Learning to Manage: A field experiment in the Indian startup ecosystem*

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Abstract

While management styles and practices have been found to be important determinants of firm performance, there is far less evidence on the extent to which management matters for entrepreneurial ventures and whether founders can learn to be more effective managers. Using a randomized field experiment with 100 high-growth technology firms, we show that founders who received advice from other founders with more "hands-on" management styles were more likely to reorient their own management activity, and subsequently experience lower employee attrition and higher rates of firm survival eight months after the intervention. For founders who already had a more hands-on management style themselves, these interactions also increased their rate of hiring. Our study demonstrates management skill can be learned by young firms via networks and subsequently influence performance.

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Introduction

The growing literature on entrepreneurial ventures has consistently documented that a sizable share of new startups fail (e.g., Wu and Knott, 2006). Scholars and practitioners attribute this poor performance to a wide array of factors including poor product-market fit (Ries, 2011), and founder inexperience and lack of social connections (Hallen, Bingham and Cohen, 2014). A large body of strategic management research suggests an important candidate explanation. This work has argued that *how a firm is managed* affects *how it performs*. Seminal research in strategy (e.g., Wernerfelt, 1984; Barney, 1991; Teece, Pisano and Shuen, 1997; Teece, 2007) maintains that competitive advantage comes from the strategic management of firm resources and capabilities. Moreover, a sizable literature on the impact of top management teams (e.g., Hambrick and Mason, 1984) seeks to establish a link between the attributes of managers, their approach to management and firm performance. More recently, scholars have focused on estimating the causal relationship between particular management styles (e.g., Fee, Hadlock and Pierce, 2013; Bertrand and Schoar, 2003) or practices (e.g., Bloom and Van Reenen, 2007; McKenzie and Woodruff, 2016) and firm performance, finding that good management can lead firms to grow faster, generate more revenue and have higher productivity (Baron and Hannan, 2002; Bloom et al., 2013).

While this research has typically been grounded in the context of mature organizations, the implication is that how young firms are managed can also influence how well they perform. But how do founders "learn to manage" their enterprises? If the best management practices are widely known, why do we still observe a substantial degree of across-firm heterogeneity in management practices, and thus performance? (Bloom and Van Reenen, 2010). In this paper, we investigate the extent to which founders can learn management practices and estimate the subsequent effects on firm performance.

To gather causal evidence in a realistic setting for our proposed inquiry, we conducted a novel field experiment that brought together founders of 100 growth-stage software product companies in India for a three day executive retreat. Our sample consists of a meaningful proportion of software startups at this stage in the entire Indian ecosystem. For comparison, in 2013 there were 43 angel investments, 74 seed investments and 34 Series A rounds in India.[1] This figure suggests that our sample captures a sizable proportion of relevant startups at the early growth stage in the Indian ecosystem.

For tractability, we focus on the extent to which founders can learn one basic kind of man-

[1] Author calculations from Preqin financing data

agement style, which can be called "intensive" or colloquially, "hands-on"[2]. Managers who have intensive styles prioritize regularly scheduled evaluations of employee strengths and weaknesses, the setting of shared milestones, and the tracking of progress toward key goals (e.g., Muczyk and Reimann, 1987; Horowitz, 2014). Such a style is particularly useful for young knowledge-intensive firms (e.g., technology firms), where the primary resource is human capital and a key task of the effective manager is to channel the talents of employees towards improving firm performance (e.g., Baron, Hannan and Burton, 2001). Managers with this style are more likely to focus "inside" the organization as opposed to "outside", an approach that has been linked to stronger performance (Bandiera et al., 2011). Our key argument is that through social interaction with their peers, a focal manager learns that she *should implement* the practices associated with a more intensive style as well as *how to implement* these practices. These kinds of social interactions via networks are particularly valuable for entrepreneurs, a literature we review in detail below. We expect intensive management (hereafter, IM) practices to have a significant impact on the human resources of the firm. Specifically, by improving the management of human resources, managers who learn and adopt IM should be able to better retain employees, hire new ones and fire those who are not making progress toward the firm's objectives.

Prior to the retreat, founders of these companies were surveyed about their work experience, educational background, management styles and firm characteristics. We construct an IM index using data from a time-use survey of each founder in our sample by averaging how often each founder engages in four management practices: providing structured feedback, conducting performance reviews, setting expectations, and establishing shared goals.

Our key experimental treatment consists of the randomized pairing of the 100 founders into 50 pairs, with some individuals paired with peers scoring high on IM and others paired with peers lower on this scale. During two days of the retreat, the paired founders discussed their businesses and their challenges, and were tasked to provide feedback and advice about management and strategy to their partners. In the final hours of the retreat, the founders completed another survey asking them for a "checklist" of items they would implement upon returning to their companies. A final phone survey was then deployed roughly eight months after the retreat that asked founders to provide information on any post-retreat changes to their teams and companies more broadly.

[2] "Hands-on management" is a frequently used term in the practitioner literature generating 129 million search results on Google, though some variation exists in how the term is applied. As an example for how variations in this style are discussed in practice, see `https://hbr.org/2014/12/dealing-with-a-hands-off-boss`. Some well-known firms also favor this style for their internal managers, as Marriott states in its management philosophy primer (`http://www.marriott.com/Multimedia/PDF/Marriott_Management_Philosophy.pdf`)

We find that founders who were exposed to peers practicing more IM retained a higher percentage of their employees (a one standard-deviation increase in the IM index of the peer reduces voluntary turnover by 20%) and were less likely to close their venture eight months after the retreat. Interestingly, we find that founders who were already more intensive managers themselves also hired more employees and experienced higher top-line growth of employees in the post-period. These results are consistent with founders learning valuable management knowledge from their peers, particularly those peers who themselves are high-IM managers.

However, since several competing mechanisms could account for this effect, we conduct further analysis. We first investigate the strategic checklist that founders composed at the retreat. Those founders who interacted with a more intensive-manager peer were more likely to include items related to management practices in their checklist, consistent with our proposed mechanism. To further rule out alternative explanations, we conduct additional analysis and find that our results cannot be mediated by other peer and organizational characteristics, including education, age, and firm size, which might suggest deference to social status as opposed to learning.

Finally, if founders are acquiring valuable knowledge, we would expect that they would be more likely to continue communicating with high-IM peers (compared to low-IM peers). To test this prediction, we tracked their communications with their peers after the retreat. Participants communicated more with peers who were more intensive managers, suggesting that founders could recognize valuable advisors after sustained interaction. This result is consistent with our proposed mechanism of knowledge transfer.

We see several contributions from this work. Strategic management research is premised on explaining persistent differences in performance and seminal work has identified the important role of management practices. However, in the context of young firms, where performance is generally highly variable, little work has been conducted to estimate the impact of specific management practices on firm performance and to what extent these practices can be learned.

Moreover, despite the demonstrated value of management, we still do not know why management does not diffuse more easily across organizations. Management appears even less transparent than technology, which, as previous work indicates (Cohen and Levinthal, 1990; Jaffe, 1986; Almeida and Kogut, 1999), diffuses imperfectly. The inherently tacit nature of management knowledge, its embodiment in *what* a manager does, and the potential difficulty in finding such knowledge in a network based on observable signals, suggests that management knowledge may diffuse quite slowly.

Next, we are the first to our knowledge to estimate the causal effect of spillovers of management knowledge on the performance of high-growth technology firms. While there is a large body of work estimating peer effects on individual-level outcomes, there is very little work that considers firm-level outcomes. The previous work most similar to our own, Cai and Szeidl (2016) and Fafchamps and Quinn (2015), study diffusion of management knowledge across more traditional small- and medium-sized enterprises. Moreover, their experimental approach uses larger groups of business owners, making it difficult to isolate the effect of a specific peer. Given that high-growth firms are the central unit of analysis for many scholars, and that inter-firm spillovers are crucial for organizational learning, we believe these dimensions to be particularly advantageous features of our study.

We also view our study as useful for developing new theory and practice. For example, consider the growing literature evaluating formal training programs and consulting arrangements that teach entrepreneurs how to manage their companies (Bloom et al., 2013; Bruhn, Karlan and Schoar, 2017; McKenzie and Woodruff, 2016). These interventions are typically expensive and may not be practical for entrepreneurs who are working full-time on their business. Some recent work has shown specific training and consulting programs to be effective, much of this work has found mixed results, often with no or very small effects. Our peer-mentoring treatment is similar to these more traditional interventions in that new knowledge is being shared with a focal founder.

However, peer learning may yield two further advantages over these approaches. First, peer learning is arguably more scalable because entrepreneurs learn from each other's experiences rather than a single instructor, and these exchanges can happen informally. Second, peer learning can be more "personalized," because information can be tailored to the specific needs or situation of the focal founder. In sum, by finding causal evidence of management spillovers in our context, we can be more confident that peer learning is an effective method to diffuse management knowledge. Our results open up new avenues for theoretical research into whether initiatives that prioritize one-to-one learning, such as mentoring programs, might have particular advantages in knowledge diffusion.

Motivation

Why Management Matters for Startups

Most efforts to improve startup performance often focus on enhancing founder human capital or alleviating credit constraints (De Mel, McKenzie and Woodruff, 2014; Fischer and Karlan, 2015). However, an important literature in strategy argues that improving management practices can also increase performance. Indeed, a fundamental motivation in the field of strategic management is that management matters for firm performance *and* that it is a scarce resource. Research on top management teams (e.g., Hambrick and Mason, 1984), dynamic capabilities (e.g., Teece, 2007), and various other literatures have established the role of management in setting and achieving a firm's strategic objectives. Work in industrial organization economics has found substantial variation in performance within industries, across firms with similar technologies and across regions (Bloom and Van Reenen, 2010). Recently, scholars have shown that this variation can be traced back to the types and styles of management implemented in firms. Firms and organizations with more systematic management practices perform better (Bloom et al., 2013). Yet, it is a puzzle as to why more systematic management is not applied more widely. Underlying this puzzle are two, mostly implicit, perspectives on how management in a particular organization can be improved.

