

Conversations and Idea Generation: Evidence from a Field Experiment

Sharique Hasan
Duke University

Rembrand Koning
Harvard University

Abstract

When do conversations lead people to generate better ideas? We conducted a field experiment at a startup bootcamp to evaluate the impact of informal conversations on the quality of product ideas generated by participants. Specifically, we examine how the personality of an innovator (openness to experience, capturing creativity) and the personalities of her randomly assigned conversational peers (extroversion, measuring willingness to share information) affects the innovator's ideas. We find that open innovators who spoke with extroverted peers generated significantly better ideas than others at the bootcamp. However, closed individuals produced mediocre ideas regardless with who they spoke, suggesting limited benefits of conversations for these people. More surprisingly, open individuals, who are believed to be inherently creative, produced worse ideas after they spoke with introverted peers, suggesting individual creativity's dependence on external information. Our study demonstrates the importance of considering the traits of both innovators and their conversational peers in predicting who will generate the best ideas.

Introduction

Having a *great* rather than an *average* product can mean the difference between success and failure for any company (e.g., Kornish and Ulrich, 2014), but this is especially true for young firms whose survival depends on introducing innovative products to the market (e.g., Vogel, 2017; Shane, 2000). It is therefore essential that a company’s product development teams have creative people who can help them generate high-quality ideas (e.g., Baum and Bird, 2010; Zhao and Seibert, 2006). At the same time, idea generation also requires access to new and varied information from potential users and other external parties (e.g., Walsh, Lee and Nagaoka, 2016; Blank, 2013; Ries, 2011; March, 1991). Having an effective idea generation process means not only hiring the most creative people, but also having them talk with others who can provide valuable insights.

Yet, prior studies have viewed these two decisions—choosing the innovator and choosing who they converse with outside the team—as theoretically distinct. On one hand, psychologists have developed a substantial literature on individual differences in creative behavior and outcomes (see, Feist, 1998; McCrae and Costa, 1997; Barron and Harrington, 1981). In these studies, researchers link differences in personality to creativity (e.g., McCrae and Sutin, 2009; John, Naumann and Soto, 2008; McCrae, 1987). On the other hand, research on innovation in the management literature highlights the importance of external information from social interactions, collaborators, and users (Laursen and Salter, 2006; Baldwin, Hienert and Von Hippel, 2006; Burt, 2004; Lilien et al., 2002). Further, individuals who converse and collaborate generate better ideas than lone inventors (Singh and Fleming, 2010; Wuchty, Jones and Uzzi, 2007; Burt, 2004). Given the inherent complementarity between these two decisions, we still know little about which innovators can best leverage external conversations, and who they should talk to.

With respect to choosing innovators, extensive research links the personality trait *openness to experience* to creative behavior and outcomes (Hammond et al., 2011; Silvia et al., 2009; Feist, 1998; McCrae, 1987). Open individuals appreciate different perspectives, are better at recombining concepts, and generate unconventional ideas—all of which makes them more creative (McCrae, 1987). However, open individuals sometimes also produce bad ideas if the organizational

context is not conducive to their style of creativity (e.g., Bell, 2007; Baer and Oldham, 2006; Burke and Witt, 2002).

One key aspect of an innovator’s context is who they talk to (Perry-Smith and Mannucci, 2015; Burt, 2004). Some conversations—with people who are willing to share their knowledge, experiences, and opinions—will be more fruitful for idea generation. Information from these conversations is important input to the creative process (Perry-Smith and Mannucci, 2015). Conversational peers who exhibit the personality trait *extroversion* are talkative, loud, and willing to share knowledge or disclose information about themselves (e.g., Cuperman and Ickes, 2009; Funder and Sneed, 1993). These behaviors, rather than their converse, will increase not just the amount of information shared, but also its novelty and idiosyncrasy. This information will provide the innovator greater grist for their product ideas (De Vries, Van den Hooff and de Ridder, 2006; Forret and Dougherty, 2001; McCrae and John, 1992).

Here we present the results of a field experiment designed to test the impact of informal conversations on the quality of an innovator’s product ideas. We embedded our field experiment in a startup bootcamp for over 100 aspiring product entrepreneurs. Specifically, we test how an innovator’s personality (openness to experience, capturing creativity) and a peer’s personality (extroversion, measuring willingness to share information) jointly affect an innovator’s ideas. Our intervention consists of randomly assigning individuals to three conversations about a specific product area (“the Indian Wedding Industry”), with each conversation lasting 14 minutes. We use the resulting random variation in the pairing of innovators and peers with different personalities to examine the impact of innovator-peer personality on the subsequent quality of the ideas subsequently generated.

Our study produces three broad findings. First, the ideas of ‘closed’ innovators do not improve or worsen based on their conversations. This finding implies an important scope condition on the value of external information for idea generation. Conversations matter primarily for people who have the ability and motivation to incorporate outside information. In contrast, the ideas of open individuals are affected by their conversations. This effect, however, is asymmetric. Open innovators paired with extroverted peers (Open-Extrovert pairs) produce the highest quality ideas. In this condition, both creative ability and the volume of novel information are at their highest. In

contrast, Open-Introvert pairs develop lower quality ideas than even closed individuals. Though a person may have creative ability and motivation, a high volume of novel information is necessary for them to leverage their natural creative ability.

This study contributes to three research streams. First, our study sheds light on the interaction between personality and the social context as they jointly pertain to idea generation (e.g., Perry-Smith and Mannucci, 2015; Fleming, Mingo and Chen, 2007; Burt, 2004). The effect of conversation on idea generation appears to be moderated by the personalities of both the sender and receiver of information. Second, our research also provides new insights for scholars of entrepreneurship and product development by showing the importance of conversations at the earliest stages of idea and product development (Girotra, Terwiesch and Ulrich, 2010; Ward, 2004; Shane, 2000, e.g.). Finally, our work links to research on brainstorming and the psychology of creativity (e.g., Kaufman and Sternberg, 2010; Paulus, 2000; Amabile et al., 2004; Amabile, 1983), highlighting the importance of personality differences in predicting who will generate the best ideas and which types of interactions will be most fruitful.

Theory and Hypotheses

The success of organizations relies on new product ideas (e.g., Schulze and Hoegl, 2008; Shane, 2000). Good ideas are especially important for young entrepreneurial teams, who must take a nascent idea and develop it over the course of weeks, months, or years into a product (Ward, 2004). Indeed, all future steps in the entrepreneurial journey depend on an essential first step: *idea generation* (Perry-Smith, 2014). During this stage, innovators generate many ideas and then choose one or a few to implement. According to Perry-Smith and Mannucci (2015) individuals must have the “cognitive flexibility to recombine disparate knowledge into new associations” as well as “access to non-redundant knowledge” to develop good ideas. Good ideas are the product of individual capabilities *and* social interaction.

Two distinct research streams examine these facets of idea generation at the individual level. One literature, mostly in psychology, studies individual differences in creative capabilities (see for a review Kaufman and Sternberg, 2010). This work usually ignores the social interactions

of creative people who are generating ideas. Another stream, in management, studies how social relationships shape information access and thus creativity (see for a review Perry-Smith and Mannucci, 2015). The latter stream has often ignored individual differences among both innovators and their conversational partners. Based on the results from this work, combining these perspectives should lead to new insights about when conversations will be most fruitful and for whom.

Below we develop a model of individual creativity and peer conversations. We build on research in psychology into the personality correlates of both creative behavior (e.g., Feist, 1998; McCrae and Costa, 1997) and information sharing (e.g., Funder and Sneed, 1993). We model innovators as varying in their openness to experience, a trait synonymous with “creative” personality (Kaufman et al., 2016; McCrae and Costa, 1997). We model conversational peers as varying in introversion and extroversion, traits linked to conversational patterns, information sharing, and the size and diversity of social networks (e.g., Landis, 2016; Cuperman and Ickes, 2009).

Our theoretical framework consists of two parts. We first describe how personality traits independently affect creative capability and information sharing. Next, we explain how innovator-peer matches on these dimensions affect the quality of ideas.

Openness to Experience and Creativity

Psychological research has long studied the antecedents to creative behavior (Feist, 1998). Although several measures of personality relate to specific facets of creativity, there is consensus that *openness to experience*, a factor in the five-factor model of personality, is predictive of creativity in many settings (e.g., Beaty et al., 2016; Baas et al., 2013; Silvia et al., 2009; McCrae and Costa, 1997; McCrae, 1987). Relatedly, openness is also linked to entrepreneurial intentions and performance (For a review of this literature, see Zhao, Seibert and Lumpkin, 2010).

Two classes of mechanisms—intrapsychic and interpersonal—link openness to creativity (McCrae and Costa, 1997; McCrae, 1996). Intrapsychic mechanisms argue that open individuals (relative to individuals with closed personalities or other personality traits) have skills and dispositions that allow them to generate better ideas. Interpersonal mechanisms enable open individuals to readily acquire novel information from their environment.

Intrapsychic Mechanisms: Several studies show that openness to experience is related to differences in creativity. In a classic study, McCrae (1987) highlights the importance of openness to the creative process. Open people possess the *ability* and *disposition* to engage in creative behavior. Their abilities make them skilled in unstructured creative tasks (Williams, 2004). They prefer ambiguity and complexity over certainty and simplicity (e.g., LePine, Colquitt and Erez, 2000). When generating ideas, open individuals deploy more representational resources, a state often called ‘absorption’ (e.g., Hammond et al., 2011; Oldham and Cummings, 1996). They also consider many perspectives and enjoy divergent thinking—e.g., exploring unrelated ideas and finding unconventional connections (George and Zhou, 2001; McCrae and Costa, 1980).

Open individuals also have a creative disposition. They seek out complex tasks and relish diverse perspectives, often preferring information that diverges from what they already know (McCrae, 1996). They also have a firm belief in their creative abilities (e.g., Karwowski et al., 2013) and are “unorthodox, free-thinking, and prone to flout convention” (McCrae and Costa, 1997).

Together, these abilities and dispositions map to what Perry-Smith and Mannucci (2015) describe as “cognitive flexibility” and the ability to “recombine disparate knowledge into new associations” required for creativity.

Interpersonal Mechanisms: Open individuals also interact with others in distinct ways (Funder and Sneed, 1993). McCrae (1996) states that when conversing with others, open individuals both solicit in-congruent information and are more prone to adapt to others’ perspectives and opinions. Open individuals are also better at recalling information that is incongruent with their own experience, giving them a wider base of information for idea generation. Finally, they delve into abstract topics (e.g., Funder and Sneed, 1993) and prefer talking to new people and initiating new conversation threads (Cuperman and Ickes, 2009). While the interpersonal mechanisms are not sufficient contributors to creativity, they allow open individuals to seize opportunities to acquire novel information.

Conversely, those *closed to experience* eschew complexity and ambiguity and prefer conven-

tional ideas (George and Zhou, 2001). They seek conversations that confirm their existing beliefs, and thus novel or dissonant information is ignored or dismissed. Being closed to experience impedes mechanisms driving creativity—i.e., recombining diverse information and experiences into new ideas. Closed individuals do not necessarily generate bad ideas, but ordinary ideas. Existing theory, therefore, predicts:

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

Having the right conversations: Extroverted peers

Generating good ideas depends on more than individual creativity. Prior work on invention and the role of social interactions in creative production provides useful analogies for understanding the impact of conversations on idea generation. For example, research on the social dimensions of innovation shows that lone inventors rarely produce breakthrough ideas (Singh and Fleming, 2010; Wuchty, Jones and Uzzi, 2007). Those who collaborate—and who, during the production process, converse with collaborators about their ideas—generate higher-quality inventions. In another analogous stream of research, scholars have found that having and using social ties affects idea generation. In this work, conversations—with coworkers, customers, acquaintances, and even strangers—constitute the specific interactions in a network that provide new information, perspectives, and opinions that can shape the quality of an idea (Burt, 2004; Perry-Smith and Mannucci, 2015). Finally, the practitioner literature on innovation and idea generation highlights the central role of talking to potential customers in shaping the quality of ideas generated by entrepreneurs (Blank, 2013; Brown et al., 2008). In this literature, conversations are an important underlying mechanism that explain why joint collaborative work or information seeking helps people generate better ideas.

Which conversational peers provide the greatest grist for idea generation? Conceptually, conversational peers should possess two characteristics. First, they must be *willing* to share their experiences and opinions. A lack of willingness to talk will limit informational *volume*. Second, the peer should have a *diverse* pool of personal and vicarious experiences to draw upon, which

will increase information variety.

While research on the effect of peer personality and idea generation is limited, scholars have linked personality to conversational dynamics. Two personality traits, in particular, *extroversion* and *agreeableness*, appear to influence interactions strongly (Cuperman and Ickes, 2009; Funder and Sneed, 1993; John and Srivastava, 1999; Goldberg et al., 1998).

