
Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

# Networking Frictions and Entrepreneurial Learning in Developing Economies

Stefan Dimitriadis, Rembrand Koning

informs
https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
*Articles in Advance*, pp. 1–19
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

# Networking Frictions and Entrepreneurial Learning in Developing Economies

**Stefan Dimitriadis,[a,*] Rembrand Koning[b]**

[a] Rotman School of Management, University of Toronto, Toronto, Ontario M5S 3E6, Canada; [b] Entrepreneurial Management, Harvard Business School, Boston, Massachusetts 02163

*Corresponding author

**Contact:** stefan.dimitriadis@rotman.utoronto.ca, https://orcid.org/0000-0003-4699-4832 (SD); rkoning@hbs.edu, https://orcid.org/0000-0002-6453-0831 (RK)

**Received:** January 30, 2022
**Revised:** February 6, 2023; November 16, 2023; February 20, 2024
**Accepted:** March 1, 2024
**Published Online in Articles in Advance:** July 10, 2024

**https://doi.org/10.1287/mnsc.2022.00281**



**Abstract.** Relationships with peers help entrepreneurs learn and improve firm performance. Recent scholarship confirms that events—social gatherings such as mixers, conferences, or training programs—can help entrepreneurs build valuable social connections. Yet, for entrepreneurs in developing economies, networking frictions may make connecting with peers challenging and undermine the benefits of events. We argue that when networking frictions are high, the value of events will lie more in connecting neighbors rather than bringing together distant peers. In the presence of networking frictions, neighbors are both less likely to be someone the entrepreneur has already learned from and easier to sustain a relationship with. To test this argument, we use data from a series of networking events in Togo during which entrepreneurs were randomly assigned to meet with peers from across the city of Lomé. We find that entrepreneurs who were assigned to neighboring peers were much more likely to sustain a relationship, learn from their peer's management knowledge, and in turn benefit more: Profits increase by 10% when entrepreneurs get to know peers who are located on average 1 km closer to them. Our results highlight the central role that networking frictions play in shaping who entrepreneurs in developing economies can successfully learn from.

**History:** Accepted by Lamar Pierce, organizations.
**Funding:** Ewing Marion Kauffman Foundation [Dissertation Fellowship] and the Strategic Management Society [SRF Dissertation Fellowship].
**Supplemental Material:** The online appendix and data files are available at https://doi.org/10.1287/mnsc.2022.00281.

**Keywords:** entrepreneur performance • networking frictions • peers • learning • events



## Introduction

Improving performance is especially challenging for entrepreneurs in developing economies. For these entrepreneurs, be they microentrepreneurs or venture-backed startups, information can be scarce (Khanna and Palepu 2000, Abebe et al. 2020), transportation can be expensive (Asher and Novosad 2020), and ethnic diversity can create divisions (Yenkey 2015, Pierce and Snyder 2017). These conditions can give rise to significant networking frictions that make it challenging to form and maintain business relationships (Dimitriadis and Koning 2022), despite their value (Chatterji et al. 2019, Dimitriadis 2021).

In more developed countries, *events*—social gatherings that bring people together in the same physical space to interact—can be powerful catalysts for creating relationships (Ingram and Morris 2007, Boudreau et al. 2017). In these countries, events reduce search costs for participants to meet and match with valuable contacts, creating relationships that are collaborative and induce knowledge sharing. Consistent with these arguments, a growing number of "social event studies"[1] show that mixers, competitions, bootcamps, celebrations, and conferences, among others, can lead to more tie formation, collaboration, and knowledge sharing (Chai and Freeman 2019, Chatterji et al. 2019, Howell and Nanda 2019, Lane et al. 2021). If events can foster the formation of collaborative ties and create knowledge spillovers for scientists and entrepreneurs in more developed economies, can they do the same for entrepreneurs in developing economies where networking frictions are especially strong?

We argue that in contexts where networking frictions are high, events can lead to the formation of valuable ties, but these ties will be limited to connections between neighboring entrepreneurs. Why? Because events primarily reduce search costs, helping entrepreneurs find potential matches, but they do not in and of themselves reduce the relational costs of sustaining relationships after the event. In many developing economies, there are significant networking frictions—due to transportation barriers, higher communication costs, concerns over trust, and weaker formal market institutions—that lead entrepreneurs to "drop" partners who are more distant even if they have already connected during an event. By contrast, entrepreneurs are likelier to maintain relationships with more geographically proximate peers because the relational costs of staying in touch are lower. Moreover, the prevalence of networking frictions means that these neighbors likely have not had a chance to meet before, making the introduction particularly valuable. Therefore, when networking frictions are high, the value of an event lies in catalyzing relationships between neighbors.

To test these arguments, we use data from an entrepreneur training program that recruited entrepreneurs from across Lomé, the capital of Togo. The training program hosted multiple networking events that randomly assigned entrepreneurs to meet three other participating business owners. Much like previous interventions (Boudreau et al. 2017), this event reduced and equalized search costs by making it equally easy to match with a neighbor as it was to match with someone dozens of kilometers away.[2] Moreover, the assignment also exposed all entrepreneurs to an equal number of peers, further ensuring that search costs were held constant across participants. At the same time, the pairings induced random variation in the geographic distance between entrepreneurs *after* the training program. As a result, each match was equally easy to form during the event, but variation in distance shifted the cost of maintaining the relationship afterward.

We combine this random assignment of peers with longitudinal data about each entrepreneur, the ties they maintained after the networking event, their managerial practices, and their performance. Results show that the smaller the geographic separation between entrepreneurs after the event, the higher the likelihood that two matched entrepreneurs sustain their relationship. Even though entrepreneurs had nearly one hour to meet each of their randomly assigned peers, we still find that peers located nearer each other are likelier to maintain their relationship. Meeting someone located within 1 km leads to a substantial—28 percentage point—likelihood that contact is sustained in the year after the program. There is indirect evidence that this effect is concentrated within a narrow radius of 2 km, beyond which the networking event does not significantly increase the likelihood of staying in touch.

Importantly, relationships with more proximate peers do not seem to be sustained because they provide more information or are perceived to be a better "match." Entrepreneurs' notes taken during the networking event show that they exchanged similar amounts of information with peers who were located near them as with more distant ones. Similarly, responses to an exit survey from the event show that entrepreneurs perceived their peers to be similarly accomplished and helpful, whether they were located near or far from them. These results suggest that neighbors are not necessarily better matches or more informative than more distant peers, rather, they are simply easier to stay in touch with because they are close by.

Entrepreneurs, however, do not merely sustain relationships with those near them; they also learn more from them. Using longitudinal data on management practices, we find that entrepreneurs adopt one new managerial best practice when assigned to peers who are on average 1 km closer. Regressions suggest that entrepreneurs are learning from neighbors but not from more distant peers since the new management practices they adopt tend to be either practices that were used by their assigned peers or practices that the pair adopt for the first time together. This is consistent with the idea that they are not just learning from each other's past experiences but also "co-experimenting" with practices together (Park and Puranam 2023).

Finally, consistent with the view that proximity enables entrepreneurs to sustain relationships and learn more, we also find that being assigned to nearby peers increases performance. Meeting peers who are on average 1 km nearer increases profits by approximately 10% over the next year. These results are robust to the inclusion of entrepreneur fixed effects for time-invariant entrepreneur and neighborhood characteristics, as well as a rich set of ego, alter, and ego-alter business characteristics that let us rule out a host of alternative peer effect mechanisms.

This study's findings make three primary contributions. First, they extend the growing body of "social event studies" (Ingram and Morris 2007, Boudreau et al. 2017, Chai and Freeman 2019) to the context of developing economies where there are higher networking frictions. Existing research, which is primarily set in more developed countries, shows that events like conferences, symposia, or bootcamps can catalyze the formation of ties and collaboration (Boudreau et al. 2017, Catalini 2018, Chai and Freeman 2019). Our study shows that when the relational costs of sustaining distant relationships are high, as they are in Togo, the benefits of events are likely concentrated among participants who happen to be neighbors. This is not to say that more distant peers are not valuable, but that when sustaining relationships with peers is challenging, events create more value by catalyzing localized learning.

Seen from a different perspective, our results also imply that entrepreneurs in settings like Togo are constrained by significant local search costs. The performance effects we find suggest that, in the absence of events, most entrepreneurs face barriers to getting to know others, even when they are within walking distance. Hence, most entrepreneurs are not connected to neighbors who have valuable advice and information to share. Entrepreneurs in places with high networking frictions, therefore, appear to face both high relational costs that limit who they keep in touch with and high search costs that limit who they get to know.

Third, our results connect to a growing body of work that looks beyond the formation of ties and explores how they are sustained and maintained (Dahlander and McFarland 2013, Samila et al. 2022). Analogous to an experiment, forming ties can be viewed as a "treatment" and maintaining the tie as "compliance" with this treatment (Hasan and Koning 2020). Historically, much of the agglomeration literature has viewed proximity as shifting who is treated. For example, entrepreneurs in a particular city or office space are treated by being able to meet other local peers (Boudreau et al. 2017, Roche et al. 2022). However, our study shows that proximity does not just involve "treating" entrepreneurs; it also shifts compliance with this treatment by reducing the costs of sustaining a relationship.

## Events and Networking Frictions

Spatial proximity affects who entrepreneurs get to know, what they learn from them, and their performance. Entrepreneurs are much likelier to meet people who are nearby and form ties with them (Powell et al. 2005, McFarland et al. 2014). For example, studies using unplanned changes in building assignments show that scientists whose workplaces move closer to each other are likelier to collaborate (Catalini 2018). Similarly, firms and entrepreneurs nearer each other are likelier to learn from each other (Arzaghi and Henderson 2008). The people near entrepreneurs even affect the quality of their ideas (Hasan and Koning 2019) and their ability to innovate (Whittington et al. 2009).

Building on the insight that entrepreneurs tend to match with and learn from those who are colocated with them, studies have explored whether events, such as conferences, corporate retreats, or mixers, can lead to similar outcomes. These studies argue that events reduce search costs, which sparks the formation of ties, promotes knowledge sharing, and increases collaboration. Indeed, people who participate in such events tend to form new ties (Ingram and Morris 2007). For scientists, participating in events often increases the probability of forming new collaborations (Boudreau et al. 2017, Chai and Freeman 2019). Similarly, participating in events can lead to learning about new technologies from other attendees (Fang et al. 2021) and gaining valuable advice and information (Cai and Szeidl 2018, Chatterji et al. 2019). These effects are not short lived and can impact collaborations years later (Lane et al. 2021).