One conceptualization views management practices and styles as embodied in the manager. Such work has attempted to quantify the impact of specific managers—often by representing the quality of a manager and her associated style and practices as a *fixed effect* (e.g., Bertrand and Schoar, 2003). Findings suggest substantial "manager effects" indeed exist, and that firms with these managers do perform better (e.g., Lazear, Shaw and Stanton, 2015). Empirical limitations of this approach aside, the findings from this research appear to suggest that one way a firm can acquire better management is by hiring better managers. At the industry level, however, if good managers are a finite resource and are merely swapped across firms, industry-level heterogeneity in management and thus performance are likely to persist.

A second conceptualization views management practices as fungible knowledge and routines. Under this view, management can be taught, learned and applied by the managers of any firm. Through the application of more systematic management practices, the marginal firm can increase its performance. Much of the empirical work in this vein attempts to teach management—through coursework and training programs—to business owners and then monitor subsequent performance. Results from this body of work have produced mixed evidence. Most training programs appear *not* to work (Fischer and Karlan, 2015), with some highly specialized training programs producing modest improvements in performance (e.g., De Mel, McKenzie and Woodruff, 2014; McKenzie and Woodruff, 2014). Fischer and Karlan (2015), in a critique of this research, argue the weak effects of training programs may be traced back to the substantial heterogeneity in firms' most pressing business problems and stage of development. Gibbons and Henderson (2012) offer relevant insights here, arguing that current activity systems, cultures and cognition may prevent firms from adopting and faithfully implementing new and beneficial practices.

Despite these important observations, both perspectives leave a gap in terms of understanding how the management of firms can be improved more broadly. Under the first perspective, improving management is a zero-sum process; under the second, firm-level heterogeneity leads to a mismatch in the kind of management knowledge transferred and its application in a specific firm.

We propose the diffusion puzzle arises due to two key attributes of management knowledge: its *tacit* nature and its need to be *specific* to the context of the firm in which it is applied (e.g, Levin and Cross, 2004; Argote, McEvily and Reagans, 2003). First, the key insights about how to implement new management practices successfully are difficult to articulate and hard to codify, hindering the acquisition of this knowledge without personal interaction. Second, the specific styles or practices that work in one organization may not be directly applicable in another due to differences in the type of work, the business model, market conditions or the prevailing organizational or national culture. As a consequence, knowledge that is tailored to the specific needs of a firm or manager is far more useful than generic advice. But how does one provide personalized insights about largely tacit practices? Below, we suggest that social networks between peers are an appropriate channel for such sharing.

The Role of Networks

Prior research has shown that network ties are particularly appropriate conduits for knowledge that is both tacit and needs to be tailored to a specific individual or firm (Borgatti and Cross, 2003). Because of the informal nature of knowledge transfer via network ties, the sender of the information can share her own experiences, offer rich descriptions of styles that worked and did not, as well as provide a more causally rich set of explanations of why a practice did or did not work (e.g., Brown and Duguid, 2001). Further, the informality of the interaction may lead the sender of information to share information that may be inappropriate to broadcast widely, including gossip, opinions or sensitive information (Podolny and Baron, 1997; Singh and Agrawal, 2011). Further, network ties are interactive and the back-and-forth dialogue between the manager receiving information and sharing it can be honed by the asking and answering of specific questions, through iterative clarification, and potentially longer-term interactions that facilitate the further sharing of information. As a result, we expect a social tie between managers to transmit relevant and applicable management knowledge and to thus affect performance (Uzzi, 1996).

Networks have been found to be particularly valuable for young firms—such as technology startups—which typically have fewer financial, technical and human resources and rely on the connections of their managers to acquire key inputs (Stuart, Hoang and Hybels, 1999). Indeed, even the decision to become an entrepreneur appears to be influenced by a person's social ties (Stuart and Ding, 2006; Nanda and Sørensen, 2010). The utility of networks for young firms has not gone unnoticed by practitioners as evidenced by the growing presence of incubators and accelerators that serve as brokers, connecting entrepreneurs to valuable network partners (e.g., Dutt et al., 2016; Chatterji, Glaeser and Kerr, 2014).

We advance the argument that management styles can indeed be learned through social networks according to the following logic. First, we assume that the managers of firms vary in their style of management, and this variation is reflected in how they conduct specific activities within their organizations. Second, we argue that social interactions among managers serve as channels through which knowledge about a specific way of managing (i.e., a style) passes from one manager to another. Finally, a focal manager then implements this learning in her firm, resulting in a change in performance.

Intensive Management

What kind of management style and related knowledge is likely to be most relevant to small and knowledge-intensive firms? The production process for such firms relies heavily on human knowledge and effort as key inputs—thus, people-management is a key lever for productivity (Chadwick and Dabu, 2009; Toole and Czarnitzki, 2009; Lazear, 1995). Basic elements of people-management include the appropriate assignment of tasks to the right people, effective monitoring, the setting of individual goals, the provision of feedback, and the coordination and aggregation of individual production. More intense people-management—where intensity is defined by how frequently managers conduct these types of activities—is likely to improve the utilization of individuals within a team (e.g., Koch and McGrath, 1996).

First, a higher frequency of and greater priority on such activities increases the information a manager holds about individual-level performance and potential frictions in the production process (e.g., Horowitz, 2014; Ross, 1973). Enhanced information should allow greater efficiency in the assignment of work and the setting of goals, thus making employees more productive individually. Second, a greater frequency of interactions between the manager and her employees should create greater alignment within the team, enhancing complementaries and thus productivity (Giroud and Mueller, 2015). Better information and alignment should enhance the match between the person and the organization, thus reducing voluntary turnover (e.g., Chatman, 1989). Further, improved information should increase a manager's visibility into the strengths and weaknesses of specific employees and allow them to fire those employees who are not productive. Finally, higher performance and a better working environment should increase the attractiveness of the firm as a place to work, facilitating employee recruitment and hiring. Through these processes, we argue that managerial knowledge acquired from a peer with a more intensive style of management should influence employee dynamics and firm survival at the focal organization.

Finally, a key assumption underlying our proposal is that networks can tailor information to be more relevant to a focal manager's stage of development or particular needs. Some of these managers will already have adopted some elements of the IM style, whereas others will be novices. Our argument suggests that those managers already using some of these management practices will be able to more readily learn and implement new knowledge in this domain. We investigate this conjecture empirically below.

An Executive Retreat for Entrepreneurs

To provide realistic evidence on the role that networks play in transmitting management knowledge across firms, we conducted a field experiment within the Indian startup ecosystem, specifically a large set of software product companies. This empirical context is appropriate because prior work has argued that although Indian startups have access to a relatively strong pool of technical knowledge and talent (Arora and Gambardella, 2005), these organizations may lack commensurate levels of managerial capacity (Bloom and Van Reenen, 2010).

We conducted a field experiment in partnership with the Indian Software Product Industry Roundtable (iSPIRT), a think tank that promotes the growth of Indian software product companies. iSPIRT advocates for Indian technology policies and provides training for entrepreneurs through a variety of programming. Their overarching goal is to help build a vibrant technology startup ecosystem in India. As part of this mission, iSPIRT planned a three-day off-site retreat for high-potential growth-stage startups to help them rethink their strategies. To encourage creativity and facilitate networking, the conference was held on the corporate campus of a large Indian technology company. All founders stayed in residences on the campus during the retreat. The retreat, in which we embedded our intervention, ran from Friday the 8th through Sunday the 10th in January 2016.

Admission to the retreat was selective. Of the over 500 founders who applied from all across India, just over 200 were accepted into the program and 173 attended the camp. Recruiting was primarily done through word-of-mouth referrals and mass emails to listserves popular with entrepreneurs. The registration fee for accepted participants was highly subsidized, costing each participant approximately $250 USD. All the startups in our experimental sample of 100 were explicitly trying to grow the size of their organization, with the mean firm having 13 employees and having been started just three years earlier. These firms were already growing fast, with the average organization having hired six people over the last year. The median firm had raised $83,000 USD, a substantial sum in the Indian context. Forty-six firms had previously raised a round of angel or institutional financing. The median age of each founder was 37 years old. Beyond the founders in attendance, each from a different startup, there were roughly 25 volunteers, including some of the most successful Indian entrepreneurs and venture capitalists.

The authors worked with iSPIRT to develop the curriculum for the three-day retreat. To maximize the chance that the founders would leave the camp with an actionable growth strategy, each half-day was designed around a case and an interactive peer-learning session. Our intervention randomized 100 of the founders in attendance into 50 pairs.[3] The pairs in our intervention spent the entire day, Saturday, working together, as part of the broader three-day retreat. The cases they discussed during the session involved a real decision made by one of the successful Indian entrepreneurs in attendance. Following the case discussion, the attendees worked in their randomly assigned pair to help each other translate the case into tangible strategies for their own startup. During these conversations, the founders used a custom learning management system developed by the authors to keep track of their ideas and evaluate the potential payoffs of these strategic actions.

On the third and final day of the retreat, founders focused on developing an individual strategic checklist or "action plan" using the learning management system. Each item in the checklist corresponded to an action the founder committed to take when they returned to their

[3] The remaining founders were separately mentored by the iSPIRT volunteers and are not considered in our analysis.

startup. For each item, an example of which is provided in Figure 1, the founder described the item in one to two sentences and then categorized the item on dimensions ranging from how long they thought it would take to start the item to whether they would delegate it. To increase the chances founders would implement their strategic checklists, we made sure the participants knew that one of our volunteers would be following up with them in the year after the retreat to check on their progress. Furthermore, the founders also knew that a subset would be randomly selected to present their checklist in front of the other participants, again providing strong incentives to take the exercise seriously.

