Social Skills Improve Business Performance: Evidence from a Randomized Control Trial with Entrepreneurs in Togo

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Abstract

Recent field experiments demonstrate that advice, mentorship, and feedback from randomly assigned peers improve entrepreneurial performance. These results raise a natural question: what is preventing entrepreneurs and managers from forming these peer connections themselves? We argue that entrepreneurs may be under-networked because they lack the necessary social skills—the ability to communicate effectively and interact collaboratively with new acquaintances—that allow them to match efficiently with knowledgeable peers. We use a field experiment in the context of a business training program in Togo to test if a short social skills training module increases the number and complementarity of peers that participants choose to learn from. We find that social skills training led entrepreneurs to match with 50% more peers and that more of those matches were based on complementary managerial skill. Finally, the training also increased entrepreneurs' monthly profits by approximately 20%. Further analyses point to improvements in networking and advice as the drivers of performance improvements. Our findings suggest that social skills help entrepreneurs build relationships that create value for both themselves and their peers.

Keywords
Social skills, business performance, entrepreneurs, peer relationships, field experiment

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1. Introduction

Strategy and entrepreneurship researchers have long studied differences in firm performance and growth. Recently, these researchers have turned to randomized control trials (RCTs) to rigorously test if different strategies—such as adopting a scientific approach to decision making, making public political statements, or sharing performance information with employees—explain why some businesses succeed while others fail (Blader et al. 2020, Burbano 2020, Camuffo et al. 2020, Chatterji et al. 2016). A recurring theme from many RCTs is that who an entrepreneur talks to about their business matters for what she learns and how well her business does (Eesley and Wu 2019, Hasan and Koning 2019, Iacovone et al. 2021, Quinn and Woodruff 2019, Vega-Redondo et al. 2019). In these field experiments, entrepreneurs who were randomized to have more peers, or peers who were more knowledgeable, performed substantially better than their counterparts, who relied only on their pre-existing relationships.

These field experiments suggest a puzzle. If researchers can exogenously introduce new peer relationships into entrepreneurs' networks, and if the returns to these interventions are significant, why don't entrepreneurs form these relationships themselves? The peer treatments deployed by researchers are simple: bringing entrepreneurs together for dinner (Cai and Szeidl 2018), a daylong work group (Sandvik et al. 2020), a weekend retreat (Chatterji et al. 2019), or even merely revealing how much nearby competitors charge for their services (Kim 2019). All of these interventions are activities entrepreneurs could do for themselves. Yet, despite the significant impact of exogenously assigned peers on entrepreneurs' performance, there is consistent evidence that entrepreneurs fail to form what should be valuable peer relationships (Caria and Fafchamps 2020, Ingram and Morris 2007, Vissa 2012).

We argue that entrepreneurs fail to build valuable peer relationships because they lack the necessary *social skills* to effectively find, connect with, and learn from their peers. We take social skills to be entrepreneurs' ability to reach out to others, communicate effectively, and approach interactions with new acquaintances collaboratively. Such social skills have been found to be valuable in jobs that involve teamwork and high levels of interaction (Argote et al. 2018, Deming 2017, Hoffman and Tadelis 2021), which suggests that they might also help business founders and owners. Despite their value, however, strategy research suggests that there is significant variation among entrepreneurs and managers in their social skills, which tend to be learned experientially (Argote and Fahrenkopf 2016, Blader et al. 2015, Hallen and Eisenhardt 2012, Zander and Kogut 1995).

Here we use a field experiment in Togo to test whether training entrepreneurs in social skills can improve relationship formation and firm performance. We worked with a business training program to develop a two-hour social skills training intervention as part of their two-day marketing training program. Crucially, we randomized which cohorts in the program received the social skills training module and which did not, holding constant the rest of the material taught. This experimental design allowed us to separate the impact of social skills from observed and unobserved differences in entrepreneurs' network composition and business ability. The 301 entrepreneurs who took part in the program were surveyed before the training, at the end of the program, six weeks after, six months after, and a year later.

Results from our analyses show that, even when limited to a brief introduction, teaching social skills leads to a cascade of changes in entrepreneurs' patterns of interaction and the relationships they form with co-participants: conversations are twice as informative, interactions are more collaborative, networks 50% larger, ties are more complementary, and connections more ethnically diverse. Indeed, we find that the treatment leads to aggregate improvements across various dimensions of entrepreneurs' social interactions both with co-participants and others outside the training program.

Alongside these social changes we find that entrepreneurs in the treatment condition were 20% more profitable than those in the control during the year after the program. Using exploratory causal mediation analysis, we show that approximately 85% of this performance effect is mediated by changes in entrepreneurs' social interactions during and after the training program. Our findings suggest that training entrepreneurs in social skills results in more useful social interactions which in turn helps entrepreneurs improve business performance.

Our findings make four primary contributions. First, we contribute to the literature on the social origins of competitive advantage. Prior work in this area has largely focused on structural forms of network advantage—occupying a brokerage position or being connected to a talented peer—that are inherently zero-sum, since only a handful of firms can be brokers or connected to superstars. Here we show that social skills enable entrepreneurs to overcome social barriers and form mutually beneficial matches with peers, which generates value in a positive-sum fashion.

Second, we add to the growing literature in strategy and entrepreneurship that uses field experiments to causally test the value of different managerial choices (Boudreau and Marx 2019, Boudreau and Lakhani 2015, Camuffo et al. 2020, Chatterji and Toffel 2016, Delecourt and Ng 2020, Gallus 2017, Guzman et al. 2020). Past RCTs in strategy have shown that entrepreneurs benefit from interventions that introduce new relationships into their networks, suggesting many entrepreneurs may be under-networked (Chatterji et al. 2019, Vega-Redondo et al. 2019). Rather than randomize ties, our RCT randomized exposure to the skills needed to build those ties.

Third, this study also contributes to the literature on the origins of inter-firm business relationships. Existing research has primarily explained the formation of business relationships and networks using the characteristics of dyads and the pre-existing networks in which they are embedded (McFarland et al. 2014). Here we show that entrepreneurs' social skills influence the kinds of ties and networks that emerge.

Finally, this study also contributes to research on entrepreneur and management training programs in developing economies (Ingram and Morris 2007, McKenzie and Woodruff 2014). A rapidly growing literature on bootcamps, accelerators, and other training programs has found mixed results about their effectiveness, particularly in developing countries (Cohen et al. 2019, McKenzie 2021). Yet management and strategy scholars have contributed relatively little to this discussion (Klüppel et al. 2018). Our findings suggest that variation in the effectiveness of these programs, particularly those set in developing countries, might be related to whether they foster effective socialization and peer learning.

2. Entrepreneur Peer Relationships

Entrepreneurs rely on a variety of relationships to grow their businesses and, among those relationships, peers are particularly influential. They often provide access to resources, information, and knowledge, which help entrepreneurs improve their businesses' performance (Stuart and Sorenson 2007). In particular, peers help entrepreneurs learn about the process of opportunity identification and how to launch a business (Lerner and Malmendier 2013, Nanda and Sørensen 2010, Vega-Redondo et al. 2019). They are sources of valuable information, including client referrals and opportunities for financing (Cai and Szeidl 2018). Their informal advice improves entrepreneurs' management practices (Chatterji et al. 2019) and peers who also happen to be executives can encourage entrepreneurs to adopt innovations (Fafchamps and

Quinn 2018, Giorcelli 2019). Finally, peers motivate business owners to continue improving their businesses in spite of challenging circumstances (Zuckerman and Sgourev 2006).

The strongest evidence about the value of peer relationships has emerged out of field experiments that exogenously introduce peers into entrepreneurs' networks through a variety of mechanisms including assignment to groups, training bootcamps, or mentoring programs (Blattman et al. 2016, Cai and Szeidl 2018, Chatterji et al. 2019, Eesley and Wang 2017, Iacovone et al. 2021). These interventions causally identify the impact of peer relationships on entrepreneurs' business performance (Quinn and Woodruff 2019). Though often overlooked, an important implication of this research is that most entrepreneurs may be under-networked and so operating far from the "social frontier."

3. Social Skills and the Formation of Peer Relationships

We argue that many entrepreneurs are under-networked, at least in part, because forming new relationships requires social skills. Qualitative research and practitioner publications have long documented the "people skills" that managers and entrepreneurs use to build relationships (Baron and Markman 2000, Bensaou et al. 2013, Casciaro et al. 2016, Edmondson 2012). These skills, which have also been called "interpersonal" or "soft," involve the ability to work well with others by communicating effectively and establishing a cooperative rapport (Borghans et al. 2014, Deming 2017, Heckman et al. 2013). This includes initiating interactions, engaging new acquaintances by asking questions, disclosing information about oneself, listening to others, and maintaining the conversations' focus (Buhrmester et al. 1988, Pichler and Beenen 2014, Riggio 1986, Riggio and Reichard 2008). In contrast to cognitive skills, which refer to individuals' technical abilities, social skills are about people's ability to engage with others.

At a high level, social skills lower the costs of forming valuable business relationships. The skills outlined above should improve interactions, which reduces the time and effort required to discover new connections (Boudreau et al. 2017, Jackson 2003, Watts 2001). Social skills also reduce the cost of building new relationships by helping individuals coordinate on a common vocabulary, establish mutual understanding, and gain trust (Lopes et al. 2004, Weber and Camerer 2003, Yamagishi et al. 1999). Once formed, social skills also lower the cost of learning within relationships, thus increasing the benefit of those relationships (Baron and Markman 2000)

4. Introducing Entrepreneurs to Social Skills

Given that social skills reduce tie formation costs and increase the benefit of interpersonal interactions, why do some entrepreneurs lack them? Crucially, social skills in business are learned (Riggio 1986, Walker et al. 1997). Individuals who possess them often acquire them by accumulating experience interacting with others in professional settings (Casciaro et al. 2016, Kuwabara et al. 2018) or are taught them from mentors, managers, or instructors in professional programs (Bensaou et al. 2013, Hallen and Eisenhardt 2012).

In fact, field experiments in non-business contexts show that augmenting existing educational programs with material focused on social and interpersonal skills leads to dramatic long-term improvements. For example, one field study of an early childhood education program found that teaching US children personality skills, especially those rooted in conflict resolution and cooperation, likely caused large improvements in employment and earnings in adulthood (Heckman et al. 2013). Similarly, another RCT found that teaching interpersonal "win-win" negotiation skills to Zambian teenage girls meaningfully improved their educational outcomes (Ashraf et al. 2020). In both cases, social skills were both taught directly by the teachers *and* through role-play and practice with peers.

These studies suggest that including social skills training as part of an existing business training program might be an effective way to improve entrepreneurs' social interactions and subsequent business performance. Not only do business training programs provide a natural setting to teach entrepreneurs new practices, but the presence of peers allows participating entrepreneurs to immediately try out their newfound social skills. Further, these within-program interactions are likely to be particularly useful as co-participants, also trained in social skills, are likely to reciprocate with valuable knowledge and advice. While we think social skills training is likely to "spill over" to interactions with outsiders, it should first and foremost impact the quality and quantity of peer-to-peer relationships within the program. Building on these arguments, in the next section we develop a set of five hypotheses focused on how teaching social skills to groups of entrepreneurs impacts interactions between co-participants and the effect of these changes on business performance.

Social Interactions

We expect that teaching entrepreneurs social skills will have a series of cascading effects, beginning with their perceptions of and engagement in interactions with other entrepreneurs who received the same training. If social skills improve entrepreneurs' ability to initiate interactions, focus those interactions on discussing business issues and involve showing interest in others' businesses, then entrepreneurs should be able to achieve meaningful conversations with new acquaintances more rapidly. Put differently, social skills reduce the cost of coordinating interactions, engaging others, and developing a mutual sense of understanding. This should make interactions feel easier and more collaborative. With an increased sense of collaboration and openness to others, these entrepreneurs should find more opportunities to give and receive advice (Hasan and Koning 2019), thus increasing the amount of information exchanged in a given conversation. Hence, social skills should make interactions feel more collaborative and more informative.

Hypothesis 1: Social skills training will lead entrepreneurs to perceive interactions as more collaborative and exchange more information during interactions.

Relationship Formation

Beyond changes in how entrepreneurs approach conversations, we also expect social skills to impact who entrepreneurs choose to build relationships with. We have argued that social skills reduce the cost and effort of interactions. A simple consequence of reducing social costs is that entrepreneurs should then interact with more of their peers and so identify more peers worth keeping in touch with. These may be people that entrepreneurs felt like they hit it off with, whom they were able to infer were trustworthy, or whom they believed to possess information that is useful to them.

Hypothesis 2: Social skills training will lead entrepreneurs to form more new relationships with other entrepreneurs from the training program after the program has ended.

Skill Complementarity

An important concern with any intervention that increases entrepreneurs' number of relationships is that the intervention might lead to additional business ties, but that that these new ties may not provide access to helpful information or new resources. We argue that, unlike mixers and other structural interventions (Carrell et al. 2013, Ingram and Morris 2007), improving entrepreneurs' social skills will result in entrepreneurs choosing to match with partners who provide value to them.

Entrepreneurs with better social skills face fewer costs in gaining information about their new acquaintances and so should be better able to evaluate the potential value of connecting with a peer. In particular, they are likelier to identify whether their peers' expertise or knowledge are redundant or complementary to their needs.

These arguments suggest that improved social skills should not just increase the number of relationships, but also the quality of the match. A first-order concern for entrepreneurs is the acquisition of better management skills and practices (Bloom et al. 2013). We expect that entrepreneurs with better social skills will be more likely to connect with peers who have complementary managerial skills. Building on Vissa's (2011) concept of task complementarity, we define skill-complementary business relationships as those that connect an entrepreneur with another entrepreneur who possesses a management skill that the focal entrepreneur wants to learn.

Hypothesis 3: Social skills training will lead entrepreneurs to form more skill-complementary relationships with other entrepreneurs from the training program after the program has ended.

Ethnic Diversity of Relationships

If entrepreneurs are forming connections on the basis of skill complementarity, then on what dimensions are they no longer building relationships? People often form relationships based on shared social characteristics—gender, ethnicity, or nationality— because these help coordinate communication and signal trustworthiness (Dahlander and McFarland 2013, Yamagishi et al. 1998). Social skills enable better communication and hence reduce entrepreneurs' need to rely on these kinds of social characteristics to assess the trustworthiness and usefulness of a prospective tie. In places that are ethnically diverse, a particularly important social characteristic that predicts the formation of relationships is co-membership in an ethnic group (Yenkey 2015). Entrepreneurs with better social skills, however, are less likely to rely on ethnic group membership as a basis for relationship formation. Rather, they are more likely to assess the value of a prospective tie on the basis of the skills and information to which they provide access. By contrast, entrepreneurs with fewer social skills are likely to form ties that are concentrated within their own ethnic group, since this a common—albeit noisy and often biased—way of inferring who is useful to talk to. As a result, we expect that entrepreneurs with better social skills will form new relationships that are less concentrated within any particular ethnic group.

Hypothesis 4: Social skills training will lead entrepreneurs to form relationships with other entrepreneurs from the training program after the program has ended that are less concentrated in one ethnic group.

Entrepreneurial Performance

In addition to changing the quantity and kinds of peer relationships that entrepreneurs form, we also expect socials skills to affect their performance. As described earlier, entrepreneurs with larger and more knowledgeable sets of peer relationships tend to perform better in terms of their survival, financing, and profitability (Baum et al. 2000, Chatterji et al. 2019, Shane and Cable 2002). Peers improve entrepreneurs' performance by providing information about market opportunities, increasing the chances that an entrepreneur will come across a valuable new practice, and by providing better access to funding and investments (Hochberg et al. 2007, Stuart and Sorenson 2007, Vega-Redondo et al. 2019). Given that entrepreneurs with better social skills are likely to form more new relationships, and especially relationships that are skill-complementary, they should have better access to sources of information, knowledge, and advice, which might lead them to learn a new managerial practice or to gain a customer referral. As a result, entrepreneurs with better social skills are not only likelier to have a larger number of peer relationships that are more diverse, they're also likelier to receive richer and more useful business advice.

Hypothesis 5: Social skills training will lead entrepreneurs to earn more profits.

5. Experimental Methods

5.1 Research Setting: "Marketing in Action" Business Training Program

To study the impact of social skills we worked with a business training program for entrepreneurs in Togo's capital, Lomé. The context of the program allowed us to exogenously change entrepreneurs' social skills by exposing a subset of participants to a social skills training module. The business training program was organized by the Association of Young Entrepreneurs of Togo (Association des Jeunes Entrepreneurs Togolais) in collaboration with the Energy Generation Academy. Both organizations are leading nonprofits in Togo that promote entrepreneurship and have been doing so in part by hosting training events for entrepreneurs since 2012. In the spring of 2017, they invited entrepreneurs to participate in a training program called "Marketing in Action," which taught entrepreneurs basic marketing practices for their businesses. In collaboration with the organizers, we created an experimental intervention to expose entrepreneurs to social skills. We randomly selected half of the participating cohorts of entrepreneurs into this "social skills" condition.[1]

Togo is a small, francophone country in West Africa that is representative of countries designated by the World Bank as low-income. According to the World Bank's "Ease of Doing Business Index," which is a measure of the challenges involved in operating a business, Togo scored 54.9 out of 100 in 2018, which is close to the regional sub-Saharan average of 52.6 (World Bank 2019). Togo is similarly representative of African countries in terms of its social capital. The 2016/2018 Afrobarometer, a survey of 37 African countries, reported that 24.6% of Togolese respondents participate in voluntary associations or community groups, which is nearly identical to the African average of 24.2% (Afrobarometer 2019). In settings such as Togo, social relationships are central to most aspects of business because formal institutions are too weak to safeguard market transactions (Khanna and Palepu 2010). Togo was therefore a promising field site because entrepreneurs were likely to place value on social ties, but not have access to training on social skills.

To better develop our intervention and understand the context, we conducted interviews with entrepreneurs in Lomé before the launch or our experiment. Appendix A1 describes the qualitative methods used and illustrative quotes from entrepreneurs interviewed. The interviews revealed that entrepreneurs were largely aware of the value of peer relationships, but often struggled to connect with new acquaintances. For example, one entrepreneur said:

[1] The surveys, intervention, and randomization were approved by the authors' Institutional Review Board (IRB) (Protocol # IRB17-0319).

> "I find that the way we are educated here is that entrepreneurs have good ideas but they cannot implement them because they cannot approach other people to discuss them." (YE 13)

When trying to understand why these difficulties existed, entrepreneurs often turned to cultural narratives related to a lack of knowledge about how to build relationships in business. One entrepreneur expressed it like this:

> "I think this is something that one has to be trained in: building relationships.
> [Interviewer:] How come?
> There may be a cultural side that plays out in this, well, for example: we go to the market, the business and entrepreneurship that we have always known there is our moms selling things, that's essentially it. And it is the customers who come to them, they never really worked out a business strategy to call people or reach out to others, all of those things just don't really exist. Is that what explains it? Well, it may be precisely a lack of training on this aspect." (YE 6)

5.2 Participating Entrepreneurs and Randomization

The Marketing in Action program solicited participants from throughout Lomé. The program was advertised to local entrepreneurs through social media and a network of local nonprofit organizations. In addition to advertising, a team of three canvassers visited businesses door-to-door in all major commercial districts to invite the owners to participate. The requirements for participation were that entrepreneurs' businesses had been in operation for at least one year and that they be based in the city of Lomé. In addition, participants were asked to pay a small participation fee (approximately 5 USD), which was reimbursed to them upon successful completion of the training. All of the entrepreneurs who participated in the training were both owners and founders of their businesses.

The recruitment process yielded 326 participants, whom we split into 14 groups, each with 20-25 entrepreneurs. Program dates were filled one after the other on a sequential basis as individuals registered. Once all the groups had been filled, 7 of the 14 groups were randomly selected into the social skills condition using a random number generator in Excel. Our sample size is larger than comparable field experimental studies on management and advice, which in one case randomized 100 entrepreneurs into 50 pairs and in another case randomized 11 manufacturing firms into 5 treatment and 6 control groups (Bloom et al. 2013, Chatterji et al. 2019). [2] The timeline and implementation of the field experiment are detailed in Appendix A1.

5.3 Business Training Content and Instructors

The training program curriculum was adapted from programs carried out by the International Labor Organization (ILO) in developing countries (for a review, see McKenzie and Woodruff (2014)). Typically, these programs bring together business owners for short courses on basic management practices. The Marketing in Action program used the ILO training course on marketing for small business owners, called the "Start and Improve Your Business Programme" (ILO 2018). The content covered eight basic marketing practices: finding out what competitors charge; their products and services; finding out what else clients would buy; researching former clients; researching suppliers; using promotions; advertising; evaluating the advertising. The training lasted for two days, from 8 a.m. to 6 p.m. each day, for an approximate total of 20 hours per cohort. Two new groups of entrepreneurs started each week, one on Monday and one on Wednesday.

The training program was taught by two instructors, who were local consultants. The instructors taught the classes together, following a strict schedule. There were catered coffee and lunch breaks each day. The program also included a networking event at the end of the two days. During this networking event, after all the teaching material had been covered, participants were randomly assigned three discussion partners from within the same class. Participants were then given space for private one-on-one conversations with each of their discussion partners. These conversations lasted approximately 30-45 minutes each. During the conversations, participants were given writing materials to take notes on their conversations.

5.4 Experimental Treatment

[2] Given operational and funding constraints we could not determine the exact sample size before launching the experiment. Ex-post power calculations based on our study's sample of 301 observations reveals that our minimum detectable effect size at conventional power levels is a 13% increase in business profits. See Appendix A10 for more details.

To test whether improving social skills shapes entrepreneurs' interactions, business relationships, and profitability, we randomly assigned cohorts of entrepreneurs in the Marketing in Action program into two conditions, a "social skills" treatment condition and a control condition. Participants in the treatment condition began the two-day training program with a two-hour training session on social skills. Prior field experimental research has used such training sessions and lectures as treatments to improve people's skills and practices (e.g., Ashraf et al. (2020); Cable et al. (2013); and Paluck (2011)). After the social skills training session, the treatment groups followed a series of interactive lectures during the remaining two days that covered marketing practices. The control group followed the exact same training program, except that they were not given the two-hour training module on social skills. Instead, the lectures on marketing practices were covered at a slightly slower pace to make up for the two hours that the treatment group spent on social skills.[3] As a result, both control and treatment groups spent exactly the same number of hours together.

Our treatment, the two-hour interactive training session, introduced entrepreneurs to social skills in business. The main objective of the training session on social skills was to equip entrepreneurs with a collaborative attitude towards interactions with peers who were previously unknown to them and to teach them how to communicate effectively about business issues.

Table 1 provides an overview of the structure of the session. During the first hour, the first 20 minutes were spent defining interpersonal interactions in business settings. This created a common baseline for all participants about what interactions entail, what steps are involved, and which interactions are about business and which are not. This gave instructors the opportunity to acknowledge that interactions with others can often be complex and difficult, especially when involving strangers. We then emphasized that entrepreneurs were part of a larger business community in Lomé, made up of other entrepreneurs, established businesses, associations, clients, and stakeholders in their businesses. As members of this community they had a vested interest in the success of others. Providing this perspective broadened the group boundaries to

[3] In order to introduce the two-hour training session into the program, we chose to condense the amount of time spent on marketing practices rather than add an additional two hours for the treatment condition because this would have represented an approximate increase of 10% in the total time that entrepreneurs in the treatment condition spent together. We chose to avoid this increase in total time spent together because it could have confounded the effects of the social skills intervention on our outcomes of interest related to relationship formation. Notably, test scores for comprehension of the marketing practices showed no difference between the control and social skills conditions (see Appendix A14 for regression results).

which entrepreneurs' felt like they belonged and decreased their sense of social distance from "generalized others" in the business community.

Having established this common baseline and common community membership, the instructors spent minutes 20 to 40 discussing what collaborative interactions entail and why they are important. Entrepreneurs were taught that collaborative interactions involve learning about others by asking them questions about their businesses and using their own experiences and knowledge to give advice (Casciaro et al. 2016). The act of giving advice signals generosity and caring, which helps establish a collaborative atmosphere for the interaction. It was then explained to entrepreneurs that collaborative interactions are important because they themselves could also gain from those interactions. Instructors illustrated the impact of the other party's gains on one's own outcomes and how early collaborative interactions could lead to long-term cooperation.

In the last 20 minutes of the first hour the entrepreneurs were taught about effective communication with other entrepreneurs. Instructors emphasized the importance of keeping the communication focused on issues related to business. They emphasized the importance of being clear and direct when asking questions or offering a perspective. Effective communication practices also involved simple steps like making sure to ask for contact information, sending thank-you notes, and following-up.

The final hour of the training session involved working through an example of two entrepreneurs interacting, which mimicked real situations that entrepreneurs might face. This case was meant to reinforce entrepreneurs' understanding of social skills in practice and to provide an opportunity for them to engage interactively with the content of the session. This was followed by time for questions and answers.

*** Insert Table 1 about here ***

The instructors who taught the social skills training session also taught the other materials in the two-day training program. The two instructors co-taught all materials; as a result, they were both present in all classes. As well as being consultants, the instructors were graduates of the local university and each had several years of experience teaching courses to entrepreneurs. One of the authors taught the two instructors the content of the social skills training session, provided detailed instructions for the delivery of the training session, and worked with the consultants to refine the presentation. Although the instructors were trained to deliver the social skills session, they were blind to the design of the field experiment and the authors' outcomes of interest. The PowerPoint slides developed with the instructors for this session can be found in Appendix A18.

6 Data

The data for this study come from six sources: (1) pre-treatment survey; (2) digitized participant notes; (3) training program exit survey; (4) six-weeks post-treatment survey; (5) six-months post-treatment survey; and (6) one-year post-treatment survey. The pre-treatment survey and the three post-treatment surveys (sources 1, 4, 5, and 6) collected information from all participant entrepreneurs about their management practices, expenditures, revenues, employees, and demographics. The three follow-up surveys conducted after the training program (sources 4, 5, and 6) contained additional questions on contact with co-participants; these were used to measure relationship formation. The digitized participant notes (source 2) are handwritten notes that participants took of their discussions with peers during a structured networking event, which were electronically scanned. The exit survey (source 3), asked all participants questions about their interactions during the two days of the program and their perceptions of one another, as well as their comprehension of the material taught. The survey questions used to construct the variables for our analyses can be found in Appendix A19.

All surveys were administered by the same two instructors who taught the training program. During registration for the program, the instructors explained to the entrepreneurs about the follow-up survey process and that they themselves would be visiting the participants later to survey them. This helped build a sense of commitment and trust between the instructors and the participants.

A total of 326 entrepreneurs signed up to participate in the training program. We have relational outcomes—collaborative perception, information exchange, ties formed, skill complementarity, ethnic concentration—for 301 participants. Our performance results include 278 entrepreneurs who reported their profits at baseline and in at least one follow-up survey. Appendix A2 provides further details that suggest that attrition is most likely random, shows that attrition is not correlated with treatment status nor pre-treatment characteristics, and that our results hold when we estimate treatment effects using Lee (2009) bounds to account for any differential attrition between the treatment and control groups.

6.1 Dependent Variables

Collaborative perception of interactions

Our first hypothesis (H1) is that entrepreneurs will perceive interactions during the training program as more collaborative than competitive after they are introduced to social skills. To measure entrepreneurs' perception of interactions, we asked them to think about the interactions they had had during the two days of the training program. We then provided them with a sheet of paper with a grid of 24 words, of which half represented concepts related to collaboration (such as *help*, *trust*) and the other half represented concepts related to competition (such as *grow*, *dominate*), and asked them to circle five words that they believed best represented these interactions.[4] Using this information, we created a measure of *collaborative perception of interactions* for each entrepreneur, which is a count variable equal to the total number of collaborative words selected from the grid of 24 words.

Information exchange

The first hypothesis (H1) also states that entrepreneurs will exchange more information after they've been trained in social skills. To measure information exchange between entrepreneurs, we used data from a structured networking event at the end of the training program, during which each entrepreneur was successively paired with three randomly selected discussion partners. All participants were given pen and paper, and at the end of the event, their written notes from their discussions were scanned. The total number of words that each participant wrote during their three discussions is used as a measure of *information exchange* (Aral and Van Alstyne 2011).

Relationship formation

To measure relationship formation (H2), we used data from the follow-up survey conducted six weeks after the training program. During the follow-up survey, all participants were asked

[4] Other collaborative words included *friendship*, *sharing*, and *alliance*, while other competitive words included *adversarial*, *beat*, and *dominate*. For the full list of words, see Appendix A19.

whether they had spoken over the phone or met in person with any other participants from the same training group after the program had ended, and they were asked to name those individuals. Using these data, we calculate the *number of relationships formed* as the total number of people entrepreneurs had kept in touch with (Piezunka and Dahlander 2019, Vissa 2011).

Skill complementarity

Hypothesis H3 relates to the proportion of relationships formed with entrepreneurs who possess complementary business skills. The measure for skill complementarity is adapted from the dyad-level measure used by Vissa (2011) for task complementarity and captures whether the focal entrepreneur formed a relationship with another training-class participant who had a skill that the focal entrepreneur expressed a desire to learn.

To construct this measure, we use survey responses in which participants were asked to describe one issue in their business that they felt was the most pressing and that they wished to address. They were asked to select which category this specific issue fell into: (1) firm financing; (2) marketing; (3) stock and inventory management; (4) accounting and record keeping; (5) planning for the future. In parallel, based on responses to the pre-treatment survey, we coded each participant according to whether they used best practices in those five categories using the list of business best practices (which cover all five areas of expertise) developed by the World Bank (McKenzie and Woodruff 2018).

Using these two data points (i.e., the skill that each participant most desired to learn and each participant's portfolio of skills), we created an indicator of skill complementarity between each pair of participants i and j which was equal to 1 if participant j showed evidence of expertise in the domain in which participant i indicated they wanted to improve. Then, to bring this measure from the dyadic level to the individual level, we summed the *number of relationships with skill complementarity* that each entrepreneur formed.

Ethnic concentration

Hypothesis H4 states that better social skills will lead to the formation of more diverse relationships. *Ethnic concentration* of relationships represents the level of concentration of the newly formed relationships across ethnic groups. Using the pre-treatment data regarding each entrepreneur's ethnicity, we calculated the ethnic concentration of the relationships formed using

Herfindahl indexes, a common approach for measuring diversity in egocentric portfolios of relationships (Uzzi 1996). The index ranges between a minimum of 1/N, where N is the number of possible categories represented in the sample, and 1. The minimum value indicates that all relationships were equally distributed among the ethnicities, and the maximum value ("1") indicates that all relationships formed were concentrated in one ethnicity or one neighborhood. In the case of ethnicities, there are five possible cases, making the minimum value of the index 0.20.

Performance

Finally, Hypothesis H5 is about the performance of entrepreneurs' businesses. The measure for business performance comes from four surveys: a pre-treatment survey at the beginning of the training and three post-treatment surveys at six weeks, six months, and one year after the training. In each survey, we asked participants about their businesses' profits in the month previous to the survey. Self-reported monthly profits is a standard measure of performance for small businesses in developing economies, which is highly correlated with other measures of performance based on accounting books (Atkin et al. 2017, De Mel et al. 2009).

6.2 Independent Variables

Treatment group

The main independent variable in the analyses was whether the individual participated in a group that received the social skills treatment. Accordingly, we created a dummy variable equal to 1 for having received the treatment, and 0 for being in the control group.