Although there is compelling evidence that events often lead to the formation of ties and sharing of knowledge, it remains unclear whether this also occurs for entrepreneurs in many developing economies where networking frictions are thought to be especially high. Such contexts are characterized by scarce information, low levels of trust, costly transportation and communication, and few formal institutional safeguards (Khanna and Palepu 2010). In contexts where information about others is scarce or unreliable, it may difficult to find out about other entrepreneurs, the quality of their operations and products, whether they are reliable and trustworthy, and whether anything can be learned from them (Abebe et al. 2020). Similarly, when generalized trust is low, entrepreneurs may hesitate to reach out to others and initiate a process of exchanging information (Fisman and Khanna 1999). Even if they do, challenging roads, limited means of transportation, and expensive communication technology may make it difficult to meet with other entrepreneurs, especially those not within walking distance, which also makes it hard to build relationships. Finally, institutions such as courts or industry associations that typically provide some degree of verification, protection of transactions, and enforcement of contracts, may be absent, making entrepreneurs skeptical of forming new matches (Rangan 2000). These factors create networking frictions for entrepreneurs, making it unclear whether events can overcome these frictions and have the same effects they do in more developed, less constrained, settings.

We argue that, although events may reduce costs related to search, they tend not to reduce the relational costs of maintaining matches. Events enable entrepreneurs to temporarily colocate, which overcomes a lot of the costs related to transportation, communication, and finding out about others. They also reduce information barriers since entrepreneurs self-select into the event, which may reveal information about them. All this contributes to reducing search costs and makes it likelier that two entrepreneurs will meet and form an initial connection.

At the same time, in the context of high networking frictions, the relational costs of sustaining a relationship after the event can remain significant for those not located near each other. Maintaining a relationship involves repeated interactions, checking-in, following up, maintaining a sense familiarity, and building trust through reciprocity (Nahapiet and Ghoshal 1998, Samila et al. 2022). The barriers and costs of doing this may be considerable in places like Togo if entrepreneurs are not within short walking distance. The less developed infrastructure—be it roads or telecommunication towers—makes it hard to meet with more distant entrepreneurs regularly. The geographic separation can also mean that there are fewer mutual acquaintances who could help broker the relationship or facilitate trust (Martin and Yeung 2006, Kleinbaum 2018).

Given that events lower search costs without necessarily affecting relational costs, we argue that their network and spillover effects are likely concentrated among people who remain near each other after the event. In the next section, we develop a set of three hypotheses focused on how spatial colocation among peers matched during events increases tie maintenance, learning, and business performance.

## Sustaining Ties

We argue that entrepreneurs whose businesses are located nearer each other after the networking event will face fewer relational costs and therefore be more likely to sustain relationships formed during the event. Spatial proximity between business locations makes it less costly to stay in touch and continue interacting, whether through planned or unplanned interactions. Travel time is shorter, leaving more time to discuss and share information. These interactions, moreover, are also likelier to be in person, rather than virtual or over the phone. There is evidence that repeated interactions are an important factor in sustaining ties and facilitating knowledge exchange (Small 2009). Moreover, continued interaction over time is key to sustaining relationships, building positive affect, and developing trust (Martin and Yeung 2006, Habinek et al. 2015). Given this, we expect that entrepreneurs paired with peers whose businesses are more proximate to their own are likelier to stay in touch and sustain relationships after the event.

**Hypothesis 1.** *Spatial proximity between matched entrepreneurs' business locations increases the likelihood of their sustaining a relationship.*

## Learning

If spatial proximity between entrepreneurs' businesses enables them to sustain relationships, it likely also enables them to learn more from each other. There is considerable evidence that people learn through their social ties (Argote and Ingram 2000, Cross and Sproull 2004) and that much of the learning, particularly of complex or tacit knowledge, happens through stronger ties (Hansen 1999, Sorenson et al. 2010). People who interact more frequently are likelier to develop a common vocabulary and understanding, are likelier to trust each other, and are likelier to build friendships (Ingram and Roberts 2000), which in turn facilitates the transfer of more complex, sensitive, and strategic knowledge (Tsai and Ghoshal 1998, Levin and Cross 2004). Spatial proximity also enables more face-to-face meetings, which have been shown to play a role in learning about new innovations and technologies (Atkin et al. 2022).

Given that spatial proximity after the event increases the likelihood of sustaining a tie, it is likely that more learning will also occur. If entrepreneurs can visit their peers' locations, interact face-to-face with them, and observe them more frequently, the likelihood of understanding a new practice or adopting a new technology from them increases. It is also likelier they will have opportunities to ask questions or seek advice, as well as receive guidance from them.

A particular type of knowledge that is likely to be transmitted when relational costs are lower are managerial best practices. Managerial best practices are sequences of tasks that often require adaptation or customization to each particular business (Bloom and Van Reenen 2007). As a result, learning them often involves the transfer of complex knowledge, which is facilitated by the availability of illustrative examples in peers (Bloom et al. 2012). Spatial proximity between entrepreneurs' businesses keeps relational costs low, enables entrepreneurs to sustain a tie, and thereby transfer more knowledge about management practices. We therefore expect that proximity between peers' businesses will increase the amount that entrepreneurs learn from each other.

**Hypothesis 2.** *Spatial proximity between matched entrepreneurs' business locations increases the adoption of managerial best practices.*

## Business Performance

In contexts with high networking frictions, entrepreneurs are less likely to know their neighbors and their neighbors, in turn, are also less likely to know each other. This implies that there may be valuable silos of information and knowledge even between neighbors. As a result, when entrepreneurs meet their neighbors during an event, this not only represents a connection to someone new, it also likely represents a connection to someone with novel, nonredundant information and managerial knowledge (McEvily and Zaheer 1999, Whittington et al. 2009). Because physical proximity increases the likelihood of sustaining a tie and learning, we expect that meeting a neighbor during an event will enable entrepreneurs to access this novel information and knowledge. This, in turn, suggests that entrepreneurs connecting to neighbors should perform better.

For example, better management practices have been shown to improve firm performance, particularly in developing economies (Bloom et al. 2013, McKenzie and Woodruff 2017). If neighbors have useful practices to share, which they likely do because networking frictions have prevented this knowledge from already diffusing in the business community, and if it is easier to sustain the kinds of relationships required for peer learning with neighbors, then matching with peers whose businesses are located nearby should lead to improvements in entrepreneurial performance.

**Hypothesis 3.** *Spatial proximity between matched entrepreneurs' businesses leads to performance gains.*

## Research Setting: Entrepreneur Training Program in Lomé, Togo

We use data from a training program for entrepreneurs in Lomé, Togo, to test our hypotheses. Situated in West Africa between Ghana and Benin, Togo is a developing economy that is representative of many sub-Saharan markets in terms of its formal institutions, industry composition, and transportation infrastructure (World Bank 2016, United Nations Development Programme 2017). With a population of approximately 2 million, Lomé is the capital of Togo and host to a rapidly growing entrepreneurial ecosystem that is widely dispersed across the city (U.S. Embassy in Togo 2019, World Bank 2022).

Within this context, we leveraged a networking event during an entrepreneurship training program to conduct our research. This setting was ideal because it brought together entrepreneurs from different parts of the city, creating the opportunity for them to match with peers whose businesses were neighboring and peers whose businesses were located much further away. To participate in the training program entrepreneurs' businesses had to have been in operation for at least one year and be located within the city. Participant entrepreneurs were recruited from across the city, which led to including entrepreneurs whose businesses were located up to 49 km apart. The program consisted of 14 cohorts of 20–25 entrepreneurs and 303 entrepreneurs completed the training over the course of two days in April and May 2017. Entrepreneurs were assigned to cohorts as they registered for the training program and each cohort was filled in sequence. The program followed the International Labor Organization's "Start and improve your business" materials for marketing practices, along with additional training in social skills. The training was conducted by two Togolese instructors who were management consultants from Lomé, each with decades of experience teaching local entrepreneurs.

At the end of the training program, when all the lectures had been completed, entrepreneurs participated in the "structured" networking event. During this event, entrepreneurs were assigned to have successive one-on-one conversations with three randomly selected entrepreneurs from their cohort. The randomization of discussion partners was done by one of the authors who was present during the training program. For each one-on-one discussion, participants were paired with other participants through random draws. Participants were given 30–45 minutes for each conversation. The two instructors managed the structured networking event, making sure that participants met with their assigned peers and switched to their next assigned peer at the right time. The networking event's format therefore resembled a slow-paced "speed dating" event.

## Research Design

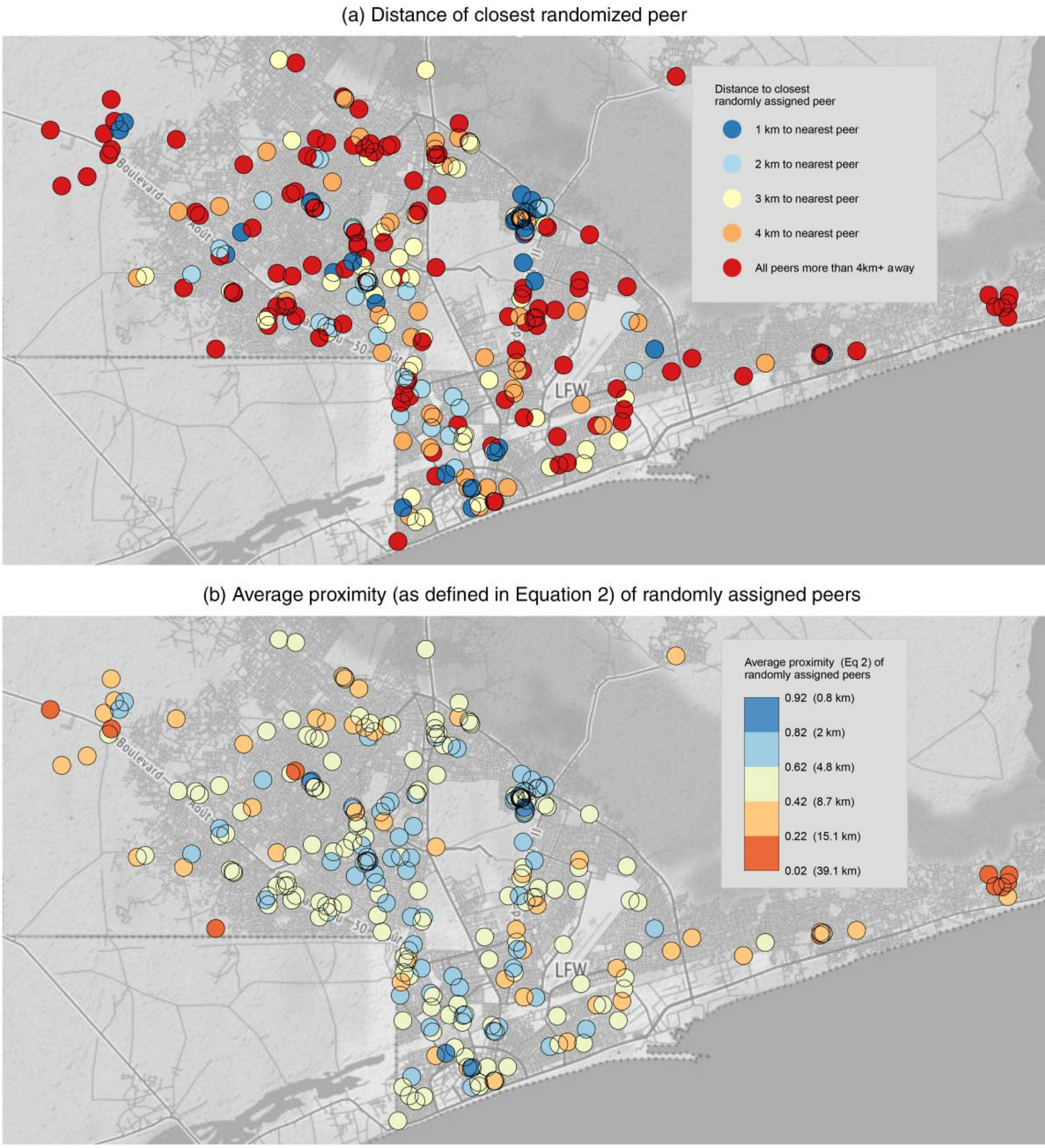
The networking event we study separates the cost of forming relationships from the cost of sustaining them. Each entrepreneur was assigned to the same number of peers, which kept the search costs constant across entrepreneurs. At the same time, because entrepreneurs in the training program owned businesses located across various parts of the city the random matching led to exogenous variation in the distance between entrepreneurs' businesses. As a result, the random matching led to variation in the relational cost of sustaining the matches after the training, because staying in touch at a distance is simply more difficult. Some entrepreneurs were randomly assigned to peers who happened to own businesses within a short distance of their own and so faced low costs of sustaining a tie, while others were assigned to meet peers whose businesses may have been on the other side of the city leading to high relational costs.