Based on qualitative and quantitative information from the post-retreat phone surveys conducted eight months after the retreat, the checklist items appear to be more than cheap talk. Qualitatively, founders talked at length about implementing particular action items. For example, founders discussed hiring a new product manager or reorganizing their team to be more efficient. Quantitatively, the founders reported having completed roughly 25% of the items they listed on their "checklist" during the bootcamp. They further reported that they had started working on roughly 25% of the checklist items, and were planning to start on 25% more in a short while. After the Sunday morning checklist exercise, participants completed a brief social network survey, provided general feedback on the retreat, and then had lunch before boarding a bus back to Bangalore or to the airport.

We also note that throughout the event, tea and meal breaks facilitated broader networking. Our founders also interacted with other individuals besides their peers, whether in their dorms or on the bus rides to and from the site. Although none of these interactions were as intensive as our intervention, we leverage them below in our analysis of endogenous network formation.

Eight months after the retreat, we conducted twenty-minute phone interviews with the 100 founders in our sample. Of our full sample, we were able to compile follow-up data for 90 of the founders. Our sample size for this study is comparable to that of recent influential field experiments on management and firm performance, including Bloom et al. (2013) (28 plants), and a recent natural experiment in strategic management at the individual-level (41 individuals) Lee and Puranam (2017).

Our post-event data included changes to staffing at the firm, employee growth, survival, changes in firm strategy and information about whether randomly paired founders sought advice from each other post-retreat. For further reference, Table 1 presents a summary of the measures used in this paper, when they were collected, and as part of which survey instrument. These measures are also described in more detail below.[4]

Research Design and Empirical Strategy

Our experimental design builds on the standard peer effects measurement approach in which participant characteristics are first measured, then participants are randomized into pairs or small groups, and finally each participant's outcome of interest is measured (Sacerdote, 2014). The econometrician can then test for causal peer effects by estimating a reduced form model that regresses a participant's outcome on the average of her group's characteristics. Because characteristics are measured before the outcome, and participants are randomly assigned into groups, the peer effects design overcomes the ubiquitous bias induced by the problems of social reflection and selection (Manski, 1993). The canonical peer effects example proceeds as follows: a researcher measures pre-treatment characteristics of a peer (and the focal individual), individuals in the sample are then randomly assigned to each other, and post-assignment outcomes are subsequently measured (Hasan and Bagde, 2013). A correlation between a peer's pre-treatment characteristics (e.g., SAT score) and the post-treatment outcomes of the focal individual (e.g., first-year GPA), indicate a causal peer effect. Our study follows this methodological approach.

To measure founder and startup characteristics, we employed a mandatory pre-retreat survey. The survey was structured into three sections. First, it explored the founder's experience and day-to-day time use. It then asked about the firm and its growth over the last year. Third, it asked how often the founder engaged with the Indian startup community, including if the founder had previously met or sought out advice from any of the other retreat participants.

Intensive Management

The first section of the survey was the foundation of the IM-Index, discussed below. The founder was asked to indicate how often she engaged in a wide variety of tasks from fund-raising to sales to product development. We included four questions, based on the World Management Survey's categories (Bloom and Van Reenen, 2007), to measure how intensively a founder focused on the management of human capital within her team.[5] Specifically, we asked the following time-use questions:

- "How often do you develop shared goals in your team?"

[4] The complete survey interface, survey questions, and post-retreat interview protocol are available upon request.

[5] Unfortunately the limits on the entrepreneurs' time prevented us from interviewing each entrepreneur using the full World Management Survey protocol.

- “How often do you measure employee performance using 360 reviews, interviews, or one-on-ones?”
- “How often do you provide your employees with direct feedback about their performance?”
- “How often do you set clear expectations around project outcomes and project scope?”

Founders could indicate that they engaged in each of these formal management routines either “Never,” “Yearly, “Monthly,” “Weekly,” or “Daily.” The distribution of responses within each question is non-degenerate. Every cell for each question has at least five responses, with the modal response being “Monthly” engagement.

These survey questions provide us with a way to develop an IM index for each founder in our study. We do not assert that “more” management is always better. To the contrary, excessive “micro-managing” could have a negative impact on firm growth. However, very few of our founders appear to be at this end of the spectrum. Our view is that the time constraints faced by founders of growth-stage companies imply that increased frequency of a given activity moves in concert with increased focus on this activity. Because a founder’s time is constrained, when she chooses management, she is nearly always making a trade-off with another potentially valuable activity. By this logic, an increase in how often a founder manages is a proxy for an increase in focus on management tasks. Consistent with this argument, related work on time use by CEOs finds that hours devoted to internal management and meetings with one’s direct reports increases performance (Bandiera et al., 2011).

IM Index (Self): To generate our IM index we aggregate the four questions above into a single index. To do so, we first assign each categorical bin a numeric value (Never=1, Yearly=2, Monthly=3, Weekly=4, Daily=5), sum across the questions, and then standardize our IM index to have mean 0 and standard deviation 1. We select even spacing between categories, as opposed to weighting by the number of days each response represents, because even spacing maintains ordinal position, but avoids putting disproportionate weight on the scale’s end points. That said, our regression results are robust to other aggregations and weighting methods.

Figure 2 is a kernel density plot of our IM index, showing that the distribution appears normally distributed. Table 2 shows the responses from seven founders selected from across the IM distribution. The table illustrates that there is substantial variation in how often a founder engages in people-management tasks. Moving from a score of -0.92 to 0.04 (about one standard deviation) represents a shift in frequency from doing practices on a yearly-monthly level to a monthly-weekly level. At the tails, we see some founders only engaging in IM practices approximately once a year, whereas others set shared goals, conduct reviews, provide feedback, and set targets at a weekly rate.

IM Index (Peer): After we constructed the IM index, we turned to the second step of our measurement approach, the peer randomization itself. We paired the 100 founders in 50 groups of two during the retreat, because dyadic pairs provide sharper evidence that a singular peer is the one responsible for any observed influence. Relative to larger group randomizations, this approach also minimizes the "without replacement" exclusion bias that can emerge when peer effects are estimated using groups that are large relative to the population being placed into groups (Caeyers and Fafchamps, 2016).

Table 4 presents balance test regressions showing that the IM index of an entrepreneur's partner is uncorrelated with the entrepreneur's own pre-retreat characteristics. This balance indicates that our randomization was successful.

Individual-level controls Complementing our IM measure we also include age and educational history controls to reduce the chance that our our IM measure is reflecting differences in generalized human capital and not differences in management style. We construct variables **Older Founder** and **Older Founder (Peer)** that are 1 when the founder is above the median within-sample age of 36. We measure age at the time of the camp using the founder's self-reported birthday. These age measures allow us to conduct a first-order test to check if differences in experience are driving our estimates. More directly, given that management intensity is a skill (potentially) learned during business education, we construct variables **MBA** and **MBA (Peer)** which indicate if a founder has received an MBA. Of our 100 founders, 23 have an MBA. Age does not appear to correlate with a founder's IM score, though we do find a weak positive correlation between having an MBA and having a higher IM score.

Firm-level Outcomes

Pre-treatment Employee Growth: We also use the pre-retreat survey to generate pre-treatment measures of firm growth and employee hiring, firing, and quitting. Specifically, the survey asked the founders to report the current number of employees who work for their company (inclusive of the founding team), along with the number who were hired, fired and quit over the last year. Specifically, we asked founders in the two-weeks before the retreat "How many people have [you hired/quit/you let go] in the last year?"[6] We use the logged count of

[6] As the retreat took place early in January 2016 the last year neatly coincided with changes during the 2015 calendar year.

employees who were hired, fired and quit in our analysis, because the distributions for these counts are skewed. The raw counts also allow us to calculate the number of employees at the firm a year ago and construct a measure of annual percentage growth, a metric practitioners commonly use to gauge a startup's performance and that researchers have shown is correlated with venture capital funding (Davila, Foster and Gupta, 2003). When our growth measure is 0, the implication is that the firm is the same size it was a year ago. Positive values indicate the firm has increased in size (100% implies the firm would have doubled in size). Negative values indicate the firm has lost employees overall (e.g., 50% decline could imply a workforce reduction of 10 to 5). Table 3 provides summary statistics for employee growth over the last year.[7]

Self-Assessed Strength/Weakness: In addition to the employee-growth measures, we use a self-reported strengths and weaknesses assessment from the pre-retreat survey to generate a measure of the startup's position at the time of the retreat. We use this measure to check if the IM index correlates with perceived strengths and weaknesses for the organization. To generate the measure, we sum up how many dimensions of the business—which include User Growth, Management, Sales, Mentorship, Execution, Foreign, Capital, and Hiring—the founder thinks are business strengths and how many she thinks need improvement (what we term weaknesses).

Post-treatment Employee Growth: To test for peer influence, we measure outcomes after the retreat. We again focus on firm-growth metrics related to hiring, firing, quitting and net employment growth. We use data from a phone-based survey conducted after the retreat during the third quarter of 2016. Specifically, we asked founders "How many people have you [hired/quit/you let go] since the retreat?" The phone survey, conducted by an assistant hired by the researchers, achieved a 90% response rate. This response rate is comparable to other surveys of small- and medium-business owners and is especially strong when compared with other surveys of high-tech entrepreneurs and investors (Baron, Hannan and Burton, 2001; Bruhn, Karlan and Schoar, 2017). Given the difficulty of comparing financial performance across early-stage startups, headcount changes and growth provide us with a common metric to gauge performance differences. Moreover, understanding the impact of management on startup employment is in and of itself important, shedding light on how firm practices and entrepreneurship shape labor dynamics and growth (Decker et al., 2014; Astebro and Tåg, 2017).

[7] As can be seen in the summary statistics, the smallest firms have only one employee (the founder). Dropping these four firms from the analysis serves to only strengthen our results. We choose to keep these firms in our primary analysis since these founders can hire employees post-retreat and have these employees quit and/or be fired.