While agreeableness relates mostly to affect during conversation (e.g., warmth, laughter, and cheerfulness), extroversion is related to both affect and the diversity and volume of information shared (Funder and Sneed, 1993). Extroverts, therefore, may be fruitful conversational partners during early ideation.

Willingness to Share Information: Several studies suggest that extroverts exhibit distinct patterns of behavior during conversations. Funder and Sneed (1993) found that extroverts were talkative, loud, and enjoyed interactions. In contrast, introverts were reserved, inexpressive, and volunteered little personal information. In conversations with strangers, extroverts took the lead and were evaluated by their partners as saying “interesting” things. Cuperman and Ickes (2009) found similar patterns. Extroverts took the lead role in conversations, were not self-conscious, and believed that interactions were ‘smooth, natural, and relaxed.’ Beukeboom, Tanis and Vermeulen (2013) found that extroverts described events and experiences in elaborate and interpretive terms. Extroverts were eager to share their knowledge with others (Matzler et al., 2008; John and Srivastava, 1999).

Higher informational volume, idiosyncratic personal details, and greater elaboration characterize the information that extroverts share.

Social Interactions and Information Variety: In addition to sharing ‘new’ or ‘interesting’ information, extroverts also have diverse networks that give them access to novel information (e.g., Landis, 2016; Watson and Clark, 1997). Totterdell, Holman and Hukin (2008); Neubert and Taggar (2004); Casciaro (1998) all find that extroverts have larger networks or are more central in their social networks. Extroverts’ ability to build larger networks also increases their ability to build weak ties (Pollet, Roberts and Dunbar, 2011), suggesting differences in access to

heterogeneous information from their many contacts (Granovetter, 1973).

In contrast, introverts are less likely to engage in self-disclosure and do not share high volumes of information. They listen and reflect (Cain, 2013). In conversations, introverts appear reserved and keep both emotional and physical distance from their partners. This behavior sometimes appears as disinterest (Funder and Sneed, 1993).

Introverts are also comfortable with others leading the conversation (Cuperman and Ickes, 2009); they listen to their partner and do not seek to dominate the conversation. This tendency means they speak less and therefore offer their partners less information. Introverts are also less likely than extroverts to engage in “small talk” and “idle chatter” that lacks informational content.

However, an introvert’s greater reflection, analytical tendencies, and thoughtfulness can lead to valuable insights for their partners (e.g., Cain, 2013; Grant, Gino and Hofmann, 2011). Götz and Götz (1979) and Feist (1999) suggest that introverts, rather than extroverts, are likely to be over-represented among scientists and artists judged to be the most creative. Researchers theorize that this overrepresentation of introverts among the most creative is due to their heightened imagination, willingness to engage in individual play, and self-sufficiency. Roy (1996) also finds that introverts are more likely to exhibit higher levels of visual creativity than extroverts. Moreover, researchers who have studied creativity across innovators varying in age have found that introverts remain creative across their lifespan as compared to extroverts (Feist and Barron, 2003). As a consequence, the individual creativity of introverts might be useful for a conversational partner who is generating new ideas assuming introverts share enough information.

On balance, introverts and extroverts, because of their different behaviors, may be valuable at different phases of the innovation process. Idea generation benefits from others’ perspectives, experiences, or opinions. Because extroverts are talkative, warm, connected, and willing to share knowledge, they will be more valuable during the early stages of ideation.

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

Innovator–Peer Interactions and Ideation

The theories outlined above link personality to individual-level behaviors. However, the mechanisms described also suggest the potential for complementarities in how some pairings perform versus others. Figure 1 depicts a model crossing innovator and peer personalities and their predicted effect on idea quality.

[Figure 1 about here.]

Closed–Extrovert Interaction: Being closed to experience means an individual has a preference for conventional ideas, ones that do not stray from expectations (McCrae and John, 1992). Thus, although an extroverted conversational peer may be talkative, share personal experiences, and provide high volumes of new information, a closed person may not benefit. They may filter out dissonant information, especially if it does not conform to what they believe. They may be uncomfortable recombining information and may prefer the ordinary over the novel. Their ideas would remain conventional even after talking with an extroverted peer. Thus, closed innovators should not benefit as much as open ones from talking to extroverts.

Closed–Introvert Interaction: Being paired with an introverted peer may not greatly affect a closed individuals’ idea quality. With introverts the volume of information may be lower; it may also lack variety, personal opinions, or detail. Nevertheless, the closed innovator would continue to develop his conventional ideas and would be just as unlikely to benefit from conversations with introverts as she would from conversations with extroverts.

Hypothesis 3 *Closed innovators will not benefit from interacting with peers who are more introverted nor more extroverted.*

Openness–extroversion interaction: In contrast, open individuals seek and appreciate interactions with people who have different perspectives. In conversations with extroverted peers, open innovators are receptive to the flow of idiosyncratic and personal information (McCrae and

Sutin, 2009), which offers them a more abundant pool of facts, emotions, ideas, opinions, and perspectives to recombine into new ideas.

Open innovators will ask probing questions, guide the conversation in useful directions, and listen more intently (McCrae, 1987). Relatedly, extroverted peers will take the lead in the conversation, causing them to share more in response to the inquisitiveness of their open partner. Together, such behaviors should amplify the amount of information received from an extroverted peer. The open innovator's ideation capabilities will lead them to recombine information in unconventional ways. However, because their ideas derive from others' experiences, the resulting product concepts will be grounded. Thus, their product ideas will be both novel and of high quality (Karwowski et al., 2013).

Open–Introversion Interaction: When paired with introverts, on the other hand, open innovators pose a theoretical challenge. While introverted peers possess analytic depth, objectivity, and a willingness to listen, they will share less of their own experiences during a conversation. Further, whereas an extroverted peer assumes a dominant role, a more introverted peer prefers the opposite. In conversations with an introvert, an open innovator will exert considerable effort getting her partner to share a relatively small amount of information.

After such a conversation, there are two possible outcomes. On the one hand, an open innovator may still develop high-quality ideas because of her natural creativity. However, the ideas may have been even better had she been paired with an extrovert. In the Openness–Introversion pairing, the complementary relationship between creativity and new information is absent. Thus, the ideas are weaker, but are still better than the ones closed individuals produce.

An alternative possibility for the Openness-Introvert pair also exists. Recombining ideas is risky, and could result in inferior ideas as well (Ferguson and Carnabuci, 2017). Although an idea may be 'original,' it may also be low quality.

Without external information about others' experiences, an open innovator might compensate by increasing their idea's novelty or unconventionality. These ideas may become detached from actual user needs without the external constraints posed by the experiences of potential users. The open individual may generate divergent ideas without converging on the good ones (Schilpzand,

Herold and Shalley, 2011).

Just as open innovators may produce higher-quality ideas after talking to extroverts, they may produce worse ideas after talking to introverts. The extent of the discrepancy across these conditions is uncertain. On the one hand, open individuals' creative ability may limit the pitfalls of lower amounts of external information. On the other, their higher levels of divergent thinking and exploration may lead them towards unorthodox and unappealing ideas.

Hypothesis 4 *More open innovators will generate better-rated ideas after talking to more extroverted peers.*

Empirical Setting and Methods

Experimental Design: An Innovation Competition

To rigorously test our predictions we embedded a field experiment in an entrepreneurship bootcamp held in New Delhi, India, in July 2014¹. This three-week program was designed to help aspiring entrepreneurs from across India to develop skills in idea generation, design thinking, prototype design, and business model development.

The ages of the participants ranged from 18 to 36, with a mean age of just over 22 years. The gender distribution was 87 men and 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 Ph.D. program. Our program was regionally diverse, with 62 of the participants from the state of Delhi and the rest from across India. The class was composed primarily of engineering and computer science degree holders (78), followed by 18 business degree holders; the remaining 16 were from the arts and sciences. Eight people were enrolled in or had graduated from advanced degree programs.

Leading members of India's startup ecosystem, including successful entrepreneurs, designers, and venture capitalists provided instruction. The program was structured into three week-long modules. The first week, on which we base this study, focused on idea-generation. To incentivize

¹The experimental nature of the bootcamp 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 bootcamp.

participation and effort, the teams with the three highest-rated prototypes won cash prizes. 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. The second week focused on business models, and during the final week participants were free to work on a business concept of their choice in self-selected teams.

To test our prediction, we used the activities from the first week and data collected before the bootcamp. All participants completed surveys, chief among which was the 44-item Big Five Inventory (John and Srivastava, 1999), giving us pre-bootcamp (thus, pre-treatment) measures of extroversion, openness to experience, neuroticism, agreeableness, and conscientiousness. We discuss the construction of our independent 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 experiment. The second day (Tuesday) began with individuals reporting to one of 40 tables, where they sat with their randomized 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:

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 wedding industry was noted as having a large market potential. Several venture capital firms are investing in software products for this market. Second, unlike finance or biotechnology, the “Indian wedding” was something that the vast majority of participants had experienced, but it represented an industry in which a subset of individuals would not have a systematic skill or knowledge advantage. Third, we chose this industry because it was complex, composed of problems ranging from finding mates, to buying wedding dresses, to post-marital counseling. Thus, the Indian wedding context could produce differentiation in the types and quality of ideas generated by the participants. For one hour, the participants entered their ideas into a software application as short paragraphs.

Individuals produced on average 6.6 ideas, each having a length of approximately 505 characters. We call these ideas “pre-treatment” ideas.

Conversational peer randomization. To test our hypotheses, we randomized each participant to a set of three conversations in the form of semi-structured “empathy interviews” with other participants at the bootcamp (e.g., Kelley and Kelley, 2013). Each conversation lasted 14 minutes. We assigned each pair to random and pre-assigned seats, with participants assigned (randomly) to an “A” and a “B” position.

The protocol of the interview was semi-structured. 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, participants could take notes about their conversation and record it in the sheet depicted in Figure A2. 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 a randomly assigned table and generate

new ideas individually for one hour.

The participants generated an average of 4.5 new ideas, with the average idea having 476 characters. We call these “post-treatment” ideas.

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 participants. Our choice of double-blind anonymous peer evaluations arises from three considerations. First, peer evaluation is perhaps the most common evaluation method in many creative 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 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; Kornish and Ulrich, 2011). Third, peer evaluation, particularly in this context, may be more reliable than evaluations by experts, who may have neither the incentive, time, nor ability to evaluate an idea’s worth (Kornish and Ulrich, 2014; Scott, Shu and Lubynsky, 2016). Finally, research indicates that peer evaluations are more accurate when the 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 3.42 complete ratings. The average ratings were 2.45 for business value, 2.59 for buy likelihood, and 2.43 for novelty.

Evaluations from Indian Consumers. To complement our anonymous peer evaluations, we also measure idea quality using another common metric of idea quality: consumer evaluations. Prior research on product development documents that online consumer evaluations predict future success, often with more accuracy than expert assessment (e.g., Kornish and Ulrich, 2014).

To ensure our raters were potential consumers we recruited 45 digitally savvy Indian consumers

on Amazon’s Mechanical Turk, a platform commonly used by firms to do early market research (e.g., Bentley, Daskalova and White, 2017). To ensure comparability with our peer evaluations, we had the Indian consumers rate the startup ideas on the same three dimensions and on the same 5-point scale. Each consumer evaluated 41 ideas on average, yielding 5.58 complete ratings per idea. The average ratings were 3.36 for business value, 3.12 for buy likelihood, and 3.27 for novelty. Beyond providing an additional metric of idea quality, the consumer evaluations serve as a partial replication of our analysis. We use exactly the same models, but estimated with the consumer evaluation data, to test whether our results are robust to different measures of idea quality.

Variable construction

Dependent variables. The key dependent variables for our analysis derive from the anonymous peer evaluations (day 3) of the raw ideas generated by individuals on day 2 as well as the text of those ideas.

The first dependent variable 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.²

To understand how our intervention affects 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 her 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 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 different semantic domains. To generate our measure of recombination, we construct a semantic similarity network between the ideas generated using 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

²While 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.

likely is. Research on the success of products, articles, and patents 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 are in the Appendix.

Independent variables. To examine the relationship between an innovator’s openness and peer extroversion on quality of the idea generated, we create three variables. First, *Openness (self)* is the average of an individual’s responses to the 10-item openness scale deployed before the bootcamp. This variable is normalized to have mean of 0 and SD of 1.

Second, *Extroversion (Peer)* measures the average extroversion score of an individual’s three randomly assigned conversational peers. Extroversion is calculated using the average of the the 8-item extroversion scale and is standardized at the individual level before being aggregated into our average peer measure.

