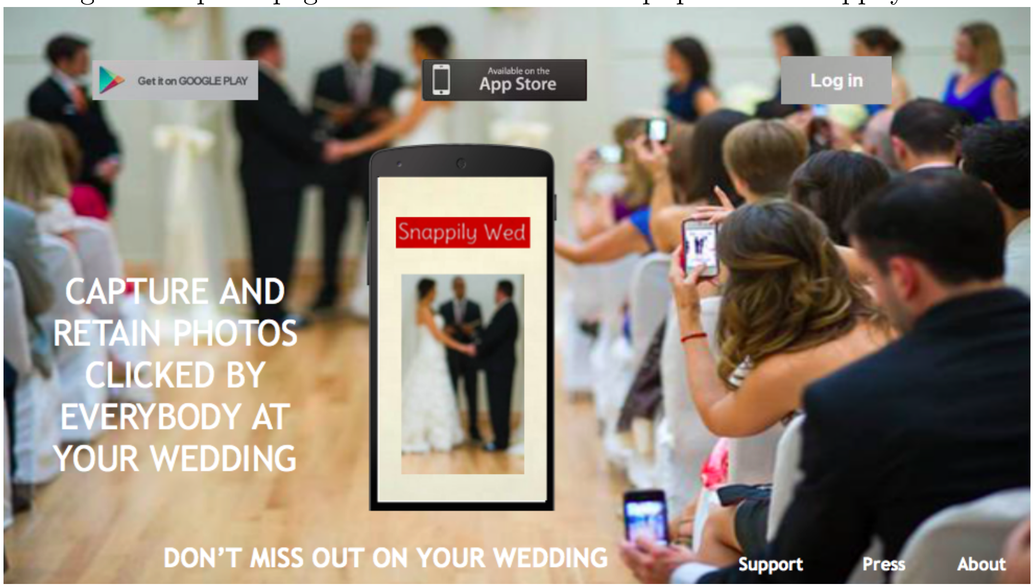


Figure 4: Splash page for submission in the middle quartile—Tender my Wedding.

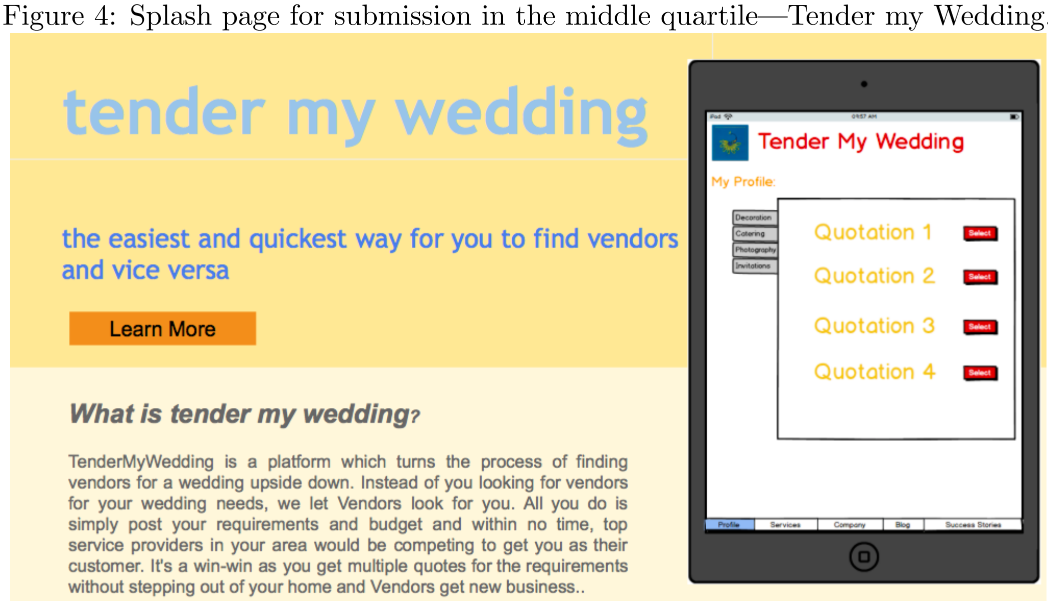


Figure 5: Splash page for submission in the bottom quartile—Invite My Pals.