This empirical design is closely related to those of recent social event studies (Boudreau et al. 2017, Chatterji et al. 2019). The randomization of entrepreneurs' discussion partners introduces exogenous variation that helps overcome challenges related to the causal identification of peer effects, which are often endogenous to entrepreneurs' performance (Manski 1993, Hasan and Bagde 2013). For example, more capable entrepreneurs are likely to interact more with others or have interactions that are more productive, making it unclear how much of their performance is due to their ability and how much due to the interactions. Similarly, more capable entrepreneurs might be likelier to interact with other high-achieving peers, making it unclear whether these dyad characteristics drive performance or vice versa. In our case, interactions are not driven by ability or preferences because they are randomly assigned.

Furthermore, in contrast to naturally occurring peer variation, which often relies on variation in large cohorts of dozens of people (Angrist and Lang 2004), the fact that in our setting participants were randomized into only three conversations ensures wide variability in our treatment, with some entrepreneurs getting to know a few neighbors and some none at all. If instead peers had been assigned to have conversations with 10 peers; statistically there would be substantially less variation in how near or far they were on average from their assigned peers.

Indeed, in Figure 1, we provide visual evidence that our randomization leads to substantial variation in how close a participant's randomly assigned conversation partners were. The figure shows the approximate location of each entrepreneur in our sample on a map of Lomé. The color and shading of each marker reflects the extent to which that entrepreneur was assigned to

**Figure 1.** (Color online) Spatial Distribution of Proximity to Peers




*Notes.* These maps show the approximate location of entrepreneurs' businesses in Lomé. Entrepreneurs' locations are color coded to reflect the extent to which they were treated, that is, the distance to the closest peer (a) or the average proximity (b) of their randomly assigned discussion peers. Darker (bluer) shades show entrepreneurs exposed to neighbors, whereas lighter (redder) shades show entrepreneurs introduced to distant peers. These figures show the treatment is not simply reducible to differences in neighborhood density, rather there is variation both across, and most importantly within, neighborhoods. For scale, the straight-line distance between the circle furthest on the lefthand and furthest on the righthand, representing the two most distant entrepreneurs in the sample, is approximately 49 km.

peers who were near or far. Darker (bluer) shades indicate that peers were nearby, while lighter (redder) shades indicate that assigned peers were farther away. The map shows that, even within neighborhoods, there is substantial variation in whether an entrepreneur got to know neighbors or more distant peers, both in terms of how far the closest peer was (Figure 1(a)) and in terms of average proximity (Figure 1(b)). In Online Appendix A2, we also present balance tables showing that the treatment—the average proximity to the randomly assigned peers—is unrelated to entrepreneurs' pretreatment characteristics.

That said, the maps do reveal some degree of clustering, which is likely related to the population density of those neighborhoods. In our Estimation Strategy section, we discuss how we use our longitudinal data along with inverse propensity score weighting to fully account for the fact that entrepreneurs in denser neighborhoods, who may well be higher or lower performing on average, appear more likely to be assigned to nearby peers.

## Data

Data for this study come from a baseline survey, a networking event exit survey, entrepreneurs' networking notes, and three follow-up surveys. The baseline survey collected data about entrepreneurs and their performance before the training program. After the networking event we scanned participants' handwritten notes from their one-on-one discussions and administered an exit survey with questions about their impressions of their assigned peers. Finally, we collected data on the impact of the networking event during three follow-up surveys. The first follow-up survey took place six weeks after the training program, the second six months after it, and the third one year after it. All surveys were conducted by the same instructors who taught the training program. To lower attrition rates they spent additional time with the entrepreneurs after each survey to provide business advice. The attrition rate over all surveys was 8%, which is relatively low compared with other studies of entrepreneurs in developing economies (McKenzie and Woodruff 2014).

### Dependent Variables

Our hypotheses describe the effect of average assigned peer proximity on three different outcomes: ties maintained, management practices, and performance.

**Tie Maintained.** Hypothesis 1 predicts that proximity leads to *tie maintenance*. We measure this as a dyad-level variable, defined for each pair of entrepreneurs who were assigned to talk during the networking event. It is equal to one if the entrepreneurs spoke on the phone or met in person since the previous survey and zero otherwise. This variable is defined only for the three posttraining time periods.

**Management Practices Score.** Hypothesis 2 predicts that proximity to assigned peers increases entrepreneurs' management best practices. We measure this using a *management practices score*, which is the proportion of 27 managerial best practices, defined by McKenzie and Woodruff (2017), that an entrepreneur uses. Following McKenzie and Woodruff (2017), the best practices were operationalized as a series of binary questions, one for each practice. The practices cover the areas of marketing, finance, planning, and stock management.

**Entrepreneur Performance.** Hypothesis 3 predicts that proximity to assigned peers improves entrepreneur performance. We use two measures of performance that are common in research on firms in developing economies (De Mel et al. 2009). Our first measure is *monthly profits (log)*. The surveyors, who had established a relationship with the participants during the training program, asked for entrepreneurs' estimated profits from the previous month. To increase the precision of entrepreneurs' reported profits the surveyors also asked them to estimate monthly expenses and sales, which helped triangulate their profits. This approach has been shown to gain accurate estimates of business performance in developing economies (De Mel et al. 2009, Fafchamps et al. 2012).[3]

Our second measure of performance was a *performance index*. This is the average of several standardized variables that are indicative of performance. We took the mean of log sales last month, log sales last month winsorized at the 1st and 99th percentiles, log sales last week, log clients last month, log clients last month winsorized at the 1st and 99th percentiles, log clients last week, and number of loans received from a bank or microfinance institution. This approach helps combine many different measures that are related to performance and reduces concerns of measurement error (Kling et al. 2007).

### Independent Variables

The main independent variable is *average proximity to assigned peers*. This measures the average proximity of the focal entrepreneur's business to their three assigned discussion partners' businesses. Using the geographic coordinates of entrepreneurs' businesses, we calculate the straight-line distance in kilometers between each dyad of participants. We then use this distance to create a measure of proximity using an exponential distance decay function. Following standard practice in economic geography (De Vries et al. 2009, Pun-Cheng 2016), we generate a proximity measure using the following equation:

$$p_{ij} = e^{-0.1d_{ij}} \quad (1)$$

Where $d_{ij}$ is the distance in kilometers between focal entrepreneur $i$ and discussion partner entrepreneur $j$. Hence, $p_{ij}$ measures the proximity of entrepreneur $i$ to entrepreneur $j$, and ranges from one for peers located at a distance of 0 km and tends toward zero as the distance increases. This approach models the effect of proximity as decaying exponentially, rather than linearly, which is consistent with a large body of work showing that proximity decays exponentially and not linearly in social interactions (Fotheringham 1981, Barthélemy 2011).[4] To create a single measure for each entrepreneur we take the average of the proximities of the three assigned discussion peers:

$$P_i = \frac{1}{3}\sum_{j=1}^{3} p_{ij}. \quad (2)$$

In addition to our average proximity measure, we also create a set of measures based on radii around each entrepreneur by counting the number of assigned discussion peers whose businesses are located within each radius. We construct this measure for radii at 1, 2, 3, and 4 km around each entrepreneur. This measure of proximity does not account for the exponentially decaying effect of distance, but it is a simple measure that lends itself to easy interpretation (Conley 2011).

In addition to our main independent variable of interest we also include two control variables in our analyses. First, we control for whether the entrepreneur received training in social skills. Although the training program taught all participants marketing skills, only half of the cohorts were trained in social skills. Hence, to ensure that our results are not driven by the social skills training that some participants received we controlled for whether the entrepreneur received social skills training.[5] Second, we control for the number of assigned discussion partners entrepreneurs knew from before the training program. Occasionally some participants found that they already knew one or more of their peers. We gave each participant a roster of their cohorts and asked them to identify any coparticipants they had met before. Using this information, we counted the number of matched discussion partners that entrepreneurs happened to already know and included it as a control variable in all our models.

We report summary statistics in Table 1. The average entrepreneur generated monthly profits of 56,500 Francs CFA (approximately $95 USD). The median entrepreneur did not know any of their discussion peers before the training and was assigned a peer from a different industry than their own. It was also rare for entrepreneurs to be assigned discussion peers they already knew and who were located within 1 or 2 km of their business. Half of the entrepreneurs received the social skills training during the program. The majority of entrepreneurs were part of the Ewe ethnic group, male, and had completed primary school. Their businesses, on average, had two employees, had been in operation for approximately 11 years, had been located in their current neighborhood for an average of 10 years and used 60% of managerial best practices that are part of the McKenzie and Woodruff (2017) index. Correlation tables and additional descriptive statistics for the dyad-level data are presented in Online Appendix A1.