Third, we create an interaction variable *Extroversion (Peer) × Openness (Self)* to test Hypothesis 3, that open individuals benefit especially from talking with extroverted partners.

Control Variables To assess the robustness of our results, we also control for a number of additional factors. To test that open innovators benefit from talking with extroverts, and not the other way around, we parallel the operations described above and construct *Extroversion (Self)*, *Openness (Peer)*, and *Extroversion (Self) × Openness (Peer)* variables. For completeness, we also generate *Openness (Self) × Openness (Peer)* and *Extroversion (Self) × Extroversion (Peer)* variables.

We also include three non-personality controls in our models that capture the abilities and talents 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 variable allows us to test whether there is any effect of being paired with someone who simply generates higher-quality ideas. The second control is a measure of each person’s general ability and talent, based on their independently evaluated bootcamp admission score.³ The admission score allows us to rule out

³Each participant’s 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.

the possibility that extroversion mainly captures differences in human capital. The third control is educational background; we construct a binary measure that indicates whether the participant has an engineering degree. Given the technological focus of the bootcamp, we can control for familiarity and experience developing web applications.

[Table 1 about here.]

Table 1 presents summary statistics for our dependent, independent, and control variables. 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 A1 in the Appendix provides 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 A2 in the Appendix tests for balance more formally by regressing an individual’s personality measures on the *Extroversion (Peer)* variable. We find no evidence for imbalance.

Modeling strategy To test our individual-level hypotheses, we used ordered logistic regression models to regress all evaluations e of idea d by individual i on the openness of the innovator, the randomized conversational peers’ average level of extroversion, and the interaction.

Since peers were randomly assigned and the assignment does not appear imbalanced, our estimate of *Extroversion (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 increase our power by removing 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.⁴

⁴While 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 appear to differ from the larger population of participants in terms of personality or ability.

Results

We first test whether open innovators develop better-rated ideas (Hypothesis 1). In Table 2 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, on average, generate worse ideas.

[Table 2 about here.]

Column 2 in Table 2 tests the main effect of conversing with more extroverted peers (Hypothesis 2). The coefficient on Extroversion (Peers) is 0.305, nearly four times the magnitude of the Openness (Self) estimate, and is statistically significant ($p < 0.05$).

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 extroversion variable is 1.36. Individuals who have extroverted peers, by 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 extroversion. A one-point increase is non-trivial, as it moves an idea up a decile in the idea quality distribution.

Column 3 includes the interaction term testing the predictions in Figure 1. In Column 3 we include a variable for individuals’ level of openness, the average peer extroversion, and an interaction of this variable with their peers’ average extroversion.⁵ The coefficients on the main effects of Openness (Self) and Extroversion (Peers) remain relatively unchanged. The coefficient on the interaction term is similar in size and significance to the Extroversion (Peers) variable. The estimate is 0.300, and the standard error of (0.142) and p-value ($p < 0.05$) indicate that the effect is different 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

⁵Openness (Peers) and Extroversion (Peers) have a correlation of 0.4, the largest correlation between our independent variables. We find no evidence that this correlation or any other correlation between our independent variables led to instability due to multicollinearity in any of the models in Table 2.

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*.

Figure 2 plots the estimated effects on idea quality for matches between Open-Extroverts, Open-Introverts, Closed-Extroverts, and Closed-Introverts. The chart plots and tests the joint effect of Openness (Self), Extroversion (Peers), and their interaction. The chart reveals that open innovators benefit from talking to extroverts but will generate worse ideas when paired with introverts; closed innovators are unaffected by the extroversion of their peers.

In Column 1, we see that an open innovator paired with extroverts generates higher quality ideas, 0.53 ($p < 0.01$) points higher than an innovator at the mean level of openness matched with partners at the mean level of extroversion. The effect is substantial, implying that the innovator is 70% more likely to generate an idea that is one decile greater in the quality distribution. In Column 2, we see that an open innovator paired with introverts generates *worse* ideas, -0.72 ($p < 0.01$) lower. Closed individuals experience little change in the nature and quality of their ideas; partnering with extroverts has an estimated effect of .11 and partnering with introverts 0.07, both insignificant.

[Figure 2 about here.]

Returning to Table 2, Column 4 extends our models by including the full set of self-peer interactions between extroversion 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 Extroversion (Peers) and its interaction with Openness (Self). Furthermore, having peers high in openness does not appear to help an innovator generate better ideas.

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 his or her admission score. The third control is our dummy for whether

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

the individual has or is pursuing an engineering degree. Including these controls at the self and peer levels does not change our primary results.

Our results do not appear to be driven by the peer’s pre-treatment idea quality, talent, or educational background. Column 6 tests the robustness of our results by including all the variables in both Columns 4 and 5. Our results hold even in this relatively demanding specification.

Finally, these findings also hold when using evaluations from Indian consumers who did not attend the bootcamp; see Appendix Table A16, which replicates 2, but using our external measure of idea quality.

Analyzing the Idea Text

We further test our arguments by examining the text content of the ideas generated by participants. Specifically, we test whether our treatment effects shape how developed and recombinative an idea is and whether these changes mediate the effects on idea quality. Table 3 presents results from this analysis, providing a further check on our hypothesized pathway.

[Table 3 about here.]

In Column 1 of Table 3 we test whether our treatment affects an idea’s development score. We regress the score (the log of the number of unique terms) on Openness (Self), Extroversion (Peers), the interaction, and the average development score of the innovator’s pre-treatment ideas.⁷

Similar to our idea quality models Table 2, we find that the coefficients on Extroversion (Peers) and its interaction with Openness (Self) are positive and similar in magnitude. A one SD increase in Extroversion (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 a one SD increase in Extroversion (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

⁷Three 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.

0.24 for innovators high in openness ($SE = 0.138, p < 0.1$). We find evidence that speaking with extroverts, especially among those high in openness, leads to more developed and recombinative ideas.

In Column 3 we examine whether higher recombination and development scores lead to better evaluations. We find that ideas with higher development scores are indeed better ideas. A one SD increase in an idea’s development score leads to improvement in idea quality by 0.314 points ($SE = 0.076, p < 0.01$). We also find a 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). Our mediation analysis tests if the effect of Extroversion (Peers) and Openness (Self) \times Extroversion (Peers) is mediated by recombination and development.

Using a multiple-mediation model we show that it is, though primarily through idea development. The total effect of Extroversion (Peers) and Openness (Self) \times Extroversion (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 ($SE = 0.112, p < 0.05$). 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, although the indirect effect through recombination is not statistically significant. The models in Table 3 provide further evidence for our causal pathway: talking with extroverts, especially for innovators high in openness, leads to developed and recombinative ideas, which are of higher quality.

Robustness checks and alternative mechanisms

Our online Appendix provides a further suite of robustness checks, which we briefly describe below.

Alternative model estimates to test for non-linearity in interactions: Appendix Table A6 replicates Table 2 using ordinary least squares instead of ordered logistic regression to confirm that the interaction effect between Openness (Self) and Extroversion (Peers) is not an artefact 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.

The effect of other peer and innovator traits: Appendix Table A8 tests the importance of experience at weddings. The table tests if our results are sensitive to the inclusion of innovator age (perhaps older participants have attended more weddings) and gender (potentially women are more familiar with the wedding industry). None of these experience-with-wedding proxies meaningfully change our results. In Appendix Table A8 we also find little evidence that openness merely reflects an innovator’s ability as measured by his or her admission score.

Alternative personality mechanisms: In Appendix Table A7 we test whether what matters is not the extroversion of an innovator’s peers but rather their neuroticism, conscientiousness, agreeableness, or self-monitoring. We find these measures to be largely insignificant, even when interacted with the innovator’s openness. Furthermore, they do not meaningfully change the coefficients on our openness and extroversion measures. Appendix Table A9 has perhaps the most demanding specification and reports the results from the fully parameterized regression that includes all 25 ego-alter pairwise personality interactions. In this regression, extroversion (peers) remains significant, although the interaction with Openness (Self) loses statistical significance but remains positive and is not statistically different from the specifications where significance at conventional levels is achieved. What matters most, however, is the joint effects. The pattern reported in Figure 2 holds; open individuals do better (worse) when they converse with extroverts (introverts) ($p < 0.01$); for closed individuals, we find no statistically different outcomes when they talk to extroverts or introverts.

Alternative dependent variables: Moving beyond alternative personality explanations, in Appendix Table A10 we show that peer extroversion and the rest of our measures have little impact on the number of ideas generated, with the exception that open individuals appear to generate slightly more ideas ($p < 0.1$). This is not surprising as prior research suggests that quality of ideas, rather than quantity, distinguishes open from closed individuals.

Peer order and mix effects: Appendix Table A11 examines whether idea generation is improved not by talking solely with extroverts, but by talking with a mix of extroverts and introverts or by talking first to extroverts and then to introverts. We test for the value of talking to a mix of peers by including the standard deviation of extroversion; we test for potential order

or sequence effects by separately including in our regression model the peer extroversion of an innovator’s first, second, and third conversation partners. We find little evidence for either. Appendix Table A12 tests whether the effects on idea quality affect the underlying dimensions of novelty, business, and buy ratings. We find our effects hold across these dimensions.

Evaluation bias: Appendix Table 13 includes controls for whether the idea evaluator knows, is friends with, or provides advice to 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 evaluator–innovator relationship status does not affect our findings. In conjunction with the fact that our models hold when using evaluations from Indian consumers, we find little evidence that our peer-based measure would systematically bias our findings.

Path dependence on Team-level outcomes: We further checked the robustness of our results by testing whether our individual-level findings could be replicated 3 days later on the performance of the 40 randomly teams to which the participants were assigned. Appendix Table 14 presents a brief description of this robustness test and our findings. In summary, we find path dependence in the team-level outcomes. Teams populated with participants higher in openness to experience and who conversed with extroverted peers during the individual pairwise conversations that constitute the main experiment produced final projects that were rated higher in the double-blind peer evaluation as well as in independent ratings by Indian consumers. This preliminary finding suggests that these early conversations may be consequential for team as well as individual performance.

Discussion

In this paper, we contribute to a growing literature on the social dimensions of idea generation. This stream of research, though diverse, suggests that social interaction—often mediated through informal social ties (Burt, 2004; Perry-Smith and Mannucci, 2015), collaborations (Singh and Fleming, 2010), and conversations with potential customers (Blank, 2013)—is an important factor that affects the quality of new business ideas or inventions. Our approach, inspired by this work,

argues that the specific conversations that individuals have with peers play an important role in idea generation. Specifically, we argue that a complementarity exists between the traits of conversational peers and focal idea generators in developing high-quality ideas. Our research examines how the personality of an innovator (openness to experience, capturing creativity) and the personality of her randomly assigned conversational peers (extroversion, measuring willingness to share information) affects the quality of the innovator’s ideas.

Our study introduces scope conditions on both the social dimensions of idea generation as well as models of creativity based on individual differences. First, we find that the ideas generated by ‘closed’ innovators are unaffected by their conversational peers, suggesting limits to when social interaction will benefit idea generation. The value of social interaction appears bounded by individual differences in the ability and motivation to incorporate outside information. Conversely, the ideas of open individuals are responsive to social interaction, but this response to peer extroversion and introversion appears asymmetric. Open innovators paired with extroverted peers produce the highest-quality ideas. In comparison, Open-Introvert pairs develop substantially lower-quality ideas. This finding suggests that even among individuals with more creative ability and motivation, external interactions can lead them to produce bad ideas.

Regarding magnitude, while the estimated effect of talking with an extrovert will not turn the lowest-quality ideas into the best ones, they can shift ideas at the margins of “good” to “very good” or “very good” to “great.” As the coefficients on Extroversion (Peers) suggests in Table 2, a one standard deviation increase in peer extroversion is equivalent to moving an idea from the 80th percentile of quality to the top decile. As the interaction effect *Openness (Self) × Extroversion (Peers)* also suggests, the effects are especially large for innovators high in openness, with ideas potentially moving up three deciles in the quality distribution when they switch from conversing with a introverted to an extroverted partner. Our magnitudes are comparable to related work on idea generation (Girotra, Terwiesch and Ulrich, 2010) and are quite robust to many alternative specifications: including models that use the text of the ideas generated, external evaluations from Indian consumers, and substantial controls for alternative personality mechanisms as well as other background characteristics of both peers and focal individuals. We also find preliminary evidence that the results of individual-level conversations affect team-level outcomes, though more research

is needed to understand how our findings interact with team processes such as social anxiousness (Camacho and Paulus, 1995) and other mechanisms at the group level (Sutton and Hargadon, 1996; Paulus, 2000).