Control Variables

Although the research design randomizes exposure to social skills, we also account for variation in the characteristics of entrepreneurs and their businesses in the regression models to improve power and further rule out the chance that our randomization was imbalanced. We control for three entrepreneur-level variables including *Ewe ethnicity*, coded as 1 if the participant was Ewe (the majority ethnic group in Lomé) and 0 otherwise, gender by including an indicator for *female* entrepreneurs, and whether participants had *completed primary school*, which was coded as 1 if the participant had completed at least primary school and 0 otherwise.

Furthermore, three control variables were included to capture various aspects of participants' businesses. We controlled for the size of participants' businesses using the number of *employees*, measured by the total number of full-time employees working in the business, the *firm age*, measured by the number of years since the business started producing and selling goods or services, and the extent to which each participant used established best practices for management in their businesses. Using the management practices score for small businesses in developing economies created by McKenzie and Woodruff (2018), we collected data through a series of "yes or no" questions about whether participants used each of the best practices in a list of 27 practices.[5] The *management practices score* of a participant's business is the proportion of the 27 questions to which the entrepreneur answered "yes."

We also include a series of 10 dummy variables created to capture entrepreneurs' sector of economic activity. The 10 sectors were tailoring and shoemaking, sale of food or drink, jewelry-making and sales, information technology sales and services, cosmetic and health services, construction, food processing and production, carpentry and metal works, rug manufacturing and weaving, and multimedia services.

Finally, we controlled for the training *class size*, which is equal to the number of entrepreneurs in each training program cohort. This was included to control for the number of prospective connections each actor had available, which could have a positive effect on the total number of relationships formed, but a negative effect on the level of familiarity with those individuals.

We report the summary statistics and bivariate correlations in Table 2. The majority of participants (78%) were members of the Ewe ethnic group and had completed primary school (75%). Approximately 64% of entrepreneurs were male. Entrepreneurs' businesses had on average one or two employees and had been in existence for 11 years. In general, larger businesses tended to be more profitable. Finally, in terms of best practices, entrepreneurs' businesses on average used about 60% of the practices defined by the World Bank for small businesses. The higher use of best practices was positively associated with firm size and age. In Appendix A2, we report balance tests, which explore whether baseline characteristics predict

[5] These best practices include, for example, recording every purchase and sale, using advertising, and having a monthly budget of expenses. See McKenzie and Woodruff (2018) for a complete list and details.

being in the treatment group. We find no statistically significant evidence that any baseline characteristics of the entrepreneurs or their businesses predicts receiving the treatment.

** Table 2 about here **

6.3 Estimation

Our estimation strategy builds on a pre-registration plan,[6] but takes into account several outcome variables and their longitudinal structure that had not been anticipated. All dependent variables are cross-sectional, except for the performance dependent variable—log profits last month—which is a panel time series with four periods.

To test hypotheses H1, H2, and H3 we used a negative binomial model, which is appropriate for models where the dependent variable is a count with nonnegative values (Cameron and Trivedi 2009). The dependent variables to test these hypotheses are collaborative words selected, words written, relationships formed, and skill complementary relationships formed which are count variables. We include an offset in the negative binomial model for skill complementary relationships that is equal to the inverse hyperbolic sine of the total relationships formed, which adjusts the treatment effect estimate for the number of opportunities entrepreneurs had to form a skill complementary relationship. To test hypothesis H4 we used fractional logit regression, which is appropriate for models where the dependent variable is a fraction, as in the case of ethnic concentration (H4) (Papke and Wooldridge 2008).

To ensure that our results are not model dependent, we also estimated the regressions testing hypotheses H1, H2, H3, and H4 using OLS. This has the added benefit of making the interpretation of the results simpler. The statistical significance of our results held unchanged using this regression approach, as did the interpretation of the magnitudes of the effects. For details on these robustness checks, see Appendix A6.

[6] We pre-registered our field experimental design and our expected outcomes with the Open Science Foundation (OSF). Our pre-registration document refers to social skills as "cultural frames of cooperation and helping" and explicitly outlines our first three hypotheses. The OSF included one prediction—that the treatment should increase "social knowledge"—for which we did not end up collecting data to test. We did not register our final two hypotheses. We did not initially think we could measure firm performance but ended up having funds for surveys after the program. For ethnic diversity, we did not realize that the prediction followed from our model until discussing our findings with colleagues. Our pre-registered analyses use OLS and hold as shown in Appendix A6.

Finally, to test hypothesis H5 we used two empirical specifications. We began with a straightforward specification assessing the effect of social skills training on profits:

$$y_{it} = \alpha + \beta SocialSkills_i + \gamma_i y_{i0} + \boldsymbol{\rho}\, Controls_{i0} + \delta_s + \tau_t + \varepsilon_{it} \qquad (1)$$

where y_{it} is our performance measure (log monthly profits), $SocialSkills_i$ is an indicator variable for whether the entrepreneur received the treatment, y_{i0} are log monthly profits at baseline, $Controls_{i0}$ is a vector of control variables measured at baseline, δ_s are business sector fixed effects, and τ_t are survey wave fixed effects. Since we control for baseline profits we cannot include observations from the baseline period in the regressions. McKenzie (2012) and Atkin et al. (2017) argue that equation (1) performs well in the context of developing economies because profit variables are often measured with noise.

Our second specification uses a difference-in-differences modelling approach:

$$y_{it} = \alpha + \beta(SocialSkills_i \times PostTreatment_t) + \theta_t PostTreatment_t + \lambda_i + \tau_t + \varepsilon_{it} \qquad (2)$$

where $PostTreatment_t$ is an indicator of post-treatment time periods, and λ_i are entrepreneur fixed effects. This approach complements model (1) by controlling for time invariant unobservable entrepreneur characteristics through the entrepreneur fixed effects. In equation (2) the coefficient of interest is β, the interaction between the treatment and post-treatment dummies, which captures the treatment effect.

Equation (1) includes only baseline values of control variables to avoid biasing our estimates of the treatment effect (Acharya, Blackwell, and Sen 2016). In studies where the treatment is randomized, conditioning on post-treatment covariates can unbalance the treatment and control groups with respect to other possible confounders, thereby making treatment estimates biased and inconsistent (Montgomery, Nyhan, and Torres 2018). We follow experimental best practices and include only baseline measures of covariates in Equation (1) (Gerber and Green 2012). These time invariant controls drop out of equation (2) due to the entrepreneur fixed effects.

Finally, in both specifications (1) and (2) above we clustered standard errors by entrepreneurs' cohort in the training program (i.e., we let observations be independent across training groups but not necessarily across the participants of the same training group).

7. Results

7.1 Collaborative Perception of Interactions and Information Exchange

Hypothesis 1 posits that entrepreneurs who have been introduced to social skills will perceive interactions with other entrepreneurs in their training program cohort as more collaborative and will exchange more information during those interactions. Table 3 presents regression results that test this hypothesis. All regressions in Table 3 are estimated using a negative binomial model because the outcomes are count variables.

In Models 1 and 2, the dependent variable is the number of collaborative words that entrepreneurs selected to describe their interactions during the training program. Model 1 estimates the effect of social skills training without any control variables, while Model 2 estimates it with control variables. In both models the coefficient estimate for social skills is positive and statistically significant at the 5% level. Using predictive margins and keeping all other variables at their means, being in the treatment group leads to selecting 0.25 more collaborative words, an increase equivalent to roughly one-quarter of a standard deviation. Entrepreneurs introduced to social skills perceived interactions as more collaborative.

Models 3 and 4 in Table 3 test whether entrepreneurs in the treatment condition exchanged more information during interactions. To measure information exchange we counted the number of words written during three discussions that each entrepreneur participated in during the structured networking event at the end of the second day of the training program. In both models the coefficient for social skills is positive and statistically significant at the 1% level. The predictive margins show that being in the treatment group increases the average number of words written by 27, which represents a doubling of the number of words written. Figure 1 plots of the kernel density function for the number of words written during the three discussions by participants in the treatment and control groups. The grey dashed line is the distribution for participants in the treatment condition, while the solid black line represents those in the control group. Figure 1 shows that the distribution for the treatment group is shifted significantly to the right of the distribution of the control group.

Further, the increased amount of information exchanged is not mere filler. For example, an entrepreneur in the treatment group noted that he learned the following after a conversation with one of his peers:

Try to register my business in a microfinance institution and try to make deposits regularly in order to be able to access credit. First, though, examine the price of the machine I want to buy to plan for the kinds of deposits I need to make to get the credit I will need. After obtaining the credit, go directly to the goal: pay for the machine. Very important: having acquired the loan, you have to intensify your efforts to honor the commitment to the microfinance institution, in order to have access to other loans in the future.

By way of comparison, an entrepreneur in the control group received advice on the same broad topic, securing capital to grow their business, but the advice they noted is less actionable, less detailed, and overall, less helpful:

There are too many competitors in the market, I lack the financial means to buy basic products. In the future, I should restart activities with a large loan to earn a lot of profits.

This pair, along with other examples presented in Appendix A15, suggest that the number of words appears to be a useful, if crude, proxy for differences in the depth and usefulness of the participants conversations. Indeed, in Appendix A16 and A17 we apply more sophisticated text-analysis tools to show that treatment nearly quadrupled the number of distinct pieces of advice shared, increased the complexity of the advice, and increased the proportion of the advice focused on work (see Table A17-6 in A17 for regressions). Overall, these results lend support to Hypothesis 1 that entrepreneurs who received social skills training exchanged more information during interactions.

*** Insert Figure 1 about here ***

*** Insert Table 3 about here ***

7.2 Relationship Formation

Hypothesis 2 states that exposure to social skills will lead to the formation of more new relationships between entrepreneurs after the training program. Figure 2 shows the plots of the kernel density functions for the number of new relationships formed by entrepreneurs in the treatment and control conditions, as measured six weeks after the end of the training program. The figure shows that the distribution for the treatment group is shifted to the right of the distribution for the control group, indicating that there is a higher frequency of larger numbers of relationships formed.

The regressions in Table 4 confirm this difference between the two conditions. Specifically, Models 1 and 2 of Table 4 estimate the effect of social skills training on the number of new relationships formed after the training program. The treatment variable is positive and statistically significant, with the predicted count of ties for participants in the control group being 1.5, compared with 2.25 in the treatment group. Given that the median participant in the control group formed approximately two ties, the addition of (about) one more tie through the treatment represents a large increase in the outcomes from the treatment. Model 2, which includes control variables, yields nearly identical results, providing further support for the prediction that entrepreneurs that have received social skills training will form more relationships with other entrepreneurs.

*** Insert Figure 2 about here ***

To further validate this result, we estimated the same models using an alternative outcome variable. Specifically, we adapted a measure from Vissa (2011), who uses the receipt of a business card to measure intention to form a relationship. To create this measure, we provided all entrepreneurs with personalized business cards with their name and phone number printed on them, and we told them they could use them as they wished. At the end of the two days, we asked the participants to show us the cards they had received from others and we took note of each card received. Following the same model specification as in Table 3, but changing the outcome variable to be the number of cards received, we replicated the result for number of relationships formed from Table 3. This helps verify that our outcome measure was accurately capturing the dynamics that better social skills lead to more new relationships. For details on these results see Appendix A6.

7.3 Skill Complementarity

We further hypothesized that entrepreneurs exposed to social skills training would form a greater proportion of relationships that exhibit skill complementarity (i.e., the target of the tie possesses a skill that the focal entrepreneur wishes to improve). The regression analyses in Models 3 and 4 of Table 4 support Hypothesis 3: the coefficient for social skills training is positive and statistically significant at the 5% level. Based on the predictive margins for these models, the predicted count of new ties that exhibit skill complementarity for treated entrepreneurs is 0.5, while the predicted count for control group entrepreneurs is 0.2. Hence, the treatment, on average, leads to the formation of more than twice as many skill complementary ties. Model 4 includes control variables and again we see nearly identical results providing further support for Hypothesis 3.

A potential concern with these skill complementarity results is that perhaps entrepreneurs were not seeking out others with the managerial skills they needed, but rather by simply making more relationships they accidentally ended up with more good matches. To confirm that the observed differences in skill complementarity were not simply the result of network growth, we ran a series of simulations where the number of new relationships that each entrepreneur formed was held at the observed value, but the targets of those relationships were randomly selected from among other participants in their training group. We then counted, for each entrepreneur, the number of skill-complementary relationships and scaled this by the total number of relationships formed. We then calculated the difference between the treatment and control groups in the proportion of skill complementary ties and repeated this for 2,000 simulations. In Appendix A4, we plot the simulated differences between the groups. The actual difference between skill complementarity in the treatment and control groups is extremely unlikely to happen by chance (less than one-tenth of a percent probability). These simulations show that forming more ties at random does not result in more useful connections.

7.4 Ethnic Diversity

Hypothesis 4 states that social skills will lead to the formation of more ethnically diverse relationships. This is tested using a measure of the concentration of new relationships formed within ethnic groups. Because this measure ranges from 0 to 1, Models 5 and 6 in Table 4 use a fractional logit model. In both models the coefficient for the treatment variable is negative and statistically significant at the 1% level, indicating that being in the treatment group decreases the ethnic concentration of new relationships formed. The effect is meaningful, with the marginal effect being –0.11, which is nearly half of a standard deviation. Model 6 also includes control variables and yet again the results are unchanged. We also find support for Hypothesis 4.[7]

*** Insert Table 4 about here ***

7.5 Business Performance

The final hypothesis, H5, posited that introducing entrepreneurs to social skills will increase their monthly profits. Table 5 shows the results from regressions testing the significance and magnitude of this effect. Models 1 and 2 in Table 5 estimate Equation (1), while Model 3 estimates Equation (2).

In all models of Table 5 the effect of social skills training on profits is statistically significant at the 5% level. According to the results in Models 1 and 2 social skills training increased monthly profits in the post-treatment period by 19%. Model 2 includes controls for ethnic group, primary school education, gender, and training class size, as well as baseline values of number of employees and management practices score. Including these pre-treatment controls does not substantively affect the statistical significance or magnitude of the treatment effect. In Model 3, which includes entrepreneur fixed effects, the social skills training was associated with an approximately 27% increase in monthly profits in the post-treatment period. The difference in magnitudes between the two estimation approaches is not statistically significant as both estimates are well within each other's 95% confidence interval.[8]

*** Insert Table 5 about here ***

These performance effects also hold using alternative performance measures. Models 1-4 in Table A9-1 replace log monthly profits with a "performance index," which is the average of 9 standardized performance variables, including log and winsorized weekly and monthly sales and profits. Models 4-6 in Table A9-1 replace log monthly reported profits with the log of the

[7] In addition to ethnic diversity, gender diversity is also an important dimension of entrepreneurs' portfolios of relationships. However, after conducting exploratory analyses, we find no effects of the treatment on the gender composition of entrepreneurs' peer relationships. For these analyses, see Appendix A5.
[8] Appendix Section A11 shows our predicted effects remain significant when we adjust for the fact that we are testing multiple hypotheses.

difference between monthly sales and expenses. Results from Table A9-1 show that the treatment effect is positive, statistically significant, and similar in magnitude to those estimated in Table 5. See Appendix A9 for additional details on alternative performance measures.

To ensure that these results were robust to potential cohort and recruitment effects we also estimated Models 1 and 2 in Table 5 with cohort fixed effects and controls for source of recruitment. Cohort fixed effects alleviate concerns that differences in the composition of cohorts might be driving the effects. As results in Appendix A12 show, cohort fixed effects do not substantively change the treatment effect. Appendix A12 also shows that controlling for the three primary ways in which entrepreneurs were recruited (in-person canvassing, referrals from entrepreneur associations, and advertising on social media) does not change our results.

Using coefficient estimates from Model 3 in Table 5, Figure 3 plots the average predicted values for log monthly profits by treatment and control group for each time period, with 95% confidence intervals. The grey dashed line represents the average predicted monthly profits for entrepreneurs in the treatment condition, which shows an increasing trend after the training program. The solid black line represents average predicted profits for the control condition. For entrepreneurs in this condition average profits did not change until one year after the training program, at which time there was a statistically significant, but modest in magnitude, increase in profits. This late increase in control groups' profits may be due to learning and implementing marketing practices.[9] Although Figure 3 shows a partial convergence between treatment and control group performance one year after the training program, the treatment effect remains positive and large, representing an increase of approximately 15%. However, our power calculations, described in Appendix 10, suggest that our study is underpowered for detecting effects of this size. Appendix A8 contains plots of median and mean log monthly profits by survey wave and treatment condition, which show that treated entrepreneurs' profits are always above the control group's in the post-treatment periods.

*** Insert Figure 3 about here ***

[9] In the absence of a pure control group that did not receive marketing practices training it is impossible to know why the control group's performance increased one year after the training. However, exploratory regressions in Appendix 14 show that control group entrepreneurs learned new marketing practices and the timing of the performance increase is consistent with results reported in Anderson et al. (2018).

These results in Table 5 and Figure 3 represent the average effect of social skills training, which do not make clear whether the effect is driven by uniformly increasing performance, only improving performance for firms that are among the bottom of performers or by strengthening the performance of top firms. To test how our treatment impacts the distribution of performance outcomes we estimated quantile treatment effects for each 5th percentile of performance between the 5th and 95th quintiles (Appendix A7 provides further details). Figure 4(A) plots the estimates of the treatment effect from the quantile regressions and shows that it is remarkably consistent across the performance distribution. Figure 4(B) plots the p-values for the quantile treatment estimates in Figure 4(A) and shows that the treatment effect is statistically significant between the 15th and 75th quintiles. Corroborating evidence is also provided by the kernel density plots of profits by treatment condition (Appendix A7), which suggest that social skills shift the distribution of realized profits to the right and do not just lift up laggards or lead to outsized gains for top performances.

To contextualize our performance results, the median firm in our sample had revenues of approximately 300 USD per month and profits of approximately 100 USD per month in the baseline period. Our regression results suggest that the social skills training increased their profits, on average, by approximately 20 USD per month in the post-training period. Given that most entrepreneurs in our sample operated on slim profit margins, these increases in performance could be related to such events as gaining a new client, finding a cheaper supplier, or improving a managerial practice, all of which could be driven by access to better advice from a larger and more diverse portfolio of peer relationships.

Furthermore, these performance effects are within range of effects reported in several other experimental interventions with entrepreneurs in developing economies. Although a number of RCTs involving general managerial practices have found null effects (McKenzie and Woodruff 2014), more targeted treatments have often reported effects on profits in the range of 10-50%. Drexler et al. (2014) found that teaching entrepreneurs in the Dominican Republic accounting rules of thumb increased profits by approximately 10%. A field experiment in Tanzania found that their entrepreneurship training program led to increases in profits of about 50% (Berge et al. 2014). Another field experiment in Togo found that a personal-initiative training led to an increase of 30% in profits for entrepreneurs (Campos et al. 2017). Finally, an RCT in Indonesia found that giving entrepreneurs a handbook of local best practices increased profits by 35% (Dalton et al. 2020). A review of field experiments involving peer and mentorship feedback finds that the effects for these interventions range from 8-22% (McKenzie 2021), suggesting that our results are at the higher end of this range. That being said, our ex-post power calculations suggest that we are powered to detect effect sizes of 15% or higher (see Appendix 10 for more details).

*** Insert Figure 4 about here ***

8. How do social skills improve business performance?

Our results show that entrepreneurs who received social skills training increased their monthly profits by roughly 20% in the year after the program compared to entrepreneurs in the control condition. According to our theory, social skills increase performance because previously "under-networked" entrepreneurs become better at discovering valuable information and advice from peers. Indeed, the results in Tables 3 and 4 show that improvements in social interactions occur along many dimensions: conversations are more informative, interactions more collaborative, networks grow larger, new ties are more complementary, and connections more diverse. Prior research suggests that each of these social mechanisms can in-and-of-itself improve performance (Baum et al. 2000, Powell et al. 1999, Vissa and Chacar 2009).

To account for all these diverse pathways, we construct a "social interaction index" that combines many measures of networking and advice into a unidimensional variable. This measure lets us quantify aggregate improvements in entrepreneurs' social interactions and so test if the bundle of social mechanisms we propose mediates the treatment effect. Table 6 presents the 17 measures we include in the index which are also described in full detail in Appendix A17. These measures reflect differences in the size and complementarity of an entrepreneur's network (i.e., who they talk to) along with differences in the kinds of advice they receive (i.e., how they talk to others). While the variables from our analyses in Tables 3 and 4, which focus on networking and advice between co-participants, are included in the index, we also include measures from our post-treatment surveys that capture interactions between participants and others who did *not* attend the program (E.g. "14. Reaching out to new acquaintances outside the program").

The index also includes more sophisticated text-based measures of advice derived from the entrepreneurs' handwritten notes (Appendix A16). These additional measures allow us to account for subtle characteristics of interactions which might be too noisy to analyze individually. In this regard, our index is similar in spirit to indices of management practices, which aggregate many related but distinct practices to shed light on overall management quality (Bloom et al. 2012, McKenzie and Woodruff 2018).

In Table 7 Model 1 we show that the social skills index is 0.83 (p= 0.000) standard deviations greater for treated than control entrepreneurs. Furthermore, in table A17-1, we show that this increase is broad based. The social skills treatment increases each sub-component of our index. This reflects improvements in networking both between participants in the training program (Model 1) and between entrepreneurs and others outside of the program (Model 3). It also improves advice giving and receiving, again both between participants (Model 2) and with program outsiders (Model 4).

Does this increase mediate our performance effect? In Table 8 we use contemporary causal mediation analysis methods to estimate the average causal mediation effect (ACME) for our index (Imai et al. 2011). This approach relies on the sequential ignorability assumption,[10] but allows us to consistently and unbiasedly estimate the percent of the randomized treatment that flows through any given mediator. Indeed, we see in Model 1 that the ACME for our index is 0.137 and that this accounts for 85.8% of the overall treatment effect. Notably the coefficient on the remaining indirect effect of the treatment is 0.039 and statistically insignificant. Furthermore, as we discuss in A17, the findings in Model 1 are relatively robust to deviations in the sequential ignorability assumption, which suggests that some alternative omitted mechanism is unlikely to instead be responsible. Lastly, in Table A17-2 in A17 we show that each sub-component of our index appears to mediate at least some of the treatment effect. About two-thirds of the effect is attributable to better networking and advice between co-participants and about one-third because the treatment improves interactions between participants and outsiders. Overall, we find strong evidence that social skills improve performance through a multitude of underlying social mechanisms.

While our social interaction index strongly mediates performance, our final set of analyses also show that alternative, non-social mechanisms do not. For example, perhaps the

[10] The sequential ignorability assumption in causal mediation analysis bears resemblance to the exclusion restriction in instrumental variables analysis. In both cases there are no objective criteria or standards for satisfying the condition, rather doing so depends on the specific empirical context and the data at hand. Given this we have followed best practices by conducting sensitivity analyses for our mediation models, reported in A17.

social skills training improved enthusiasm and affect for treated entrepreneurs, motivating them to work harder at their businesses. Indeed, in Model 2 of Table 7 we show that treated entrepreneurs' advice notes are 37 percentage points more likely to exhibit positive sentiment than the control participants' notes. We use a natural language processing algorithm, "BERT", which is trained on data from a corpus of billions of French documents by Google (Le et al. 2019, Martin et al. 2019) to assign each note a probability of expressing a positive sentiment[11]. Perhaps this gain in affect and enthusiasm drives improvements in motivation and hence performance. However, in Model 2 of Table 8 we find no evidence that our positive affect measure mediates performance, with an ACME of 0.022.

Relatedly, our treatment might have increased engagement with the marketing training, leading to improved use of marketing practices that in turn increased performance. In Model 3 of Table 8 we find no evidence that marketing practices differ between the treated and control groups.[12] Consistent with this null effect, in Model 3 of Table 8 we again find no evidence that marketing practices mediate performance outcomes with an ACME of -0.000. Appendix A14 further rules out these channels using additional measures and analysis strategies. Overall, we find little evidence that non-social mechanisms matter. Instead, our evidence suggests that social mechanisms as the causes of improved business performance.

9. Discussion and Conclusion

We find that teaching small business entrepreneurs in Togo social skills results in a cascade of changes. These entrepreneurs perceive conversations as more collaborative, they learn more form their peers, and they build larger networks with more complementary and diverse peers. Indeed, aggregating these shifts into a single index shows that the treatment substantially improves social interactions and our mediation analyses suggest that these improved interactions are associated with stronger business performance in the year after treatment. Taken together, these results indicate that entrepreneurs are likely "under-networked," but that teaching social

[11] This approach to assessing sentiment in texts may potentially be limited by the fact that the algorithm was trained on language in a context that was relatively different from the one to which it was applied. To ensure this did not fundamentally shape our results, we also replicated these results using the French edition of Linguistic Inquiry and Word Count (LIWC) software, which has been more widely validated (Piolat et al. 2011). For more details please refer to Appendix A16.

[12] We do find, however, that entrepreneurs in both the treatment and control conditions learned and used the marketing practices taught. There was simply no difference in learning between the two conditions. See Appendix A14 for details about learning of marketing practices.

skills can help them unlock the value inherent in learning from peers. That said, there are important boundary conditions and thus opportunities for future research, to which we now turn.

9.1 Boundary Conditions and Future Research Directions

To ensure that the social skills intervention would shift behaviors we administered it to groups of entrepreneurs, simultaneously, within the context of a two-day business training program where the participants would have ample time to get to know one another. It is unclear how the results would change if the social skills training had been given instead to only randomly selected individuals before they joined the training program. The results from our mediation analyses provide suggestive evidence that social skills enabled entrepreneurs to gain more advice from their contacts outside the training program, which in turn improved performance (see Table Table A17-2 in A17). However, the impact on performance of this non-program advice is about half that from within the program. This suggests that improvements in social skills can improve access to advice even when only one party in the interaction possesses them, but that the effect is substantially weaker. Future studies should explore if there are complementarities between being part of a training group and social skills, if longer training can increase the impact in interactions with people with fewer social skills, and whether individual training is effective.

Another limitation of our experimental design is that we did not have a control group that was simply left alone and we do not have evidence from training programs that taught topics other than marketing. In the absence of a third “left alone” arm we are unable to evaluate the causal impact of the marketing content on performance. However, we do find that both the control and treatment conditions used more marketing practices post-treatment and that control entrepreneurs increase their profits over time (Figure 3 and Table A14-1). Similarly, as our intervention was embedded in a marketing training program it is difficult to say if the treatment would have been more or less effective if it had been embedded in a program teaching different business skills. We do, however, expect social skills training to be effective regardless of the setting, since the social skills training content does not depend on particular technical managerial knowledge and our qualitative data suggests advice covered both marketing and non-marketing topics (A15).

Similarly, our experimental design included a relatively short intervention. Rather than teach an entire course on social skills, we limited our treatment to a two-hour introduction. Although this approach led to rapid and large improvements in entrepreneur performance--proving that social skills can be taught and do matter for entrepreneurial performance--Figure 3 suggests that in the long run there is a partial convergence between treatment and control groups. This could mean that our intervention was not extensive enough to create permanent improvements in performance. Hence, it may be that entrepreneurs need to re-invest in their social skills over time in order to maintain their performance advantage. We hope that future studies will explore this by conducting RCTs where the intervention is an entire course on social skills, rather than a 2-hour session.

The composition of our sample also presents limitations. First, by focusing on marketing practices we likely attracted business owners who were particularly keen to grow their businesses. It is less clear whether teaching social skills to less ambitious business owners will have as large an effect, since participants in our program selected into it out of a desire to grow their firms. Second, our experimental design restricted participation to entrepreneurs with businesses in operation for at least a year, in order to improve power and reduce attrition. However, we expect that entrepreneurs at other stages, such as the "pre-launch" phase, will also likely benefit from social skills training, since much of their work revolves around getting feedback on business ideas and networking to secure funding (Bennett and Chatterji 2019). Third, entrepreneurs paid a participation fee and although it was refunded to them at the end of the program, it may have prevented some less successful or struggling entrepreneurs from participating. Although our quantile analyses suggest that the social skills training had similar impacts across different levels of performance, our experimental sample might not be fully representative of entrepreneurs in very precarious financial conditions. Future work will have to assess the impact of social skills training on these kinds of entrepreneurs and how that effect may depend on their level of motivation.

Finally, in the context of strategy and entrepreneurship research the most salient boundary condition is the larger context: Togo. We selected Togo because there remains a dearth of development-focused research in strategy and because it was a setting where we believed entrepreneurs would be receptive to the social skills training (Assenova and Sorenson 2017, Dimitriadis 2021, George et al. 2016). Our qualitative data suggests Togo is a context in which many entrepreneurs recognize the value of peer relationships, but face high costs in forming new ties. Research suggests these relational concerns likely extend to other developing economies where generalized trust is often low and there are institutional voids (Khanna 2018). Thus, at a minimum, our results suggest that social skills might be an important driver of entrepreneurial success in the developing world.

That said, we think the social mechanisms at the heart of our paper are likely universal. Forming new business relationships and learning more from others is costly and challenging for entrepreneurs be they in Lomé, London, or Los Angeles. This is echoed by the fact that courses on social skills at top business schools are particularly popular among MBA students (Baron and Markman 2000, Bedwell et al. 2014, Poets & Quants 2021) and that employers in developed economies increasingly seek to hire people with strong social skills (Börner et al. 2018, Deming 2017). Of course, the pre-existing emphasis on building social skills among knowledge workers, managers, and entrepreneurs might well mean that additional "social skills trainings" would have less of an effect because the "control group" may already have been "treated" in ecosystems like Silicon Valley. Moreover, cultural norms that determine levels of generalized trust can also affect how people evaluate others' trustworthiness and their baseline propensity to form new business relationships, hence the effect of social skills training may be diminished in cultures with higher levels of generalized trust (Baldassarri 2020, Yamagishi et al. 1999). Although well beyond the scope of our study, our findings suggest that future work should explore if variation in "social skills" helps explain why some ecosystems are more successful than others and whether there is still room to improve social interactions for entrepreneurs in places like Silicon Valley (Saxenian 1994). We hope future studies will unpack how these cultural, institutional, and economic forces drive variation in where teaching social skills might have the largest impact.

9.2 Contributions

This study demonstrates the strategic value of social skills for entrepreneurs. The majority of existing research on social skills has focused on the demand for those skills in established firms and the returns to them in labor markets (Börner et al. 2018, Deming 2017). Recent studies have begun to explore the effect of managers' social skills on firm productivity (Hoffman and Tadelis 2021), but these have largely focused on the impact of social skills in the context of a single firm. Here we show that social skills cause differences in between-firm performance, a central concern of strategy researchers.

Moreover, the benefits of social skills are positive-sum, separating them from many other forms of socially derived competitive advantage that are nearly always zero-sum. Unlike other forms of network advantage, such as occupying a brokerage position, being randomly assigned to a section with experienced business school peers, or partnering with superstar collaborators, the benefits of social skills scale (Azoulay et al. 2010, Lerner and Malmendier 2013, Ryall and Sorenson 2007). This is because social skills appear to help entrepreneurs discover who is the best match for their particular needs, thus enabling them to form relationships that create value for both parties as against trying to compete to partner with whomever is (perceived) as most successful or similar (Azoulay et al. 2017).

This study also contributes to research on business and entrepreneurship training (McKenzie 2021). This research ranges from tests of whether management consulting improves manufacturing productivity (Bloom et al. 2013) to whether high-technology incubators and accelerators kickstart startup growth (Yu 2020) to evaluating whether a scientific approach to early-stage entrepreneurship is especially effective (Camuffo et al. 2020). Although these studies help explain the efficacy of different management training programs and incubator structures, they have largely overlooked training entrepreneurs in "softer" social skills. This study shows that training programs can also effectively teach soft skills and that these skills pay off. Put differently, our study raises the possibility that much of the value created by these training programs may be less in the materials and frameworks they teach, and more in the culture they build and the connections they enable.