## Estimation Strategy

We estimate two models, one for the dyad-level data and one for the entrepreneur-level data. The dyadic data defines outcomes at the level of each matched pair of entrepreneurs in the sample. This enables us to test Hypothesis 1, which argues that proximity between entrepreneurs' business locations increases the likelihood that a tie will be maintained. Using the dyadic data, we estimate

$$TM_{ijt} = \beta P_{ij} + \gamma X_{ij} + \alpha_i + \rho_j + \delta_t + \varepsilon_{ijt}, \tag{3}$$

where $TM_{ijt}$ is an indicator for whether a tie is maintained between entrepreneurs $i$ and $j$ in time period $t$ after the training program; $P_{ij}$ is the proximity of entrepreneur $i$ to their peer $j$ as defined by Equation (1); $X_{ij}$ is a binary control variable for whether the matched pair $i$ and $j$ had met before the training program; $\alpha_i$ are entrepreneur fixed effects; $\rho_j$ are assigned peer fixed effects that control for time-invariant characteristics of entrepreneurs and peers; and $\delta_t$ are survey wave fixed effects that control for time trend effects, such as general economic conditions in Lomé. Given that ties are formed after the baseline survey, this specification includes only the three time periods which occurred after the training program.

To test Hypotheses 2 and 3 we use entrepreneur-level data. This estimation approach compares how the management practices and performance of entrepreneurs who were assigned to more proximate peers changed relative to how the management practices and performance of entrepreneurs who were assigned to less proximate peers changed. The model we estimate is

$$\begin{aligned} Y_{it} = {} & \beta(P_i \times PostTraining_t) + \gamma(\mathbf{X_i} \times PostTraining_t) \\ & + \alpha_i + \delta_t + \varepsilon_{it}, \end{aligned} \tag{4}$$

where $Y_{it}$ is the management practices score or the logged monthly profits for entrepreneur $i$ in survey wave $t$; $P_i$ is the average proximity of assigned discussion peers, as described in Equation (2). *PostTraining* is a dummy variable equal to one for time periods after the training program and zero for the baseline period. $\mathbf{X_i}$ is a vector of two control variables, receiving social skills training and the number of matched peers the entrepreneur knew from before the training. Both are time invariant and thus absorbed by the fixed effects. However, to account for the fact that these variables might have a time-varying effect we interact each with the *PostTraining* time indicator.[6]

Regressions using dyadic data cluster standard errors at the ego, alter, and dyad levels (Kleinbaum et al. 2013). Regressions using entrepreneur-level data cluster standard errors at the neighborhood level letting observations be independent across neighborhoods but not across participants in the same neighborhood.

Including entrepreneur fixed effects in our models is critical because they control for differences in the kinds of neighborhoods that entrepreneurs are located in, which is likely related to the number of local peers they are assigned and their performance. In particular, entrepreneurs in crowded neighborhoods are more likely to be assigned neighboring discussion peers simply because there are more of them but are also likely to

**Table 1.** Baseline Summary Statistics

| | Mean | Standard deviation | Minimum | 25th percentile | Median | 75th percentile | Maximum |
|---|---|---|---|---|---|---|---|
| *Profits (log)* | 10.942 | 1.146 | 8.294 | 10.127 | 10.820 | 11.608 | 14.670 |
| *Performance index* | 0.017 | 0.631 | −0.670 | −0.305 | −0.144 | 0.139 | 4.801 |
| *Ave. proximity* | 0.534 | 0.155 | 0.017 | 0.440 | 0.536 | 0.644 | 0.917 |
| *Peers within 1 km* | 0.142 | 0.390 | 0 | 0 | 0 | 0 | 2 |
| *Peers within 2 km* | 0.270 | 0.499 | 0 | 0 | 0 | 0 | 2 |
| *Peers within 3 km* | 0.500 | 0.653 | 0 | 0 | 0 | 1 | 2 |
| *Peers within 4 km* | 0.745 | 0.751 | 0 | 0 | 1 | 1 | 3 |
| *Peers known from before* | 0.478 | 0.844 | 0 | 0 | 0 | 1 | 3 |
| *Social skills training* | 0.504 | 0.501 | 0 | 0 | 1 | 1 | 1 |
| *Management practices score* | 0.593 | 0.257 | 0 | 0.407 | 0.630 | 0.778 | 1 |
| *Local association member* | 0.113 | 0.317 | 0 | 0 | 0 | 0 | 1 |
| *Firm age* | 11.223 | 7.756 | 0 | 4.5 | 10 | 17 | 42 |
| *Ewe ethnic group* | 0.785 | 0.412 | 0 | 1 | 1 | 1 | 1 |
| *Years in current location* | 9.661 | 8.367 | 0 | 4 | 7 | 14 | 42 |
| *Peers from same industry* | 0.547 | 0.700 | 0 | 0 | 0 | 1 | 2 |
| *Peers known from before within 1 km* | 0.051 | 0.237 | 0 | 0 | 0 | 0 | 2 |
| *Peers known from before within 2 km* | 0.099 | 0.311 | 0 | 0 | 0 | 0 | 2 |

*Note.* $N = 274$.

operate in more competitive environments that might lower their performance. As a result, the probability of treatment (i.e., assignment to a neighbor) would end up correlated with underlying business performance. However, given that entrepreneurs' neighborhoods are fixed and do not shift during our one-year study, entrepreneur fixed effects will account for all such differences.

Whereas fixed effects can remove selection bias, they can also introduce their own bias because of the way models with fixed effects weigh and average the underlying within effects (Gibbons et al. 2019). Fortunately, when analyzing experiments, inverse propensity weights (IPW) can be used to fully address this weighting-induced fixed effect bias. Because we know the *exact* assignment procedure we can calculate the *actual* probability of assignment, and so the inverse propensity weight, for each observation. We include IPWs in all our models.[7]

Finally, Equations (3) and (4) do not include control variables that vary posttreatment to avoid biasing our estimates (Acharya et al. 2016). The two control variables we do include—social skills and the number of assigned peers known from before—are both measured pretreatment and so *cannot* be the result of our treatment.

## Results

### Ties to Proximate Peers Are More Sustaining

Hypothesis 1 argues that entrepreneurs assigned to neighboring peers during the networking event will be likelier to sustain relationships with them. We estimate Equation (3) to test this and Table 2 shows the regression results. In Model 1, the coefficient for proximity is positive and statistically significant, indicating that the closer two discussion partners are located, the more likely they will sustain a relationship.

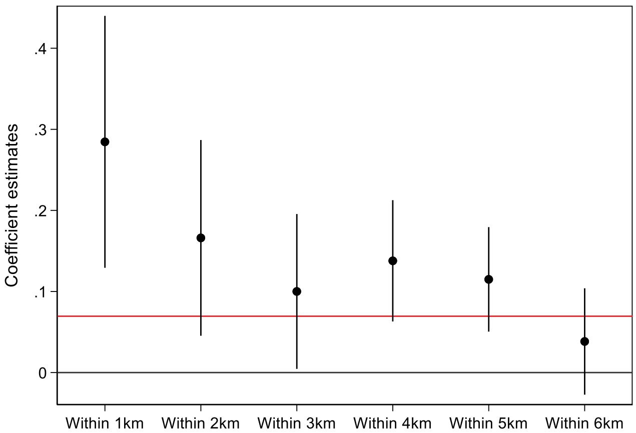
Models 2–5 in Table 2 estimate the effect of assigned peers being within different radii on sustaining a tie. The coefficients gradually decrease in magnitude as the radii increase, suggesting that the likelihood of sustaining a tie decreases as the radii increase. Being assigned to a peer within 1-km increases the likelihood of sustaining a relationship with them on average by approximately 30 percentage points over the next year. These results suggest strong support for the hypothesis that peers whose businesses are more proximate are likelier to sustain ties. The coefficients from these radii regressions are plotted in Figure 2, along with additional

**Table 2.** Effect of Proximity on Tie Maintenance

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Proximity* | 0.281*** | | | | |
| | (0.089) | | | | |
| *Peer within 1 km* | | 0.285** | | | |
| | | (0.079) | | | |
| *Peer within 2 km* | | | 0.166** | | |
| | | | (0.061) | | |
| *Peer within 3 km* | | | | 0.100* | |
| | | | | (0.048) | |
| *Peer within 4 km* | | | | | 0.138*** |
| | | | | | (0.038) |
| Survey wave fixed effects | Yes | Yes | Yes | Yes | Yes |
| Entrepreneur fixed effects | Yes | Yes | Yes | Yes | Yes |
| Peer fixed effects | Yes | Yes | Yes | Yes | Yes |
| *N* | 2,286 | 2,286 | 2,286 | 2,286 | 2,286 |
| Dyads | 425 | 425 | 425 | 425 | 425 |
| Entrepreneurs | 274 | 274 | 274 | 274 | 274 |

*Notes.* All models control for whether the matched pair knew each other from before the event. The outcome is an indicator of whether a matched tie was sustained after the training program; therefore, there are three posttraining time periods. Robust standard errors multiway clustered by ego, alter, and dyad in parentheses.

**Figure 2.** (Color online) Proximity Increases the Probability of Tie Maintenance




*Notes.* This figure shows coefficient estimates from Table 2, which indicate the effect of proximity on sustaining a tie between the entrepreneur and each of their assigned peers. Proximity is measured at different radii around the entrepreneur. The figure shows that as the radius around the entrepreneur increases, the likelihood they will remain in touch with their assigned peer decreases. The horizontal line above zero represents the baseline effect of being in the same cohort on sustaining a tie, which is approximately 7%.

coefficients not shown in Table 2 for radii of 5, 6, and 7 km. There is a clear decrease in the effect size as the randomly assigned peers are farther away.

The horizontal line above zero in Figure 2 represents the mean probability of sustaining a tie among any pair of entrepreneurs in their cohort of roughly 20 entrepreneurs, excluding pairs from the “speed dating” event. This probability is approximately 7% and provides us with a baseline likelihood of sustaining a tie without the encouragement of the “speed date.” Comparing this baseline probability to the coefficient estimates reveals that at distances greater than 3 km a “speed date” does not increase the probability of sustaining a relationship over and above simply attending the same larger event. Put differently, although events can engineer ties to neighbors, we find no evidence that the random assignment can spark relationships with peers who are farther than 3 km away.

A concern with these results could be that they reflect baseline differences in the value of the matches rather than differences in the cost of maintaining them. In other words, perhaps entrepreneurs stayed in touch with neighbors because their initial meetings with them went better. If this were true, then entrepreneurs would be maintaining ties with more proximate peers not because the relational costs of sustaining them are lower, but because they perceive there is more valuable information to be gained from neighbors. To rule out this alternative explanation, we use data that describes entrepreneurs’ first meetings with their assigned peers obtained from the exit survey and entrepreneurs’ handwritten notes. Using these sources of data, we created the following variables:

*Perceived quality of peer* measures the extent to which the focal entrepreneur perceived their matched peer to be a competent and successful entrepreneur. Entrepreneurs responded on a five-point Likert scale in the exit survey.