This study speaks to three research streams. First, our research provides new insights for scholars of entrepreneurship and new product development by showing the importance of conversations at the earliest stages of business idea generation (e.g., Ward, 2004; Shane, 2000). Second, a diverse body of research has examined the role of collaboration and social interaction in invention (Fleming, Mingo and Chen, 2007) and idea generation in organizations (e.g., Perry-Smith and Mannucci, 2015; Burt, 2004). Our results use this prior work as analogy to provide a closer look at conversations—which often make up the basic social interactions that drive such collaborative or network effects. The effects of conversations appear to be moderated by the personalities of both the senders and receivers of information. Finally, our work links research on brainstorming and the psychology of creativity (e.g., Kaufman and Sternberg, 2010; Paulus, 2000; Amabile et al., 2004; Amabile, 1983; Taylor, Berry and Block, 1958). Our findings highlight the importance of personality differences in predicting which types of interactions will be more generative for new ideas during early stages of the brainstorming and creative process (Litchfield, 2008), and for what problems (e.g., Kavadias and Sommer, 2009).

How should entrepreneurs, innovators and managers view our results? The simplest takeaway is that if developing creative ideas matters for your team, then closed people are unlikely to help. However, being open to experience is not enough. Innovative teams must strive to get external information from individuals who provide both a higher volume of information as well as share more personal information. Getting this balance right—between the internal composition of the team and the sources of external knowledge—is critical not just for the initial ideas generated, but also for team performance in the longer term. Future research should examine this process for product development teams in established firms, but also at various stages of the idea journey (Perry-Smith and Mannucci, 2015).

Our study also contributes to the literature from a methodological perspective. In this article, we used data from a field setting (an entrepreneurship bootcamp) that is a growing source for new startups worldwide (Cohen, 2013; Dutt et al., 2016). We were able to randomize social

interactions well as measure detailed data on ideation and individual characteristics. While the bootcamp we studied is just one example of a larger phenomenon, we believe startup incubators and bootcamps offer a fruitful research site to study important social mechanisms and outcomes—e.g., the creation of new products and firms.

That said, it is worth noting several limitations of the bootcamp setting and, more generally, of the present study. We focused on a specific interaction—short conversations early in the idea generation stage—and specific personality traits that prior research has identified as relevant to creativity and information sharing. A more general account of the value of external conversations should no doubt consider conversations at other stages (e.g., idea refinement and feedback on a developed product) and the individual differences in both the seekers and providers of that advice.

Second, our idea generation exercise focused on the Indian wedding industry, and many of our conversational peers are also potential end users (e.g., Von Hippel, 1978). However, in the course of idea generation, innovators may also converse with other external parties, including producers of complementary technologies, venture capitalists, early adopters, colleagues, and even competitors. While we believe that the basic psychological mechanisms outlined in this paper should hold, we expect that the effect of conversations in more specialized domains will be moderated by the domain knowledge of the peer (Poetz and Schreier, 2012).

Third, we conducted our study in the context of new product ideas for startups (Scott, Shu and Lubynsky, 2016). While there are commonalities between product development teams in startups and in established firms, there are also differences. Innovators in established organizations face different constraints, including those imposed by existing product lines, organizational boundaries, and bureaucracy (e.g., Dougherty and Hardy, 1996). These constraints may limit how novel the ultimate product ends up being, independent of the idea generation process.

Finally, we also see these limitations as possibilities for future research. While our study focuses on how individual differences and peer conversations affect entrepreneurial idea generation, future work should explore how the complementarity between an innovator and her conversation partner operate within established enterprises, in conversations with consumers, or when developing technical and specialized ideas. We hope our study provides a template for future researchers by demonstrating how a peer randomization design can be used to simultaneously

shed light on the individual and social dimensions that affect creativity, entrepreneurial ideas, and inventiveness.

References

- Ai, Chunrong and Edward C Norton. 2003. "Interaction terms in logit and probit models." *Economics Letters* 80(1):123–129.
- Amabile, Teresa M. 1983. "The social psychology of creativity: A componential conceptualization." *Journal of Personality and Social Psychology* 45(2):357.
- Amabile, Teresa M, Elizabeth A Schatzel, Giovanni B Moneta and Steven J Kramer. 2004. "Leader behaviors and the work environment for creativity: Perceived leader support." *The Leadership Quarterly* 15(1):5–32.
- Amabile, Teresa M, Sigal G Barsade, Jennifer S Mueller and Barry M Staw. 2005. "Affect and creativity at work." *Administrative Science Quarterly* 50(3):367–403.
- Baas, Matthijs, Marieke Roskes, Daniel Sligte, Bernard A Nijstad and Carsten KW De Dreu. 2013. "Personality and creativity: The dual pathway to creativity model and a research agenda." *Social and Personality Psychology Compass* 7(10):732–748.
- Baer, Markus and Greg R Oldham. 2006. "The curvilinear relation between experienced creative time pressure and creativity: moderating effects of openness to experience and support for creativity." *Journal of Applied Psychology* 91(4):963–970.
- Baldwin, Carliss, Christoph Hienert and Eric Von Hippel. 2006. "How user innovations become commercial products: A theoretical investigation and case study." *Research policy* 35(9):1291–1313.
- Baron, Reuben M and David A Kenny. 1986. "The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations." *Journal of Personality and Social Psychology* 51(6):1173–1182.
- Barron, Frank and David M Harrington. 1981. "Creativity, intelligence, and personality." *Annual Review of Psychology* 32(1):439–476.
- Baum, J Robert and Barbara J Bird. 2010. "The successful intelligence of high-growth entrepreneurs: Links to new venture growth." *Organization Science* 21(2):397–412.
- Beaty, Roger E, Scott Barry Kaufman, Mathias Benedek, Rex E Jung, Yoed N Kenett, Emanuel Jauk, Aljoscha C Neubauer and Paul J Silvia. 2016. "Personality and complex brain networks: the role of openness to experience in default network efficiency." *Human Brain Mapping* 37(2):773–779.
- Bell, Suzanne T. 2007. "Deep-level composition variables as predictors of team performance: a meta-analysis." *Journal of applied psychology* 92(3):595.
- Bentley, Frank R, Nediya Daskalova and Brooke White. 2017. Comparing the Reliability of Amazon Mechanical Turk and Survey Monkey to Traditional Market Research Surveys. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. ACM pp. 1092–1099.
- Beukeboom, Camiel J, Martin Tanis and Ivar E Vermeulen. 2013. "The Language of Extraversion: Extraverted People Talk More Abstractly, Introverts Are More Concrete." *Journal of Language and Social Psychology* 32(2):191–201.
- Blank, Steve. 2013. "Why the lean start-up changes everything." *Harvard Business Review* 91(5):63–72.
- Boudreau, Kevin J, Eva C Guinan, Karim R Lakhani and Christoph Riedl. 2016. "Looking Across and Looking Beyond the Knowledge Frontier: Intellectual Distance, Novelty, and Resource Allocation in Science." *Management Science* 62(10):2765–2783.
- Brown, Tim et al. 2008. "Design thinking." *Harvard Business Review* 86(6):84.
- Burke, Lisa A and L.A. Witt. 2002. "Moderators of the openness to experience–performance relationship." *Journal of Managerial Psychology* 17(8):712–721.
- Burt, Ronald S. 2004. "Structural holes and good ideas." *American Journal of Sociology* 110(2):349–399.
- Cain, Susan. 2013. *Quiet: The power of introverts in a world that can't stop talking*. Broadway Books.
- Camacho, L Mabel and Paul B Paulus. 1995. "The role of social anxiousness in group brainstorming." *Journal of personality and social psychology* 68(6):1071.
- Casciaro, Tiziana. 1998. "Seeing things clearly: Social structure, personality, and accuracy in social network perception." *Social Networks* 20(4):331–351.
- Cohen, Susan. 2013. "What Do Accelerators Do? Insights from Incubators and Angels." *Innovations: Technology, Governance, Globalization* 8(3):19–25.
- Cooper, Steve and Mehran Sahami. 2013. "Reflections on Stanford's MOOCs." *Communications of the ACM* 56(2):28–30.

- Cuperman, Ronen and William Ickes. 2009. "Big Five predictors of behavior and perceptions in initial dyadic interactions: Personality similarity helps extraverts and introverts, but hurts disagreeables." *Journal of Personality and Social Psychology* 97(4):667–684.
- de Vaan, Mathijs, Balazs Vedres and David Stark. 2015. "Game Changer: The Topology of Creativity." *American Journal of Sociology* 120(4):1144–1194.
- De Vries, Reinout E, Bart Van den Hooff and Jan A de Ridder. 2006. "Explaining knowledge sharing the role of team communication styles, job satisfaction, and performance beliefs." *Communication Research* 33(2):115–135.
- Dougherty, Deborah and Cynthia Hardy. 1996. "Sustained product innovation in large, mature organizations: Overcoming innovation-to-organization problems." *Academy of management journal* 39(5):1120–1153.
- Dutt, Nilanjana, Olga Hawn, Elena Vidal, Aaron Chatterji, Anita McGahan and Will Mitchell. 2016. "How open system intermediaries address institutional failures: The case of business incubators in emerging-market countries." *Academy of Management Journal* 59(3):818–840.
- Feist, Gregory J. 1997. "Quantity, quality, and depth of research as influences on scientific eminence: Is quantity most important?" *Creativity Research Journal* 10(4):325–335.
- Feist, Gregory J. 1998. "A meta-analysis of personality in scientific and artistic creativity." *Personality and Social Psychology Review* 2(4):290–309.
- Feist, Gregory J. 1999. "The Influence of Personality on Artistic and Scientific Creativity." *Handbook of creativity* p. 273.
- Feist, Gregory J and Frank X Barron. 2003. "Predicting creativity from early to late adulthood: Intellect, potential, and personality." *Journal of research in personality* 37(2):62–88.
- Ferguson, John-Paul and Gianluca Carnabuci. 2017. "Risky recombinations: Institutional gatekeeping in the innovation process." *Organization Science* 28(1):133–151.
- Fleming, Lee, Santiago Mingo and David Chen. 2007. "Collaborative brokerage, generative creativity, and creative success." *Administrative Science Quarterly* 52(3):443–475.
- Forret, Monica L and Thomas W Dougherty. 2001. "Correlates of networking behavior for managerial and professional employees." *Group & Organization Management* 26(3):283–311.
- Funder, David C and Carl D Sneed. 1993. "Behavioral manifestations of personality: an ecological approach to judgmental accuracy." *Journal of Personality and Social Psychology* 64(3):479–490.
- George, Jennifer M and Jing Zhou. 2001. "When openness to experience and conscientiousness are related to creative behavior: an interactional approach." *Journal of Applied Psychology* 86(3):513–524.
- Girotra, Karan, Christian Terwiesch and Karl T Ulrich. 2010. "Idea generation and the quality of the best idea." *Management Science* 56(4):591–605.
- Goldberg, Lewis R, Dennis Sweeney, Peter F Merenda and John Edward Hughes. 1998. "Demographic variables and personality: The effects of gender, age, education, and ethnic/racial status on self-descriptions of personality attributes." *Personality and Individual Differences* 24(3):393–403.
- Götz, Karl Otto and Karin Götz. 1979. "Personality characteristics of successful artists." *Perceptual and Motor Skills* 49(3):919–924.
- Granovetter, M. S. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78(6):1360–1380.
- Grant, Adam M, Francesca Gino and David A Hofmann. 2011. "Reversing the extraverted leadership advantage: The role of employee proactivity." *Academy of Management Journal* 54(3):528–550.
- Hammond, Michelle M, Nicole L Neff, James L Farr, Alexander R Schwall and Xinyuan Zhao. 2011. "Predictors of individual-level innovation at work: A meta-analysis." *Psychology of Aesthetics, Creativity, and the Arts* 5(1):90–105.
- Hargadon, Andrew and Robert I Sutton. 1997. "Technology brokering and innovation in a product development firm." *Administrative Science Quarterly* 42(4):716–749.
- John, Oliver P, Laura P Naumann and Christopher J Soto. 2008. "Paradigm shift to the integrative big five trait taxonomy." *Handbook of Personality: Theory and Research* 3:114–158.
- John, Oliver P and Sanjay Srivastava. 1999. "The Big Five trait taxonomy: History, measurement, and theoretical perspectives." *Handbook of personality: Theory and research* 2(1999):102–138.
- Karwowski, Maciej, Izabela Lebeda, Ewa Wisniewska and Jacek Gralewski. 2013. "Big Five Personality Traits as the Predictors of Creative Self-Efficacy and Creative Personal Identity: Does Gender Matter?" *The Journal of Creative Behavior* 47(3):215–232.