Much of the early research on social skills was done by scholars in psychology and organizational behavior, who developed a wide range of measures of social skills (Klein et al. 2006). Although most of these social skills measures are based on studies of college students, the majority of them emphasize communication and collaborative relationship building (Hayes 2002), both of which are part of our theoretical framework. Our study builds on these core psychological assumptions about social skills by extending them to the context of entrepreneurship and causally identifying their performance implications at the business level.

The idea of social skills also opens up new avenues for the study of business relationships. Existing research has primarily explained the formation of business relationships and networks using the characteristics of dyads and the pre-existing networks they are embedded in. This work has emphasized homophily (McPherson et al. 2001), proximity (Hasan and Bagde

2015), mutual ties (McFarland et al. 2014), and common organizational membership (Small 2009) as drivers of business relationships. Yet, when scholars have tried to use these social forces to engineer new and improved social connections the results backfire (Carrell et al. 2013, Hasan and Koning 2019). Trying to directly build a new connection in the network, be it through co-location or shared team membership, fails because managers and entrepreneurs exert agency in who they choose to connect with (Hasan and Koning 2020). Instead, we argue that policymakers and executives can move to the "social frontier" by teaching managers and entrepreneurs how to search, discover, and build effective relationships themselves. This suggests that future work should explore whether there is strategic value in shaping individuals' incentives and beliefs about the social matching process in and between organizations.

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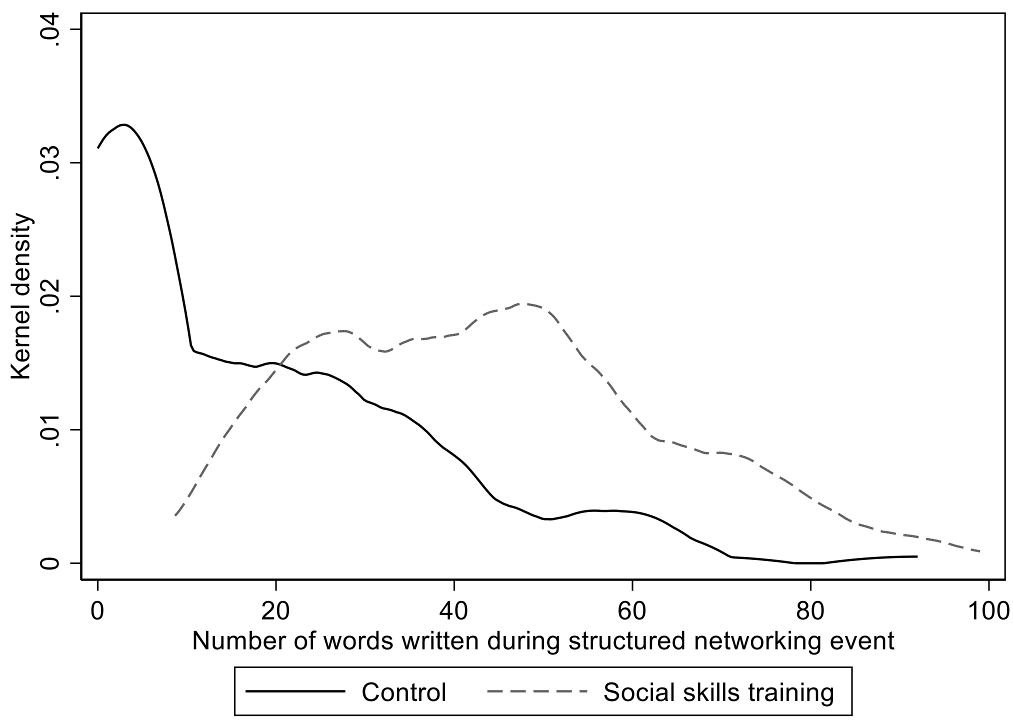
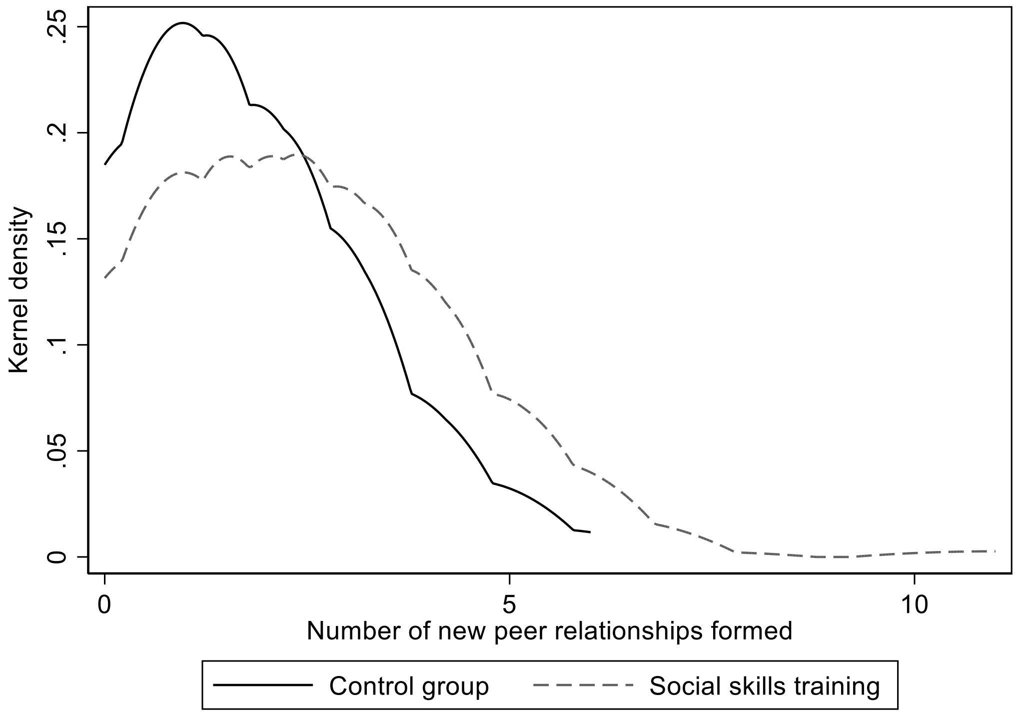
FIGURES AND TABLES

Figure 1. Social Skills Increase Information Exchange



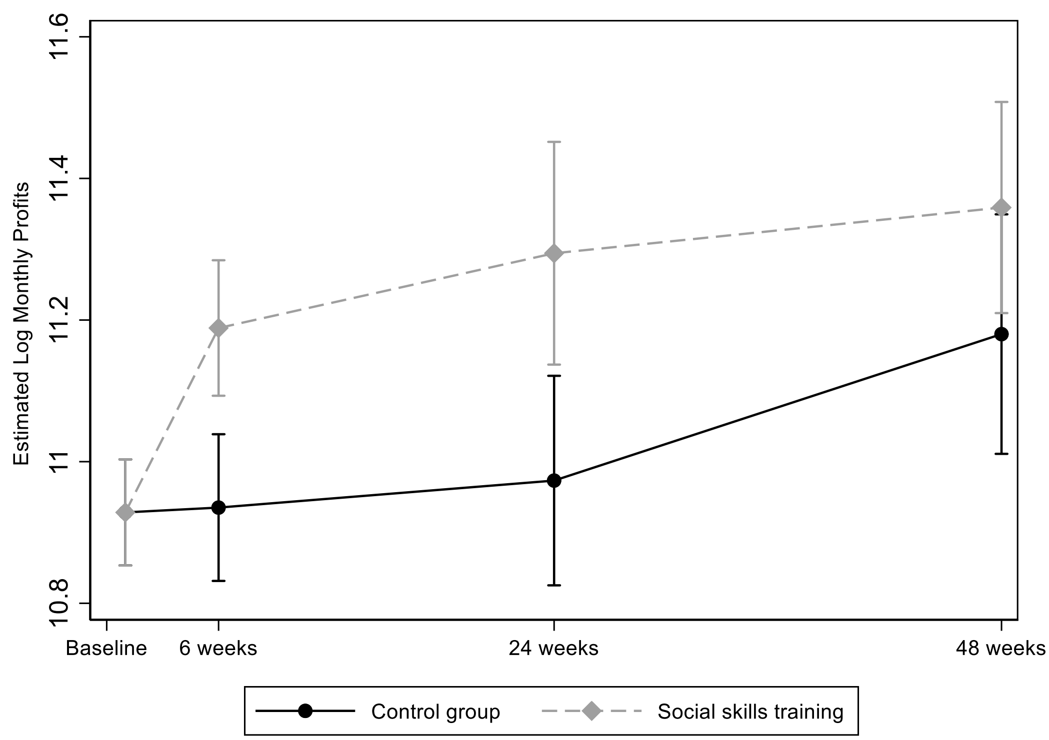
The kernel density plots above compare the number of words written by entrepreneurs in the control and treatment groups. For entrepreneurs in the control group (black solid line), the density is much higher at lower numbers of words, indicating that most entrepreneurs wrote fewer than 20 words when describing their exchanges with peers. By comparison, the density plot for entrepreneurs in the treatment group (grey dashed line) is shifted to the right, with a median near 50 words, indicating that in general these entrepreneurs had more to describe after interactions with peers.

Figure 2. Social Skills Increase Relationship Formation



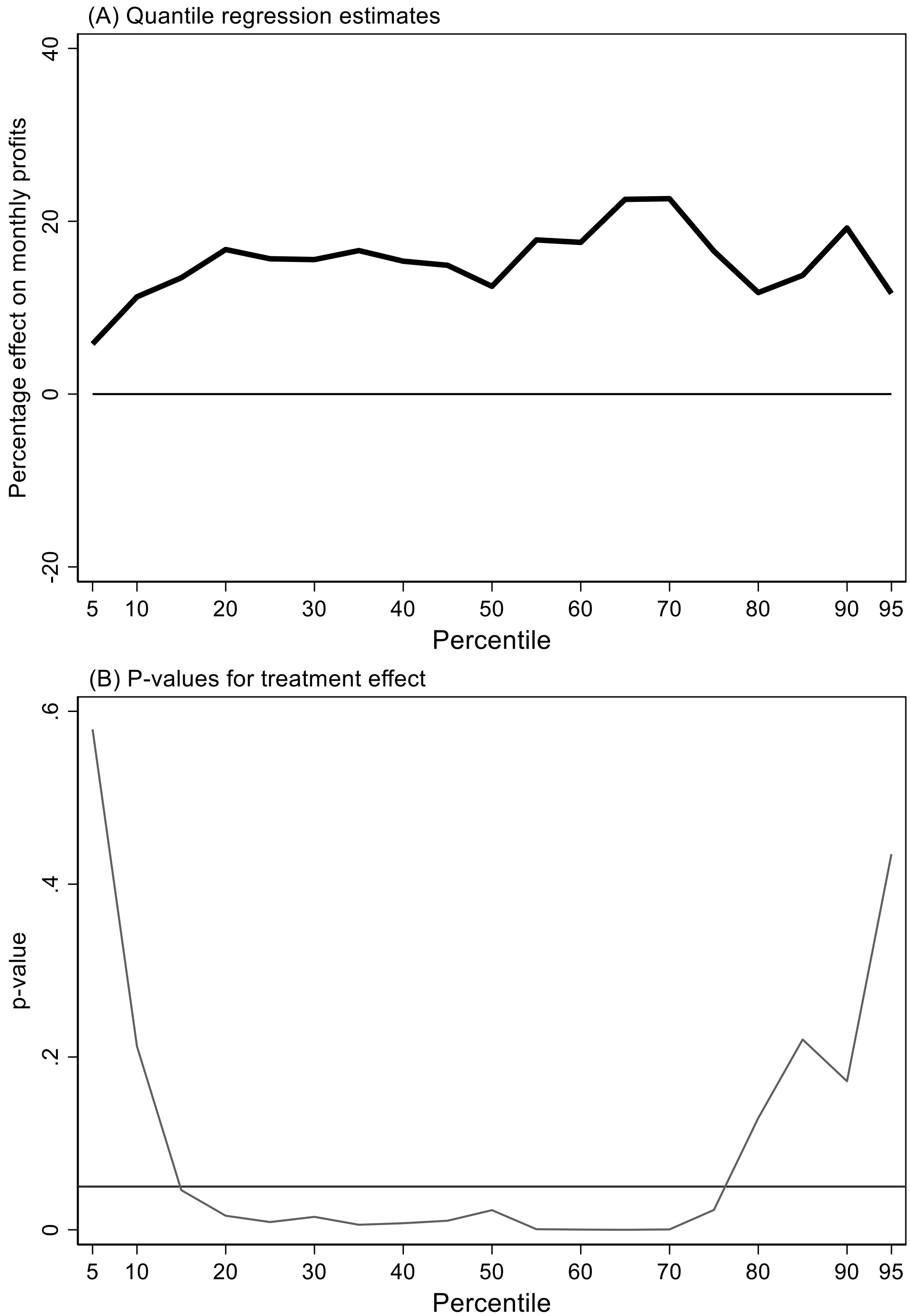
The kernel density plots above compare the number of relationships formed by entrepreneurs in the control group and treatment group. Relationships are measured six weeks after the completion of the training program. The density plot for entrepreneurs in the control group (black solid line) is skewed to the left and peaks at about one relationship formed, while the plot for those in the treatment group (grey dashed line) is shifted to the right of control group and peaks at about two relationships formed, indicating that entrepreneurs in the treatment formed more new relationships.

Figure 3. Social Skills Increase Profits



The plots above compare the average predicted log monthly profits, based on the estimates in Model 3 of Table 5, for entrepreneurs in the control group and in the social skills treatment group. Bars represent 95% confidence intervals. The profits for entrepreneurs in the control group (black solid line) do not significantly shift between baseline and 24 weeks after the training program. Profits for those in the treatment group (grey dashed line) increase soon after the program and remain above the control group in all periods. The predictions include entrepreneur fixed effects, and so accounts for baseline performance differences.

Figure 4. Quantile Regression Estimates and P-Values



Panel (A) above shows the estimates of the treatment effect at each fifth quantile from the quantile regressions. According to the plot, social skills training improved performance uniformly across the distribution of profits. Panel (B) presents the p-values from the quantile regressions, testing whether the effect of social skills training is statistically indistinguishable from zero at each quintile. The figure shows that we reject the null that the treatment effect is zero at every quintile between the 15^{th} and approximately the 75^{th}.

Table 1. Structure of Social Skills Training Session

Step	Duration	Content
1	20 minutes	*Interactions in business*: Instructors bring attention to interpersonal interactions in business. They define interpersonal interactions and describe what they often involve. Emphasize that entrepreneurs are members of the local business community, which includes other entrepreneurs, and that they have a vested interest in others' success.
2	20 minutes	*Adopting a collaborative approach*: Having created a common starting point, instructors continue by teaching how entrepreneurs can use a collaborative approach in their interactions with others. This involves asking questions about others' businesses, identifying problems or struggles others may be facing, and trying to offer help based on their own experiences and knowledge.
3	20 minutes	*Communicating about business*: Having described what collaborative interactions look like, the instructors show entrepreneurs what interactions that focus on business topics look like. These interactions consist of discussing developments in their businesses, as well as challenges. Communicating directly and clearly about business topics is a focus of this section.
4	1 hour	*Case study and questions*: This section begins with a description of practical steps for interactions: how to talk to new acquaintances, reaching out, following up. An interactive case discussion and commentary follows. The session ends with time for questions and answers.

Table 2. Summary Statistics and Bivariate Correlations

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Collaborative perception of interactions	2.691	0.928													
2	Information exchange	30.872	23.929	0.004												
3	Num. of relationships formed	1.983	1.704	0.062	0.134											
4	Skill complementarity	0.155	0.300	0.048	0.126	0.122										
5	Ethnic concentration	0.833	0.256	-0.037	-0.134	-0.382	-0.070									
6	Profits at baseline (log)	10.938	1.141	-0.122	-0.0552	-0.141	0.025	0.027								
7	Social skills training	0.518	0.500	0.131	0.571	0.229	0.134	-0.170	-0.050							
8	Ewe ethnicity	0.781	0.414	-0.008	0.099	0.188	0.039	0.031	0.047	0.015						
9	Female	0.355	0.479	0.057	0.021	0.042	-0.089	-0.005	-0.097	0.059	-0.083					
10	Completed primary school	0.748	0.435	-0.076	-0.022	-0.001	-0.085	-0.108	0.020	-0.107	-0.112	0.006				
11	Employees	1.795	3.341	-0.002	-0.086	-0.074	-0.129	0.066	0.286	-0.086	-0.044	-0.058	0.009			
12	Firm age	10.590	7.649	0.002	0.070	0.095	0.108	0.096	0.088	0.113	0.234	0.019	-0.410	0.032		
13	Management practices score	0.577	0.266	0.004	0.040	0.065	0.189	0.023	0.257	0.033	0.077	0.017	-0.126	0.128	0.261	
14	Class size	23.465	2.777	0.084	0.297	0.123	-0.092	-0.035	-0.100	0.397	0.057	0.076	-0.013	-0.055	-0.001	-0.114

* N = 301 except for profits at baseline, which has an N of 278. This is because 23 participants had not tallied revenue and costs before the baseline survey. The high correlation between the social skills training and class size is due to the small number of training groups, the association is not statistically significant as shown in the balance table in Appendix A2.

Table 3. Negative Binomial Regressions Show Social Skills Increase Entrepreneurs' Collaborative Perceptions and the Amount of Information Exchanged

	Collaborative perception		Information exchange	
	(1)	(2)	(3)	(4)
Social skills training	0.106**	0.098*	0.994**	1.000**
	(0.039)	(0.044)	(0.213)	(0.248)
N	301	301	301	301
Sector Fixed Effects	No	Yes	No	Yes
Control Variables	No	Yes	No	Yes

All models estimated using negative binomial regression. The outcome variable in Models 1 and 2 is the number of collaborative words selected by each participant to describe interactions. The outcome variable in Models 3 and 4 is the number of words written by individual participants during the networking session, during which they spoke to three randomly selected peer entrepreneurs. Control variables include ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Robust standard errors clustered at the training-class level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 4. Social Skills Increase the Number of Relationships Formed, Increase the Proportion of Relationships Formed that are Skill-Complementary, and Reduce the Level of Ethnic Concentration in Relationships Formed

	Relationships formed		Skill complementarity		Ethnic concentration	
	(1)	(2)	(3)	(4)	(5)	(6)
Social skills training	0.388**	0.360**	0.659**	0.814**	-0.660*	-0.870**
	(0.143)	(0.109)	(0.225)	(0.280)	(0.283)	(0.178)
N	301	301	301	301	301	301
Sector fixed effects	No	Yes	No	Yes	No	Yes
Control variables	No	Yes	No	Yes	No	Yes

Models 1, 2, 3 and 4 are estimated using negative binomial regressions. Models 3 and 4 include the inverse hyperbolic sine of the number of relationships formed as an offset. The outcome variable in Models 1 and 2 is the number of peer relationships to other participants from the same class that each entrepreneur formed six weeks after the training program. The outcome variable in Models 3 and 4 is the number of relationships formed that exhibit skill complementarity. Models 5 and 6 were estimated using fractional logit regressions and the outcome variable is the Herfindahl index of concentration among ethnic groups of the relationships formed. Control variables include ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Robust standard errors, clustered at the training group level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: **Social skills increase monthly profits**

	Monthly Profits (log)		
	(1)	(2)	(3)
Social skills training	0.170*	0.171*	
	(0.058)	(0.062)	
Social skills training x Post-treatment			0.251*
			(0.103)
Post-treatment			0.008
			(0.073)
N	768	768	1046
Entrepreneurs	278	278	278
Survey wave FE	Yes	Yes	Yes
Baseline profits	Yes	Yes	No
Sector FE	No	Yes	No
Control variables	No	Yes	No
Entrepreneur FE	No	No	Yes

The outcome is log monthly profits. Models 1 and 2 pool the post-treatment periods and include sector and survey wave FE controlling for baseline profits, ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Model 3 uses a diff-in-diff specification with entrepreneur FE. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6: Constructing the social interactions index

Type of interaction	Description	Component variables
Networking between training program co-participants	Measures the number of interactions and the quality of matches made during the training program.	1.Cooperative words 2. Number of participants entrepreneurs exchanged contact information with; 3.Number of participants entrepreneurs received advice from; 4. Number of participants entrepreneurs formed relationships with 5.Average profits (log) of participants with whom they formed ties; 6.Average skill complementarity of the participants with whom they formed ties. 7. Ethnic concentration ×(-1) of participants with whom they formed ties.
Advice received during the training program	Measures the relevance, complexity, and quantity of advice transmitted during networking event.	8.Total number of words written; 9 Proportion of words that were related to work; 10.Proportion of six-letter words; 11.Words per sentence; 12.Number of pieces of advice.
Networking with others outside the training program	Measures networking behavior after the training camp and the size of entrepreneurs' relationship portfolio.	13.Engaging in referrals; 14.Reaching out to new acquaintances outside the program; 15.Participating in an event with other entrepreneurs; 16.Number of advice contacts.
Advice received from others outside the training program	Measures the extent to which entrepreneurs activated existing ties to peer entrepreneurs to seek advice.	17.Number of peer advice relations outside the program that entrepreneurs reached out to for help.

Table 7: First stage of mediation for social interaction index and alternative mechanisms

	Social interactions index	BERT positive affect score	Marketing practices index
	(1)	(2)	(3)
Social skills training	0.829**	0.375**	0.014
	(0.150)	(0.050)	(0.091)
N	257	257	278
Entrepreneurs	257	257	278
Sector FE	Yes	Yes	Yes

The outcomes in Models 1 and 2 were measured during the training program, while the outcome in Model 3 is an average across all post-treatment periods. Hence all models are cross-sections. The sample size in Models 1 and 2 is 257 because we could not obtain scanned networking notes for one training cohort. All regressions include sector fixed effects. Robust standard errors clustered by training group in parentheses.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 8: Second stage of mediation for social interaction index and alternative mechanisms

	Monthly Profits (log)		
	(1)	(2)	(3)
Social skills training	0.039	0.173*	0.170*
	(0.060)	(0.079)	(0.058)
Social interactions index	0.158**		
	(0.027)		
BERT positive affect score		0.009	
		(0.118)	
Marketing practices index			0.039
			(0.075)
Survey wave FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
N	710	710	768
Entrepreneurs	257	257	278
ACME	0.137	0.022	-0.000
	[0.082, 0.199]	[-0.071, 0.113]	[-0.010, 0.008]
% of Tot. Eff. Mediated	0.858	0.137	-0.003
	[0.478, 3.060]	[0.076, 0.527]	[-0.010, -0.002]
ρ at which ACME = 0	0.162	0.016	0.019

Data are from three post-treatment survey rounds and show average impact over the post-training period. All regressions include sector and survey wave fixed effects, and control for baseline profits (log). The number of entrepreneurs in Models 1 and 2 is 257 because scanned networking notes for one training cohort were missing. Robust standard errors clustered by training group in parentheses. ACME = Average Causal Mediation Effect. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

ONLINE APPENDIX

Social Skills Improve Business Performance

Oct 8, 2021

Contents:

A1. Togo, qualitative evidence, and experimental procedures

Togo

Togo is a small country in West Africa, with a population of approximately seven million people, about two million of whom reside in the capital Lomé. It is bordered on the west by Ghana, on the east by Benin, and to the north by Burkina Faso, to the south it rests on the Gulf of Guinea. As a former French colony, the main language for business is French. Togo became an independent country in 1960, but since then it has been largely isolated from the international community due to the dictatorial political regime and the human rights abuses the regime has committed. Togo is an income poor country. In terms of per capita income at purchasing power parity it ranked 207th of 216 countries in 2017 (World Bank 2018). Similarly, the UN's Human Development Index (2017) ranked Togo 166th of 188 countries in 2017. Over 54% of the population lived under the poverty line of $1.90 per day and the mean years of schooling for inhabitants was 4.7 years in 2017 (United Nations Development Programme 2017).

Togo is made up of multiple ethnic groups. The majority ethnic group in the south of the country is the Ewe group, whereas in the north it is the Kabiye group. Beyond these two main groups there are also significant populations of the Ana, Yoruba, and Kotokoli ethnic groups throughout the country.

Qualitative data on entrepreneurs in Togo

During three trips to Lomé between 2015 and 2017 one of the authors conducted 47 semi-structured interviews with local entrepreneurs, each of which lasted between 30 and 90 minutes. Interviews included entrepreneurs at every stage of growth, from recently launched to several decades in business. The sample of entrepreneurs also covered a diverse array of sectors, including food processing, construction, clothing manufacturing, and electronics.

The sample of interviewees was built using a staggered referral approach (Small 2009). The starting point were several local nonprofit associations whose social mission was the promotion of entrepreneurship. The author used a grounded theory approach in their interviews (Charmaz 2014). The interviews began with general questions about what entrepreneurs felt were significant challenges in doing business in Togo and what they felt were important ways of overcoming those challenges.

After the first few interviews a pattern emerged that forming relationships was a complex process for entrepreneurs. Many complained about feeling isolated and having to manage alone the difficulties of doing business in Togo. Talking to entrepreneurs revealed that the process of connecting was often sidetracked because they were unable to get to the point where they could talk about their businesses or develop a foundation of mutual respect and trust. Table A1-1 below provides illustrative quotes of these themes from the interviews.

Table A1-1: Illustrative Quotes

Interview code	Theme	Quote
YE 12	Creating contacts	I find that to get help in Togo it's complicated, because there's no information really. There are no real contacts, because you reach out to people through their emails and their websites, but you never get a response. Similarly, you send letters to request a meeting and it's as if you never did anything. It's frustrating.
KK1	Creating contacts	Here, when you want to meet someone, you must have someone closely connected to you to put you in touch with them, that introduces you. If you have not been introduced the contact is dead on arrival. It's a little complicated, but for us we cannot get in touch with anyone in the ministry, despite all of our achievements.
YE 4	Creating contacts	[…] entrepreneurs here are not able to reach out to people. Even mentors tell you not to talk to others about your business. All this slows down the evolution of your business.
YE13	Creating contacts	I'm stressed talking to others, it's a little difficult. You know it's a little difficult here in Africa to speak in public, here it’s like we are afraid of people we didn't know.
YE7	Creating contacts	I would say that especially here in our locality, in our country, it is a little difficult, in the business field, to make contacts.
YE 13_2	Creating contacts	What I can say is that they [entrepreneurs] have good ideas but they cannot realize them because they cannot approach other people to discuss with them.
SY 1	Importance of relationships	Today if you do not know people your business does not pass.
AY 3	Lack of collaboration; Training to form ties	It's very difficult! Entrepreneurs prefer to work alone, unfortunately. But our job is that too: to be able to sensitize them, train them, explain to them the merits of living together and working together.

Field experimental procedures

The setting for the field experiment was the business training program “Marketing in Action.” The offices of the business training program were based in the suburb of Kegue, in Lomé. We registered all participants there between the 14th of February and 31st of March 2017. The first group of participants began their training on April 3rd 2017 and the last group finished their training on May 18th 2017. After the end of the training program the offices remained open for several months in case any of the participants had questions or comments.

One author was present during the entirety of the training program in order to ensure that the registration of participants, the randomization into the treatment, the teaching of the program, and the discussion of social skills were done correctly. In addition to the author, there were three full-time employees: one administrative assistant and two instructors. The administrative assistant helped manage the registration process and organize the teaching space during the training. The two instructors were consultants from Lomé, who had previously taught similar training programs to Togolese entrepreneurs at the local university and in programs organized by the World Bank. The instructors were intimately familiar with the teaching material and how to convey them appropriately to local entrepreneurs. Finally, to help with the recruitment of participants, three local university students were hired to walk through the main business districts of Lomé and advertise the training program to business owners. We also advertised the training program to local entrepreneurs through a number of local nonprofits, incubators, business associations, Facebook pages, and WhatsApp groups. The canvassing and advertising produced 326 registrants into the training program.

The structure of the two-day training program “Marketing in Action” is described in detail for the treatment and control conditions in Figure A1-1. As the figure shows, in the treatment condition the training began with the social skills module and then continued on to the marketing practices, whereas in the control condition entrepreneurs only covered marketing practices during the two days. The figure also illustrates when the participants had lunch and coffee breaks, as well as when the networking event took place. As shown, both control and treatment conditions spent the same amount of time together in total during the two days.

Figure A1-1: The Structure of the Training Program

Treatment Group

Time	Day 1	Day 2
8:00	Brief introduction to the Training Program	Session 3 – Marketing practices 4-5
8:30	Social Skills	Session 3 – Marketing practices 4-5
9:30	Social Skills	Session 3 – Marketing practices 4-5
10:30	Coffee break (15 minutes)	Coffee break (15 minutes)
10:45	Session 1 – Marketing practices 1	Session 4 – Marketing practices 6-8
12:00	Session 1– Marketing practices 1	Session 4 – Marketing practices 6-8
12:30	Lunch break (30 minutes)	Lunch break (30 minutes)
13:00	Session 2 – Marketing practices 2-3	Networking session
14:00	Session 2 – Marketing practices 2-3	Networking session
16:00	Session 2 – Marketing practices 2-3	Networking session
17:00	Session 2 – Marketing practices 2-3	Test on business practices; Exit survey
18:00	End of Day1	End of Program

Control Group

Day 1	Day 2
Brief introduction to the Training Program	Session 3 – Marketing practices 4-5
Session 1 – Marketing practices 1	Session 3 – Marketing practices 4-5
Session 1 – Marketing practices 1	Session 4 – Marketing practices 6-7
Coffee break (15 minutes)	Coffee break (15 minutes)
Session 2 – Marketing practices 2-3	Session 4 – Marketing practices 6-8
Session 2 – Marketing practices 2-3	Session 4 – Marketing practices 6-8
Lunch break (30 minutes)	Lunch break (30 minutes)
Session 2 – Marketing practices 2-3	Networking session
Session 3 – Marketing practices 4-5	Networking session
Session 3 – Marketing practices 4-5	Networking session
Session 3 – Marketing practices 4-5	Test on business practices; Exit survey
End of Day1	End of Program

Legend

Yellow	Social Skills
Blue	Marketing practices
Green	Networking session

Data collection

Data collection was built around five different time points in the field experiment, the flow of which is shown in Figure A1-2. A *pre-treatment survey* was administered as individuals arrived for the first day of the training program. At the end of the second day of the training program, participants were given a training program *exit survey*, which included questions related to their experiences, their interactions with others, and a word-map for the word selection exercise. The third data collection point was the *first follow-up survey* six weeks after the training program, between May and June 2017. Instructors followed-up in person with the participants to survey them at the location of their business. It was important for the instructors to survey them and not a third party because there was an important bond of trust between the instructors and participants. The *second follow-up survey*, which took place six months after the training program, from November to December, 2017 and our final and third survey was completed a year after the program. Finally, the *third follow-up survey* occurred approximately one year after the training program. Appendix A2 describes the sample sizes and attrition in detail.