*Intention to follow-up* is a binary variable indicating whether the focal entrepreneur declared their intention to follow-up with their matched peer in the weeks after the training program in the exit survey.

*Contact information* is a binary variable indicating whether the focal entrepreneur exchanged contact information, such as phone number or email, with their matched peer. This is another indicator of entrepreneurs’ intention to stay in touch and maintain their tie with their peer, measured in the exit survey.

*Perceived usefulness of advice* measures the extent to which entrepreneurs perceived the advice they received from their matched peer to be useful and actionable. Entrepreneurs answered on a seven-point Likert scale in the exit survey.

*Words written* is an indicator of the amount of information exchanged between matched peers. This variable was constructed by scanning entrepreneurs’ handwritten notes after their discussions and counting the number of words each entrepreneur wrote. Although this measure captures only information that was jotted down, it approximates the amount of advice received during each discussion.

To estimate the impact of spatial proximity on the quality of entrepreneurs’ initial interactions we use the same modeling approach as for the tie maintenance results in Table 2, described by Equation (3). For these analyses, however, the data concern only the initial meeting and therefore are only observed in the baseline time period. As a result, there are no survey wave fixed effects, however we preserve the ego and alter fixed effects, because each entrepreneur rated three partners.

Table 3 presents the results from regressing each of the outcomes described previously on the proximity of entrepreneurs to their matched peers. The results suggest that there are no systematic differences in the kinds of initial meetings that entrepreneurs had with neighboring peers or in the impressions they formed of them. This is reflected in the fact that none of the variables described previously, capturing perceptions of peers or aspects of their meetings, are associated with spatial proximity in a statistically significant manner. Moreover, coefficient magnitudes are generally small and near zero.

## Proximate Peers Improve Entrepreneurs’ Management Practices

Hypothesis 2 argues that meeting peers who are nearer improves managerial best practices. To test this, we

**Table 3.** Proximity and Interaction Characteristics

| | Perceived quality of peer (1) | Intention to follow-up (2) | Contact information (3) | Perceived usefulness of advice (4) | Words written (5) |
|---|---|---|---|---|---|
| *Proximity* | 0.005 | 0.116 | 0.093 | 0.220 | −10.006 |
| | (0.205) | (0.117) | (0.077) | (0.226) | (6.649) |
| Entrepreneur fixed effects | Yes | Yes | Yes | Yes | Yes |
| Peer fixed effects | Yes | Yes | Yes | Yes | Yes |
| *N* | 741 | 741 | 741 | 741 | 741 |
| Entrepreneurs | 274 | 274 | 274 | 274 | 274 |

*Notes.* Outcome variables were measured during the exit survey for the networking event. Because these outcomes are observed only once per matched dyad these models do not include survey wave fixed effects but still include ego and peer fixed effects. The models were estimated using OLS. Robust standard errors clustered by dyad, ego, and alter in parentheses in all models.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

regress entrepreneurs' management practices score on average peer proximity using the difference-in-differences estimation approach described by Equation (4). The results, shown in Table 4, suggest that entrepreneurs' management practice score improves as peers are located nearer to them. The coefficient for average peer proximity in Model 1 is positive and statistically significant. A one-standard-deviation increase in average proximity (about 2 km) is associated with an increase of six percentage points in entrepreneurs' management score. At baseline, the average entrepreneur in our sample used approximately 60% of best practices in the index of McKenzie and Woodruff (2017), which implies that increasing the average proximity of three matched peers by 2 km should increase the average entrepreneur's management score from 60% to 66%. This change is approximately equivalent to the adoption of one new management best practice by the entrepreneur. Models 2–5 show a similar pattern using measures of colocation based on radii. As assigned peers are located further away, entrepreneurs' management practices tend to improve less.

Figure 3 provides a graphical depiction of the impact of meeting neighbors on management practices. It plots the average predicted management practices score for entrepreneurs who were assigned peers one standard deviation above or below the mean in proximity, using estimates from Model 1 in Table 4. According to the figure, after six weeks, entrepreneurs assigned more proximate peers increase the number of management practices they use compared with those assigned to more distant peers.

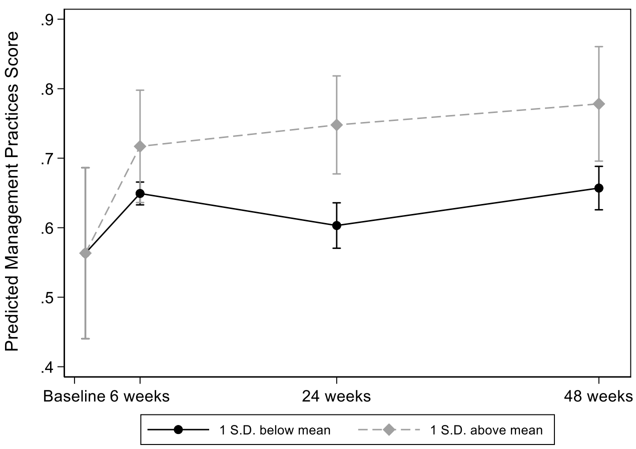
Having shown that entrepreneurs' management practices improve when assigned nearer peers, we explore whether this improvement is driven by entrepreneurs adopting their peers' practices, which would

**Table 4.** Impact of Average Peer Proximity on Management Practices Score

| | Management practices score | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Post-Training × Ave. proximity* | 0.377** | | | | |
| | (0.125) | | | | |
| *Post-Training × Peers within 1 km* | | 0.104* | | | |
| | | (0.040) | | | |
| *Post-Training × Peers within 2 km* | | | 0.080* | | |
| | | | (0.035) | | |
| *Post-Training × Peers within 3 km* | | | | 0.036 | |
| | | | | (0.028) | |
| *Post-Training × Peers within 4 km* | | | | | 0.051* |
| | | | | | (0.022) |
| Entrepreneur fixed effects | Yes | Yes | Yes | Yes | Yes |
| Survey wave fixed effects | Yes | Yes | Yes | Yes | Yes |
| *N* | 1,033 | 1,033 | 1,033 | 1,033 | 1,033 |
| Entrepreneurs | 274 | 274 | 274 | 274 | 274 |

*Notes.* All models control for the number of assigned peers entrepreneurs knew from before the program interacted with the posttraining indicator and training in social skills interacted with the posttraining indicator, as well as an indicator for posttraining time periods. IPW weights included in all models. Robust standard errors clustered by entrepreneurs' neighborhood in parentheses.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

**Figure 3.** Effect of Peer Proximity on Management Practices




*Notes.* This figure plots the average predicted management score for entrepreneurs who were one standard deviation above and below the mean in terms of the proximity of their assigned peers. The predicted values are based on the coefficient estimates from Table 4. The pattern illustrated by the figure is that entrepreneurs with peers who are nearby continue to learn over time, after their initial meeting at baseline.

suggest that entrepreneurs are *learning* from them. To test this, we estimate the following model:

$$\begin{aligned} Use\_Practice_{pi,t>0} = {} & \theta\ Use\_Practice_{pi,t=0} \\ & + \delta\ Peers\_Use_{pi,t=0} \\ & + \beta(P_i \times Peers\_Use_{pi,t=0}) \\ & + \gamma Practice\_Prevalence_{p,t=0} + \alpha_i \\ & + \varepsilon_{pi}, \end{aligned}$$

where $Use\_Practice_{pi,t>0}$ is a binary indicator for whether entrepreneur $i$ ever used managerial practice $p$ during the posttraining time periods. There are 27 managerial best practices that entrepreneurs can use, as defined by McKenzie and Woodruff (2017). $Use\_Practice_{pi,t=0}$ is an indicator for whether the focal entrepreneur used practice $p$ at baseline ($t = 0$) before the networking event. Similarly, $Peers\_Use_{pi,t=0}$ is the share of entrepreneur $i$'s assigned peers who used practice $p$ at baseline. $P_i$ is our measure of average peer proximity. $Practice\_Prevalence_{p,t=0}$ is the percentage of all entrepreneurs in the sample, excluding the focal entrepreneur and their assigned peers, who use management practice $p$ at baseline, which controls for the prevalence of each practice and how easy it may be to implement. Finally, $\alpha_i$ are entrepreneur fixed effects. In this model, the level of analysis is the entrepreneur practice. Hence, all posttraining time periods are collapsed, which is why there are no time fixed effects.

Table 5 shows the regression results. Model 1 regresses use of a practice on whether it was used at baseline, the share of assigned peers who used it at baseline, and the average proximity of assigned peers, without including any fixed effects. As would be expected, using a practice at baseline is predictive of continuing to use it after the training. Also, peers' use of a practice at baseline is positively associated with the focal entrepreneur using that practice afterward. Finally, there is no statistically significant relationship between the average proximity of peers and the use of managerial practice after the training.

Model 2 introduces the interaction between average peer proximity and peers' use of a practice at baseline, which is positive and statistically significant. A focal entrepreneur in the posttraining period is more likely to use a practice that was used by their assigned peers at baseline, the closer those assigned peers are located. Model 3 introduces entrepreneur fixed effects to account for differences between entrepreneurs in their location and types of businesses. The interaction term remains positive and statistically significant in this model as well.

The coefficient estimates suggest that a one-standard-deviation increase in average peer proximity, which represents an increase of approximately 2 km in the three peers' proximity, increases the probability that a practice used by all assigned peers at baseline will later be used by the focal entrepreneur by 1 percentage point. Of course, given that there are 27 practices, the cumulative probability of learning at least one new practice from peers increases substantially as proximity to peers increases.

Beyond these direct spillovers, in Online Appendix A20, we show that neighboring entrepreneurs are also more likely to "co-experiment" and adopt new practices together (Park and Puranam 2023). These are practices that neither had used before the training program. This coexperimentation suggests the value of getting to know a neighbor lies not just in diffusing existing knowledge but potentially in promoting experimentation and discovery of new business practices that can spur performance and growth.

## Proximate Peers Improve Entrepreneurs' Performance

Table 6 presents regressions testing the effect of proximity to peers after the networking event on performance. All regressions in Table 6 estimate Equation (4). In Models 1–5, the outcome is monthly profits (log), whereas in Model 6 the outcome is the performance index.