The qualitative data indicates that the majority of founders made at least one substantial business change since the retreat. Seven of the 90 firms surveyed had shut down operations. To account for the fact that firms were surveyed at different times, and to make comparisons with our pre-retreat measures easier, we transform the number of reported hires, fires and quits into estimated annual measures. Similar to the pre-treatment-growth measure, we then generate an annual growth rate by dividing the adjusted employee count one year from the retreat by the number of employees at the time of the retreat. Table 3 provides summary statistics on these post-retreat measures. As expected, the pre-retreat pace of growth has slowed, with average annual growth dropping from 50% in the year before the retreat to a 25% annual growth rate post retreat. We expected this decline in growth because the firms are generally larger in terms of the absolute number of employees than they were one year prior.

The pre-retreat survey, randomization, and post-retreat outcome data provide us with the necessary components to test whether peers influence management practices and subsequent firm outcomes. As stated above, this approach directly addresses the problems of selection and reflection that typically plague observational analyses of networks, spillovers, and peer influence (Manski, 1993). However, we do not directly observe the managers in action after the retreat. Due to the limited duration of the post-retreat survey we were unable to measure changes in management time-use and so cannot verify whether founders who are exposed to a high IM peer see increases in their own IM index. However, we do use two other approaches to make inferences on this point. First, we show below that the firm-level metrics we measure (growth, hiring, etc.) are correlated with IM in the cross-sectional pre-retreat survey. Any changes we see in these metrics in the post-treat survey in a pattern that accords with the randomization serves as evidence that the channel is via intensive management. Second, we analyze the strategic checklist items founders developed at the end of the retreat to test if founders who worked with a high IM partner develop more management focused items.

Strategic Checklist Items: In most studies of this kind, understanding the intentions of the managers and the specific plans they have for changing their management practices has been challenging. To capture managerial intentions, we use novel data from the retreat to provide more evidence on the question of whether founders are actually learning about management. We analyze the strategic checklist items generated by the founders on the third and final day of the retreat. Analyzing the checklist provides us with at least two benefits. First, because the checklist is generated at the end of the camp, but before the founder returns to their firm, it allows us to test if the founder learned about management without the potentially confounding effects of poor execution. Second, the checklist directly measures the extent to which the paired conversations are translated into a plan of action that may or may not involve different management practices. In this manner, the checklist provides us with more insight into the causal chain that converts interactions with a management-intensive partner into startup growth.

Each founder generated just under seven strategic checklist items on average. Examples of these items can be seen in Figure 1. Example items include (a) resolutions about the next hire the founder would make, (b) proposed changes in the firm's business model, and (c) planned shifts in the geographic markets the firm would sell to in the upcoming year.

To estimate how being assigned to a management-intensive partner influenced these checklist items, we use the founder's own categorical evaluations of their checklist items. Specifically, for each checklist item, a founder evaluated the item on a variety of dimensions, three of which relate to management. First, they marked if the item would be delegated, responding to the following statements:

- "I will do this item myself."
- "I will delegate doing this item to someone in my startup."

Second, the founders indicated what parts of the business are involved in the checklist item. They could select as few or as many of the following options as they wished:

- Sales and Growth
- Technology and Engineering
- Product Development
- Marketing and PR
- Hiring and Team Building
- Finance and Fundraising
- Operations and Management

For our analysis, we focus on the two "management" related categories, "Operations and Management" and "Hiring and Team Building." We generate two binary measures for each of these categories. Finally, we also generate a "Total Management Score" for each item by creating a variable that is the sum of the binary Delegation, Operations and Management, Hiring and Team Building variables. These variables allow us to test if a partner's IM not only affects subsequent growth of the peer firm, but also the management intensity of a founder's strategic checklist. As discussed above, we view this exercise as a "mechanism check" of the causal chain of logic we propose.

We also analyze two additional variables from the strategic checklist to test if managers are leaning more than management, perhaps learning to update the ends they are aiming for after talking with a higher IM peer who is often running a firm that is growing faster. Specifically, we focus on each founder's subjective assessment of the impact each checklist item would eventually have on revenue growth and user growth. Founders rated each item's growth potential on a five-point likert-style scale with the following ordered categories: "0X-1X," "1-2X," "3-5X," "5-10X," "10X+". While estimating the causal impact of any decision is exceedingly difficult, these subjective estimates provide us with a way to measure differences in founder ambition after talking with their randomized peer, even if these expectations are largely inflated.

Network Formation

We complement the primary analysis above with an additional analysis to develop insights about how entrepreneurs network in practice. Even if we find evidence that valuable information about management flows through randomized peer networks, it does not mean that the "best" management practices will disseminate widely in practice. An important factor is whether entrepreneurs can recognize peers with valuable information and continue to engage with them. If not, the most appropriate management practices seem unlikely to diffuse across large networks in the absence of interventions.

Intentions and Actual Follow up with Partner: To gain insight on this issue, we analyze data on how entrepreneurs select who they will keep in touch with post-retreat, both within their randomized pair and within our experimental sample of randomized pairings. To test if founders are more likely to get advice when they are assigned to a more management-intensive partner, we use two data sources. First, we use the founder's response to an exit survey question that asked the following question: "I will seek more advice from my partner after the retreat." Founders responded on a 5-point Likert scale that ranged from "Strongly Disagree" to "Strongly Agree." Complementing this measure of intention, we asked founders during the post-retreat phone survey if they had interacted with their partner since. These two measures provide us with a reliable measure of whether founders recognized the value of learning from a more management-intensive partner.

Follow up Intentions for Non-partner Participants: Beyond the pair, and again as part of the exit survey, founders indicated if they planned to get further advice from any of the 98 other founders outside their randomized partner. Participants were presented with the names of the other founders in attendance and simply clicked on the name if they "got advice from and planned to meet up with [NAME OF FOUNDER]". Given social events, breaks and the bus rides to and from the campus, a given participant presumably acquainted herself with a significant proportion of her fellow participants. This network formation data allow us to test if founders seek out new advice partners who could hypothetically improve their management practices and firm outcomes. In combination with the within-partner results, these data allow us to understand how the endogenous network formation and relationship self-selection process shapes which individuals end up connected to management-intensive partners and which do not, which has potentially significant implications for practice.

Results

Intensive management and growth at the cross-section

Intensive Management and Human Resources: We begin by examining whether our IM index has predictive validity in the cross-section (for similar strategies see Bloom and Van Reenen, 2007; McKenzie and Woodruff, 2016). Specifically, we estimate models regressing employee growth, hiring, firing and quitting on a founder's own pre-treatment IM-index. These estimates, though not statistically causal, shed light on whether the index is capturing the underlying construct of interest—a managerial style reflective of more frequent activities aimed at utilizing the human capital within a firm more effectively with the goal of improving performance.

Table 5 presents the cross-sectional results. All models control for the total number of employees and use robust standard errors. In model 1, we find that a one standard-deviation increase in the focal founder's IM-index is related to a 16% increase in hires over the past year ($p = 0.04$). We further tested a non-linear specification with a quadratic IM-index variable, and we find no evidence of any such effect. This observation suggests unproductive "micro-management," with firm performance declining at very high levels of IM, is not an issue our sample. In model 2, we find that a one standard-deviation increase in the IM index is related to a 12% increase in firing employees ($p = 0.03$). However, in model 3, we do not find evidence for any change in the likelihood of employees quitting, either positive or negative, as a function of a founder's level of IM ($p = 0.26$). In aggregate, as can be seen in model 4, we find a 26% growth rate for firms whose managers have more intensive management styles ($p = 0.06$).

Together these results support the idea that managers who prioritize tasks related to meeting with employees, providing feedback, and aligning employees' goals with firm goals, have different firm-level outcomes related to human resource management. The only result inconsistent with our theory is the null effect on employee retention; both high and low IM-index founders appear to have similar levels of employees leaving voluntarily. We surmise this effect might be due to low-IM firms being smaller (as in Model 3), and thus having much less scope for losing employees than the larger firms. Under this scenario, high-IM firms also do not lose employees, not because of size, but rather better management of the team.

Intensive Management and Perceived Strengths and Weaknesses of the Firm: We next examine whether high-IM founders perceive their firms to have more strengths and fewer weaknesses than low-IM founders. Models 5 and 6 regress firm-level strength and weakness scores on the founder's IM index. We find a positive and significant relationship between IM index and self-reported strengths ($p = 0.05$). Although we find a slight negative coefficient in the weaknesses regression score, it is not statistically significant. This result may merely be due to explicit weaknesses being socially undesirable to state, and thus weakness more likely being reflected as the absence of a strength, as would be captured already by Model 5.

Nonetheless, the general pattern of the cross-sectional results supports our claim that more intensive management styles of founders affect firm performance, primarily through the management of human resources. Further, founders who devote more time to such people-management activities perceive their firms to be stronger on more dimensions than those with weaker people-management.

Peer effects on firm growth

We now turn to our key claim—that the IM style can be learned and that it will influence firm performance. We regress the focal founder's personnel changes and business outcomes eight months after the retreat on the IM index of that founder's randomly assigned peer. To test our baseline peer effect, we construct a two-period panel data set and include firm-fixed effects (De Mel, McKenzie and Woodruff, 2008). We observe each firm's employee and growth figures twice in our sample (e.g., pre- and post-retreat). We then include a dummy variable for the post-retreat period and include our peer treatment (the IM index of each founder's randomized peer) as an interaction with the post-treatment-period dummy variable. Standard errors are cluster-corrected at the pair level. The firm-level fixed effect and the random assignments provide a highly demanding specification and rule out the possibility that our estimates are artificial and due to unobserved heterogeneity in the focal firm or founder's characteristics.

The baseline results are presented in Table 6. In models 1 and 2, we find no evidence that interacting with a high-IM peer increases hiring or firing. However, we do see evidence of a decline in quit rates for firms whose founders interacted with a high-IM peer. The effect size is substantial, with a one standard-deviation increase in the IM index of a peer resulting in a 20% decline in voluntary turnover ($p = 0.02$). Given that the mean (median) firm has 12.6 (9) employees, this effects is roughly equivalent to the retention of roughly person. Relatedly, we find that being paired with a high-IM peer also modestly reduces the likelihood that a firm shuts down after the retreat ($p = 0.08$).