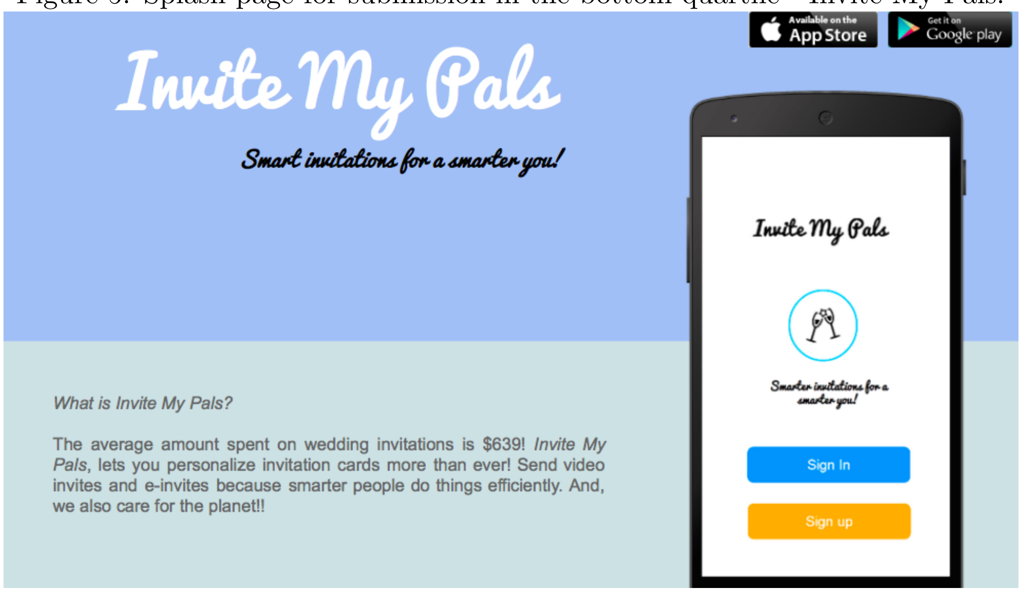


Table 6: Correlations at the individual participant level.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Average Idea Quality (Self)	1.00																
2 Extraversion (Self)	0.01	1.00															
3 Openness (Self)	0.04	0.30	1.00														
4 Conscientious (Self)	-0.09	0.24	0.19	1.00													
5 Agreeableness (Self)	0.05	0.03	0.03	0.27	1.00												
6 Neuroticism (Self)	0.05	-0.21	-0.34	-0.32	-0.21	1.00											
7 Admission Score (Self)	-0.02	0.02	0.16	0.16	-0.13	0.03	1.00										
8 Engineer (Self)	-0.13	0.01	-0.06	-0.03	-0.01	-0.10	-0.01	1.00									
9 Pre-treatment Idea Quality (Self)	0.17	-0.00	-0.03	-0.30	0.00	-0.01	0.05	0.03	1.00								
10 Extraversion (Peers)	0.12	0.05	0.01	0.00	0.04	-0.00	-0.05	0.16	-0.05	1.00							
11 Openness(Peers)	-0.18	0.01	-0.19	-0.02	0.02	0.05	0.13	0.12	-0.08	0.40	1.00						
12 Conscientious (Peers)	-0.06	-0.04	-0.04	0.05	0.07	0.14	0.10	-0.01	-0.05	0.09	0.17	1.00					
13 Agreeableness (Peers)	-0.12	-0.03	-0.00	0.08	-0.08	0.06	0.02	-0.06	-0.05	0.05	0.04	0.20	1.00				
14 Neuroticism (Peers)	0.16	0.01	0.06	0.13	0.07	-0.22	0.03	-0.27	-0.05	-0.31	-0.36	-0.31	-0.23	1.00			
15 Admission Score (Peers)	0.14	-0.02	0.13	0.07	0.04	-0.01	-0.04	-0.08	-0.10	0.01	0.21	0.26	-0.19	0.08	1.00		
16 Engineer (Peers)	0.09	0.12	0.13	0.04	-0.03	-0.23	-0.04	0.14	0.08	0.16	-0.04	0.01	-0.04	-0.07	-0.03	1.00	
17 Pre-treatment Idea Quality (Peers)	0.06	-0.01	-0.05	-0.10	-0.05	-0.07	-0.09	0.08	0.04	0.04	0.03	-0.36	0.00	0.09	-0.09	0.02	1.00