- Kaufman, James C and Robert J Sternberg. 2010. *The Cambridge handbook of creativity*. Cambridge University Press.
- Kaufman, Scott Barry, Lena C Quilty, Rachael G Grazioplene, Jacob B Hirsh, Jeremy R Gray, Jordan B Peterson and Colin G DeYoung. 2016. "Openness to experience and intellect differentially predict creative achievement in the arts and sciences." *Journal of Personality* 84(2):248–258.
- Kavadias, Stylianos and Svenja C Sommer. 2009. "The effects of problem structure and team diversity on brainstorming effectiveness." *Management Science* 55(12):1899–1913.
- Kelley, Tom and David Kelley. 2013. *Creative confidence: Unleashing the creative potential within us all*. Crown Business.
- Kim, Kyung Hee. 2006. "Can we trust creativity tests? A review of the Torrance Tests of Creative Thinking (TTCT)." *Creativity Research Journal* 18(1):3–14.
- Kornish, Laura J and Karl T Ulrich. 2011. "Opportunity Spaces in Innovation: Empirical Analysis of Large Samples of Ideas." *Management Science* 57(1):107–128.
- Kornish, Laura J and Karl T Ulrich. 2014. "The importance of the raw idea in innovation: Testing the sow's ear hypothesis." *Journal of Marketing Research* 51(1):14–26.
- Landis, Blaine. 2016. "Personality and social networks in organizations: A review and future directions." *Journal of Organizational Behavior* 37(1):107–121.
- Laursen, Keld and Ammon Salter. 2006. "Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms." *Strategic management journal* 27(2):131–150.
- LePine, Jeffrey A, Jason A Colquitt and Amir Erez. 2000. "Adaptability to changing task contexts: Effects of general cognitive ability, conscientiousness, and openness to experience." *Personnel Psychology* 53(3):563–593.
- Lilien, Gary L, Pamela D Morrison, Kathleen Searls, Mary Sonnack and Eric von Hippel. 2002. "Performance assessment of the lead user idea-generation process for new product development." *Management science* 48(8):1042–1059.
- Litchfield, Robert C. 2008. "Brainstorming reconsidered: A goal-based view." *Academy of Management Review* 33(3):649–668.
- Manning, Christopher D and Hinrich Schütze. 1999. *Foundations of statistical natural language processing*. MIT Press.
- March, James G. 1991. "Exploration and exploitation in organizational learning." *Organization Science* 2(1):71–87.
- Marsh, Herbert W, Upali W Jayasinghe and Nigel W Bond. 2008. "Improving the peer-review process for grant applications: reliability, validity, bias, and generalizability." *American Psychologist* 63(3):160–168.
- Matzler, Kurt, Birgit Renzl, Julia Müller, Stephan Herting and Todd A Mooradian. 2008. "Personality traits and knowledge sharing." *Journal of Economic Psychology* 29(3):301–313.
- McCrae, Robert R. 1987. "Creativity, divergent thinking, and openness to experience." *Journal of Personality and Social Psychology* 52(6):1258–1265.
- McCrae, Robert R. 1996. "Social consequences of experiential openness." *Psychological Bulletin* 120(3):323–337.
- McCrae, Robert R and Angelina R Sutin. 2009. "Openness to experience." *Handbook of Individual Differences in Social Behavior* pp. 257–273.
- McCrae, Robert R and Oliver P John. 1992. "An introduction to the five-factor model and its applications." *Journal of Personality* 60(2):175–215.
- McCrae, Robert R and Paul T Costa. 1980. "Openness to experience and ego level in Loewinger's Sentence Completion Test: Dispositional contributions to developmental models of personality." *Journal of Personality and Social Psychology* 39(6):1179–1190.
- McCrae, Robert R and Paul T Costa. 1997. "Conceptions and correlates of openness to experience." *Handbook of personality psychology* pp. 825–847.
- Neubert, Mitchell J and Simon Taggar. 2004. "Pathways to informal leadership: The moderating role of gender on the relationship of individual differences and team member network centrality to informal leadership emergence." *The Leadership Quarterly* 15(2):175–194.
- Oldham, Greg R and Anne Cummings. 1996. "Employee creativity: Personal and contextual factors at work." *Academy of Management Journal* 39(3):607–634.

- Paulus, Paul. 2000. "Groups, teams, and creativity: The creative potential of idea-generating groups." *Applied Psychology* 49(2):237–262.
- Perry-Smith, Jill E. 2014. "Social network ties beyond nonredundancy: An experimental investigation of the effect of knowledge content and tie strength on creativity." *Journal of Applied Psychology* 99(5):831.
- Perry-Smith, Jill and Pier Vittorio Mannucci. 2015. "From creativity to innovation: The social network drivers of the four phases of the idea journey." *Academy of Management Review* 42(1):59–79.
- Poetz, Marion K and Martin Schreier. 2012. "The value of crowdsourcing: can users really compete with professionals in generating new product ideas?" *Journal of product innovation management* 29(2):245–256.
- Pollet, Thomas, Sam Roberts and Robin Dunbar. 2011. "Extraverts have larger social network layers." *Journal of Individual Differences* 32(3):161–169.
- Reily, Ken, Pam Ludford Finnerty and Loren Terveen. 2009. Two peers are better than one: aggregating peer reviews for computing assignments is surprisingly accurate. In *Proceedings of the ACM 2009 international conference on Supporting group work*. pp. 115–124.
- Ries, Eric. 2011. *The lean startup: How today's entrepreneurs use continuous innovation to create radically successful businesses*. Crown Books.
- Roy, Debdulal Dutta. 1996. "Personality model of fine artists." *Creativity Research Journal* 9(4):391–394.
- Schilpzand, Marieke Catharine, David M Herold and Christina E Shalley. 2011. "Members' openness to experience and teams' creative performance." *Small Group Research* 42(1):55–76.
- Schulze, Anja and Martin Hoegl. 2008. "Organizational knowledge creation and the generation of new product ideas: A behavioral approach." *Research policy* 37(10):1742–1750.
- Scott, Erin L, Pian Shu and Roman Lubynsky. 2016. "Are 'Better' Ideas More Likely to Succeed? An Empirical Analysis of Startup Evaluation." *SSRN Working Paper* (2638367).
- Shane, Scott. 2000. "Prior knowledge and the discovery of entrepreneurial opportunities." *Organization Science* 11(4):448–469.
- Silvia, Paul J, Emily C Nusbaum, Christopher Berg, Christopher Martin and Alejandra OConnor. 2009. "Openness to experience, plasticity, and creativity: Exploring lower-order, high-order, and interactive effects." *Journal of Research in Personality* 43(6):1087–1090.
- Simonton, Dean Keith. 1990. "Lexical choices and aesthetic success: A computer content analysis of 154 Shakespeare sonnets." *Computers and the Humanities* 24(4):251–264.
- Simonton, Dean Keith. 1999. *Origins of genius: Darwinian perspectives on creativity*. Oxford University Press.
- Singh, Jasjit and Lee Fleming. 2010. "Lone inventors as sources of breakthroughs: Myth or reality?" *Management Science* 56(1):41–56.
- Sutton, Robert I and Andrew Hargadon. 1996. "Brainstorming groups in context: Effectiveness in a product design firm." *Administrative Science Quarterly* pp. 685–718.
- Taylor, Donald W, Paul C Berry and Clifford H Block. 1958. "Does group participation when using brainstorming facilitate or inhibit creative thinking?" *Administrative Science Quarterly* pp. 23–47.
- Torrance, E Paul. 1972. "Predictive validity of the Torrance Tests of Creative Thinking." *The Journal of Creative Behavior* 6(4):236–252.
- Totterdell, Peter, David Holman and Amy Hukin. 2008. "Social networkers: Measuring and examining individual differences in propensity to connect with others." *Social Networks* 30(4):283–296.
- Uzzi, Brian, Satyam Mukherjee, Michael Stringer and Ben Jones. 2013. "Atypical combinations and scientific impact." *Science* 342(6157):468–472.
- Vogel, Peter. 2017. "From venture idea to venture opportunity." *Entrepreneurship Theory and Practice* 41(6):943–971.
- Von Hippel, Eric. 1978. "Successful industrial products from customer ideas." *The Journal of Marketing* pp. 39–49.
- Walsh, John P, You-Na Lee and Sadao Nagaoka. 2016. "Openness and innovation in the US: Collaboration form, idea generation and implementation." *Research Policy* 45(8):1660–1671.
- Ward, Thomas B. 2004. "Cognition, creativity, and entrepreneurship." *Journal of Business Venturing* 19(2):173–188.
- Watson, David and Lee Anna Clark. 1997. "Extraversion and its positive emotional core." *Handbook of Personality Psychology* pp. 767–793.

- Williams, Scott David. 2004. "Personality, attitude, and leader influences on divergent thinking and creativity in organizations." *European Journal of Innovation Management* 7(3):187–204.
- Wuchty, Stefan, Benjamin F Jones and Brian Uzzi. 2007. "The increasing dominance of teams in production of knowledge." *Science* 316(5827):1036–1039.
- Zhao, Hao and Scott E Seibert. 2006. "The Big Five Personality Dimensions and Entrepreneurial Status: A Meta-Analytical Review." *Journal of Applied Psychology* 91(2):259–271.
- Zhao, Hao, Scott E Seibert and G.t. Lumpkin. 2010. "The relationship of personality to entrepreneurial intentions and performance: A meta-analytic review." *Journal of Management* 36(2):381–404.

Figure 1: Summary of theoretical arguments for the Innovator–Peer conversation interaction and its impact on idea quality.

		Peers' Personality	
		Introvert	Extrovert
Innovator Personality	Closed	<p>Low volume of novel information + Low (a) responsiveness to new ideas, (b) divergent thinking, (c) comfort with unconventional ideas.</p> <p><i>Idea quality low</i></p>	<p>High volume of novel information + Low (a) responsiveness to new ideas, (b) divergent thinking, (c) comfort with unconventional ideas.</p> <p><i>Idea quality low</i></p>
	Open	<p>Low volume of novel information + High (a) responsiveness to new ideas, (b) divergent thinking, (c) comfort with unconventional ideas.</p> <p><i>Idea quality uncertain</i></p>	<p>High volume of novel information + High (a) responsiveness to new ideas, (b) divergent thinking, (c) comfort with unconventional ideas.</p> <p><i>Idea quality high</i></p>

Figure 2: Estimated effects on idea quality for self-peers matches displayed in Figure 1. Open (closed) indicates an individual one standard deviation above (below) the mean; extroverts (Introverts) one standard deviation above (below) the mean. Whiskers display standard errors for each estimate. The effects for Open-Extrovert and Open-Introvert are both significant at the 1% level.

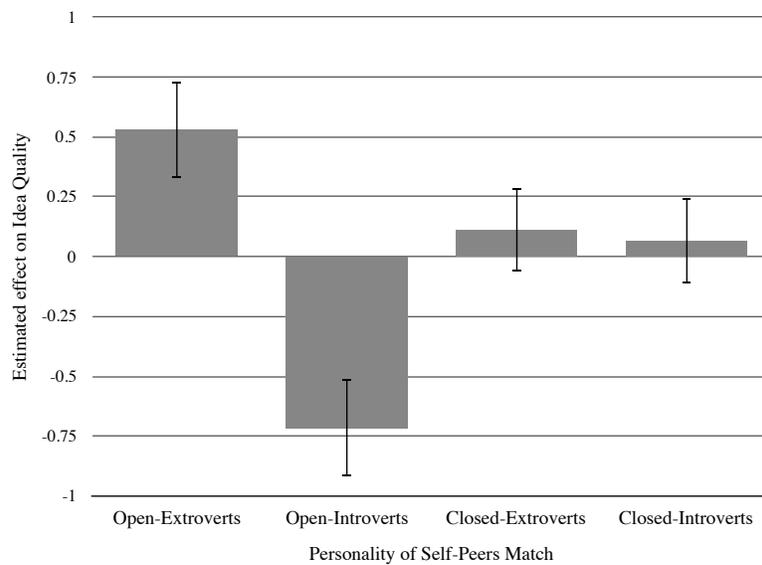


Table 1: Summary statistics at the individual participant level

	count	mean	sd	min	max
Average Idea Quality (Self)	108	7.696	1.245	5.000	12.000
Extroversion Raw Score (Self)	112	3.502	0.545	1.875	4.750
Openness Raw Score (Self)	112	3.896	0.405	2.700	4.700
Conscientious Raw Score (Self)	112	3.627	0.535	2.444	4.889
Agreeableness Raw Score (Self)	112	3.755	0.495	2.444	4.778
Neuroticism Raw Score (Self)	112	2.492	0.618	1.125	3.875
Extroversion (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
Extroversion (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)	112	2.536	0.178	2.114	3.096
Observations	112				

Table 2: Do conversations with extroverted peers increase an open individual's idea quality?