Given our sample size of 100 firms, it is worthwhile exploring whether our study has sufficient power to justify the effect sizes we find. While our sample compares favorably to other influential field experiments with firms, three specific elements of our design also increase our statistical power. First, our sample is homogeneous in terms of size, stage, and industry. This feature minimizes power loss due to idiosyncratic industry or temporal shocks (Bloom et al., 2013). Second, by measuring personnel changes before and after the retreat, we can include fixed-effects for both time-invariant firm-level differences as well as between-firm period effects. Third, the random pairing of founders eliminates both selection bias and reduces intra-cluster correlation between founders, thereby increasing power. To better quantify our power, we perform ex-post power calculations to test if our design can detect effects of the size reported in Table 6. Results from the simulation indicate that our design detects effects at the 10% level 75% of the time and at the 5% level, 65 percent of the time.[8]

Returning to our findings, the striking differences in how a founder's own IM index (in Table 5) affects her own firm and how a peer's IM index affects her firm (in Table 6) raises a question about what exactly is being transmitted through the social interaction. One possible explanation is partial implementation of IM practices. On one hand, a high-IM founder should have both the knowledge and the experience to implement associated practices in her firm. As a result, she should experience a wide range of benefits associated with IM. On the other hand, a founder who has little previous knowledge of IM may be more constrained in how much she

[8] Specifically, we assumed an effect of 0.2 on the peer IM-score, that firm-level errors were distributed with standard deviation 0.4 (half the amount of the population log(quit) standard deviation), and pair-level errors with a standard deviation of 0.2. We then simulated outcomes 1,000 times and fit the same model as reported in Table 6 to each of these simulated datasets. Our power calculations are robust to relaxing these assumptions.

can learn and implement.

Consider the following scenario: a modal founder with a moderate IM index may have to resolve issues in her current team before she can hire new people. If the firm is at risk of failure, hiring might not be a priority, but keeping her employees from leaving is. As a result, in the eight month window we observed, we may observe the effects of learning IM on keeping the firm afloat via retention as opposed to expansion and hiring. Relatedly, though a founder may be aware of under-performing employees who might be candidates for termination, she may attempt first to re-assign tasks, mentor such employees, or adjust workflow to avoid bottlenecks. Such internal adjustment may be preferable to firing for some organizations. Firing an employee could reduce morale and cause more disruption, leading to more exits at a beleaguered organization.

These arguments imply that exploring the impact of the focal founder's own IM index would be informative. To further validate the partial-implementation mechanism posed above, we test whether peer effects are substantively different when the focal founder has a high-IM index herself. Table 7 presents these results. When we interact a focal founder's IM index with her peer's IM index, we find some evidence for a positive and significant interaction between the two. A founder with an IM score of 1 hires 28% more people ($p = 0.01$) when paired with another high-IM founder, and her firm experiences 20% more employment growth post-retreat ($p = 0.07$), than a founder with an IM score at the mean (i.e. IM=0). Further, consistent with our argument about a moderate-IM index founder struggling to survive, we find that in addition to a lower number of quits for these kinds of founders, they also have firing levels that are about 15% lower ($p = 0.08$).

However, because our IM measures are continuous and centered at 0, the estimates in Table 7 only capture the estimated interaction effect *relative to a founder and peer at the mean of the distribution* and so may be misleading when considering low (high) IM $\times$ low (high) IM interactions. While adding a positive number to recenter our index to be strictly above 0 can be helpful, it comes at the cost of making the main effect coefficients hard to interpret[9]. Thus, to better understand how the IM peer effect varies with the founder's IM index at the tails of the distribution, in Table 8 we bin a focal founder and peer's IM scores into terciles (reflecting "low," "medium," and "high" IM scores). We then generate the full set of focal-peer interactions while setting the low IM terciles as the reference group. Consistent with our partial-implementation mechanism, we find that the founders in the top tercile who are paired with a founder in the middle and top terciles experience greater growth and more hiring ($p = 0.04$). That said, the

[9]That said, refitting the models with re-centered fully above-zero measures does not lead to meaningfully different estimates.

binned analysis also reveals the limited sample we have at our disposal, as the main effects for firing and hiring cannot be detected at each tercile level independently. Thus, given that our binned analysis is largely consistent with our continuous interaction analysis, throughout the rest of the paper we focus on the continuous-continuous interaction terms.

As a final robustness check, we test if the impact of peer IM is robust to the inclusion of related, but distinct, peer characteristics. In Table 9 we include the peer's lagged dependent variable (i.e. the pre-retreat measure), the peer's MBA indicator, and an indicator for whether the peer is an older founder (above the median age of 36). We also include the focal founder's measures as well. The IM results in Table 9 are, if anything, stronger than the estimates without these controls. We find that being paired with a peer with a 1 SD higher IM score decreases the number of employees who quit by 20% ($p = 0.01$) and the number fired by 21% ($p = 0.02$). Consistent with Tables 7 and 8 we find that a 1 SD increase in IM for both the focal and peer founder increases the growth rate and number of hires increases by 25% and 30%, respectively ($p = 0.01$). Intriguingly, we find that founder's with an MBA appear to run companies that hire more and have higher growth rates, though this effect does not appear to transfer through peer interaction. Age does not appear to have any impact on personnel growth either directly or through a founder's peer. The only lagged peer dependent variable that is significant is firing, indicating that perhaps peers who have fired help a focal founder come to terms with how to best let employees go. On the whole, the estimates in Table 9 provide evidence for the argument that founders learn about management from their high IM peers and alleviate concerns that the estimated effects are merely capturing the transfer of other types of generalized knowledge.

The results in Tables 5, 6, 7, 8, and 9 suggest IM affects firm outcomes—primarily through the retention, strategic management and hiring of talent. In terms of learning and implementing the IM style, we find differential results based on the IM index of the focal founder. Low-IM founders who have smaller firms to begin with, such that when they learn from high-IM peers, the effect is to focus on stabilizing the firm before expanding. Conversely, high-IM founders may have the foundation in place to apply this new management knowledge directly to growing their business.

What are founders learning from peers?

Having established that peers' management styles affect firm outcomes, we seek a deeper understanding of *what* is being learned. To further test our hypothesized management channel, we focus on the post-event "checklist" founders developed immediately after interactions with their randomized peers at the conclusion of the retreat. A perennial question in the peer effects literature is whether an individual, through social interaction, is (a) acquiring concrete knowledge, which she then implements, or (b) being inspired by a role model to pursue some particular end (Zuckerman and Sgourev, 2006; Hasan and Bagde, 2013). That is, are individuals learning *means* or are they redefining their *ends*? We focus on two elements of the checklist to attempt to tease out the nature of what is being learned. If founders are learning the means to more effectively manage their teams, we should see changes in *how* they manage tasks within their startup. If founders are inspired to change their ends (e.g., develop greater ambitions related to their firm), then we should observe changes in founders' expectations about the consequences of particular actions.

To test our *means* mechanism, we begin by examining whether the peer's IM index affects if a founder develops a checklist that involves hiring, management and delegation. We model these data at the founder-checklist-item level, giving us 672 observations. We cluster standard errors at the founder and randomized-pair level to account for non-independence. Table 10 presents these results. We find that founders paired with high-IM peers appear to have more management-focused checklists, with particular emphasis on delegating tasks more (rather than doing it themselves). Working with a partner with a one standard deviation higher IM score increases the chance a strategic item involves delegated by 11% ($p = 0.01$). Though we do not find such pairings significantly change a founder's likelihood of focusing on hiring or team-building specifically, we do see that founders who themselves are high-IM do indeed focus more on these more "managerial" dimensions. This pattern of results suggests that the focal manager is learning to delegate more. This greater focus should translate into more clearly defined tasks for current team members and also create a greater impetus for hiring in the future.

Finally, as a robustness check, we test if our treatment changed the "ends" sought out by an entrepreneur. We test if each founder generated more ambitious checklist items when partnered with a peer with a high IM index. Table 11 finds at best weak evidence for the ambition causal pathway. The bulk of our evidence suggests that founders are learning the "means"—practices related to an IM style—that alter how a founder *manages* her team as opposed to developing new ideas about the "ends".

Follow-up intentions with randomized partner

Moving beyond the specific interactions facilitated at the event, we also wanted to examine what implications our findings might have in more general networking contexts (e.g., not engineered through an intervention). Here, we focus on (1) the extent to which a founder was more likely to *want* to follow up with her peer if that peer was high-IM, (2) the extent to which the founder *actually* followed up with that peer post-retreat, and (3) whether high-IM founders at the retreat were more sought out for follow-ups by *anyone* at the retreat, for example, in recognition of their managerial skill.

We begin in Table 12 by testing whether a focal founder expressed interest in receiving additional advice from her peer post-retreat. Model 1 uses an ordered logit to regress this intention on the IM-index of a founder's randomly assigned peer. We find some evidence of such a preference ($p = 0.05$). However, the interaction between the focal founder's IM index and her peer's is negative. This negative effect is simple to interpret because it appears to eliminate the positive preference for following up with a peer who has a high-IM index. Thus, our findings suggest that low-IM Index founders have a preference to follow up with high-IM founders, but other founders do not appear to have similar preferences.

However, when examining the *actual* post-event follow-up, we see a substantial 35% increase in the probability of following up with a high-IM peer ($p = 0.04$). Indeed, this result holds for both founders with low, moderate, and high IM indexes. Even in such a short interaction, individuals appear to recognize who might have useful management knowledge and do indeed follow up with them at higher rates, suggesting networks might endogenously allow for more productive management styles to diffuse.