Figure A1-2: Research Design Timeline

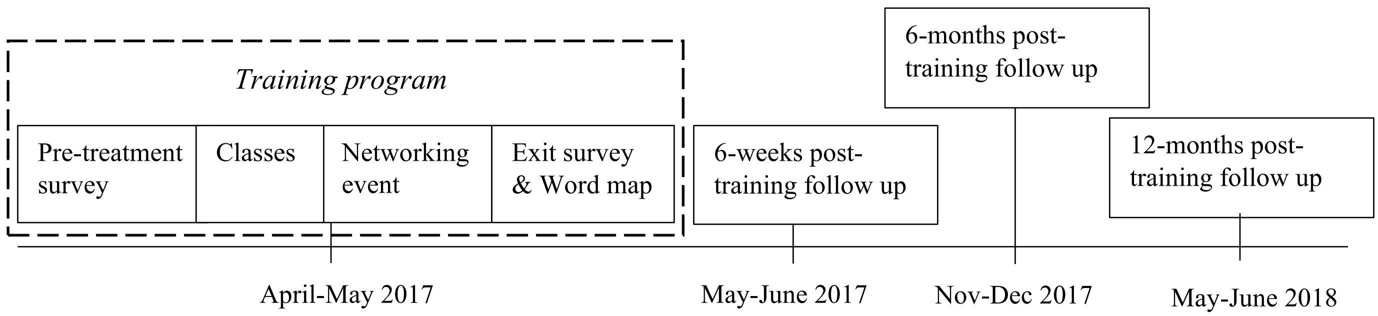
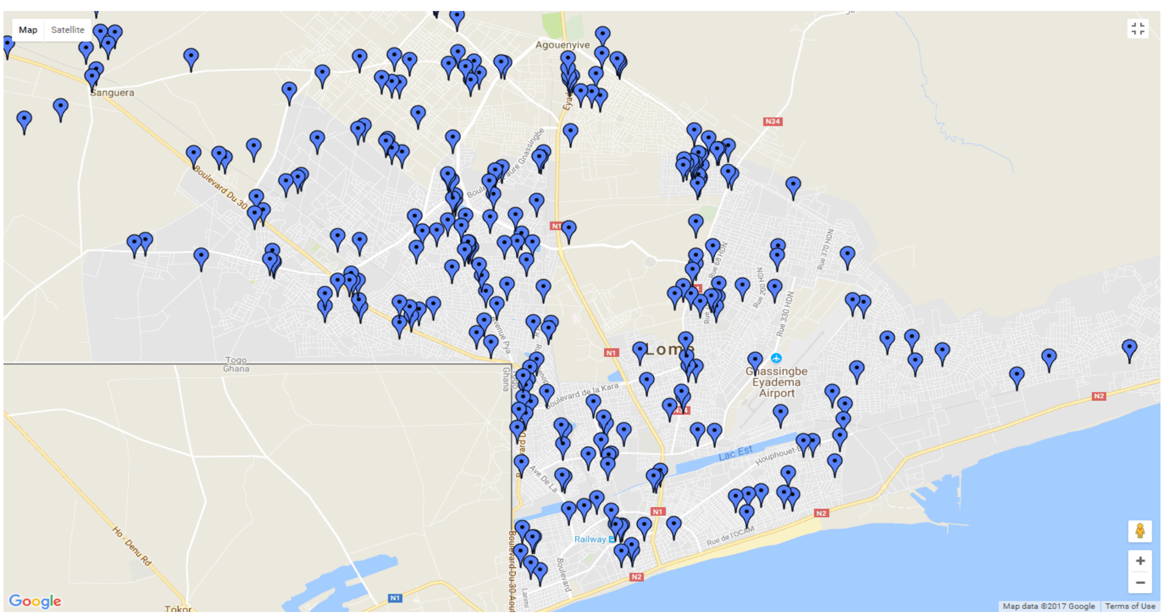


Figure A1-3, below, shows the geographic distribution of the 301 entrepreneur participants across the city of Lomé that completed the training program and the follow-up surveys. It is worth noting that the broad canvassing and online advertising produced a geographically diverse set of participants.

Figure A1-3: Approximate geographic location of study participants in Lomé

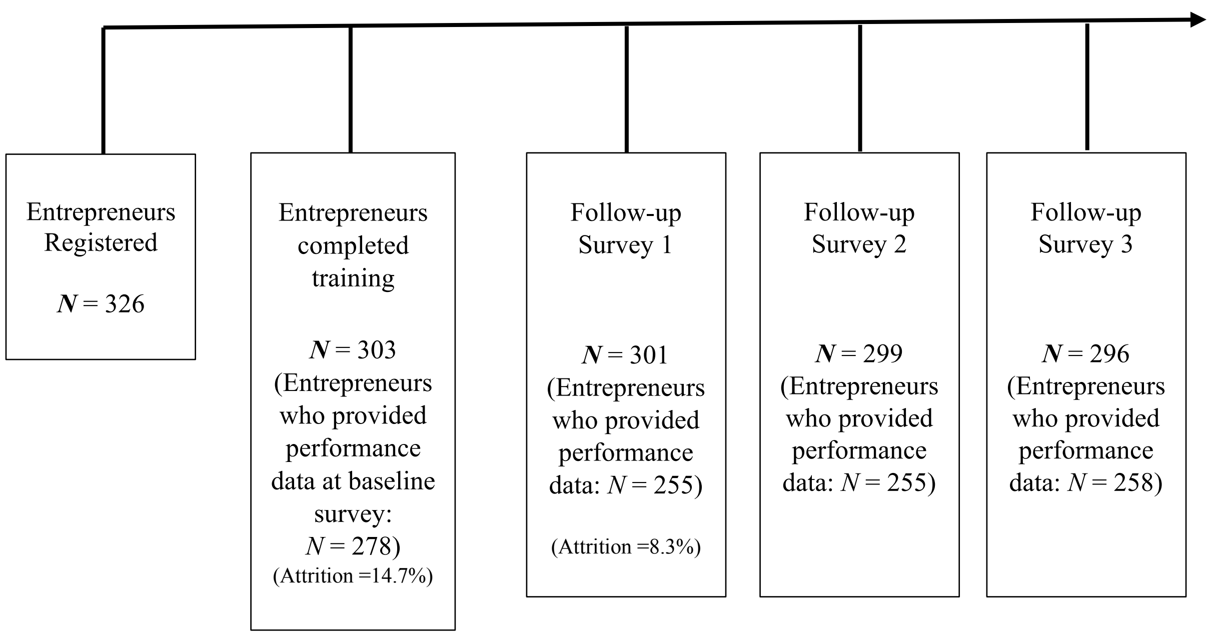


A2. Sample, balance, and attrition

Sample

Figure A2-1 outlines the sample size at each stage of the field experiment. 326 entrepreneurs registered to participate in the program, 303 completed the training, 301 participated in the first follow-up survey, 299 in the second follow-up, and 296 in the third follow-up (see Figure A1-2 above for timing of surveys). Among the 23 entrepreneurs who attrited after registering and before completing the training, 18 entrepreneurs never came to the training program and 5 entrepreneurs completed the first day of the training program but dropped out after that.

Figure A2-1: Timeline and Sample



In each survey wave, among those who participated there were entrepreneurs who were unable to provide performance data because they had not completed their accounting. As a result, although these entrepreneurs responded to questions about their networking and business activities, they could not provide data about their profits or sales. The sample size for entrepreneurs who provided financial performance data is therefore smaller in each survey wave than the sample size for questions about networking and business activities. We report the sample size for entrepreneurs who provided performance data in parentheses in Figure A2-1. In all our calculations of attrition rates and tests for attrition bias we used the sample of entrepreneurs who provided financial information.

In our analyses of the networking outcomes and the performance outcomes we used all the available data we had at our disposal. This meant including entrepreneurs who had not responded to the performance questions in our analyses of the networking outcomes, which led to two samples for our analyses.

Networking outcomes sample (N=301) In our analyses of the networking outcomes, such as number of ties formed and skill complementarity of ties formed, we used the cross-section of data from the first follow-up survey, which had a total of 301 respondents, out of 303 entrepreneurs who completed the training program. Hence, the sample for the relationship-building analyses, which tested Hypotheses 1-4, use this sample of 301 entrepreneurs.

Performance outcomes sample (N=278) Similarly, in our performance analyses, which tested Hypothesis 5, we relied on longitudinal data from all survey waves. For these analyses we restricted our sample to entrepreneurs who provided performance information in the baseline (pre-treatment) survey and at least one post-treatment follow-up survey. There were 278 entrepreneurs, of the 303 who completed the training program, who met this criterion, which led to a sample of 1,046 observations for our performance analyses. Note that this sample size excludes 24 observations that were data entry errors (these are discussed in Appendix A3).

Balance

To test the balance between the treatment and control groups and validate our randomization we ran a series of regressions, which are presented in Table A2-1. In each model the treatment, a binary variable indicating whether an entrepreneur received the social skills treatment, is regressed on variables that capture entrepreneur and business characteristics. Models 1 to 12 test each entrepreneur characteristic on its own, while Model 13 tests all variables simultaneously. None of the coefficients in any of the models are statistically significant at conventional levels. This indicates that none of the entrepreneurs' or their businesses' characteristics are strongly associated with receiving the treatment and that therefore the randomization of the treatment was successful, producing balanced control and treatment groups.

Among the variables tested in Table A2-1 *class size*—which is the count of entrepreneurs in each 2-day training group—was positively associated with the treatment at the 10% significance level, suggesting that training groups in the treatment condition may have been slightly larger than training groups in the control condition. The difference in mean class size between treatment and control groups was approximately 2 participants, which is not a substantively large difference that would be likely to affect the quality of the teaching, the treatment, or create a significantly different classroom environment. When testing as many covariates as we are the probability of falsely rejecting the null that a covariate is unrelated to the treatment increases substantially. Assuming that the covariates we are testing for balance on are largely independent, the estimated probability of a false rejection of at least one variable we tested at the 10% significance level is over 70% (=1-0.9^12). Therefore, the fact that class size was marginally statistically significant is not cause for concern. Rather, we follow best practice for RCTs and ensure that this variable is included as a control in all of our analyses (Bruhn and McKenzie 2009).

Table A2-1: Sample balance at baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Ewe ethnicity	0.043												-0.006
	(0.095)												(0.077)
Female		0.095											0.055
		(0.058)											(0.052)
Completed primary school			-0.124										-0.078
			(0.100)										(0.075)
Employees				-0.014									-0.011
				(0.011)									(0.009)
Firm age					0.008								0.007
					(0.009)								(0.005)
Management practices score						0.049							0.092
						(0.270)							(0.162)
Class size							0.072+						0.069+
							(0.033)						(0.034)
Registered by canvassing								-0.054					-0.028
								(0.147)					(0.207)
Registered by referrals									0.009				-0.054
									(0.100)				(0.157)
Registered by social media										0.023			-0.130
										(0.219)			(0.237)
Days between registration and attendance											0.001		0.005
											(0.010)		(0.008)
Profits monthly (log)												-0.021	-0.014
												(0.046)	(0.024)
N	301	301	301	301	301	301	301	301	301	301	301	278	278

Models 1-12 use our "networking outcomes" sample of 301 businesses. Model 12 and 13 restrict the sample to the 278 businesses we have at least one pre-treatment and post-treatment performance measure. All models are estimated using OLS. Robust standard errors clustered by training group in parentheses + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Attrition

The rates of attrition were approximately 15% between the registration and baseline survey, and 8% between the baseline survey and the first follow-up survey, six weeks later. There was no attrition after the first follow-up survey. The average attrition rate across all survey rounds was therefore 5.75%, which is well below those reported by comparable RCTs with entrepreneurs in Africa. For example, Anderson et al. (2018) reported an average attrition rate of 24%, Campos et al. (2017) reported an average attrition rate of 9%, and Atkin et al. (2017) report an average attrition rate of 11%. Table A2-3 presents regression analyses on survey attrition, to test whether attrition was related to treatment. Models 1 and 2 regress attrition between registration and participation on treatment, while models 3 and 4 regress attrition between the baseline survey and first follow-up survey on treatment. In both cases the attrition was not related to the treatment condition in a statistically significant way and the magnitudes of the coefficients is nearly zero.

Table A2-3: Effect of treatment on survey response rates

	Attrition between registration and baseline survey		Attrition between baseline and first follow-up survey	
	(1)	(2)	(3)	(4)
Social skills training	0.031	-0.003	0.036	0.015
	(0.050)	(0.027)	(0.029)	(0.017)
Ewe ethnicity		-0.013		-0.246**
		(0.017)		(0.037)
Female		0.019		0.003
		(0.033)		(0.038)
Completed primary school		-0.004		0.048*
		(0.026)		(0.020)
Employees		-0.003		-0.002
		(0.002)		(0.003)
Firm age		-0.004		0.002+
		(0.002)		(0.001)
Management practices score		-0.154		-0.000
		(0.089)		(0.057)
Class size		0.010*		0.009**
		(0.004)		(0.002)
N	326	326	326	326
Entrepreneurs	326	326	326	326
Sector FE	No	Yes	No	Yes

Outcome is a binary indicator of whether the entrepreneur was present in the survey wave. Robust standard errors clustered by training group in parentheses. All models estimated using OLS. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Although there is no evidence from Table A2-3 that attrition was related to the treatment, we conducted two tests to ensure that the performance results were robust to the attrition. First, we explored what would happen to our results under the extreme assumption that an equal number of attritors had dropped out of the treatment and control groups and that the additional attritors from the treatment group also happened to be the top performers in that group. This assumption balances the number of attritors in the treatment and control group by eliminating the appropriate number of top performers in the treatment group. This leads to dropping 59 observations. The regression using this sample is shown in Model 2 of Table A2-4 below. The treatment effect in this model is slightly smaller by about 2 percentage points than our main performance result, reproduced in Model 1 of Table A2-4. The overall magnitude of the coefficients are similar.

The second way we explored the potential effects of attrition was by testing another extreme assumption: that all those who dropped out of the control group were as good as the best performers in the treatment group. To test this, we replaced the missing values for monthly profits for those who had attrited from the control group with randomly selected monthly profits from entrepreneurs in the treatment group who ranked in the 95th, 90th, and 85th percentiles. Doing so adds 31 observations to our sample. In this case, when the missing profits for attritors in the control group are replaced with the values from entrepreneurs in the 95th percentile of the treatment group, the treatment effect is reduced substantially, as shown in Model 3 of Table A2-4. As the table shows, the coefficient is still large in magnitude but no longer statistically significant. This, of course, is quite an extreme assumption about attrition. As we replace the hypothetical performance of control group attritors with less extreme assumptions, that they might all rank in the 90th (Model 4) or 85th (Model 5) percentiles of performers, we see that the treatment effect remains robust and similar in magnitude to the original estimate in Model 1.

Table A2-4: Robustness of Primary Outcomes to Differential Attrition

	Original result	Top	95th	90th	85th
	(1)	(2)	(3)	(4)	(5)
Post-treatment	0.008	-0.065	0.106	0.079	-0.026
	(0.073)	(0.069)	(0.074)	(0.073)	(0.074)
Post-treatment X Social skills training	0.251*	0.233*	0.153	0.190+	0.193*
	(0.091)	(0.100)	(0.088)	(0.089)	(0.088)
Survey wave FE	Yes	Yes	Yes	Yes	Yes
Entrepreneur FE	Yes	Yes	Yes	Yes	Yes
N	1046	987	1077	1077	1077
Entrepreneurs	278	268	281	281	281

The outcome variable in all models is log monthly profits. Model 1 reproduces the results from model 3 in Table 5 in the main paper. Model 2 drops 59 observations from top performers in the treatment group, while Models 3-5 replace missing observations in the control group with performance levels from varying percentiles of the treatment group. Standard errors clustered by training group. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

A3. Identifying surveyor coding errors

A common concern with survey data are coding errors. Experienced surveyors can make mistakes when entering numbers or may misunderstand data entry instructions. To detect potential coding errors in our measure of performance—monthly profits—we began by implementing standard procedures for exploring our data for outlier observations.

We did this by calculating Cook's Distance and DF Beta for each observation, which are measures of observation influence (Stevens 1984). They approximate the degree to which coefficients change when each observation is omitted. Cook's Distance estimates the aggregate influence of each observation on all coefficients in the model, while DF Beta calculates the influence of each observation on the treatment coefficient specifically.

Having calculated these measures, we manually inspected the data. A cluster of observations at the minimum of the distribution for monthly profits stood out because of their abnormally high influence and their values that were inconsistent with other observations. We ranked the 50 smallest values for monthly profits in the dataset and inspected them (these are reproduced in Table A3.1 below, splitting them by surveyor). At the bottom of the distribution were several observations that were either "0" or "1." In Togolese currency, 1 FCFA is equivalent to approximately 0.2 cents in USD, which has no buying power and does not accord with any intuition about the performance of Togolese entrepreneurs. Research in development economics frames profits in such contexts as akin to entrepreneurs' take-home pay, which is typically a positive sum since there are no social safety nets and small business entrepreneurs often have few savings (De Mel et al. 2009). Moreover, the next highest value after "1" was "5,000," which is a more meaningful sum in the context of Togo (equivalent to about 10 USD – a small but not insignificant sum for monthly earnings in Togo). We therefore examined these observations more closely.

In doing so we found that all of the "0" or "1" observations had been entered by one of the two surveyors (Surveyor 2), as shown in Table A3-1. Then we found that for these observations all other financial metrics, such as sales or expenses, were also all "0" or "1" or missing, meaning that no other financial information had been supplied for these entrepreneurs. Third, comparing the Cook's Distance and DF Beta statistics for these observations we found that that they were significantly higher than those for the next highest observations. Table A3-1 below shows the 28 minimum values for monthly profits entered by each surveyor, along with their Cook's Distance and DF Beta statistics. The table shows that 24 observations had either "0" or "1" for profits, that these occurred with one surveyor, and that there were significant increases in Cook's distance and DF Beta for these observations.

Table A3-1: The 28 minimum values for monthly profits entered by each surveyor, along with their Cook's Distance and DF Beta statistics.

	Surveyor 1				Surveyor 2			
Obs. rank	Monthly Profits	Cook's D	DF Beta	Suspected coding error	Monthly Profits	cook's D	DF Beta	Suspected coding error
1	5000	0.0029	-0.0814	No	0	0.0104	0.1276	Yes
2	5000	0.0029	-0.0814	No	0	0.0104	0.1276	Yes
3	5000	0.0018	-0.0262	No	0	0.0120	-0.1427	Yes
4	5000	0.0029	-0.0814	No	0	0.0120	-0.1427	Yes
5	7000	0.0010	0.0456	No	0	0.0097	0.0772	Yes
6	7000	0.0015	0.0250	No	0	0.0095	0.0760	Yes
7	8000	0.0011	-0.0217	No	0	0.0104	0.1276	Yes
8	8000	0.0008	0.0416	No	0	0.0104	0.1276	Yes
9	9000	0.0017	-0.0621	No	0	0.0088	-0.0706	Yes
10	9000	0.0017	-0.0621	No	1	0.0458	0.3155	Yes
11	10000	0.0006	0.0349	No	1	0.0458	0.3155	Yes
12	10000	0.0009	-0.0186	No	1	0.0386	-0.1288	Yes
13	10000	0.0010	0.0207	No	1	0.0458	0.3155	Yes
14	10000	0.0006	0.0349	No	1	0.0458	0.3155	Yes
15	10000	0.0010	0.0207	No	1	0.0386	-0.1225	Yes
16	10000	0.0015	-0.0586	No	1	0.0458	0.3155	Yes
17	10000	0.0006	0.0349	No	1	0.0384	0.1256	Yes
18	10000	0.0006	0.0349	No	1	0.0384	0.1256	Yes
19	10000	0.0015	-0.0586	No	1	0.0384	0.1256	Yes
20	10000	0.0009	0.0191	No	1	0.0458	0.3155	Yes
21	10400	0.0005	0.0338	No	1	0.0386	-0.1225	Yes
22	11500	0.0013	-0.0540	No	1	0.0386	-0.1288	Yes
23	12000	0.0012	-0.0526	No	1	0.0458	0.3155	Yes
24	12000	0.0007	-0.0170	No	1	0.0384	0.1256	Yes
25	12000	0.0012	-0.0526	No	5000	0.0029	-0.0814	No
26	224000	0.0016	-0.0578	No	5000	0.0020	0.0290	No
27	248000	0.0010	0.0469	No	5000	0.0029	-0.0814	No
28	250000	0.0007	-0.0176	No	5000	0.0018	-0.0262	No

Given this, we suspected that observations with "0" or "1" for profits were likely to be missing observations. It was likely that the entrepreneurs had been unable to provide financial information to the surveyor and the surveyor must have made a coding error: rather than entering "." or "99," as they had been instructed, they entered "1" or "0".

To confirm that these were indeed coding errors, we leveraged the fact that all the outlier observations had been recorded by one of the surveyors. We split the sample by the two surveyors who conducted the surveys and estimated our regressions on each subsample. We could do this because the entrepreneurs were split relatively equally between the two surveyors (142 for Surveyor 1; 136 for Surveyor 2) and each surveyor conducted all follow-up rounds with the participants originally assigned to them. Moreover, the surveyors were assigned to follow-up with entrepreneurs in a way that was uncorrelated with the treatment. Table A3-2 below shows that selection into being surveyed by Surveyor 1, as opposed to Surveyor 2, is not associated with receiving the treatment or most other observable characteristics (with the exception of Ewe ethnic group).

Table A3-2: Entrepreneurs selected into being surveyed by Surveyor 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social skills training	-0.085								-0.026
	(0.111)								(0.110)
Ewe ethnicity		-0.302**							-0.282**
		(0.040)							(0.053)
Female			-0.012						-0.022
			(0.063)						(0.068)
Completed primary school				0.037					-0.023
				(0.083)					(0.082)
Employees					-0.002				-0.003
					(0.007)				(0.008)
Firm age						-0.006			-0.001
						(0.005)			(0.004)
Management practices score							-0.20		-0.180
							(0.112)		(0.129)
Class size								-0.026	-0.022
								(0.017)	(0.019)
N	278	278	278	278	278	278	278	278	278
Entrepreneurs	278	278	278	278	278	278	278	278	278

The outcome variable is a binary indicator for whether an entrepreneur was followed-up with by Surveyor 1. All models estimated using OLS. Robust standard errors clustered by training group in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Splitting the sample by surveyor revealed that the treatment effect was considerably larger and inconsistent across estimation approaches in data supplied by Surveyor 2, who had entered the 24 suspected coding errors. These regressions are presented in Table A3-3(A). As these results show, the treatment is statistically not significant in Models 1 and 2 while the treatment leads to a highly improbable increase of over 100% in monthly profits in Model 3. On the other hand, performance results using the sample from Surveyor 1 for whom there were no suspected coding errors, shown in Table A3-3(B), suggested treatment effects that were more intuitively reasonable in magnitude and, importantly, were robust to model specification.

Table A3-3(A) Performance Effects with Surveyor 2 (24 suspected errors)

	(1)	(2)	(3)
Social skills training	0.211	0.344	
	(0.200)	(0.242)	
Social skills training X Post-Treatment			1.002*
			(0.408)
Post-Treatment			0.004
			(0.165)
Survey wave FE	Yes	Yes	Yes
Entrepreneur FE	No	No	Yes
Sector FE	Yes	Yes	No
Control variables	No	Yes	No
N	348	348	484
Entrepreneurs	136	136	136

Table A3-3(B) Performance Effects with Surveyor 1 (no suspected errors)

	(1)	(2)	(3)
Social skills training	0.179+	0.217+	
	(0.100)	(0.097)	
Social skills training X Post-Treatment			0.310+
			(0.149)
Post-Treatment			0.009
			(0.108)
Survey wave FE	Yes	Yes	Yes
Entrepreneur FE	No	No	Yes
Sector FE	Yes	Yes	No
Control variables	No	Yes	No
N	444	444	586
Entrepreneurs	142	142	142

In both tables the outcome is monthly profits for entrepreneurs. Models 1 and 2 use OLS with sector and survey wave FE controlling for baseline profits and dropping the baseline time period (see Equation 1 in the paper). Model 3 uses a difference-in-differences estimation approach with entrepreneur FE. Control variables in Models 1 and 2 include ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Given the above results, we suspected that the difference between the treatment effect for Surveyor 1 and 2 may be related to the "0" or "1" coding errors. We therefore replaced these 24 observations with missing values. Table A3-4 below shows that there is no imbalance in these 24 observations with respect to the treatment or other observable covariates. The sample size in Table A3-4 is 1070, which is the number of observations from baseline and all follow-up surveys, including the 24 observations that are suspected data entry errors. We use this sample to detect imbalance because the suspected coding errors occur in different survey waves.

Table A3-4: Observations dropped from Surveyor 2 due to data entry errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social skills training	0.010								0.008
	(0.009)								(0.008)
Ewe ethnicity		-0.007							-0.008
		(0.013)							(0.012)
Female			-0.005						-0.007
			(0.010)						(0.009)
Completed primary school				0.007					0.007
				(0.018)					(0.014)
Employees					-0.000				-0.000
					(0.001)				(0.001)
Firm age						-0.000			-0.000
						(0.001)			(0.001)
Management practices score							0.006		0.010
							(0.016)		(0.012)
Class size								0.001	0.002
								(0.001)	(0.002)
N	1070	1070	1070	1070	1070	1070	1070	1070	1070
Entrepreneurs	278	278	278	278	278	278	278	278	278

The outcome variable is a binary indicator for whether the observation was dropped. All models estimated using OLS. Robust standard errors clustered by training group in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

After removing the suspected coding errors we re-estimated the performance models for Surveyor 2, from whom the problematic observations had been dropped. Table A3-5 shows the results. The performance effect with data from Surveyor 2 now resemble very closely the results from Surveyor 1 (Table A3-3(B)), both in terms of magnitude and statistical significance. Moreover, the results are now consistent across modelling approaches. This gives us considerable confidence that the identified observations were indeed coding errors and that the data now better reflect the true treatment effects.

Table A3-5: Performance Effects with Surveyor 2, after dropping problematic observations

	(1)	(2)	(3)
Social skills training	0.160*	0.129	
	(0.074)	(0.088)	
Social skills training X Post-Treatment			0.210+
			(0.099)
Post-Treatment			0.001
			(0.083)
Survey wave FE	Yes	Yes	Yes
Entrepreneur FE	No	No	Yes
Sector FE	Yes	Yes	No
Control variables	No	Yes	No
N	324	324	460
Entrepreneurs	136	136	136

In all models the outcome is monthly profits for entrepreneurs. Models 1 and 2 use OLS with sector and survey wave FE controlling for baseline profits and dropping the baseline time period. Model 3 uses a diff-in-diff estimation approach with entrepreneur FE. Control variables include ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

In the rest of our manuscript, when we analyze firm performance, we drop these 24 incorrectly inputted observations.

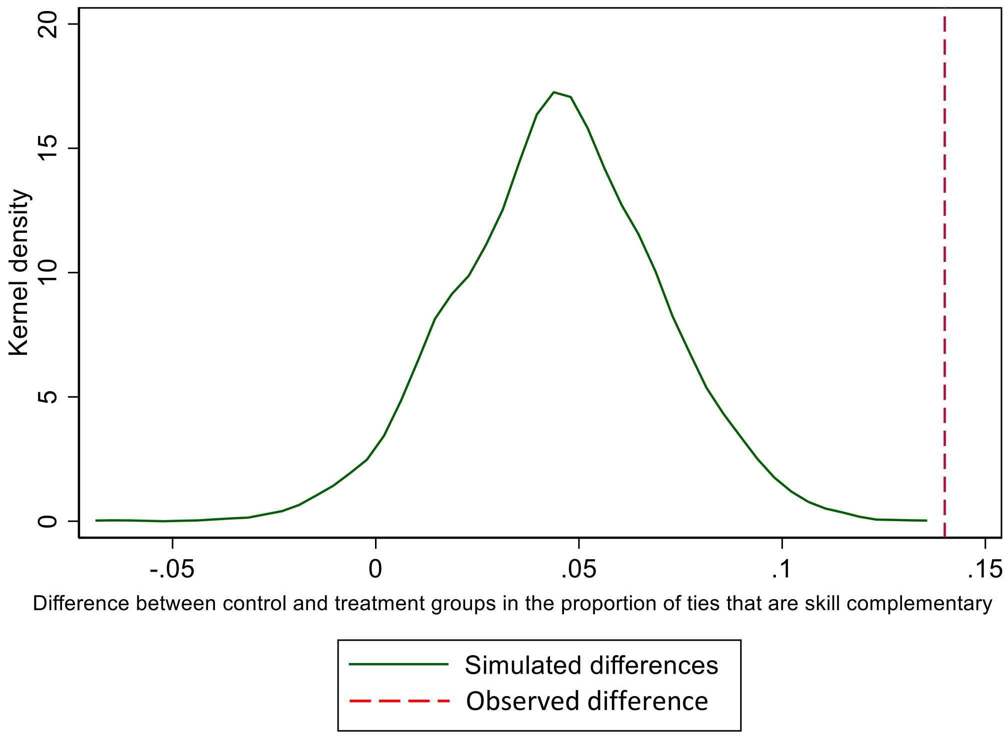
A4. Skill complementarity simulations

A potential concern with our results is that the treatment led to more skill-complementary ties simply as a byproduct of entrepreneurs forming more relationships. To show that the observed increases in skill complementarity in entrepreneurs' relationships are driven by the social skills and not by the fact that they form more new relationships we ran a series of simulations.

Our simulation begins with the real data we gathered on participating entrepreneurs. For each entrepreneur we know the number of business relationships they formed and the co-participants they formed them with. For the simulation, we take each entrepreneur and the number of relationships they formed and we direct these to a new set of randomly selected co-participants from within their training class. Having done so, we calculate for each entrepreneur the proportion of ties formed that are skill complementary based on this random assignment of ties. We calculate proportions because we are interested in the rate of skill complementarity rather than the absolute number. In our regression models in Table 4 we account for the number of "opportunities" each entrepreneur has to form a skill complementary tie by including an offset equal to the log of total ties formed. In our simulations we achieve this by scaling by the total number of ties formed. For each such simulation, we estimate the difference between treated entrepreneurs and control group entrepreneurs in the proportion of their ties that are skill complementary. We repeat this simulation process 2,000 times and this produces a distribution of values for the difference between the simulated control and treatment groups.

Figure A4-1 plots the distribution of the simulated values of the difference between control and treatment groups in the skill complementarity of entrepreneurs' relationships. The vertical dashed line shows the observed difference in task complementarity between the treatment and control groups. As the figure shows, all the simulated values are substantially below the observed value and near zero. The mean value of the difference in skill complementarity for the simulated data are not statistically different from zero.

Figure A4-1: Simulated and observed difference between control and treatment group in proportion of skill complementary relationships



A5. Gender diversity

Research on gender and entrepreneurship has stressed the differences in women entrepreneurs' ability to form new and diverse business relationships (Abraham 2019, Renzulli et al. 2000). Given this, a theoretically relevant dimension of diversity for entrepreneurs' portfolios of relationships is gender. Since our experimental treatment is theorized to affect the ethnic diversity of relationships, it is worth exploring whether it also affects the gender diversity of entrepreneurs' relationships. Table A5-1 tests this by estimating the effect of social skills on the concentration of entrepreneurs' new relationships by gender. The effect of the treatment is negative, which aligns with our theoretical prediction that the treatment should make relationships more diverse. However, it is not statistically significant. This could be because there were not enough women entrepreneurs participating or that gendered cultural beliefs about entrepreneurship are so deeply entrenched that the treatment was not strong enough to have an effect. In either case, this is an important question for future research to pursue further.