	(1)	(2)	(3)	(4)	(5)	(6)
	Idea	Idea	Idea	Idea	Idea	Idea
	Quality	Quality	Quality	Quality	Quality	Quality
Openness (Self)	-0.077 (0.065)		-0.092 (0.060)	-0.074 (0.060)	-0.111* (0.056)	-0.121* (0.057)
Extroversion (Peers)		0.305* (0.123)	0.323** (0.109)	0.428** (0.117)	0.371** (0.104)	0.513** (0.116)
Openness (Self) \times Extroversion (Peers)			0.300* (0.142)	0.342* (0.153)	0.328* (0.141)	0.365* (0.158)
Extroversion (Self)				-0.103 (0.066)		-0.081 (0.069)
Openness (Peers)				-0.220* (0.106)		-0.311** (0.113)
Openness (Self) \times Openness (Peers)				0.023 (0.137)		0.063 (0.121)
Extroversion (Self) \times Openness (Peers)				-0.138 (0.149)		-0.144 (0.134)
Extroversion (Self) \times Extroversion (Peers)				-0.177 (0.158)		-0.301 [†] (0.176)
Pre-treatment Idea Quality (Self)					0.456 [†] (0.247)	0.499* (0.233)
Pre-treatment Idea Quality (Peers)					0.314 (0.378)	0.490 (0.378)
Admission Score (Self)					0.013 (0.059)	0.088 (0.066)
Admission Score (Peers)					0.199 [†] (0.107)	0.277** (0.106)
Engineer (Self)					-0.158 (0.152)	-0.062 (0.154)
Engineer (Peers)					-0.045 (0.283)	-0.074 (0.270)
Observations	1150	1150	1150	1150	1141	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 3: Do conversations with extroverted peers change the content of an individual's ideas?

	<i>Dependent variable:</i>		
	Idea Development	Idea Recombination	Standardized Idea Quality
	(1)	(2)	(3)
Openness (Self)	-0.114 (0.084)	-0.104 [†] (0.059)	-0.050 (0.069)
Extroversion (Peers)	0.379* (0.160)	0.245* (0.118)	0.271* (0.114)
Openness (Self) X Extroversion (Peers)	0.340 [†] (0.205)	0.240 [†] (0.138)	0.230 (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)
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 evaluator fixed effects.
Standard errors clustered at the individual innovator level.

Overview of the appendix

This appendix provides additional summary statistics, details on how we constructed our text-based measures, a variety of robustness checks, more details about the bootcamp, and examples of the ideas and projects generated during the camp.

Section 1 provides a table outlining the day-by-day structure of the bootcamp.

Section 2 reports individual-level bivariate correlations along with balance tests at the individual level.

Section 3 reports the team-level bivariate correlations along with team-level balance tests.

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

In Sections 5 through 13 we report numerous robustness checks at the individual level, including a replication of Table 3 using evaluations from Indian consumers and models that include a variety of alternative personality-peer interactions.

In Section 14 we present preliminary findings showing that teams with, members who are on average higher in openness to experience and who had spoken with extroverts during the individual ideation conversations also generate higher quality ideas.

In Sections 16 and 17 we report robustness checks at the team level.

In the final three sections we provide more details about the bootcamp, the ideas generated, and the team projects. In Section 18 we describe the recruitment process and bootcamp in more detail. Section 20 provides further details on the ideas generated. Section 21 provides examples of the projects generated at the end of the first week.

1 Overview of bootcamp structure

The table below provides a day-by-day overview of the bootcamp schedule, data collection points, and the treatment timeline.

[Figure A1 about here.]

2 Individual level correlations and balance tests

Table A1 presents the correlations between the variables used in our primary analysis. Table A2 regresses our measure of peer extroversion on an individual's personality measures. We find no significant relationships, indicating that the randomization was successful at the individual level.

[Table A1 about here.]

[Table A2 about here.]

3 Team level correlations and balance tests

Table A3 presents the correlations between the variables used in our primary analysis. Table A4 regresses our measure of peer extroversion on a teams's average personality score. We find no significant relationships, indicating that the randomization was successful at the team level.

[Table A3 about here.]

[Table A4 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 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 standardizing the variable to have a mean of 0 and a standard deviation of 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 standardized the variable to have a mean of 0 and a standard deviation of 1.

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

5 Evaluations by Indian consumers

In Table A5 we replicate Table 3 using evaluations from digitally savvy Indian consumers. We recruited evaluators using Mechanical Turk, restricting the sample to Mechanical Turkers who are in India and had master status. We recruited 46 participants to do the evaluations, although one participant was dropped from the analysis because they took part in earlier piloting of the idea evaluations. Participants could rate up to 120 different ideas on the same three dimensions used in the peer evaluations. In the end each participant rated an average of just under 41 ideas. In Column 3 we find little evidence for a main extroversion (peer) effect, while in Columns 4, 5, and 6 we find evidence for both the main peer effects and their interaction with Openness (Self).

[Table A5 about here.]

6 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 the model specification. Indeed, the interaction terms in Table A6 remain positive and significant.

[Table A6 about here.]

7 Peer extroversion or other peer personality measures?

Tables A7 tests if other personality interactions drive our results. We find little evidence that our findings are being driven by other peerpersonality constructs.

[Table A7 about here.]

8 Does wedding experience or ability matter?

Table A8 includes a number of controls to proxy for an individual's experience attending and interest in weddings. It includes age, gender, and self-monitoring. Older participants should have attended more weddings. Women could be potentially more interested in weddings. Self-monitors may receive more invites. We have no evidence that any of these measures correlates with idea quality, nor do they impact our estimates of interest.

Column 3 in Table A8 tests if our openness measure is capturing ability or intelligence. We find little evidence that it does. Including our measure of ability, admission score, and its interaction with peer extroversion does not impact the effect of openness nor the effect of openness interacted with peer extroversion.

[Table A8 about here.]

9 Is it the Openness-Extroversion match or other personality matches?

In Table A9 we include the full set of personality variables for the self, peer, and the interaction between the two. For 5 personality constructs across the self and peers there are 25 interactions. Including the full set

of self and peer personality measures does not meaningfully change our findings. Extroversion (peers) holds at the 1% level across all four models. While we lose significance on the Openness (Self) X Extroversion (Peers) interaction in Columns 3 and 4, the coefficient remains relatively large and positive. Furthermore, joint tests reveal that matching on these two dimensions still matters. Using using the estimates from the model we replicate the analysis underlying Figure 2. We find that pairing an open innovator with an extrovert [introvert] has an estimated effect on idea quality of 0.78 ($p < 0.01$) [-0.94 ($p < 0.01$)]. For a closed innovator paired with an extrovert [introvert] the estimated effects are reduced to 0.43 ($p < 0.1$) [-0.27 [$p > 0.1$]], and the estimated effects are not statistically distinct from one another.

[Table A9 about here.]

10 What about the number of ideas?

Table A10 tests if peer extroversion and its interaction with innovator openness changes the number of ideas generated. We find little evidence for any such effect, with the only significant effect (10% level) being that open individuals generate more ideas.

[Table A10 about here.]

11 Testing for variance and order effects

One possible alternative is that idea generation is improved not by talking with extroverts only but also by talking with a mix of extroverts and introverts. Building on this idea that it is the variance that is important, perhaps what really matters is the sequence of conversations. Perhaps introverts improve idea quality when encountered after talking with extroverts? Table A11 tests these alternative models. Model 1 shows that the standard deviation of peer extroversion does not appear to improve idea quality nor does its interaction with the focal innovator's openness. Model 2 disaggregates the effects, including separate extroversion 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, although the estimates have wider standard errors since we lose power by estimating the extroversion of each conversation partner separately.

[Table A11 about here.]

12 Do our results hold on disaggregated quality measures?

In Table A12, we examine whether our results hold in the more disaggregated versions of the post-treatment idea ratings. We find that peer Extroversion (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 A12 about here.]

13 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 A13, 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 A13 about here.]

14 Team level process description

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), the 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). The 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.⁹ As with the individual ideas, after the bootcamp we recruited Indian consumers on Mechanical Turk to evaluate each project on the same set of dimensions used in the peer evaluation. On average, each evaluator rated just under nine projects. These third-party evaluations allow us to test if our team-level models of project quality generalize to external measures of quality. Appendix Figure A1 summarizes the process of the experiment, the randomizations, and the data collection.

15 Testing the Team-Level Effects

Dependent variables. To test whether our results replicate at the team-level, 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 extroversion of the peers each person worked with on the second day of the camp. Specifically, we calculate *Openness (Team)*, which measures the average level of extroversion of the team’s members. We create *extroversion (Peers)*, which measures the average of all team members’

⁹The ranking analysis is available upon request.

peers extroversion scores. To test for path dependence in team-level outcomes, we create a variable *Openness (Team) × 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 extroversion, openness, admission score, engineering background, and pre-treatment idea quality.

[Table A14 about here.]

Table A14 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 A3 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 A4 in the Appendix explicitly tests for balance by regressing a team’s average personality scores on the *Extroversion (Peer)* variable for the team. We find no evidence for imbalance.

Modeling strategy To test these 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 extroversion 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.

Team-level results

We replicate our individual-level results by testing whether our individual-level findings could be replicated 3-days later on the performance of the 40 randomly teams into which the participants were assigned. Similar to our individual-level analysis, we regress measures of each team’s final project quality on team member openness, the extroversion of team-members’ randomized peers during the individual empathy interviews, and the interaction of these two variables. Table A15 presents our results. All models include evaluator fixed effects and cluster standard errors at the team level.

[Table A15 about here.]

Column 1 in Table A15 regresses the project quality score on team-level measures of our key independent variables. Our results provide some support for the prediction that teams 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 A15 regresses project quality on the average extroversion 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) × Extroversion (Peers)* term. We find evidence that there is path dependence in team-level outcomes. The coefficient is 0.311 ($SE = 0.162, p < 0.05$), which is positive, significant, and meaningful in magnitude, about 2.5 times larger in magnitude than the *Openness (Team)* measure.

Columns 4 and 5 in Table A15 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 extroversion and openness interactions, we find that the results remain relatively unchanged, although 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 *Extroversion (Peers)* increases in magnitude to 0.183 and becomes statistically significant ($SE = 0.083, p < 0.05$). In Column 6 we include all the variables from Columns 4 and 5. The results are largely consistent with the earlier columns, although we again lose statistical significance for the *Extroversion (Peers)* main effect. That said, in Appendix Table A16 we run the same models in Columns 16, but using evaluations from Indian consumers. The results are remarkably consistent, and we again find a positive effect for *Openness (Team) × Extroversion (Peers)* ($p < 0.01$) across all models and a positive effect for *Extroversion (Peers)*, although

the effect is only significant in Appendix Table A16 Columns 4 and 6. It does not appear that our idea quality measures capture something idiosyncratic to the social setting in which the ideas were generated.

We report further robustness tests in the Appendix. In Appendix Table A17 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 extroverts and introverts. Our effects remain largely unchanged when including the standard deviation of team openness or the standard deviation of peer extroversion. It does not appear that extroversion or openness diversity drives differences in a team's project quality.

16 Evaluations by Indian consumers at the team level

We replicate Table 5 using evaluations from web-savvy Indian consumers. We recruited the consumers on Mechanical Turk, limiting participation to Indians with master status. Participants read the same prompt, the same packet of materials, and rated projects on the same dimensions as described in main text. In the end, the 34 participants completed 291 evaluations, an average of just over 8 evaluations per project. As with Table 5, we find weak effects for the main extroversion peer effect; however, we again find a strong and significant effect of peer extroversion when the team itself is high in openness.

[Table A16 about here.]

17 Testing for variance/diversity effects at the team level

Table A17 tests if our results hold even when including controls for different types of team dynamics. Column 1 tests if teams with more open and more extroverted members perform better. Column 2 tests if what matters is having one very open individual or one member with very extroverted peers. Column 3 tests if having a team with a mix of open individuals leads to greater team performance. Across all three models we find that teams with open individuals who conversed with extroverted peers perform the best. While we have no doubt that team dynamics play a role, these early conversations appear to lead to ideas that have a lasting impact on team outcomes.

[Table A17 about here.]

18 Setting description, participant recruitment and participant characteristics

The program, 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 IIT-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 prototypes 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 1, 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 might also be interested. We recruited applicants through a number of different means including Facebook ads, social media posts, entrepreneurship organizations, and word-of-mouth referrals. Over 1,247 people started the full application, 58 started a short

version of the standard application we launched after the February 1st deadline, and 71 people completed a wait-list Google Form application that was designed to attract last-minute applicants; a total of 1,376 applications were started. We received 508 fully completed applications, of which 437 were standard applications and 71 were from the last-minute Google Form applications (these applications did not allow the user to save their work and submit at a later date, hence providing the perfect pass through rate).