Follow-up intentions with non-partners at bootcamp

The tests in Table 12 highlight the propensity of the focal founder to continue to seek advice from high-IM peers vs. low-IM peers, suggesting that they recognize this as a valuable peer trait. However, in most contexts, people must search for possible advice givers among potentially dozens or hundreds of possible alters. In such a situation, it is unclear whether individuals who have high IM indexes would be significantly more sought out than those who do not, because their knowledge may be difficult to observe. On the other hand, if such individuals were also charismatic and thus observably different from their peers who had a lower IM index, we may still see a correlation between a high IM index and follow-up intentions beyond a randomized pair.

We test for this possibility in Table 13. We estimate dyadic models (excluding the randomized pair) with each observation representing a potential relationship between one founder (referred to as ego) and one of the other 98 founders in our sample (referred to as alter). This approach gives us 9,800 directed relationships where an ego founder indicates if she wants to meet with and get additional advice from an alter founder in the future. To account for the non-independence that is present in network data, we robustly cluster at the ego, alter, and ego-alter levels (Cameron, Gelbach and Miller, 2011). Model 1 presents results from a logistic regression testing if an ego and alter's IM indexes affect the likelihood of intended follow-up. None of the coefficients are significant and the point estimates are near zero. These estimates suggest search frictions are present in finding and seeking advice from the more able managers—even in a small hundred-person group.

Models 2 and 3 test whether other factors explain who intends to follow up with whom after the retreat, controlling for the existence of a prior relationship. Results strongly indicate that founders from the same metro region (e.g., Bangalore, Mumbai, Delhi/NCR) are more likely to say they are going to follow up with each other ($p = 0.01$). Further, we find evidence that founders who themselves are older are more likely to follow up with each other, but that younger founders prefer to get advice from one another. This pattern of results may indicate that founders who are more advanced in their careers may expect that they have more in common and perhaps can learn more from each other. Finally, because these results are intuitive, they also provide some confidence that our follow-up intentions measure is capturing the construct of interest.

Taken together, our results suggest that although a founder can recognize *after* a sustained interaction that her peer has relevant and useful knowledge, she has difficulty figuring out who has that knowledge *a priori*. From a methodological perspective, Tables 12 and 13 highlight an important nuance about the nature of selection bias in observational peer effects studies. While, there does not appear to be selection on the IM-index in the larger group, there is indeed *significant* selection effect in the retention of high-IM peers after a pairing has been made. Together, these results highlight the fact that selection bias in peer effects may be the result of differential rates of tie decay rather than differences in who forms ties with whom. As a consequence, analyzing peer effects using only the realized post-retreat network would upwardly bias estimates since ties to low IM partners are more likely to dissolve.

Our results suggest that analysts should consider selection effects at both the initial network formation stage as well as dissolution stage. From a policy perspective, these tables imply that there may be significant potential for entrepreneurial ecosystems to more effectively leverage networks, possibly to facilitate more significant interaction as opposed to the frequent approach of "speed-dating" or networking "happy hours", which might preclude informed assessments about the utility of a given peer. Further, our evidence for selection at the *retention* stage suggests that if there were "mistakes" in the initial pairing, self-selection of ties to high-IM peers may be a valuable corrective.

Conclusion

An influential body of research has advanced the argument that strategic management can explain differences in performance across firms (Wernerfelt, 1984; Barney, 1991; Teece et al., 1997; Teece, 2007). However, we know less about the role of management in new firms and the extent to which management practices can be learned by entrepreneurs. We leverage prior work on social networks as conduits of knowledge to understand whether management practices can spill over between founders and influence firm performance. We focus on one kind of management, an intensive management style, which prioritizes a higher frequency of interactions with one's employees, the provision of feedback, and the alignment of employee goals with firm goals. We propose that if management knowledge can be diffused via networks, founders can learn intensive management from their peers and will be more effective at managing and growing their teams.

Our findings from a novel randomized experiment consisting of 100 high-technology firms in India support the idea that management can be learned and can impact performance, but not without significant contingencies. Founders in our sample learned IM through network ties, and this learning translated into differences in firm performance, specifically in talent management and employee growth. The actual pattern of our results are much more nuanced than we had expected, and suggests social interactions may not lead to one-to-one correspondence in the performance of a peer's firm and that of a focal founder. For the modal founder (e.g., those with moderate levels of attention to people-management), peer interaction (with a high-IM peer) primarily affects the internal management of a team, substantially reducing quit rates and the likelihood of closing the firm. Founders with preexisting tendencies towards intensive management appear to also hire more and thus their organizations grow larger. This pattern of results suggests that the learning and implementation of management practices depends on the existing level of management within a firm.

Besides the first-order peer effects on firm performance, additional analyses also shed light on the important mechanisms. We find that founders paired with high-IM peers are more keen to delegate tasks to employees, suggesting an enhanced focus on more effectively utilizing human resources. Further, we find evidence that high-IM peers are more sought after post-retreat by their partners, but not necessarily by the larger group of attendees. This latter result suggests short interactions are not always informative about an individual's value as a peer or mentor. Sustained interaction appears to be a far more useful instrument to reveal which individuals are worth keeping in touch with. Thus, a high-IM style might not necessarily have observable markers—such as charisma—that lead to networks coalescing around these more able managers and founders.

Our study contributes to the academic literature in several ways. First, our results show promising evidence that one mechanism—peer learning—can be a conduit through which young entrepreneurial firms can acquire effective management styles and practices, all else being equal. But management spillovers are likely to flow slowly and imperfectly. We posit that management practices are largely tacit and the diffusion requires a base level of understanding and the will to implement new processes. Coupled with the results above regarding follow-up intentions, we should not expect networks to naturally equilibrate to configurations in which the best managers are disseminating their advice more widely. Search frictions exist, preventing even individuals in small groups from determining whom they solicit advice. If particularly effective management styles do diffuse, the process will happen unevenly and slowly.

Second, in recent years, scholars in management and strategy have worked to strengthen the empirical identification of important phenomena in organizations; however, much of this work is observational (Stuart, Hoang and Hybels, 1999) or at the individual level (Hasan and Bagde, 2015). Our work provides a rare field experiment that studies *real* firms and the consequence of actual social interactions on their future performance. Our methodological contribution is similar to recent working papers by Cai and Szeidl (2016) and Fafchamps and Quinn (2015). However, unlike Fafchamps and Quinn (2015), we do find spillovers across firms in performance. Unlike Cai and Szeidl (2016), we focus on high-technology firms, which rely on knowledge-intensive human capital, rather than small-scale manufacturing or retail. Thus, we see our study as providing some of the first field experimental evidence for inter-firm spillovers between entrepreneurs and thus opening up opportunities for future research.

From a practical perspective, our results suggest that peer learning might be fruitfully leveraged to increase employee growth, but not without a deeper understanding of selection processes. On one hand, our findings imply that entrepreneurs do not naturally match with the most useful peers. Thus, merely encouraging networking among entrepreneurs might yield only marginal results. That is, if entrepreneurs cannot endogenously find and seek advice from peers with higher management skill, then the diffusion of high-growth management practices might be slow or uneven. The latter indicates at least some degree of inefficiency—e.g., why doesn't everyone want advice from a high-IM peer if they are so useful? However, if ecosystems can make it easier to find and highlight managers with useful knowledge, one-to-one learning could be leveraged to disseminate knowledge more effectively. How do ecosystems find such managers? Our results indicate it may be useful to ask people who they want to *continue getting advice from* amongst their current peers rather than who they would *want to get advice from in the ecosystem in general.*

Relatedly, our current empirical strategy was to compare the outcomes of entrepreneurs learning from peers with different levels of intensive management. Future theoretical work could also contrast the impact of peer learning and mentoring, for example, with more general training and consulting help. Assessing the benefits from different kinds of interventions against the costs would also be important, with the aim of developing insights for policymakers seeking the best approach to promote the management quality and performance of small firms.

Our results also provide insight into whether management matters for small firms, given that practitioners often encourage these organizations to focus narrowly on attributes of the product market (e.g., Ries, 2011). Both our cross-sectional and peer effects results categorically support the idea that management is a fundamental input for these firms, shaping whether new employees can be hired, the retention of existing employees, and the ability to maintain team cohesion and performance. Though beyond the scope of the present study, our results suggest that lack of managerial ability may be one reason why the preponderance of new ventures fail to create new jobs for anyone beyond the founder (Astebro and Tåg, 2017).

From the perspective of a founder or manager, the results of our study imply two considerations. First, we find a first-order effect of intensive management on firm outcomes. Because many young companies face both technological and market risks, founders may prioritize dealing with these challenges rather than the more mundane aspects of human resource management. Our findings suggests that *ceteris paribus* more intensive people-management is a worthwhile investment of a founder's time. Second, founders who may lack experience in these practices should seek out peers who can share know-how and advice. Our results underline, however, that the most visible peers or mentors might not be the most appropriate ones to learn from. Founders should attempt to learn *what* a peer does, not just *who* she is.

Our work has several important limitations as well. First, our results come from a sample of firms in a specific industry, at a specific point in their life, and from a specific country. These factors all clearly reduce the generalizability of our results. Although we are comforted by some importance consistencies between our findings and prior work, particularly related to our cross-sectional results, more research in different contexts should be conducted.

A second limitation is that because of data limitations, we cannot shed further light on the mechanisms underlying our effects. Although we are confident our effects represent the causal effect of peers on firm outcomes, we cannot be absolutely certain this effect is due to learning of "the means", the reorienting of "the ends", or whether more complex psychological reasons exist for why a founder was affected more by a high-IM peer than a low-IM one. Exploring these specific mechanisms would be excellent directions for future research. However, our results provide some suggestive insights. The checklist items for those who interacted with high-IM peers are more focused on management, but are not necessarily more ambitious. This finding suggests our intervention influenced more of the "means" as opposed to the "ends". Further, we find our strongest effects when the focal manager is herself an intensive manager. This pattern implies the information peers are passing between each other is less focused on new information (which would presumably benefit less intensive managers the most) and more focused on particular management practices, which is broadly consistent with the checklist results.