Model 1 estimates the effect of average peer proximity on entrepreneurs' log monthly profits. According to the results, increasing the average proximity of the three assigned peers by 1 km leads to an increase in monthly profits of approximately 10%. Described differently, increasing the average proximity of peers by one standard deviation—equivalent to the three

**Table 5.** Adopting Practices from Peers

| | Practice used during posttreatment | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Average peer proximity × Number of assigned peers using practice at baseline* | | 0.069* | 0.065* |
| | | (0.025) | (0.030) |
| *Average peer proximity* | 0.016 | −0.094 | |
| | (0.029) | (0.056) | |
| *Number of assigned peers using practice at baseline* | 0.006 | −0.031* | −0.029 |
| | (0.007) | (0.015) | (0.018) |
| *Practice used by focal entrepreneur at baseline* | 0.070** | 0.070** | 0.053** |
| | (0.010) | (0.010) | (0.011) |
| *Leave-out mean of sample using practice* | 0.011** | 0.011** | 0.011** |
| | (0.000) | (0.001) | (0.001) |
| Entrepreneur fixed effects | No | No | Yes |
| *N* | 7,398 | 7,398 | 7,398 |
| Management practices | 27 | 27 | 27 |
| Entrepreneurs | 274 | 274 | 274 |

*Notes.* Level of analysis is the entrepreneur-management practice. The outcome variable in all models is whether a managerial practice $p$ was used by entrepreneur $i$ after the training program. All models control for social skills training and the number of assigned entrepreneurs known from before. Robust standard errors clustered by entrepreneurs' neighborhood in parentheses.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

matched peers being 1.9 km nearer—leads to a 21% increase in monthly profits.

These effect sizes are difficult to compare with other studies that explore the effect of matching peers, because those studies tend not to measure the geographic proximity of matched peers. However, in general, our findings seem to fall within the lower range of what previous studies show. For example, Cai and Szeidl (2018) find a 30% increase in profits from being assigned to a group of peers located in the same region compared with being assigned to no peers. Fafchamps and Quinn (2018) find that assigning a manager to a committee of four to five other managers, increases the likelihood of adopting certain business practices by 8%–12%, which is higher than what we find. Lafortune et al. (2018) randomly assign entrepreneurs to meet a role model, which leads to an increase in profits of about 30%. Finally, Chatterji et al. (2019) find that entrepreneurs connected to peers with better management practices grew their businesses by 28% two years later. Although the comparison is imperfect, these studies suggest that the performance and learning effects we find are within the range of what other studies report.

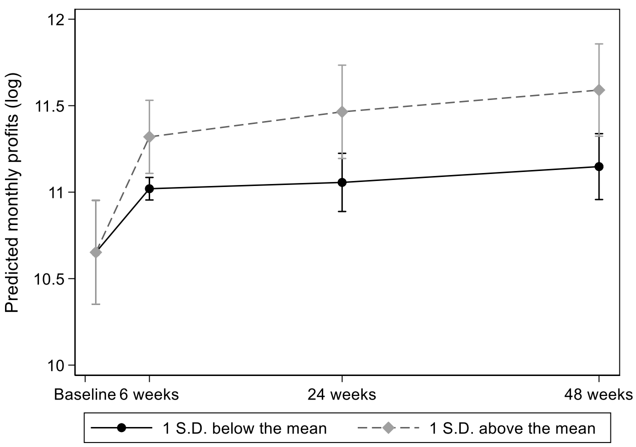
We plot the performance effects in Figure 4.[8] The dashed gray line shows the average predicted log monthly profits at each survey wave for entrepreneurs

**Table 6.** Impact of Average Peer Proximity on Performance

| | Monthly profits (log) | | | | | Performance index |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Post-Training × Ave. proximity* | 1.247* | | | | | 1.100* |
| | (0.516) | | | | | (0.441) |
| *Post-Training × Peers within 1 km* | | 0.329** | | | | |
| | | (0.108) | | | | |
| *Post-Training × Peers within 2 km* | | | 0.230** | | | |
| | | | (0.079) | | | |
| *Post-Training × Peers within 3 km* | | | | 0.146* | | |
| | | | | (0.062) | | |
| *Post-Training × Peers within 4 km* | | | | | 0.140 | |
| | | | | | (0.091) | |
| Entrepreneur fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey wave fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 1,033 | 1,033 | 1,033 | 1,033 | 1,033 | 1,033 |
| Entrepreneurs | 274 | 274 | 274 | 274 | 274 | 274 |

*Notes.* All models control for the number of assigned peers entrepreneurs knew from before the program interacted with the posttraining indicator and training in social skills interacted with the posttraining indicator, as well as an indicator for posttraining time periods. Inverse propensity score weights included in all models. Robust standard errors clustered by entrepreneurs' neighborhood in parentheses.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

**Figure 4.** Proximate Discussion Peers Increase Performance




*Notes.* The plot compares the predicted log monthly profits for entrepreneurs who were randomly assigned discussion peers one standard deviation below and above the mean in terms of their proximity. Bars represent 95%confidence intervals. Profits for entrepreneurs with peers one standard deviation above the mean (gray dashed line) indicate an increasing pattern, whereas those assigned peers one standard deviation below the mean do not show significant increases in performance.

whose assigned peers were one standard deviation above the mean in average proximity. The solid black line shows the predicted log monthly profits for entrepreneurs whose discussion peers were one standard deviation below the mean in average proximity. The average performance for entrepreneurs with peers who are more proximate is higher than that of entrepreneurs whose peers are further away beginning six weeks after the training.

Figure 4 also illustrates that entrepreneurs assigned more distant peers may also experience increases in performance, although these are smaller. Hence, being assigned distant peers is not bad; rather, it produces smaller returns than forming ties with neighbors.

Models 2–5 in Table 6 measure peer proximity as the number of discussion peers within a given radius around the focal entrepreneur. Model 2 uses a radius of 1 km and estimates the impact on profits of being assigned an additional discussion peer located within 1 km. Coefficient estimates suggest that, on average, being assigned another peer that is 1 km or nearer increases profits by approximately 30% with a confidence interval from 12% to 55%. Similarly, being assigned an additional peer within 2 km of leads on average to an increase of approximately 20% and being assigned a peer within 3 km leads to an approximately 10% increase in performance.

By construction, these measures of proximity based on radii tend to overstate the impact of proximity on performance because in each case the reference group are entrepreneurs who were assigned a peer *anywhere outside that radius*. In other words, the performance effect of being assigned a peer less than 1 km away is compared with the average performance effect of peers from any other location across the city further than 1 km away. This comparison tends to stack the odds in favor of finding a large effect for peers who are within 1 km because they are being compared with peers in a variety of locations that we might not expect to have a meaningful relevance to the focal entrepreneur.

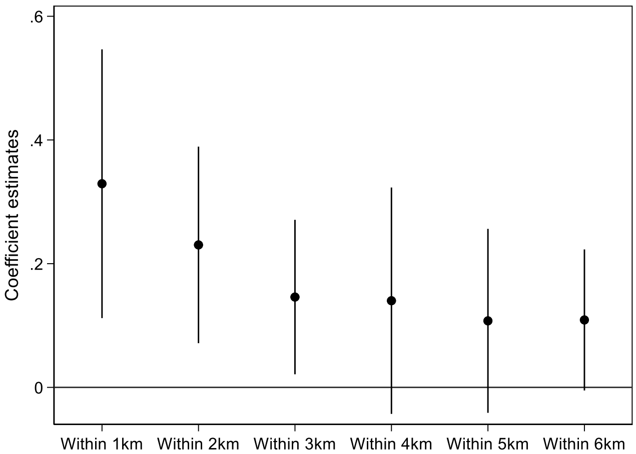
These radial measures of proximity are instead meant to be compared against each other. On its own the coefficient for being assigned a peer within 1 km tells us relatively little. However, compared with the impact of being assigned a peer within 2 km, it conveys much more. From this perspective, being assigned a peer within 1-km increases performance by nearly 10% compared with being assigned a peer within 2 km. Similarly, being assigned a peer within 2 km, rather than 3 km, increases the performance impact of that peer by about 8%. The pattern that emerges from these coefficients is that increasing the proximity of assigned peers increases their impact on performance, which is consistent with the effect estimated using the continuous measure of proximity.

In Figure 5, we plot the coefficients from these regressions and include coefficients for radii of 5 and 6 km. The plotted coefficients show that as the distance from the focal entrepreneur increases, the effect of peers decreases. It is important to note that, because all entrepreneurs received the same number of discussion peers, the reference group in these models is not "not receiving a peer" but rather "receiving a peer outside the radius." Hence, the models do not suggest that meeting an additional peer is not valuable when they are 4 km or more away, but rather that the difference between them being inside the radius or not is no longer significant. Moreover, as we describe in Online Appendix A11, at distances of 4 km or more the proportion of entrepreneurs not treated decreases, reducing our statistical power to detect effects, which suggests that we may also be underpowered to detect small performance effects at larger distances.

Finally, Table 6 also estimates the effect of average peer proximity on the performance index in Model 6. The performance index is an alternative approach to measuring entrepreneur performance that helps mitigate concerns related to measurement error and outlier observations (Kling et al. 2007). The results from Model 6 suggest very similar performance effects from meeting more proximate peers. The coefficient is positive and statistically significant and is similar in magnitude as the coefficient in Model 1.

In Online Appendix A8 we replicate these performance results using dyad-level data. In those regressions the unit of observation is the entrepreneur-peer match, and we regress the focal entrepreneurs' performance on their distance from each assigned peer, including ego and alter fixed effects.

**Figure 5.** Coefficient Plot of Discussion Peers' Performance Effect by Expanding Radii




*Notes.* The points plotted represent coefficient estimates from regressions of monthly profits on the number of discussion peers within different radii of the focal entrepreneur, shown in Table 6. The vertical bars represent standard errors, which were clustered at the neighborhood level in the regressions. As expected, the effect of peers on performance decreases with distance.

## Robustness Checks

In peer effects studies, such as ours, interactions between individuals with different treatment status can pose a threat to unbiased causal inference (Manski 2013, Bramoullé et al. 2020). We used randomization inference to check whether the effects we find are driven by "peers-of-peers." Online Appendix A19 presents our methodology and results in detail. We find no evidence that the effect of being matched with a neighbor is driven by that neighbor's other matched peers or their peer's peers from the networking event.

We also used randomization inference to calculate exact *p* values for the direct effect of matched peers on the focal entrepreneur's profits, which helps account for randomization uncertainty (Aronow 2012, Athey et al. 2018). The results are provided in Online Appendix A19, and they reject the null that there are no direct peer effects.

We also checked that various entrepreneur and peer characteristics were not driving our results. In Online Appendices A9 and A12, we show that our results do not change when we include additional controls for entrepreneurs' ethnicity, gender, education, and their business' age. We also control for the number of assigned peers who are in the same industry as the focal entrepreneur, share the same gender, their average management practices score, their average firms' age, the average size of their firms in terms of employees, and the average number of entrepreneurs peers knew.