From these applications we accepted 358 standard applicants and 18 last-minute applicants. From this pool of accepted students, 178 enrolled by May 1st and signed our initial online IRB consent form. This form clearly stated that the program was being conducted for research purposes and that digital, video, and audio data would be collected. 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 completed the the shorter standard application, and 3 completed the last-minute application. From these 112 graduates of the program, 38 learned 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 was from 18 to 36, with a mean age of just over 22. Our program had 25 women and everyone had, or was enrolled in, college, with 60 of the participants enrolled in a college, master's, or Ph.D. program. Our program was regionally diverse, with 62 of the participants from the state of Delhi and the rest from across India. The class was primarily comprised of engineering and computer science degree holders (78), followed by 18 business degrees, and the rest came from the arts and sciences. A total of eight people were enrolled in or had graduated from advanced degree programs. The participants came from a broad spectrum of universities including Delhi University, IIT-Delhi, Jaypee University, Delhi Technological University, and the IITs. It is important to note that universities in India are composed of relatively independent colleges, and thus most of the participants in our program did not know one another, even when they came from the same university. For example, of the 26 participants from Delhi University, half are the only representative from their college, and the most popular college from Delhi University supplied only three participants. Everyone in the program spoke English since proficiency in English was an application requirement, and nearly all the participants were multi-lingual, with Hindi, Urdu, Bengali, Punjabi, and Tamil being the most common other languages.

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

19 Empathy note-taking sheet

Note-taking sheet used by participants during each empathy interview. The participants used a new sheet for each interview.

[Figure A2 about here.]

20 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.

21 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 as follows:

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

Their splash page depicted in figure A3, is clear and visually appealing:

[Figure A3 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 A4:

[Figure A4 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 A5:

[Figure A5 about here.]

Figure A1: 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 Randomizations. 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 Project 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.
<i>Pre Bootcamp (Before Day 0)</i>		<i>Monday (Day 1)</i>	<i>Tuesday (Day 2)</i>	<i>Wednesday (Day 3)</i>	<i>Thursday (Day 4)</i>	<i>Friday (Day 5)</i>

Figure A2: 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 A3: Splash page for submission in the top quartile—Snappily Wed.

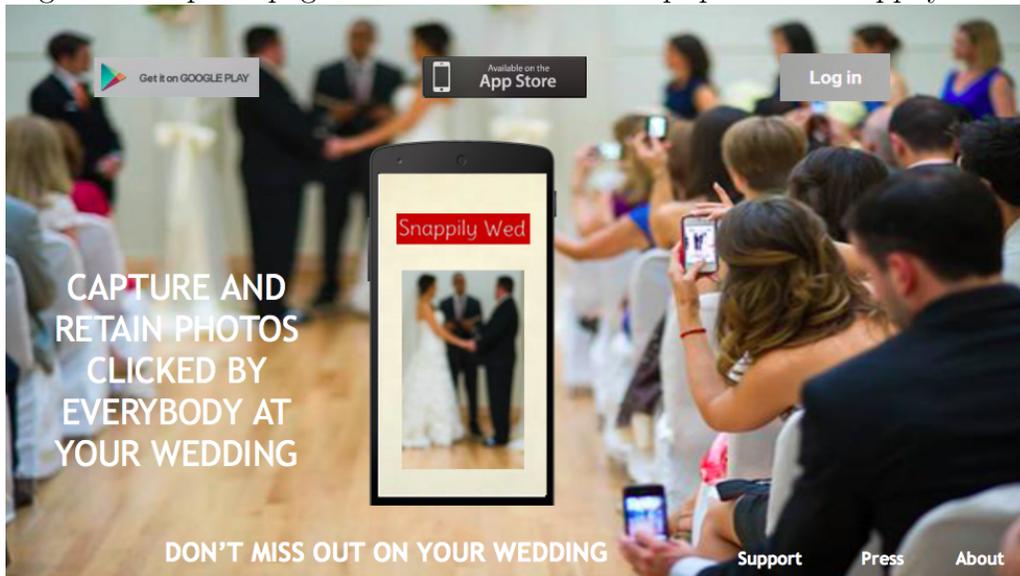


Figure A4: Splash page for submission in the middle quartile—Tender my Wedding.

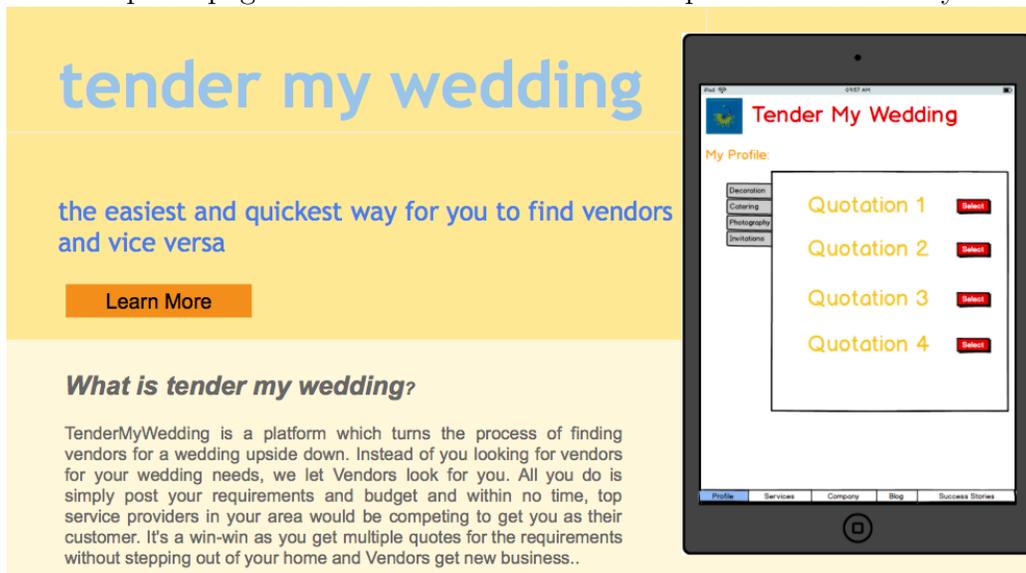


Figure A5: Splash page for submission in the bottom quartile—Invite My Pals.

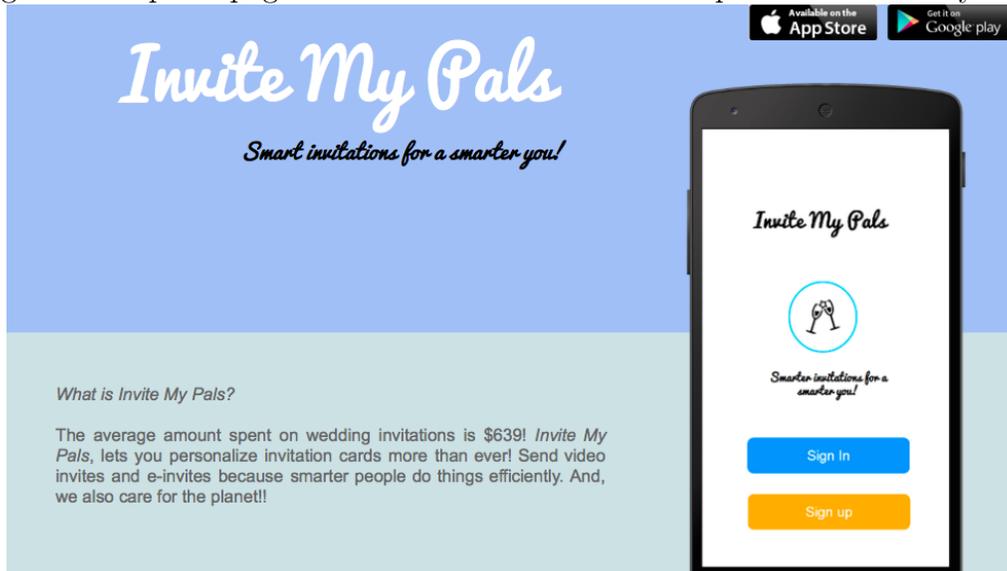


Table A1: Correlations at the individual participant level.

	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 Extroversion (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 Extroversion (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 A2: Peer randomization are balanced at the individual level.

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

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A3: 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 Extroversion (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 Extroversion (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 A4: Peer randomizations are balanced at the team level.

	(1)	(2)	(3)	(4)	(5)
	Openness (Team)	Extroversion (Team)	Conscientious (Team)	Agreeableness (Team)	Neuroticism (Team)
Extroversion (Peers)	0.118 (0.228)	0.027 (0.316)	0.162 (0.228)	-0.076 (0.260)	-0.095 (0.299)
Constant	0.016 (0.091)	0.008 (0.100)	0.004 (0.088)	-0.004 (0.100)	0.005 (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 A5: The results in Table 3 hold when using evaluations from Indian consumers.

	(1)	(2)	(3)	(4)	(5)	(6)
	Externally Evaluated Idea Quality					
Openness (Self)	-0.080 (0.052)		-0.084 [†] (0.049)	-0.096 [†] (0.051)	-0.073 (0.047)	-0.108* (0.049)
Extroversion (Peers)		0.128 (0.112)	0.156 (0.097)	0.241** (0.091)	0.167 [†] (0.096)	0.275** (0.092)
Openness (Self) × Extroversion (Peers)			0.229* (0.102)	0.208 [†] (0.110)	0.248* (0.105)	0.221* (0.107)
Extroversion (Self)				-0.022 (0.047)		0.000 (0.041)
Openness (Peers)				-0.230* (0.093)		-0.297** (0.094)
Openness (Self) × Openness (Peers)				0.024 (0.123)		0.032 (0.116)
Extroversion (Self) × Openness (Peers)				-0.021 (0.110)		-0.013 (0.101)
Extroversion (Self) × Extroversion (Peers)				-0.138 (0.130)		-0.244* (0.109)
Pre-treatment Idea Quality (Self)					0.229 [†] (0.128)	0.288 [†] (0.158)
Pre-treatment Idea Quality (Peers)					0.247 (0.277)	0.432 (0.275)
Admission Score (Self)					-0.025 (0.047)	0.042 (0.044)
Admission Score (Peers)					0.061 (0.085)	0.130 (0.081)
Engineer (Self)					0.063 (0.109)	0.150 (0.099)
Engineer (Peers)					-0.053 (0.209)	-0.084 (0.174)
Observations	1839	1839	1839	1839	1823	1823

Standard errors in parentheses

Ordered Logistic Regression with fixed effects for the 45 Indian Mechanical Turk evaluators.

All tests are two tailed. Standard errors clustered at the individual innovator level.

[†] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A6: The results in Table 3 hold when using ordinary linear regression.

	(1)	(2)	(3)	(4)	(5)	(6)
	Idea	Idea	Idea	Idea	Idea	Idea
	Quality	Quality	Quality	Quality	Quality	Quality
Openness (Self)	-0.088 (0.085)		-0.099 (0.081)	-0.087 (0.082)	-0.122 (0.075)	-0.140 [†] (0.076)
Extroversion (Peers)		0.363* (0.161)	0.383** (0.142)	0.499** (0.156)	0.470** (0.137)	0.621** (0.149)
Openness (Self) × Extroversion (Peers)			0.418* (0.193)	0.408* (0.205)	0.445* (0.184)	0.412* (0.201)
Extroversion (Self)				-0.088 (0.091)		-0.050 (0.090)
Openness(Peers)				-0.305* (0.145)		-0.408** (0.153)
Openness (Self) × Openness (Peers)				0.095 (0.186)		0.147 (0.167)
Extroversion (Self) × Openness (Peers)				-0.165 (0.201)		-0.163 (0.180)
Extroversion (Self) × Extroversion (Peers)				-0.239 (0.192)		-0.412 [†] (0.210)
Pre-treatment Idea Quality (Self)					0.576* (0.282)	0.653* (0.271)
Pre-treatment Idea Quality (Peers)					0.554 (0.491)	0.868 [†] (0.505)
Admission Score (Self)					0.032 (0.077)	0.117 (0.084)
Admission Score (Peers)					0.244 [†] (0.137)	0.341* (0.135)
Engineer (Self)					-0.270 (0.210)	-0.131 (0.211)
Engineer (Peers)					-0.141 (0.351)	-0.181 (0.326)
Observations	1150	1150	1150	1150	1141	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 A7: The results in Table 2 are robust to the inclusion of alternative peer-personality interactions.

	(1)	(2)	(3)	(4)
	Idea Quality	Idea Quality	Idea Quality	Idea Quality
Openness (Self)	-0.096 (0.081)	-0.104 (0.079)	-0.056 (0.084)	-0.098 (0.082)
Extroversion (Peers)	0.480** (0.145)	0.359* (0.140)	0.390** (0.142)	0.379** (0.138)
Openness (Self) × Extroversion (Peers)	0.495* (0.220)	0.397* (0.197)	0.338† (0.195)	0.411* (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)
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 A8: The results in Table 2 are robust to the inclusion of variables that reflect experience at weddings and intelligence.