In addition, we have 100 firms in our sample, a sample size that is comparable to other recent field experiments in management and strategy and represents a significant share of the relevant population of firms we seek to study (i.e., early-stage Indian technology startups). However, the sample size is not sufficient to tease out further heterogeneous effects of our intervention. The process of learning across firms is much more nuanced than we can accommodate here, and a larger sample might allow us to further understand who learns what from whom. For example, the value of management knowledge could be contingent on attributes of the firm, such that management can be learned but not always applied in every instance. Nevertheless, our present results do indicate that not all founders or firms benefit in the same way from comparably intensive (or "hands-on" peers).

Finally, our treatments were one-to-one, whereby one founder learns from one peer. However, one peer is unlikely to possess all the relevant knowledge that a founder needs, and future research should investigate the sets of knowledge that can be accumulated through a collection of peers, perhaps with non-overlapping expertise, such as that proposed by the work of Burt (1992). In sum, our study provides some of the first causal evidence that management can be learned via networks, despite some important limitations. We hope this endeavor provides guidance for future research on this topic to better understand the utility of networks to improve the performance of organizations.

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Table 1: Description of our measures

Variable Name	**Data source**	**When**	**Description**
IM-Index	Pre-retreat survey	Q4 2015	Index from time-use survey questions
Startup Age	Pre-retreat survey	Q4 2015	Years since founding
Person Age	Pre-retreat survey	Q4 2015	Age of founder in years
Strengths	Pre-retreat survey	Q4 2015	Sum of self reported strengths in 9 categories*
Weaknesses	Pre-retreat survey	Q4 2015	Sum of self reported weaknesses in 9 categories*
Employees (pre-retreat)	Pre-retreat survey	Q4 2015	Number of employees at time of retreat
Hired (pre-retreat)	Pre-retreat survey	Q4 2015	Number of employees hired in year before retreat
Fired (pre-retreat)	Pre-retreat survey	Q4 2015	Number of employees hired in year before retreat
Quit (pre-retreat)	Pre-retreat survey	Q4 2015	Number of employees hired in year before retreat
Percentage Growth (pre-retreat)	Pre-retreat survey	Q4 2015	Annual employee growth percentage in the last year
Same Region?	Pre-retreat survey	Q4 2015	Do the founders work in the same metropolitan region?
Ego knows Alter pre-retreat?	Pre-retreat survey	Q4 2015	Did the founders already know one another before the retreat?
Will Delegate?	Strategic checklist	Q1 2016	Did the checklist item involve delegation?
Hiring and team Building	Strategic checklist	Q1 2016	Did the checklist item involve hiring and team building?
Operations and Management	Strategic checklist	Q1 2016	Did the checklist item involve operations and management?
Combined Management Focus	Strategic checklist	Q1 2016	Sum of the three management-focused checklist items
Revenue Growth Potential	Strategic checklist	Q1 2016	Estimated revenue impact of completing the item
User Growth Potential	Strategic checklist	Q1 2016	Estimated user impact of completing the item
Combined Growth Potential	Strategic checklist	Q1 2016	Sum of the two growth potential measures
Advice from partner?	Retreat Survey	Q1 2016	Is the founder interested in getting more advice?
Interacted Post-retreat?	Post-retreat survey	Q3 2016	Interacted (phone, Internet, in person) after the retreat?
Employees (post-retreat)	Post-retreat survey	Q3 2016	Number of employees at time of survey
Hired (post-retreat)	Post-retreat survey	Q3 2016	Number of employees hired since the retreat
Fired (post-retreat)	Post-retreat survey	Q3 2016	Number of employees hired since the retreat
Quit (post-retreat)	Post-retreat survey	Q3 2016	Number of employees hired since the retreat
Percentage Growth (post-retreat)	Post-retreat survey	Q3 2016	Annualized employee growth percentage since retreat
Shutdown?	Post-retreat survey	Q3 2016	Has the company shutdown since the retreat?

*Categories include Management, Sales, Mentorship, Execution, Foreign, Capital, and Hiring.

Table 2: How often do founders engage in formal people-management tasks?

	IM-Index	Median Frequency	Sets Shared Goals	Conducts Reviews	Provides Feedback	Provides Targets
1	-1.56	Never-Yearly	Never	Yearly	Weekly	Never
2	-0.92	Yearly-Monthly	Yearly	Monthly	Weekly	Never
3	-0.6	Monthly	Monthly	Monthly	Yearly	Monthly
4	0.04	Monthly-Weekly	Weekly	Daily	Monthly	Never
5	0.68	Weekly	Weekly	Monthly	Weekly	Weekly
6	1.32	Weekly	Weekly	Weekly	Daily	Weekly
7	1.64	Weekly-Daily	Daily	Weekly	Weekly	Daily

Data from 7 founders representing the span of our intensive-management index.

Table 3: Startup growth summary statistics.

	min	median	max	mean	sd	N
Employees	1	9	55	12.62	10.83	100
Company Age	0.44	2.78	17.04	3.46	2.77	100
Founder Age	23	36	66	36.84	7.79	100
Hired (pre-retreat)	0	4.5	35	5.93	6.67	100
Fired (pre-retreat)	0	1	70	3.18	8.75	100
Quit (pre-retreat)	0	1	23	2.43	3.72	100
Percentage Growth (pre-retreat)	-0.43	0.13	4.92	0.51	1.24	100
Hired (post-retreat)	0	5.5	66.01	7.89	11.05	90
Fired (post-retreat)	0	0	19.84	2.5	3.92	90
Quit (post-retreat)	0	1.96	28.22	3.01	4.44	90
Percentage Growth (post-retreat)	-2.64	0	2.36	0.22	0.99	90

Hired, fired, quit, and percentage change pre-retreat are for the prior year.
Hired, fired, quit, and percentage change post-retreat are annually adjusted.

Table 4: Balance tests indicate founder characteristics are uncorrelated with their randomly assigned partner.

	Focal founder's characterstics			
	IM-Index	Log(Employees)	Startup Age	Person Age
	(1)	(2)	(3)	(4)
IM-Index (Peer)	−0.062	0.059	0.152	0.243
	(0.148)	(0.059)	(0.220)	(0.763)
Constant	−0.000	2.344	3.456	36.840
	(0.102)	(0.067)	(0.278)	(0.889)
Observations	100	100	100	100
R^2	−0.006	−0.004	−0.007	−0.009

Robust SEs clustered at the randomized pair level.

Table 5: Intensive management is positively correlated with pre-retreat startup employment growth.

	Dependent variable:					
	log(Hired)	log(Fired)	log(Quit)	Percent Change	Strengths	Weaknesses
	(1)	(2)	(3)	(4)	(5)	(6)
IM-Index	0.163	0.124	0.053	0.258	0.180	−0.018
	(0.080)	(0.057)	(0.047)	(0.139)	(0.090)	(0.149)
log(Employees)	0.236	0.632	0.568	−0.716	−0.010	0.023
	(0.088)	(0.108)	(0.073)	(0.153)	(0.132)	(0.145)
Constant	1.073	−0.509	−0.348	2.083	2.260	2.511
	(0.198)	(0.200)	(0.136)	(0.415)	(0.316)	(0.353)
Observations	100	100	100	100	98	98
R^2	0.110	0.464	0.443	0.286	0.032	0.0004

OLS regressions with robust SEs in parentheses. log(x) = ln(x+1).
Hired, fired, and quit are counts over the past year.
Percent Change is winsorized at the 5% level.
Strengths and weaknesses are the sum over the following self-reported binary categories:
User Growth, Management, Sales, Mentorship, Execution, Foreign, Capital, and Hiring
Two participants did not complete the strengths and weaknesses assesments.

Table 6: Founders who are randomly paired with a partner who has a higher IM score experience less turnover after the retreat and their startups are somewhat less likely to fail.

	(1)	(2)	(3)	(4)	(5)
	Percent Change	log(Hires)	log(Fired)	log(Quit)	Shutdown
Post Retreat	-0.322	-0.0436	-0.111	0.0480	
	(0.137)	(0.130)	(0.111)	(0.111)	
Post Retreat X IM-Index (Peer)	0.0319	0.0591	-0.0756	-0.194	-0.799
	(0.164)	(0.107)	(0.147)	(0.0846)	(0.458)
Constant	0.546	1.585	0.885	0.894	-2.754
	(0.0684)	(0.0651)	(0.0556)	(0.0553)	(0.503)
Period Fixed Effects	Yes	Yes	Yes	Yes	No
N	180	180	180	180	90

Standard errors in parentheses.
Regressions with robust SEs clustered at the pair level in parenthesis. log(x) = ln(x+1).
Hired, fired, and quit count dependent variables are adjusted to expected year counts.
Percent Change is winsorized at the 5% level.
Shutdown includes distress sale (1 company) or disbanded (6 companies).
We were able to follow up with 90 of the 100 startups in our sample.

Table 7: Founders with higher IM score respond to high IM peers more. Not only do they retain talent at higher rates; they also appear to hire more and experience greater team growth.

	Dependent variable:			
	Percent Change	log(Hired)	log(Fired)	log(Quit)
	(1)	(2)	(3)	(4)
IM Index	−0.065	0.197	0.167	0.112
	(0.131)	(0.136)	(0.090)	(0.089)
IM Index (Peer)	0.059	0.017	−0.158	−0.211
	(0.132)	(0.132)	(0.089)	(0.090)
IM Index X IM Index (Peer)	0.203	0.275	−0.031	−0.003
	(0.111)	(0.112)	(0.081)	(0.071)
Constant	0.245	1.577	0.774	0.944
	(0.095)	(0.123)	(0.102)	(0.113)
Observations	90	90	90	90
R^2	0.057	0.082	0.070	0.072

Regressions with robust SEs clustered at the pair level in parentheses. log(x) = ln(x+1).
Hired, fired, quit, and percentage change are annually adjusted.
Percent Change is winsorized at the 5% level

Table 8: Only founders in the top IM tercile appear to experience hiring and growth rate effects when paired with other high IM founders.