Similarly, to rule out that our results are driven by neighborhood-specific shocks we replicate our results with neighborhood-by-survey wave fixed effects, which helps account for potential neighborhood specific shocks during the period of observation. The effect of average peer proximity is still positive and statistically significant across outcomes. We present these regressions in Online Appendix A13.

In addition to different control variables and fixed effects, we also tested different versions of our outcome and explanatory variables. We replicated our performance results using a winsorized measure of profits at the 1st and 99th percentiles. Online Appendix A8 shows these results. Similarly, the measure of peer proximity we use in our analyses is based on the straight-line distance between entrepreneurs (Gibson and McKenzie 2007). Using Google Maps API, we calculated the travel distance in kilometers and the walking time in minutes between each entrepreneur and their assigned peers. We replicate all our results using these alternative measures of distance in Online Appendix A17.

Finally, a potential concern with our empirical setting is that some cohorts of entrepreneurs also received training in social skills. To ensure that our effects were not unduly influenced by the social skills training, we split our sample by social skills training and estimated the regressions using each subsample. All our effects hold in each subsample and are not statistically different in magnitude across them, as shown in Online Appendix A14.

## Entrepreneurs Are Locally Undernetworked

Our results show that the value of events for entrepreneurs in Togo lies in facilitating introductions to neighbors. These introductions are valuable because the relational cost of sustaining those relationships is lower, which reveals something about search costs in Togo. The fact that introductions to neighbors has such a significant performance effect suggests that search costs in places like Togo are so high that entrepreneurs tend not to know their neighbors, despite their physical proximity. We label this phenomenon as entrepreneurs being "locally undernetworked." In our sample, the correlation between knowing a matched peer from before the training and that peer being located within only 1 km of the focal entrepreneur is only about 8% (see Table A1.3 in Online Appendix A1), which aligns with our description of these entrepreneurs as undernetworked. Moreover, if the average entrepreneur knew their neighbors, there would be little impact on performance from getting to know yet another neighbor. Entrepreneurs in places like Togo may be undernetworked because information about neighbors is scarce and unreliable, it could be driven by the lack of local brokering organizations and networking venues, or it could be driven by a lack of generalized trust that makes approaching strangers difficult (Small 2009). Whatever the source of frictions, entrepreneurs in these environments seem to be constrained in their ability to develop local business networks, preventing them from knowing peers they could benefit from.

If this argument is correct, we would expect those few entrepreneurs who are not locally under-networked to benefit less from meeting neighbors during the event we study. To test this, we proxy for the extent to which an entrepreneur knows others locally by using a measure of local embeddedness from the social capital literature: *membership in local associations* (Putnam 2000, Ruef and Kwon 2016). Only about 10% of entrepreneurs in our sample were members of one or more local associations. We expect entrepreneurs who are members of local associations to know more people in their neighborhoods and therefore be less likely to be under-networked. These entrepreneurs should therefore not benefit as much from being matched to another neighbor during the event.

Results in Table A7.2 in Online Appendix A7 show that for entrepreneurs who were members of a local association, being matched with a distant peer was more valuable than being matched with a neighbor. In Models 1 and 2, the three-way interaction term is negative and statistically significant, suggesting that for entrepreneurs who participate in local associations the value of a new acquaintance decreases the closer they are located to them. All models in Table A7.2 include controls for social skills training and peers known from before, as well as continuous IPW. These results confirm the intuition that entrepreneurs who are not locally undernetworked do not benefit from meeting neighbors.

These results indirectly suggest that entrepreneurs in Togo face substantial local search costs, which constrains their ability to form local business networks. This in turn makes events valuable opportunities to overcome these local search frictions.

# Discussion

Research shows that events often lead to new ties and knowledge spillovers. We extend this literature on events to high-friction environments and argue that events in these contexts generate value mostly among participants who remain colocated after the event. Although events reduce search costs, making it easier for participants to match, they do not reduce the relational costs of sustaining those matches. As a result, in high-friction environments, only colocated peers are likely to stay in touch after the event, concentrating the various knowledge-sharing effects of events among neighboring participants.

We find support for these arguments using data from a series of networking events in Lomé, Togo, that randomly matched entrepreneurs with peers. Our results show that in Togo the benefits of events are driven by introducing neighbors to each other. These results imply that, on average, entrepreneurs in Togo tend to be constrained by networking frictions that limit their ability to form local business networks. Taken together, our results show that forming a match or connection is not sufficient to generate knowledge sharing and performance effects, maintaining it also plays a critical role. In the language of experiments, distance shapes both who an entrepreneur is treated with and which treatments they "comply" with.

## Managerial Implications

Our results have several managerial implications. First, our results suggest that in contexts with networking frictions, networking events that seek to generate knowledge spillovers should bring together participants who will remain located near each other after the event. This should enable entrepreneurs to form more connections that last and from which they can learn. For example, rather than focusing on citywide or nationwide conferences, mixers, or trainings, organizers may instead focus on creating smaller neighborhood events. If this is not possible, event organizers might still generate spillovers among otherwise distant peers if they are able to provide support for participants to sustain the ties they form. Such support may include travel vouchers or access to video conferencing technology, that enables entrepreneurs to keep contact with those they meet despite being far apart.

Second, our results also have implications for how entrepreneurs in high networking friction environments should network. Given the high costs of maintaining ties in these contexts, entrepreneurs in these contexts should focus their efforts on first getting to know their neighbors. This can be achieved by participating in local events or, potentially, by reaching out directly. Doing this will enable entrepreneurs to tap into local managerial knowledge while incurring fewer relational costs. Of course, for those entrepreneurs who already know many of their neighbors, it is important that they begin reaching out to more distant contacts who may possess more novel information. Taken together our results suggest that entrepreneurs may benefit from beginning locally and expanding outwards in their networking.

## Limitations and Future Research Directions

It is important to note that this study has several limitations and boundary conditions. First, our sample of entrepreneurs is from a single institutional environment, characterized by a lack of legal protections, poor transportation infrastructure, limited communication technology, and a lack of local organizations that promote entrepreneurship. Although these conditions are representative of many sub-Saharan African economies, they are not representative of more developed economies. Therefore, it is unclear whether the peer effects we find generalize to more developed contexts. Entrepreneurs in higher income contexts may find more distant peers to be more valuable. Future work should explore whether events can generate valuable matches over larger geographic distances in more developed economies.

Another limitation with this study is that it does not shed light on what networking frictions consist of and why more local ties do not form endogenously. Existing research suggests that a variety of complex factors may constrain entrepreneurs' ability to network with their neighbors in places like Togo. Factors such as a lack of legal protections or ascribed characteristics such as ethnicity and gender could be barriers to building local relationships. This study cannot identify which of these factors create networking frictions for Togolese entrepreneurs. Our hope is that future research will explore these dynamics in more detail.

In addition to this, our data are also limited in terms of the geographic distances between entrepreneurs. Entrepreneurs in our sample were all from Lomé, which means that the furthest distance between matched entrepreneurs was the span of the city (approximately 50 km). It is possible that beyond a certain distance peers become more valuable despite the relational costs. Future studies will hopefully explore whether there might be a u-shaped relationship between peer distance and performance, whereby peers beyond certain distances become similarly valuable to neighbors.

Furthermore, this study is only focused on the role of geographic distance in affecting the value of meeting a peer entrepreneur. In Online Appendix A15, we also explore how various other peer characteristics might affect performance, including peer similarity, size, performance, management practices, and network size. In all cases the regressions do not provide evidence that any of these factors affect focal entrepreneurs' performance. Future studies should explore whether, in addition to meeting neighboring peers, entrepreneurs also benefit more from meeting coethnic or same gender entrepreneurs.

Finally, the event we studied was in-person, making it difficult to generalize to online events, which are becoming increasingly prevalent. Although our theoretical arguments about relational costs and the importance of sustaining ties after the event should generalize to the case of online events, it may be possible that online events create a digital means of maintaining relationships over large distances without ever meeting in person. We believe the possibility that online events generate a new kind of knowledge spillover is an exciting area for future research.

Events that bring together entrepreneurs and attempt to replicate powerful agglomerative conditions have the potential to improve entrepreneurs' outcomes and hold great promise as a tool for supporting entrepreneurship. In this study, we show that in high friction environments the benefits of events may lie in encouraging entrepreneurs who are located near each other to form ties and share knowledge. These results suggest that entrepreneurs in these settings may be under-networked, making events particularly valuable for them.

## Endnotes

[1] We find it helpful to label the growing number of studies that explore social or professional events as "social event studies." These "social event studies" should not be confused with financial event studies focused on changes in the value of the firm after announcements and other exogenous shocks.

[2] The training program brought entrepreneurs together from considerable distances. The average distance between entrepreneurs in the same training cohort was 7.6 km, with a minimum distance of 50 meters and a maximum distance of 49 km.

[3] In Online Appendix A8, we show that our performance results also hold when our measure of profits is winsorized at the 1st and 99th percentiles.

[4] Although we believe this decay function is the most appropriate for our data, Online Appendix A5 also shows results using two alternative decay functions. The magnitude of coefficients and their statistical significance still hold under those alternative operationalizations.

[5] As an additional robustness check we also estimated all models after splitting the sample by social skills training and found no substantive differences between the subsamples. These regression tables are shared in Online Appendix A14.

[6] In Online Appendix A9, we estimate these models without these two control variables and the results remain unchanged, both in terms of statistical significance and the magnitude of the coefficients. We also present models which add other entrepreneur and peer controls in Online Appendix A12. We find that these also do not affect the magnitude or statistical significance of our results.

[7] In Online Appendix A2, we provide a simple example of the kind of bias that can be introduced by fixed effects, and in Online Appendix A3 we show that our performance results also hold when we do not include IPWs.

[8] The regressions used for Figure 4 are shown in Online Appendix A6.

## References

Abebe G, Caria S, Fafchamps M, Falco P, Franklin S, Quinn S, Shilpi F (2020) Matching frictions and distorted beliefs: Evidence from a job fair experiment. Report, Department of Economics, Oxford University, Oxford, UK.

Acharya A, Blackwell M, Sen M (2016) Explaining causal findings without bias: Detecting and assessing direct effects. *Amer. Political Sci. Rev.* 110(3):512–529.

Angrist JD, Lang K (2004) Does school integration generate peer effects? Evidence from Boston's Metco Program. *Amer. Econom. Rev.* 94(5):1613–1634.

Argote L, Ingram P (2000) Knowledge transfer: A basis for competitive advantage in firms. *Organ. Behav. Human Decision Processes* 82(1):150–169.

Aronow PM (2012) A general method for detecting interference between units in randomized experiments. *Sociol. Methods Res.* 41(1):3–16.

Arzaghi M, Henderson JV (2008) Networking off Madison Avenue. *Rev. Econom. Stud.* 75(4):1011–1038.