Table 7: Peer assignments appears balanced at the individual level.

	(1) Openness (Self)	(2) Extraversion (Self)	(3) Conscientious (Self)	(4) Agreeableness (Self)	(5) Neuroticism (Self)
Extraversion (Peers)	0.015	0.087	0.006	0.066	-0.002
	(0.141)	(0.150)	(0.173)	(0.203)	(0.162)
Constant	0.018	-0.026	0.011	-0.008	0.018
	(0.098)	(0.097)	(0.095)	(0.096)	(0.097)
Observations	108	108	108	108	108

Standard errors in parentheses
Linear Regression.
All tests are two tailed. Standard errors clustered at the individual innovator level.

Table 8: Correlations at the team level.

	(1)																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Average Project Quality (Team)	1.00																
2 Extraversion (Team)	-0.01	1.00															
3 Openness (Team)	0.22	0.07	1.00														
4 Conscientious (Team)	0.09	0.11	0.02	1.00													
5 Agreeableness (Team)	-0.15	-0.08	-0.00	0.24	1.00												
6 Neuroticism (Team)	0.12	-0.09	-0.29	-0.31	-0.23	1.00											
7 Admission Score (Team)	0.17	-0.01	0.21	0.10	-0.25	0.10	1.00										
8 Engineer (Team)	-0.02	-0.05	-0.06	0.15	-0.07	-0.10	-0.08	1.00									
9 Pre-treatment idea quality (Team)	-0.02	0.01	-0.19	-0.07	0.13	-0.05	-0.14	-0.02	1.00								
10 Extraversion (Peers)	0.13	0.02	0.08	0.10	-0.05	-0.06	-0.25	0.26	0.14	1.00							
11 Openness (Peers)	-0.14	-0.07	-0.22	-0.18	-0.02	-0.09	-0.02	0.16	0.02	0.35	1.00						
12 Conscientious (Peers)	-0.20	-0.20	-0.18	-0.01	0.04	0.33	0.04	0.01	0.08	0.04	0.12	1.00					
13 Agreeableness (Peers)	-0.18	-0.29	-0.31	0.05	-0.13	0.08	-0.20	-0.05	0.19	-0.02	-0.13	0.25	1.00				
14 Neuroticism (Peers)	-0.16	0.27	0.17	0.19	0.16	-0.13	0.28	-0.32	-0.32	-0.53	-0.37	-0.29	-0.29	1.00			
15 Admission Score (Peers)	0.04	-0.05	0.25	0.12	0.21	-0.01	0.04	0.16	-0.35	-0.08	0.04	0.37	-0.19	0.14	1.00		
16 Engineer (Peers)	-0.15	0.06	0.29	-0.03	-0.04	-0.17	-0.16	-0.06	0.15	0.18	-0.12	-0.12	0.03	-0.01	0.17	1.00	
17 Pre-treatment idea quality (Peers)	0.12	-0.02	-0.01	0.14	-0.08	0.12	0.19	0.20	-0.08	-0.01	0.29	-0.28	0.07	-0.07	-0.17	-0.01	1.00

Table 9: Peer assignments appears balanced at the team level.