	Dependent variable:			
	Percent Change	log(Hired)	log(Fired)	log(Quit)
	(1)	(2)	(3)	(4)
2nd Tercile IM	−0.267	−0.026	0.124	−0.249
	(0.496)	(0.556)	(0.386)	(0.490)
3rd Tercile IM	−0.945	−0.653	0.391	0.345
	(0.621)	(0.661)	(0.393)	(0.458)
2nd Tercile IM (Peer)	−0.787	−0.452	−0.110	0.218
	(0.420)	(0.520)	(0.413)	(0.504)
3rd Tercile IM (Peer)	−0.612	−0.638	−0.007	−0.450
	(0.527)	(0.538)	(0.458)	(0.479)
2nd Tercile IM X 2nd Tercile IM (Peer)	0.489	−0.354	−0.361	−0.579
	(0.536)	(0.654)	(0.558)	(0.699)
2nd Tercile IM X 3rd Tercile IM (Peer)	0.410	0.072	−0.393	0.135
	(0.639)	(0.799)	(0.604)	(0.629)
3rd Tercile IM X 2nd Tercile IM (Peer)	1.485	1.201	0.007	−0.766
	(0.760)	(0.866)	(0.604)	(0.625)
3rd Tercile IM X 3rd Tercile IM (Peer)	1.315	1.646	−0.212	0.082
	(0.647)	(0.752)	(0.606)	(0.612)
Constant	0.686	1.815	0.744	1.094
	(0.374)	(0.448)	(0.240)	(0.395)
Observations	90	90	90	90
R^2	0.080	0.109	0.056	0.112

Regressions with robust SEs clustered at the pair level in parenthesis. log(x) = ln(x+1).
Hired, fired, quit, and percentage change are annually adjusted.
Percent Change is winsorized at the 5 percent level

Table 9: Both the primary peer IM effects, and the interactions with a founder's own IM score, are robust to the inclusion of alternative peer spillover channels.

	Dependent variable:			
	Percent Change	log(Hired)	log(Fired)	log(Quit)
	(1)	(2)	(3)	(4)
IM Index	−0.132	0.070	0.158	0.049
	(0.117)	(0.104)	(0.079)	(0.082)
IM Index (Peer)	0.010	0.030	−0.212	−0.203
	(0.118)	(0.111)	(0.091)	(0.081)
IM Index X IM Index (Peer)	0.252	0.303	−0.018	−0.057
	(0.091)	(0.102)	(0.068)	(0.093)
Lagged D.V.	0.134	0.400	0.122	0.479
	(0.097)	(0.131)	(0.124)	(0.146)
Lagged D.V. (Peer)	0.086	−0.115	0.319	0.083
	(0.076)	(0.118)	(0.140)	(0.129)
Older Founder	−0.525	−0.509	−0.080	−0.041
	(0.228)	(0.210)	(0.220)	(0.190)
MBA	0.642	0.702	0.075	−0.070
	(0.208)	(0.266)	(0.228)	(0.209)
Older Founder (Peer)	−0.155	−0.314	−0.297	0.008
	(0.232)	(0.212)	(0.191)	(0.185)
MBA (Peer)	−0.162	−0.442	−0.072	−0.294
	(0.198)	(0.255)	(0.216)	(0.194)
Constant	0.364	1.490	0.585	0.547
	(0.161)	(0.321)	(0.205)	(0.289)
Observations	90	90	90	90
R^2	0.256	0.391	0.168	0.239

Regressions with robust SEs clustered at the pair level in parenthesis. log(x) = ln(x+1).
Older founder indicates founder above median age of 36
Hired, fired, quit, and percentage change are annually adjusted.
Percent Change is winsorized at the 5 percent level

Table 10: Founders are more likely to generate management-focused checklist items when paired with a partner who has a higher IM score.

	Dependent variable:			
	Will Delegate	Hiring and Team Building	Operations and Management	Combined Management Focus
	(1)	(2)	(3)	(4)
IM Index	0.124	0.353	0.349	0.330
	(0.077)	(0.189)	(0.153)	(0.096)
IM Index (Peer)	0.201	0.177	−0.001	0.211
	(0.070)	(0.129)	(0.137)	(0.084)
IM Index X IM Index (Peer)	−0.038	0.147	0.257	0.138^{*}
	(0.056)	(0.111)	(0.102)	(0.071)
Constant	−0.137	−1.857	−1.271	
	(0.061)	(0.134)	(0.134)	
Observations	672	672	672	672

Regressions at the checklist-item level.
Models 1-3 logistic regression. Model 4 ordered logit.
Robust SEs clustered at the ego and pair level.

Table 11: Founders are only weakly more likely to generate higher growth-potential checklist items when partnered with a high IM manager .

	Dependent variable:		
	Revenue Growth Potential	User Growth Potential	Combined Growth Potential
	(1)	(2)	(3)
IM-Index	0.160	0.030	0.082
	(0.113)	(0.126)	(0.114)
IM Index (Peer)	0.157	0.199	0.188
	(0.104)	(0.117)	(0.114)
IM Index X IM Index (Peer)	−0.054	−0.005	−0.025
	(0.121)	(0.140)	(0.134)
Observations	637	637	637

Regressions at the checklist-item level.
Ordered logistic regressions.
For 35 of the 672 items, a founder did not indicate growth potential.
Robust SEs clustered at the ego and pair level.

Table 12: Founders want to get additional advice from their randomized partner when the partner has a higher IM score.

	Dependent variable:	
	Interest in getting more advice from partner	Interacted post-retreat?
	(1)	(2)
IM Index	−0.075	0.010
	(0.201)	(0.229)
IM Index (Peer)	0.374	0.501
	(0.192)	(0.247)
IM Index X IM Index (Peer)	−0.352	−0.068
	(0.172)	(0.209)
Constant		−0.677
		(0.252)
Observations	99	90
χ^2 (df = 3)	8.950	4.461

Model 1 is an ordered logit from 1 (Strong Disagree) to 5 (Strong Agree).
Model 2 is standard logistic regression.
Robust SEs clustered at the randomized pair level.

Table 13: Founders search for advice partners on the basis of past relationships, region, and age homophily, but not on do not appear to seek out new relationships on the basis of an alter's IM score.

	Dependent variable:		
	Does ego plan to meet with alter for additional advice?		
	(1)	(2)	(3)
IM Index (Ego)	−0.066	−0.053	−0.051
	(0.114)	(0.122)	(0.122)
IM Index (Alter)	0.041	0.029	0.026
	(0.079)	(0.071)	(0.071)
IM Index (Ego X Alter)	−0.034	−0.051	−0.045
	(0.056)	(0.059)	(0.059)
Ego knows Alter pre-retreat		2.418	2.396
		(0.242)	(0.256)
Ego from same region as Alter		0.553	0.567
		(0.171)	(0.167)
MBA (Ego)			−0.024
			(0.336)
MBA (Alter)			0.078
			(0.209)
MBA (Ego X Alter)			−0.168
			(0.369)
Older Founder (Ego)			−0.343
			(0.297)
Older Founder (Alter)			−0.823
			(0.279)
Older Founder (Ego X Alter)			1.259
			(0.306)
Constant	−3.746	−4.068	−3.859
	(0.136)	(0.142)	(0.224)
Observations	9,800	9,800	9,800
Log Likelihood	−1,078.203	−1,008.808	−997.269

Dyadic logistic regression excluding within-randomized-pair dyads.
Robust SEs clustered at ego, alter, and dyad level.
Older founder indicates if the founder is above the median age of 36.

Figure 1: Example of how the strategic checklist items were tagged and evaluated.

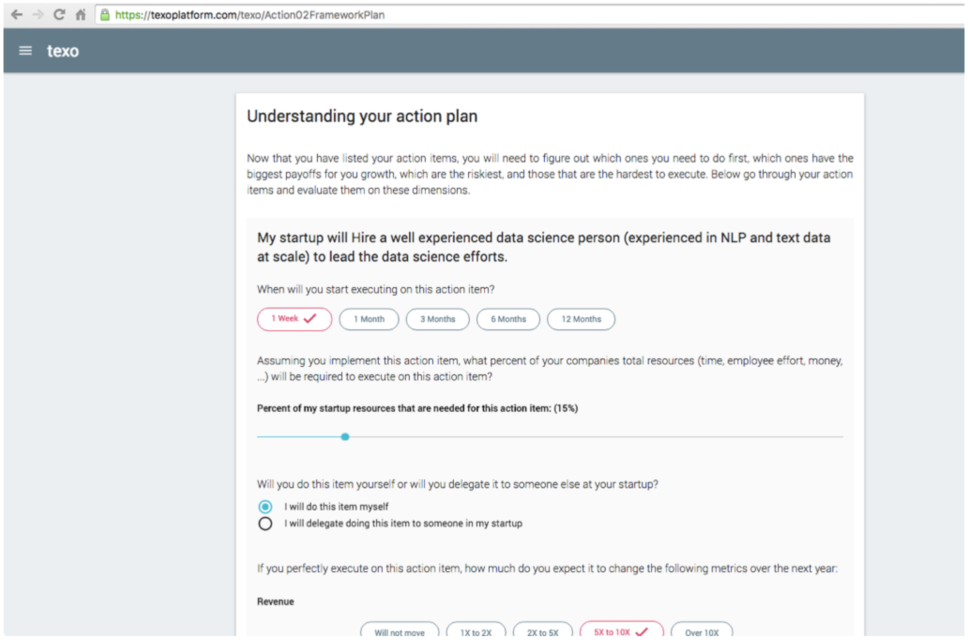

Figure 2: Kernel density plot of our IM Index with bandwidth=0.4