Asher S, Novosad P (2020) Rural roads and local economic development. *Amer. Econom. Rev.* 110(3):797–823.

Athey S, Eckles D, Imbens GW (2018) Exact p-values for network interference. *J. Amer. Statist. Assoc.* 113(521):230–240.

Atkin D, Chen MK, Popov A (2022) The returns to face-to-face interactions: Knowledge spillovers in Silicon Valley. NBER Working Paper No. 30147, National Bureau of Economic Research, Cambridge, MA.

Barthélemy M (2011) Spatial networks. *Phys. Rep.* 499(1–3):1–101.

Bloom N, Van Reenen J (2007) Measuring and explaining management practices across firms and countries. *Quart. J. Econom.* 122(4):1351–1408.

Bloom N, Genakos C, Sadun R, Van Reenen J (2012) Management practices across firms and countries. *Acad. Management Perspective* 26(1):12–33.

Bloom N, Eifert B, Mahajan A, McKenzie D, Roberts J (2013) Does management matter? Evidence from India. *Quart. J. Econom.* 128(1):1–51.

Boudreau KJ, Brady T, Ganguli I, Gaule P, Guinan E, Hollenberg A, Lakhani KR (2017) A field experiment on search costs and the formation of scientific collaborations. *Rev. Econom. Statist.* 99(4):565–576.

Bramoullé Y, Djebbari H, Fortin B (2020) Peer effects in networks: A survey. *Annu. Rev. Econom.* 12:603–629.

Cai J, Szeidl A (2018) Interfirm relationships and business performance. *Quart. J. Econom.* 133(3):1229–1282.

Catalini C (2018) Microgeography and the direction of inventive activity. *Management Sci.* 64(9):4348–4364.

Chai S, Freeman RB (2019) Temporary colocation and collaborative discovery: Who confers at conferences. *Strategic Management J.* 40(13):2138–2164.

Chatterji A, Delecourt S, Hasan S, Koning R (2019) When does advice impact startup performance? *Strategic Management J.* 40(3): 331–356.

Conley JF (2011) Estimation of exposure to toxic releases using spatial interaction modeling. *Internat. J. Health Geography* 10(1):1–12.

Cross R, Sproull L (2004) More than an answer: Information relationships for actionable knowledge. *Organ. Sci.* 15(4):446–462.

Dahlander L, McFarland DA (2013) Ties that last: Tie formation and persistence in research collaborations over time. *Admin. Sci. Quart.* 58(1):69–110.

De Mel S, McKenzie DJ, Woodruff C (2009) Measuring microenterprise profits: Must we ask how the sausage is made? *J. Development Econom.* 88(1):19–31.

De Vries JJ, Nijkamp P, Rietveld P (2009) Exponential or power distance-decay for commuting? An alternative specification. *Environment. Planning* 41(2):461–480.

Dimitriadis S (2021) Social capital and entrepreneur resilience: Entrepreneur performance during violent protests in Togo. *Strategic Management J.* 42(11):1993–2019.

Dimitriadis S, Koning R (2022) Social skills improve business performance: Evidence from a randomized control trial with entrepreneurs in Togo. *Management Sci.* 68(12):8635–8657.

Fafchamps M, Quinn S (2018) Networks and manufacturing firms in Africa: Results from a randomized field experiment. *World Bank Econom. Rev.* 32(3):656–675.

Fafchamps M, McKenzie D, Quinn S, Woodruff C (2012) Using PDA consistency checks to increase the precision of profits and sales measurement in panels. *J. Development Econom.* 98(1):51–57.

Fang TP, Wu A, Clough DR (2021) Platform diffusion at temporary gatherings: Social coordination and ecosystem emergence. *Strategic Management J.* 42(2):233–272.

Fisman R, Khanna T (1999) Is trust a historical residue? Information flows and trust levels. *J. Econom. Behav. Organ.* 38(1):79–92.

Fotheringham AS (1981) Spatial structure and distance-decay parameters. *Ann. Assoc. Amer. Geography* 71(3):425–436.

Gibbons CE, Serrato JCS, Urbancic MB (2019) Broken or fixed effects? *J. Econom. Methods* 8(1):2017–2029.

Gibson J, McKenzie D (2007) Using global positioning systems in household surveys for better economics and better policy. *World Bank Res. Observations* 22(2):217–241.

Habinek J, Martin JL, Zablocki BD (2015) Double-embeddedness: Spatial and relational contexts of tie persistence and re-formation. *Soc. Networks* 42:27–41.

Hansen MT (1999) The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Admin. Sci. Quart.* 44(1):82–111.

Hasan S, Bagde S (2013) The mechanics of social capital and academic performance in an Indian college. *Amer. Sociol. Rev.* 78(6):1009–1032.

Hasan S, Koning R (2019) Conversations and idea generation: Evidence from a field experiment. *Res. Policy* 48(9):103811.

Hasan S, Koning R (2020) Designing social networks: Joint tasks and the formation and endurance of network ties. *J. Organ. Design* 9(4):1–19.

Howell ST, Nanda R (2019) Networking frictions in venture capital, and the gender gap in entrepreneurship. Report, Harvard Business School, Boston.

Ingram P, Morris MW (2007) Do people mix at mixers? Structure, homophily, and the "life of the party". *Admin. Sci. Quart.* 52(4):558–585.

Ingram P, Roberts PW (2000) Friendships among competitors in the Sydney hotel industry. *Amer. J. Sociol.* 106(2):387–423.

Khanna T, Palepu K (2000) Is group affiliation profitable in emerging markets? An analysis of diversified Indian business groups. *J. Finance* 55(2):867–891.

Khanna T, Palepu KG (2010) *Winning in Emerging Markets: A Road Map for Strategy and Execution* (Harvard Business School Press, Cambridge, MA).

Kleinbaum AM (2018) Reorganization and tie decay choices. *Management Sci.* 64(5):2219–2237.

Kleinbaum AM, Stuart TE, Tushman ML (2013) Discretion within constraint: Homophily and structure in a formal organization. *Organ. Sci.* 24(5):1316–1336.

Kling JR, Liebman JB, Katz LF (2007) Experimental analysis of neighborhood effects. *Econometrica* 75(1):83–119.

Lafortune J, Riutort J, Tessada J (2018) Role models or individual consulting: The impact of personalizing micro-entrepreneurship training. *Amer. Econom. J. Appl. Econom.* 10(4):222–245.

Lane JN, Ganguli I, Gaule P, Guinan E, Lakhani KR (2021) Engineering serendipity: When does knowledge sharing lead to knowledge production? *Strategic Management J.* 42(6):1215–1244.

Levin DZ, Cross R (2004) The strength of weak ties you can trust: The mediating role of trust in effective knowledge transfer. *Management Sci.* 50(11):1477–1490.

Manski CF (1993) Identification of endogenous social effects: The reflection problem. *Rev. Econom. Stud.* 60(3):531–542.

Manski CF (2013) Identification of treatment response with social interactions. *Econom. J.* 16(1):S1–S23.

Martin JL, Yeung K-T (2006) Persistence of close personal ties over a 12-year period. *Soc. Networks* 28(4):331–362.

McEvily B, Zaheer A (1999) Bridging ties: A source of firm heterogeneity in competitive capabilities. *Strategic Management J.* 20(12): 1133–1156.

McFarland DA, Moody J, Diehl D, Smith JA, Thomas RJ (2014) Network ecology and adolescent social structure. *Amer. Sociol. Rev.* 79(6):1088–1121.

McKenzie D, Woodruff C (2014) What are we learning from business training and entrepreneurship evaluations around the developing world? *World Bank Res. Observations* 29(1):48–82.

McKenzie D, Woodruff C (2017) Business practices in small firms in developing countries. *Management Sci.* 63(9):2967–2981.

Nahapiet J, Ghoshal S (1998) Social capital, intellectual capital, and the organizational advantage. *Acad. Management Rev.* 23(2):242–266.

Park S, Puranam P (2023) Vicarious learning without knowledge differentials. *Management Sci.* 70(5):2705–3380.

Pierce L, Snyder JA (2017) The historical slave trade and firm access to finance in Africa. *Rev. Financial Stud.* 31(1):142–174.

Powell WW, White DR, Koput KW, Owen-Smith J (2005) Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences. *Amer. J. Sociol.* 110(4): 1132–1205.

Pun-Cheng LS (2016) Distance decay. Richardson D, Castree N, Goodchild MF, Kobayashi A, Liu W, Marston RA, eds. *International Encyclopedia of Geography: People, the Earth, Environment and Technology* (Wiley-Blackwell, Hoboken, NJ), 1–5.

Putnam RD (2000) *Bowling Alone: The Collapse and Revival of American Community* (Simon and Schuster, New York).

Rangan S (2000) The problem of search and deliberation in economic action: When social networks really matter. *Acad. Management Rev.* 25(4):813–828.

Roche MP, Oettl A, Catalini C (2022) (Co-)working in close proximity: knowledge spillovers and social interactions. NBER Working Paper No. 30120, National Bureau of Economic Research, Cambridge, MA.

Ruef M, Kwon S-W (2016) Neighborhood associations and social capital. *Soc. Forces* 95(1):159–190.

Samila S, Oettl A, Hasan S (2022) Helpful behavior and the durability of collaborative ties. *Organ. Sci.* 33(5):1701–2083.

Small ML (2009) *Unanticipated Gains: Origins of Network Inequality in Everyday Life* (Oxford University Press, Oxford, UK).

Sorenson O, Rivkin JW, Fleming L (2010) Complexity, networks and knowledge flows. Boschma R, Martin R, eds. *Handbook of Evolutionary Economic Geography* (Edward Elgar Publishing, Cheltenham, UK), 316–352.

Tsai W, Ghoshal S (1998) Social capital and value creation: The role of intrafirm networks. *Acad. Management J.* 41(4):464–476.

United Nations Development Programme (2017) Human development indicators: Togo. Jahan S, Jespersen E, eds. *Human Development Report* (UNDP, New York), 204–269.

U.S. Embassy in Togo (2019) Creating a new ecosystem of social entrepreneurs. Accessed June 23, 2024, https://tg.usembassy.gov/creating-a-new-ecosystem-of-socialentrepreneurs/.

Whittington KB, Owen-Smith J, Powell WW (2009) Networks, propinquity, and innovation in knowledge-intensive industries. *Admin. Sci. Quart.* 54(1):90–122.

World Bank (2016) *Country Highlights Togo* (World Bank Group, Washington, DC).

World Bank (2022) *Togo Country Economic Memorandum 2022: Toward Sustainable and Inclusive Growth* (World Bank Group, Washington, DC).

Yenkey CB (2015) Mobilizing a market: Ethnic segmentation and investor recruitment into the Nairobi Securities Exchange. *Admin. Sci. Quart.* 60(4):561–595.