Table A5-1: Regressions estimating the effect of social skills on the gender diversity of relationships formed

	Gender diversity	
	(1)	(2)
Social skills training	-0.291	-0.217
	(0.639)	(0.563)
Ewe ethnicity		-0.400
		(0.416)
Female		-0.963*
		(0.481)
Completed primary school		-1.173*
		(0.556)
Employees		0.047
		(0.082)
Firm age		-0.014
		(0.014)
Management practices score		-0.288
		(0.427)
Class size		-0.166
		(0.097)
Sector fixed effects	Yes	Yes
N	301	301
Entrepreneurs	301	301

All models estimated using fractional logit regressions. The outcome variable is the gender concentration of the relationships formed. Robust standard errors in parentheses, clustered at the training class level. + p < 0.10, * p < 0.05, ** p < 0.01

A6. Alternative networking models and measures

Estimating models using linear regression

In Tables A6-1 and A6-2 we replicate our results from Tables 3 and 4 in the paper using ordinary least squares (OLS) regressions in place of the negative binomial and fractional logit regressions. Replicating the results using OLS helps show that the key results of the paper are not model dependent and therefore more robust.

The coefficients in these Tables replicate closely the results in Tables 3 and 4 respectively. The coefficient signs and levels of statistical significance are comparable, as are the interpretations of their magnitudes.

Table A6-1: OLS regressions explaining the number of collaborative words chosen and the amount of information exchanged

	Collaborative perception		Information exchange	
	(1)	(2)	(3)	(4)
Social skills training	0.326**	0.265*	27.822**	26.849**
	(0.111)	(0.124)	(2.287)	(2.543)
Ewe ethnicity		-0.035		2.035
		(0.135)		(2.763)
Female		0.196		-0.956
		(0.133)		(2.735)
Completed primary school		-0.140		2.686
		(0.143)		(2.942)
Employees (log)		-0.008		-0.120
		(0.023)		(0.471)
Firm age		-0.002		-0.047
		(0.009)		(0.175)
Management practices score		0.136		2.649
		(0.233)		(4.782)
Class size		0.017		0.669
		(0.023)		(0.477)
Sector fixed effects	Yes	Yes	Yes	Yes
N	301	301	301	301
Entrepreneurs	301	301	301	301

All models estimated using OLS. The outcome variable in Models 1 and 2 is the number of collaborative words selected by each participant to describe interactions. The outcome variable in Models 3 and 4 is the number of words written by each participant during the networking session, during which they spoke to three randomly selected peer entrepreneurs. Robust standard errors clustered at the training class level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A6-2: OLS regressions estimating the number of relationships formed, proportion of relationships formed that are skill complementary, and ethnic concentration of relationships formed

	Relationships formed		Skill complementarity		Ethnic concentration	
	(1)	(2)	(3)	(4)	(5)	(6)
Social skills training	0.710**	0.678*	0.117*	0.109*	-0.083*	-0.108**
	(0.223)	(0.279)	(0.049)	(0.048)	(0.035)	(0.028)
Ewe ethnicity		0.609**		0.028		-0.006
		(0.194)		(0.034)		(0.034)
Female		-0.044		-0.088		-0.055
		(0.352)		(0.046)		(0.054)
Completed primary school		0.152		-0.010		-0.071**
		(0.270)		(0.049)		(0.024)
Employees (log)		-0.041		-0.022**		0.013*
		(0.041)		(0.007)		(0.005)
Firm age		0.008		0.002		0.001
		(0.008)		(0.001)		(0.001)
Management practices score		0.431		0.201*		-0.020
		(0.493)		(0.072)		(0.063)
Class size		0.004		-0.020**		0.007
		(0.044)		(0.004)		(0.005)
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	301	301	301	301	301	301
Entrepreneurs	301	301	301	301	301	301

All models are estimated using OLS. The outcome variable in Models 1 and 2 is the number of peer business relationships to other participants from the same class that each entrepreneur formed six weeks after the training program. The outcome variable in Models 3 and 4 is the proportion of all relationships formed that exhibit skill complementarity. The outcome variable in Models 5 and 6 is the Herfindahl index of concentration among ethnic groups of the relationships formed. Robust standard errors, clustered at the training class level are in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Alternative measures of tie formation

In Table A6-3 we replicate the result that exposure to social skills leads to increases in the number of peer business relationships formed using an alternative measure of relationship formation. In Models 1 and 2 of Table 4 of the paper we used the number of co-participant entrepreneurs that each entrepreneur met up with or spoke to on the phone as an indication of a relationship. In Table A6-3 we use the number of business cards that each entrepreneur received by the end of the training program. Business cards have been used to measure relationship formation in other studies of entrepreneurs (e.g. see Vissa (2011)) and it helps to provide additional validation of a key outcome in this study. As Table A6-3 shows, the treatment variable is positive and statistically significant. It is worth noting that the sample size is slightly smaller ($N = 271$) because during the field experiment the handing out of personalized business cards to participants failed in the first class that was taught, as a result we lost those observations.

Table A6-3: Regressions estimating the number of business cards received

	(1)	(2)
Social skills training	0.732**	0.624**
	(0.203)	(0.163)
Ewe ethnicity		0.044
		(0.054)
Female		0.047
		(0.069)
Completed primary school		0.030
		(0.069)
Employees (log)		0.019*
		(0.008)
Firm age		-0.006
		(0.007)
Management practices score		0.151
		(0.165)
Class size		0.060*
		(0.027)
Sector fixed effects	Yes	Yes
N	271	271
Entrepreneurs	271	271

The outcome in all models is the number of business cards received from other participants in the same business training class. The models were estimated using negative binomial regressions. Robust standard errors clustered at the training class are in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Building on Table A6-3, we also replicate our relationship formation results using a symmetric tie measure. In our main analyses reported in Table 4, we used a unidirectional measure of tie formation. Here we measure tie formation as occurring only when both members of a dyad report having interacted. As Table A6-4 shows, our results hold using this alternative approach. The magnitude of the coefficients is similar to those reported in Table 4, although a little larger, suggesting that the unidirectional measure was more conservative in terms of measuring treatment effects.

Table A6-4: regressions estimating the number of relationships formed, skill complementary, and ethnic concentration of relationships formed

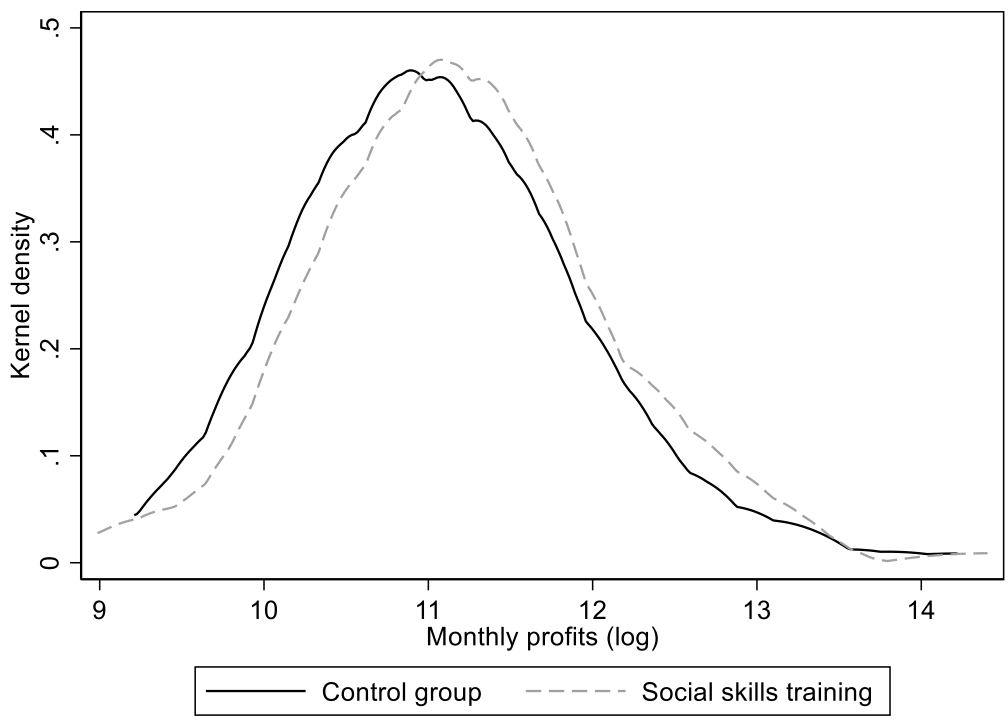
	Relationships formed		Skill complementarity		Ethnic concentration	
	(1)	(2)	(3)	(4)	(5)	(6)
Social skills training	0.586*	0.554*	0.980+	0.876*	-1.130*	-0.867*
	(0.289)	(0.276)	(0.528)	(0.398)	(0.497)	(0.395)
N	301	301	301	301	303	301
Sector fixed effects	No	Yes	No	Yes	No	Yes
Control variables	No	Yes	No	Yes	No	Yes

Models 1, 2, 3 and 4 are estimated using negative binomial regressions. Models 3 and 4 include the inverse hyperbolic sine of the number of relationships formed as an offset. The outcome variable in Models 1 and 2 is the number of peer relationships to other participants from the same class that each entrepreneur formed six weeks after the training program. The outcome variable in Models 3 and 4 is the number of relationships formed that exhibit skill complementarity. Models 5 and 6 were estimated using fractional logit regressions and the outcome variable is the Herfindahl index of concentration among ethnic groups of the relationships formed. Control variables include ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Robust standard errors, clustered at the training group level in parentheses.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

A7. Quantile treatment effects

Our empirical specifications in Table 5 of the paper estimate the average impact of the treatment on performance. Yet, we are also interested in whether the treatment affected entrepreneurs at different levels of performance differently. To explore whether this is the case we began by plotting the kernel density functions for monthly profits in the control and treatment groups, shown in Figure A7-1 below. This figure plots the distribution of log monthly profits for entrepreneurs in the control group and the treatment group, six months after the training program. The figure shows that the entire distribution of profits for the treatment group is shifted to the right, which means that entrepreneurs at most profit levels increased their performance. This provides evidence that the social skills treatment seems to have helped entrepreneurs across different levels of performance.

Figure A7-1: Kernel density plots of log monthly profits



Note: The kernel density plots above compare the log monthly profits earned by entrepreneurs in the control group and the treatment group, measured six months after the training program. The distribution of the profits for entrepreneurs in the treatment group (grey dashed line) is shifted to the right of the distribution of profits for entrepreneurs in the control group (black solid line), indicating higher profits on average.

Building on our kernel density plot, we also estimated the quantile treatment effects in order to explore more thoroughly how the treatment affected the distribution of performance outcomes for entrepreneurs. Specifically, we use Equation (1) from the paper (estimated in Models 1-2 of Table 5 of the paper) to estimate the effect of treatment on each quintile between the 5th and 95th quintiles. This specification pools data across all three follow-up rounds, controlling for survey round effects, sector of activity, and baseline profits and clusters standard errors by training group. We used the Stata program qreg2 to estimate the models. Our estimation of quantile effects follows the same methodology used by Campos et al. (2017).

Figure A7-2 plots the performance effect estimates at each fifth quintile. The figure shows that social skills training improved performance uniformly across the entire distribution of profits. In particular, the figure presents the estimates of quantile treatment effects on the log monthly profits at each fifth quintile between the 5th and 95th. The results show that the treatment effect of social skills on entrepreneur performance are not disproportionately driven by one segment of the distribution. Instead, the estimated impact of treatment on profits is relatively similar across the distribution.

Figure A7-2: Quantile treatment effects show gains from social skills across the performance distribution

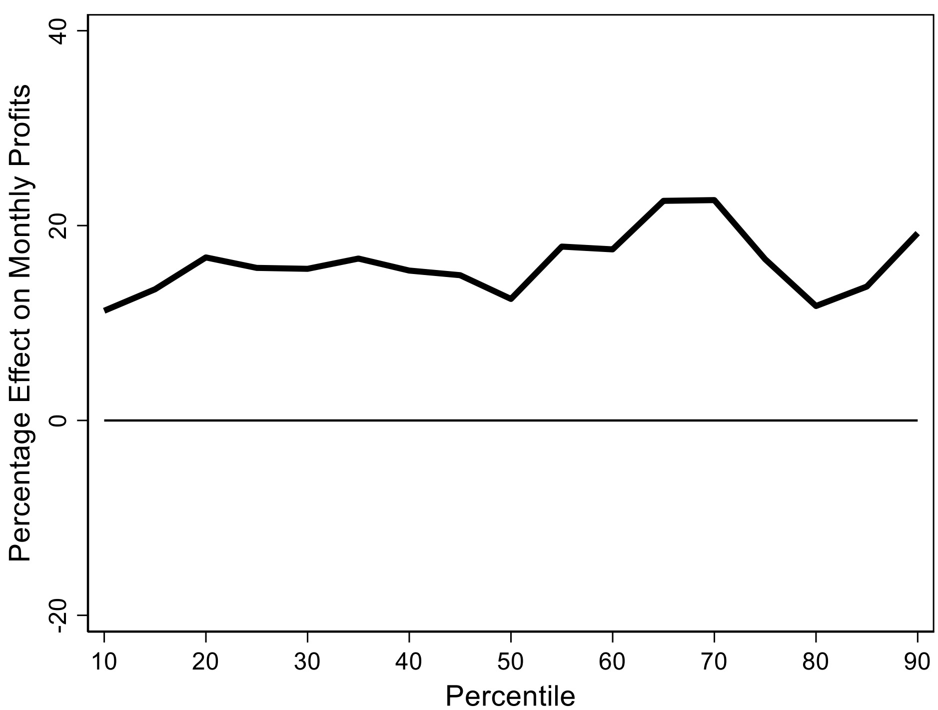
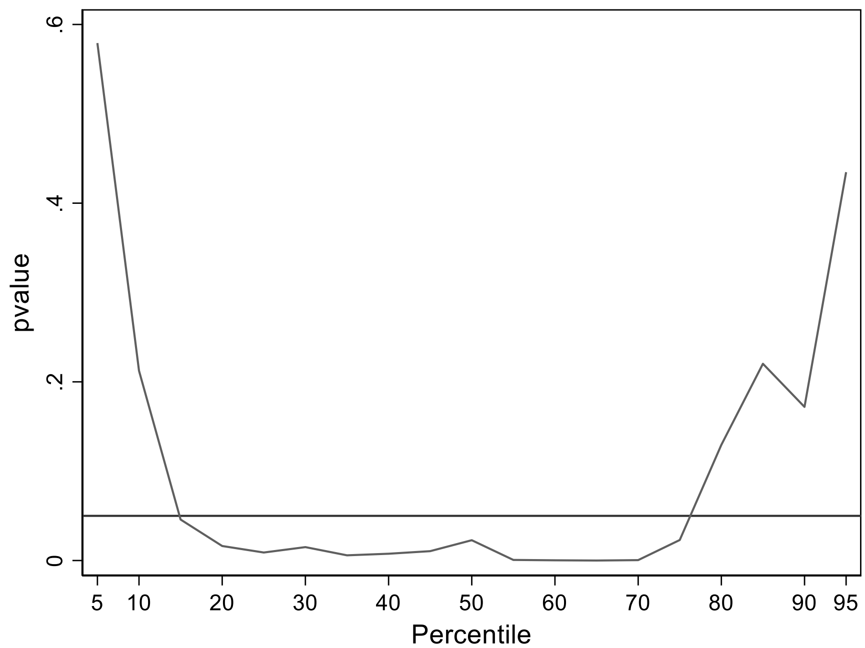


Figure A7-3 presents the p-values from the quantile regressions. In particular, the p-values test whether the effect of social skills training is equal to zero at each quintile. The figure shows that we reject the null that the treatment effect is zero at every quintile between the 15th and approximately the 75th.

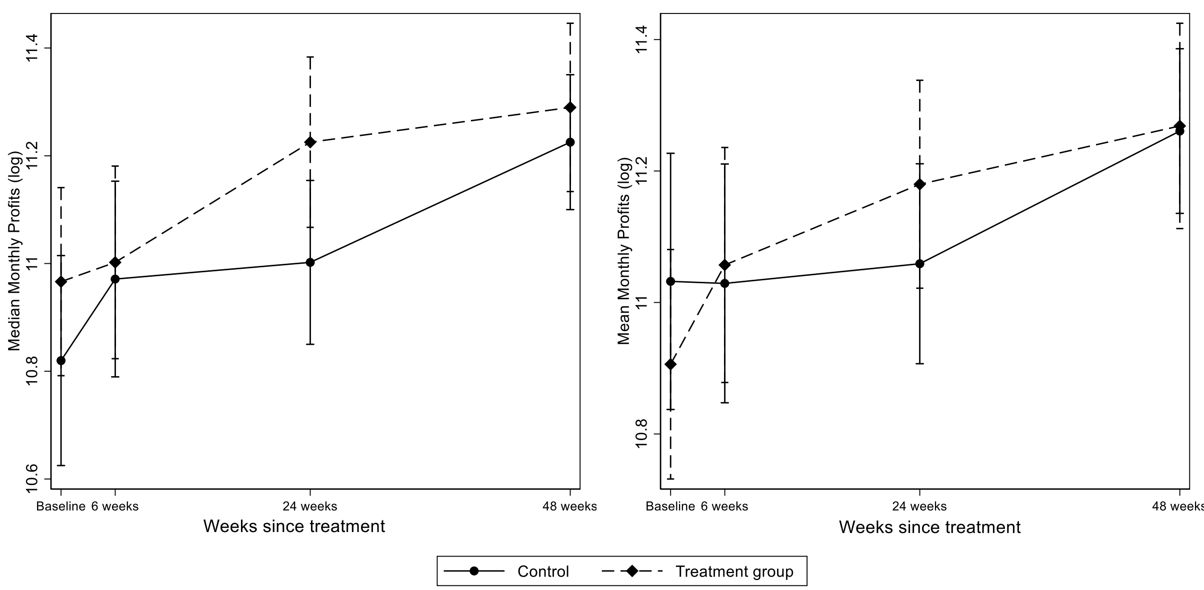
Figure A7-3: P-Values testing whether treatment effect is zero



A8. Treatment dynamics

To better understand how the treatment changed entrepreneurs' performance over time we plotted entrepreneurs' median and mean monthly profits (log) for each survey wave with 95% confidence intervals in Figure A8-1. Importantly, both median and mean monthly profits were higher for the treatment group than the control group after treatment. The plots, therefore, show a general pattern of entrepreneurs in the treatment consistently outperforming those in the control group over time after treatment. The plots show that treated entrepreneurs' monthly profits begin to diverge from the control group from the first follow-up survey, at 6 weeks, and this difference peaks at the second follow-up survey, 24 weeks after the treatment. The difference in median monthly profits between control and treatment groups 24 weeks after the treatment (2nd follow-up survey) is statistically significant at the 5% level. Although the difference in means at 24 weeks is less pronounced, it remains statistically significant at the 10% level. It is worth noting that in Figure A8-1 the control group's median and mean performance shows a slightly increasing pattern after the baseline survey which may be related to the training in marketing practices they received.

Figure A8-1: Median and Mean of Log Monthly Profits (95% CI)



The large confidence intervals in Figure A8-1, as well as the notable differences in the median and mean plots at baseline, suggest that there is likely significant between-entrepreneur variance in performance. This is not uncommon in developing country contexts, where entrepreneurs often exhibit a wide range of entrepreneurial ability and managerial skills (Bruhn et al. 2010). For example, our sample included both entrepreneurs who did not complete primary school and entrepreneurs who held university degrees, which represents potentially very large differences in entrepreneurial ability and makes summary statistics relatively noisy. Moreover, entrepreneurial performance in developing economies tends to vary significantly over time, meaning that even able entrepreneurs can experience significant fluctuations in performance during short periods of time (De Mel et al. 2009, McKenzie 2012). These factors make it important to control for entrepreneur and time fixed effects when trying to estimate the effect of treatment on entrepreneurs' performance.

In using this approach, we explore the treatment dynamics parametrically using a difference-in-differences model, similar to that estimated in Table 5 in the paper. In this model we include survey round dummies and entrepreneur fixed effects. The results from these regressions are shown in Table A8-1 below. The regression results confirm the intuition from Figure A8-1: the treated entrepreneurs' performance begins to diverge from the control group from the first follow-up survey and peaks during the second follow-up survey.

Table A8-1: Treatment dynamics

	(1)
Social skills training X Follow-up survey 1	0.248**
	(0.079)
Social skills training X Follow-up survey 2	0.321*
	(0.138)
Social skills training X Follow-up survey 3	0.177
	(0.143)
Follow-up survey 1	0.008
	(0.065)
Follow-up survey 2	0.045
	(0.100)
Follow-up survey 3	0.255*
	(0.112)
Entrepreneur fixed effects	Yes
N	1046
Entrepreneurs	278

The outcome variable is log monthly profits. The variables of interest are the interactions between the dummy for treatment group and survey wave. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

To graphically illustrate the results from Table A8-1, we plot the average predicted values for log monthly profits using the coefficient estimates from Model 1 in Table A8-1. The results are plotted in Figure 3 in the paper. This figure confirms the insights from the median and mean plots in Figure A8-1 that the treatment group consistently outperforms the control group in post-treatment time periods. Furthermore, the magnitude of the difference peaks approximately 24 weeks after the treatment. Figure 3 in the paper nets out the entrepreneur heterogeneity and potential time period effects revealing clearly the treatment effect on performance.

A9. Alternative performance measures

As A3 shows, and unlike accounting profits in developing settings, the surveyed profits in our sample are never below zero. This is partially because profits reflect the "take home pay" of entrepreneurs in this setting, because capital is hard to come by so even short-term losses lead firms to exit, and because of simple desirability self-report bias. Therefore, it is important to test that results are robust to how we measure performance.

Here we follow established practice in development economics and triangulate our standard self-reported profit measure with two complementary measures of performance (De Mel et al. 2009, Fafchamps et al. 2012). First, following Campos et al. (2017) we create an index of performance, which averages variables that are indicative of profitability. Regrouping families of variables of interest using this methodology into an index helps reduce the odds of Type I errors (Kling et al. 2007). Our performance index consisted of the following standardized variables: profits last month, log profits last month, winsorized profits last month, log sales last month, sales last month, winsorized sales last month, log profits last week, profits last week, and winsorized profits last week. The index is defined as the equally weighted average of z-scores of its components. The z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation.

The results using this outcome variable are shown in Models 1-3 of Table A9-1. Models 1 and 2 estimate Equation (1) from the paper (the same as Models 1 and 2 in Table 5 of main paper). The coefficient for the treatment is positive, statistically significant and similar in magnitude to those in Table 5, where the log of monthly profits was the outcome variable. The same is true of Model 3 in Table A2.1, which uses the difference-in-differences specification (Equation 2 in the paper). The variable of interest in this model is the treatment and post-treatment interaction term, which is positive, statistically significant, and similar in magnitude to the coefficients in the main regression Table 5.

The second measure follows Atkin et al. (2017) who construct profits from two survey questions that ask firms to report their total revenues and total costs from the previous month. Using entrepreneurs' reported total sales and costs, we estimate profits as the difference between sales and costs. Taking the logarithm of this difference creates our second alternative measure of performance. This variable is used as our outcome in models 4-6 in Table A9-1. As with the performance index, the two first regressions estimate Equation (1), while model 6 uses a difference in differences estimation with entrepreneur fixed effects. In all three models the treatment effect is positive and statistically significant. This measure of performance is considerably noisier than the others and more likely to be subject to measurement error (Fafchamps et al. 2012), which likely explains why the treatment effect is considerably larger in model 3 than in other models.

Table A9-1: Performance effects with alternative performance measures

	Performance Index			Log (Sales-Expenses)		
	(1)	(2)	(3)	(4)	(5)	(6)
Social Skills Training	0.123*	0.146*		0.198*	0.203*	
	(0.059)	(0.074)		(0.089)	(0.084)	
Social Skills Training X Post-Treatment			0.226*			0.481+
			(0.080)			(0.242)
Post-treatment			-0.082			-0.394
			(0.068)			(0.184)
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	No	No	Yes	No
Baseline profits	Yes	Yes	No	Yes	Yes	No
Control variables	No	Yes	No	No	Yes	No
Entrepreneur FE	No	No	Yes	No	No	Yes
N	768	768	1046	768	768	1046
Entrepreneurs	278	278	278	278	278	278

The outcome variable for Models 1, 2, 3 is an index of performance indicators, while the outcome variable for Models 4, 5, 6, is the log of the difference between monthly sales and costs. All models estimated using OLS. Models 1, 2, 4, and 5 use sector and survey wave FE controlling for baseline profits and dropping the baseline time period. Control variables include ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Robust standard errors clustered by training group in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

A10. Power calculations

Benchmarking our sample size against prior studies

To determine the necessary sample size, we reviewed prior randomized control trials focused on social and managerial interventions. A core paper we build off is Chatterji et al.'s (2019) field experiment studying when advice impacts startup performance. That study included 100 startups with performance outcomes measured twice before and twice after treatment. They find robust performance effects of receiving advice from another founder who is a better manager and report power calculations suggesting that their "difference-in-differences" design could detect a result of the size they find with 95% power. Indeed, building on McKenzie's (2012) analysis of power in RCTs with multiple measures, Chatterji et al. (2019) illustrate how the panel-structure of their data substantially improves statistical power. Indeed, Bloom et al.'s (2013) experiment on the effectiveness of management practices relies on a sample size of 28 plants from 17 firms, making up for the small N by relying on many repeated performance measures. Similarly, Camuffo et al.'s (2020) study of scientific experimentation in startups relies on a sample of only 116 startups. Finally, a recent review of the business training RCT literature by McKenzie et al. (2020) highlight that while there have been a few studies with sample sizes in the thousands of businesses, the majority of studies have sample sizes in the low hundreds.

Given this prior work and our own budget constraints, our goal was to recruit 400 entrepreneurs split evenly into treatment and control groups. As outlined in our pre-registration plan, we always planned to rely on repeated measures to improve power. In the end, we were able to recruit 326 business owners. In terms of repeated performance measures, we measured profits before treatment and three times after treatment.

Estimating ex post Minimum Detectable Effect (MDE) sizes for our study

Unfortunately, given that our baseline data was collected at the start of the two-day training program we were unable to use baseline data to conduct *ex ante* power calculations. As discussed above, our sample size was largely determined *ex ante* by benchmarking against prior work and by our own budget constraint. That said, in this section we present *ex post* calculations of our study's Minimum Detectable Effect (MDE) size and argue that our study appears adequately powered. We try not to present direct *ex post* power estimates that rely on our estimated treatment effect since such calculations are extremely biased and noisy, as discussed in this blog post by McKenzie and Ozier: https://blogs.worldbank.org/impactevaluations/why-ex-post-power-using-estimated-effect-sizes-bad-ex-post-mde-not Instead, our MDE calculations show the smallest effect for a given dependent variable we can identify with 80% power given our sample size and the standard deviation of the dependent variable. Since the MDE doesn't rely on the estimated treatment effect—an estimate that in small samples suffers from both type S and type M errors (Gelman and Carlin 2014)—the *ex post* MDE is significantly less likely to overstate or understate a study's *ex ante* power.

Beginning with our cross-sectional outcome measures we take the mean and standard deviation of the control group and assuming a study with N=301 participants (the number of firms we have cross-sectional data for) and 80% power we calculate the MDE for each variable. Again, the MDE tells us the minimum estimate we can detect with 80% power. If the MDE appears implausibly large (e.g., doubling profits or requiring entrepreneurs to befriend 10 more peers) this indicates that our study is likely underpowered no matter the observed treatment effect. Further, statistically significant effects that are much smaller than the MDE should be taken with a grain of salt as the study is then likely not powered at the 80% level to detect such estimates.

The results of these cross-sectional MDE calculations are presented in Table A10-1. For comparison's sake, we also present the mean and standard deviation in the treatment group along with estimated treatment effect and a simple difference-in-means two-sample two-sided t-test. We sidestep the additional complexity in terms of statistical testing that our clustered experimental design induces and for ease of exposition assume each observation is independent, though see Appendix Section A13 for evidence that our results are robust to alternative clustering schemes.

Overall, the only variable where we might be underpowered is "collaborative perception," where the MDE is 0.29 and the estimated effect 0.23, suggesting that we might not be powered at the 80% level to detect the changes in collaboration we observe. A study with 60% power and our sample size would have an MDE equal to our observed effect. That said, we caution against such implicit *ex post* power calculations and instead think it better to try and gauge the MDE without focusing on the observed treatment effect. For this variable, the MDE says we can detect with 80% power whether the treatment led participants to circle an additional collaborative word about a third more often than the control. This seems like a reasonable effect size to detect, especially since the measure comes at the end of the two days and not months after the treatment occurred. Put differently, if we can't get one-in-three treated participants to circle an extra collaborative word the effect is likely inconsequential.

The rest of our cross-sectional outcome variables appear adequately powered. In terms of information exchange, which is the number of words an entrepreneur writes when taking notes on their conversations, we see the MDE is 5.72 words, roughly an additional sentence. It seems reasonable to think that our treatment would have such an effect. In fact, we find that the observed treatment effect is an additional 27.88 words, a treatment effect that is nearly five times as large as the MDE. Further, as Figure 1 shows, this treatment isn't the result of outliers, but a shift across the entire distribution.

Similarly, for number of relationships formed, we find an MDE of 0.46, suggesting that our study could detect if our experiment caused one in two treated participants to connect with one more peer. Again, for our social skills training to significantly impact performance the treatment likely needs to be at least this large. In fact, we find that the treatment effect is 0.78, well above the MDE of 0.46 additional relationships—though again these comparisons must be made cautiously. For skill complementarity and ethnic concentration, the MDE and observed treatment effects are similar in size, suggesting that we are powered at roughly 80% to pick up these effects. Again, we caution against putting too much weight on gauging power using the observed treatment effects.

The final three rows in Table A10-1 include the estimates from our exploratory mediation analysis. The MDE for our social skills index suggests we can detect changes of roughly a quarter of a standard deviation, again an effect size that we think is reasonable to expect in this setting and one that is necessary if our treatment matters for firm performance. In fact, we find that our treatment increased social skills by nearly one-full standard deviation, well above our MDE. Further, such an effect seems reasonable given that the intervention focused on teaching social skills which impact the quality of relationships and advice that this index directly measures. We are also well powered to pick up effects on positive affect and can detect changes in marketing practices that are above a third of a standard deviation.

Table A10-1: Observed treatment effects and Minimum Detectable Effects (MDE) assuming 80% power and an N=301 for our cross-sectional outcome measures.

	Control Group			Treatment Group			Minimum Detectable Effect	Observed Treatment Effect	Treatment t-value (p-vaue)
	Mean	S.D.	N	Mean	S.D.	N			
Collaborative perception	2.57	0.88	145	2.80	0.96	156	0.29	0.23	-2.15 (p=0.032)
Information exchange	16.42	18.63	145	44.30	20.23	156	5.72	27.88	-12.41 (p=0.000)
Number of relationships	1.58	1.42	145	2.36	1.86	156	0.46	0.78	-4.07 (p=0.000)
Skill complementarity	0.11	0.27	145	0.19	0.32	156	0.09	0.08	-2.33 (p=0.020)
Ethnic concentration	0.88	0.22	145	0.79	0.28	156	-0.07	-0.09	2.98 (p=0.003)
Social interactions index	-0.34	0.74	142	0.52	0.76	146	0.24	0.83	-9.81 (p=0.000)
Bert positive affect score	0.39	0.30	121	0.76	0.20	146	0.10	0.37	-11.95 (p=0.000)
Marketing practices index	0.26	0.61	142	0.28	0.69	146	0.20	0.01	-0.29 (p=0.768)

This table shows the mean, standard deviation, and number of firms in our treated and control groups. The MDE is calculated using the standard deviation observed in the control group and assuming 80% power with a N=301 split evenly across the treated and control groups. The observed treatment effect is simply the difference between treatment and control group means. The t-value and p-values are calculated using a simple difference-in-means two-sample two-sided t-test assuming each observation is independent (i.e., results are not clustered by training cohort).