	(1) Openness (Team)	(2) Extraversion (Team)	(3) Conscientious (Team)	(4) Agreeableness (Team)	(5) Neuroticism (Team)
Extraversion (Peers)	0.118	0.027	0.162	-0.076	-0.095
	(0.228)	(0.316)	(0.228)	(0.260)	(0.299)
Constant	0.016	0.008	0.004	-0.004	0.005
	(0.091)	(0.100)	(0.088)	(0.100)	(0.101)
Observations	40	40	40	40	40

Standard errors in parentheses.
Linear Regression.
All tests are two tailed. Standard errors clustered at the individual innovator level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: The results in Table 3 hold when using ordinary linear regression.

	(1) Idea Quality	(2) Idea Quality	(3) Idea Quality	(4) Idea Quality	(5) Idea Quality
Openness (Self)	-0.088		-0.099	-0.087	-0.122
	(0.085)		(0.081)	(0.082)	(0.075)
Extraversion (Peers)		0.363^{**}	0.383^{***}	0.499^{***}	0.470^{***}
		(0.161)	(0.142)	(0.156)	(0.137)
Openness (Self) × Extraversion (Peers)			0.418^{**}	0.408^{**}	0.445^{**}
			(0.193)	(0.205)	(0.184)
Extraversion (Self)				-0.088	
				(0.091)	
Openness(Peers)				-0.305^{**}	
				(0.145)	
Openness (Self) × Openness (Peers)				0.095	
				(0.186)	
Extraversion (Self) × Openness (Peers)				-0.165	
				(0.201)	
Extraversion (Self) × Extraversion (Peers)				-0.239	
				(0.192)	
Pre-treatment Idea Quality (Self)					0.576^{**}
					(0.282)
Pre-treatment Idea Quality (Peers)					0.554
					(0.491)
Admission Score (Self)					0.032
					(0.077)
Admission Score (Peers)					0.244^{*}
					(0.137)
Engineer (Self)					-0.270
					(0.210)
Engineer (Peers)					-0.141
					(0.351)
Constant	4.972^{***}	4.952^{***}	4.962^{***}	5.113^{***}	2.385
	(0.358)	(0.342)	(0.348)	(0.348)	(1.467)
Observations	1150	1150	1150	1150	1141

Standard errors in parentheses
Linear Regression with evaluator fixed effects.
All tests are two tailed. Standard errors clustered at the individual innovator level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: The results in Table 3 are robsut to the inclusion of alternative peer-personality interactions.

	(1) Idea Quality	(2) Idea Quality	(3) Idea Quality	(4) Idea Quality
Openness (Self)	-0.096	-0.104	-0.056	-0.098
	(0.081)	(0.079)	(0.084)	(0.082)
Extraversion (Peers)	0.480***	0.359**	0.390***	0.379***
	(0.145)	(0.140)	(0.142)	(0.138)
Openness (Self) × Extraversion (Peers)	0.495**	0.397**	0.338*	0.411**
	(0.220)	(0.197)	(0.195)	(0.194)
Neuroticism (Peers)	0.352**			
	(0.162)			
Openness (Self) × Neuroticism (Peers)	0.049			
	(0.183)			
Conscientious (Peers)		-0.245*		
		(0.143)		
Openness (Self) × Conscientious (Peers)		-0.238*		
		(0.142)		
Agreeableness (Peers)			-0.067	
			(0.149)	
Openness (Self) × Agreeableness (Peers)			0.204*	
			(0.109)	
Self Monitoring (Peers)				0.042
				(0.125)
Openness (Self) X Self Monitoring (Peers)				0.028
				(0.102)
Constant	4.903***	4.925***	4.947***	4.954***
	(0.357)	(0.330)	(0.341)	(0.356)
Observations	1150	1150	1150	1150

Standard errors in parentheses
Linear Regression with evaluator fixed effects.
All tests are two tailed. Standard errors clustered at the individual innovator level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Individuals who talk with a mix of extraverts and intraverts do not appear to generate higher quality ideas. Furthermore, the order of who an individual converses with does not appear to have a significant impact on idea quality.