	(1)	(2)	(3)
	Idea Quality	Idea Quality	Idea Quality
Openness (Self)	-0.078 (0.061)	-0.095 (0.061)	-0.111 [†] (0.058)
Extroversion (Peers)	0.360** (0.120)	0.290** (0.110)	0.325** (0.106)
Openness (Self) × Extroversion (Peers)	0.306* (0.142)	0.337* (0.155)	0.287* (0.134)
Self-Monitoring (Self)	0.023 (0.064)		
Self-Monitoring (Peers)	0.004 (0.105)		
Self-Monitoring (Self) X Self-Monitoring (Peers)	-0.117 (0.110)		
Age (Self)		0.085 (0.176)	
Age (Peers)		0.147 (0.171)	
Age (Self) X Age (Peers)		-0.005 (0.008)	
Female (Self)		0.034 (0.152)	
Female (Peers)		0.408 (0.356)	
Female (Self) X Female (Peers)		-0.053 (0.683)	
Admission Score (Self)			0.011 (0.059)
Admission Score (Peers)			0.159 (0.114)
Admission Score (Self) X Extroversion (Peers)			0.213 (0.217)
Observations	1150	1150	1150

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 A9: The results in Table 2 are largely robust to the inclusion of the full set of ego-alter personality interactions. Joint tests reveal that even in Column 4 pairing an open innovator with an extrovert (introvert) will improve (decrease) estimated idea quality; for a closed innovator the extroversion barely matters.

	(1)	(2)	(3)	(4)
	Idea Quality	Idea Quality	Idea Quality	Idea Quality
Openness (Self)	-0.092	-0.064	-0.044	-0.079
Extroversion (Peers)	0.323**	0.458**	0.538**	0.606**
Openness (Self) X Extroversion (Peers)	0.300*	0.271*	0.235	0.255
Conscientious (Self)		-0.128*	-0.161*	-0.116
Extroversion (Self)		-0.051	0.005	0.065
Agreeableness (Self)		-0.022	0.091	0.127*
Neuroticism (Self)		0.029	0.034	0.080
Openness (Peers)		-0.165	-0.214*	-0.319**
Conscientious (Peers)		-0.141	-0.129	-0.224*
Agreeableness (Peers)		-0.016	0.018	0.103
Neuroticism (Peers)		0.188	0.162	0.112
Openness (Self) X Openness (Peers)			0.126	0.162
Extroversion (Self) X Openness (Peers)			-0.285 [†]	-0.328*
Extroversion (Self) X Extroversion (Peers)			-0.035	-0.123
Openness (Self) X Conscientious (Peers)			-0.079	-0.151
Openness (Self) X Agreeableness (Peers)			0.066	0.092
Openness (Self) X Neuroticism (Peers)			0.037	0.045
Conscientious (Self) X Openness (Peers)			-0.128	-0.106
Conscientious (Self) X Openness (Peers)			0.074	0.306
Conscientious (Self) X Extroversion (Peers)			0.142	0.103
Conscientious (Self) X Agreeableness (Peers)			0.208	0.105
Conscientious (Self) X Neuroticism (Peers)			0.209	0.213
Agreeableness (Self) X Openness (Peers)			0.038	0.038
Agreeableness (Self) X Openness (Peers)			0.279*	0.175
Agreeableness (Self) X Extroversion (Peers)			0.180	0.154
Agreeableness (Self) X Openness (Peers)			-0.163	0.062
Agreeableness (Self) X Neuroticism (Peers)			0.263	0.288 [†]
Extroversion (Self) X Conscientious (Peers)			-0.231 [†]	-0.221 [†]
Extroversion (Self) X Agreeableness (Peers)			0.295*	0.430**
Extroversion (Self) X Neuroticism (Peers)			0.183	0.231 [†]
Neuroticism (Self) X Openness (Peers)			-0.139	-0.186
Neuroticism (Self) X Conscientious (Peers)			0.123	0.029
Neuroticism (Self) X Extroversion (Peers)			0.109	0.062
Neuroticism (Self) X Agreeableness (Peers)			0.084	0.073
Neuroticism (Self) X Neuroticism (Peers)			0.127	0.104
Pre-treatment Idea Quality (Self)				0.449
Pre-treatment Idea Quality (Peers)				0.157
Admission Score (Self)				0.105
Admission Score (Peers)				0.401**
Engineer (Self)				0.184
Engineer (Peers)				0.075
Observations	1150	1150	1150	1141

Ordered Logistic Regression with evaluator fixed effects.

All tests are two tailed. Standard errors clustered at the individual innovator level.

[†] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table A10: Does peer extroversion and innovator openness explain the number of ideas generated?

	(1)
	Number of Ideas
Openness (Self)	0.113 [†] (0.068)
Extroversion (Peers)	-0.184 (0.118)
Openness (Self) × Extroversion (Peers)	-0.098 (0.152)
Extroversion (Self)	-0.060 (0.061)
Openness (Peers)	0.049 (0.125)
Openness (Self) × Openness (Peers)	0.140 (0.138)
Extroversion (Self) × Openness (Peers)	0.035 (0.141)
Extroversion (Self) × Extroversion (Peers)	0.257 (0.158)
Pre-treatment Idea Quality (Self)	-0.113 (0.191)
Pre-treatment Idea Quality (Peers)	-0.296 (0.346)
Admission Score (Self)	0.103 (0.064)
Admission Score (Peers)	0.079 (0.109)
Engineer (Self)	0.270 [†] (0.141)
Engineer (Peers)	-0.112 (0.231)
Constant	2.015* (1.001)
Inalpha Constant	-3.464** (1.299)
Observations	107

Standard errors in parentheses

Negative Binomial Regression at the innovator-level.

All tests are two tailed.

[†] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A11: Individuals who talk with a mix of extroverts and introverts 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)	(2)
	Idea Quality	Idea Quality
Openness (Self)	-0.133 (0.197)	-0.067 (0.084)
Extroversion (Peers)	0.477** (0.132)	
Openness (Self) \times Extroversion (Peers)	0.351 [†] (0.185)	
Extroversion S.D. (Peers)	0.227 (0.172)	
Openness (Self) \times Extroversion S.D. (Peers)	0.021 (0.190)	
Extroversion (First Peer)		0.135 [†] (0.071)
Extroversion (Second Peer)		0.299** (0.074)
Extroversion (Third Peer)		0.096 (0.067)
Extroversion (First Peer) \times Openness (Self)		0.014 (0.070)
Extroversion (Second Peer) \times Openness (Self)		0.336** (0.097)
Extroversion (Third Peer) \times Openness (Self)		0.157 [†] (0.083)
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 A12: The randomized conversations appear to impact the business, buy, and novelty dimensions of an individual’s idea quality equally.

	(1)	(2)	(3)
	Business Rating	Buy Rating	Novelty Rating
Openness (Self)	-0.047 (0.058)	-0.059 (0.058)	-0.105 [†] (0.055)
Extroversion (Peers)	0.234* (0.109)	0.272** (0.093)	0.264* (0.122)
Openness (Self) × Extroversion (Peers)	0.320* (0.154)	0.334** (0.115)	0.336** (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 A13: Our results are robust when controlling for the presence of a innovator-evaluator relationship.

	(1)	(2)	(3)
	Idea Quality	Idea Quality	Idea Quality
Openness (Self)	-0.104 (0.063)	-0.105 [†] (0.063)	-0.105 [†] (0.063)
Extroversion (Peers)	0.333** (0.115)	0.334** (0.115)	0.334** (0.114)
Openness (Self) × Extroversion (Peers)	0.296* (0.143)	0.296* (0.143)	0.296* (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 A14: Summary statistics at the team level.

	count	mean	sd	min	max
Average Project Quality (Team)	40	2.791	0.205	2.439	3.294
Extroversion (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
Extroversion (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 A15: Do teams with open members that conversed with extroverted peers generate higher quality projects?

	(1)	(2)	(3)	(4)	(5)	(6)
	Project Quality	Project Quality	Project Quality	Project Quality	Project Quality	Project Quality
Openness (Team)	0.124 [†] (0.063)		0.133 [†] (0.067)	0.130* (0.064)	0.138* (0.062)	0.146* (0.058)
Extroversion (Peers)		0.107 (0.093)	0.124 (0.085)	0.095 (0.087)	0.183* (0.083)	0.149 (0.091)
Openness (Team) × Extroversion (Peers)			0.331* (0.162)	0.825** (0.197)	0.335* (0.149)	0.848** (0.174)
Extroversion (Team)				-0.120* (0.052)		-0.116* (0.047)
Openness (Peers)				-0.022 (0.095)		-0.045 (0.105)
Openness (Team) × Openness (Peers)				-0.463** (0.170)		-0.503** (0.159)
Extroversion (Team) × Openness (Peers)				0.043 (0.123)		0.020 (0.135)
Extroversion (Team) × Extroversion (Peers)				0.113 (0.140)		0.102 (0.157)
Pre-treatment idea quality (Team)					0.325 (0.254)	0.306 (0.243)
Pre-treatment idea quality (Peers)					0.146 (0.326)	0.179 (0.322)
Admission Score (Team)					0.103 (0.074)	0.088 (0.058)
Admission Score (Peers)					0.024 (0.095)	-0.027 (0.114)
Engineer (Team)					-0.111 (0.099)	-0.115 (0.109)
Engineer (Peers)					-0.188 (0.221)	-0.184 (0.234)
Observations	556	556	556	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.

[†] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A16: The results in Table 5 hold when using evaluations from Indian consumers.

	(1)	(2)	(3)	(4)	(5)	(6)
	Externally Evaluated Project Quality					
Openness (Team)	0.107 (0.073)		0.124 [†] (0.073)	0.071 (0.084)	0.088 (0.067)	0.049 (0.080)
Extroversion (Peers)		0.090 (0.090)	0.115 (0.078)	0.158* (0.069)	0.131 (0.092)	0.191 [†] (0.103)
Openness (Team) × Extroversion (Peers)			0.430** (0.143)	0.510** (0.186)	0.454** (0.158)	0.485* (0.206)
Extroversion (Team)				-0.034 (0.068)		-0.038 (0.062)
Openness (Peers)				-0.172 [†] (0.101)		-0.170 (0.122)
Openness (Team) × Openness (Peers)				-0.185 (0.153)		-0.140 (0.159)
Extroversion (Team) × Openness (Peers)				-0.016 (0.102)		-0.033 (0.132)
Extroversion (Team) × Extroversion (Peers)				0.180 (0.146)		0.186 (0.173)
Pre-treatment idea quality (Team)					-0.137 (0.219)	-0.099 (0.240)
Pre-treatment idea quality (Peers)					-0.388 (0.408)	-0.215 (0.437)
Admission Score (Team)					0.088 (0.053)	0.072 (0.055)
Admission Score (Peers)					-0.009 (0.103)	0.020 (0.132)
Engineer (Team)					0.059 (0.114)	0.038 (0.115)
Engineer (Peers)					0.188 (0.231)	0.011 (0.277)
Observations	291	291	291	291	291	291

Standard errors in parentheses

Linear Regression with fixed effects for the 34 Indian Mechanical Turk evaluators.

All tests are two tailed. Standard errors clustered at the team level.

[†] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A17: Teams with open individuals who were paired with extroverts have higher quality projects, even when controlling for within-team openness-extroversion matching, the maximum openness of team members, and the diversity of team member openness.

	(1)	(2)	(3)
	Project Quality	Project Quality	Project Quality
Openness (Team)	0.147* (0.061)	0.203 [†] (0.100)	0.115 [†] (0.067)
Extroversion (Peers)	0.133 (0.096)	0.148 (0.225)	0.317* (0.129)
Openness (Team) × Extroversion (Peers)	0.465* (0.173)	0.510* (0.250)	0.302 [†] (0.166)
Extroversion (Team)	-0.112* (0.046)		
Openness (Team) X Extroversion (Team)	0.024 (0.122)		
Max Openness (Team)		0.043 (0.130)	
Max Openness (Team) X Extroversion (Peers)		-0.117 (0.274)	
Max Openness (Peers)		0.397 (0.357)	
Max Openness (Team) X Max Extroversion (Peers)		-0.333 (0.349)	
Std. Dev. Openness (Team)			-0.041 (0.052)
Std. Dev. Openness (Team) × Extroversion (Peers)			-0.223* (0.098)
Constant	2.796** (0.028)	2.708** (0.145)	2.840** (0.064)
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.

[†] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$