Turning to firm performance, the MDE calculation is less straightforward because we measure profits once before and three times after the training program. To account for the additional power that stems from using panel data we rely on Burlig, Preonas, and Woerman (2020). Using the Stata program *pc_dd_analytic* developed as part of their paper we can estimate the MDE given a sample size, an estimate of the auto-correlation of the dependent variable, and an estimate of the residual standard deviation of the dependent variable. Crucially, the residual standard deviation is not the standard deviation of the raw dependent variable. As the authors note in their documentation for their Stata program: "*Note that these are not variances [standard deviations] of the composite error term, but rather of the idiosyncratic error term, after partialing out unit and time period fixed effects (i.e., e_it in the equation above).*" where the equation is "*Y_it = b*D_it + fe_i + fe_t + e_it*."

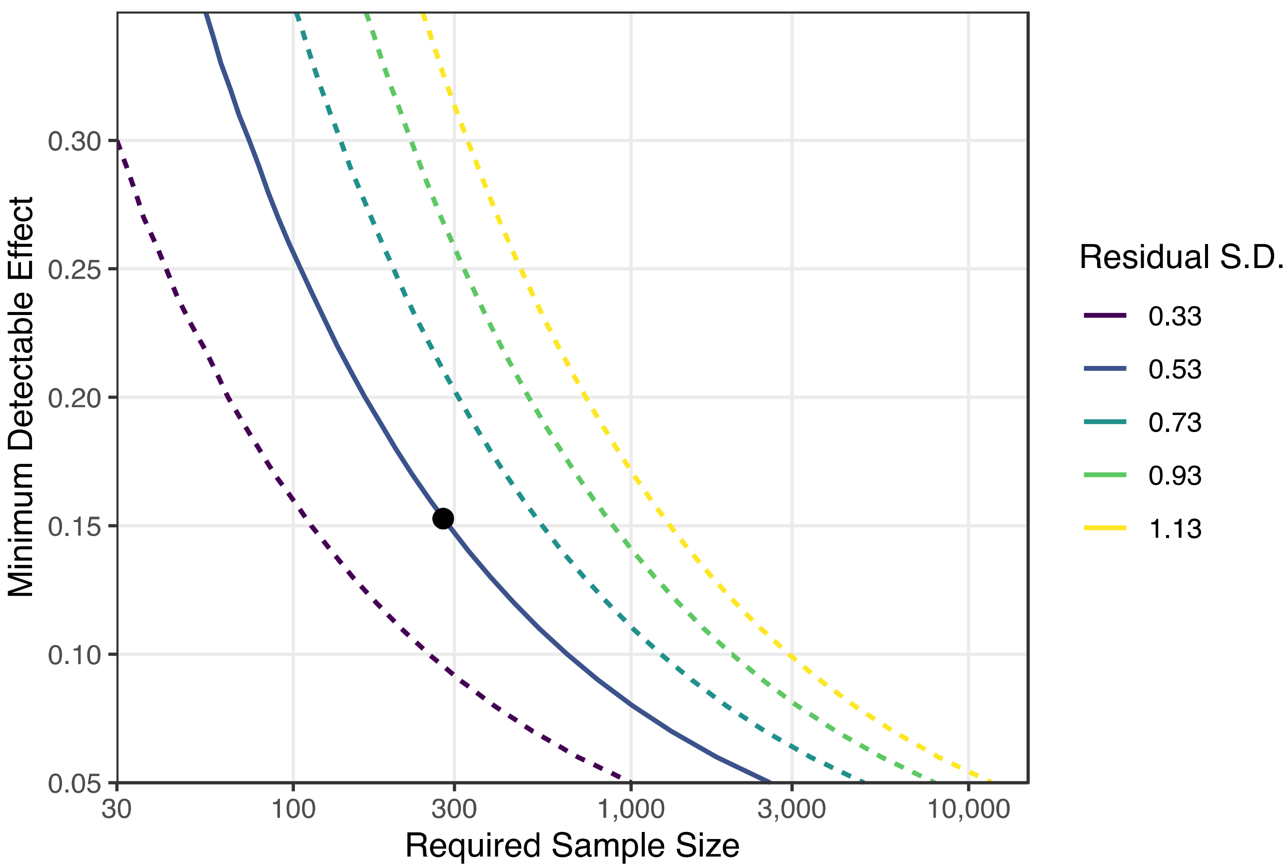
This distinction between residual and raw standard deviations is crucial. Our panel sample size is 278 firms and the auto-correlation in logged profits is 0.7. The raw standard deviation is 1.14. Following Burlig, Preonas, and Woerman (2020) we find the standard deviation after taking into account firm and time-period fixed effects drops to 0.53. If we mistakenly use the raw standard deviation, again assuming 80% power, the MDE for our study rises to 0.33, suggesting that our treatment would have to raise profits by 33% for us to reliably detect the effect. However, plugging in the appropriate residual standard deviation of 0.53 yields an MDE of 0.15.

Is an effect of 15% reasonable to expect? A recent review piece by McKenzie (2021) uses a meta-analysis to show the impact of standard classroom training programs on SME profits is about 10% [95% CI: 4%, 16%] and that training programs that rely on peer and mentorship feedback have slightly larger effects of 15% [95% CI:8%, 22%]. Given this prior work it appears our study is adequately powered. Finally, though we caution against comparisons to our estimated treatment effect, the MDE is smaller than the effects we find, which range from 17% to 25%.

To further illustrate why our study is adequately powered, Figure A10-1 illustrates how important the level of residual standard deviation is to our study's power. The plot shows the MDE against different sample sizes assuming a study with 80% power. Each line shows a different residual standard deviation, ranging from 0.33 to 1.13. The dot is where our study lands. Notice that if the residual standard deviation was only 0.33 then we would be powered at 80% to detect effects around 9% even with only 278 firms. However, if the residual standard deviation was 1.13, we would need well over 1,000 participants to detect an effect of 0.15 and we would still need about 800 participants if we aimed for an MDE of 0.2. The firm and time-period fixed effects matter.

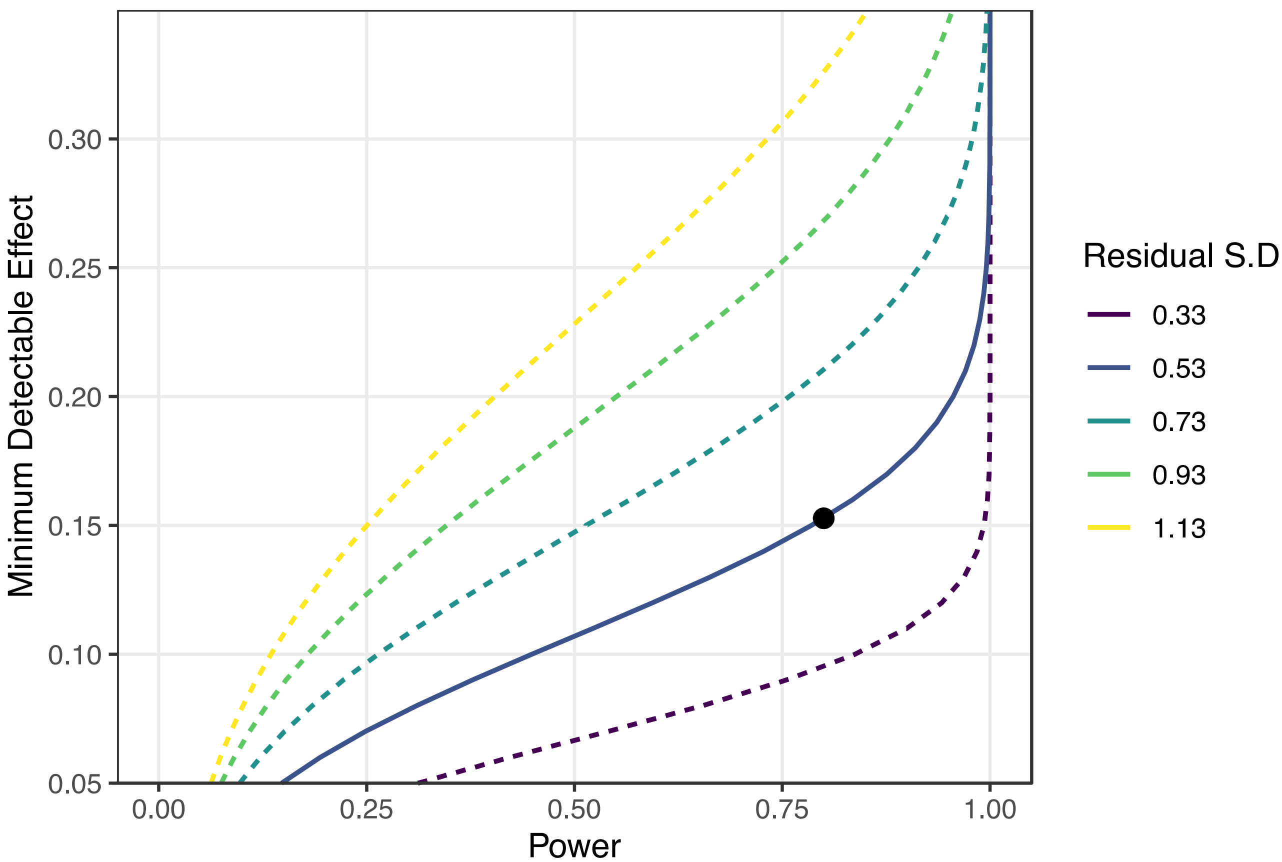
Figure A10-2 is similar to A10-1 but shows the tradeoff between MDE and power for a study with 278 firms. Again, the dot shows our study assuming we are powered at the 80% level. Notice if we assume 50% power the MDE for our study drops to 0.11; assuming 95% power the MDE jumps to only about 0.2. Overall, this suggests we are well powered to detect performance effects as long as they are greater than about 15%.

Figure A10-1: MDE against necessary sample size assuming different residual standard deviations for a study with 80% power. The x-axis is scaled logarithmically.



Minimum Detectable Effect (MDE) for logged profits by sample size for a study with 80% power where profits were measured once before treatment and three times post-treatment. Each line shows the relationship between MDE and sample size assuming different values of the residual standard deviations of the dependent variable after accounting for firm and time-period fixed effects. The solid line reflects the estimated residual standard deviation observed in our study. The dot shows where our study lands assuming 80% power. The x-axis is scaled logarithmically.

Figure A10-1: MDE against power assuming different residual standard deviations for a study with 278 firms.



Minimum Detectable Effect (MDE) for logged profits by power level for a study with 278 firms where profits were measured once before treatment and three times post-treatment. Each line shows the relationship between MDE and power assuming different values of the residual standard deviations of the dependent variable after accounting for firm and time-period fixed effects. The solid line reflects the estimated residual standard deviation observed in our study. The dot shows where are study lands if we assume 80% power.

A11. Multiple hypothesis testing

In this study we test five hypotheses, re-iterated in Table A11-1 below.

Table A11-1: Hypotheses tested in this study

Hypothesis 1	Social skills training will lead entrepreneurs to perceive interactions as more collaborative and exchange more information during interactions.
Hypothesis 2	Social skills training will lead entrepreneurs to form more new relationships with other entrepreneurs from the training program after the program has ended.
Hypothesis 3	Social skills training will lead entrepreneurs to form more skill-complementary relationships with other entrepreneurs from the training program after the program has ended.
Hypothesis 4	Social skills training will lead entrepreneurs to form relationships with other entrepreneurs from the training program after the program has ended that are less concentrated in one ethnic group.
Hypothesis 5	Social skills training will lead entrepreneurs to earn more profits.

These five hypotheses involve testing the effect of our treatment (social skills training) on six different outcome variables: perception of interactions, information exchange, relationships formed, skill complementarity of relationships formed, ethnic concentration of relationships formed, and performance.

When testing multiple hypotheses there can be a fear of falsely rejecting null hypotheses, that is of committing Type I errors. The null hypothesis for each outcome variable states that the treatment effect is statistically indistinguishable from zero. As the number of hypotheses being tested increases, the probability that a null hypothesis is falsely rejected increases.

One way to address this potential issue is to compute sharpened False Discovery Rate (FDR) q-values (Anderson 2008). The FDR is the expected proportion of rejections of null hypotheses that are Type I errors and q-values are p-values that have been adjusted to account for the FDR. The algorithm developed by Anderson (2008) and Benjamini, Krieger, and Yekutieli (2006) adjusts the p-values generated by regression analyses for the number of hypotheses being tested with those data, the number of null hypotheses rejected and the confidence with which they have been rejected. Applying this adjustment produces sharpened q-values for each hypothesis, which are presented in the second row of Table A11-2 below. As shown in Table A11-2, the sharpened q-values reject the null hypotheses for all of our hypotheses at the 95% level.

In addition to sharpened q-values, we also compute Bonferroni-Holm and Sidak-Holm adjusted p-values, which adjust p-values for the family-wise error rate (FWER). The FWER is the probability of falsely rejecting at least one hypothesis within a family of related hypotheses. Hence, adjusting p-values for FWER is a more conservative test than the sharpened q-values (Anderson 2008). The results from these adjustments are also included in Table A11-2. According to this table, adjusting the p-values from our analyses leads to slight increases in those values. This leads to adjusted p-values for Hypotheses 3, 4, and 5 that are slightly above the threshold for statistical significance at the 5% level, while the other hypotheses remain statistically significant at the 5% level.

Given the variety of different approaches used to control for multiple hypothesis testing and their relatively conservative effect on our regression results we feel confident that the results from our regression analyses are not at significant risk of Type I errors.

Table A11-2: Adjusted p-values for multiple hypothesis testing

	H1 (perception of interactions)	H1 (exchange information)	H2	H3	H4	H5
Original p-value	0.026	0.000	0.021	0.013	0.000	0.022
Sharpened q-value	0.018	0.001	0.018	0.018	0.001	0.018
Bonferroni-Holm adjusted p-values	0.037	0.000	0.053	0.052	0.053	0.053
Sidak-Holm adjusted p-values	0.037	0.000	0.052	0.051	0.052	0.052

Note: H = hypothesis

In addition to the analyses above, we conducted several mediation analyses (see Appendix A16), which illustrate the mechanisms through which the treatment affects entrepreneurs' performance. These analyses, in contrast to those described above, did not test a set of theoretically derived hypotheses, rather they were exploratory. Exploratory analyses frequently require a flexible design, a large number tests, and don't have a clear family-structure of tests, making it difficult to conduct multiple hypothesis testing adjustments (Bender and Lange 2001). Therefore, statistical best practices do not recommend applying multiple hypothesis adjustments for analyses involving data collected with a general exploratory objective (Goeman and Solari 2014, O'Brien 1983). We therefore did not perform multiplicity adjustments with our mediation analyses, but we are careful to label our results as exploratory and stress the need for further confirmatory studies.

As a precaution, we included the mediator variable "social interactions index" (Table A16-4) in the adjustment of p-values procedures described above and the results remained substantively unchanged. The adjusted p-values for the Bonferroni-Holm and Sidak-Holm procedures are 1-2 percentage points higher for each hypothesis. Under these conditions our results are still robust to adjustments for multiple hypothesis testing.

A12. Robustness to cohort and recruitment effects

Although the treatment was balanced across the sources from which entrepreneurs were recruited and it was balanced across the timing of entrepreneurs' registration (see Table A2-1), we ran a series of regressions to ensure that the treatment effects were robust to additional concerns about recruitment and cohort effects.

Recruitment source effects

Table A12-1 shows the results from regressing monthly log profits on treatment while controlling for entrepreneurs' source of recruitment. The three variables that control for this are indicators of whether the entrepreneur was recruited through in-person canvassing, referrals from associations, or social media. The reference group in these models are entrepreneurs recruited from miscellanea sources, such as entrepreneurs who saw the sign in front of the building and walked in or those who heard about the program incidentally. Table A12-1 estimates Equation (1) from the paper, similar to Models 1 and 2 of Table 5. The results show that none of the controls for recruitment source are statistically significant. Moreover, the treatment effect is statistically significant and unchanged in magnitude from the estimate presented in the paper.

To further explore whether our results are sensitive to the source from which entrepreneurs were recruited we also split our sample by recruitment source. Table A12-2 shows the results from regressing profits on treatment in each subsample defined by recruitment sources. Each column in Table A12-2 represents a different recruitment source. The coefficient for treatment is positive and statistically significant in all cases. For entrepreneurs recruited through social media, the treatment effect is substantially larger than for entrepreneurs recruited from other sources. Although this may suggest that entrepreneurs who use social skills might be particularly receptive to social skills training, our sample size is too small to conclusively make this determination.

Taken together, the results from Tables A12-1 and A12-2 show that the source from which entrepreneurs were recruited does not affect our treatment estimate.

Table A12-1: Performance effects controlling for source of recruitment

	(1)	(2)
Social skills training	0.187**	0.178*
	(0.058)	(0.061)
Registered by phone/canvass	-0.031	-0.109
	(0.207)	(0.238)
Registered (referrals)	-0.266	-0.330
	(0.251)	(0.283)
Registered (social media)	-0.032	-0.100
	(0.243)	(0.279)
Survey wave FE	Yes	Yes
Sector FE	No	Yes
Baseline profits	Yes	Yes
Control variables	No	Yes
N	768	768
Entrepreneurs	278	278

The outcome is monthly log profits. Models use OLS with sector and survey wave FE controlling for baseline profits and dropping the baseline time period. Control variables include ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A12-2: Performance effects splitting sample by recruitment source

	Registered by in-person canvasing	Social Media	Referrals from associations
	(1)	(2)	(3)
Social skills training	0.136*	0.840**	0.206*
	(0.064)	(0.073)	(0.100)
Survey wave FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Baseline profits	Yes	Yes	Yes
N	396	63	282
Entrepreneurs	144	22	101

The outcome is monthly log profits. Models use OLS with sector and survey wave FE controlling for baseline profits and dropping the baseline time period. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Cohort effects

Given that our treatment was administered at the training group (cohort) level we followed established best practice and clustered standard errors at the training group level in all our empirical specifications throughout this paper. This accounts for the fact the performance of entrepreneurs from the same classrooms may be non-independent and accounts for potential differences between training groups. Given that the same instructors taught all 14 training groups within the span of six weeks, differences between groups should be relatively small and clustering standard errors should account for any potential classroom level effects.

Nevertheless, there could be additional concerns that a small number of highly performing treatment groups or underperforming control groups are driving the observed treatment effects. To address this potential concern, we estimated our models including training group fixed effects. Given that our difference-in-differences specification uses entrepreneur level fixed effects we cannot include training group fixed effects in this specification. However, we can include them in our Equation (1) OLS specification, which also includes sector and survey wave fixed effects.

We present these models in Table A12-3 below. Model 1 does not include any control variables, while Model 2 includes our standard set of time invariant controls. In both regressions we include a new set of dummy variables for the training group that the entrepreneur belonged to and we cluster standard errors at the training group level. In both models the treatment effect on performance is statistically significant and larger in magnitude than in our alternative specifications. These regressions, therefore, show that the treatment effect remains robust to concerns of cohort-level heterogeneity.

Table A12-3: Performance effects with training group dummies

	(1)	(2)
Social skills training	0.480**	0.403**
	(0.039)	(0.058)
Training group FE	Yes	Yes
Survey wave FE	Yes	Yes
Sector FE	Yes	Yes
Baseline profits	Yes	Yes
Control variables	No	Yes
N	768	768
Entrepreneurs	278	278

The outcome is monthly log profits. Models use OLS with sector and survey wave FE controlling for baseline profits and dropping the baseline time period. Control variables include ewe ethnicity, female, completed primary school, number of employees, firm age, and management practices score. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Appendix 13 Clustering standard errors

There is an ongoing discussion in econometrics research about the appropriate level at which standard errors should be clustered in analyses of field experimental data, and indeed whether they should be clustered at all (Cameron and Miller 2015). Recently, Abadie et al. (2017) recommended that researchers should determine whether to cluster standard errors based on their experimental design. Specifically, according to the authors, the critical factor in determining whether to cluster and, if so, at what level is whether the randomization of the treatment was also clustered. Hence, in experiments where units are embedded in groups and the treatment is randomized at the group level, the standard errors in analyses of those data should be clustered at the group level. This is the case whether researchers use unit-level fixed effects or not.

Moreover, it is particularly important to cluster standard errors at the group randomization level when the experimental design exploits interactions between participants within each group, creating dynamic group effects (Kim 2021). Emerging research points to evidence that studies using unit-level clustering when the randomization occurred at the group or strata level often report standard errors that are significantly downwards biased (Chandar et al. 2019, de Chaisemartin and Ramirez-Cuellar 2020). In the absence of cluster randomization, standard errors need not be clustered, unless there are multiple time periods, in which case researchers should cluster at the unit level because otherwise it would imply that the randomization took place at the unit-time period level (Abadie et al 2017).

In light of this research and emerging consensus in development economics that analyses of data from cluster randomized field experiments should cluster standard errors at the randomization level (Chandar et al. 2019) (see also David McKenzie's 2017 blog post: https://blogs.worldbank.org/impactevaluations/when-should-you-cluster-standard-errors-new-wisdom-econometrics-oracle), we opted to use cluster robust standard errors with clustering at the training group level in our analyses. In our field experiment, the randomization occurred at the training group level – meaning that all entrepreneurs within a given training cohort were treated—and hence this seemed appropriate.

Nevertheless, to ensure that our results are not contingent on a particular approach to estimating standard errors, we replicate our regression results using individual-level clustered standard errors and individual-level bootstrapped standard errors. Table 13.1 below replicates the results from Table 5 in the paper, estimating the impact of social skills on entrepreneurs' performance, using a cluster robust variance estimator for the standard errors at the individual level. The standard errors in Table 13.1 are broadly similar to those reported in Table 5 in all models. In Models 1 and 2, which rely on a pooled cross-section approach the standard errors are slightly larger, while in the difference-in-differences approach they are slightly smaller than in Table 5. Regardless of these differences, however, the interpretation of the statistical significance of these results does not change in any of the models.

In addition to clustering standard errors at the individual level, we also estimated all models in Table 5 using an individual-level bootstrapping approach to estimating standard errors, these results are presented in Table 13.2. The standard errors estimated in Table 13.2 are very similar to those in Table 13.1, and all our results remain statistically significant at the same level as reported in the main paper.

Table 13.1: Social skills impact on monthly profits, cluster robust SE by individual

	Monthly Profits (log)		
	(1)	(2)	(3)
Social skills training	0.170*	0.171*	
	(0.069)	(0.077)	
Social skills training X Post-treatment			0.251**
			(0.094)
Post-treatment			0.220**
			(0.078)
N	768	768	1,046
Entrepreneurs	278	278	278
Survey wave FE	Yes	Yes	Yes
Baseline profits	Yes	Yes	No
Sector FE	No	Yes	No
Control variables	No	Yes	No
Entrepreneur FE	No	No	Yes

Models 1 and 2 pool the post-treatment periods, include survey wave fixed effects, and control for baseline profits. Model 2 includes additional controls for ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Model 3 uses a diff-in-diff specification with entrepreneur fixed effects. Robust standard errors clustered by individual in all models.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 13.2: Social skills impact on monthly profits, individual bootstrapped errors SE

	Monthly Profits (log)		
	(1)	(2)	(3)
Social skills training	0.170*	0.171*	
	(0.071)	(0.080)	
Social skills training X Post-treatment			0.251**
			(0.095)
Post-treatment			0.217**
			(0.077)
N	768	768	1046
Entrepreneurs	278	278	278
Survey wave FE	Yes	Yes	Yes
Baseline profits	Yes	Yes	No
Sector FE	No	Yes	No
Control variables	No	Yes	No
Entrepreneur FE	No	No	Yes

Models 1 and 2 pool the post-treatment periods, include survey wave fixed effects, and control for baseline profits. Model 2 includes additional controls for ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Model 3 uses a diff-in-diff specification with entrepreneur fixed effects. Bootstrapped standard errors at the individual level estimated in all models.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Finally, to demonstrate that clustering standard errors at the entrepreneur-level does not alter our mediation analyses in Table 8, we estimate the same models in Table 8 while clustering standard errors at the entrepreneur level, rather than the training group level. We present the results in Table 13.3 below, which shows that the results remain unchanged in terms of their statistical significance.

Table 13.3: Second stage of mediation for social interaction index and alternative mechanisms, clustering standard errors at the individual level

	Monthly Profits (log)		
	(1)	(2)	(3)
Social skills training	0.023	0.151*	0.163*
	(0.080)	(0.066)	(0.055)
Social interactions index	0.155**		
	(0.043)		
BERT positive affect score		0.046	
		(0.107)	
Marketing practices index			0.030
			(0.055)
Survey wave FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
N	710	710	768
Entrepreneurs	257	257	278
ACME	0.137	0.022	-0.000
	[0.059, 0.219]	[-0.068, 0.109]	[-0.007, 0.005]
% of Tot. Eff. Mediated	0.851	0.137	-0.003
	[0.463, 3.809]	[0.070, 0.652]	[-0.012, -0.001]
ρ at which ACME = 0	0.162	0.016	0.019

Data are from three post-treatment survey rounds and show average impact over the post-training period. All regressions include sector and survey wave fixed effects, and control for baseline profits (log). The number of entrepreneurs in Models 1 and 2 is 257 because scanned networking notes for one training cohort were missing. Robust standard errors clustered by entrepreneur. ACME = Average Causal Mediation Effect. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Wild Cluster Bootstrap

Given that our main estimation strategy clusters standard errors at the level of the training group, for the reasons described above, it is important to address how the number of clusters in the experimental design may affect our standard error estimates and the statistical significance of our results. Bertrand et al. (2004) argue that having too few clusters can lead to biased standard errors in difference-in-differences models. There is some debate in the context of field experiments about how many clusters are needed to avoid this issue (see for example the following blog post by Berk Ozler: https://blogs.worldbank.org/impactevaluations/beware-of-studies-with-a-small-number-of-clusters). Nevertheless, to reduce potential concerns about the number of clusters in our experimental design, we use wild cluster bootstrapping to generate confidence intervals for our coefficient estimates. This approach was developed by Cameron, Gelbach, and Miller (2008) to improve inference in settings where some assumptions related to large-sample theory might not hold and econometric research shows that wild clustered standard errors improve the reliability of estimates in these contexts (MacKinnon and Webb 2018).

For each model in Table 5, which estimates the impact of social skills training on performance, we used wild cluster bootstrapping to create confidence intervals for each coefficient estimate. We rely on confidence intervals since this process does not estimate standard errors (Roodman et al. 2019). Despite wild bootstrapping being a significantly more conservative approach, all our performance results remain statistically significant at the same level. Table 13.4 bellow shows the CI for each point estimate for each of the three models from Table 5. In all cases the confidence intervals generated by the wild cluster bootstrap are wider than those generated by the cluster robust variance estimator used in Table 5. Despite this all results remain statistically significant at the 5% level.

Table 13.4: Social skills impact on monthly profits, using wild cluster bootstrapped 95% confidence intervals

	Monthly Profits (log)		
	(1)	(2)	(3)
Social skills training	0.170*	0.171*	
	[0.019, 0.316]	[0.008, 0.325]	
Social skills training X Post-treatment			0.251*
			[0.011, 0.462]
Post-treatment			0.008
			(0.073)
N	768	768	1046
Entrepreneurs	278	278	278
Survey wave FE	Yes	Yes	Yes
Baseline profits	Yes	Yes	No
Sector FE	No	Yes	No
Control variables	No	Yes	No
Entrepreneur FE	No	No	Yes

Models 1 and 2 pool the post-treatment periods, include survey wave fixed effects, and control for baseline profits. Model 2 includes additional controls for ewe ethnicity, female, completed primary school, number of employees, firm age, management practices score, and training class size. Model 3 uses a diff-in-diff specification with entrepreneur fixed effects. 95% confidence intervals estimated in all models using wild bootstrap clustering at the training group level.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Finally, to summarize and compare the estimates from the three different approaches described above, we also present the p-values for each coefficient estimated in Table 13.5. Each column represents the equivalent model estimated in Tables 13.1, 13.2, and 13.4 above, and each row represents a different approach to estimating standard errors. All of the p-values indicate that the coefficient estimates for the effect of social skills on performance are below the 5% significance level.

Table 13.5: P-values from performance regressions

	Outcome: Monthly Profits (log)		
	Model 1	Model 2	Model 3
	p-value	p-value	p-value
Individual bootstrapped	0.017	0.003	0.008
Cluster robust at the individual level	0.016	0.027	0.008
Wild cluster bootstrap at training group level	0.026	0.048	0.045

A14. Testing alternative mechanisms: Marketing knowledge and enthusiasm

Marketing Practices

As part of the experimental design entrepreneurs received a 2-day training in marketing practices. This raises a natural question: did our treatment merely increase engagement with the marketing training and so improve performance by improving the treated group's knowledge of marketing practices? To be clear, the marketing training was not randomized and was given to all entrepreneurs. Without heroic assumptions there is no way to causally identify the impact of the marketing training on participants' post-training performance. We can, however, assess whether entrepreneurs learned new marketing practices, whether this was associated with changes in performance, and—most importantly—whether there were differences between the control and treatment groups in learning the marketing practices.

To explore whether there is a relationship between participating in the study and learning marketing practices, we explored the change in entrepreneurs' use of the 8 marketing best practices that were taught during the training program. The marketing best practices, which were derived from the ILO entrepreneur training program "Improve your business" (McKenzie and Woodruff 2018) were: 1) finding out what competitors charge; 2) finding out competitors' products and services; 3) asking existing clients what other products and services they would buy; 4) asking former clients why they stopped buying; 5) asking suppliers what other products and services are popular in my sector; 6) using a promotional sale or offer; 7) use of advertising; 8) measure the impact of advertising.

To explore the extent to which entrepreneurs learned these practices we regressed entrepreneurs' use of the marketing best practices on a post-treatment indicator. The coefficient for the post-treatment period represents the change in use of the marketing practices from the baseline period. These regressions are presented in Table A14-1. Models 1-8 examine the change in the use of each best practice after the training camp, while Model 9 examines the change in an index of all the marketing best practices. With the exception of Model 6, which tests for whether entrepreneurs used more promotional sales, entrepreneurs used all other marketing best practices more after the training program. These results support the conclusion that entrepreneurs learned about marketing best practices during the two-day training program and were likelier to use them. The coefficient for the marketing practices index suggests that on average entrepreneurs reported using approximately 2.4 more marketing best practices in the post-treatment periods, a substantial gain.

Table A14-1: Post-training camp changes in marketing practices

	What competitors charge	What competitors sell	What clients want	Question former clients	Suppliers recommend	Used promotion	Used advertising	Evaluated advertising	Marketing practices index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-Treatment	0.287**	0.253**	0.271**	0.290**	0.452**	0.106	0.318**	0.336**	0.289**
	(0.055)	(0.048)	(0.038)	(0.042)	(0.042)	(0.071)	(0.044)	(0.056)	(0.040)
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entrepreneur FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1046	1046	1046	1046	1046	1046	1046	1046	1046
Entrepreneurs	278	278	278	278	278	278	278	278	278

In each column the outcome variable is an indicator for whether the entrepreneur used a given marketing best practice. The outcome variable in Model 9 is an index of the preceding 8 marketing practices. Post-treatment is a variable equal to '1' for all time periods after the treatment and '0' for the baseline, pre-treatment period. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

To understand whether the use of marketing best practices was associated with increases in performance we regressed entrepreneurs' performance on the use of marketing practices in the post-treatment period. These regressions are presented in Table A14-2. The outcome in these regressions in monthly profits (log) and the independent variable of interest is the use of a marketing practice in the post-treatment periods. This outcome of interest is captured by the interaction of a dummy variable for use of each marketing practice and a dummy for post-treatment time periods. Each model tests the use of a marketing best practice on profits. The final column, model 9, shows the effect on performance of the marketing practices index.