	(1) Idea Quality	(2) Idea Quality
Openness (Self)	-0.133	-0.067
	(0.197)	(0.084)
Extraversion (Peers)	0.477^{***}	
	(0.132)	
Openness (Self) × Extraversion (Peers)	0.351^{*}	
	(0.185)	
Extraversion S.D. (Peers)	0.227	
	(0.172)	
Openness (Self) × Extraversion S.D. (Peers)	0.021	
	(0.190)	
Extraversion (First Peer)		0.135^{*}
		(0.071)
Extraversion (Second Peer)		0.299^{***}
		(0.074)
Extraversion (Third Peer)		0.096
		(0.067)
Extraversion (First Peer) × Openness (Self)		0.014
		(0.070)
Extraversion (Second Peer) × Openness (Self)		0.336^{***}
		(0.097)
Extraversion (Third Peer) × Openness (Self)		0.157^{*}
		(0.083)
Constant	4.800^{***}	4.957^{***}
	(0.359)	(0.325)
Observations	1144	1150

Standard errors in parentheses
Linear Regression with evaluator fixed effects.
All tests are two tailed. Standard errors clustered at the individual innovator level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: The randomized conversations appear to impact the business, buy, and novelty dimensions of an individual's idea quality equally.

	(1) Business Rating	(2) Buy Rating	(3) Novelty Rating
Openness (Self)	-0.047	-0.059	-0.105*
	(0.058)	(0.058)	(0.055)
Extraversion (Peers)	0.234**	0.272***	0.264**
	(0.109)	(0.093)	(0.122)
Openness (Self) $\times$ Extraversion (Peers)	0.320**	0.334***	0.336***
	(0.154)	(0.115)	(0.130)
Observations	1203	1352	1765

Standard errors in parentheses
Ordered Logistic Regression with evaluator fixed effects.
All tests are two tailed. Standard errors clustered at the individual innovator level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Our results are robust when controlling for the presence of a innovator-evaluator relationship.

	(1) Idea Quality	(2) Idea Quality	(3) Idea Quality
Openness (Self)	-0.104	-0.105*	-0.105*
	(0.063)	(0.063)	(0.063)
Extraversion (Peers)	0.333***	0.334***	0.334***
	(0.115)	(0.115)	(0.114)
Openness (Self) $\times$ Extraversion (Peers)	0.296**	0.296**	0.296**
	(0.143)	(0.143)	(0.143)
Evaluator knows innovator	0.062		
	(0.319)		
Evaluator is friends with innovator		-0.000	
		(0.504)	
Innovator sought advice from evaluator			0.021
			(0.412)
Observations	1132	1132	1132

Standard errors in parentheses
Ordered Logistic Regression with evaluator fixed effects.
All tests are two tailed. Standard errors clustered at the individual innovator level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Teams with a mix of open and closed individuals or who talk with a mix of intraverts and extraverts do not outperform teams that are simply more open and talk to more extraverts.

	(1) Project Quality	(2) Project Quality	(3) Project Quality
Openness (Team)	0.115*	-0.105	-0.086
	(0.067)	(0.208)	(0.212)
Extraversion (Peers)	0.317**	0.125	0.319**
	(0.129)	(0.094)	(0.153)
Openness (Team) × Extraversion (Peers)	0.302*	0.555*	0.479*
	(0.166)	(0.277)	(0.276)
Std. Dev. Openness (Team)	-0.041		-0.035
	(0.052)		(0.050)
Std. Dev. Openness (Team) × Extraversion (Peers)	-0.223**		-0.215**
	(0.098)		(0.106)
Std. Dev. Extraversion (Team)		0.151	0.166
		(0.143)	(0.144)
Openness (Team) × Std. Dev. Extraversion (Peers)		0.439	0.375
		(0.350)	(0.353)
Constant	2.840***	2.729***	2.759***
	(0.064)	(0.075)	(0.090)
Observations	556	556	556

Standard errors in parentheses
Linear Regression with evaluator fixed effects.
All tests are two tailed. Standard errors clustered at the team level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$