In all models the interaction term between the post-treatment period and each marketing practice is *not* statistically significant. For some of the practices, the coefficient estimate is negative. Overall, these results suggest that although entrepreneurs used more marketing best practices after the training program, their use was not strongly associated with statistically significant improvements in performance. It is possible that marketing practices did not increase profits because they also generated additional costs. It is important to note that field experiments testing the effects of marketing practices on entrepreneurial performance have used training programs that were much longer than ours, such as Anderson et al. (2018) who implemented a marketing training program that lasted 10 weeks.

It bears repeating that we lack a proper counterfactual to assess whether the marketing practices training improved performance. Thus, even though the results in Table A14-3 are consistent with no effect, it's possible a clean RCT might show a positive impact. Figure 3 in the paper seems to suggest this, since it shows that both the treatment and control groups see profits rise in the year after the camp. If we think profits are in some sort of stable equilibrium then this increase could be taken as evidence of a treatment effect, but again, our study was not designed to test the causal impact of marketing practices on firm performance.

Table A14-2: Marketing practices effect on monthly profits (log)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Marketing practice 1 X Post-treatment	-0.347								
	(0.447)								
Marketing practice 1	0.182								
	(0.137)								
Marketing practice 2 X Post-treatment		-0.475							
		(0.438)							
Marketing practice 2		0.155							
		(0.127)							
Marketing practice 3 X Post-treatment			0.097						
			(0.115)						
Marketing practice 3			0.061						
			(0.099)						
Marketing practice 4 X Post-treatment				0.036					
				(0.083)					
Marketing practice 4				0.002					
				(0.075)					
Marketing practice 5 X Post-treatment					-0.074				
					(0.289)				
Marketing practice 5					0.022				
					(0.084)				
Marketing practice 6 X Post-treatment						-0.122			
						(0.120)			
Marketing practice 6						0.084			
						(0.099)			
Marketing practice 7 X Post-treatment							-0.062		
							(0.111)		
Marketing practice 7							0.146		
							(0.109)		
Marketing practice 8 X Post-treatment								0.068	
								(0.118)	
Marketing practice 8								0.076	
								(0.137)	
Marketing practices index X Post-treatment									0.087
									(0.359)
Marketing practices index									0.228
									(0.197)
Post-treatment	0.413	0.551	0.021	0.099	0.196	0.212+	0.129+	0.062	-0.008
	(0.425)	(0.128)	(0.109)	(0.069)	(0.285)	(0.104)	(0.068)	(0.068)	(0.277)
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entrepreneur FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1046	1046	1046	1046	1046	1046	1046	1046	1046
Entrepreneurs	278	278	278	278	278	278	278	278	278

The outcome variable in all models is log monthly profits. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Most importantly, given that entrepreneurs appear to have learned new marketing practices from the experimental design, we also assessed whether our social skills treatment affected entrepreneurs' ability to learn them. Table A14-3 explores whether there were differences between the treatment and control groups in their use of marketing practices after the training program. Using the same 8 practices and the index of marketing practices as above, we regressed each practice on the interaction between the post-treatment time period and receiving the treatment. This interaction term is meant to capture whether entrepreneurs in the treatment condition used more marketing best practices than the control condition.

In Table A14-3, Models 1-8 test whether the social skills treatment affected the use of each marketing practice after the training program, while model 9 tests the effect on an index of all 8 practices. The coefficients on the interaction between treatment and post-treatment time period are all near zero and not statistically significant. There is no evidence of a difference between the two groups in their use of marketing best practices. These results also suggest that the learning process and efficacy for the marketing practices was similar across the treatment and control groups.

Table A14-3: Treatment effect on learning marketing practices

	What competitors charge	What competitors sell	What clients want	Question former clients	Suppliers recommend	Used promotion	Used advertising	Evaluated advertising	Marketing practices index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-Treatment X Social skills training	-0.127	-0.073	-0.041	0.014	-0.070	0.127	0.099	0.070	-0.000
	(0.098)	(0.092)	(0.073)	(0.075)	(0.079)	(0.087)	(0.096)	(0.121)	(0.051)
Post-Treatment	0.351**	0.289**	0.292**	0.283**	0.488**	0.042	0.269**	0.301**	0.289**
	(0.084)	(0.064)	(0.040)	(0.051)	(0.053)	(0.045)	(0.050)	(0.089)	(0.051)
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entrepreneur FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1046	1046	1046	1046	1046	1046	1046	1046	1046
Entrepreneurs	278	278	278	278	278	278	278	278	278

In each column the outcome variable is an indicator for whether the entrepreneur used a given marketing best practice. The outcome variable in Model 9 is an index of the preceding 8 marketing practices. Robust standard errors clustered by training group in all models.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Finally, to further explore whether entrepreneurs in the treatment group learned more about marketing practices than entrepreneurs in the control group, we also compared participants' performance on a multiple-choice test on marketing practices that was administered at the end of the two-day program. The test consisted of 10 multiple choice questions and was meant to evaluate participants' understanding of the basic practices that had been taught. The test was written by the instructors and administered by them. The same test was given to all groups of participants. Table A14-4 below regresses entrepreneurs' test score on the treatment. The coefficients for the treatment variable in models 1 and 2 are not statistically significant and are relatively small in magnitude compared to some of the control variables in model 2. These results offer further evidence that the social skills training did not affect entrepreneurs' comprehension or learning of the marketing practices that were taught during the training program.

Table A14-4: Effects of treatment on marketing test scores

	(1)	(2)
Social skills training	-0.246	0.330
	(0.411)	(0.190)
Ewe ethnicity		-0.499*
		(0.221)
Female		-0.567*
		(0.247)
Completed primary school		1.309**
		(0.326)
Employees		0.052+
		(0.028)
Firm age		-0.079**
		(0.016)
Management practices score		-0.093
		(0.489)
Class size		-0.069+
		(0.035)
Sector FE	No	Yes
N	301	301

The outcome is the test score (out of 10) on a test on the marketing practices, administered during the training. All models estimated using OLS. Robust standard errors clustered by training groups. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Enthusiasm

Another plausible alternative is that the social skills training didn't impact networking or the quality of advice, but merely increased the enthusiasm and motivation of the treatment group which in turn improved future performance. Given that the social skills training was new material for the instructors, it is possible that it felt more exciting for them and created a more energetic and enthusiastic classroom experience. By contrast, the control group classrooms may have felt less exciting and slower to the instructors, which could have negatively affected participants' experience by making them feel bored and demotivated. This demotivation could reduce future effort exerted and performance.

To rule out this possibility, here we show that there is no evidence of a difference between treatment and control groups in their subjective evaluation of the training program nor in their levels of participation. These supplementary analyses suggest that entrepreneurs in the control group do not seem to have experienced the training program more negatively than their peers in the treatment condition and do not seem to have been less motivated to complete it.

First, following Anderson et al. (2018), we show that entrepreneurs' subjective evaluation of the training program did not differ significantly between the treatment and control groups. At the end of the training program entrepreneurs were asked whether they would be interested in participating in another similar training program in the future and responded on a 5-point Likert scale ranging from "Yes" to "No." 85% of entrepreneurs responded "Yes" to this question. We therefore collapsed all other responses (ranging from "probably yes" to "no") into one "Not Yes" category. The resulting variable was a binary indicator of 1 for "yes" and 0 for any other level of enthusiasm about attending a similar training program in the future. Table A14-5 below shows the results of regressing this variable on treatment. In both models, with and without controls, the effect of treatment is not statistically significant and the coefficient is negative suggesting that if there was a difference between the groups, the treatment group would be less certain of participating in future training programs. These results support the idea that the treatment did not substantially influence entrepreneurs' level of enthusiasm about the program.

Table A14-5: Treatment effect on intention to attend in the future

	(1)	(2)
Social skills training	-0.027	-0.022
	(0.050)	(0.041)
Ewe ethnicity		-0.076+
		(0.042)
Female		-0.133*
		(0.058)
Completed primary school		-0.032
		(0.047)
Employees		-0.002
		(0.004)
Firm age		0.003
		(0.002)
Management practices score		0.224*
		(0.094)
Class size		-0.005
		(0.006)
Sector FE	No	Yes
N	301	301

The outcome is a binary indicator of whether the entrepreneur is interested in attending a similar training again. Models use OLS. Robust standard errors clustered by training group in all models. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

In addition to participants' subjective evaluations of the training program, we also collected instructors' subjective evaluations of each class they taught. Figure A14-1 below is a scanned anonymized copy of one of the daily reports that the instructors submitted to the researchers. In it they were asked to record the number of participants expected to attend, the number who attended, absences, details about attempts to reach absent participants, materials taught that day, surveys and tests administered, and the overall performance level of the class. Under the performance level of the class, they were meant to report whether there had been any issues with that particular class in terms of teaching the materials and the overall level of participants' understanding of the materials. In Figure A14-1 this portion of the instructors' report is circled in red. The instructors never reported any issues with any of the classes they taught. Every report stated the level of the classes was "Good." As a result, there is no evidence from instructors' subjective evaluation that treated classes went better than control classes or that students in one condition were more enthusiastic than the other.

Figure A14-1: Sample of instructor daily report

MARKETING IN ACTION
LOME, 2017

RAPPORT JOURNALIER DE LA FORMATION

PARTICIPATION

Date : 02/05/2017

Nom des Formateurs : [redacted] ET [redacted]

LIEU DE FORMATION : EGA LOME

DESIGNATION	
Nombre d'entrepreneurs attendu	29
Présents	26
Absents	05 (cinq)

10 femmes
16 hommes

02 participants non programmés ont suivi la formation
- ADJETEY-BAHUN Daniela
- AMEMASSOVOR EKI

Les absents :

Nom et prénoms	Actions entreprise	Résultat	Observation
[redacted]	Appel	Ligne occupée	A reprogrammer
[redacted]	Appel	S'est trompé de date	Revient jeudi/Vendredi
[redacted]	Appel	Souffrant	Revient jeudi/Vendredi
[redacted]	Appel	Souffrant	A reprogrammer
[redacted]	Appel	Sa fille est malade	A reprogrammer

MODULES / SUJETS DEVELOPPES

1. Le Réseautage
2. Le Marketing et votre entreprise
3. Le Positionnement de votre produit
4. Le Produit
5. La Place
6. Le Prix
7.
8.
9.
10.

EVALUATION / SONDAGE/ JEU

1. Test de demarrage
2. Activités 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
3. Evaluations 1, 2, 3, 4, 5

NIVEAU DE LA CLASSE : BON

La liste de présence, les évaluations, les sondages et les jeux sont annexés au présent rapport.

NOM ET SIGNATURE DES FORMATEURS : [redacted] [redacted]

In addition to subjective evaluations, the daily reports allowed us to identify participants who dropped out of the training program after the first day. These participants would have been exposed to the treatment if they were in the treatment group and would have spent enough time in the program to gain a good understanding of what it entailed. In the 14 groups of entrepreneurs that were trained, 5 participants dropped out after the first day and only one of them was from the control group. Hence, the majority of entrepreneurs who dropped out after the first day were from the treatment group. This provides a strong indication that the control group was not particularly demotivating or that entrepreneurs in the control condition did not have a sense that their time was being wasted. This helps allay fears that the design of the RCT could have a created a demotivated or unenthusiastic control group.

Finally, as discussed in Appendix Section A17, we do find evidence that entrepreneurs in the treatment condition describe the advice they received in more positive terms. Thus, while we find no evidence for meaningful differences in individual-level enthusiasm or motivation, we do find evidence that social skills lead to more positive impression of the advice received. However, we find no evidence that this increase in “positive affect” mediates our performance outcomes. Instead, as described in detail in A17, we find much stronger evidence that what matters is the quality of advice received and not whether the notes exhibit positive or negative sentiment.

A15. Examples of peer advice

Social skills improve entrepreneurs' performance, at least in part, because they enable them to communicate better and hence gain more useful advice. In this section we show illustrative examples of the kinds of advice that entrepreneurs in the treatment and control conditions received from their peers. These examples provide a concrete sense of the kinds of interactions that entrepreneurs had during the training program and how starkly those interactions differed between the treatment and control conditions.

The examples presented below are handwritten notes that entrepreneurs took during the networking session, when they were randomly assigned a discussion partner from their training cohort. Their notes were scanned, digitized, and translated by the researchers. Examples 1-8 are from entrepreneurs in the treatment condition, while examples 9-13 are from entrepreneurs in the control condition.

Social skills training condition

Example 1

An entrepreneur who owned a bar and restaurant stated in the baseline survey that their goal was to "open a VIP area to better serve clients" and noted the following piece of advice from a discussion partner:

Have themed days. Create a song playlist. Have promotional sales. Install a large screen during football matches with a sale on BB [local beer brand]. Revise the framework of operations to brake the norm and get out of the ordinary. Also review the decoration. Change the paint to a very attractive color. Compare menus with those of competitors. Make great fish recipes with Akpan on skewers. Often organize themed evenings. Find a solution where the customer can park and have security for their car. (ID: 90058058; Partner ID: 90289616)

Example 2

An entrepreneur who owned an art and music production company stated in their survey response that their goal was to "Improve my business' market position." They received the following advice from another entrepreneur:

1) Introduce music lessons. 2) Put on a monthly show at the Church, distribute flyers there. 3) Promote my productions by offering deals. 4) Bring artists together and offer them lower prices. 5) Create a compilation album with artists from churches (musical groups or choirs). 6) Advertise on morning shows (6-8, local) 7) Do digital marketing (WhatsApp, community management). (ID: 90271153; Partner ID: 91379697)

Example 3

An entrepreneur who owned an IT school stated that their goal was to "learn about managing finances and recruit an accountant." The advice they received was:

1) Reach out to institutions about participating in their training programs (E.g. FAIEJ, PRADEB). 2) Also learn from the internet (Google). 3) Build on relationships: surround yourself *with people who are in my field. 4) Exchange contact information with a growing participant in this field: [name redacted]. (ID: 98275189; partner id: 91663093)*

Example 4

One of the entrepreneurs in the training program owned a fabric weaving and manufacturing business. They wrote in our survey that: "I want to grow my business." During the networking event they wrote the following piece of advice:

You must first open an account with an institution (bank, microfinance). I advise you to open an account with the CECA (Caisse d'Épargne et de Crédit des Artisans). You must regularly go and deposit the money at the cashier or microfinance that you want. Apply for a loan after a few months. Be regular in repaying the loan to receive others afterwards. Be faithful to the institution. You have to reassure the institution by respecting your commitment to it. You can organize with others who have the same financial problems as you to advocate your cause with a financial institution in order to have the financing for your projects. You must learn about the institutions to find out which one has the low interest rate in order to easily pay the credit. (ID: 91645748; Partner ID: 91898862)

Example 5

The owner of a salon wrote that she wanted to "put into practice the things we learned" and got the following advice from another entrepreneur during the networking event:

Have an account book that records what you sold during the day, you must write them down every day and take stock at the end of each month. Then you divide it into 3 or 4 parts (rent, electricity, your salary, your own salary) to prepare for next month, to see what you have won or lost, and next month you make changes. Continue until the end of the year and then you do your annual report. (ID: 90676960; Partner ID: 90377153)

Example 6

A retailer of cosmetics wrote that her goals was to "increase my profit margin." During the networking event she wrote down the following piece of advice:

Advertise products to those in need, collect their impressions of my products take them into account and serve them accordingly and offer them a loyalty card. Finally, to encourage them, periodically reward the most deserving among the clients. Reassure them about the qualities of my products and what differentiates them from others and the advantages that this can provide them, follow up after sales to customers. NB: In line with rewarding clients, make sure not to go beyond your profits. Each time you show up at an event try to create contacts who will refer new customers by always holding your business card with the image of your business and exchange it, if possible, for the business card of others. Otherwise, make contact with everyone with whom you wish to build relationships and follow up on those relationships to gain future customers. (ID: 90018298)

Example 7

A grocery store owner, whose business had been in operation for about 6-7 years, declared that their main business goal was to "learn how to find financing for buying stock inventory" and that in general they wished to improve their stock management. During the networking event they wrote down the following piece of advice:

Because of the competition, choose a rare product in the market, sell it wholesale and advertise it by inviting the resellers (retailers) to come and visit the store, guaranteeing them to get them good prices. New Products, Different Products, Competitive, Advertising, Promotion. NB: Examples of new products: take away disposable dishes, disposable glasses, and disposable spoons, tissue paper, tea towel, disposable forks, toilet paper. (ID: 90182156)

Example 8

Have a product to sell. An existing clientele. Review the product communication strategy. Seek advice from potential customers. Discuss with lost customers to understand it and get them brought back. Review the value for money equation. Or simply allow customers to pay in installments to ease their payment in several stages. Identify the basic needs of the target in relation to the products / services. See if these meet their needs. Encourage family and friends to use my products to promote them. Proximity: gain the trust of people around you to expand your network. (ID: 91999020)

Control condition

Example 9

An entrepreneur involved in construction and masonry, whose business was about 3 years old, stated that "over the course of the next two months I would like to put together a plan for the future for my business." They wrote:

It's a good thing to put everything we've learned into practice and also make my own business cards, use photos of my old achievements. My partner gives me encouragement to continue my business and put all that into practice. (ID: 90329904)

Example 10

An entrepreneur who owns a carpentry workshop, started their business two years ago, and wanted to learn to plan better for the future and manage their funds better. They wrote:

My hope is that I would like to grow my business by going to the West to get new products to better satisfy my retail and wholesale clients and gain other clients to grow my business and hire workers who help me work in my area. (ID:)

Example 11

An entrepreneur who owned a business manufacturing and repairing shoes in operation for approximately 2 years wanted to learn more about welcoming clients and how to produce different kinds of shoes.

Lack of sales, exhibitions last over a month. People rarely come to buy a shoe or two. But there is the rent to pay, the electricity bill and food. It's difficult in short, no profit. That's why I'm going to look for the wholesalers and try to do some work for them. (ID: 97416030)

Example 12

Owner of a photography store, in operation since 2014, wanted to learn to develop new strategies or methods that would give him "an advantage in the market." They wrote:

Meetings don't give me time to be in my studio. So these meetings take my time. So much so that the apprentices I had were devastated. So there, I created a bar that I personally run every night. Future: I said to myself, being old, I must continue sewing and create a haberdashery which should help me in addition for the future. (ID: 90211270)

Example 13

A retailer of shoes and sandals, in operation for about 13 years, wanted to learn how to keep better records for their business. They wrote:

Sandals, closed toe shoes, shoe repair of all kinds, belts. In my workshop the biggest challenge I face as a craftsman is lack of sales. Exhibitions throughout the year. My income is mainly the repair of shoes and my big sister lives in Mali and sends me tobacco that I sell sometimes. (ID: 90841704)

A16. Coding the peer advice handwritten notes

To measure differences in the kinds of conversations that entrepreneurs had and the kinds of advice they exchanged, we use the handwritten notes they took during the structured networking event at the end of the training camp. During this event each entrepreneur was successively paired with 3 *randomly selected* other entrepreneurs for one-on-one discussions. Given that this networking event was structured in a "speed dating" format, each entrepreneur spoke with their partner for the same amount of time, approximately 30-45 minutes. They were given pen and paper to take notes, which we scanned before they left the training program. This resulted in approximately 720 pages of notes, which were transcribed into a machine-readable digital format by four research assistants. These notes offer a unique glimpse into the content of the exchanges that entrepreneurs engaged in and the kinds of advice transmitted.

Using this text, we measure two key aspects of the conversation. First, we measure the quantity, complexity, and relevance of the advice the entrepreneur received. Second, we measure the sentiment of the text to capture differences in enthusiasm.

Measuring the characteristics of advice

Our first pass at measuring differences in the kind of advice received, as discussed in the body of the paper and presented in Figure 1 and Table 3, was to simply count the number of words each entrepreneur used in their notes. Using the text length as a measure of "idea" quantity or depth is a common practice (Blumenstock 2008), though it is an admittedly crude measure. Here we describe four measures that help us get at differences in the informative-ness, depth, and complexity of the advice received. Again, our goal is not to test which of these measures is more responsible for our treatment effect, but instead to test whether variation in the relevance and complexity of advice—an admittedly multi-dimensional construct—mediates our performance effects.

Our first two measures of advice come from LIWC, the Linguistic Inquiry and Work Count method (Pennebaker et al. 2001). LIWC is among the few linguistic text analysis software that can analyze French text, thereby avoiding issues of translation. Moreover, the results from LIWC analyses have been validated in a number of studies, which makes them more reliable and the output easier to interpret (Oswald et al. 2020, Piolat et al. 2011, Short et al. 2018). We use LIWC to measure two different characteristics of the advice: the proportion of words related to work and the proportion of words that are six letter words.

Work-related words represent a "content" category for words (Chung and Pennebaker 2007). The proportion of words that relate to work helps capture the extent to which the notes are focused on advice related to the entrepreneurs' work and their business (Wang et al. 2016). Notes that contain a higher proportion of words related to work are likelier to contain substantive and actionable advice, rather than abstract general statements.

The average number of six letter words in a communication is often used as an indicator of cognitive complexity in linguistics (Arguello et al. 2006, Tausczik and Pennebaker 2010). Communication that exhibits more cognitive complexity is often associated with deeper thinking and higher levels of reasoning (Slatcher et al. 2007), as well as expertise (Toma and D'Angelo 2015). Therefore notes that feature six letter words are likely to convey more complex concepts with authority, which suggests that the advice received is more nuanced and complex.

Our third approach is simple: we count the average number of words per sentence. Prior work has established that sentence length proxies for the complexity and amount of detail in language (Buck and Penn 2015).

Our fourth and final approach is to count the number of distinct pieces of advice written down by the entrepreneur in their notes. We did so by hiring two research assistants, fluent in French, to read the notes carefully and evaluate the number of distinct pieces of advice recorded in each note. This evaluation was based on the number of different topics covered in the notes and the number of different, actionable statements the entrepreneur recorded on those topics. Each note was read by both coders and scored independently, the final count of pieces of advice was the mean of the coders' scores. We found that the average note listed 3 pieces of advice, with a standard deviation of 2.5. Comparing the control and treatment groups we get averages of 1 and 4.8, respectively.

Finally, we avoided subjective evaluations of the quality of advice. During the training rounds of coding, we did ask the two coders to evaluate the quality level of advice in the notes, but the disagreement between coders was very high and it was difficult to reconcile these differences through changes in the coding process. It is likely that the reason for the disagreement between coders was that neither were entrepreneurs nor were they familiar with the Togolese context. It was therefore easy for each to reach different conclusions about the notes. Given this, we decided not to have our coders evaluate the notes on a quality scale and instead rely on our LIWC derived measures.

Measuring enthusiasm

Finally, perhaps what matters is less the quality or quantity of advice, but the fact that the better conversations led the entrepreneurs to be more enthusiastic and motivated. Indeed, as discussed in A14, a plausible alternative explanation for our findings is that the social skills treatment increased enthusiasm and excitement. Thus, perhaps the advice doesn't matter, but the better conversations led to happier and so more motivated entrepreneurs who then outperformed the control group. While we find no evidence in A14 that control group entrepreneurs are more likely to drop out of the control group (a proxy of motivation) nor any less likely to want to attend the program in the future, here we also measure the positive or negative sentiment of the notes.

Specifically, we use "BERT," a state-of-the-art natural language processing algorithm (Blard 2020) to estimate the sentiment of the notes. BERT is trained on data from a corpus of billions of French documents by Google (Le et al. 2019, Martin et al. 2019). A key feature of BERT is that the model can then be adapted to specific uses. Here, we use a model that relies on BERT, along with data from thousands of reviews on different French language websites, to predict whether a piece of text is likely to leave a positive or negative rating. The richness of the BERT language model means that it avoids common syntactic and semantic errors that plague many other sentiment classifiers. The end result is that, for each note, we have a probability that the sentiment expressed is “positive.”

Further, as discussed in detail A17, by measuring the notes’ sentiment along with the quantity and complexity of advice we can test if (1) the treatment impacts both the nature of advice and the sentiment of the entrepreneur and (2) if both these increases mediate the treatment effect. Indeed, while we find strong evidence that the complexity/quantity of advice mediates the treatment effect, we find no evidence that sentiment mediates the treatment effect, even though the notes in our treatment group exhibit substantially more positive sentiment.

A17. Mediating performance through changes in social interactions

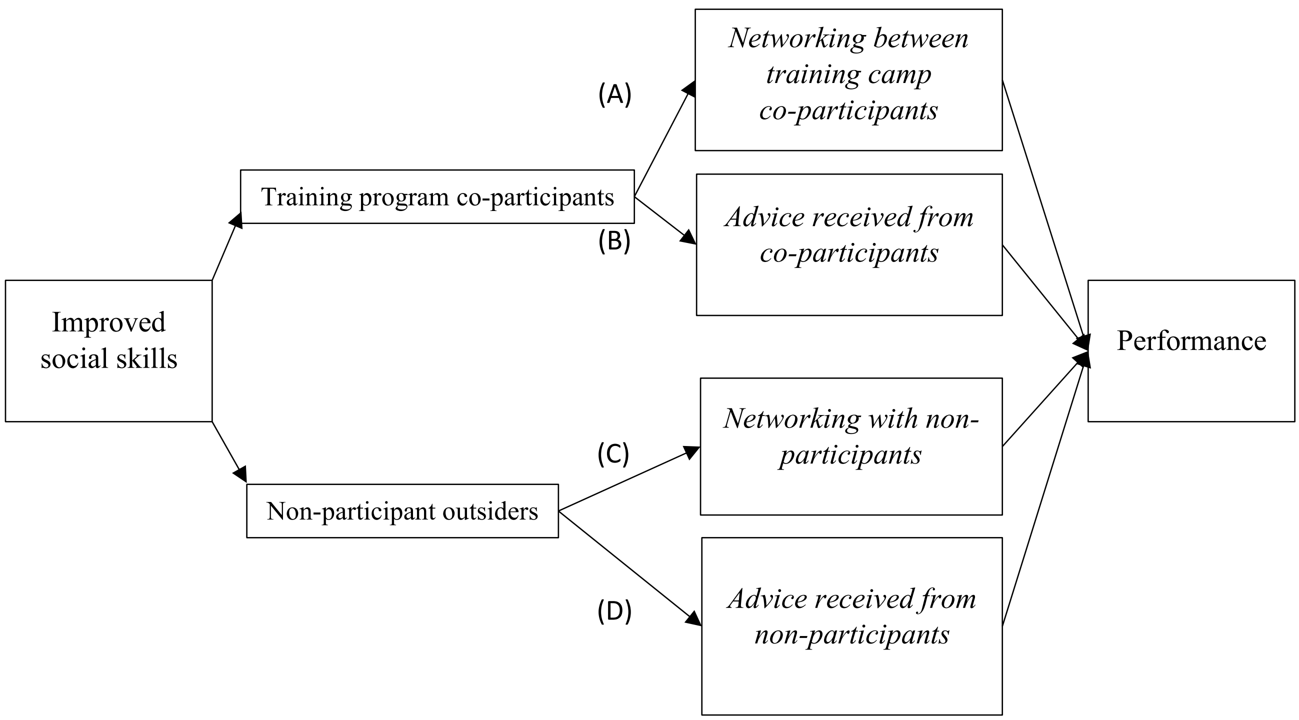
How do social skills increase entrepreneurs' performance? We show that teaching entrepreneurs social skills increases profits by approximately 20% in the year after the training. In this appendix section, we explore the mechanisms underlying this improvement.

According to our theory, social skills involve communicating effectively about business and approaching business interactions with new acquaintances collaboratively. We have shown that entrepreneurs with improved social skills interact differently (they perceive interactions more collaboratively and exchange more information – H1), they form more matches with peers (H2) and those matches tend to be more valuable in terms of the skills they provide access to (H3). Hence, when we think about the social mechanisms underlying our treatment effect, we can think about shifts in *matching* (who an entrepreneur talks to) and shifts in *obtaining advice* (how entrepreneurs talk to their peers). Again, we are not aiming to cleanly separate these channels—they are more than likely interdependent—but rather to explore if both these channels mediate our performance effects, and if they do, which is larger.

These changes in who an entrepreneur matches with and their ability to gain advice can occur both with co-participants and with others outside of the two-day training program. That is, our social skills training may be largely context dependent, and so may only cause entrepreneurs to network better and gain advice from their peers who also have gone through the training. However, the training might well extend beyond the program, helping entrepreneurs network better outside the training program and gain advice from people outside the program.

The arguments above suggest that there are four potential pathways from the treatment to the performance effects, shown in Figure A17-1 below. The first pathway (A) is that the social skills training helps entrepreneurs search for the right peers to talk to in the training program and so helps them match with those who can offer the most useful information. The second pathway (B) is that social skills training improves the advice received, no matter who an entrepreneur is talking to, during the training program. The third (C) is that social skills could change how an entrepreneur networks after the training program enabling them to make more and more useful new connections to others outside of the program. Finally, the fourth pathway (D) is that social skills enable entrepreneurs to get more advice from their existing contacts outside the training program.

Figure A17-1: Potential pathways from social skills training to performance



We test each of these potential mechanisms by constructing four separate measures. To test the first pathway—networking and matching with peers during the training program—we created a *between co-participants networking index*, which is the mean of seven standardized variables: cooperative words selected, number of participants that entrepreneurs exchanged contact information with, the number of participants they received advice from during the program, the average profits (log) of the participants with whom they formed ties, the average task complementarity of the participants with whom they formed ties, the average ethnic diversity of those ties. Each of these variables captures the extent to which entrepreneurs interacted with more peers during the program and the quality of their matches with peers from the program. The effect of social skills on each of these components of the index is shown in Table A17-5. Training in social skills increases all four components.

To test the second mechanism—the kind of the advice entrepreneurs received from peers during the training—we created a *co-participant advice index* variable. This measure is based on the handwritten notes that entrepreneurs took during the networking event, during which they were randomly paired with co-participants. Thus, this measure reflects the quantity, complexity, and relevance of the advice entrepreneurs received from randomly selected peers, rather than the peers that entrepreneurs themselves sought out in the program. Having scanned and digitized the notes, we used LIWC and manual coding to conduct a content analysis of the text (see description in Appendix A16). Our variable for within-camp advice was the mean of five standardized variables: total words written, words per sentence, number of six letter words, proportion of words related to work, and number of pieces of advice. Words per sentence and six letter words are indicators of cognitive and linguistic complexity in communication (Arguello et al. 2006, Tausczik and Pennebaker 2010). Communication that exhibits more cognitive complexity often is associated with deeper thinking and higher levels of reasoning (Slatcher et al. 2007), as well as expertise (Toma and D'Angelo 2015). Therefore notes that feature longer sentences and six letter words are likely to convey more complex concepts, which suggests that the advice received is also more complex and nuanced. The proportion of words related to work captures the extent to which the notes contained words related to work, which approximates the extent to which the advice is focused and relevant to business issues (Wang et al. 2016). The more relevant the advice, the likelier it is to be actionable and useful to the entrepreneur. Finally, the number of pieces of advice was manually coded by two independent coders, who read each piece of text and estimated the number of distinct, complete pieces of advice. This variable quantifies the amount of advice received by entrepreneurs. Together, these five variables measure the extent to which the advice recorded during the networking event included multiple pieces of advice, was detailed, and related to entrepreneurs' work. The effect of social skills training on each component of the index is shown in Table A17-6. Appendix A15 presents examples of these notes taken by entrepreneurs during the networking event.

We created a *non-program networking index* to test the third mechanism: entrepreneurs' networking behavior and advice networks outside the training camp. This index is the mean of four standardized variables, three of which measure networking behaviors and one measures entrepreneurs' network size. The four components of the index are: engaging in referrals, reaching out to other entrepreneurs to learn from them, participating in an event with other entrepreneurs, and number of advice contacts (who did not participate in the training program). Engaging in referrals, reaching out to peers, and participating in events were binary indicator variables for whether the entrepreneur engaged in those behaviors during the past six months. The effect of treatment on each of these behaviors in shown in Table A17-7 and shows that social skills training affects referral making behavior and learning from others, but not other aspects of entrepreneurs' non-training camp networking.

Finally, we created a measure of *non-program advice activation*, which is intended to explore the fourth mechanism that social skills enabled entrepreneurs to access better advice from their existing contacts outside the training camp. We measured non-camp advice activation using the number of advice relationships with other entrepreneurs from whom the focal entrepreneur sought advice during the past six months. This counts the number of entrepreneurs, <u>*who had not participated in the training program*</u>, that participants sought out for advice after the training program. This measure helps show the extent to which social skills enabled entrepreneurs to activate existing ties to access more and presumably better advice.

Table A17-1 shows how each of our four measures are related to the social skills treatment. Each column regresses one of the four measures on the treatment. In all four cases, the social skills training has a positive effect.

Table A17-1: Mechanisms through which training operates

	Co-participant networking index	Co-participant advice index	Non-program networking index	Non-program advice activation
	(1)	(2)	(3)	(4)
Social skills training	0.250**	0.881**	0.226**	0.308*
	(0.067)	(0.145)	(0.063)	(0.154)
Sector FE	Yes	Yes	Yes	Yes
N	278	257	278	278
Entrepreneurs	278	257	278	278

The outcomes in Models 1 and 2 are based on measures from the training program, while the outcomes in Models 3 and 4 are based on averages across all post-treatment periods. Hence all models are cross-sections. The sample size in Model 2 is 257 because we could not obtain scanned networking notes for one training cohort. All regressions include sector fixed effects. Robust standard errors clustered by training group in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

To test whether the mechanisms in Table A16-1 mediate the effect of improved social skills on entrepreneur performance, we used the causal mediation analysis algorithm developed by Imai et al. (Imai et al. 2010, Imai et al. 2010). This causal mediation analysis calculates the average mediation effect by simulating predicted values of the mediator and outcome variables. This is done by specifying a model for the treatment effect on the mediator and a model for the treatment effect on the outcome of interest, controlling for the mediator. These models are then fitted with the available data using regressions and the output from these models are used to simulate the model parameters based on their approximate asymptotic distribution. The algorithm simulates model parameters from their sampling distributions using King, Tomz, and Wittenberg's (2000) quasi-Bayesian Monte Carlo approximation. For each draw of model parameters, the analysis generates potential values of the mediator, and based on that it generates a value for the outcome variable, and finally the average causal mediation effect. Having repeated the simulations 3,000 times, these are used to generate point estimates and confidence intervals.

We show the results of our causal mediation analyses in Table A17-2. The outcome variable for the regressions in Table A17-2 are monthly profits (log). The model specification used is Equation (1) described in the main paper and the same as Models 1 and 2 in Table 5. The results show the effect of each mediator on performance, while including the treatment effect. They show that all four pathways mediate, to varying degrees, the treatment effect.

The causal mediation analysis (stata command "medeff") provides a point estimate and a 95% confidence interval for the average causal mediation effect (ACME). We present these in the bottom rows of Table A17-2. According to these results, the treatment increased profits by 5% because of entrepreneurs' networking during the training camp, which represents a mediation of about 30% of the total effect of the treatment. The same approach shows that profits increased by about 8% because of the quality of the advice received during the training, which explains the approximately 46% of the total treatment effect. Non-camp networking increased profits by approximately 4%, which accounts for 27% of the total treatment effect. Finally, the activation of entrepreneurs' non-camp advice network, consisting of other entrepreneurs who did not participate in the training program, led to an increase of about 3% in entrepreneurs' profits, accounting for about 20% of the total treatment effect.

Table A17-2: Mediation analysis results

	Monthly Profits (log)			
	(1)	(2)	(3)	(4)
Social skills training	0.119*	0.096+	0.151**	0.128*
	(0.058)	(0.055)	(0.054)	(0.058)
Co-participant networking index	0.201**			
	(0.053)			
Co-participant advice index		0.120**		
		(0.038)		
Non-program networking index			0.193**	
			(0.052)	
Non-program advice activation				0.058**
				(0.017)
Sector FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
N	768	710	768	768
Entrepreneurs	278	257	278	278
ACME	0.052	0.078	0.043	0.034
	[0.016, 0.098]	[0.025, 0.135]	[0.013, 0.081]	[0.002, 0.077]
% of Tot. Eff. mediated	0.322	0.464	0.267	0.208
	[0.178, 1.166]	[0.267, 1.597]	[0.145, 1.040]	[0.120, 0.672]
ρ at which ACME = 0	0.109	0.087	0.134	0.119

Data are from three survey rounds and show average impact over the post-training period. The outcome variable are monthly profits (log). All regressions include sector and survey wave fixed effects, as well as a control for baseline profits. The number of entrepreneurs in Models 1 and 2 is 257 because scanned networking notes for one training cohort were missing. Robust standard errors clustered by training group in parentheses. ACME = Average Causal Mediation Effect. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Composite social interaction index and alternative mechanisms

Building on the above analyses of the four mechanisms derived from our theory, we combine all of them into a composite index, which we label *social interactions index*. This variable is a mean of all standardized variables that were used to test the four mechanisms theorized above. Combining these variables into one index, we explore whether it mediates the treatment effect on performance. Model 1 in Table A17-3 below shows the first step of the mediation: that treatment significantly increases the social interactions index. Model 1 in Table A17-4 then shows the second step of the mediation along with the point estimate of the ACME. The coefficient for the social interactions index is positive and large in magnitude, while the treatment variable is no longer statistically significant, which suggests a full mediation. According to the causal mediation analysis, on average the treatment increased profits by approximately 14% because of its effect on the variables that make up the social interactions index, *which accounts for approximately 85% of the total effect of the treatment on performance.*

Having tested the mechanisms relevant to our theory, we also test two alternative mechanisms that may also be at play: 1) entrepreneurs' enthusiasm; 2) entrepreneurs' learning of marketing practices.

Using our sentiment analyses of entrepreneurs' notes based the BERT NLP algorithm (See A16 for further details), we test whether entrepreneurs' enthusiasm mediates the treatment effect. The BERT text analysis assigned each entrepreneur's notes a probability for expressing an overall positive sentiment. This variable captures potential differences between treatment and control groups in levels of enthusiasm that could explain some of the performance outcomes. Obviously, better social interactions should result in more positive affect. However, higher levels of enthusiasm might simply motivate entrepreneurs, leading them to put in a greater amount of effort after the training program, which caused the performance increases, without necessarily having learned anything from their peers.

Using the same causal mediation analysis approach as above we tested whether positive affect, our proxy for enthusiasm, mediated the effect of social skills on performance. Model 2 in Table A16-3 below shows that our treatment leads to more positive sentiment, as detected from entrepreneurs' notes.

Model 2 in Table A17-4 shows the second step of the mediation analysis: the effect of positive sentiment on performance controlling for the treatment. According to Model 2 and the ACME point estimate, positive sentiment has no mediating effect on performance. The ACME point estimate only accounts for a small proportion of the treatment effect and the estimates are not statistically significant. Taken together, these results point to the fact that positive sentiments do not mediate the performance effect, but that our training did increase enthusiasm, a pattern consistent with our theoretical arguments.

Another mechanism that can explain the treatment effect is entrepreneurs' learning of the marketing practices, which were taught during the bulk of the training program. It is possible that the treatment created a better learning environment for entrepreneurs and so they learned better marketing practices, which led to their improved performance relative to the control group. To test this potential mediation, we use the marketing practices index constructed in Appendix section A14. It is the proportion of 8 marketing best practices used by entrepreneurs and which were taught during the training program.

We test whether treatment is associated with learning marketing practices in Model 3 of Table A17-3. The coefficient for the treatment is nearly zero and is not statistically significant, indicating that there is little association between receiving the treatment and improving marketing practices. Next, Model 3 in Table A17-4 tests the second step in the mediation model, which regresses monthly profits on the marketing practices index controlling for treatment. In this model the coefficient for the marketing practices index is not statistically significant and is negative, suggesting that marketing practices do not mediate the effect of the treatment. Moreover, the estimate of the ACME is not statistically significant and is zero in magnitude, again suggesting that there is no evidence of a mediation. In combination, these results suggest that the treatment did not affect performance through an effect on learning marketing practices.

Table A17-3: Mediation of composite social index and alternative mechanisms

	Social interactions index	BERT positive affect score	Marketing practices index
	(1)	(2)	(3)
Social skills training	0.315**	0.375**	0.003
	(0.057)	(0.050)	(0.021)
Sector FE	Yes	Yes	Yes
N	257	257	278

The outcomes in Models 1 and 2 were measured during the training program, while the outcome in Model 3 is an average across all post-treatment periods. Hence all models are cross-sections. The sample size in Models 1 and 2 is 257 because scanned networking notes for one training cohort were missing. All regressions include sector fixed effects. Robust standard errors clustered by training group in parentheses+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A17-4: Mediation of composite social index and alternative mechanisms

	Monthly Profits (log)		
	(1)	(2)	(3)
Social skills training	0.039	0.173*	0.170*
	(0.060)	(0.079)	(0.058)
Social interactions index	0.418**		
	(0.073)		
BERT positive affect score		0.009	
		(0.118)	
Marketing practices index			0.166
			(0.321)
Survey wave FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
N	710	710	768
Entrepreneurs	257	257	278
ACME	0.137	0.022	-0.000
	[0.082, 0.199]	[-0.071, 0.113]	[-0.010, 0.008]
% of Tot. Eff. Mediated	0.858	0.137	-0.003
	[0.478, 3.060]	[0.076, 0.527]	[-0.010, -0.002]
ρ at which ACME = 0	0.162	0.016	0.019

Data are from three post-treatment survey rounds and show average impact over the post-training period. All regressions include sector and survey wave fixed effects, and control for baseline profits (log). The number of entrepreneurs in Models 1 and 2 is 257 because we could not obtain scanned networking notes for one training cohort. Robust standard errors clustered by training group in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Sensitivity analyses

Tables A17-2 and A17-4 report in the bottom row the value of ρ at which the average causal mediation effect (ACME) estimate is zero. Here ρ is the correlation between the error terms in the first and second stage regressions in the mediation model. This metric is used as an indicator of the robustness of the mediation effect.

Causal mediation analyses assume that the treatment and the mediators are ignorable given observed pre-treatment variables, i.e. that ρ is zero (Imai et al. 2010). This is often referred to as the sequential ignobility assumption. Estimating the value of ρ at which ACME would go to zero tells us how strong the correlation would have to be between the errors in the mediation and outcome model in order for the mediation point estimate to no longer be statistically significant. The larger this value of ρ the more robust the ACME estimate is to potential deviations of ρ from zero and so more robust to alternative mediators explaining the mediated treatment effect.

Unfortunately, there are no objective standards for assessing whether values of ρ when ACME equals zero are robust. Rather, ρ indicates a relative level of robustness, specific to the data used, the empirical phenomenon, and modelling assumptions. Prior work has shown massive variation in credible ρ values across studies (Imai and Yamamoto 2013, Keele et al. 2015).

To benchmark our ρ values we use the estimate for the alternative enthusiasm and marketing practices mechanism as useful comparisons. At the bottom of Table A17-4, the values of ρ at which the ACME for the positive sentiment effect is exactly zero is 0.016, while the equivalent value for the marketing practices mediator is 0.019. In comparison, for our composite social interaction index, Model 1 in Table A17-4, the ρ value is 0.162, which is an order of magnitude larger than the values for the two alternative mechanisms. It does not seem likely that our social interaction index is capturing an observed alternative mediator, and this is especially so when we compare this mediator to plausible alternatives like the learning of marketing skills and greater enthusiasm.

Finally, the values of ρ for the theoretically motivated mediators tested in Table A17-2—within-program networking, within-program advice quality, non-program advice activation, and non-program networking—range from 0.087 to 0.134. Compared to the baseline for low values set at 0.016 and 0.019, these are also considerably large values of ρ. This suggests that those results are also likely to be robust to slight deviations from the causal mediation analyses' assumptions. That said, it also suggests that any individual social mediator might well be confounded by the other measures. We see an opportunity for future work to try and disentangle these different social sub-mechanisms.

Details about the mediating indexes

Here we present regressions showing our treatment's effect on each individual measure used to construct the three indexes we use in our mediation analyses above.

Table A17-5: Details about the co-participant networking index

	Cooperative words	Number of contacts who gave advice	Number of contacts made	Ethnic diversity	Ties formed	Alter Skill Complementarity	Alter monthly profits (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social skills training	0.249+	3.444*	7.080**	0.078*	0.678*	0.077*	-2.129
	(0.116)	(1.159)	(1.771)	(0.033)	(0.226)	(0.036)	(2.380)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	278	278	278	278	278	278	278

The outcome variables in Models 1, 2, and 3 were measured at the end of the training program, while the outcome variables in Models 4, 5, 6, and 7 are averages of those variables across all post-treatment periods. Hence all models are cross-sections with one time period. All regressions include sector fixed effects. Robust standard errors clustered by training group in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A17-6: Details about co-participant advice index

	Total words written	Work related	Six letter words	Words per sentence	Number of recommendations
	(1)	(2)	(3)	(4)	(5)
Social skills training	27.998**	2.555**	6.049*	17.717**	3.601**
	(4.045)	(0.612)	(2.220)	(5.709)	(0.251)
Sector FE	Yes	Yes	Yes	Yes	Yes
N	257	257	257	257	257

The outcome variables in all models are derived from entrepreneurs' notes during the structured networking event. The sample size is 257 because we could not obtain scanned networking notes for one training cohort. All regressions include sector fixed effects. Robust standard errors clustered by training group in parentheses. + p < 0.10, * p < 0.05, ** p < 0.01

Table A17-7: Details about non-camp networking index

	Make referrals	Learn from others	Participate in networking events	Advice network size
	(1)	(2)	(3)	(4)
Social skills training	0.047*	0.016+	0.048	0.590
	(0.021)	(0.007)	(0.029)	(0.892)
Sector FE	Yes	Yes	Yes	Yes
N	278	278	278	278

The outcome variables are averages over the three post-treatment periods. Hence all models are cross-sectional. All regressions include sector fixed effects. Robust standard errors clustered by training group in parentheses. + p < 0.10, * p < 0.05, ** p < 0.01

A18. "Social skills" training slide deck (in English)

Below we share the slides that were developed by the instructors and the authors to lead the training on social skills. These slides are English translations of the original French used in the teaching (original French slides available upon request).

WELCOME TO THE TRAINING

Networking-Marketing

MARKETING IN ACTION
LOME, 2017

METHODOLOGY:

« MANAGE YOUR BUSINESS BETTER (GERME) »

MARKETING IN ACTION 2

THE RULES OF TRAINING

MARKETING IN ACTION 3

THE TRAINERS

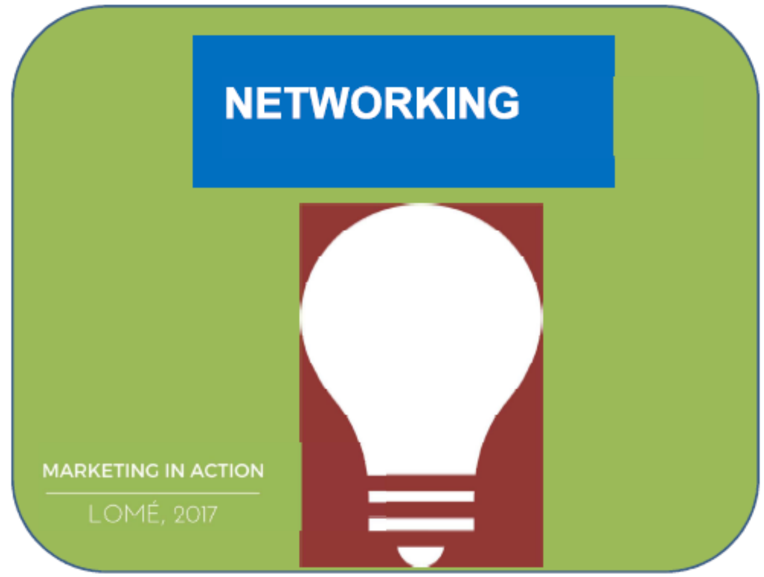
?

MARKETING IN ACTION 4

And you, who are you?

?

And what are your expectations for this Training?



WHAT IS RELATION BUILDING ?

Networking is the process through which new relations are developed and maintained with the people around us.

Networking allows you to open up and go meet new people, to talk to them about your business, and to listen to them talk about theirs.

Every entrepreneur faces a multitude of obstacles, that a network of contacts makes easier to overcome.

The fundamental process of network buidling involves the following key elements:

- Meet new people
- Learn more about them
- Talk to them about yourself
- Help each other reach your professional goals by sharing knowledge, resources time, energy, and friends.
- Keep in touch and maintain the relationship

Engaging with others leads to the development of a personal relationship based on mutual trust and mutual affection.

Example :

- Kodjo goes to an event for active young entrepreneurs by a local non-profit association at Lomé. At the event, there is a lot of people – businessmen, officials, leaders, and others – most of which Kodjo had ever seen before. During a presentation, Kodjo sits next to Ephrem, another young entrepreneur. Even if it seemed a bit difficult, Kodjo says hi to Ephrem and introduces himself. It turns out that Ephrem is also a young entrepreneur. They start to talk about their respective businesses and the challenges they have faced.

- It turns out they share many common experiences regarding starting a business. They talk about them and Kodjo feels happy because he found someone who faced the same obstacles. They decide to keep in touch and to continue discussing the issues which they have faced as businessmen. Kodjo saves Ephrem's number on his cellphone. Later that day, he sens a text to Ephrem to thank him again. That also assured him that Ephrem would have his contact info if he wanted to get in contact with him.

COMMENTS ON KODJO'S BEHAVIOR ?

How relationships can help achieve your goals as an entrepreneur.

A. THE BOOMERANG EFFECT

If you have the initiative to give, participate and contribute with new knowledge, the benefits will come to you without doubt, even if they don't come immediately necessarily.

By helping the other businessmen around us to learn, to improve their work and to innovate, we improve our chances of success.

B. Non zero-sum

By getting people in contact with one another, by giving your time and your experience and sharing them freely, you contribute to the success of others, which broadens the tax base and is beneficial for everyone.

IMMEDIATE ADVANTAGES OF BUILDING RELATIONS

1- Access to new information

The new knowledge established through networking can provide us with reliable and important information about opportunities we didn't know beforehand.

They can let us know about financing opportunities, contests or fairs in which we could participate. In addition, they can also provide us with information regarding the market, like, for example, information on the prices of our competitors or the products from suppliers.

2. Access to knowledge

Frequently, the people in our network possess in-depth knowledge on a wide variety of subjects which could be useful to us at different moments.

3. Access references

New contacts can introduce you to people you couldn't meet otherwise. They could be people you have never heard about before or they could be well-known but hard to get in touch with.

4. Access to advice

When you know a lot of people, you can ask them for their advice and opinion on your business. The more people you know, the more probable it will be that you receive a useful commentary, and what's more, it is possible that someone will propose an important improvement.

5. Access to emotional support

The bigger the amount of people you have a trusty relationship with, the more you will be in a position to get support for your business. This support could lead to new clients for your business, but it could also include support declarations for your business from the local leaders that are well respected. In addition, this people could give you emotional support and encourage you to pursuit your work, despite all the hardships you will encounter.

6. Access to resources

The bigger the amount of people with which you have a good relationship, the more probable it will be that some of them will give you useful resources. For example, during tough times, they could give you a loan or lend you a piece of equipment you need.

HOW TO BUILD A POWERFUL NETWORK.

1. Make it a habit

Entrepreneurs must go to several events, participate in associations and non-profit organizations, be active in their communities and make the maximum effort to speak to new people. But, to accomplish this, it is necessary above all to make a constant effort and be patient.

2. Exchange information

The sharing of information creates the base for discussion. Pay special attention to what other says; listening actively will be the key that will allow you to possess engaging follow-up questions. Making the right questions then leads to the discovering of really useful information that others can offer to you.

3. Establish trust with the people you meet

True networking consists in finding ways to lead those that are part of your network towards success. It consists of working hard to give others more than you receive. Relationships are solidified with trust. You earn trust not by asking what others can do for you, but what you can do for them. In other words, the currency of true networking is not greed, but generosity.

The practical steps when building a new connection for our network.

1. Identify new people to meet

The first step consists in thinking about the type of people that could be useful for you in the future.

You must then mentally specify the types of people you must aim to meet.

To get in contact with them; start with a list of all the people that you already know, their job, and their location. Then, think of how they could connect you to the people you desire.

It is important that you meet with this people before asking for their help. You should not reach out only when you need their help.

2. Meet someone for the first time

Meeting someone for the first time is not easy, it is not enough to only tell people what you do, you must also keep them interested. To do this, it is important to create a conversation that is both memorable and engaging.

Listen to what they say. The more you put the person in the spotlight, the more they'll feel inclined to have a positive impression of you. Remind yourself that people love talking about themselves, so that you pose reflective and open questions like, «What project do you like more? » This way you allow yourself to understand what this person is passionate about.

To overcome the difficulty related to first encounters, it is useful to have an organized script like the following:

a) State the situation. It is logical that before you can speak in a persuasive way, in other words, before talking from a position of passion and personal experiences, you have to know where you are standing.

b) Express your feelings. We minimize the influence of emotions in our daily meetings, particularly in the business world. We tell ourselves that vulnerability is a bad thing and that we must be prudent when revealing our feelings. But we will feel more comfortable when using the words "I feel" with others, and our encounters will be more profound and

sincere. Your emotions are a gift of respect and kindness to your listeners.

c) Use an open question. A request expressed as a question – to which we can't just answer yes or no – is less menacing. «How do you feel about this topic? » «How can be solve this problem? » With a suggestion or an open question, you invite the other person to work towards a solution with you.

3. Follow-up

- Whenever you run into someone you would like to establish a relationship with, do one small complementary step to be sure he will never forget you: the follow-up. Being sure that a new connection will remember your name (and the favorable impression that you created) is a process you must carry out right after your meeting.

- Each time you meet someone, make sure to get an email, a phone number, or an address, and to save it correctly. Business cards are an excellent way to obtain this information, don't be afraid to ask for one and to give out yours/ Next, give yourself between 12 and 24 hours after the meeting for the follow-up. You can send a text, a WhatsApp message, and email or a letter in the mail.

Here are some reminders of what to include in your follow-ups:

a) Always express your gratitude.

b) Make sure to include an interesting element of your reunion or conversation – a joke or a humorous moment.

c) Reaffirm the commitments you both made.

d) Be brief and to the point.

e) Always address the thank you note to the person by name.

f) Use email and the postal service. The combination adds a personalized touch.

g) Speed is essential. Send these as soon as possible after the reunion or the interview.

h) A lot of people wait for the holidays to say thank you. Why way? Your follow-ups will be timelier, more appropriate, and they will be better remembered.

i)Don't forget to also follow-up with the one that acted as an intermediary. Let them know how the conversation went and express your appreciation for their aid.

j) Make the follow-up a habit. Make it automatic.

A19. Survey questions

The variables used in our analyses relied on survey questions that were administered to entrepreneurs participating in the field experiment, as described in Appendix A. Below are the survey questions that correspond to data used in the construction of variables used in the analyses for Tables 3, 4, and 5.

1. **Entrepreneur gender ("female")**

Q13 Sexe:
- ❍ Masculin
- ❍ Féminin

2. **Ethnic group ("Ewe ethnicity")**

Q14 Quelle langue parlez-vous à la maison?
- ❍ Ewe
- ❍ Français
- ❍ Kabye
- ❍ Kotokole
- ❍ Autre: |__|__|__|__|__|__|__|__|

3. **Entrepreneur education ("Completed primary school")**

Q16 Quel est votre niveau scolaire?
- ❍ Aucune scolarité complète
- ❍ École primaire complète (CEPD)
- ❍ Collège complet (BEPC)
- ❍ Lycée complet (BAC)
- ❍ Brevet de technicien supérieur (BTS)
- ❍ Licence universitaire
- ❍ Master ou Doctorat

4. **Year the business was started ("Firm age")**

Q33 En quelle année avez-vous commencé votre entreprise? |__|__|__|__|

5. **Employees in entrepreneurs' business ("Employees (log)")**

Q44 Maintenant, je vais vous poser quelques questions concernant le nombre d'employés travaillant dans votre entreprise actuellement. (Par emploi à temps plein je veux dire qu'on travaille 8 heures par jour ou plus.)

	Nombre total
Combien d'employés à temps plein avez-vous?	|__|__|
Combien d'employés à temps partiel avez-vous?	|__|__|
Combien de stagiaire ou apprenti avez-vous employé?	|__|__|

6. Management practices score items

Q148 Dans les derniers 6 mois avez-vous:

Q50 Visité un de vos concurrents pour voir quel prix ils demandent?
- ❍ Oui (1)
- ❍ Non (2)

Q51 Visité un de vos concurrents pour voir quels produits ils vendent ?
- ❍ Oui (1)
- ❍ Non (2)

Q52 Demandé à vos clients existants s'il y a d'autres produits qu'ils aimeraient que vous vendiez ou produisiez?
- ❍ Oui (1)
- ❍ Non (2)

Q53 Parlé avec au moins un ancien client pour savoir pourquoi ils ont cessé d'acheter de votre entreprise?
- ❍ Oui (1)
- ❍ Non (2)

Q54 Demandé à un fournisseur quel produits se vendent bien dans votre secteur?
- ❍ Oui (1)
- ❍ Non (2)

Q57 Au cours des trois derniers mois, avez-vous utilisé une offre spéciale pour attirer des clients?
- ❍ Oui (1)
- ❍ Non (2)

Q56 Au cours des trois derniers mois, avez-vous utilisé une forme de publicité?
- ❍ Oui (1)
- ❍ Non (2)

Q59 Avez-vous fait quelque chose pour mesurer l'efficacité de la publicité?
- ❍ Oui (1)
- ❍ Non (2)

Q58 Au cours des trois derniers mois, avez-vous tenté de négocier avec un fournisseur pour un meilleur prix sur vos matières premières?
- ❍ Oui (1)
- ❍ Non (2)

Q69 Au cours des trois derniers mois, avez-vous comparé le prix ou la qualité offerte par d'autres fournisseurs à celle de votre fournisseur actuel ?
- Oui (1)
- Non (2)

Q66 Est-ce que il y a eu un moment où l'entreprise n'a pas eu assez de stock ou de matières premières pendant les 3 derniers mois?
- Oui (1)
- Non (2)

Q62 Gardez-vous des documents commerciaux écrits?
- Oui (1)
- Non (2)

Q61 Enregistrez-vous chaque achat et vente faite par l'entreprise?
- Oui (1)
- Non (2)

Q76 Pouvez-vous utiliser vos documents pour voir facilement combien d'argent est disponible à votre entreprise à tout moment?
- Oui (1)
- Non (2)

Q75 Utilisez-vous régulièrement vos documents pour savoir si les ventes d'un produit particulier augmentent ou diminuent d'un mois à l'autre?
- Oui (1)
- Non (2)

Q74 Avez-vous calculé le coût de production de chacun de vos produits principaux?
- Oui (1)
- Non (2)

Q73 Savez-vous lesquels de vos produits vous apportent le plus profit par unité?
- Oui (1)
- Non (2)

Q72 Avez-vous un budget écrit, qui vous indique combien vous devez payer chaque mois pour le loyer, l'électricité, l'entretien de l'équipement, le transport, la publicité, et d'autres dépenses de l'entreprise?
- Oui (1)
- Non (2)

Q80 Si vous vouliez demander un prêt bancaire, et vous étiez demandé de fournir des documents pour montrer que vous avez assez d'argent chaque mois pour rembourser un prêt, est-ce que vos documents vous permettraient de le démontrer à la banque?
- Oui (1)
- Non (2)

Q79 Examinez-vous la performance financière de votre entreprise et analysez-vous les points à améliorer chaque mois?
- ❍ Oui (1)
- ❍ Non (2)

Q78 Avez-vous un objectif pour les ventes au cours de la prochaine année?
- ❍ Oui (1)
- ❍ Non (2)

Q77 Est-ce que vous comparez votre performance à cette cible au moins une fois par mois?
- ❍ Oui (1)
- ❍ Non (2)

Q82 Avez-vous fait un budget des coûts auxquels votre entreprise fera face l'an prochain?
- ❍ Oui (1)
- ❍ Non (2)

Q83 Avez-vous fait un compte de résultats?
- ❍ Oui (1)
- ❍ Non (2)

Q131 Avez-vous fait un tableau de flux de trésorerie au cours de l'an passé?
- ❍ Oui (1)
- ❍ Non (2)

Q132 Avez-vous fait un bilan annuel pour l'an passé?
- ❍ Oui (1)
- ❍ Non (2)

Q133 Avez-vous fait l'état de vos résultats / dépenses annuelles?
- ❍ Oui (1)
- ❍ Non (2)

7. Entrepreneurs' business performance ("Profits last month, log")

Q110 Quelle était la valeur de vos bénéfices en FCFA au cours de

	La semaine dernière (1)	Le mois dernier (2)
Valeur estimée (1)		

8. Interactions with co-participants (“Relationship formation”)

Q0.2 Depuis la formation, est-ce que vous avez rencontré des personnes qui ont fait la formation avec vous ?

- ❍ Oui
- ❍ Non

Q0.3 Si oui, s’il vous plait nommez-les :

Personne 1 |__|__|__|__|__|__|__|__|__|__|__|

Personne 2 |__|__|__|__|__|__|__|__|__|__|__|

Personne 3 |__|__|__|__|__|__|__|__|__|__|__|

Personne 4 |__|__|__|__|__|__|__|__|__|__|__|

Personne 5 |__|__|__|__|__|__|__|__|__|__|__|

Personne 6 |__|__|__|__|__|__|__|__|__|__|__|

9. Collaborative words

S’il vous plaît, encerclez les **5 mots** qui décrivent le mieux la formation que nous avons fait :

Concurrence	Rivalité	Connecter
Discuter	Echanges	Abattre
Amitié	Partenariat	Compétition
Rapporter	Collaboration	Bénéfices
Association	Pouvoir	Adversaire
Maximiser	Aider	Eloigner
Communication	Partage	Gagner
Dominer	Alliance	Confiance

10. Skill entrepreneur wants to learn (“Skill complementarity”)

Dans l'espace ci-dessous, veuillez décrire une chose que vous aimeriez améliorer dans votre entreprise au cours des deux prochains mois:

____

____

Veuillez choisir s'il s'agit d'un changement dans:

- Marketing
- Comptabilité
- Financement
- Tenue des dossiers
- Recherche de fournisseurs
- Achat de stock
- Employés et embauche

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